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**Formulation and Solution Methods for
Locating Charging Stations and Routing of
Electric Vehicles**

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Ph.D. Dissertation

August 2023

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Abstract

The "electrification" of transport is one of the key features of the future of transport. As legislation becomes more and more stringent in terms of greenhouse gas emissions, the pressure to introduce 'green' technologies in the transport sector is increasing. Electric vehicles are one of the most direct ways of achieving this. The introduction of electric vehicles requires a special effort, as they are called upon to face a transport system based exclusively on fossil fuels, with the possibility of refuelling in every corner of the planet and at high speed.

Many companies have introduced or are about to introduce electric vehicles into their vehicle fleet and in order to manage them better, new algorithms must be developed that take into account the visits to charging stations, the effect of the vehicle load, the distance that the electric vehicles can travel, the charging rate of the batteries for correct completion of the vehicle routes and all the problems that arise based on the above.

Consequently, the Electric Vehicle Routing Problem is an important new problem, crucial for the success of the integration of electric vehicles in the supply chain. The new problems presented by electric vehicles stem from the use of batteries and electric motors, as opposed to a conventional diesel vehicle.

At the current level of development of energy storage technology, it is not possible to achieve the energy density of fossil fuels. As a result, the required charging frequency increases. This parameter alone would probably not be a problem for a conventional vehicle, but for an electric vehicle it is very important, as the charging time is much longer than the refuelling time of a conventional vehicle. This adds to the cost, given the driver's waiting time to charge the vehicle.

An additional level of difficulty is introduced by the fact that charging stations are required for electric vehicles. Such charging stations for electric vehicles are not as frequently found as petrol stations. The installation of new charging stations will be a very important parameter for the successful use of electric vehicles since new charging stations will have to be set up. The placement of these stations is extremely important to reduce the cost of vehicle travel, as stations located off the vehicle's route will contribute to the increase in costs. On the other hand, adding new charging stations without careful prior study will be a waste of resources, not only resources to set up the stations but also the resources that vehicles will waste in getting to these stations.

One option to consider is to use existing stations and add chargers to them, but the long charging times will become a cause of congestion.

An aspect of the Electric Vehicle Routing Problem that should be studied concerns a problem with a fleet of identical electric vehicles with limited battery capacity and space, while considering various strategies for managing charging periods, which can be either single or multiple, full or partial charging. The purpose of solving this problem is to create feasible solutions to the above problem with minimum cumulative cost and minimum number of vehicles. The addition of service

time windows would be interesting to explore.

The aim of the research is not to develop or improve vehicles or related technologies, but to successfully manage a set of such vehicles and minimise costs. The solution to this problem is complex as it involves solving and optimising not a simple Vehicle Routing Problem, but a problem with the additional constraints arising from the nature of electric vehicles. The additional difficulty concerns the intermediate stops that a vehicle may have to make at a charging station and the incorporation of realistic parameters for its solution. The aim is to represent the problem as realistically as possible.

For the solution, both metaheuristic and nature inspired algorithms will be implemented. These algorithms will either be based on pre-existing techniques that have already been tested on similar problems or will be completely new techniques and algorithms that can be applied to a wide range of Vehicle Routing Problems, such as those studied in this thesis.

Curriculum Vitae

Themistoklis Stamidianos graduated from the School of Production and Management Engineering in 2020, and since then he has been continuously engaged in scientific research. His great interest in automobiles and technology were inseparably combined in the context of this Ph.D. Dissertation. The following publications were published as a result:

- Stamadianos, T., Kyriakakis, N. A., Marinaki, M., & Marinakis, Y. (2023, May). Routing Problems with Electric and Autonomous Vehicles: Review and Potential for Future Research. In Operations Research Forum (Vol. 4, No. 2, p. 46). Cham: Springer International Publishing.
- Stamadianos, T., Kyriakakis, N. A., Marinaki, M., & Marinakis, Y. (2023). A hybrid simulated annealing and variable neighborhood search algorithm for the close-open electric vehicle routing problem. *Annals of Mathematics and Artificial Intelligence*, 1-24.
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., & Marinakis, Y. (2023). Dataset for the Cumulative Unmanned Aerial Vehicle Routing Problem. *Data in Brief*, 109296.
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., & Marinakis, Y. (2022). The electric vehicle routing problem with drones: An energy minimization approach for aerial deliveries. *Cleaner Logistics and Supply Chain*, 4, 100041.
- Stamadianos, T., Marinaki, M., Matsatsinis, N., & Marinakis, Y. (2022, June). A Hybridization of GRASP and UTASTAR for Solving the Vehicle Routing Problem with Pickups and Deliveries and 3D Loading Constraints. In International Conference on Learning and Intelligent Optimization (pp. 505-520). Cham: Springer International Publishing.
- Stamadianos, T., Marinaki, M., Matsatsinis, N., & Marinakis, Y. (2022, May). A DSS for the Multi-criteria Vehicle Routing Problem with Pickup and Delivery and 3d Constraints. In Decision Support Systems XII: Decision Support Addressing Modern Industry, Business, and Societal Needs: 8th International Conference on Decision Support System Technology, ICDSST 2022, Thessaloniki, Greece, May 23–25, 2022, Proceedings (pp. 177-189). Cham: Springer International Publishing.
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., Matsatsinis, N., & Marinakis, Y. (2022, September). A Bee Colony Optimization Approach for the Electric Vehicle Routing Problem with Drones. In International Conference on Machine Learning, Optimization, and Data Science (pp. 219-233). Cham: Springer Nature Switzerland.

- Stamadianos, T., Kyriakakis, N. A., Marinaki, M & Marinakis, Y., A Hybrid Genetic Algorithm For The Budget-constrained Charging Station Location Problem (Accepted for publication in: Conference Proceeding of Optimization, Simulation and Control – ICOSC 2022, Springer)
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., & Marinakis, Y., A Discrete Cuckoo Search Algorithm for the Cumulative Capacitated Vehicle Routing Problem (Accepted for publication in: Handbook of Formal Optimization, Springer)
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., & Marinakis, Y., A Greedy and Variable Neighborhood Search Metaheuristic Approach for the Cumulative Unmanned Aerial Vehicle Routing Problem (Accepted for publication in: Industrial Internet in Smart Manufacturing, Logistics, and Supply Chain Management, Springer)
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., & Marinakis, Y., A Simulated Annealing Heuristic Approach for the Energy Minimizing Electric Vehicle Routing Problem with Drones (Accepted for publication in: Industrial Internet in Smart Manufacturing, Logistics, and Supply Chain Management, Springer)
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., & Marinakis, Y., A Discrete Cuckoo Search Algorithm for the Cumulative Capacitated Vehicle Routing Problem (Accepted for publication in: Handbook of Formal Optimization, Springer)
- Stamadianos, T., Kyriakakis, N. A., Marinaki, M & Marinakis, Y., Meeting the Charging Demand of Electric Vehicles in Greece: Enabling Intercity Trips (Submitted for publication.)
- Stamadianos, T., Kyriakakis, N. A., Marinaki, M & Marinakis, Y., The Close-Open Mixed-Fleet Electric Vehicle Routing Problem (Submitted for publication.)
- Kyriakakis, N. A., Stamadianos, T., Marinaki, M., & Marinakis, Y., A GRASP Approach for the Energy Minimizing Electric Vehicle Routing Problem with Drones (Submitted for publication.)

Acknowledgements

As this chapter of my life draws to a close, I find it essential to express my heartfelt gratitude to the individuals who have been by my side throughout my Ph.D. studies.

First and foremost, I would like to extend my appreciation to my supervisor, Dr. Yannis Marinakis. His unwavering support, both in scientific matters and beyond, has been invaluable to me. His guidance, encouragement, and trust in my abilities have been instrumental in shaping the successful outcome of my studies.

Additionally, I would like to express my sincere gratitude to Dr. Magda Marinaki. Her contribution to the progress of my research cannot be overstated. Her expertise, and willingness to offer her valuable insights have been crucial in refining my work and ensuring its quality.

Furthermore, I am immensely grateful to Dr. Nikolaos A. Kyriakakis for his invaluable contribution to my work. His expertise and resoursfulness have been indispensable.

I would also like to extend my thanks to the other members of my three-member committee: Dr. Nikolaos Matsatsinis and Dr. Athanasios Migdalas. Their commitment to reviewing my work and offering constructive feedback has been immensely helpful in refining my ideas and ensuring the academic integrity of my dissertation.

Moreover, I would like to express my gratitude to the other esteemed members of the seven-member committee: Dr. Fotios Kanellos, Dr. Evangelos Grigoroudis, Dr. Ilias Kotsireas, and Dr. Eleftherios Doitsidis. Their valuable time, thoughtful comments, and critical insights have enriched my research and broadened my perspective.

Last, but certainly not least, I want to acknowledge and thank my sister Maria for her unwavering patience throughout this demanding process. Her support and understanding have been a constant source of strength for me. I am also deeply grateful to my parents for their unyielding support and belief in my abilities. Additionally, I extend my heartfelt appreciation to Marilena for her unconditional aid and support during this challenging period.

Extended Abstract in Greek

Μοντελοποίηση και Επίλυση Προβλημάτων Χωροθέτησης Σταθμών Φόρτισης Και Δρομολόγησης Ηλεκτρικών Οχημάτων

Εισαγωγή

Από τη δημιουργία των πρώτων οχημάτων δρόμου ως σήμερα, ο τομέας των μεταφορών έχει γνωρίσει τρομερή άνθηση και έχει υποστεί πολλούς μετασχηματισμούς. Οι τελευταίες εξελίξεις έχουν φέρει ξανά στο προσκήνιο τα ηλεκτρικά οχήματα σε μια προσπάθεια μετρίωσης των εκπομπών αερίων του θερμοκηπίου ώστε να επιβραδυνθεί ο ρυθμός της κλιματικής αλλαγής. Τα πρώτα ηλεκτρικά οχήματα παρουσιάστηκαν από τα μέσα κιόλας του δέκατου ένατου αιώνα, αναπτύχθηκαν παράλληλα με τα οχήματα εσωτερικής καύσης, αλλά η δυνατότητα χρήσης των τελευταίων μακριά από τα αστικά κέντρα οδήγησε στη σταδιακή υποχώρηση τους ως και την εξαφάνισή τους.

Το ενδιαφέρον για την ηλεκτροκίνηση αναζωπυρώθηκε εκ νέου πριν το τέλος του εικοστού αιώνα εξαιτίας της ραγδαίας κλιματικής αλλαγής, με χώρες όπως η Ιαπωνία και πολιτείες όπως η Καλιφόρνια των Η.Π.Α. να θεσπίζουν τα πρώτα κίνητρα για αγορά ηλεκτρικών οχημάτων, καθώς και να απαιτούν από κατασκευαστές να εισάγουν ηλεκτρικά οχήματα στη γκάμα τους. Η απότομη αυτή αλλαγή δεν απέφερε την επιθυμητή αλλαγή, όμως στις δυο δεκαετίες που ακολούθησαν η ραγδαία εξέλιξη της τεχνολογίας και συγκεκριμένα των μπαταριών οδήγησε στην σύσταση νέων εταιριών ηλεκτρικών οχημάτων, καθώς και στην παρουσίαση νέων ηλεκτρικών μοντέλων από εδραιωμένες αυτοκινητοβιομηχανίες.

Τα οχήματα εσωτερικής καύσης έχουν λίγο ως πολύ ένα ορισμένο σχήμα και μέγεθος που υπαγορεύεται από το κινητήριο σύνολο τους. Εν αντιθέσει, το μεγαλύτερο στοιχείο ενός ηλεκτρικού συνόλου είναι η μπαταρία, η οποία δεν είναι απαραίτητο να έχει ένα συγκεκριμένο σχήμα ή μέγεθος. Ως αποτέλεσμα, πολλές εταιρίες έχουν αναπτύξει πλατφόρμες τύπου «σκατεβοαρδ», αλλά, έχει δοθεί και ευκαιρία για τη δημιουργία νέων τύπων οχημάτων που θα ήταν διαφορετικά ανέφικτο.

Παραδείγματα νέων τύπων οχημάτων είναι τα μικρό-οχήματα πόλης και μικρά οχήματα μεταφορών κατάλληλα για μικρές αποστάσεις και φορτία. Ένα άλλο παράδειγμα είναι τα μη στελεχωμένα εναέρια οχήματα, κοινώς γνωστά ως «δρονες». Επιπρόσθετα, οχήματα που κατά παράδοση ήταν πετρελαιοκίνητα, όπως φορτηγά και βαν, πλέον στρέφονται προς την ηλεκτροκίνηση.

Όλα τα παραπάνω εναρμονίζονται με τη γενικότερη τάση υιοθέτησης βιώσιμων τρόπων λειτουργίας στον τομέα των μεταφορών και της μετακίνησης, καθώς περίπου το ένα τέταρτο των ρύπων του θερμοκηπίου προέρχονται από τις μεταφορές. Όμως, πέρα από το οικονομικό και περιβαλλοντικό κόστος που θα είχε η πλήρης και άμεση μετάβαση στην «καθαρή» ηλεκτροκίνηση, αυτή ενέχει εμπόδια λειτουργικού χαρακτήρα που πρέπει να διευθετηθούν. Η αυτονομία των ηλεκτρικών οχημάτων και η διαθεσιμότητα σταθμών φόρτισης αποτελούν τροχοπέδη για τη μετάβαση σε ηλεκτρικά οχήματα και για ιδιώτες αλλά και για επιχειρήσεις.

Πιο συγκεκριμένα, η εφοδιαστική αλυσίδα που έχει επιτρέψει τον σημερινό τρόπο ζωής δισεκατομμυρίων ανθρώπων ανά την υφήλιο αναμένεται να επηρεαστεί ιδιαίτερα από την επικείμενη ηλεκτρισκοποίηση. Το βασικό πρόβλημα προκύπτει από το συνδυασμό της μικρής ενεργειακής πυκνότητας των μπαταριών σε σχέση με τα ορυκτά καύσιμα και του υφιστάμενου δικτύου φορτιστών. Επιπλέον, ο ρυθμός κατανάλωσης ενέργειας επηρεάζεται σε σημαντικό βαθμό από το μεταφερόμενο φορτίο όταν αυτό είναι μεγάλου βάρους, ενώ η ενεργειακή απόδοση επηρεάζεται και από παράγοντες όπως η θερμοκρασία και η κλίση του δρόμου, σε ασύγκριτα μεγαλύτερο βαθμό από ότι ένα συμβατικό όχημα.

Τα λειτουργικά προβλήματα που μπορούν να προκύψουν από το ανεπαρκές και αναξιόπιστο δίκτυο φορτιστών είναι επίσης πολλά, ιδίως αν η εύρυθμη λειτουργία μιας επιχείρησης εξαρτάται από αυτό. Ανεπάρκεια του δικτύου ηλεκτροδότησης, μη λειτουργικοί σταθμοί, μεγάλοι χρόνοι αναμονής και χαμηλή διαθεσιμότητα εκτός των αστικών κέντρων είναι μερικά από τα βασικά θέματα προς διευθέτηση.

Κατά συνέπεια, τα ηλεκτρικά οχήματα δεν μπορούν απλά να αντικαταστήσουν τα συμβατικά χωρίς καμία αλλαγή στον τρόπο διαχείρισής τους. Αυτό το γεγονός, αποτελεί κίνητρο για την παρούσα διδακτορική διατριβή που έχει ως στόχο να ερευνήσει εναλλακτικά και καινοφανή επιχειρησιακά μοντέλα. Επιπλέον, αυτή η έρευνα αφορά μόνο τα αμιγώς ηλεκτρικά οχήματα, καθώς τα υβριδικά ή τα ηλεκτρικά οχήματα που εξοπλίζονται με μηχανές εσωτερικής καύσης που λειτουργούν ως γεννήτριες ρεύματος, δεν υπόκεινται στους ίδιους περιορισμούς χρήσης.

Συνολικά εξετάζονται τέσσερα προβλήματα, με το πρώτο να περιλαμβάνει μια εκτενή προσομοίωση ταξιδιών με ηλεκτρικά οχήματα με σκοπό να μελετηθεί η δυνατότητα χρήσης ηλεκτρικών οχημάτων στην Ελλάδα, αλλά και να προταθεί ένα πλάνο ανάπτυξης του δικτύου. Το Πρόβλημα Δρομολόγησης Ηλεκτρικών Οχημάτων (ΠΔΗΟ) μελετήθηκε στα επόμενα τρία κεφάλαια και παρουσιάστηκαν το Κλειστό-Ανοιχτό ΠΔΗΟ (ΚΑΠΔΗΟ), το ΚΑΠΔΗΟ με Μεικτό Στόλο (ΚΑΠΔΗΟΜΣ) και τέλος το ΠΔΗΟ σε συνδυασμό με Μη Στελεχωμένα Εναέρια Οχήματα (ΠΔΗΟΜΕΕΟ). Για την λύση των προβλημάτων αυτών προτείνονται ευρετικοί και μεθευρετικοί αλγόριθμοι κατάλληλα τροποποιημένοι για χρήση στα αναφερθέντα προβλήματα, καθώς γίνεται και εκτενής ανάλυση ευαισθησίας ώστε να επιβεβαιωθεί η καλή τους απόδοση.

Το Πρόβλημα Τοποθέτησης Σταθμών Φόρτισης Ηλεκτρικών Οχημάτων

Οι πωλήσεις ηλεκτρικών οχημάτων έχουν αυξηθεί ραγδαία την τελευταία δεκαετία. Το 2022, το 12,1% των νέων αυτοκινήτων που πωλήθηκαν στην Ευρώπη ήταν ηλεκτρικά, μια σημαντική αύξηση από μόλις 1,9% το 2019. Στη Νορβηγία, η οποία είναι ο ηγέτης στην υιοθέτηση ηλεκτρικών οχημάτων στην Ευρώπη, οκτώ στα δέκα νέα οχήματα που πωλήθηκαν το 2022 ήταν αμιγώς ηλεκτρικά. Στις ΗΠΑ, το 2022 ήταν επίσης μια καλή χρονιά για τα ηλεκτρικά οχήματα. Ωστόσο, όχι τόσο εντυπωσιακό, με το ποσοστό των νέων ηλεκτρικών να είναι μικρότερο του 6%. Συνολικά, οι πωλήσεις νέων ηλεκτρικών οχημάτων αναμένεται να αυξηθούν παγκοσμίως, παρά τον σκεπτικισμό σχετικά με το εάν τα ηλεκτρικά μπορούν να αντικαταστήσουν πλήρως τα συμβατικά οχήματα.

Η ευρεία υιοθέτηση των ηλεκτρικών οχημάτων εξαρτάται σε μεγάλο βαθμό από τη διαθεσιμότητα ενός αξιόπιστου δικτύου φόρτισης, μια πρόκληση που υφίσταται ακόμα και σε χώρες με υψηλή διείσδυση ηλεκτρικών οχημάτων. Συνεπώς, το πρώτο και πιο σημαντικό πρόβλημα που πρέπει να συζητηθεί είναι οι υποδομές φόρτισης. Η πυκνότητα των σταθμών φόρτισης μπορεί να αλλάξει δραματικά μεταξύ διαφορετικών περιοχών και χωρών. Οι ταχύτητες φόρτισης μπορεί επίσης να διαφέρουν ανάλογα με το διαθέσιμο εξοπλισμό, ενώ ενδέχεται κάποιοι σταθμοί να βρίσκονται εκτός λειτουργίας.

Η πρακτικότητα των ηλεκτρικών οχημάτων συχνά διερευνάται στο πλαίσιο της αστικής χρήσης, ωστόσο, καθώς όλο και περισσότεροι άνθρωποι μεταβαίνουν στα ηλεκτρικά οχήματα στην Ελλάδα κάθε χρόνο, είναι ασφαλές να υποθέσουμε ότι θα χρησιμοποιούνται όλο και περισσότερο για ταξίδια μεγάλων αποστάσεων.

Η χρήση συμβατικών οχημάτων για ταξίδια μεγάλων αποστάσεων είναι αβίαστη, καθώς υπάρχει πληθώρα πρατηρίων υγρών καυσίμων σε όλο τον κόσμο. Αντίθετα, η χρήση ενός ηλεκτρικού μπορεί να μην είναι τόσο απλή. Επιπλέον, το λεγόμενο άγχος αυτονομίας ενισχύεται για ταξίδια μεγάλων αποστάσεων. Στόχος αυτής της έρευνας είναι να απαντηθούν δύο σημαντικά ερωτήματα. Το πρώτο ερώτημα είναι «Πόσο πρακτικά είναι τα ηλεκτρικά οχήματα για ταξίδια μεγάλων αποστάσεων στην Ελλάδα» και το δεύτερο είναι «Πώς θα πρέπει να αναπτυχθεί το δίκτυο φόρτισης ώστε τα ταξίδια μεγάλων αποστάσεων να είναι εφικτά».

Σε αυτήν τη μελέτη, η υιοθέτηση ηλεκτρικών οχημάτων συζητείται στο πλαίσιο της Ελλάδας, παρέχοντας πολύτιμες πληροφορίες για την αγορά ηλεκτρικών οχημάτων και την κατάσταση των υποδομών φόρτισης. Υπάρχουσες αναφορές υποδεικνύουν ότι η Ελλάδα βρίσκεται σε ένα κρίσιμο σταυροδρόμι, βιώνοντας την ταχεία υιοθέτηση ηλεκτρικών οχημάτων αλλά συνάμα την αργή επέκταση του δικτύου φόρτισης.

Το ενδιαφέρον για τις μελέτες που αφορούν την ηλεκτροκίνηση στην Ελλάδα μόλις ξεκίνησε να κερδίζει το ενδιαφέρον των ερευνητών, με μερικές δημοσιεύσεις σχετικά με προβλήματα τοποθέτησης σταθμών φόρτισης σε αστικές περιοχές, σχετικά με τα οφέλη για την υγεία και τα κοινωνικά οφέλη από την υιοθέτηση ηλεκτρικών οχημάτων, σχετικά με τον αντίκτυπο των κινήτρων στην Ελλάδα, ακόμα και στην ηλεκτροκίνηση των ελληνικών νησιών. Σε αντίθεση με αυτές τις δημοσιεύσεις, αυτή η μελέτη εστιάζει στην προσομοίωση ταξιδιών μεγάλων αποστάσεων και στο σχηματισμό προτάσεων για την επέκταση του δικτύου φόρτισης των μεγάλων αυτοκινητοδρόμων.

Σε αυτό το πλαίσιο, υλοποιείται μια προσομοίωση Μοντε-κάρλο, για να αξιολογηθεί η εφικτότητα των ταξιδιών μεγάλων αποστάσεων με ηλεκτρικά οχήματα στην Ελλάδα και να προταθεί ένας συνολικός σχεδιασμός για την ανάπτυξη του δικτύου φόρτισης. Η προσομοίωση περιλαμβάνει μια αναπαράσταση του οδικού δικτύου της Ελλάδας σε μορφή γραφήματος, δημιουργώντας τυχαία ταξίδια μεταξύ κόμβων του δικτύου, λαμβάνοντας υπόψη απρόβλεπτες συνθήκες μέσω ενός στοχαστικού μοντέλου κατανάλωσης ενέργειας. Τα ταξίδια αυτά δημιουργούνται τυχαία από λίστες σημείων προέλευσης και προορισμού εντός της ηπειρωτικής Ελλάδας. Για την προσομοίωση χρησιμοποιούνται διάφορα ηλεκτρικά οχήματα με στόχο να διερευνηθεί πώς διαφορετικά χαρακτηριστικά τους μπορούν να επηρεάσουν την πρακτικότητά τους.

Μια κρίσιμη πτυχή αυτής της προσομοίωσης είναι η χρήση ρεαλιστικών δεδομένων. Οι αποστάσεις μεταξύ των κόμβων του ελληνικού οδικού δικτύου αντλούνται από την πλατφόρμα Open Street Maps. Η κατανάλωση ενέργειας των ηλεκτρικών οχημάτων είναι επίσης μια παράμετρος που είναι δύσκολο να μοντελοποιηθεί. Η διαφορά μεταξύ της θεωρητικής και της πραγματικής κατανάλωσης ενέργειας, καθώς και οι διαφορές στις τεχνικές προδιαγραφές μεταξύ των ηλεκτρικών οχημάτων απαιτούν τη χρήση εξατομικευμένων τιμών κατανάλωσης για κάθε όχημα. Για το σκοπό αυτό, τα δεδομένα ρυθμού κατανάλωσης ενέργειας αντλούνται από μια διαδικτυακή πηγή που προσφέρει ένα περιορισμένο σύνολο δεδομένων που προέρχονται από πραγματικές μετρήσεις.

Οι προσομοιώσεις πραγματοποιούνται για δύο διαφορετικές θερμοκρασίες και τα πρόσθετα φορτία και οι εξωτερικές συνθήκες που επηρεάζουν αρνητικά την κατανάλωση ενέργειας αναπαρίστανται χρησιμοποιώντας ένα στοιχείο στοχαστικής κατανάλωσης. Η επιπρόσθετη αυτή κατανάλωση δύναται να φτάσει ως και 15% επιπλέον της αναμενόμενης, με το ακριβές ποσό να υπολογίζεται με τυχαίο τρόπο για κάθε ένα χιλιόμετρο που διανύεται.

Τα αποτελέσματα της προσομοίωσης χωρίζονται σε δύο μέρη, με το πρώτο να αφορά τα οχήματα και το δεύτερο το δίκτυο φορτιστών. Αρχικά μελετήθηκε η σχέση μεταξύ διάφορων επιπέδων χρήσης της αποθηκευμένης ενέργειας και του πλήθους των στάσεων φόρτισης για τα 11 οχήματα που εξετάστηκαν. Τα επίπεδα που εξετάστηκαν ήταν χρήση 80%, 90% και 100% της μπαταρίας. Σύμφωνα με τα αποτελέσματα για κάθε επιπλέον 10% μπαταρίας που χρησιμοποιείται, τα οχήματα μείωσαν τις στάσεις

τους κατά περίπου 12%, ανεξαρτήτως οχήματος και χωρητικότητας μπαταρίας. Επιπλέον, παρατηρήθηκε μεγάλο εύρος στο πλήθος των στάσεων. Το όχημα με τη μικρότερη μπαταρία έκανε κατά μέσο όρο 10,25 στάσεις φόρτισης σε κάθε ταξίδι, ενώ το όχημα με τη μεγαλύτερη χρειάστηκε μόνο 3,22 στάσεις κατά μέσο όρο. Γενικότερα, παρατηρήθηκε πως υπάρχει συσχετισμός μεταξύ μεγέθους μπαταρίας και πλήθους φορτίσεων, με εξαίρεση ένα από τα οχήματα που εξετάστηκαν.

Επίσης, εξετάστηκε η σχέση του πλήθους στάσεων φόρτισης με το μήκος των διαδρομών, και του μήκους διαδρομών με την κατανάλωση ενέργειας. Στο πρώτο, έγινε ανάλυση με παλινδρόμηση πολλαπλών επιπέδων, με το αποτέλεσμα να δίνει μια λύση με δυο ευθύγραμμα τμήματα. Στο τελευταίο, παρατηρήθηκε μια γραμμική σχέση μεταξύ των δυο εξεταζόμενων παραμέτρων με μεγαλύτερο εύρος τιμών για μεγάλες αποστάσεις. Ακολούθως, ένας θερμικός χάρτης που παρουσιάζει τη μέση απόσταση ταξιδιού για κάθε διαφορετική χωρητικότητα μπαταρίας σε σχέση με το πλήθος των στάσεων, χρησιμοποιήθηκε για να αναπαρασταθεί η αυτονομία με εύληπτο τρόπο.

Όσο αφορά την ανάπτυξη του δικτύου, σύμφωνα με τα αποτελέσματα της προσομοίωσης, αναγνωρίστηκαν οι ακμές του γραφήματος πάνω στις οποίες προέκυψαν οι περισσότερες στάσεις φόρτισης και τα είκοσι πρώτα αναπαραστάθηκαν στο γράφημα του οδικού δικτύου. Σχηματίστηκαν δυο μονοπάτια τα οποία σε συνδυασμό μπορούν να υποστηρίξουν την μετακίνηση με ηλεκτρικά οχήματα στο μεγαλύτερο μέρος της ηπειρωτικής Ελλάδας.

Η παρούσα έρευνα έχει κατατεθεί για δημοσίευση.

Το Κλειστό-Ανοιχτό Πρόβλημα Δρομολόγησης Ηλεκτρικών Οχημάτων

Στον τομέα των μεταφορών, η ακρίβεια και η τυπικότητα είναι δύο πολύ ενδεικτικές παράμετροι της επιχειρησιακής επιτυχίας. Προκειμένου να βελτιωθούν αυτές οι πτυχές όταν γίνεται χρήση ηλεκτρικών οχημάτων, προτείνεται το Κλειστό Ανοιχτό Πρόβλημα Δρομολόγησης Ηλεκτρικών Οχημάτων.

Τα ΠΔΗΟ περιλαμβάνουν συνήθως δραστηριότητες φόρτισης που πραγματοποιούνται μεταξύ των επισκέψεων σε πελάτες. Ωστόσο, αυτή η μελέτη παρουσιάζει μια νέα στρατηγική φόρτισης, όπου η υποχρεωτική επίσκεψη σε ένα σταθμό φόρτισης αφαιρείται, επιτρέποντας στα ηλεκτρικά οχήματα να επισκέπτονται ένα σταθμό φόρτισης μόνο αφού εκπληρώσουν τις παραδόσεις που τους έχουν ανατεθεί. Εάν η υπολειπόμενη ενέργεια ενός οχήματος δεν επαρκεί για να επιστρέψει στην αποθήκη, το όχημα επισκέπτεται τον πλησιέστερο σταθμό φόρτισης για να επαναφορτιστεί επαρκώς πριν επιστρέψει. Αντίθετα, εάν η εναπομένουσα ενέργεια κρίνεται επαρκής, το όχημα επιστρέφει απευθείας στην αποθήκη χωρίς να επισκεφθεί κανέναν σταθμό φόρτισης. Αυτή η διαφορά κατηγοριοποιεί τη δρομολόγηση σε 'ανοιχτές' ή 'κλειστές' διαδρομές, ανάλογα με την παρουσία ή την απουσία επίσκεψης σε σταθμό φόρτισης.

Η νέα αυτή παραλλαγή προκύπτει από πρακτική αναγκαιότητα και δεν είναι απλά μια εναλλακτική προσέγγιση, καθώς οι χρήστες ηλεκτρικών οχημάτων συναντούν συχνά περιπτώσεις όπου οι σταθμοί είναι εκτός λειτουργίας και παραμένουν μη λειτουργικοί για παρατεταμένες περιόδους. Αξίζει να σημειωθεί, πως είναι η πρώτη περίπτωση όπου εξετάζεται η ανοιχτή δρομολόγηση στο πλαίσιο των ηλεκτρικών οχημάτων. Ενώ το ΠΔΗΟ είναι ένα δημοφιλές ερευνητικό θέμα, δεν έχει ακόμη διερευνηθεί σε ανοιχτή παραλλαγή. Επιπλέον, η υπάρχουσα βιβλιογραφία για την ανοιχτή δρομολόγηση έχει επικεντρωθεί κυρίως σε ενοικιαζόμενα οχήματα και όχι σε ιδιότητα. Ωστόσο, η ενσωμάτωση ανοιχτής δρομολόγησης στο πλαίσιο των ηλεκτρικών οχημάτων μπορεί να αποφέρει σημαντικά οφέλη.

Η έρευνα παρουσιάζει το μαθηματικό μοντέλο του ΚΑΠΔΗΟ, με βάση την προαναφερθείσα στρατηγική δρομολόγησης. Ιδιαίτερη έμφαση δόθηκε στη δημιουργία μιας αντικειμενικής συνάρτησης που θα εξισορροπεί την κατανάλωση ενέργειας και το απαραίτητο πλήθος οχημάτων.

Για να επιτευχθεί αυτό, η συνάρτηση αποτελείται από δύο μέρη, με το πρώτο να ελαχιστοποιεί την ενέργεια και το δεύτερο το πλήθος των οχημάτων. Η συνολική ενέργεια που δαπανάται από όλα τα οχήματα διαιρείται με την ποσότητα ενέργειας που έχει κάθε όχημα, ώστε να διατηρείται η κατανάλωση

ενέργειας στην ίδια τάξη μεγέθους με τον αριθμό των οχημάτων. Δεδομένων των θεωρητικών αριθμών που χρησιμοποιήθηκαν σε αυτήν την έρευνα, πραγματοποιήθηκαν δοκιμές για τον προσδιορισμό των βαρών για τα δύο μέρη της αντικειμενικής συνάρτησης.

Επιπρόσθετα, ο ρυθμός κατανάλωσης ενέργειας συσχετίζεται μεταξύ άλλων με το ωφέλιμο φορτίο των οχημάτων, συνεπώς μοντελοποιήθηκε με βάση το έργο που απαιτείται για την μετακίνηση του φορτίου κάθε οχήματος σε κάθε ακμή του γραφήματος. Αυτή η λεπτομέρεια εισάγει έναν επιπλέον βαθμό δυσκολίας στην επίλυση του προβλήματος, καθώς κάθε μετακίνηση αντικειμένων από ένα όχημα σε ένα άλλο, απαιτεί την επαναξιολόγηση της εφικτότητας των διαδρομών που επηρεάζονται.

Με την ποσοτικοποίηση του έργου που απαιτείται για κάθε παράδοση, οι ερευνητές μπορούν να αξιολογήσουν την απόδοση και την αποτελεσματικότητα διαφορετικών στρατηγικών δρομολόγησης, λαμβάνοντας υπόψη διάφορους παράγοντες όπως η χωρητικότητα του οχήματος, οι απαιτήσεις των πελατών και οι απαιτήσεις χρέωσης. Επιπλέον, γίνεται η υπόθεση ότι κάθε ηλεκτρικό όχημα αναχωρεί από την αποθήκη με πλήρως φορτισμένη μπαταρία και ότι οι σταθμοί φόρτισης είναι διαθέσιμοι.

Για την λύση του προτεινόμενου προβλήματος, αναπτύσσεται μια μεθυστική προσέγγιση που ενσωματώνει τον αλγόριθμο Μεταβλητής Γειτονιάς Αναζήτησης (ΜΓΑ) με τον αλγόριθμο Προσομοιωμένης Ανόπτησης (ΠΑ). Η μέθοδος ΜΓΑ έχει κερδίσει σημαντική αναγνώριση στον τομέα των ΠΔΟ. Το λειτουργικό του πλαίσιο, που χαρακτηρίζεται από απλότητα και αποτελεσματικότητα, μπορεί να χωριστεί σε τρεις διακριτές φάσεις. Η πρώτη φάση περιλαμβάνει την «ανακίνηση», όπου επιλέγεται μια λύση, ενώ ακολουθεί η τοπική αναζήτηση για τη βελτίωση της λύσης. Τέλος, εκτελείται μια μετάβαση σε μία από τις λύσεις που ελήφθησαν κατά τη φάση της τοπικής αναζήτησης. Συγκεκριμένα, στο αλγόριθμο ΜΓΑ, μια κίνηση επιτρέπεται μόνο εάν οδηγεί σε μια ανώτερη λύση σε σύγκριση με την τρέχουσα.

Όπως υποδηλώνει το όνομά του, ο αλγόριθμος ΠΑ αντλεί το όνομά του από την αναλογία του με την κατεργασία της ανόπτησης στη μεταλλουργία. Η αλγοριθμική εφαρμογή εστιάζει στην ελεγχόμενη φάση ψύξης της ανόπτησης, χρησιμοποιώντας ένα παρόμοιο εννοιολογικό πλαίσιο για να καθοδηγήσει τον αλγόριθμο προς την πραγματοποίηση προοδευτικά πιο συντηρητικών κινήσεων σε μεταγενέστερες επαναλήψεις.

Στην παρούσα μελέτη, ο προαναφερόμενος αλγόριθμος ΜΓΑ ενσωματώνεται με τη μέθοδο ΠΑ για να επιταχύνει τη σύγκλιση προς βέλτιστες λύσεις. Ο μηχανισμός της ΠΑ είναι ενσωματωμένος στην τρίτη φάση, δηλαδή στη φάση μετακίνησης. Σε αυτή τη φάση, οι κινήσεις προς καλύτερες λύσεις γίνονται δεκτές με πιθανότητα αποδοχής 100%. Με την χρήση της ΠΑ, αντί να απορρίπτονται κινήσεις σε χειρότερες καταστάσεις, η αποδοχή τέτοιων κινήσεων αξιολογείται με βάση την τιμή της αντικειμενικής συνάρτησης, με πιθανότητα αποδοχής μικρότερη του 100%. Η αποτελεσματικότητα αυτής της μεθόδου πηγάζει από την εξέταση όλων των πιθανών κινήσεων, καθεμία με πιθανότητα επιλογής, ακόμη και αν η πιθανότητα είναι χαμηλή.

Καθώς ο αλγόριθμος ΠΑ/ΜΓΑ δεν μπορεί να δημιουργήσει λύσεις, η χρήση μιας εναλλακτικής μεθόδου είναι απαραίτητη. Ενώ θα μπορούσαν να είχαν χρησιμοποιηθεί απλούστερες τεχνικές όπως η προσέγγιση του πλησιέστερου γείτονα, επιλέχθηκε η μέθοδος δημιουργίας λύσεων από την Διαδικασία Άπληστης Τυχαιοποιημένης Προσαρμοστικής Αναζήτησης (ΔΑΤΠΑ). Πρόκειται για έναν εξαιρετικά αποτελεσματικό μεθυστικό αλγόριθμο που έχει επιδείξει σημαντική επιτυχία στην επίλυση ΠΔΟ και επιλέχθηκε για την ικανότητά του να δημιουργεί διαφορετικές αρχικές λύσεις, βοηθώντας στην εξερεύνηση του χώρου λύσεων. Ενσωματώνει μια Περιορισμένη Λίστα Υποψηφίων (ΠΛΥ), η οποία είναι μια μικρή ομάδα κοντινών κόμβων προς επίσκεψη στη συνέχεια. Σε κάθε επανάληψη, ένας από τους κόμβους που περιέχονται στην ΠΛΥ επιλέγεται τυχαία ως ο επόμενος κόμβος. Το κριτήριο επιλογής βασίζεται στην απόσταση μεταξύ του τρέχοντος κόμβου και των υποψηφίων. Το μέγεθος αυτής της λίστας παίζει καθοριστικό ρόλο στον προσδιορισμό των χαρακτηριστικών της λύσης. Οι μικρότερες λίστες τείνουν να παράγουν πιο συντηρητικές λύσεις, ενώ οι υπερβολικά μεγάλες λίστες αυξάνουν την

πιθανότητα δημιουργίας μη βέλτιστων λύσεων.

Παρά όλα τα περιγραφόμενα πλεονεκτήματα, για να αποτραπεί η συνεχής επιλογή μη βέλτιστων κινήσεων, επιβάλλεται ένας περιορισμός, ο οποίος περιορίζει τον αλγόριθμο σε μέγιστο τρεις διαδοχικές μη βέλτιστες κινήσεις. Σε περίπτωση που ο αλγόριθμος φτάσει σε αυτό το όριο, αναγκάζεται να κάνει μια κίνηση που βελτιώνει την τιμή της αντικειμενικής συνάρτησης, διασφαλίζοντας έτσι την πρόοδο προς καλύτερες λύσεις.

Όσον αφορά τους τελεστές της τοπικής αναζήτησης που χρησιμοποιούνται στη δεύτερη φάση του αλγόριθμου ΠΑ/ΜΓΑ, χρησιμοποιούνται τρεις τελεστές, και συγκεκριμένα η 1 προς 1 ανταλλαγή μεταξύ διαφορετικών διαδρομών, η 1 προς 1 ανταλλαγή μεταξύ της ίδιας διαδρομής, και τέλος η μετακίνηση ενός πελάτη από μια διαδρομή σε μία άλλη. Αυτοί οι τελεστές επιτρέπουν την εξερεύνηση πιθανών μετακινήσεων εντός και μεταξύ των διαδρομών. Οι υποψήφιες μετακινήσεις αξιολογούνται σε σχέση με τους περιορισμούς ωφέλιμου φορτίου και ενέργειας, διασφαλίζοντας ότι λαμβάνονται υπόψη μόνο κινήσεις που συμμορφώνονται με αυτούς τους περιορισμούς. Η τυχαία επιλογή των πελατών και των οχημάτων για αυτές τις μετακινήσεις γίνεται με ομοιόμορφη κατανομή.

Για την αξιολόγηση του προτεινόμενου αλγόριθμου, προτείνεται ένα σετ προβλημάτων για το ΚΑΠ-ΔΗΟ, βασισμένο σε υπάρχον σετ προβλημάτων από την βιβλιογραφία. Τα αποτελέσματα κατανάλωσης ενέργειας του προτεινόμενου ΠΑ/ΜΓΑ και του εμπορικού λογισμικού για προβλήματα πέντε και δέκα πελατών παρουσιάζουν παρόμοια αποτελέσματα, ενώ ο ΠΑ/ΜΓΑ υπερτερεί στις μισές από τις περιπτώσεις δεκαπέντε πελατών. Ωστόσο, η σημαντικότερη διαφορά μεταξύ των δύο μεθόδων έγκειται στο χρόνο εκτέλεσής τους. Το εμπορικό λογισμικό χρειάζεται σημαντικά περισσότερο χρόνο, με τα προβλήματα δέκα πελατών να απαιτούν τουλάχιστον δέκα φορές περισσότερο χρόνο από τον ΠΑ/ΜΓΑ, ενώ η επίλυση προβλημάτων δεκαπέντε πελατών διαρκεί κατά μέσο όρο σαράντα φορές περισσότερο. Κατά συνέπεια, τα μεγαλύτερα παραδείγματα εκατό πελατών επιλύονται αποκλειστικά με τη χρήση της ΠΑ/ΜΓΑ. Αξίζει να σημειωθεί πως το πλήθος οχημάτων που χρησιμοποιήθηκε ήταν το ίδιο και τις δυο μεθόδους.

Οι συγκρίσεις μεταξύ ΠΑ/ΜΓΑ και ΜΓΑ χωρίς την ΠΑ αποκαλύπτουν ότι ο προτεινόμενος συνδυασμός μειώνει την κατανάλωση ενέργειας κατά 5,71%. Επιπλέον, διεξάγονται διάφορες δοκιμές στους τελεστές και τις μεταβλητές του ΠΑ/ΜΓΑ. Ο ρυθμός ψύξης της ΠΑ που καθορίζεται από τον αριθμό των επαναλήψεων ΠΑ/ΜΓΑ, δοκιμάζεται με τέσσερις διαφορετικές τιμές, αποδεικνύοντας ότι τρεις χιλιάδες επαναλήψεις αποδίδουν τα καλύτερα αποτελέσματα. Ο μέγιστος αριθμός των κινήσεων τοπικής αναζήτησης που παράγονται σε κάθε επανάληψη εξετάζεται επίσης, με μέγιστο αριθμό εβδομήντα πέντε κινήσεων να αποδεικνύεται βέλτιστος. Τέλος, δοκιμάζονται οι τελεστές τοπικής αναζήτησης αναδεικνύοντας την αναγκαιότητα όλων τους για την επίτευξη των επιθυμητών αποτελεσμάτων. Η μελέτη αυτή έχει δημοσιευθεί στο επιστημονικό περιοδικό « Annals of Mathematics and Artificial Intelligence».

Το Κλειστό-Ανοιχτό Πρόβλημα Δρομολόγησης Ηλεκτρικών Οχημάτων με Μικτό Στόλο

Η εξέταση ενός μικτού στόλου ιδιόκτητων και μισθωμένων ηλεκτρικών οχημάτων είναι η φυσική εξέλιξη του ΚΑΠΔΗΟ που παρουσιάστηκε λεπτομερώς στην προηγούμενη ενότητα.

Το προτεινόμενο Κλειστό-Ανοιχτό Πρόβλημα Δρομολόγησης Ηλεκτρικών Οχημάτων με Μικτό Στόλο (ΚΑΠΔΗΟΜΣ) προσφέρει αρκετά θετικά στοιχεία από επιχειρηματική άποψη. Η ικανοποίηση των καθημερινών αναγκών της επιχείρησης πραγματοποιείται μέσω του ιδιόκτητου στόλου, ενώ παράλληλα επιπλέον ηλεκτρικά οχήματα ενοικιάζονται από μια εξωτερική επιχείρηση ενοικιάσεων ανάλογα με τις ανάγκες. Επιπλέον, το σχέδιο επιτρέπει ευελιξία στη δρομολόγηση, καθώς τα οχήματα του ιδιόκτητου στόλου έχουν τη δυνατότητα να ολοκληρώνουν τις διαδρομές τους είτε σε σταθμούς φόρτισης είτε στην αποθήκη της εταιρείας. Από επιχειρηματική άποψη, η προσέγγιση αυτή προσφέρει δυναμικά

πλεονεκτήματα όπως το χαμηλότερο κόστος και η επεκτασιμότητα. Η ενοικίαση πρόσθετων οχημάτων αντί της εκ των προτέρων απόκτησης ενός μεγαλύτερου στόλου μπορεί να οδηγήσει σε εξοικονόμηση κόστους, επιτρέποντας στην επιχείρηση να διαχειριστεί αποτελεσματικότερα τα κεφάλαια της.

Επιπλέον, η ευελιξία στη δρομολόγηση παρέχει τη δυνατότητα βελτιστοποίησης της επιχειρησιακής αποτελεσματικότητας, μείωσης του χρόνου αδράνειας και βελτίωσης της συνολικής αποδοτικότητας. Επιπλέον, το σχέδιο ευθυγραμμίζεται με τους στόχους περιβαλλοντικής βιωσιμότητας δεδομένης της χρήσης ηλεκτρικών οχημάτων. Η προσέγγιση αυτή ανταποκρίνεται στην αυξανόμενη ζήτηση για φιλικές προς το περιβάλλον πρακτικές και ευνοεί την προσέλκυση περιβαλλοντικά ευαισθητοποιημένων πελατών. Μειώνοντας τις εκπομπές ρύπων, η εταιρεία μπορεί να συμβάλει σε ένα πράσινο οικοσύστημα μεταφορών και να ενισχύσει την εικόνα της.

Το μαθηματικό μοντέλο που παρουσιάζεται για το ΚΑΠΔΗΟΜΣ έχει αρκετές ομοιότητες με το ΚΑΠΔΗΟ. Η αντικειμενική συνάρτηση και σε αυτή την περίπτωση λαμβάνει υπόψη την ενέργεια που καταναλώνεται και το πλήθος των οχημάτων με στόχο να ελαχιστοποιηθούν και τα δυο. Η διαφορά σε αυτή την περίπτωση έγκειται στο γεγονός πως μόνο το πλήθος των ενοικιαζόμενων οχημάτων (αν υπάρχουν) ελαχιστοποιείται. Η μοντελοποίηση και ο υπολογισμός της καταναλισκόμενης ενέργειας υπολογίζεται με την ίδια μέθοδο που χρησιμοποιήθηκε και το ΚΑΠΔΗΟ. Μια ακόμα διαφορά στη μοντελοποίηση είναι η έλλειψη συντελεστών στα δυο μέρη της αντικειμενικής συνάρτησης.

Για την επίλυση του προτεινόμενου ΚΑΠΔΗΟΜΣ, αναπτύσσονται δύο μεθόδευρητικοί αλγόριθμοι και συγκρίνονται μεταξύ τους. Αυτοί οι αλγόριθμοι ανήκουν στην κατηγορία των αλγορίθμων Νοημοσύνης Σμήνους (ΝΣ), οι οποίοι έχουν σχεδιαστεί ειδικά για την αντιμετώπιση διακριτών προβλημάτων βελτιστοποίησης και όχι συνεχών. Ο πρώτος αλγόριθμος που χρησιμοποιείται είναι ο αλγόριθμος Βελτιστοποίησης Αποικίας Μελισσών (BAM), που μιμείται τη συμπεριφορά αναζήτησης τροφής των μελισσών για την εύρεση βέλτιστων λύσεων. Ο δεύτερος είναι ο αλγόριθμος Βελτιστοποίησης Αποικίας Μυρμηγκιών, μια άλλη προσέγγιση εμπνευσμένη από τη φύση, που μιμείται τη συμπεριφορά των μυρμηγκιών για την αποτελεσματική εξερεύνηση χώρων λύσεων για την εύρεση τροφής. Στην περίπτωση του αλγορίθμου βελτιστοποίησης αποικίας μυρμηγκιών, διερευνώνται δύο παραλλαγές: το Σύστημα Αποικίας Μυρμηγκιών (ΣΑΜ) και το Μέγιστο-Ελάχιστο Σύστημα Αποικίας Μυρμηγκιών (ΜΕΣΑΜ), που εισάγουν διαφορετικούς μηχανισμούς και στρατηγικές για την ενίσχυση των δυνατοτήτων εξερεύνησης και εκμετάλλευσης του αλγορίθμου.

Στο πλαίσιο της ΚΑΠΔΗΟΜΣ, οι μέλισσες αντιπροσωπεύουν έναν πληθυσμό λύσεων. Κάθε μέλισσα ξεκινάει το ταξίδι της από την αποθήκη και επισκέπτεται διαδοχικά τους πελάτες μέχρι να μην είναι εφικτές άλλες επισκέψεις. Στη συνέχεια, η μέλισσα είτε επιστρέφει στην αποθήκη είτε σταματά σε έναν σταθμό φόρτισης για να ολοκληρώσει το τρέχον ταξίδι, ανάλογα με τα αποθέματα μπαταρίας και το αν πρόκειται για ιδιόκτητο όχημα ή όχι. Η διαδικασία αυτή επαναλαμβάνεται μέχρι να εξυπηρετηθούν όλοι οι πελάτες. Εάν προκύψουν παραβιάσεις περιορισμών κατά την κατασκευή μιας λύσης, αυτή απορρίπτεται.

Είναι σημαντικό να σημειωθεί ότι η ίδια η BAM δεν δημιουργεί αρχικές λύσεις, έτσι, ένας μηχανισμός παρόμοιος με αυτόν που χρησιμοποιείται στο ΚΑΔΠΗΟ, εμπνευσμένος από το ΔΑΤΠΑ, χρησιμοποιείται για τη δημιουργία αρχικών λύσεων. Στη συνέχεια, κάθε μέλισσα δημιουργεί μια νέα λύση με βάση την αρχική λύση. Εάν μια νέα λύση είναι καλύτερη από την τρέχουσα καλύτερη λύση, η μέλισσα εκτελεί ένα «χορό», υποδεικνύοντας την ανακάλυψη μιας καλύτερης λύσης. Μόλις κάθε μέλισσα δημιουργήσει μια λύση, ο αλγόριθμος ΜΓΑ επιλέγει τη συνολικά καλύτερη λύση και στοχεύει στην περαιτέρω βελτιστοποίησή της. Αυτή η επαναληπτική διαδικασία επαναλαμβάνεται για έναν καθορισμένο αριθμό επαναλήψεων, με σκοπό την εύρεση της καλύτερης δυνατής λύσης.

Οι μέλισσες που παρατηρούν το χορό πρέπει να πάρουν μια απόφαση σχετικά με το αν θα υιοθετήσουν τη νέα λύση ή θα συνεχίσουν με τη δική τους λύση. Η απόφαση αυτή βασίζεται στην τιμή της

αντικειμενικής συνάρτησης, με προτίμηση στις λύσεις που δίνουν χαμηλότερες τιμές της αντικειμενικής συνάρτησης, καθώς ο στόχος είναι η ελαχιστοποίησή της. Κάθε εναλλακτική λύση έχει μια πιθανότητα επιλογής, η οποία είναι αντιστρόφως ανάλογη της τιμής της αντικειμενικής συνάρτησης.

Η συμπεριφορά αναζήτησης τροφής των μυρμηγκιών αποτέλεσε πηγή έμπνευσης για την ανάπτυξη της οικογένειας αλγορίθμων βελτιστοποίησης αποικιών μυρμηγκιών. Αντί για άμεση επικοινωνία, τα μυρμήγκια αφήνουν ίχνη φερομόνης στο έδαφος, τα οποία μπορούν να ανιχνευθούν από άλλα μυρμήγκια. Αυτή η μορφή επικοινωνίας είναι γνωστή ως στιγμεργία. Τα μυρμήγκια τείνουν να ακολουθούν μονοπάτια με υψηλότερες συγκεντρώσεις φερομόνης, ενώ η φερομόνη σε λιγότερο ευνοϊκές διαδρομές εξατμίζεται πιο γρήγορα. Ως αποτέλεσμα, η αποικία μυρμηγκιών συγκλίνει σταδιακά στο καλύτερο μονοπάτι, οδηγώντας στο σχηματισμό των γραμμών μυρμηγκιών που παρατηρούνται στη φύση.

Ο αλγόριθμος ΣΑΜ ενσωματώνει τόσο τοπικές όσο και εξωτερικές ενημερώσεις φερομόνης κατά τη φάση κατασκευής λύσεων, με στόχο να ενθαρρύνει την εξερεύνηση του χώρου λύσεων. Από την άλλη πλευρά, ο αλγόριθμος ΜΕΣΑΜ διατηρεί τα επίπεδα φερομόνης εντός ενός συγκεκριμένου εύρους τιμών για την προώθηση ενός ποικιλόμορφου πληθυσμού λύσεων καθ' όλη τη διάρκεια της διαδικασίας επίλυσης και χρησιμοποιεί μόνο έναν εξωτερικό μηχανισμό ενημέρωσης.

Για να ενισχυθεί η απόδοση των αλγορίθμων ΒΑΜ, ΣΑΜ και ΜΕΣΑΜ και να επιτευχθούν οι καλύτερες δυνατές λύσεις, χρησιμοποιήθηκε η μέθοδος ΜΓΑ με τους ίδιους τελεστές τοπικής αναζήτησης που παρουσιάστηκαν στο ΚΑΠΔΗΟ.

Δημιουργήθηκε ένα σετ προβλημάτων κατάλληλο για το ΚΑΠΔΗΟΜΣ όπως και στο ΚΑΠΔΗΟ. Σε αυτήν την περίπτωση το πλήθος των ιδιοτήτων οχημάτων ορίστηκε στα τρία, καθώς αυτά επαρκούν για την κάλυψη της ζήτησης πολλών μικρών προβλημάτων. Όπως και προηγουμένως, έτσι και σε αυτή την περίπτωση τα προβλήματα μικρού μεγέθους επιλύθηκαν και με την χρήση εμπορικού λογισμικού, επιπλέον της λύσης με τους προτεινόμενους αλγόριθμους.

Το εμπορικό λογισμικό βρήκε βέλτιστες λύσεις για όλα τα προβλήματα με πέντε πελάτες και τρία προβλήματα με δέκα πελάτες. Επιπλέον, παρουσίασε μέση απόκλιση 0,05% από την βέλτιστη λύση που βρέθηκε στα μεγαλύτερα προβλήματα με δεκαπέντε πελάτες.

Οι τρεις προτεινόμενοι αλγόριθμοι έλυσαν αποτελεσματικά κάθε πρόβλημα και παράγααν λύσεις που ήταν συγκρίσιμες ή και ανώτερες από εκείνες που προέκυψαν με τη χρήση του εμπορικού λογισμικού. Όπως αναμενόταν, το τελευταίο παρουσίασε γρήγορους χρόνους επίλυσης για τα μικρότερα προβλήματα με πέντε πελάτες. Ωστόσο, καθώς αυξανόταν το μέγεθος του προβλήματος, ο χρόνος εκτέλεσης επίσης κλιμακώνονταν, καθιστώντας αναγκαία την εφαρμογή των μεθυσρετικών για την επίλυση μεγαλύτερων προβλημάτων.

Ένας σημαντικός παράγοντας που επηρεάζει τους χρόνους εκτέλεσης είναι η χρήση των υπολογιστικών πόρων. Το εμπορικό λογισμικό εκμεταλλεύεται και τα τέσσερα νήματα της ΉΥ, ενώ οι υλοποιήσεις ΒΑΜ, ΣΑΜ και ΜΕΣΑΜ είναι εφαρμογές ενός νήματος. Κατά συνέπεια, οι χρόνοι εκτέλεσης μεταξύ του εμπορικού λογισμικού και των μεθυσρετικών αλγορίθμων δεν είναι άμεσα συγκρίσιμοι.

Μεταξύ των προσεγγίσεων που δοκιμάστηκαν το ΣΑΜ βρήκε τα καλύτερα αποτελέσματα σε 37 από τα 56 προβλήματα, παρουσιάζοντας μικρότερη ευαισθησία στις τιμές των παραμέτρων. Η ΣΑΜ και η ΜΕΣΑΜ είχαν πλεονέκτημα έναντι της ΒΑΜ καθώς είναι ικανές να παράγουν αρχικές λύσεις, ενώ η ΒΑΜ βασίζεται σε μια αρχική λύση που παρέχεται από τον μηχανισμό αρχικής λύσης ΔΑΤΠΑ. Αυτή η διάκριση μπορεί να εξηγήσει το γεγονός ότι η ΒΑΜ έχει υψηλότερο μέσο αριθμό οχημάτων. Το ΣΑΜ υπερείχε έναντι του ΜΕΣΑΜ λόγω το ενδιαμέσου σταδίου τοπικής ενημέρωσης φερομόνης, το οποίο παρέχει ταχύτερη ανατροφοδότηση σε σύγκριση με το ΜΕΣΑΜ όπου η ενημέρωση πραγματοποιείται μόνο μετά την ολοκλήρωση μιας πλήρους λύσης.

Η παρούσα έρευνα έχει κατατεθεί προς δημοσίευση.

Πρόβλημα Δρομολόγησης Ηλεκτρικών Οχημάτων με Μη Στελεχωμένα Εναέρια

Οχήματα

Η υιοθέτηση ηλεκτρικών οχημάτων στις μεταφορές έχει εισαγάγει νέες και πολύπλοκες προκλήσεις στον προγραμματισμό παράδοσης. Αυτές οι προκλήσεις προκύπτουν από το συνδυασμό δύο σημαντικών παραγόντων: της περιορισμένης ενεργειακής χωρητικότητας και της χρονοβόρας φύσης της διαδικασίας φόρτισής τους. Αυτοί οι περιορισμοί καθιστούν επιτακτική τη διερεύνηση καινοτόμων προσεγγίσεων για να ξεπεραστούν αυτά τα εμπόδια και να διασφαλιστούν αποτελεσματικές και βιώσιμες λειτουργίες παράδοσης.

Τα τελευταία χρόνια, ερευνητές και εταιρίες έχουν στρέψει την προσοχή τους στην ενσωμάτωση των Μη Στελεχωμένων Εναέριων Οχημάτων (ΜΣΕΟ), ως μια πολλά υποσχόμενη κατεύθυνση για την αντιμετώπιση πολλών προκλήσεων, που κυμαίνονται από την αντιμετώπιση καταστροφών έως τη γεωργία, την παρακολούθηση και τις παραδόσεις. Παρά τα παραπάνω, ο συνδυασμός ηλεκτρικών οχημάτων δρόμου και ΜΣΕΟ στον τομέα των μεταφορών δεν έχει προταθεί προηγουμένως και έχει μεγάλες δυνατότητες να φέρει επανάσταση στον τρόπο με τον οποίο πραγματοποιούνται οι παραδόσεις.

Η ενσωμάτωση των ηλεκτρικών οχημάτων και των ΜΣΕΟ βασίζεται στα κοινά χαρακτηριστικά αυτών των οχημάτων. Τόσο τα ηλεκτρικά οχήματα όσο και τα ΜΣΕΟ αντιμετωπίζουν παρόμοιους περιορισμούς, όπως περιορισμένη ενεργειακή χωρητικότητα και έντονη εξάρτηση της κατανάλωσης ενέργειας από το βάρος του φορτίου. Αξιοποιώντας τα οχήματα συνεργατικά, καθίσταται δυνατή η βελτιστοποίηση των λειτουργιών παράδοσης και η επίτευξη των καλύτερων δυνατών αποτελεσμάτων. Μοιράζονται επίσης ορισμένα πλεονεκτήματα, όπως μηδενικές τοπικές εκπομπές και μεγάλες δυνατότητες ενσωμάτωσης τεχνολογίας.

Στο κεφάλαιο αυτό εισάγεται το Πρόβλημα Δρομολόγησης Ηλεκτρικών Οχημάτων με ΜΣΕΟ (ΠΔΗΟΜΣΕΟ). Σε αυτό το πρόβλημα, στα ηλεκτρικά οχήματα ανατίθεται το κρίσιμο καθήκον της μεταφοράς των ΜΣΕΟ σε στρατηγικά επιλεγμένες τοποθεσίες εντός της περιοχής παράδοσης. Αυτές οι τοποθεσίες έχουν καθοριστεί προσεκτικά για να διασφαλιστεί ότι τα ηλεκτρικά οχήματα μπορούν να σταθμεύσουν χωρίς να εμποδίζουν τη ροή της κυκλοφορίας, ενώ περιμένουν την επιστροφή των ΜΣΕΟ. Μόλις απογειωθούν, τα ΜΣΕΟ καλύπτουν την εναπομένουσα απόσταση για να εξυπηρετήσουν τους πελάτες, μειώνοντας αποτελεσματικά τη συνολική απόσταση ταξιδιού και την κατανάλωση ενέργειας των ηλεκτρικών οχημάτων. Τα ηλεκτρικά οχήματα δεν εκτελούν παραδόσεις.

Η χρήση των ΜΣΕΟ δεν περιορίζεται, καθώς μπορούν να εκτελούν πολλαπλές παραδόσεις ανά πτήση, βελτιώνοντας έτσι την αποτελεσματικότητα και βελτιστοποιώντας τη χρήση των πόρων. Αυτή η προσέγγιση παρουσιάζει μια πολλά υποσχόμενη λύση για την υπέρβαση των περιορισμών των ηλεκτρικών οχημάτων στον τομέα των μεταφορών.

Το μαθηματικό μοντέλο του προβλήματος περιλαμβάνει μια αντικειμενική συνάρτηση που αποσκοπεί στην ελαχιστοποίηση της συνολικής ενέργειας που καταναλώνεται και από τους δυο τύπους οχημάτων. Επιπλέον, οι περιορισμοί του προβλήματος αφορούν και το πλήθος και το βάρος των αντικειμένων που μεταφέρονται. Γίνεται η παραδοχή πως κάθε πελάτης έχει ζήτηση ενός μόνο αντικειμένου. Το κάθε αντικείμενο ανήκει σε μια κατηγορία βάρους από μια ως τρεις μονάδες βάρους, ενώ το μέγιστο βάρος που μπορεί να μεταφέρει ένα ΜΣΕΟ είναι τέσσερις μονάδες βάρους. Όπως και στα προηγούμενα δυο προβλήματα που παρουσιάστηκαν, έτσι και εδώ το βάρος των αντικειμένων που μεταφέρονται επηρεάζει τον ρυθμό κατανάλωσης ενέργειας.

Για την επίλυση του ΠΔΗΟΜΣΕΟ, παρουσιάστηκαν τέσσερις προσεγγίσεις, καθεμία από τις οποίες αξιοποιεί διαφορετικές τεχνικές βελτιστοποίησης. Οι δυο μέθοδοι ευφυίας σμήνους που παρουσιάστηκαν στην προηγούμενη ενότητα, δοκιμάστηκαν και σε αυτό το πρόβλημα. Πέρα αυτών, δοκιμάστηκαν δυο παραλλαγές της μεθόδου ΔΑΤΠΑ και τρεις παραλλαγές της μεθόδου ΠΑ.

Η μέθοδος BAM χρησιμοποιήθηκε με τον ίδιο τρόπο. Όσο αφορά τους αλγόριθμους ΣΑΜ με ΜΕΣΑΜ, χρησιμοποιήθηκαν όχι μόνο με την αρχική τους μορφή αλλά παρουσιάστηκαν και από μια

εναλλακτική εκδοχή για τον κάθε ένα. Οι εκδοχές αυτές διαφέρουν εξαιτίας της χρήσης μόνο μιας αρχικής λύσης και βελτίωσης αυτής, σε αντίθεση με τις αρχικές μεθόδους που ερευνούν πολλές διαφορετικές αρχικές λύσεις. Οι εναλλακτικές αυτές μέθοδοι έχουν παρουσιαστεί στην βιβλιογραφία για χρήση σε άλλα ΠΔΟ.

Οι δύο μέθοδοι ΔΑΤΠΑ που παρουσιάστηκαν διαφέρουν ως προς τον τρόπο συμπλήρωσης της ΠΛΥ, με την μία μέθοδο να περιλαμβάνει όλους τους κόμβους που πληρούν ένα κριτήριο απόστασης, ενώ η άλλη μέθοδος ορίζει ένα μέγιστο μέγεθος της λίστας. Όσο αφορά την μέθοδο ΠΑ, εξετάστηκαν τρεις διαφορετικές συναρτήσεις για τον προσδιορισμό της «θερμοκρασίας» σε κάθε επανάληψη (γραμμική, λογαριθμική και εκθετική).

Για περαιτέρω βελτίωση της απόδοσης αυτών των προσεγγίσεων, εφαρμόζεται και εδώ η μέθοδος ΜΓΑ. Συνδυάζοντας αυτές τις διαφορετικές τεχνικές, αναπτύσσονται ισχυροί και αποτελεσματικοί αλγόριθμοι, ικανοί να λύσουν το ΠΔΗΟΜΣΕΟ και να βελτιστοποιήσουν αποτελεσματικά την προτεινόμενη ενσωμάτωση τόσο των ηλεκτρικών φορτηγών όσο και των ΜΣΕΟ στον προγραμματισμό των δρομολογίων παράδοσης. Σε αυτό το πρόβλημα χρησιμοποιήθηκαν οκτώ νέοι τελεστές τοπικής αναζήτησης, με τους επτά να εστιάζουν στα ΜΣΕΟ και έναν να εστιάζει στα ηλεκτρικά οχήματα. Για την αξιολόγηση των προτεινόμενων μεθόδων, αναπτύχθηκε ένα σετ προβλημάτων για το ΠΔΗΟΜΣΕΟ, με βάση ένα άλλο πρόβλημα της βιβλιογραφίας.

Όπως παρατηρήθηκε από τα αποτελέσματα, ο αλγόριθμος ΜΕΣΑΜ επέδειξε το υψηλότερο επίπεδο απόδοσης, βρίσκοντας τις καλύτερες λύσεις σε εννέα από τα προβλήματα και παρουσιάζοντας γενικά τη μικρότερη μέση απόκλιση από τα καλύτερα αποτελέσματα σε άλλα προβλήματα. Ο εναλλακτικός ΜΕΣΑΜ αλγόριθμος παρουσίασε τη δεύτερη καλύτερη μέση απόκλιση, αν και βρήκε την καλύτερη λύση για μόνο ένα πρόβλημα. Αντίθετα, ο αλγόριθμος ΣΑΜ εμφάνισε συγκριτικά μεγαλύτερη μέση απόκλιση από τα καλύτερα αποτελέσματα αλλά ήταν υπεύθυνος για τέσσερα από αυτά.

Ο αλγόριθμος ΒΑΜ κατάφερε να βρει μόνο ένα από τα καλύτερα αποτελέσματα, όπως και η εκδοχή του ΠΑ με την γραμμική συνάρτηση. Ωστόσο, η παραλλαγή με την εκθετική συνάρτηση κατάφερε να βρει τέσσερις καλύτερες λύσεις. Η λογαριθμική εκδοχή και ο εναλλακτικός ΣΑΜ ήταν οι μόνοι δύο αλγόριθμοι που δεν βρήκαν κανένα από τα καλύτερα αποτελέσματα.

Συγκρίνοντας την μέση απόδοση των αλγορίθμων, τα αποτελέσματα δείχνουν ξανά την υπεροχή των μεθόδων αποικίας μυρμηγκιών, με την μέθοδο ΜΕΣΑΜ να είναι και πάλι η καλύτερη. Επιπλέον, αξίζει να σημειωθεί πως η μέση απόδοση της ΒΑΜ ήταν αρκετά κοντά στην απόδοση των μεθόδων αποικίας μυρμηγκιών. Σύμφωνα με το στατιστικό τεστ που διεξήχθη, η απόδοση της είναι συγκρίσιμη με τις μεθόδους ΣΑΜ, καθώς και την εναλλακτική της και την εναλλακτική μέθοδο ΜΕΣΑΜ.

Οι σχετικές μελέτες έχουν δημοσιευθεί στο επιστημονικό περιοδικό «Cleaner Logistics and Supply Chain» και στα πρακτικά του «8th International Conference In Machine Learning, Optimization, and Data Science», ενώ μια ακόμα μελέτη έχει γίνει δεκτή προς δημοσίευση στο βιβλίο με τίτλο «Industrial Internet in Smart Manufacturing, Logistics, and Supply Chain Management» και μια ακόμα έχει κατατεθεί προς δημοσίευση.

Συμπεράσματα

Ο αγώνας δρόμου για την αντιμετώπιση της κλιματικής αλλαγής και των εκτεταμένων συνεπειών της έχει οδηγήσει στην ευρεία υιοθέτηση των ηλεκτροκίνητων οχημάτων. Αυτή η στροφή στην αυτοκινητοβιομηχανία αντανακλά μια συντονισμένη προσπάθεια για το μετριασμό των εκπομπών αερίων του θερμοκηπίου, τη μείωση της εξάρτησης από τα ορυκτά καύσιμα και την προώθηση ενός βιώσιμου οικοσυστήματος μεταφορών με χαμηλές εκπομπές άνθρακα.

Στόχος της παρούσας διατριβής είναι η υποστήριξη της μετάβασης προς την πράσινη κινητικότητα με έμφαση στις επιχειρήσεις μεταφορών, έναν τομέα που θέτει σημαντικές προκλήσεις και απαιτεί μεγάλες

αλλαγές. Οι προκλήσεις αυτές προκύπτουν λόγω διαφόρων παραγόντων, όπως η τεράστια κλίμακα των εργασιών, η εξάρτηση από συμβατικούς τρόπους μεταφοράς και το περίπλοκο δίκτυο των αλυσίδων εφοδιασμού. Επιπλέον, η χρονικά ευαίσθητη φύση των εργασιών εφοδιαστικής, σε συνδυασμό με την ανάγκη διασφάλισης της σχέσης κόστους-αποτελεσματικότητας, εισάγει περαιτέρω πολυπλοκότητα στην εφαρμογή τέτοιων βιώσιμων πρακτικών.

Δύο σημαντικές κατευθύνσεις μπορούν να αναγνωριστούν όσον αφορά τη μετάβαση στην πράσινη κινητικότητα, η ανάπτυξη υποδομών και η έρευνα δρομολόγησης ηλεκτρικών οχημάτων, οι οποίες εξετάστηκαν στην παρούσα μελέτη. Η πρώτη κατεύθυνση, η ανάπτυξη υποδομών, περιλαμβάνει τη δημιουργία του φυσικού και τεχνολογικού πλαισίου που απαιτείται για την υποστήριξη της ενσωμάτωσης βιώσιμων συστημάτων μεταφορών. Στην επιδίωξη αυτού του στόχου, η παρούσα διατριβή συμβάλει με την ανάπτυξη ενός μοντέλου προσομοίωσης διαδρομών που ενσωματώνει στοχαστικά στοιχεία. Πρωταρχικός σκοπός του εν λόγω μοντέλου είναι ο εντοπισμός των ακμών του οδικού δικτύου που παρουσιάζουν σημαντικό όγκο κυκλοφορίας, προσδιορίζοντας έτσι τις περιοχές που θα αποκομίσουν το μεγαλύτερο όφελος από την ανάπτυξη υποδομών φόρτισης. Με την ενσωμάτωση στοχαστικών στοιχείων στο πλαίσιο προσομοίωσης, ενισχύεται ο ρεαλισμός και η ακρίβεια της ανάλυσης, επιτρέποντας μια πιο ισχυρή αξιολόγηση για τη βέλτιστη ανάπτυξη υποδομών.

Η δεύτερη κατεύθυνση περιστρέφεται γύρω από την έρευνα δρομολόγησης, με πρωταρχικό στόχο την ελαχιστοποίηση της κατανάλωσης ενέργειας. Αυτό περιλαμβάνει τη διατύπωση νέων μοντέλων λειτουργίας των επιχειρήσεων, λαμβάνοντας υπόψη τους επιπλέον περιορισμούς που θέτουν τα ηλεκτρικά οχήματα και τις απαιτήσεις μεταφοράς. Στο πλαίσιο αυτό, η παρούσα διατριβή εισάγει τρεις νέες παραλλαγές του ΠΔΟ. Δύο από αυτές τις παραλλαγές επικεντρώνονται σε εναλλακτικές στρατηγικές φόρτισης, με στόχο τη βελτιστοποίηση των δρομολογίων των οχημάτων λαμβάνοντας υπόψη τις επιχειρησιακές απαιτήσεις. Η τρίτη παραλλαγή διερευνά την ενσωμάτωση ηλεκτρικών οχημάτων και ΜΣΕΟ, διερευνώντας τις πιθανές συνέργειες και την αποδοτικότητα που μπορεί να επιτευχθεί μέσω αυτής της υβριδικής προσέγγισης. Συλλογικά, αυτές οι παραλλαγές ΠΔΟ συμβάλλουν στην πρόοδο παρέχοντας λύσεις που προσαρμόζονται στους περιορισμούς και τις ευκαιρίες που σχετίζονται με τα ηλεκτρικά οχήματα, ενώ ταυτόχρονα ανταποκρίνονται στις εξελισσόμενες απαιτήσεις της εφοδιαστικής αλυσίδας. Αξιοποιώντας μεθυσματικούς αλγόριθμους, αναλύσεις δεδομένων και μοντέλα προσομοίωσης, η παρούσα έρευνα στοχεύει στην ενίσχυση της λειτουργικής αποδοτικότητας και της βιωσιμότητας των δικτύων μεταφορών υπό το πρίσμα της συνεχιζόμενης επανάστασης της ηλεκτρικής κινητικότητας.

Υπάρχουν πολυάριθμοι δρόμοι για μελλοντική έρευνα ώστε να προωθηθεί η βάση γνώσεων σχετικά με την ηλεκτροκίνηση. Κατ' αρχάς, η ανάπτυξη των σταθμών φόρτισης χρήζει διερεύνησης σε τοπικό επίπεδο, καθώς δεν υπάρχει καθολική προσέγγιση που να μπορεί να αντιμετωπίσει μοναδικά αυτή την πρόκληση. Συνεπώς, είναι ζωτικής σημασίας να εξεταστεί και να κατανοηθεί το συγκεκριμένο πλαίσιο κάθε τοποθεσίας, λαμβάνοντας υπόψη παράγοντες όπως τις υποδομές, τη ζήτηση και τις απαιτήσεις των χρηστών. Επιπλέον, θα πρέπει να δοθεί ιδιαίτερη προσοχή στην ακριβή καταγραφή και αναπαράσταση των προτιμήσεων και των αναγκών, διασφαλίζοντας ότι τα δίκτυα σταθμών φόρτισης σχεδιάζονται και προσαρμόζονται ώστε να ανταποκρίνονται στους χρήστες τους.

Επιπλέον, υπάρχει η ανάγκη να επεκταθεί και να διευρυνθεί το πρόβλημα δρομολόγησης οχημάτων ώστε να συμπεριλάβει ένα ευρύτερο φάσμα οχημάτων, που να περιλαμβάνει διάφορα μεγέθη, επίπεδα αυτονομίας και να αξιοποιήσει τις μοναδικές τους δυνατότητες στο μέγιστο δυνατό βαθμό. Οι ερευνητές θα πρέπει να δώσουν προτεραιότητα στην ανάπτυξη καινοτόμων στρατηγικών δρομολόγησης που ενσωματώνουν προηγμένα επίπεδα αυτοματοποίησης. Με την αξιοποίηση αναδυόμενων τεχνολογιών όπως η τεχνητή νοημοσύνη και η μηχανική μάθηση, μπορούν να επινοηθούν νέοι αλγόριθμοι βελτιστοποίησης, οι οποίοι θα παρουσιάζουν εξαιρετικές δυνατότητες προσαρμογής και θα εγκαταλείπουν τις στατικές μεθοδολογίες λύσεων που χρησιμοποιούνταν ως τώρα. Τέλος, η ενσωμάτωση δεδομένων

του πραγματικού κόσμου στις ερευνητικές μεθοδολογίες έχει τη δυνατότητα να ενισχύσει την ακρίβεια και την αξιοπιστία των ερευνητικών ευρημάτων. Αυτή η εμπειρική προσέγγιση θα συμβάλει στην πληρέστερη κατανόηση της χρηστικότητας των ηλεκτρικών οχημάτων, ενώ θα επιτρέψει την επικύρωση των μοντέλων προσομοίωσης και των αλγορίθμων βελτιστοποίησης.

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Chapter 1

Introduction

Since the advent of the automobile in the late 19th century, the transportation sector has undergone several significant transformations. The recent reintroduction of Electric Vehicles (EVs) has disrupted the status quo and redefined the expectations for all means of transportation.

EVs have emerged as the next iteration of the automobile in response to environmental challenges facing the transportation sector, as it is one of the largest contributors to Greenhouse Gases (GhG) emissions, which accelerate climate change (Pal et al., 2023). To address this issue, governments and organisations around the world are implementing policies and initiatives to reduce emissions from transportation.

Despite the recent resurgence of EVs in the car and light truck market, they are not new. The first EVs were presented in the mid-19th century (Kirsch, 1997). In 1837, Scottish inventor Robert Anderson developed the first crude electric vehicle, which was powered by non-rechargeable primary cells. Then, in 1859, French physicist Gaston Planté invented the lead-acid battery that made electric vehicles more practical (Wakefield, 1998).

In the late 1800s and early 1900s, EVs were more popular than gasoline-powered cars because they were cleaner, quieter, and easier to operate. However, as gasoline engines became more efficient and gasoline became widely available, gasoline-powered cars became the dominant mode of transportation. Interest in EVs began to pick up again in the 1960s and 1970s due to concerns about air pollution and dependence on foreign oil. Since then, EV technology has continued to improve, and EVs have become more popular and practical as battery technology has advanced.

The modern EV industry started in the 1990s, when a number of factors came together to make EVs more practical and attractive to consumers. One of the key factors was advances in battery technology, which made it possible to build EVs with tolerable driving ranges and charging times. In addition, concerns about air pollution and climate change led to increased interest in EVs as a cleaner and more sustainable alternative to gasoline-powered vehicles.

Another important development was the introduction of government incentives and regulations to encourage the adoption of EVs. In the 1990s, several countries, including the United States, Japan, and France, introduced policies to promote EVs, such as tax credits and subsidies for EV purchases, and regulations requiring automakers to produce a certain percentage of zero-emission vehicles (Ford, 1994; Segal, 1995).

These factors led to the emergence of several new EV companies, such as Tesla, which was founded in 2003 and has since become a leader in the EV industry (Teece, 2018). Other established

automakers also began to invest in EV technology and produce their own electric models. Recently, Chinese manufacturers such as BYD and Maxus have also started to offer compelling EVs and compete globally with established manufacturers.

Today, the EV industry is continuing to grow rapidly, driven by advances in battery technology, improvements in charging technology, and increasing consumer demand for more sustainable transportation options. EVs have no tailpipe emissions, which makes them a cleaner alternative to traditional gasoline or diesel-powered vehicles [Stamadianos et al. \(2023\)](#). Air pollution is a major health issue in many cities around the world, with studies showing that exposure to air pollution can cause a range of health problems, including respiratory illnesses and heart disease ([Brunekreef and Hoffmann, 2016](#)). EVs can help to reduce air pollution by eliminating tailpipe emissions, which are a major source of air pollution. This can lead to improved air quality and public health.

1.1 Types of Electric Vehicles

The emergence of EVs has revolutionized the transportation industry, offering a cleaner and more sustainable alternative to conventional Internal Combustion Engine (ICE) vehicles. Electric passenger cars are the most well-known and widely adopted type of EVs. They offer the advantages of lower operating costs, reduced maintenance requirements, and a quieter and smoother driving experience ([Melo et al., 2014](#)). With advancements in battery technology, the range and charging time of electric cars have improved, making them a viable option for everyday commuting ([Ren et al., 2022](#)).

Micro-EVs, also known as neighborhood EVs, are compact vehicles designed for short-distance urban travel. These vehicles have a limited top speed and range, typically up to 45 km/h and 50-100 kilometers, respectively. Micro-EVs are ideal for running errands, commuting in urban areas, or as last-mile transportation options. Their compact size and low energy consumption make them an efficient and environmentally friendly choice for short trips.

Electric bikes (e-bikes) and electric scooters are an alternative mode of transportation for short-distance travel. E-bikes are bicycles equipped with electric motors, providing pedal-assist or full electric modes. They are popular among commuters, offering a convenient and eco-friendly way to navigate through congested urban areas while promoting physical activity. Electric scooters, have gained attention as shared mobility solutions ([Bieliński and Ważna, 2020](#)). They are commonly used for short trips and are particularly popular in urban environments due to their compact size and maneuverability.

Electric vans and trucks are also gaining popularity as commercial transportation solutions ([Lee et al., 2013](#); [Bhardwaj and Mostofi, 2022](#)). Electric vans offer emission-free deliveries, making them well-suited for urban logistics and local delivery services. Electric trucks, ranging from light-duty to heavy-duty, provide a sustainable alternative for cargo transportation, significantly reducing air pollution and noise levels associated with traditional diesel trucks. The market of electric vans and trucks has developed slower than the passenger EV market. The first electric vans were electrified variants of existing vans from established manufacturers. Today the market has expanded with electric vans in a variety of sizes and battery capacities. Although challenges such as limited range and charging infrastructure remain, the increasing availability of electric vans and trucks demonstrates the potential for a cleaner and more efficient commercial transportation sector.

Another type of vehicle that can be classified as electric, are Drones, also known as Unmanned Aerial Vehicles (UAVs). They have quickly become a versatile and efficient technology with appli-

cations in various domains. As the world strives for cleaner and more sustainable energy sources, the integration of drones in transportation shows great potential (Bambury, 2015). Drones offer increased efficiency and cost-effectiveness compared to conventional vehicles. Advancements in battery technology allow drones to cover longer distances and remain airborne for extended periods. This translates to increased productivity, reduced downtime, and improved cost-effectiveness in various sectors, including delivery, infrastructure, and surveillance (Aabid et al., 2022).

1.2 Electric Vehicles in the Supply Chain

The modern supply chain has revolutionized the way we live by making goods and services more accessible, affordable, and efficient. The advent of new technologies, such as automation and digitalization, has enabled the creation of highly interconnected supply chain networks that span the globe. These changes have had a significant impact on the global economy and on the way we live our lives.

The rise of EVs is set to have a significant impact on the modern supply chain. One of the main ways EVs will affect the supply chain is by changing the way goods are transported. Electric delivery vehicles offer a cleaner, more efficient alternative to traditional gasoline or diesel-powered vehicles. This will have a positive impact on the environment and on public health by reducing GHG emissions and air pollution. Furthermore, EVs can be powered by renewable energy sources, which can reduce the dependence on fossil fuels and the carbon footprint.

EVs will also impact the supply chain by creating new opportunities for innovation and collaboration (Muñoz-Villamizar et al., 2017). As more companies invest in EV technology, there will be a growing demand for new components, materials, and services. This will create opportunities for businesses to collaborate and develop new products and services that can help accelerate the transition to a more sustainable future. Additionally, the growing market for EVs will drive innovation in areas such as battery technology, energy storage, and charging infrastructure.

While EVs can have numerous benefits on the modern supply chain, there are also some potential problems that need to be addressed. The two most significant are their limited range and their battery capacity (Mruzek et al., 2016). Unlike traditional fuel-powered vehicles, EVs may require frequent recharging, which can limit their ability to cover long distances. This can be particularly problematic for long-haul transportation, where vehicles may need to travel hundreds or even thousands of miles. Furthermore, EVs may require long charging times, which can lead to delays in delivery and impact the efficiency of the supply chain.

Another potential problem with EVs in supply chains is the lack of charging infrastructure. While the number of Charging Stations (CSs) is increasing, particularly in urban areas, there is still a significant lack of charging infrastructure in many regions (Levinson and West, 2018). This can make it difficult for EVs to operate in remote areas or along less-traveled routes. Additionally, there may be challenges associated with the availability of CSs in many occasions, i.e. peak demand hours, holiday seasons, etc., which can further impact the efficiency of the supply chain. Combined with the charging times which can be lengthy compared to filling a tank of gas or diesel, availability can become a substantial limitation.

Finally, the supply chain disruptions caused by the transition to EVs can also pose significant challenges. The shift to EVs may require changes to the supply chain infrastructure, including the redesign of distribution centers and the adoption of new processes and technologies (Wu et al., 2019). Additionally, the supply chain disruptions caused by the shift to EVs may require companies

to adjust their sourcing strategies, which can result in increased costs and potential supply chain disruptions.

1.3 Current EV applications in logistics

Despite the potential setbacks, EVs are being increasingly employed in logistics operations. Several prominent companies have adopted EVs for various logistics applications, exemplifying the potential and benefits of this technology in the industry.

For instance, Amazon, a global e-commerce giant, has collaborated with Rivian, an EV manufacturer, to develop customized electric delivery vans for last-mile operations (Garrido, 2020). By incorporating EVs into its fleet, Amazon aims to achieve carbon neutrality while enhancing the efficiency and environmental sustainability of its package deliveries. Similarly, UPS, a logistics company, has embraced the use of various types of EVs, including cargo bikes and trikes, for last-mile deliveries. These EVs provide a cost-effective solution for navigating congested urban areas and delivering smaller packages efficiently. UPS's adoption of electric bikes and trikes demonstrates a commitment to reducing carbon emissions and optimizing its last-mile delivery operations, contributing to a more sustainable logistics ecosystem. DHL, another well-known logistics company, has recognized the advantages of EVs for urban freight transportation. The company has integrated electric trucks into its operations in cities like London and New York. By leveraging these EVs, DHL reduces emissions and improves air quality, particularly in densely populated urban areas. FedEx, another delivery services company, has incorporated electric vans into its fleet to support last-mile deliveries in a similar fashion.

In the realm of shared mobility and micro-logistics, companies like Uber Eats and Deliveroo have recognized the potential of electric bikes and scooters for efficient and eco-friendly food deliveries (Lord et al., 2023; Galati et al., 2020).

In the beverage industry, companies such as Frito-Lay (Frito-Lay) and Coca-Cola have introduced electric trucks for the distribution of their products. In the field of waste management, companies like Republic Services have integrated electric trucks for collection and transportation of waste and recycling materials. IKEA, in addition to its use of electric forklifts and pallet trucks in distribution centers, has also implemented electric delivery vehicles for home deliveries. These EVs enable emission-free transportation of furniture (Ikea).

These examples underscore the diverse applications of EVs, ranging from last-mile delivery to urban freight and reverse logistics. Through the adoption of EVs, companies across various industries demonstrate their dedication to reducing emissions, enhancing operational efficiency, and contributing to a more sustainable logistics ecosystem. The growing adoption of EVs in logistics highlights their potential to revolutionize the industry and pave the way for a greener and more environmentally responsible future.

1.4 Goals and Contribution

Based on the information presented in the previous subsections, it can be inferred that EVs are not capable of directly replacing ICE vehicles without necessitating changes in their usage. This realization prompts the research objective of this thesis, which aims to investigate alternative operational approaches to adapt EVs for daily use and to explore novel applications facilitated by their electric nature.

EVs possess unique characteristics and advantages arising from their electric propulsion systems; however, their widespread adoption and integration into existing transportation systems requires a reevaluation of traditional practices and the development of innovative solutions. Merely substituting ICE vehicles with EVs without addressing the associated challenges may prove insufficient and fail to fully exploit the potential benefits of electric mobility.

The first step in adapting EVs for daily use is to analyze the current uses of ICE vehicles and identify areas where adjustments can be made to accommodate the specific characteristics of EVs. Factors such as range limitations, and charging infrastructure need to be considered to ensure that EVs can effectively meet the demands of daily transportation requirements. This may involve developing efficient charging networks, establishing new operational protocols, and exploring technology advancements to enhance the capabilities of EVs.

This thesis seeks to explore new ways to adapt EVs for daily use. By addressing the challenges and by leveraging the unique capabilities of EVs, the full potential of electric mobility can be realized.

This research endeavors to make significant contributions to the ongoing efforts aimed at transitioning towards sustainable and efficient transportation systems. In order to achieve this objective, a novel approach to infrastructure planning is presented, complemented by the introduction of novel variants of the Vehicle Routing Problem (VRP), employing EVs and drones.

The first contribution of this research lies in the development of mathematical formulations for the VRPs. These formulations provide a solid foundation for addressing the challenges associated with incorporating EVs as well as drones in transportation planning. To demonstrate the effectiveness of the proposed formulations, smaller-scale instances of the two Close Open variants are solved utilizing a commercial solver.

To shorten the computational times for the VRPs, a diverse range of solution algorithms is thoroughly tested and adapted from existing literature. These algorithms are selected based on their suitability for addressing the complexities and constraints inherent in the VRPs. Detailed descriptions of each algorithm are provided, and their parameters are carefully set through sensitivity analyses to ensure optimal performance.

Furthermore, instances for the newly proposed formulations are created based on existing instances available in the literature. This approach enables a comprehensive evaluation of the problem scenarios and allows for future comparisons.

The subsequent paragraphs will delve into the detailed contributions of each problem presented in this thesis. By addressing the research gaps and leveraging advanced methodologies, this thesis aims to provide valuable insights and recommendations for achieving sustainable and efficient transportation systems.

The first and most important problem to discuss is charging infrastructure. The widespread adoption of EVs relies heavily on the availability of a dependable charging network, a challenge present even in countries with high EV penetration. In this investigation, EV adoption is discussed in the context of Greece, providing valuable insights into the EV market, related incentives, and the state of charging infrastructure. Existing reports indicate that Greece finds itself at a critical turning point, experiencing rapid EV adoption but slow development of Charging Stations (CSs). To this end, a Monte Carlo simulation approach is employed to assess the viability of long-distance EV trips within Greece and propose a comprehensive plan for infrastructure development. The simulation encompasses a virtual representation of Greece's road network, generating random trips between network nodes, while accounting for unpredictable conditions through a stochastic energy consumption model. The primary objective of this research is to inform stakeholders and policymakers about

the current status of EV adoption in Greece and present a strategic roadmap for the expansion of charging infrastructure. In addition, the proposed methodology can be adapted for use in different road networks and with tailored itineraries fit to other applications.

The second problem discussed in this thesis presents a new operational model for EVs in the context of logistics. Most companies that have adopted EVs for their deliveries do not plan charging stops outside their own facilities, due to the many uncertainties regarding the operation and availability of CSs. To help counter that uncertainty, the novel Close Open Electric Vehicle Routing Problem (COEVRP) is proposed. This new variant of VRP is the first to consider open routing and EVs. To minimize the risk of visiting stations that are out-of-order or full and endangering the timely deliveries, the COEVRP model only considers charging after the last delivery. This difference, compared to traditional EVRP models, allows for EVs to either return to the depot for a recharge or visit the closest charging station and avoid a mid-delivery charge that may derail their schedule. The mathematical formulation for the COEVRP is presented along with new instances based on the Electric VRP with Time Windows (EVRPTW) instances of [Schneider et al. \(2014\)](#). To solve the problem, a hybrid Variable Neighborhood Search (VNS) Algorithm with Simulated Annealing (SA) is proposed. To generate initial solutions a method inspired by the Greedy Randomized Adaptive Search Procedure (GRASP) was used. Small instances with up to fifteen customers are solved with a commercial solver and the proposed algorithm, while larger instances are solved only with the proposed algorithm. The problem considers an energy consumption function based on the traveled distance and the payload over each arc. This is necessary as the payload of the EVs can have a significant impact on the energy consumption. Since the weights and distances are arbitrary numbers set by the creators of the original instances, the energy consumption is represented by the mechanical work necessary to move the items. This work has been published in the Journal "Annals of Mathematics and Artificial Intelligence".

The following problem discussed is an extension of the COEVRP presented earlier. More specifically, the COEVRP with a Mixed Fleet (COMF-EVRP) of rented and owned EVs is presented. In this variant, it is assumed that companies own a small fleet of EVs, sufficient for most of their day to day needs and rent more vehicles whenever necessary. This can lower their initial purchase costs and their space requirements, as well as their charging infrastructure investment needs. A mathematical model for the COMF-EVRP is presented with the objective function aiming to minimize both the number of rented vehicles and the total energy consumption. The instances developed for COEVRP were also used in COMF-EVRP, with the addition of the number of owned EVs. In all cases, the number of owned EVs was set to three which was enough to satisfy the demand for many of the small instances. Two discrete optimization meta-heuristic algorithms, the Bee Colony Optimization (BCO) and the Ant Colony Optimization (ACO) algorithms were proposed for the problem. Two variations of the ACO framework, the Ant Colony System (ACS) and the Max-Min Ant System (MMAS) were included. All of the meta-heuristics were combined with a VNS algorithm that makes use of four Local Search (LS) operators. Small instances were solved by both BCO and ACO, as well as a commercial solver. The larger, 100-customer instances were solved by just BCO and ACO. Out of all the proposed methods, ACS was proven to be most successful. This variant used the same energy consumption model presented in the COEVRP.

The final work presented in this thesis is an extension of VRP that includes EVs and drones, the Electric VRP with Drones (EVRPD). While the use of drones in deliveries may not be widespread at the time of writing, drones are already being used for deliveries. Numerous medicine-related applications exist ([Matternet](#)), and companies like Mercedes-Benz are developing integrated ground and aerial delivery systems with EVs and drones. The proposed operational scheme lowers the total

energy consumption, the carbon footprint of the operations, does not contribute to road congestion and can help expedite deliveries in urban centers. The continuously increasing drone operation automation will have a significant impact on the applicability of such methods. In the proposed EVRPD, the ground EVs are used as a mobile depot from where drones operate. The combined use of these two types of EVs has benefits for both of them. The EVs have to travel less, as the drones handle the last part of the delivery and drones travel less, as the EVs carry them closer to their destinations. In addition, drones are not limited to a single delivery per flight, they are allowed to make as many deliveries as possible. The mathematical formulation presented for EVRPD has the objective of minimizing the total energy consumption which was once again model to represent the amount of work necessary to transport the items. The battery capacity of the drones was set to a tenth of the capacity of the EVs. Two-echelon instances were used to generate new instances for the EVRPD, since they include facility locations which are used to represent EV parking spaces. A number of different methods were used to solve EVRPD, among them the ACO and BCO introduced earlier, as well as new variants of GRASP, and SA, adapted to solve EVRPD. Once again, the ACO method was the most successful. The EVRPD studies have been published in the Journal of "Cleaner Logistics and Supply Chain", and in the proceedings of the "8th International Conference In Machine Learning, Optimization, and Data Science".

The structure of the thesis is the following: Section 2 presents the literature review for the related fields of study, Section 3 presents the Charging Station Location Problem (CSLP), Sections 4 and 5 present the two close-open variants of the EVRP, Section 6 presents the EVRPD and lastly, Section 7 presents the conclusions of the thesis as well as future research directions.

Chapter 2

Literature Review

The objective of this review is to provide the state-of-the-art for the problems presented in this thesis. The review can be separated in two sub-categories. The first will present and discuss publications related to the CSLP, while the second will include research in the relevant VRP fields, namely variants of Open VRP (OVRP), COVRP, EVRP, and VRP with Drones (VRPD).

2.1 Charging Station Location Problems

The increasing use of EVs around the world has stimulated research on region-specific charging networks. This section aims to provide a wide range of information related to the study; however, it is not a systematic literature review. It includes studies similar to the one presented in this thesis, conducted in other countries and regions to identify best practices and general trends in this field of research. More specifically, the first subsection focuses on EU-wide research and interoperability of CS, and the following subsection focuses on publications with studies in Greece, as well as Norway and China, which have the highest EV adoption per capita and highest number of registered EVs, respectively.

The EV Charging Station Location Problem is a variant of the facility location problem that specifically deals with determining the optimal locations for EV charging stations. The goal of the EV charger location problem is to place the charging stations in such a way that they are easily accessible to EV drivers while minimizing costs and maximizing the number of EVs that can be served.

Some authors take different approaches in their research, such as considering the potential for down-time at CSs (Ahangar et al., 2022), the cost of installation (Li et al., 2023) and maintenance (Ahmad et al., 2022a), and the availability of renewable energy sources (Saadati et al., 2022; Li et al., 2022; Ghodusinejad et al., 2022).

Others use specific case studies or simulation-based experiments (Jordán et al., 2022; Yi et al., 2022) to determine the best locations for CSs. Some papers focus on the use of different charging speeds (Wang et al., 2021; Bian et al., 2022) and the use of mobile CSs (Afshar et al., 2022; Cui et al., 2022), while others examine the costs of electricity and service costs, or the impact on the environment (Zhou et al., 2022). All of the papers discussed the importance of considering various factors when determining the optimal location for CSs for EVs.

Equal access to the CSs (Iravani, 2022), charging behavior (Ouyang and Xu, 2022), and the satisfaction of both the CS users and owners (Wang et al., 2022a) were also researched. Besides cars, other forms of transportation are being electrified as well. In Ayyildiz (2022); Altintasi and Yalcinkaya (2022), the goal was to find the optimal CS locations for electric scooters, while Tzamakos et al. (2022); de Briñas Gorosabel et al. (2022) solved the same problem for electric buses.

Numerous studies have focused on the combined problem of CS location and EVRP and have employed different techniques such as linear programming, integer programming, heuristics, and meta-heuristics. Various factors have been considered, such as the number of EVs, the expected demand for charging (Hung et al., 2022), the cost of installing and operating the CSs (Chen et al., 2020), and the availability of electricity. Some of the studies have also considered the limitations imposed by the EVs (Almouhanna et al., 2020), topology (Yang et al., 2022), and customers (Guo et al., 2020). Others have considered realistic functions to approximate the available energy (Guo et al., 2022a), and battery degradation (Guo et al., 2022b). In Kmay et al. (2021), the option to follow longer routes to reduce the need to recharge was researched, while the potential for traffic and willingness to sacrifice some range was studied in Yazdekhasti et al. (2021).

Several reviews on the topic of CS location were also published recently. In Mastoi et al. (2022) the authors provided a comprehensive examination of the various aspects of electric vehicle charging. They delved into the various charging speeds and technologies currently available, as well as the management of charging requests and the anticipation of future charging needs. Additionally, the authors discussed different incentives that could be implemented to encourage the adoption of electric vehicles. In Savari et al. (2022), the authors expanded upon the existing technology and infrastructure by also discussing how privacy concerns can impact the use of certain services. In Ahmad et al. (2022b), the authors presented an examination of the different methods used to address the problem of locating charging stations and the impact that these stations have on the power grid.

2.1.1 Research In Europe

Europe is a continent renowned for its remarkable diversity, encompassing an array of unique cultures, languages, and socio-economic backgrounds. These variations in population characteristics across Europe can be observed in the vast differences in income levels, educational attainment, and access to resources between different regions and people. Subsequently, infrastructure research is expected to differ as well.

When it comes to EVs, Europe’s diversity is a factor to consider. The continent is home to various markets, each with unique characteristics and consumer preferences. For example, Northern European countries have traditionally been more receptive to EVs due to their high levels of environmental awareness and strong government incentives (Schulz and Rode, 2022), while Southern European countries have been slower to adopt EVs due to lower purchasing power and a lack of charging infrastructure (Tromaras et al., 2017).

Furthermore, the diversity of Europe’s populations means that there are varying needs and challenges when it comes to EV adoption. For example, urban areas may require different charging infrastructure solutions than rural areas (Funke et al., 2019), and some populations may face barriers to EV ownership due to factors such as income or accessibility (Falchetta and Noussan, 2021). As such, it is necessary for policymakers and industry stakeholders to take a nuanced approach to EV promotion and infrastructure development to ensure that the needs of all populations are adequately addressed.

Some studies have undertaken comparative analyses of European countries and their current

state of EV adoption. [Cavallaro et al. \(2018\)](#) investigated EV adoption and the current policies in relation to emissions in Europe. The authors mention that non-subsidy incentives should also be given. In-depth comparisons of different types of vehicles were made across 28 countries. At the time of the study, Greece had the most polluting energy mix across all countries; therefore, making EVs heavier polluters than ICE vehicles. Since then, the energy mix has shifted with coal use lowered by more than 60% ([International Energy Agency, 2023](#)). [Falchetta and Noussan \(2021\)](#) presented the development of public CSs in Europe over the past five years. The number of CSs have risen quickly, but fast chargers have increased at a slower pace. Nonetheless, accessibility remains an issue, with Greece and Spain being mentioned as the countries with the lowest accessibility. The paper underscores the importance of prioritizing access to CSs for citizens outside urban areas, while concurrently optimizing the energy system through the implementation of smart charging strategies and flexibility measures, to efficiently decarbonize the transportation system. [Sæther \(2022\)](#) presented an empirical analysis of the impact of policy packages and infrastructure on the market share of EVs in Europe from 2009 to 2019. The study found that increasing the availability of large CSs leads to higher EV adoption rates. They identified that the most effective policy package includes incentives related to purchasing and ownership costs and local incentives. Moreover, they supported that more attention should be given to fast CSs infrastructure, rather than personal incentives. The study did not provide any insights specifically for Greece.

Interoperability within the EU Interoperability among the charging networks of different countries is important for the wider adoption and usability of EVs globally. Without it, EV drivers may face challenges finding compatible charging infrastructure when traveling across borders. This would be a significant step forward in Europe, where each country and each provider has different access and use implementation for their CSs, despite the universal CS hardware. [Ferwerda et al. \(2018\)](#) provided insights on interoperability, presenting the existing systems and discussing the development of the Open Charge Point Interface to provide a better charging experience in Europe. [Hardman et al. \(2018\)](#) studied the effect of CS infrastructure on small passenger EVs, focusing on the preferences of the users and the user experience. The authors argue that home charging is the most important for most users, while public charging is the least important. In addition, they mention that increasing the interoperability of CS can positively impact the adoption of EVs. In a recent study, [Gutjar and Kowald \(2023\)](#) suggested that authentication via the charging cable, payment by card, and charging for the energy spent instead of total charging time are the preferred characteristics. Such characteristics could make interoperability a reality in Europe. A simulation of EVs used in logistics operations was presented in [Speth et al. \(2022\)](#). The authors replicated the European road network using data from the European Transport policy Information System. Based on it, a sizeable simulation took place, focusing on truck movement within the EU and using a queuing model to determine the size of each CS; however, the study did not mention interoperability.

2.1.2 Country and Region Specific Research

Country or region-specific charging infrastructure research focuses on understanding the unique needs and challenges of each location. Such research typically includes an assessment of the existing establishments, as well as an analysis of the charging needs of EV users in the region. Their findings can be used to develop policies and programs to support the expansion of charging infrastructure and promote the adoption of EVs.

Despite the existing body of literature on the subject, limited attention has been devoted to their

examination in the context of Greece, with scarce empirical evidence available to date. [Efthymiou et al. \(2017\)](#) proposed a solution for the optimal CS locations utilizing Genetic Algorithms (GAs) and Origin-Destination (OD) pairs. They carried out a case study in Thessaloniki indicating the need for 15 stations to cover 80% of the expected demand based on limited available data. [Geronikolos and Potoglou \(2021\)](#) presented a paper on EV adoption in Greece, interviewing six stakeholders. The study discusses the low market share of EVs, the incentives provided by the government, and the infrastructure, which they deemed inadequate. They highlighted the long time needed to construct new stations, the strain on the grid, and the necessity of fast chargers. A limitation of this study is the small number of participants.

The research of [Karolemeas et al. \(2021\)](#) aimed to create an index of the suitability of a location for the construction of new CSs in Greece. EV parking spaces, proximity to transit, and proximity to recreational places were found to be the three most influential factors. The study did not account for coverage or congestion. Interviews with stakeholders were also included, presenting a range of arguments, but with the common view of using EVs as part of multi-modal trips. The study of [Nikiforiadis et al. \(2022\)](#), found a connection between habits at home and the willingness to make green transportation choices for holidays. In this case, the subject of interest is the willingness to use electric car-sharing services for local transportation at their destination. Among cars, motorcycles, and bikes, the first are expected to become the most popular. The study focused on the island of Rhodes, Greece.

[Zafeiratou and Spataru \(2022\)](#) focused on the electrification of the Greek islands, given their small size and short distances. A significant drawback is the energy mix and the existing grid, but the authors propose the use of Vehicle-to-Grid technology as well as planned charging to shift the charging demand away from the peak demand and help support the grid. [Kouridis and Vlachokostas \(2022\)](#) presented a methodology for estimating the social benefits of EV adoption in three urban areas of Greece (Athens, Thessaloniki, and Patra). The results focus on the health benefits associated with lower local pollution and the social benefits measured in monetary value.

[Mpoi et al. \(2023\)](#) studied the impact of incentives and demographic characteristics on the intention to purchase an electric vehicle in Athens, Greece. The results suggest that a dense charging network, partnerships, and user-based marketing policies will support the transition to EVs. In addition, it is reported that the willingness to purchase is related to financial incentives.

The country at the forefront of EV adoption is Norway, with a very high rate of EV ownership per capita. Norway's ambitious policies, including generous subsidies, tax exemptions, and infrastructure development, have contributed significantly to the growth of the EV market in the country. As of 2022, EVs account for the majority of new car sales in Norway ([Nayum and Thøgersen, 2022](#)). Their strong commitment to a sustainable and green future has made it a model for other nations transitioning to low-carbon transportation. However, despite the successes, the country still faces challenges, such as the environmental impact of producing batteries and the need for further investment in CS infrastructure to support the increasing number of EVs on the road ([Schulz and Rode, 2022](#)).

[Funke et al. \(2019\)](#) compared the framework conditions for EV infrastructure in the Netherlands, the US, Germany, China, and Norway. The analysis focuses on the availability of detached houses and private parking spaces, the ratio of EVs to CSs, and the share between AC and DC CSs. The authors suggest that home charging is crucial in countries with a high proportion of detached houses, whereas public CSs are more important in densely populated areas where home charging is usually not an option. A subsequent conclusion is that the ratio of EVs to CSs is not a very useful index in

solidarity. [van der Kam et al. \(2020\)](#) used public charging data from a charging provider in Norway, collected over a two-year period. The authors studied the link between specific policies and charging behavior and developed a policy decision tree. They also highlighted the benefits of area-specific policy implementation, especially for photovoltaic integration. This aspect of the research is very important as renewable energy generation will enable sustainable transportation.

The mature EV market of Norway offers opportunities for new research. [Hasan \(2021\)](#) questioned Norwegians who already own EVs on their intention to consider an EV as their next vehicle and recorded a positive outlook by current EV users.

A key takeaway from the EV market of Norway is that the importance of infrastructure is tremendous; with most researchers concluding that there is a need for more fast CSs.

China has emerged as the largest EV market in the world (by the total number of EVs on the road), with a vast array of domestic and international companies offering various EV models to Chinese consumers. The government's policy support for EVs, along with the country's commitment to reducing air pollution, has been a driving force behind the rapid growth of EV adoption in China. [Shahraki et al. \(2015\)](#) studied the travel patterns of taxis in a Chinese region in order to find the optimal CS locations. The authors compared the efficiency of existing stations to their potential efficiency if they were located at the optimal sites, which were found to be significant. The candidate locations were the existing gas stations. One limitation of the study is that the focus is only on taxis. Nonetheless, their study highlights the importance of the CS locations. [Wang et al. \(2018\)](#) presented three algorithms with the objective of determining the location and size of fast CSs along a highway network, under budget constraints. A case study for a Chinese region was presented to showcase the proposed algorithm. [Kong et al. \(2019\)](#) also carried out a case study for the location of fast CSs in the center of Beijing. The problem is solved in two stages, with the first stage considering the locations from the perspective of the stakeholders, and the second stage focusing on driver satisfaction and general feasibility metrics. This approach could be employed in other regions as well.

The research of [Wang et al. \(2019\)](#) focused on enabling intercity EV traveling by planning for the size and location of CSs. A case study for the Chinese region was carried out with the intention of finding the optimal places for the new stations. While the road network and the distances were realistic, the range of EVs was unrealistically low, as the objective was to make traveling without recharging impossible. [Bian et al. \(2022\)](#) aimed to find the optimal locations for CSs based on multiple objectives with the goal of providing the best solution for all stakeholders. [Che et al. \(2023\)](#) presented a case study in China, proposing a new CS location model for tourist attractions; however, the research emphasized the Particle Swarm Optimization (PSO) algorithm employed, its parameters, and its efficiency. Their objective was to determine which five locations out of the available ten would be the best to install new CSs.

Overall, research in China is very diverse, and insights from the deployment of solutions there can impact future CS developments in other regions.

2.2 Open Vehicle Routing Problems

The OVRP was initially introduced by [Schrage \(1981\)](#) as a solution for businesses with high delivery requirements but limited pickup demand. Schrage proposed the engagement of a delivery company to handle a portion of the deliveries.

To address the OVRP, [Sariklis and Powell \(2000\)](#) devised the first heuristic approach, employing a two-step process involving clustering and routing. Subsequently, [Brandão \(2004\)](#) developed a

Tabu Search (TS) algorithm for the OVRP. This algorithm utilized the nearest neighbor method and incorporated an improvement phase based on previous research findings. [Tarantilis et al. \(2004a\)](#) contributed to the OVRP literature by developing a Decision Support System, while in a separate study [Tarantilis et al. \(2004b\)](#), they introduced a threshold accepting methodology. Additionally, [Tarantilis et al. \(2005\)](#) proposed a meta-heuristic approach for the OVRP, leveraging a single parameter. [Fu et al. \(2005\)](#) focused on enhancing the OVRP through the development of a tabu-search-based heuristic method. [Aksen et al. \(2007\)](#) extended the OVRP framework by considering specific destination nodes for trips and incorporating delivery deadlines. [Repoussis et al. \(2007\)](#) presented a mathematical model for the OVRP with Time Windows, and alongside it, a heuristic algorithm to solve the problem. Similarly, [Li et al. \(2007\)](#) introduced a record-to-record travel algorithm for the OVRP, which employed a fixed-size neighbor list. Initial solutions were generated using a sweep algorithm. [Letchford et al. \(2007\)](#) presented a branch and cut algorithm for the OVRP. Furthermore, they proved that a Close VRP can be transformed to an OVRP, but the opposite cannot happen. Their experiments were carried on CPLEX and both open and closed variants were solved. In one case, the open variant was solved ten minutes quicker than the closed counterpart. For large instances they provided the bound they acquired after one hour per instance.

OVRP with variable travel times was considered in [Yanwei et al. \(2008\)](#). A PSO algorithm was presented and a sensitivity analysis followed, to determine the best settings for the method. The multi-start VNS for OVRP was presented in [Fleszar et al. \(2009\)](#). Tests were carried on benchmarks from the literature and comparisons with other publications were made. A heuristic for the OVRP was developed by [Salari et al. \(2010\)](#). Customers are randomly removed from routes and each time the problem is solved again. The method obtained some of the best known solutions from the literature.

Another PSO implementation for the OVRP was developed by [MirHassani and Abolghasemi \(2011\)](#). The TS heuristic was combined with a GA by [Yu et al. \(2011\)](#) to solve a small real instance of OVRP. A TS based multi-start heuristic was developed for a variant of OVRP in [Li et al. \(2012\)](#). The described problem uses a non-homogeneous set of vehicles. A Swarm Intelligence algorithm for the OVRP was presented in [Marinakis and Marinaki \(2014\)](#). The proposed Bumble Bee Mating Optimization algorithm was combined with an Iterated Local Search (ILS) algorithm and tested against other algorithms from the literature and its performance was found to be excellent, comparable to the Hybrid Evolution Strategy algorithm proposed in [Repoussis et al. \(2010\)](#). The tests were carried on various instances from the literature.

[López-Sánchez et al. \(2014\)](#) set the goal of minimizing the maximum time spent in a vehicle by a single operator and they called this variant the balanced OVRP. They developed a two stage multi start algorithm. In the first stage, a solution is generated and in the second phase, LS takes place. Their memory-less approach solved successfully benchmarks from the literature, providing new best solutions for some of them. [Şevkli and Güler \(2017\)](#) presented a two-stage, cluster first and route second algorithm. A VNS is applied separately for intra and inter route optimization. Benchmarks and real-world data were used for the tests, while the results provided significant cost reductions for both. [YousefiKhoshbakht and Mahmoodi Darani \(2019\)](#) developed an ACO and TS heuristic algorithm for the OVRP. A new transition rule was introduced for the ACO, while TS is used as LS. Comparison to other results from the literature ensured the quality of the algorithm.

The OVRP with Time Windows (TWs) was proposed in [Repoussis et al. \(2007\)](#), along with a heuristic method to provide solutions, an insertion heuristic method based in the literature. [Brandão \(2018\)](#) presented an ILS algorithm for the OVRP with Time Windows. The ILS includes steps that help the algorithm further and more efficiently explore the solution space. [Babagolzadeh et al.](#)

(2019) aimed to minimize the sum of costs for deliveries in a two-echelon OVRP with soft TWs, employing planes in the first echelon and trucks in the second. The authors paid attention to the environmental part as well by considering the fuel consumption of the vehicles as part of the cost. A solution is presented for demonstration purposes but not solution method is proposed.

Tarantilis and Kiranoudis (2002) introduced the Multi-Depot OVRP (MDOVRP) in the context of meat distribution. Pichka et al. (2014) presented a variant of the MDOVRP in which each depot has limited vehicle space. A solution approach with SA and four LS operators was presented but matched the optimum in less than half of the instances; however, they were small randomly generated instances. A study on the potential savings that an open implementation may offer in comparison to the traditional closed one was presented in Čičková et al. (2015), analyzing many VRP variants. The authors considered multiple depots and different vehicle mixes. For their tests they used real world locations and distances, and an exact method was employed. The fixed costs of each vehicle type was not disclosed.

Soto et al. (2017) solved the MDOVRP with neighborhood search algorithm that moves from one neighborhood to the next in an ordered manner, not randomly. Moreover, it was combined with a TS method. The proposed algorithm was tested on both OVRP and MDOVRP benchmarks and it outperformed other algorithms in terms of execution time. A variant of MDOVRP with TW was studied in Shen et al. (2018), minimizing total costs, including the environmental costs in the form of emissions trading. They employed a two phase algorithm with PSO first and TS second, and stated that it is suitable for small instances. Their experiments focused more on the effects of emissions costs. Niu et al. (2018) introduced the Green OVRP variant with TWs. Their objective is to minimize two costs, the cost of GhG emissions and the salaries of the vehicle drivers. All three types of trucks were considered, light, medium, and heavy duty, with the first being the most cost effective regardless of the number of customers that need to be served. The authors considered only single-type fleets and not mixed fleets. Furthermore, the simulated traffic congestion showed that the costs increase dramatically when the speed is lowered, as a result of more pollution and more work hours for the drivers. The provided solutions were generated by TS algorithm with neighborhood operators to optimize the results, with a speed optimization algorithm employed after the routes have been determined. Brandão (2020) studied the MDOVRP and proposed an ILS algorithm with a memory component that significantly improved the perturbation phase of the solution, providing 9 new best solutions and matching many of the previous ones.

In Vincent et al. (2016), the OVRP with cross-docking is proposed. In this variant, only rented vehicles are used. These vehicles pickup items to be delivered at the dock. Some of the vehicles will leave the dock loaded with items to be delivered and will return to the logistics depot at the end of the operations, while vehicles that are not used for deliveries will immediately return to the logistics depot. In case the vehicles are not enough, more vehicles will be sent to the dock to assist in the delivery process. The authors proposed a SA solution method, combined with three LS operators. The algorithm was tested on the benchmarks for the closed variant of the problem and performed adequately.

Cao et al. (2014) studied an OVRP variant with undetermined demands. Two objectives are presented, the overall travel cost and unmet demand minimization. Four different methodologies for tackling the problem were presented. Ruiz et al. (2019) solved the OVRP with a modified GA. The objective was the minimization of total trip length. The algorithm separates the genomes in two pools, based on their fitness. For the crossover, a good candidate is crossed with either another good or a non-good candidate, and the better the fitness of the candidate the higher the chance for the genome to be inherited. The GA was tested on three sets of instances, providing new best solutions

and better upper bounds. Its performance was better for randomly distributed nodes, while the extensive LS limited the number of encoding and decoding needed by helping the solution converge faster.

Zhen et al. (2021) presented a crowd-sourced OVRP variants, in which drivers in a certain radius around the depot can be allocated with the delivery tasks. The drivers are compensated with a flat fee for traveling from their position to the depot, in addition to their compensation for the delivery. The proposed algorithm is based on Column Generation; however, tests were carried on small instances, with the proposed method having an average gap of about 0.9% from the CPLEX solutions. Nucamendi-Guillén et al. (2021) solve a variant which considers the collection items from various places and their delivery to a single location. The problem was modeled as a MDOVRP with more than one carriers being considered, each with limit number of different vehicles and different costs. The rented vehicles have a fixed renting cost and a variable cost based on the traveled distance. They employ a two phase solution method, with solution generation first and improvement second. It was applied on a case study and on modified instances from the literature. The results on the modified instances were within 5% of the solutions obtained by CPLEX. The case study was solved to optimality, but its small size is not indicative of the actual performance. Atefi et al. (2018) studied a variant of OVRP that may employ more than one carrier to make a delivery. In their study, vehicles leave from the factory and visit some of the nodes and then reach a decoupling point. From that point forward another carrier handles the rest of the trip. This tactic helps keep the vehicles closer to their station and lower the total operational costs. The solution algorithm is based on ILS and tests were carried both on traditional OVRP benchmarks and on the new real-world based instances. One new BKS was found for the OVRP indicating the effectiveness of the algorithm. None of the new instances were solved to optimality as CPLEX reached the time limit for every instance, but the ILS solutions were at least as good as the CPLEX solutions. It should be noted that each ILS solution needs less than two seconds compared to the three hour limit of the commercial solver.

2.3 Close Open Vehicle Routing Problems

The Close Open variant of VRP considers both external and internal vehicle fleets, in contrast to the plain OVRP variant. While the OVRP has received considerable attention in the research community, the COVRP remains relatively underexplored, with limited scholarly investigation dedicated to its study and solution methodologies. The COVRP was first presented in Liu and Jiang (2012). In this variant, a combination of owned and rented vehicles is coordinated for the successful completion of the deliveries, with the rented vehicles routed in an open fashion. To solve it, a memetic algorithm was proposed with crossover mechanisms and LS procedures. The algorithm itself was benchmarked on other VRP variants using instances from the literature, and new problem specific instances were created for the COVRP. In all tests MA surpassed the performance of CPLEX.

Brito et al. (2016) introduced a VNS approach for the COVRP with TWs. They developed several variations of the VNS algorithm and even combined it with GRASP and VND. In their evaluation, they utilized benchmark instances from the existing literature and real-world data from a logistics company to assess the performance of their VNS variants. Their findings indicated that VND with chain-generated neighbors yielded the best results.

In another study, Sun (2020) proposed a knowledge-guided Local Search algorithm for the Close Open variant, with the objective of minimizing overall routing expenses. Their approach involved calculating the polar coordinates of the customers and subsequently adding customers to the route in a circular motion, as long as space permitted. Once a solution was formed, intra and inter-route

LS operators were applied iteratively until a termination condition was met. The authors conducted a small-scale experiment for illustrative purposes.

Azadeh and Farrokhi-Asl (2019) presented a novel solution methodology for the Close Open Multiple Depot Vehicle Routing Problem, which combined a multi-criteria method with a heuristic approach. They compared the performance of their hybrid Analytic Hierarchy Process and GA algorithm against a simple GA implementation and a commercial solver. The results demonstrated the effectiveness of their hybrid approach.

Tavakkoli-Moghaddam et al. (2019) investigated a two-objective variant of the COVRP with multiple depots, owned and rented vehicles at each depot, and the objectives of minimizing total costs and driver dissatisfaction costs. Their study aimed to determine the most influential cost factor, and they employed two multi-criteria methods to ascertain that the total cost objective was the most sensitive.

Fernando et al. (2022) proposed a variant of the COVRP with multiple depots, where owned vehicles start and end their trips at the same depot, while rented vehicles are assigned to a depot but do not originate from it. They created a greedy initial solution and then employed three heuristic methods to further enhance it. The Guided LS, SA, and TS algorithms were tested, with SA performing the worst and Guided LS exhibiting comparable performance to TS but with faster execution times. The proposed solution methodology demonstrated high capacity utilization.

In a study by Wang et al. (2022b), a complex Close Open variant was presented, involving two types of depots for distribution and pickups, along with customers having various combinations of requests. Vehicles were allowed to travel between depots of the same type, and a vehicle could perform deliveries and pickups on the same trip, provided capacity constraints were satisfied. The solution process began with customer clustering based on their requirements, followed by the application of a meta-heuristic to optimize the routing. The authors combined PSO with a GA to solve this intricate problem, achieving good performance. They also applied the algorithm to a real-world case, resulting in significant cost improvements.

Zhen et al. (2022) investigated the Multi-Depot Close Open VRP, considering occasional drivers for open routing and incorporating store location pickups. The delivery requests were categorized into mandatory and optional deliveries based on their source. Mandatory requests were fulfilled using owned vehicles, while occasional drivers were assigned to handle optional deliveries.

2.4 Electric Vehicle Routing Problem

The inclusion of EVs in routing operations has emerged as a prominent trend within the VRP field in recent years. A precursor to both the EVRP and the Green Vehicle Routing Problem (GVRP) was introduced in Conrad and Figliozzi (2011), which exhibited many similarities to the EVRP. Notably, the study employed vehicles with limited range that necessitated refueling at customer locations, without explicitly disclosing them as EVs.

Research focusing on VRP with Alternative Fuel Vehicles (AFVs) has been predominantly explored through the GVRP, initially presented in Erdoğan and Miller-Hooks (2012). In contrast to traditional VRP, the GVRP specifically aims to minimize environmental impact, often by targeting GhG emissions. Although EVs fall under the category of AFVs, EVRP and GVRP are treated as distinct variants due to their different objectives. Nonetheless, there are a few studies that are related to both.

An exemplar of such research is the work conducted by Vincent et al. (2021), which investigated a variant of the EVRP considering both energy expenditure and associated GhG emissions. The

authors proposed an Adaptive Large Neighborhood Search (ALNS) algorithm and evaluated its performance on benchmark instances sourced from existing literature, as well as on new problem instances.

[Schneider et al. \(2015\)](#) presented a related problem termed the VRP with Intermediate Stops, in which intermediate stops could encompass a wide range of purposes and incorporate various charging and refueling technologies.

[Kara et al. \(2007\)](#) introduced a novel variant called the Energy Minimizing VRP, with the objective of minimizing total energy consumption of the vehicles. Energy expenditure was computed based on factors such as distance traveled and the load carried by the vehicles at each point. The authors employed a commercial solver to solve the proposed simulation, and the obtained solutions indicated that longer routes with lower energy consumption yielded optimal outcomes.

2.4.1 Time Windows

The most common addition to EVRP, is the adoption of Time Windows (EVRPTW). [Schneider et al. \(2014\)](#) introduced the first EVRPTW benchmark instances that later proved to be the most successful ones, based on those of [Solomon \(1987a\)](#). The newly introduced instances were solved using a combination of a VNS algorithm and a TS heuristic. [Grandinetti et al. \(2016\)](#) studied a pickup and delivery variant of EVRPTW and employed the weighted sum method. [Keskin and Çatay \(2018\)](#) set to minimize the cost of recharging while utilizing as few vehicles as possible. Large instances were solved using an ALNS algorithm alongside an exact method, to obtain better results. [Bruglieri et al. \(2015\)](#) developed a VNS Branching algorithm, and using CPLEX they solved some of [Solomon \(1987a\)](#) instances to determine the quality of the two models that they developed; however, just six instances were solved. [Erdelić et al. \(2019\)](#) set the objective of minimizing the total distance traveled and the fleet size. Small instances were solved using MATLAB's integrated function, while a meta-heuristic is developed for larger ones. [Keskin et al. \(2019\)](#) solved the EVRP with soft TWs and incorporated time-dependent waiting times at CSs. They aimed to minimize all costs and penalties for late arrivals. Their study showed that costs may increase up to a quarter due to waiting times. [Rezgui et al. \(2019\)](#) proposed the employment of modular EVs for last mile deliveries.

[Wang et al. \(2023\)](#) presented a variant of EVRPTW with shared operational network that can minimize the operational costs and help adhere to the time windows of the customers.

2.4.2 Vehicle-to-Grid

The research of [Alqahtani and Hu \(2022\)](#) aims to combine EVRP with a scheduling problem related to recharging. The EVs in the scenario presented act as mobile batteries that provide power through a V2G system, where and when needed. Furthermore, the vehicles are equipped with solar panels. A reinforcement learning method with multiple agents was employed with good results. [Etesami et al. \(2020\)](#) presented an EVRP in which the EVs may use a CS to either recharge or provide energy back to the grid. The price of energy is variable and is used to help distribute the EVs across the existing CS network. They concluded that depending on the number of EVs, different pricing scenarios are necessary. [Lin et al. \(2021\)](#) presented an EVRPTW with time-dependent energy costs and V2G capabilities. The operational time range is split with a different price to sell and buy energy in each time slot, while the decision to buy or sell can not change within the slot. The function between time and energy is linear and does not depend on any external factor. A case study and benchmarks were solved. [Deng et al. \(2022\)](#) consider the use of EVs both for deliveries and for providing power to

the depot when they are idle. Their aim is to minimize the energy and transportation cost. Napoli et al. (2021) studied a variant of EVRPTW with a depot that can provide the EVs with renewable energy. They performed a case study and accounted for the payload in the energy consumption.

2.4.3 Fast Charging

Çatay and Keskin (2017) conducted a comparative analysis to assess the benefits of incorporating quick charging strategies in route planning, in contrast to a single charging policy. They specifically focused on the impact of quick charging on cost reduction and fleet size optimization. To evaluate their findings, they solved a set of instances from Schneider et al. (2014), selecting the smaller instances for their analysis.

Erdem (2022) considered an extension of the waste collection problem employing EVs. In their variant, two distinct depots exist, one has three kinds of EVs and the other has two. Each of the points to be visited may have multiple types of waste, subsequently some points will be visited by more than one vehicles. EVs may replenish the lost energy at a CS, with higher lever charging compared to the depot. A modified VNS was used and compared to a commercial solver, showing the great performance of the VNS. The tests were carried on new benchmarks derived from real world data. They discovered, that considering the truck is full at half its capacity had benefit in costs. Lastly, an average speed of 50kph yielded the lowest costs.

2.4.4 Battery Swapping

In their study, Raeesi and Zografos (2020) presented the EVRPTW incorporating Synchronized Mobile Battery Swapping (SMBS). This variant allows EVs to request on-the-fly battery swaps as a means of replenishing energy. A dedicated battery swap vehicle is dispatched to the designated meeting point specified by the EV driver to facilitate the battery swap process. The proposed model aims to mitigate range anxiety associated with EV operations. They modified the instances of Schneider et al. (2014) for the SMBS variant and, also, tested SMBS against traditional charging stations, which they estimated to cost almost four times more. Raeesi and Zografos (2021) enrich the EVRPTW with both CSs and Battery Swap Stations (BSSs). They identify and solve four different business models of operation. The first model includes only CSs, the second replaces CSs with EVs that carry replacement batteries for the EVs transporting goods, the third model combines the previous two, while the fourth and last model considers traditional vehicles that transport replacement batteries. The main target is the minimization of the total vehicles, with both an exact and a heuristic method being employed. The authors aimed to highlight the potential saving of the third model and despite the evident lack of realism they argued that it would outperform the other models since it would provide a fail-safe mechanism for EVs. Mao et al. (2020) proposed an EVRPTW model with both battery recharging and replacement as options. An Ant Colony algorithm combined with LS was used to solve it. Tests were carried on the original EVRPTW instances from Schneider et al. (2014), showing cost improvements.

2.4.5 Planned charging

Tookanlou et al. (2021) presented an operational scheme that involves planning the routing and charging one day in advance by collecting information on the trips to be made. The formulation considers the lowest travel distance for each trip, and each EV has its own lowest battery level needs. The authors considered only fast chargers and V2G availability. A large case study for a real world

location was presented. [Shahkamrani et al. \(2021\)](#) also proposed a similar system to [Tookanlou et al. \(2021\)](#), but included many environmental and topology parameters in their study. They presented a case study too. [Sweda et al. \(2017a\)](#) proposed a solution method for EVRP that pre-selects the charging strategy the EV will follow, as well as alternatives. In their study, the chance of each CSs being available, and expected waiting when it's not, are known at the planning stage.

2.4.6 Partial Recharging

Different charging strategies are a common occurrence in EVRP. Some researchers choose to recharge the EVs to full capacity, while others choose to charge the battery as necessary, to avoid losing a time window and avoid spending more by charging the vehicle at a public CS.

Besides time loss, fully recharging a battery leads to faster battery degradation, as explained in [Sweda et al. \(2017b\)](#). This scenario is referred to as a partial recharge (PR) and is implemented often.

[Keskin and Çatay \(2016\)](#) solved a variant with Partial Recharging using an ALNS algorithm. In another study, [Desaulniers et al. \(2016\)](#) solved four different variations of EVRPTW, each with a different charging plan, and concluded that opting for multiple PRs is the best approach compared to more restrictive scenarios.

[Ferro et al. \(2018\)](#) considered charging parameters such as different energy pricing in relation to time, and the efficiency of the onboard EV charging equipment. They aimed to minimize total distance and total charging cost and solved eighteen randomly generated instances. [Bruglieri et al. \(2017\)](#) introduced a three phase mat-heuristic to minimize the number of utilized vehicles and the total operation time. The solution was provided by the combination of an exact method and a variant of the VNS algorithm, using CPLEX. [Ding et al. \(2015\)](#) considered the limited charging capacity of charging stations and explore the partial recharging strategies to improve charging times. Their goal was to have conflict free recharging to diminish lost time and revenue. They based their model on [Schneider et al. \(2014\)](#).

2.4.7 Non-Linear Charging

Researchers strive to create models as realistic as possible to obtain results close to reality. When modeling an EVRP one of the options is to use a Non-Linear Charging Function (NLCF or NL) that mimics a realistic charging behavior. A non-linear charging function is also presented in [Montoya et al. \(2017\)](#), when solving EVRP-NL.

In their research, [Zuo et al. \(2019\)](#) proposed a novel model for the EVRP, incorporating a concave non-linear charging function. The objective of their model was to minimize the overall operational costs.

Furthermore, [Froger et al. \(2017\)](#) investigated the EVRP with a NLCF and the presence of charging stations with limited capacity. They developed a meta-heuristic algorithm that constructs a final solution by assembling routes from a pool of potential solutions. The performance of their approach was evaluated using benchmark instances from [Montoya et al. \(2017\)](#), demonstrating satisfactory results.

[Froger et al. \(2019\)](#) provided an improved formulation for the problem. The differentiating factor is the arc-based approach compared to a classic node based. Their path-based model improved several BKS. To solve the instances of [Montoya et al. \(2017\)](#) a version of Gurobi was used, thus only small problems can be solved. The results showed that their newly proposed tracking model

yields significantly better results than the previously proposed ones. [Karakatić \(2020\)](#) presented a Two-Layer GA for solving EVRPTW with Multiple Depots and Partial, NL charging. Modified instances of [Cordeau et al. \(2001\)](#) were used to test the effectiveness of their meta-heuristic.

[Zang et al. \(2022\)](#) introduced the non linear depth of discharge EVRPTW problem. They aim to minimize the long-term cost of owning an EV fleet by minimizing the damage to their batteries, by providing routing plans that consider the Depth of Discharge (DoD), studying both partial and full recharging policies. The partial charging combined with DoD provided the overall best results. A branch-cut-price algorithm was proposed in [Lam et al. \(2022\)](#) for the EVRPTW with additional CS constraints and a more realistic charging curve; however, discharging remains linear. The vehicles may be recharged partially and may not visit two CSs in a row. The authors modified the EVRPTW instances of [Schneider et al. \(2014\)](#), lowering the number of CSs and limiting the number of chargers at each CS.

[Kim and Do Chung \(2023\)](#) presented a variant with NLCF that depends on the battery charge level. An ILS was proposed to solve the problem. It was observed that based on the proposed model, the EVs tend to charge more when visiting fast charging stations and also they spend more time charging at the first charging stop.

2.4.8 Uncertainty

Another aspect of realism inclusion in EVRP, is to consider possible uncertainties, either on travel time, or even on charging times and charger availability. [Kullman et al. \(2018\)](#) explore Dynamic EVRP and allow for both public and private charging. Public charging station waiting times are uncertain. They created their own instances based on previous literature with the goal of proving that public charging is a viable option. [Zhang et al. \(2020\)](#) introduce a novel Fuzzy EVRPTW. The fuzzy aspects are service time, energy consumption and travel time. They propose a ALNS algorithm with a fuzzy simulation model. To evaluate the ALNS algorithm, they compared it with other studies that also used [Schneider et al. \(2014\)](#) instances, while they developed their own fuzzy instances.

In [Keskin et al. \(2021\)](#), an extension of EVRPTW that considers unknown waiting times at CSs is studied. The first phase of the solution process considers a waiting time which is different for each CS. When the vehicle arrives at the CS if the actual waiting time is longer, then the algorithm adapts the solution. An ALNS algorithm was developed and compared to the literature. The results indicate that the proposed method is suitable for cases of high waiting times. [Basso et al. \(2022\)](#) developed a reinforcement learning method to dynamically route EVs that may receive transportation requests during their trip, creating the Dynamic and Stochastic EVRP. The EV may have to deviate from the originally planned tour, either to satisfy a new request or to visit a CS. The proposed learning method showed an improvement in energy consumption, compare to an online method.

[Amiri et al. \(2023\)](#) presented an EVRP with electric trucks, with a bi-objective optimization model that minimizes costs and maximizes satisfaction, considering uncertain quantity requests and travel time. Besides testing on instances from the literature, the authors also carried out a Monte Carlo simulation. They highlighted that higher levels of uncertainty can lead to significant more charging stops.

2.4.9 Other affecting factors

The EVRPTW has been explored from various angles in the literature. One approach is to consider the energy consumption rate as a function of vehicle speed and load, as investigated in [Xiao et al. \(2019\)](#).

Similar to other VRP variants, numerous factors can influence the efficiency of EVs. [Omidvar and Tavakkoli-Moghaddam \(2012\)](#) examined the impact of traffic on VRPs involving AFVs. To simulate the effect of traffic, they introduced a travel time function that adjusted vehicle speed based on the time of day. The authors employed a SA algorithm and a GA algorithm, comparing their performance on instances from [Solomon \(1987a\)](#).

[Rastani et al. \(2019\)](#) focused on the influence of ambient temperature on vehicle routing, considering the need to maintain a tolerable cabin temperature and the reduced efficiency of EVs in cold environments. Their objectives encompassed minimizing fleet size and total energy consumption. They utilized an ALNS algorithm and instances from [Schneider et al. \(2014\)](#). It is worth noting that passenger vehicles were used as EVs in their study, which may introduce inaccuracies when compared to freight vehicles.

Payload considerations were also explored in [Lin et al. \(2016\)](#), where a heterogeneous EV fleet was employed, encompassing both pickups and deliveries. Full charging was assumed, and the average speed varied across different arcs. The authors provided a realistic example to illustrate their approach.

In the work of [Alesiani and Maslekar \(2014\)](#), a GA was developed specifically for electric vehicles. The algorithm considered the load of the charging station and aimed to minimize associated costs.

[Zhang et al. \(2018\)](#) solved the EVRP using both an ACO algorithm and an ALNS algorithm. Their objective was to minimize the total energy consumption rather than distance traveled, considering factors such as weight, speed, and road friction. The proposed algorithms were tested on instances created specifically for the problem, and the results were compared against optimal solutions provided by CPLEX, demonstrating the effectiveness of their approach.

[Basso et al. \(2019\)](#) formulated the Two-stage EVRP, which involved developing an improved energy consumption model accounting for topography and speed profiles. The authors applied an evaluation of the road network, followed by a two-stage approach to find the solution. Experiments were conducted on the Swedish road network, with an average deviation of 2.28%, indicating promising results.

[Shao et al. \(2017\)](#) introduced a new formula for energy consumption that considered speed and weight factors. They evaluated the performance of their hybrid GA on a Beijing road network.

In [Rastani et al. \(2019\)](#) given the requirement for reasonable cabin temperature and the fact that EVs perform worse in cold climates, the ambient temperature it was taken into consideration for trip planning. The goal was to reduce the number of employed EVs and the amount of energy used overall. Since a commercially available electric car was used in place of the electric van, some inconsistencies with the real world may occur. To solve the EVRPTW they employed an ALNS algorithm, adapted from previous literature. Moreover, the ability to add multiple CS visits to a trip was added to the ALNS. The instances from [Schneider et al. \(2014\)](#) were adapted for the problem. The results indicate that the harsher the conditions, the fewer instances could be solved and both the energy consumption and number of EVs were higher. A case study revealed the same insights.

[Comert and Yazgan \(2023\)](#) introduced a multi-objective variant of EVRP, with a total of five objectives. They proposed three different formulations that become increasingly complex. To solve

them, they also proposed a solution structure including ACO, Artificial Bee Colony Optimization, and SA.

Energy recuperation has also been researched in the scope of EVRP. [Kumar et al. \(2023\)](#) presented the first EVRP considering both a start/stop system and an energy recuperation system.

2.4.10 2-Echelon Models

As a means of separating long distance hauling from short distance deliveries, a 2-echelon model can be developed. [Breunig et al. \(2019\)](#) solved a 2-echelon EVRP (2e-EVRP) aiming to keep larger trucks out of city centers. They develop a Local Neighborhood Search algorithm with promising results when tested on their new benchmarks. It is worth mentioning that a battery capacity of 80 km would make the use of EVs an unviable option, while a range of 150 km would result in a big diminution of charging detours. [Jie et al. \(2019\)](#) also solved a 2e-EVRP but with BSSs in place of CSs. They developed a hybrid algorithm, combining column generation and ALNS. They develop their own benchmark instances for 2e-EVRP-BSS based on [Perboli et al. \(2011\)](#). Their algorithm performed exquisitely on small instances and provided results for bigger instances on moderate computing times.

[Agárdi et al. \(2019\)](#) presented a 2e-EVRP in which the EVs start their trip from the CS, travel to the satellites to load, proceed with the deliveries and end their trips at the CS. [Caggiani et al. \(2021\)](#) presented a 2e variant combining electric trucks and electric bikes. The authors provided solutions for instances from the literature and instances of their own making.

2.4.11 Mixed Fleets

For many businesses, it is considered unreasonable to completely overhaul their fleet of vehicles, either due to the prohibiting cost, or due to their demand for long distance hauling. Therefore, in-between a classic VRP and EVRP, lies the Mixed fleet (MF) VRP, introduced by [Gheysens et al. \(1984\)](#). [Goeke and Schneider \(2015\)](#) propose EVRPTW-MF combined with a realistic energy consumption model. An ALNS algorithm is used to solve their new benchmark instances and three objective functions. [Hiermann et al. \(2016\)](#) introduced the Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations. The fleet is non homogeneous and the fleet composition uncertain. Furthermore, they created and solved their own set of instances, using a hybrid heuristic. In a later study, [Hiermann et al. \(2019\)](#) combined a GA with a VNS algorithm, to solve the EVRPTW-PR-MF, which in this case included traditional vehicles, hybrids, and EVs. They also developed their own instances based on the popular [Schneider et al. \(2014\)](#) instances and performed a sensitivity analysis to prove the quality of their algorithm. [Macrina et al. \(2019\)](#) introduced the GVRP with TW, MFs and PR and tested their work based on modified [Schneider et al. \(2014\)](#) instances. They devised an ILS algorithm and tested it for different parameter values. [Sassi et al. \(2015\)](#) strived to make the problem realistic by having different types of charging technologies, TWs and, most importantly, time dependent charging cost, and PR. [Mirmohammadi et al. \(2017\)](#) considered important to have service times be altered depending on the time of the day, since congested roads may significantly affect the travel time of the vehicles. [Kopfer and Vornhusen \(2019\)](#) solved the Energy VRP for a mixed fleet of vehicles. They tried to avoid charging if possible and analyzed many different vehicle compositions on the instances they generated.

In contrast to most EV applications, [Schiffer et al. \(2021\)](#) focused on the deployment of EVs in mid-haul applications. Following their experiments and case study, the authors suggest that a MF

of both ICE vehicles and EVs is the optimal choice; however, it is heavily dependent on the energy capacity of the EV. In all calculations, the cost for CS infrastructure was also considered. Moreover, when the delivery requests are spread in terms of time, they favor the use of EVs.

2.5 Drone Assisted Deliveries

2.5.1 The Traveling Salesman Problem with Drones

VRP is a variant of the Traveling Salesman Problem (TSP), which deals with finding the optimal route for a single vehicle.

In the realm of drone integration within supply chain logistics, researchers have explored various formulations and strategies to tackle the challenges associated with the VRP and TSP. To begin with, [Murray and Chu \(2015\)](#) introduced the concept of the Traveling Salesman Problem with a Flying Sidekick (FSTSP), which aimed to integrate drones into the routing problem. This early work laid the foundation for subsequent studies in the field. Expanding upon the FSTSP formulation, [Kitjacharoenchai et al. \(2019\)](#) aimed to address the multiple Traveling Salesman Problem with Drones (mTSPD). Their approach allowed drones to return to any vehicle, increasing flexibility and optimizing the delivery process. They recognized the potential of leveraging drones to improve the efficiency of the overall system. In a similar fashion, [Jeong et al. \(2019\)](#) extended the drone integration concept by considering possible detours to circumvent areas where drones are not allowed to operate. They recognized the importance of complying with regulations and restrictions in real-world scenarios and aimed to incorporate these constraints into the routing optimization process. In subsequent research, [Murray and Raj \(2020\)](#) investigated the effectiveness of serving all customers with drones and found that this strategy may not always be the most optimal. Their study highlighted the need for careful analysis and consideration of various factors, such as customer locations and drone capabilities, to determine the best approach for integrating drones into the delivery process.

[Raj and Murray \(2020\)](#) further explored the multiple FSTSP, specifically examining the impact of varying drone speeds. They discovered that dense delivery locations can diminish the positive effects of drone integration, highlighting the importance of considering spatial factors in the routing optimization process. [Gonzalez-R et al. \(2020\)](#) introduced a broader model for drone integration in the VRP, which did not explicitly determine the meeting points of the truck and drones. This flexible approach allowed for dynamic decision-making and increased adaptability in real-world scenarios. [Pina-Pardo et al. \(2021\)](#) explored a practical implementation of using drones to resupply vehicles while on the road. Their study showed significant time savings, up to a fifth of the total time, by integrating drones into the supply chain logistics process. They argued that this implementation represents a more realistic and efficient approach in current contexts. [Luo et al. \(2021\)](#) presented a model in which a drone could visit multiple nodes per trip, further enhancing the efficiency of the delivery process. By optimizing the routes and leveraging drones' capabilities, they aimed to minimize the overall delivery time and costs. [Gu et al. \(2023\)](#) proposed a dynamic variant of TSPD and included many operational constraints as well as on demand item pick up.

2.5.2 The Vehicle Routing Problem with Drones

In addition to the integration of drones, researchers have addressed the VRPD, which encompasses the broader context of vehicle routing. [Wang and Sheu \(2019\)](#) were the first to address the VRPD

and presented a mixed-integer problem formulation. However, their assumption of identical travel speeds for both vehicles and drones undermined the full potential of drone capabilities. To overcome these limitations, [Coindreau et al. \(2019\)](#) proposed a generalized approach that considered the VRP with transportable resources, including drones. This broader formulation allowed for more flexibility in the utilization of resources and enabled the optimization of both vehicle and drone routes simultaneously. [Schermer et al. \(2019\)](#) took a different approach by first routing the trucks and then applying a meta-heuristic algorithm to optimize the drone operations. Their objective was to minimize the makespan, which represents the total duration of the entire delivery process. [Sacramento et al. \(2019\)](#) introduced an ALNS method specifically tailored for the VRPD. Their focus was on cost minimization, taking into account the relationship between the range of drones and potential savings. [Chiang et al. \(2019\)](#) equipped vehicles with a single drone and utilized a GA to solve the VRP. Their study incorporated considerations of emissions and cost as primary concerns, aiming to strike a balance between environmental sustainability and economic efficiency.

[Hu et al. \(2019\)](#) approached the VRPD by addressing truck and drone path planning separately and then jointly optimizing them. By considering the unique characteristics and capabilities of each vehicle type, they aimed to find an optimal coordination strategy that maximizes overall efficiency. [Karak and Abdelghany \(2019\)](#) proposed a realistic formulation that involved transporting drones on trucks, which also served as depots and battery swapping stations. This approach allowed for multiple deliveries by drones and enabled them to return to any station, making multiple trips if necessary. By leveraging the mobility and flexibility of trucks, they aimed to enhance the overall delivery process. [Moshref-Javadi et al. \(2020\)](#) focused on reducing customer waiting time by allocating multiple drones per truck. Their study conducted a comprehensive case study analysis to demonstrate the effectiveness of this approach. By carefully coordinating the activities of multiple drones and optimizing the truck routes, they aimed to minimize customer waiting time and improve service quality. [Deng et al. \(2020\)](#) went beyond drones and tackled a broader movement synchronization VRP applicable to other means of transport. Their research aimed to optimize the coordination and synchronization of multiple vehicles, including drones, trucks, and potentially other modes of transportation. By synchronizing the movements of different vehicles, they aimed to minimize overall travel time and improve operational efficiency. In [Rossello and Garone \(2020\)](#), deliveries were exclusively carried out by drones, while trucks served as transportation vehicles to predefined points designated by the city's governing body. This approach aimed to maximize the utilization of drones for last-mile deliveries, leveraging their capabilities in urban environments where space and accessibility constraints are present.

[Pugliese et al. \(2020\)](#) concluded that the integration of drones and ground vehicles in logistics operations brings significant benefits, including cost savings and environmental advantages. Their study emphasized the potential for reducing operational costs, improving delivery speed, and reducing carbon emissions through efficient coordination and optimization of vehicle routes. [Kitjacharoenchai et al. \(2020\)](#) and [Li et al. \(2020\)](#) adopted a two-echelon approach in their respective studies on drone integration. Both studies employ trucks as mobile depots, with [Li et al. \(2020\)](#) specifically allowing for direct drone deliveries from the depot, which are addressed separately. [Tamke and Buscher \(2021\)](#) introduced a branch and cut algorithm, while [Euchi and Sadok \(2021\)](#) presented a hybrid sweep algorithm designed for the VRPD. [Liu et al. \(2021\)](#) focused on drone scheduling with the objective of minimizing the number of drones required. They propose the use of a GA and suggest that higher customer density or a larger delivery radius would necessitate an increased number of drones. [Shahzaad et al. \(2021\)](#) presented a drone delivery system that closely simulates real-world conditions. The study takes into account factors such as no-fly zones and wind conditions,

and assumes that rooftops of city buildings can serve as charging points for delivery coordinates. [Nguyen et al. \(2022\)](#) tackled the routing of drones and trucks independently. In their study, drones are restricted to making a single delivery each time, and their primary limitation is determined to be battery capacity. Additionally, the authors enhance existing benchmark instances by proposing improvements in their research.

Furthermore, several researchers have explored different aspects and specific applications of drone routing and related problems. [Thibbotuwawa et al. \(2019\)](#) investigated the effects of weather conditions on drone deliveries and incorporated collision avoidance strategies into their routing algorithms. [Liu \(2019\)](#) focused on dynamic VRP for food delivery applications, where demand and customer locations change over time. They developed innovative algorithms to dynamically optimize the routes and schedules based on real-time data, ensuring timely deliveries and efficient resource utilization.

[Lemardelé et al. \(2021\)](#) conducted extensive experiments to evaluate the potential of autonomous vehicles, including drones, for delivery operations. They concluded that drones are more suitable for low-density areas or locations with large delivery radii, while ground vehicles excel in dense urban environments. Their findings shed light on the importance of considering the specific characteristics of delivery areas when designing efficient routing strategies.

[Chauhan et al. \(2019\)](#) addressed a maximum coverage problem with drones, aiming to maximize the number of covered locations within certain constraints. Their study focused on optimizing the selection and routing of drones to achieve maximum coverage and improve service reach. [Gu et al. \(2020\)](#) presented a set-covering problem for instant deliveries, aiming to minimize both the number of vehicles required and the makespan. They proposed a comprehensive optimization framework that considered various factors such as vehicle availability, delivery time windows, and drone take-off locations to achieve efficient and cost-effective delivery operations. [Macias et al. \(2020\)](#) focused on selecting the optimal hub location for delivering essential supplies in disaster relief scenarios. Their study aimed to identify the most suitable hub location that maximizes the coverage of affected areas and ensures timely and effective delivery of essential goods. [Ghelichi et al. \(2021\)](#) introduced a new formulation to address the specific demands of medical supply delivery using drones. They proposed a comprehensive model that considered the urgency, perishability, and specific requirements of medical supplies. By optimizing the routing and scheduling of drones, they aimed to enhance the timely delivery of critical medical resources.

[Rashid et al. \(2020\)](#) aimed to minimize the cost of surveillance by optimizing the deployment of drones in monitoring and surveillance operations. Their study focused on developing efficient routing strategies that cover critical areas while minimizing resource utilization and operational costs. [Zhen et al. \(2019\)](#) considered not only the visiting sequence but also the altitude of drones to save energy whenever possible. By optimizing the altitude of drone flights, they aimed to minimize energy consumption and improve the overall efficiency of the delivery process. [Cheng et al. \(2020\)](#) placed particular emphasis on energy consumption in drone routing. They developed a non-linear function to model the energy consumption of drones, comparing it to a linear approximation. Their findings highlighted the importance of accurate energy modeling for effective optimization of drone routes, with potential energy savings of up to 10% on average. They also took into account the transported weight of goods, as it affects the energy consumption of drones.

In a recent publication, [Xia et al. \(2023\)](#) introduced a variation of the VRPD, taking into account payload considerations for the drones. In their study, the energy consumption of the drones is modeled as a linear function of the payload. [Yin et al. \(2023\)](#) conducted an investigation on a variant of VRPD that incorporates TWs. They developed both an exact method and a heuristic method to address this problem, aiming to optimize the routing of drones while respecting the

imposed time constraints. Furthermore, [Ermagun and Tajik \(2023\)](#) proposed a heuristic approach to tackle a VRPD scenario characterized by disruptions. In this particular formulation, the ground vehicles solely serve the purpose of replenishing the energy of the drones, having an auxiliary role in the operations.

In addition to individual studies, there have been numerous reviews on drone routing and related problems in the literature. [Vidal et al. \(2020\)](#) referred to drone-integrated routing problems as an emerging field of research, highlighting the increasing interest in leveraging drones for improved logistics operations. [Macrina et al. \(2020\)](#) conducted a comprehensive review focusing on routing problems with drones. They reviewed the TSP, VRP, and drone-only routing problems, as well as the combination of these three. Their review provided insights into the current state of research and identified research gaps in the field. [Cheikhrouhou and Khoufi \(2021\)](#) conducted a comprehensive review of the literature specifically addressing drone integration in multiple TSP (mTSP). Their review included an extensive list of recent studies that explored various aspects of mTSP with drone integration, providing valuable insights into the different approaches and methodologies employed. [Moshref-Javadi and Winkenbach \(2021\)](#) presented a valuable review that not only summarized the existing literature but also proposed a taxonomy for classifying different practical applications of drone routing. Their review covered a wide range of application areas and discussed the challenges, opportunities, and potential benefits of drone integration in logistics operations. [Li et al. \(2021\)](#) conducted a review of the drone integration problem from a two-echelon perspective, focusing on both strategic and operational aspects. They explored various modeling perspectives and examined related issues such as vehicle routing, resource allocation, and coordination strategies. Their review provided a comprehensive overview of the research landscape in the field. In addition to discussing problem variants and solution methods, [Chung et al. \(2020\)](#) discussed the factors that impede the real-world applications of drone routing and highlighted the existing research gaps. They emphasized the importance of addressing practical challenges such as regulatory constraints, safety considerations, and scalability issues to enable the widespread adoption of drone-based logistics solutions.

The studies and reviews mentioned above illustrate the diverse approaches and methodologies employed in the field of drone routing and integration in logistics operations. Researchers have explored various problem variants, ranging from the classical TSP and VRP to more specialized scenarios such as mTSPD, maximum coverage problems, and dynamic routing for food delivery applications. These studies have highlighted the potential benefits of integrating drones into logistics operations, including cost savings, improved delivery speed, reduced carbon emissions, and enhanced service quality. However, they have also identified several challenges and limitations, such as regulatory constraints, weather conditions, energy consumption, and the need for effective coordination and optimization strategies.

Chapter 3

The Charging Station Location Problem

3.1 Introduction

Electric Vehicles are the next major iteration of the automobile, a shift that is necessary to be in line with the sustainable goals of humanity (Karakostas and Sifaleras, 2022). In the developed world, this trend has gained significant momentum in the past decade, with many old and new automakers offering EVs. In 2022, 12.1% of new cars sold in Europe were electric, a significant rise from just 1.9% in 2019 (Deutsche Welle, 2023). In Norway, which has been the leader in EV adoption in Europe, eight out of ten new vehicles sold in 2022 were Battery EVs (Thronsen, 2023). In the US, 2022 was also a good year for EVs; however, not as impressive, with the percentage of new EVs being less than 6% (Cox Automotive, 2023). Overall, the sales of new EVs are expected to grow globally, despite the skepticism of whether or not EVs can fully replace traditional ICE vehicles.

Besides the use of cars for daily commuting, cars are also used for leisure and traveling. Using an ICE vehicle for long-distance traveling is effortless, as there is an abundance of gas stations around the world. In contrast, using an EV may not be as straightforward since the charging infrastructure has not yet reached the same level of development as gas infrastructure (Savari et al., 2022). This difference between EVs and ICE vehicles is expected to impact the decisions of individuals wishing a transition to an EV. Moreover, the so-called range anxiety is amplified for long-distance trips.

In addition, charging infrastructure differs significantly from place to place. The density of the CSs can change dramatically when moving from one region to another. Charging speeds can also vary depending on the available CS hardware and on the operational status of the CS, which may be out of order. That is especially important for trips that require a charging stop.

The present research is motivated by the increasing market share of EVs in Greece and the underdeveloped infrastructure that cannot support long-distance trips in its current form. Each year Lease Plan, a car leasing company, provides an index of EV readiness for 22 European countries, including Greece. In their latest report (LeasePlan, 2022), Greece stood out as the country with the most improvements, ranking three positions higher than last year, at 14th place. The report attributes this change to the rise of EV market share and lower ownership costs. The weakest aspect is infrastructure, given the lowest score.

The objective of this research is to answer two important questions. The first question is "How practical are EVs for long-distance traveling in Greece?" and the second is "How to develop charging infrastructure to support long-distance traveling?"

The practicality of EVs is often explored in the context of urban use (Kong et al., 2019; Efthymiou et al., 2017); however, with more and more people transitioning to EVs in Greece each year, it is safe to assume that they will increasingly be used for long-distance trips. The development of charging infrastructure goes hand in hand with EV adoption, as it is a key ingredient for the successful transition to electric mobility.

To achieve the above, a Monte Carlo simulation of EV trips is carried out. These trips are generated randomly from lists of origin and destination points within the mainland of Greece. A variety of EVs are used for the simulation with the goal of exploring how different EV characteristics can affect their practicality. Furthermore, the trips take place on a graph representation of the Greek road network. The frequency of charging stops on each segment of the road will provide guides for the development of charging infrastructure.

A critical aspect of this simulation is the use of realistic data. The distances between the nodes of the Greek road network are queried from Open Street Maps; subsequently, real distances will be used for all calculations.

The energy consumption of the tested EVs is also a parameter hard to model. The disparity between theoretical and actual energy consumption as well as the technical specification differences between EVs require the use of realistic and vehicle-specific consumption values. To this end, the energy consumption data is extracted from an online source offering a limited set of real-life EV data. This research is only concerned with battery-powered EVs, as Hybrids or Range-Extender EVs can always use the onboard internal combustion engine.

Simulations are carried out for two different temperature settings, and additional loads and external conditions that negatively affect energy consumption are represented using a stochastic consumption element.

Interest in EV studies in Greece has only recently gained attention, with a few publications on charging station location problems in urban areas (Karolemeas et al., 2021), on the health and social benefits of EV adoption (Kouridis and Vlachokostas, 2022), on the impact of incentives in Greece (Mpoi et al., 2023), and even on the electrification of Greek islands (Zafeiratou and Spataru, 2022). In contrast to these publications, this study focuses on simulating long-distance traveling and highway charging infrastructure development.

Through the extensive Monte Carlo simulation, this research addresses a key gap in knowledge and provides valuable insights into the potential viability of EVs for long-distance travel in Greece, as well as strategies for improving the charging infrastructure to enable more widespread use. Additionally, it provides a framework for future research in this area and it contributes to the broader goal of promoting sustainability and environmentally friendly practices. Furthermore, this research is the first to consider an extensive simulation combining real-world trip scenarios, real EV consumption data, as well as different temperatures, and a stochastic consumption element.

The only similar study found in the literature is that of Napoli et al. (2019). Their study also focused on a country-wide development of charging infrastructure using a road network and EV data; however, different modeling approaches were used. Another similar work is that of He et al. (2019); however, they did not need to simulate trips as trip data was available. Another element setting this study apart from the other two is the Monte Carlo simulation in place of the traditional deterministic solution methods.

The rest of the paper is structured as follows. Section 2 includes a literature review of related

studies and similar research. Section 3.3 gives an insight into the simulation and all of its parameters, and lastly, Sections 3.4 and 3.5 discuss the results and conclusions respectively.

3.2 The case of Greece

In this section, two topics are addressed; the EV market of Greece and the existing public CS infrastructure of Greece. A closer look at the EV sales and the government incentives in Greece is provided. The CS infrastructure is explored, with an analysis of the charging speeds, the accessibility, the pricing, and their source of energy.

3.2.1 The EV Market In Greece

The first EVs were introduced in Greece around the early 2010s; however, the initial uptake was slow due to the lack of charging infrastructure and high costs compared to traditional ICEVs.

Since then, the adoption of EVs in Greece has been steadily increasing. The number of EVs on Greek roads today is undefined because there is some disparity in the number of EV registrations, with different numbers reported by different sources. Some numbers have been verbally announced in sessions of the Greek Parliament in the context of the EV incentive program called "I Move Electrically"; however, no official statistics have been published by the Ministry of Transportation. The only official source of EV registrations is the Association of Motor Vehicle Importers Representatives (AMVIR). While some EVs are reported through the official manufacturer dealerships; many are imported by independent dealerships that are not part of the association.

The yearly EV registrations published by AMVIR are presented in detail in Figure 3.1. It should be mentioned that the available data for 2023 refers to the first three months of the year, from January first to the end of March.

Greece has had long-standing financial incentives for individuals and companies that adopt EVs. The first phase of the EV purchase incentive program called "I Move Electrically" running up to the end of 2022 had mediocre success with less than half of the allocated budget being used. The applications for the second phase of the program that is currently running have already exceeded the application of the previous one, having attracted more than 17,000 new applications, with about 30% of them regarding EVs. While this is a great push towards electric mobility, reaching the goals of the Greek government with one in three cars being electric by 2030 seems far-fetched (Eleftheria Nikitara, 2021).

The list that follows presents the 2022 incentives of Greece as reported by the European Automobile Manufacturers Association (ACEA) (ACEA, 2022a). The CO₂ emissions used in the description of the incentives are the reported numbers from the New European Driving Cycle (NEDC) and the Worldwide Harmonised Light Vehicle Test Procedure (WLTP).

- Road Tax and Ownership Tax Incentives
 - 75% lower road tax for PHEVs up to 50g CO₂/km.
 - 50% lower road tax for HEVs and PHEVs emitting more than 50g CO₂/km.
 - Full road tax exemption for electric trucks.
 - HEVs with engine capacity less or equal to than 1,549cc and registered before 31 October 2010 are exempt from circulation tax.

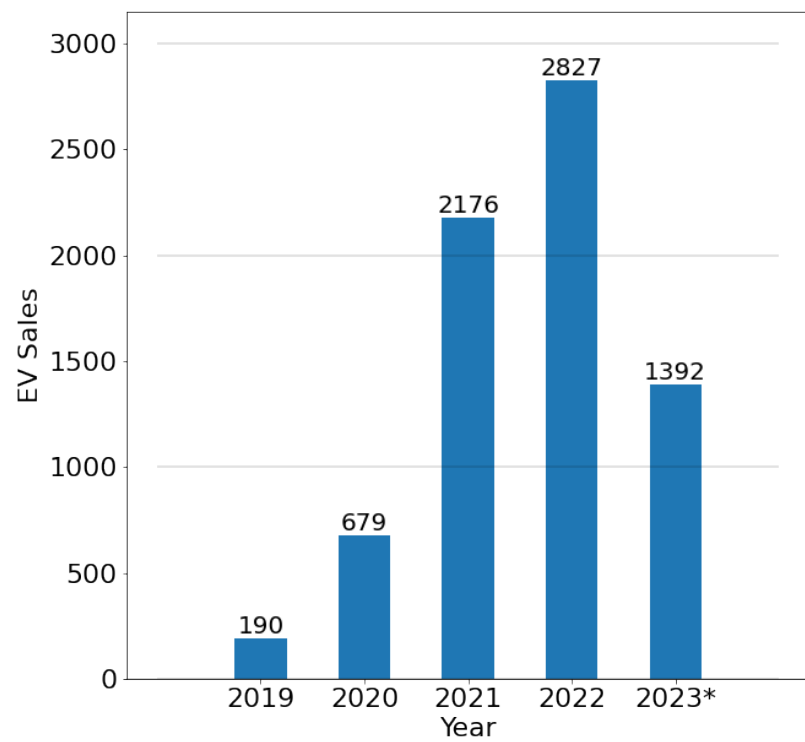


Figure 3.1: EV Sales in Greece <https://seaa.gr/segments-μμ-μ-bev-phev/>

- 60% lower circulation tax for HEVs with engine capacity more than 1,550cc registered before 31 October 2010.
- Circulation tax exemption for cars emitting less than 90g CO₂/km (NEDC) or 122g (WLTP).
- Exemption of BEVs from the personal income presumption system.
- Company Car Incentives
 - Exemption of the benefit in kind tax for BEVs and PHEVs emitting less than 50g CO₂/km with net retail price (NRP) less or equal to €40,000.
 - Deductible of €40,000 in the NRP for BEVs and PHEVs up to 50g CO₂/km with higher NRP value.
- Purchase and Scrapping Incentives
 - 15 – 20% cashback for BEV cars (up to €5,500- 6,000, max NRP: €50,000).
 - Cashback of €1,000 for scrapping a car older than 10 years.
 - 25% cashback for BEV taxis (max: €8,000).
 - 15% cashback for PHEVs taxis with less than 50g CO₂/km.
 - Cashback of €2,500 for scrapping an old taxi.
 - 15% cashback for vans (max: €5,500 for BEVs; €4,000 for PHEVs).
 - Cashback of €1,000 for scrapping an old van.

3.2.2 Greek Infrastructure

The majority of EU nations possess a substandard quantity of CSs, and most of them are inadequate in terms of charging speed, as per the ACEA (ACEA, 2022b). The ACEA’s data demonstrates that six EU nations possess less than one CS for every 100 kilometers of road, 17 nations possess fewer than five CSs per 100 kilometers of road, with only five nations having more than 10 CSs per 100 kilometers of road. Greece stands at the penultimate position, with only one charger available per 250 kilometers.

The CS network of Greece has been described as very poor in various reports and in the literature. Recently, the government released a new platform that provides a list of all the CSs in Greece (<https://electrokinisi.yme.gov.gr/public/ChargingPoints/>). This list keeps expanding over time, and the objective of the government is to make this information readily available. A total of 368 CSs are reported on this platform, with 1500 plugs available (Ministry of Infrastructure and Transportation, GR, 2023).

The availability of the CSs is another important issue. Most of the CSs are found in or around Athens, the capital of Greece. The rest of them are scattered throughout the Greek mainland. With the exception of Crete, the largest island in Greece, the other islands have only a few CSs.

Figure 3.2 presents the current recorded infrastructure of Greece, as well as a closer look at the density of CSs at Athens in Figure 3.3. The figures are screenshots for t

An important element of the existing network is the charging speed of the CSs. The Public Power Corporation (PPC) is the main supplier for most of the stations. They provide either 7kW three-phase AC charging or 50kW DC fast charging, with the latter being more scarce. In the past

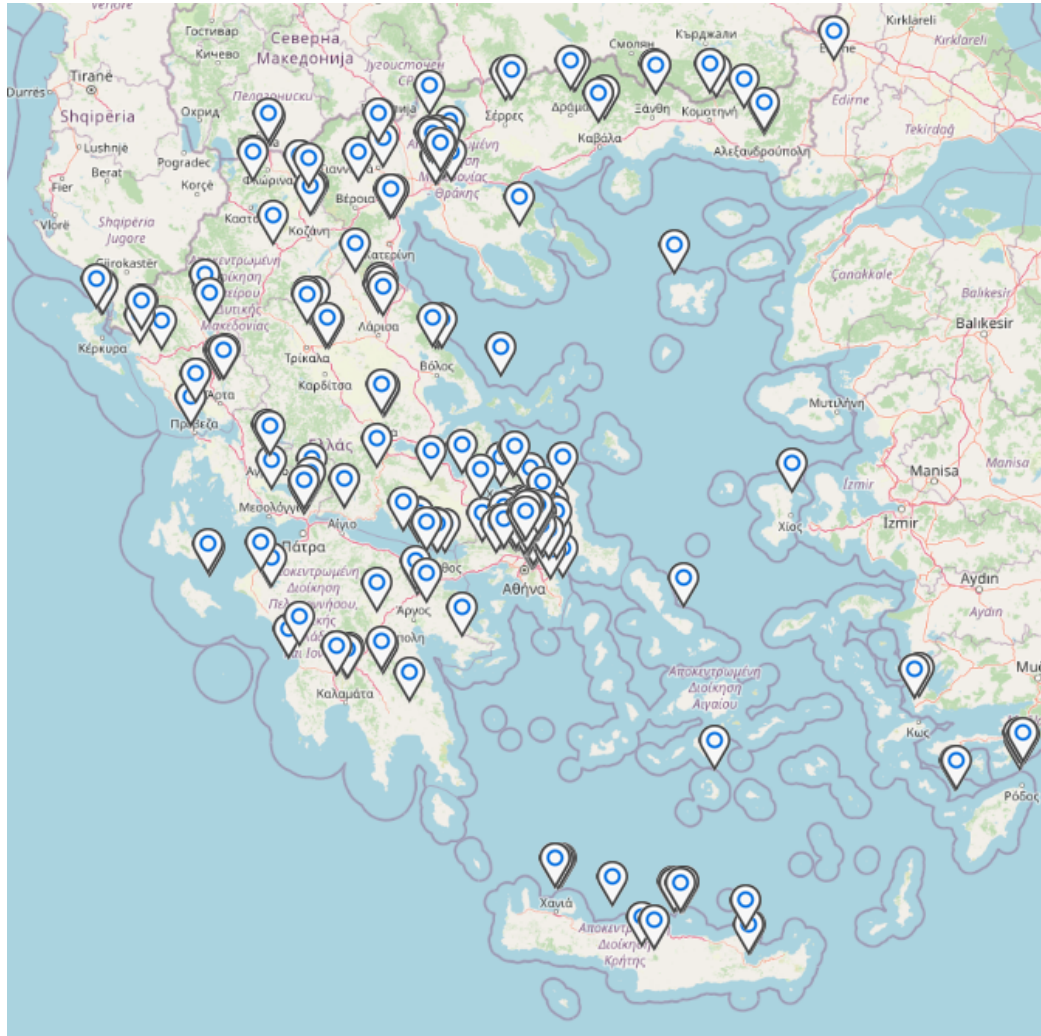


Figure 3.2: Greek CS Infrastructure

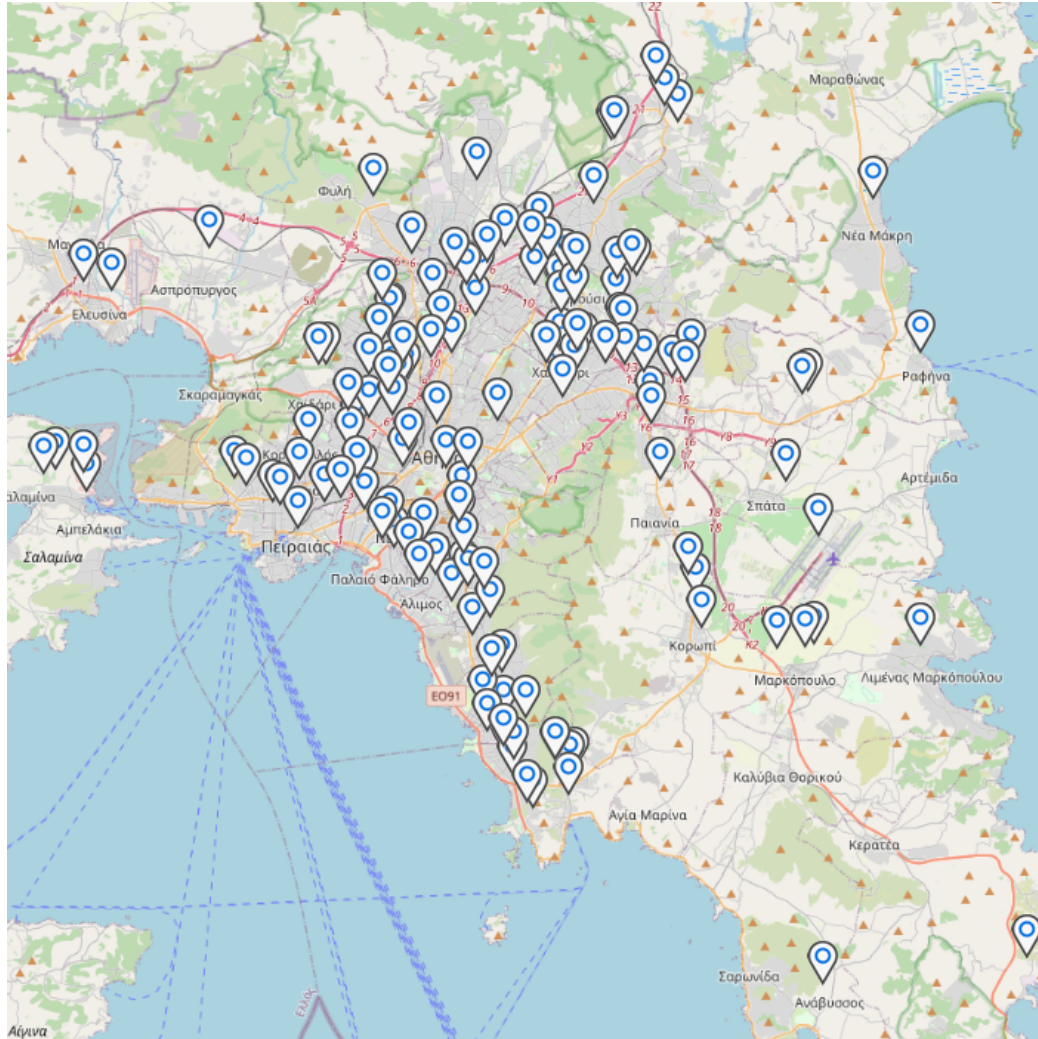


Figure 3.3: CS Infrastructure of Athens

7kW chargers were adequate, compared to wall charging; however, a 7kW charger is not sufficient for any use except overnight charging. For example, a 7kW charger needs approximately 9 hours to fully charge a Tesla Model 3 with a 57.5kWh usable battery capacity, adding about 41km of range per hour ([EV Database, 2021](#)). In contrast, a 50kW DC charger will fully charge the same battery in just under an hour. Subsequently, the charging speed should not be overlooked when planning for future infrastructure development. It is worth mentioning that PPC has installed a few rapid chargers, ranging from 150kW to 300kW, but they are only a handful. While the cost of installing a fast charger is higher, fewer of them will be needed for a given number of vehicles, as they use them for a shorter amount of time. Nonetheless, slower chargers can be used effectively by electric bikes.

Fast charging stations are scarce throughout Europe, with just one in seven CSs possessing a capacity of over 22 kW ([ACEA, 2022b](#)). ACEA has suggested a significant rise in the number of CSs to achieve carbon dioxide emission targets and to encourage individuals to switch to electric vehicles.

The charging speed is not only a concern in regards to convenience. Fast charging is a necessity, as a great number of the stations shown in the previous figures are located in supermarket parking lots, which are increasingly relocating outside city centers. The slow charging rate of these stations may limit their usability for drivers who require a rapid charging option. This may particularly affect drivers who have long commutes or need to travel long distances and have no access to overnight home or work charging.

As most stations are powered by the PPC, the charging costs are the same across the country, at 0.45€/kWh for AC charging and 0.65€/kWh for DC charging.

A part of the infrastructure inherently associated with EVs is the electricity production infrastructure. EVs have emerged as a promising alternative to traditional fossil fuel-powered vehicles due to their potential to reduce GhG emissions and combat climate change. However, the environmental benefits of EVs are contingent upon the source of their electricity. If EVs are powered by electricity generated from non-renewable sources, such as coal-fired power plants, their environmental impact may not be significantly different from that of gasoline-powered vehicles. Therefore, EVs must be powered by Renewable Energy Sources (RESs), such as wind, solar, and hydropower, to maximize their potential as a sustainable and low-carbon transportation solution.

By utilizing RES to power EVs, we can reduce the carbon footprint of transportation and mitigate the adverse effects of climate change. Additionally, using RES to power EVs can also promote energy independence, as it reduces reliance on imported fossil fuels and enhances domestic energy security. While there are still challenges associated with the adoption of EVs and the scaling up of RESs, such as infrastructure development and technological limitations, prioritizing the integration of RESs into the electric grid is an essential step toward a cleaner and more sustainable future.

The energy mix of Greece has changed substantially in the past five years. Figure 3.4 presents the energy mix of Greece from 2011 to 2022. The included data is based on the first ten months of each year. Each line represents the energy production from each power source in GWh.

As observed, the use of lignite has been reduced dramatically, while RESs have been on the rise ever since 2011. The transition away from lignite has lowered significantly the CO₂ emissions of Greece, which were less than 60 gigatonnes in 2021, while they were more than 90 a decade earlier. While earlier studies placed Greece as a country in which EVs did not offer any environmental benefits ([Cavallaro et al., 2018](#)), the change in energy sources and the lower emissions steadily make the use of EVs a greener option.

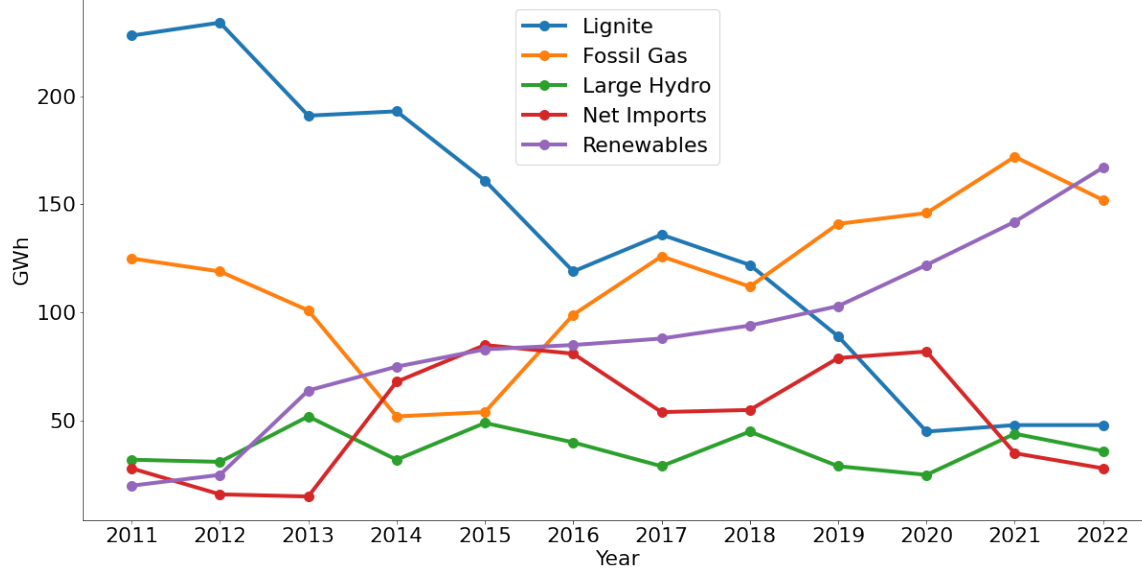


Figure 3.4: Greek Energy Mix, Source: <https://www.admie.gr>

3.3 Simulation Methodology & Setup

This section presents the Monte Carlo simulation and the data used. The objectives of the simulation are the following: assess the ability of long-distance EV traveling in the Greek mainland and identify the road segments of the Greek road network where CSs should be installed.

To achieve these goals, the Monte Carlo simulation of EV trips will take place on a graph representation of the Greek road network. This section will describe the methodology and assumptions of the simulation.

3.3.1 Electric Vehicle Data

In the literature, there have been many attempts to simulate the energy consumption behavior of EVs and create the most realistic consumption models possible, but the differences between the power plants of EVs are hard to emulate. For this reason, it was decided that the best option for the simulation presented in this study is the use of data from existing EVs.

As stated in the previous sections of this study, acquiring EV data for Greece is not currently possible; therefore, some of the EVs selected for the simulation are based on the publications of AMVIR for EV sales in Greece in 2022 (AMVIR, 2023).

The included EVs represent a variety of body types, battery sizes, and price brackets. Four of them, namely the VW ID.4, VW ID.3, Tesla Model Y, and Tesla Model 3 are in the top ten list according to AMVIR.

One of the most readily available sources for EV energy consumption data is the [ev-database.org](https://www.ev-database.org) website. Besides the information provided by the manufacturers, real-world consumption values are also listed, for different temperatures and road types; however, they are not available for all vehicles.

For the purposes of this research, data on combined energy consumption for two different temperature ranges were considered. The cold temperature rating assumes a worst-case scenario of $-10^{\circ}C$ and the use of cabin heating, while the mild temperature rating assumes a best-case scenario of about $23^{\circ}C$.

Table 3.1 presents the consumption data for the 11 tested EVs. The first column presented the model of the EV along with the usable battery capacity, while the following two columns present the energy consumption for Combined-Cold (CC) conditions, and Combined-Mild (CM) conditions, respectively.

Table 3.1: List of EV Specifications

EV Model (Usable Battery)	CM(Wh/Km)	CC(Wh/Km)
Mini Cooper SE (28.9kWh)	138	193
VW e-Up (32.3kWh)	135	190
Nissan Leaf (39kWh)	142	195
Renault Zoe ZE50 R110 (52.0kWh)	142	196
VW ID.4 Pure (52.0kWh)	160	217
VW ID.3 Pro Performance (58.0kWh)	145	197
Ford Mach E AWD (70.0kWh)	177	237
Ford Mach E RWD (70.0kWh)	173	230
Porsche Taycan 4S (71.0kWh)	156	212
Tesla Model Y LR-DM (72.0kWh)	148	203
Tesla Model 3 LR-DM (75.0kWh)	134	188

While it is possible to find real data for different temperatures, other parameters have not been documented to the same extent. To simulate the external effect of energy consumption parameters that cannot yet be accounted for due to the lack of data, i.e. the condition of the road, its slope, or the load the EVs carry, a stochastic consumption generator was used. For each of the edges in a trip, a stochastic consumption element is added to the energy consumption rate. This stochastic element can range from 0% to 15% of the energy consumption rate for each vehicle, as presented in Table 3.1, and will vary throughout each trip.

3.3.2 Trip Design

A very important aspect of this simulation is the exploration of different itineraries for the EVs involved. To achieve that, a list of the Greek cities with the highest population according to official population data was created to use as origin points, with the destinations being other cities from the same list, as well as additional touristic places through the Greek mainland.

To represent each point coordinates were extracted from Google Maps. A comprehensive list of the coordinates is provided in the Appendix. The population statistics were obtained from [City Population \(2023\)](#), which provides the data in English. A list of all possible trips was created.

To represent the road network of Greece, a graph was created, using the `networkx` library in Python. Each city and destination for the list described previously represents a node in the graph, while the edges that connect the nodes were manually added to the graph. This representation helps determine the edges over which the most charging requests occur. To determine the length of each edge, the Open Route Service API was used, which extracts data from open street maps. This

length represents the driving distance between the two nodes connected by each edge. Figure 3.5 presents the graph generated.

3.3.3 Simulation Parameters

The total number of possible itineraries allows for multiple repetitions of the tests. This is important given the non-static nature of this experiment. Each EV completed each trip a total of 100,000 times for each of the two temperature settings. In addition, each trip is a round trip.

As with any simulation of the real world, some assumptions have to be made. The assumptions made in this simulation are the following:

- EVs start their trips fully charged.
- EVs leave the destination with the same State-of-Charge that they arrived with.
- Additional local driving when the destination is reached is not accounted for.
- The fastest way to travel within the network are the included highways.

3.4 Simulation Results and Discussion

An extensive analysis of the results was carried out, to provide insights both into the suitability of the EVs, as well as the infrastructure development needs. The analysis is carried out in two parts, the first focused on EVs and the second on CSs.

3.4.1 Assessment of EV Traveling Abilities

Table 3.2: CS stops for different battery use scenarios

EV Model (Usable Battery)	CS Stops		
	80%	80% to 90%	90% to 100%
Tesla Model 3 LR-DM (75.0kWh)	3.22	-13.13%	-12.62%
Tesla Model Y LR-DM (72.0kWh)	3.81	-12.88%	-11.65%
Porsche Taycan 4S (71.0kWh)	4.11	-12.61%	-11.68%
Ford Mach E RWD (70.0kWh)	4.66	-12.35%	-11.37%
VW ID.3 (58.0kWh)	4.80	-12.31%	-11.41%
Ford Mach E AWD (70.0kWh)	4.82	-12.28%	-11.40%
Renault Zoe (52.0kWh)	5.40	-12.10%	-11.06%
VW ID.4 (52.0kWh)	6.14	-12.22%	-10.85%
Nissan Leaf (39.0kWh)	7.49	-11.80%	-10.61%
VW e-Up (32.3kWh)	8.89	-11.36%	-10.62%
Mini Cooper SE (28.9kWh)	10.25	-11.21%	-10.24%

The average number of charging stops for each EV per trip is presented in Table 3.2. The data is presented in ascending order of charging stops. The first column presents the EV model as well as the usable battery size. The second column presents the number of CS stops if the drivers only use

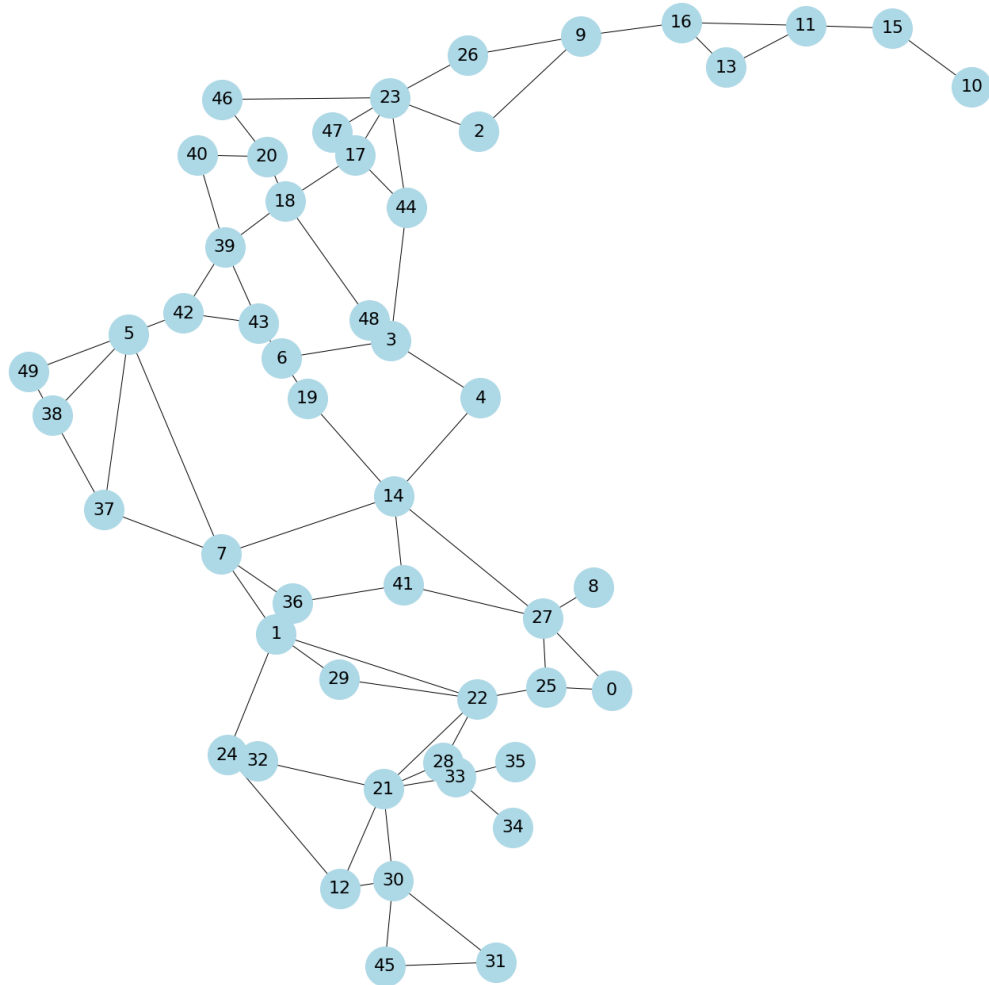


Figure 3.5: Road network graph of Greece based on the selected nodes.

80% of the battery. The next column presents how many fewer charging stops would be necessary if the drivers used up to 90% of the capacity. The difference is presented as a percentage that is more easily perceptible. The last column presents the same information for the users willing to use the full battery capacity, compared to those willing to use up to 90%.

As observed, the number of charging stops is proportionate to the size of the battery; however, it is worth mentioning that the VW ID.3 is an exception to the rule, as its battery is about 17% smaller than the two Ford Mach E variants that surround it. In addition, all values range between 10% and 13%, meaning that using an additional 10% of the battery capacity will result in about 10 – 13% reduction of charging stops.

However, an element that is not discussed here which is of high relevance, is the charging speed in relation to the SoC. Subsequently, users who are willing to wait for a full recharge may end up waiting in total, the same amount of time as those that opt to use only 80% of the battery, as the charging time gets longer and longer when the battery reaches higher SoC.

While experiments were carried out for 80%, 90%, and 100% battery use, the analysis that follows is based on the results of the tests with 90% battery use.

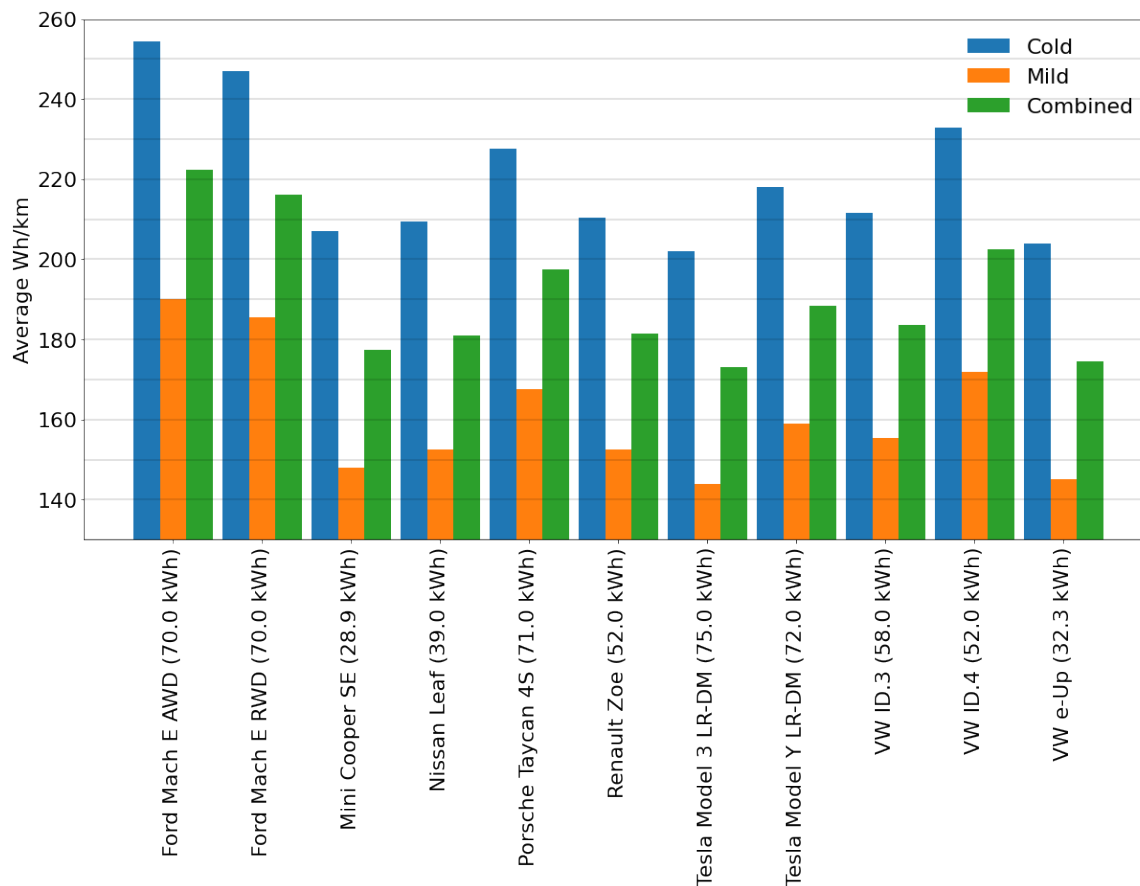


Figure 3.6: Average Wh/km for each EV in different temperatures

In Figure 3.6 the average energy consumption of each EV over all trips is presented. The bars in blue represent the average energy consumption of vehicles in cold conditions, the bars in orange represent the average energy consumption in mild temperature conditions, and the bars in green are the average values from the previous two. The most efficient vehicle regardless of the temperature settings was the Tesla Model 3, while the second most efficient was the VW e-UP; both being generally small and the cheapest offerings from their respective companies.

In cold conditions, the third place was almost a tie between the VW ID.3 and the Mini Cooper SE, with Tesla Model Y and the Nissan Leaf falling shortly behind. In mild temperatures, the Nissan Leaf, Renault Zoe, Tesla Model Y, and VW ID.3, performed very similarly. The Nissan Leaf and Renault Zoe share similar underpinnings as the two companies have an extensive ongoing collaboration.

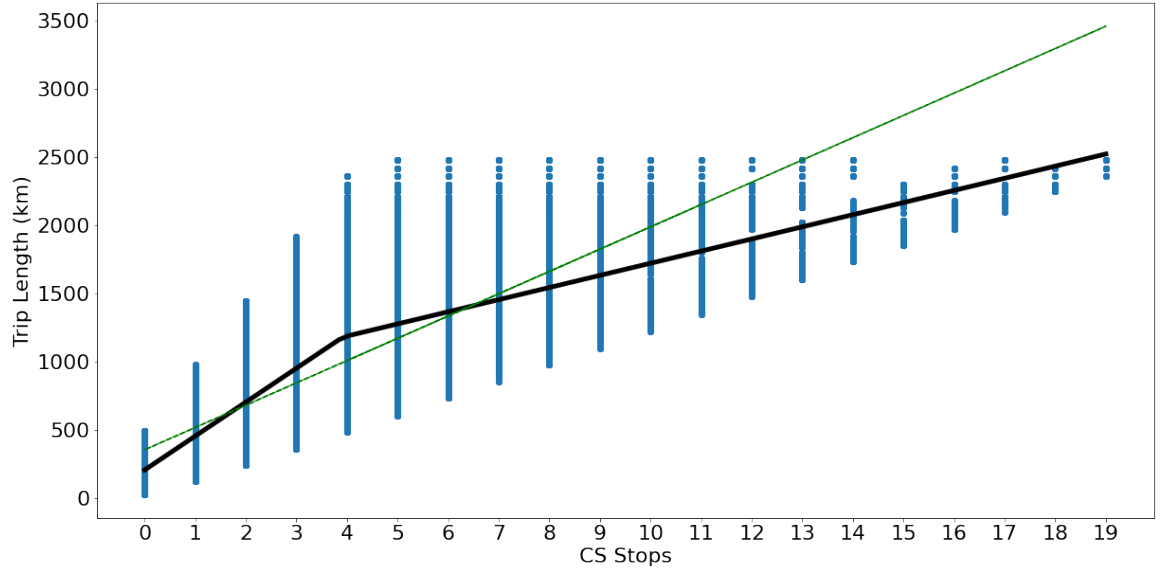


Figure 3.7: CS Stops in relation to Trip Length

The relationship between the trip length and the number of charging stops for the tested fleet is presented in Figure 3.7. The green dashed line represents the linear trend-line of the data presented, with a slope of $s = 163.35$, and an intercept of $i = 352.90$. The solid black line was created using a Multi-layer Perceptron regressor with 50 neurons and 1000 maximum iterations, resulting in a better representation of the data. The difference between the two methods can be attributed to the density of data for different trip lengths, given there are fewer long trips.

The total energy consumption in relation to the trip length is presented in Figure 3.8. The data points in blue represent the energy consumption in cold conditions, while the green points represent the energy consumption in mild conditions. Their trend lines are presented in magenta and red respectively. The cold trend line has a slope of $s = 0.2204$ and an intercept of $i = 0.001256$. The mild trend-line has a slope of $s = 0.1610$ and an intercept of $i = -0.0005319$.

The solid black line in the middle was generated using all the data regardless of temperature and has a slope of $s = 0.1907$, while the intercept value is $i = 0.000362$. In general, longer trips have

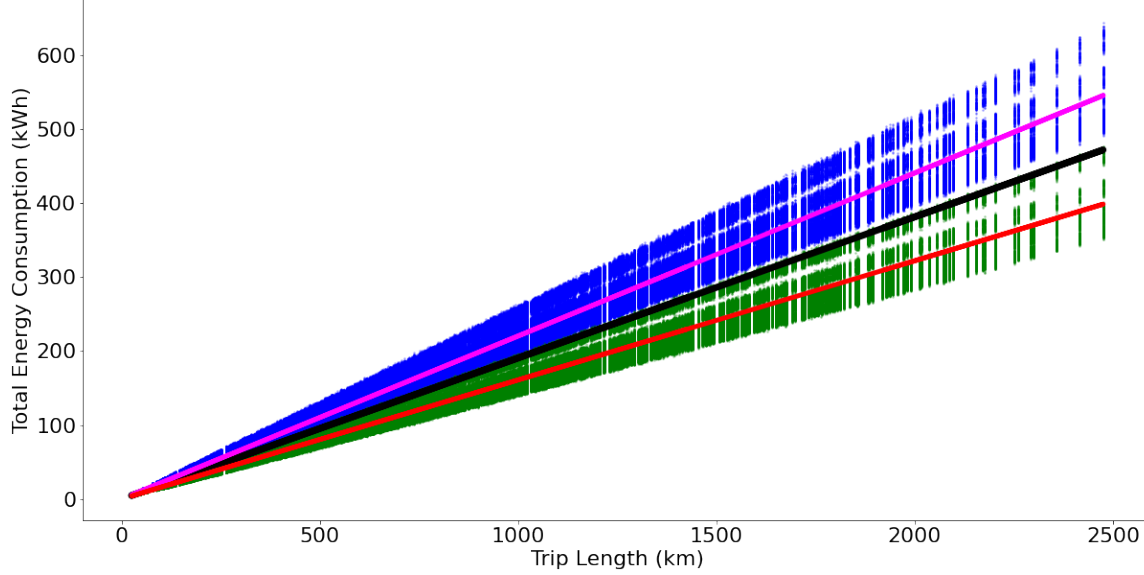


Figure 3.8: Trip Length compared to Total Energy Consumption

greater fluctuation of energy consumption which is attributed to the various conditions which keep changing. On the other hand, the energy consumption of shorter trips could be predicted within a tighter margin of error.

Figure 3.9 presents a heat map describing the relationship between different battery capacities and the charging stop needs. The values in each cell represent the average energy consumption for each combination of the parameters. The Renault Zoe and the VW ID.4 have the same capacity at $52.0kWh$ and the two variants of the Ford Mach-E also share the same battery capacity at $70.0kWh$.

The first columns of the heat map are of the highest interest, as they showcase the traveling abilities of EVs with only a few charging stops. For example, the Tesla Model 3 which also happens to be the most efficient, has a battery capacity of $75.0kWh$ and can travel more than $600km$ with just a single charging stop, or about $980km$ with a second one. On the other hand, an EV with a small battery like the Mini Cooper SE with a battery of just $28.9kWh$ would have to make many more stops. The results for the two Ford models at $70.0kWh$ and the VW ID.3 with a $58.0kWh$ battery are very close, but the VW model managed to avoid a 12th stop throughout the simulation. This is impressive, given the gross weight of the VW ID.3 model presented here is almost $100kg$ more than that of both Fords. It is important to highlight that these values are the average values extracted from the simulation, meaning the additional energy consumption component that increases energy consumption has been included in these calculations, providing an additional element of realism.

An observation based on the results of the Monte Carlo simulation is that the selection of an EV compatible with the needs of its user is essential. Generally, there is a linear association between the size of the battery and the autonomy of the vehicle; however, outliers such as the Ford Mach-E exist. The efficiency of the EV should be a critical factor when buying a new EV. For long-distance traveling, the optimal choice would be a vehicle of high battery capacity and high efficiency; however, medium-length trips of $200 - 300km$ in length could be achieved by any of the EVs included in this

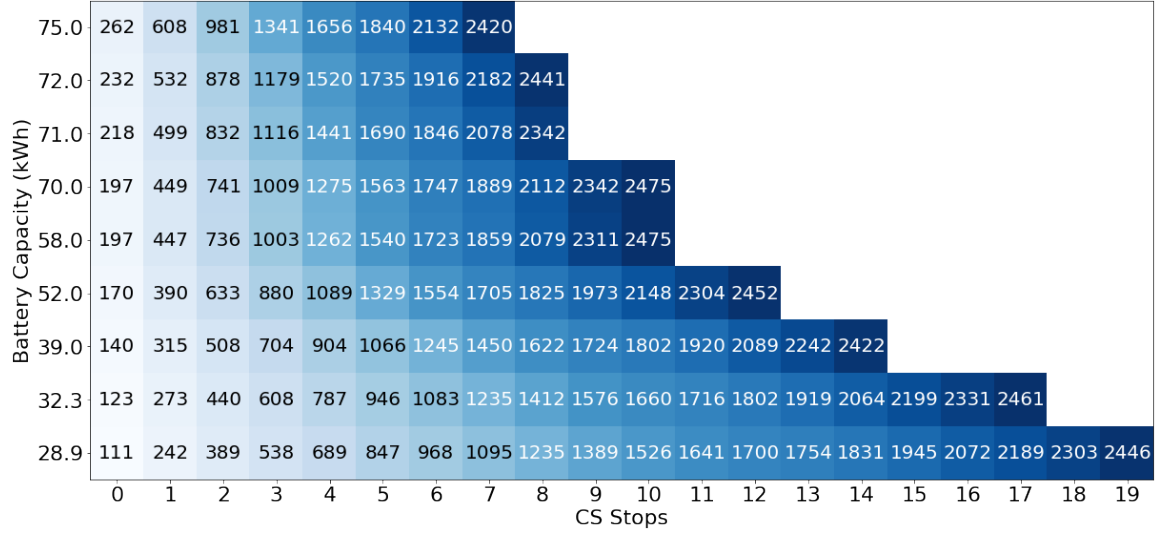


Figure 3.9: Heatmap of average range for different CS Stops and Battery Capacity combinations.

research with a maximum of three charging stops.

An additional note is that planning trips with the optimal conditions for an EV may extensively extend its range (i.e. not using the HVAC system, avoiding stop-and-go traffic, etc.); however, the objective of this research is to assess the use of EVs as replacements for ICEVs, with little to no changes in the use scenarios.

3.4.2 Charging Station Development

In Figure 3.10, the suggested edges for the placement of new CSs based on the results of the simulation are presented. The numbers displayed on the edges denote their priority. Two different lines can be identified on the graph. The one on the left starts from node 24 and ends at node 17. Edge (5, 7) was found to be third on the priority list, which can be attributed to the length of the edge. The rest of the edges on this list are of much lower priority.

The right line is way longer, starting at node 21 and ending at node 13. It connects 14 nodes of the graph and provides access to many large cities. The inner part of the line, with the exception of (6, 19), includes nine of the ten most important edges from the list. The short break on the edge (6, 19) is sensible, as the two nodes that form the edge are too close.

The last four edges out of the twenty are those at the borders of the network, more specifically, edges 17, 18, and 19 are on the bottom of the graph, while the last edge is on the top right of the graph.

The exact placement of the CSs is also an important subject but it is not within the scope of this research. Finding the optimal position on an edge will have to be determined based on space availability, proximity to power stations, and other parameters that are not explored here. The terrain of Greece is also challenging; therefore, it is important to study the topology of the areas of interest. In addition, the concurrent planning of RES installation would make the network more environmentally friendly while providing additional power for spikes in energy demand and fast

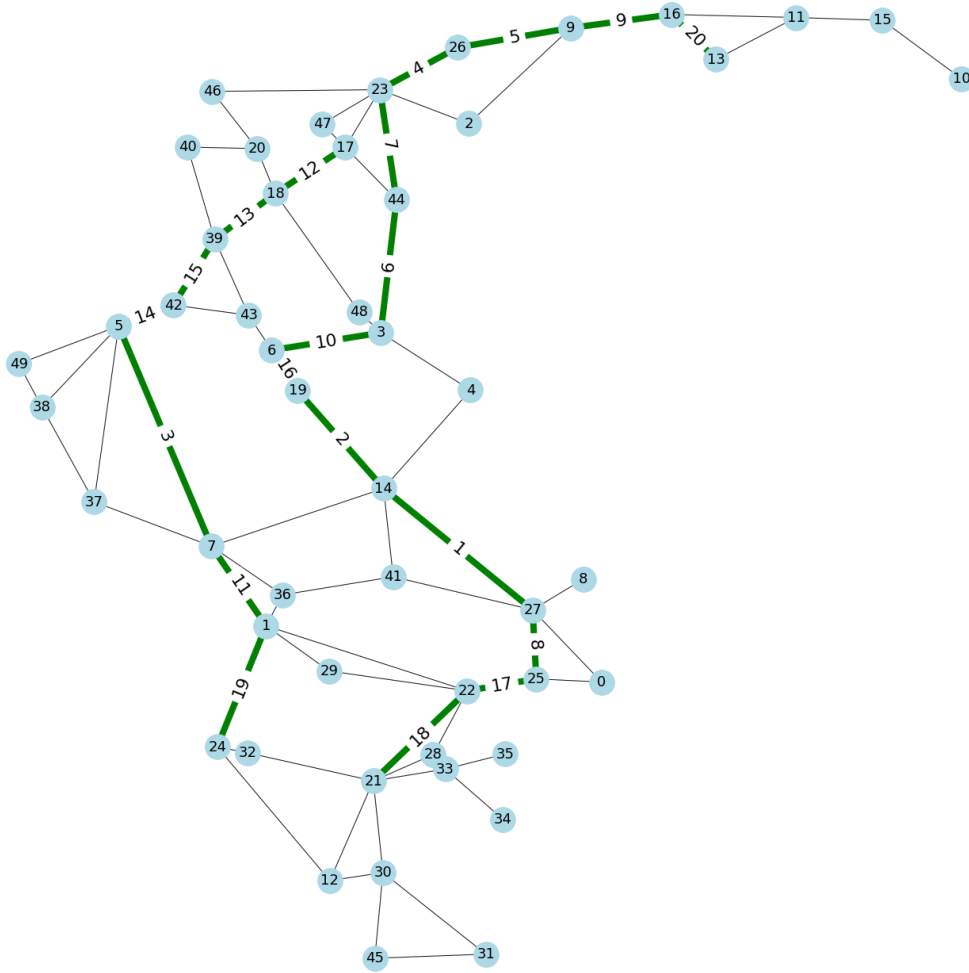


Figure 3.10: Road network graph of Greece with CS installation suggestions.

Table 3.3: EV Charging Times

EV Model	22kW AC	50kW DC	150kW DC	300kW DC
Mini Cooper SE	3h15m	29m		
VW e-Up	5h30m	48m		
Nissan Leaf	12h45m	43m		
Renault Zoe	3h	56m		
VW ID.4 Pure	8h30m	57m	33m	
VW ID.3 Pro Performance	6h15m	51m	31m	
Ford Mach E AWD	7h30m	66m	40m	
Ford Mach E RWD	7h30m	66m	40m	
Porsche Taycan 4S	7h45m	-	22m	17m
Tesla Model Y LR-DM	7h45m	71m	34m	29m
Tesla Model 3 LR-DM	8h15m	74m	33m	27m

charging of multiple EVs.

The success of any CS infrastructure plan, especially on highways, is heavily influenced by the available charging speed. It is essential to install fast CSs to enable quick stops.

Table 3.3 presents the charging times for the EVs used in the simulation with various chargers. More specifically, charging times for 22kW AC chargers and 50, 150, and 300 kW DC chargers are presented. AC chargers rely on the onboard charger of the EV to convert the Alternating Current to Direct Current, while DC chargers provide power directly to the battery, bypassing the onboard charger. Depending on the use of AC or DC chargers, the charging speed limits are different; however, DC limits are substantially higher than AC. Some EVs have as optional equipment a faster onboard charger, but in this case, the reported charging time does not assume any optional extras. More information on charging technology can be found in [Stamadianos et al. \(2023\)](#).

The data presented in Table 3.3 showcases the immense difference in charging time between different technologies and speeds. For example, a Nissan Leaf with standard charging equipment can take half a day to recharge, while it would take less than an hour to charge at a 50kW DC station. A limited number of EVs can also take advantage of 300kW DC stations, with the Porsche Taycan 4s can fully charge in 17 minutes in such a station. While this is a unique case and only a few 300kW stations exist, 50kW stations seem to perform adequately with charging speeds ranging from 29 to 74 minutes for the included EVs. Given that a driver will not fully drain the battery, charging times could be even lower.

Tesla EVs have access to the Supercharger Network Tesla, which usually offers the fastest supported speeds for Tesla EVs. In Greece, a total of three such stations exist. Since early 2023 the Tesla Supercharger Network has gradually started allowing other EVs to use the CSs, providing adapters from Tesla charging connectors to Combined Charging System (CCS) connectors.

In addition, the Nissan Leaf is one of the few remaining EVs using CHAdeMO charging plugs instead of the CCS the other EVs use. Newer EVs from Nissan offered in the USA and Europe have transitioned to CCS charging technology. Tesla vehicles also have a proprietary connector but all of them include an adapter.

3.4.3 Policy proposals

As the number of EVs on the road increases, there is a parallel rise in the demand for CSs. The higher demand for charging infrastructure subsequently incentivizes more businesses to enter the market, seeking to capitalize on the growing EV market. This positive feedback loop between CSs and EV purchases creates a self-reinforcing cycle, fostering continuous growth in both sectors.

Financial incentives, including tax credits and subsidies, have facilitated the widespread adoption of EVs for numerous businesses and individuals on a global scale. In the Greek context, besides the incentives and benefits of buying and EV presented in Section 3.2, the installation of a CS for prospective EV buyers is also subsidized, but only for individuals.

Subsequently, the next step involves the introduction of incentives for CS businesses. These incentives not only offset the initial costs of setting up CS but also create an economically viable business model for small-size CS operators. By promoting the profitability of CSs, governments can incentivize private sector participation, leading to a rapid expansion of the charging infrastructure network (Wangsa et al., 2023).

This will lead to the creation of a well-established network of CS instills confidence in prospective EV buyers, as it alleviates concerns about the availability and accessibility of charging facilities. When potential buyers perceive that charging their EVs will not pose significant challenges, they are more likely to make the transition from conventional vehicles to electric ones (Zhang et al., 2021). Therefore, the proliferation of CSs through incentivization schemes directly influences the decision-making process of consumers, driving EV purchases. In this context, providing incentives to CS businesses emerges as a strategic approach to enable the growth of both EV adoption and charging infrastructure.

Furthermore, incentivizing CS businesses aligns with broader sustainability goals and environmental commitments. Governments can incorporate green building requirements and sustainability criteria in incentive programs, encouraging CS operators to adopt eco-friendly practices. These measures may include the use of renewable energy sources for CS operations or the integration of energy storage systems to optimize power consumption (Khan et al., 2023). By linking incentives to sustainable practices, policymakers ensure that the growth of charging infrastructure is not only quantitatively significant but also environmentally responsible.

Lastly, the benefits from expanding the charging network with the intent of intercity traveling will have an impact on other means of transportation, like vans and trucks. This will help take electric variants of these types of vehicles away from city centers (Kyriakakis et al., 2022) and use them in long distance applications too.

3.5 Conclusions

The increasing need for sustainable transportation has made EVs the inevitable future of mobility. The most prominent problem of EVs is the combination of relatively small ranges and slow charging stations, which means they cannot be used as a direct replacement for ICEVs. This paper aims to assess the usability of EVs in the Greek mainland for long-distance trips and provide guidance towards the development of charging infrastructure.

To achieve that, a Monte Carlo simulation was conducted. Real-world EV energy consumption data was used to model trips between selected cities in the region, and 100,000 trips were simulated. The trips were generated at random from two lists, a list of the top thirty cities based on population and a list of twenty popular touristic destinations. The trip distances represent the real-world driving

distance between the nodes to have an even more accurate simulation. A list of eleven EVs was curated, based on the availability of real-use data and the limited available statistics on the EVs registered in Greece. Given the volatility of the energy consumption rate, an additional stochastic energy consumption generator was crafted, based on evidence from the literature. Since data were available for two different temperature ranges, the tests were carried out twice.

The simulation results provide useful information on the benefits and challenges of using EVs for long-distance travel, which can guide policymakers and stakeholders in the transportation industry. It was shown that the number of charging stops is affected by the battery capacity the driver is willing to use and that the energy consumption of different EVs can differ substantially and should be considered a decisive factor when buying an EV. In addition, it was shown that longer trips can be more unpredictable in terms of total energy consumption. From the perspective of infrastructure, the simulation provided a list of the highway sections, represented by the edges of the graph, which will be the most influential toward enabling long-distance traveling.

By assessing the feasibility of using EVs for long-distance travel in the Greek mainland, this study could serve as a model for other regions that are seeking to promote sustainable transportation and reduce their reliance on fossil fuels. This could have a significant positive impact on global efforts to mitigate climate change and promote environmental sustainability through the use of EVs. Using a Monte Carlo simulation is a promising approach for research, as it can provide valuable insights.

The Monte Carlo simulation used in the study provided a useful framework for understanding the variability in EV energy consumption, and the effect of external factors on their range. Future research could consider the impact of additional factors as long as data is made available. The effects of the payload on the batteries could also make future simulations more realistic, given the weight of additional passengers and luggage can have a big effect on consumption. Expansions can also be made to include different types of EVs, for example, electric vans or trucks, it can be applied in higher resolution road networks and include a lot of road types and different speeds. The charging profiles of EVs which can differ dramatically could also be included to determine the charging time and total travel time. Research on the preferences of EV users in regard to long-distance traveling could provide valuable insights as well.

Overall, these future research suggestions could help to further refine our understanding of the potential for promoting sustainable transportation in the Greek mainland and beyond, and identify strategies for overcoming the practical and social barriers to adoption of EV-based transportation.

Chapter 4

The Close Open Electric Vehicle Routing Problem

4.1 Introduction

In the domain of logistics operations, accuracy and punctuality are two very indicative parameters of operational success. In order to enhance these aspects, the Close Open Electric Vehicle Routing Problem (COEVRP) is proposed. Traditional EVRPs typically involve charging activities occurring between customer visits. However, this study introduces a novel charging strategy, wherein the obligatory visit to a CS is eliminated, allowing EVs to visit a CS only after fulfilling their assigned deliveries. If the remaining energy of an EV is insufficient to return to the depot, the vehicle visits the nearest CS to recharge adequately before heading back. Conversely, if the remaining energy is deemed adequate, the EV proceeds directly to the depot without visiting a CS. This distinction categorizes the routing into "open" or "closed" routes, depending on the presence or absence of a CS visit.

This new variant arises from a practical necessity rather than a mere alternative approach, as EV users frequently encounter instances where CSs are out of order and remain non-functional for extended periods. Notably, this study marks the first instance where open routing is considered in the context of EVs. While EVRP has been a popular research topic, it has not yet been explored in either an open or close-open variant. Existing literature on open routing has primarily focused on vehicles that are rented rather than owned. However, incorporating open routing in the context of EVs and charging can yield significant benefits.

The research presents the mathematical model of the COEVRP, incorporating the aforementioned routing strategy. Based on insights from the literature review, the energy consumption function is correlated with the payload of the vehicles. In addition, a meta-heuristic approach is introduced to solve the COEVRP, which integrates VNS with SA. New instances specifically designed for the COEVRP are introduced, building upon the instances proposed by [Schneider et al. \(2014\)](#). Instances with up to fifteen customers were solved using a commercial solver, as well as the meta-heuristic approach. However, instances with a hundred customers were exclusively solved using the meta-heuristic method due to computational constraints.

In the following subsections, the problem is explained further, the mathematical formulation and

the solution algorithm are described, and lastly the results of the computational experiments are presented and discussed.

4.2 Problem Description

The COEVRP represents an extension not only to the EVRP but also to the COVRP. The primary objective of the COEVRP is to effectively meet the demands of all customers exclusively through the utilization of an EV-only fleet. It is important to note that each customer can only be visited once during the course of the routing process. The journey for all vehicles starts from the depot and ends either at the depot itself or at a CS. Both energy and payload capacities impose constraints on the vehicles, with these constraints being the same for the entire fleet. The assumption is made that each EV departs from the depot with a fully charged battery and that the CSs will be available upon completion of each trip.

The rate at which energy is consumed by the EVs is the most important element in the formulation of the COEVRP. The performance of the EVs is significantly influenced by the weight they carry, prompting the objective function to aim at minimizing the amount of work required to deliver the objects. This particular formulation was chosen due to its theoretical neutrality and applicability in experimental scenarios. Work, in this context, refers to the measure of force necessary to move an object of a specific weight over a designated distance. The basis for this formulation can be traced back to the energy minimization variant of the VRP as presented in the work of [Kara et al. \(2007\)](#).

Expanding upon the aforementioned formulation, it is worth noting that energy consumption is a crucial aspect in the efficient operation of EVs. As the weight of the payload increases, the energy required for the EVs to traverse the assigned routes also increases. Therefore, by minimizing the work associated with the delivery process, the overall energy consumption can be reduced. This objective aligns with the growing emphasis on sustainable transportation and the need to optimize energy usage in the context of EV operations. Furthermore, the choice of this formulation for the COEVRP is grounded in its theoretical appeal and suitability for experimental testing. By quantifying the work required for each delivery, researchers can evaluate the performance and efficiency of different routing strategies, taking into account various factors such as vehicle capacity, customer demands, and charging requirements.

4.2.1 Mathematical Formulation

Table 4.1 presents the notation for the COEVRP model, including all sets, variables and other characteristics.

Objective Function:

$$w_1 \times \left(\sum_{i \in V} \sum_{j \in V} \sum_{k \in K} (1 + f_{ijk}) \times d_{ij} \times x_{ijk} \right) / E + w_2 \times \sum_{k \in K} \sum_{j \in V} x_{0jk} \quad (4.1)$$

Subject to:

$$\sum_{k \in K} \sum_{j \in V} x_{ijk} = 1, \forall i \in V_C, i \neq j \quad (4.2)$$

$$\sum_{j \in V} x_{ijk} = \sum_{j \in (V_C \cup V_D)} x_{jik}, \forall i \in V_C, k \in K, i \neq j \quad (4.3)$$

Table 4.1: Notation used for the COEVRP formulation.

Sets	
V_D	Set of Depots (one depot in this case), $V_D = \{v_D\}$
V_C	Set of customers to serve, $V_C = \{v_{C1}, v_{C2}, \dots, v_{Cn_c}\}$
CS	Charging Stations set, $CS = \{CS_1, CS_2, \dots, CS_{n_{cs}}\}$
V_E	Set of ending nodes (Depot and CSs), $V_E = V_D \cup CS$
V	Superset of all previous sets, $V = V_D \cup V_C \cup CS$
K	Set of electric vehicles, $K = \{k_1, k_2, \dots, k_{n_{ev}}\}$
Characteristics	
d_{ij}	Distance from node i to node j
n_c	Total number of customers
n_{cs}	Total number of Charging Stations (CS)
n_{ev}	Total number of electric vehicles
q_i	Demand of customer i
Q	Maximum load capacity for each electric vehicle
E	Maximum energy capacity for each electric vehicle
w_1	Energy consumption weight for the objective function
w_2	Number of vehicles weight for the objective function
Decision Variables	
f_{ijk}	Saves the payload of EV k traveling from i to j .
x_{ijk}	If arc (i, j) is crossed, $x_{ijk} = 1$, otherwise $x_{ijk} = 0$.

$$\sum_{j \in V_C} x_{0jk} \leq 1, \forall k \in K \quad (4.4)$$

$$\sum_{j \in (V_C \cup V_D)} \sum_{k \in K} f_{jik} - \sum_{j \in V} \sum_{k \in K} f_{ijk} = q_i, \forall i \in V_C, i \neq j \quad (4.5)$$

$$q_j \times x_{ijk} \leq f_{ijk} \leq (Q - q_j) \times x_{ijk}, \forall i \in V, j \in V, k \in K \quad (4.6)$$

$$\sum_{i \in V} \sum_{j \in V} (1 + f_{ijk}) \times d_{ij} \times x_{ijk} \leq E, \forall k \in K \quad (4.7)$$

$$x_{ijk} = 0, \forall i \in V_D, j \in V_E, k \in K \quad (4.8)$$

$$x_{ijk} = 0, \forall i \in CS, j \in V, k \in K \quad (4.9)$$

$$x_{iik} = 0, \forall i \in V, k \in K \quad (4.10)$$

$$x_{ijk} \in \{0, 1\}, \forall i \in (V_C \cup V_D), j \in (V_C \cup V_E), k \in K, i \neq j \quad (4.11)$$

The objective function (4.1) has to balance the use of EVs and the total energy they will spend. To achieve that, the function comprises of two parts, the first minimizing the energy and the second the vehicles. The total energy spent by all EVs is divided by the amount of energy capacity each EV has, to keep the energy consumption at the same order of magnitude as the number of vehicles. Given the theoretical numbers used in this research, tests were carried to determine the weights for part of this scalarized objective. In the end, the parameters were set to $w_1 = 10$, and, $w_2 = 2$; however, these numbers are problem specific.

Constraints (4.2) limit the number of incoming arcs to each customer to one. Next, constraints (4.3) pair the incoming arc of a customer with an outgoing one, meaning that no route may end at a customer location. Constraints (4.4) limit the outgoing arcs for each vehicle from the depot to not exceed one, subsequently, each vehicle may be deployed once. Constraints (4.5) enforce payload restrictions. When vehicle k departs from customer i , the demand of the customer must be subtracted from the load of the vehicle. The load of each vehicle is capped by constraints (4.6) at each customer node. When vehicle k does not travel on arc (i, j) , the decision variable $x_{i,j,k} = 0$, meaning the load is also zero. The maximum energy spent by each vehicle is limited by constraints (4.7). Constraints (4.8), (4.9), and (4.10), are sub-tour elimination constraints. The binary constraints for the decision variable $x_{i,j,k}$ are found in constraints (4.11)

Both the objective function (4.1), and constraints (4.7) are non-linear. The commercial solver employed automatically generates a piecewise-linear approximation, transforming the model to a linear one.

4.3 The proposed SA and VNS hybrid algorithm

To solve the COEVRP, a hybrid algorithm was created, using the very effective VNS algorithm and infusing it with the perks of a SA method. Both of them have a proven track record on numerous VRP variants. The resulting algorithm will be referred to as the SA/VNS.

4.3.1 Greedy Randomized Adaptive Search Procedure

As the SA/VNS algorithm cannot create solutions, the utilization of an alternative method is necessary. While simpler techniques such as the nearest neighbor approach could have been employed, this study opted for the GRASP as the initial solution generation method. GRASP is a highly effective meta-heuristic that has demonstrated considerable success in solving VRPs. It was originally presented in [Feo and Resende \(1995\)](#). GRASP was selected for its capability to generate diverse initial solutions, aiding in the exploration of the solution space.

The GRASP algorithm incorporates a Restricted Candidate List (RCL), which serves as a short pool of customers for potential nodes that can be visited next. The size of this list plays a crucial role in determining the characteristics of the solution. Smaller lists tend to produce more conservative solutions, while excessively large lists increase the likelihood of generating suboptimal solutions.

During each iteration of the algorithm, the solution construction mechanism seeks to find a subset of the closest candidates to the current node. These candidates are stored in the initially empty RCL, which is populated as the process unfolds. In case the RCL exceeds its capacity, the worst candidate is removed to maintain the list size. Once all potential nodes have been evaluated, one of the nodes contained in the RCL is randomly selected as the next node to be visited. The selection criterion is based on the distance between the current node and the candidates.

The algorithm outlining the solution construction method described above is presented in Algorithm 1. By employing GRASP, this study aims to generate diverse and promising initial solutions, which will subsequently be refined and optimized using the SA/VNS algorithm to obtain high-quality solutions for the COEVRP.

Algorithm 1: Initial Solution Algorithm

Data: Available Customers
Result: customer (a customer to be served with the current vehicle)

```

1 customer  $\leftarrow (-1)$ ;
2 RCL = { }; // (Restricted Customer List)
3 for Available Customers do
4   | if available customer is eligible then
5   |   | RCL.add_customer(available customer);
6 end
7 if RCL.empty() == false then
8   | customer = RCL.random_customer();
9 return customer;
```

4.3.2 Simulated Annealing

As its name suggests, the Simulated Annealing algorithm derives its name from its analogy to the annealing process in metallurgy. In metallurgical annealing, the physical and, in some cases, chemical properties of a material are intentionally modified. This process involves subjecting the material to elevated temperatures above its melting point for a specific duration, followed by controlled cooling, resulting in enhanced elasticity and reduced hardness, facilitating ease of manipulation.

The algorithmic implementation of SA focuses on the controlled cooling phase of annealing, utilizing a similar conceptual framework to guide the algorithm towards making progressively more conservative moves in later iterations. When applied to the VRP, SA determines the probability of transitioning from the current solution to an alternative one. Initially, at the highest temperature, all potential solutions have an equal probability of being selected. However, as the temperature decreases, the selection probabilities begin to differ, based on the quality of the new solutions. This approach ensures a gradual convergence towards optimal solutions. The termination criterion for the SA algorithm can be either a predefined number of iterations or reaching the lowest allowed temperature. Notably, the efficacy of this method stems from the consideration of all potential moves, each with a chance of being selected, even if the probability is low.

Equation (4.12) describes the mechanism used to determine the possibility of a solution with cost c' being selected to replace the current solution with cost c . T is the current temperature and is calculated according to equation (4.13), based on the iteration of the algorithm. As it is obvious, in this case the initial temperature is $T = 1$ and the $T_{cool} = 0$.

$$P_{accept} = e^{(c'-c)/T} \quad (4.12)$$

$$T = 1 - (iter + 1)/iter_{max} \quad (4.13)$$

4.3.3 Merging Simulated Annealing and Variable Neighborhood Search

The VNS meta-heuristic, initially proposed by Mladenović and Hansen (1997), has gained significant recognition in the field of VRPs. Its operational framework, characterized by simplicity and effectiveness, can be divided into three distinct phases. The first phase involves shaking, wherein a solution is selected, followed by the application of a LS mechanism to improve the solution. Finally,

a move to one of the solutions obtained during the LS phase is executed. Notably, in VNS, a move is only permitted if it leads to a superior solution compared to the current one.

In the present study, the aforementioned VNS algorithm is integrated with the SA method to expedite convergence towards optimal solutions. The SA mechanism is incorporated in the third phase of VNS, namely the move phase. In this phase, moves to better solutions are accepted with a probability of acceptance $P_{acceptance} = 1$. Rather than discarding moves to worse states, the acceptability of such moves is evaluated based on the objective function value, given a possibility of acceptance $P_{acceptance} < 1$.

Despite all of the described benefits, to prevent continuous selection of sub-optimal moves, a constraint is imposed, limiting the algorithm to a maximum of three consecutive sub-optimal moves. Once this threshold is reached, the algorithm is forced to make a move that improves the objective function value, thereby ensuring progress towards better solutions.

Regarding the LS operators utilized in the second phase of the SA/VNS algorithm, three operators are employed, namely the *1-1 Inter-route Swap*, *1-1 Intra-route Swap*, and *1-0 Relocate*. These operators enable the exploration of potential moves within and between routes. The feasibility of candidate moves is assessed with respect to both payload and energy constraints, ensuring that only moves abiding to these restrictions are considered. The selection of customers and vehicles for these moves is performed using a uniform distribution.

- *1-1 Inter-route Swap* : This operator involves two different customers from two different EVs, which take the place of one another.
- *1-1 Intra-route Swap*: This operator involves two different customers from the same EV, which take the place of one another. Despite this move involving only one EV, feasibility calculations have to be repeated, since the weight distribution over the arcs will change, and be an infeasible move in terms of energy expenditure.
- *1-0 Relocate*: This operator involves a single customer that is removed from an EV and is placed in a different EV.

The proposed structure of the SA/VNS algorithm is presented in Algorithm 2. Initially, after the solution generation step of the GRASP algorithm, the temperature parameter is initialized to $T = 1$. Two routes are selected from the current solution, which will be utilized by the three LS operators described earlier. Local search moves are then generated, and their quality is evaluated. If feasible moves are obtained, the selection of a move is based on the acceptance probability ($P_{acceptance}$). If the selected move leads to a superior solution, the best found solution is updated accordingly, and lastly, the temperature is lowered.

4.4 Computational Experiments

4.4.1 Problem Instances

COEVRP is a novel problem, necessitating the creation of new instances to assess the proposed model and solution algorithm. Instead of developing entirely new instances from scratch, the instances introduced by [Schneider et al. \(2014\)](#), which are derived from the instances of [Solomon \(1987b\)](#) for the VRPTW, were adapted for the COEVRP.

In the case of the COEVRP, the absence of TWs renders that information irrelevant. However, [Schneider et al. \(2014\)](#) updated the instances by incorporating CS locations and maximum energy

Algorithm 2: SA/VNS outline

Data: *instance_data*, *vns_iter*, *iter_max*, *T_cool*, *T_max*
Result: Solution S_{best}

```

1  $S \leftarrow \text{generate\_initial\_solution}(\text{instance\_data})$ ;
2  $S_{best} \leftarrow S$ ;
3  $T \leftarrow T_{max}$ ;                                     /* Initial temperature for SA */
4  $iter \leftarrow 0$ ;
5  $candidates \leftarrow \{\}$ ;                             /* Save possible moves */
6 while  $T > T_{cool}$  do
7    $iter \leftarrow iter + 1$ ;
8   for  $vns\_iter$  do
9      $\{route1, route2\} \leftarrow \text{random\_routes}(S)$ ;
10     $candidates \leftarrow \text{intra\_route\_swap}(route1, T)$ ;
11     $candidates \leftarrow \text{inter\_route\_swap}(route1, route2, T)$ ;
12     $candidates \leftarrow \text{reloc\_1\_0}(route1, route2, T)$ ;
13  end
14  if  $candidates.empty() == \text{false}$  then
15     $S \leftarrow \text{select\_move}(candidates)$ ;               /* Based on  $P_{accept}$  */
16    if  $S_{best}.cost < S.cost$  then
17       $S_{best} \leftarrow S$ ;
18     $T = 1 - (iter + 1)/iter_{max}$ ;
19 end

```

capacities for the vehicles, both of which are essential for this research. The data pertaining to the customer locations, demands, depot location, and CS locations were used as provided. The payload capacity of the vehicles remained unchanged, while the energy capacity was modified. The maximum number of vehicles was not explicitly specified. In order to establish an upper limit for the available vehicles, which is a crucial aspect of this research, experiments were conducted using both Gurobi (a commercial solver) and the SA/VNS algorithm. The minimum number of vehicles obtained across all instances was designated as the maximum number of vehicles allowed. This approach ensures the comparability of results, as outcomes obtained with different fleet sizes would not be directly comparable.

The instances were separated based on the spatial distribution of the customers in each instance. The three distinct types are referred to as "clustered," "random," and a combination of both, denoted as 'c,' 'r,' and 'rc,' respectively.

To determine the energy capacity of the vehicles, the disclosed capacity of the EVRPTW instances was multiplied by thirty. Consequently, the resulting energy capacity was set to 2333 energy units for both the 'c' and 'rc' instance types, and 1818 energy units for the 'r' instances. Given the energy consumption function used for the COEVRP variant, maintaining the original energy consumption function would result in the use of thirty to forty vehicles, which is unrealistic for a customer pool of one hundred customers.

4.4.2 SA/VNS parameters

The SA/VNS algorithm relies on two important parameters for its operation. The first parameter determines the number of initial solutions generated using the GRASP algorithm. Having a larger number of initial solutions increases the likelihood of discovering good solutions in the later stages of the algorithm, as it allows for a more comprehensive exploration of the solution space. However, an excessive number of initial solutions can significantly slow down the SA/VNS algorithm and lead to longer waiting times. To strike a balance between thorough exploration and computational efficiency, the number of initial solutions was set differently, depending on the size of the problem instance. For small instances with up to fifteen customers, the number of initial solutions was set to twenty times the number of customers. For larger instances, the maximum allowed number of initial solutions was restricted to half of the total number of customers. It is worth noting that this limitation may not apply to larger problem instances with thousands of customers, as the largest instances solved in this research contained a hundred customers.

The second parameter of the SA/VNS algorithm is the number of iterations, which determines the speed at which the algorithm converges to the final temperature, denoted as T_{cool} and set to zero in this study. The cooling rate must be slow enough to allow for a wide search in the solution space, but not excessively long. To investigate the impact of the cooling rate on the COEVRP, three instances with fifteen customers, each having different spatial distributions, were solved using four different cooling rates. The cooling rates ranged from zero SA/VNS iterations, meaning the SA/VNS component was not activated, to three thousand iterations.

The experimental findings are summarized in Table 4.2. The first column of the table displays the instance name, followed by the number of SA/VNS iterations, the achieved energy expenditure, and the gap from the optimal energy expenditure, the Best Solution Found (BSF). Each experiment was conducted ten times, and the presented results represent the average values. The results indicate a significant relationship between the number of iterations and the achieved outcomes. Further testing on smaller instances with five and ten customers demonstrated that a hundred repetitions

were sufficient to obtain reliable results.

Table 4.2: SA/VNS Iterations Test

Instance	$iter_{max}$	Energy	$Gap_{BSF}\%$
c208C15	0	9864.52	16.77
c208C15	30	9425.09	12.89
c208C15	300	8433.51	2.64
c208C15	3000	8210.68	0
r209C15	0	7895.17	14.84
r209C15	30	7835.06	7.45
r209C15	300	7692.33	573
r209C15	3000	7251.46	0
rc204C15	0	13321.56	15.82
rc204C15	30	12738.92	11.97
rc204C15	300	11749.11	4.56
rc204C15	3000	11213.68	0

In addition to the number of iterations, the maximum number of moves generated during the LS phase of the SA/VNS algorithm plays a crucial role in determining the quality of the results. To investigate the impact of the moves limit on the solution quality, the same three instances with fifteen customers were utilized. The experiments aimed to identify the optimal maximum number of moves that would yield high-quality solutions.

The maximum number of moves was tested by varying it from half to twice and three times the initially set value. Following the same experimental procedure as before, the SA/VNS algorithm was executed for each moves limit, and the results were recorded. The outcomes of these tests are presented in Table 4.3, which includes the instance name in the first column, the energy consumption in the second column, the moves limit in the third column, and the CPU time in seconds in the last column. It can be observed that any moves limit other than seventy-five led to similar outcomes, albeit with slower execution times. It is important to note that the presented values represent the average results obtained from ten independent runs for each instance. The findings demonstrate that setting the maximum number of moves to seventy-five is the most efficient choice, as it yields comparable results to other limits while ensuring faster execution times.

4.4.3 LS operators

In order to assess the significance of each individual LS operator and their combinations, a series of tests were conducted, and the results are summarized in Table 4.4. The table includes the instance name in the first column, followed by the LS operators employed in the second column. The subsequent columns present the energy consumption, execution time, and the gap from the best energy consumption value achieved. The reported values are the averages obtained from ten independent runs.

The LS operators were tested both in isolation and in combination with other operators. The results indicate that the combination of the *1-1 Intra-route Swap* and *1-0 Relocate* operators performs equivalently to using all three LS operators, while exhibiting nearly identical execution times.

Table 4.3: VNS Iterations Test

Instance	Energy	vns_{iter}	Time (s)
c208C15	8210.68	225	48.3
c208C15	8210.68	150	41.2
c208C15	8210.68	75	35.8
c208C15	8210.68	38	39.1
r209C15	7251.46	225	59.3
r209C15	7251.46	150	46.1
r209C15	7251.46	75	40.3
r209C15	7251.46	38	48.3
rc204C15	11213.68	225	45.0
rc204C15	11213.68	150	41.8
rc204C15	11213.68	75	38.5
rc204C15	11213.68	38	39.1

Although it may be possible to achieve comparable results by using only these two operators, the inclusion of the *1-1 Inter-route Swap* operator does not compromise performance and, in some cases, leads to improved outcomes. This observation is further supported in Table 4.5, which compares the average energy consumption achieved using all three LS operators with the average energy consumption achieved using only the *1-1 Intra-route Swap* and *1-0 Relocate* operators, along with the corresponding gap between the solutions. A slight, yet discernible, gap of 0.70% can be observed. It should be noted that this difference could become more pronounced in larger instances.

The findings highlight the significance of considering all three LS operators, as they collectively contribute to obtaining higher-quality solutions in the COEVRP. The combination of the *1-1 Intra-route Swap* and *1-0 Relocate* operators provides a competitive alternative, but the inclusion of the *1-1 Inter-route Swap* operator offers additional improvement potential, especially for larger instances.

Table 4.4: Comparison of all possible LS combinations for SA/VNS.

Instance	LS operators	Energy	Time (s)	Gap_{best} %
rc204C15	Intra Swap	13074.93	27.3	14.24
rc204C15	Inter Swap	11648.32	28.2	3.73
rc204C15	Relocate	12744.41	28.6	12.01
rc204C15	Intra & Inter Swap	11779.91	34.1	4.81
rc204C15	Intra Swap & Relocate	11213.68	38.3	0.00
rc204C15	Inter Swap & Relocate	11513.13	41.0	2.60
rc204C15	All	11213.68	38.5	0.00

Table 4.5: Comparison of two LS combinations for SA/VNS.

Instance	Vehicles	All LS operators	Intra Swap & Relocate	Gap %
		$Energy_{avg}$	$Energy_{avg}$	
c103c15	7	8666.84	8711.91	0.52
c106c15	4	5465.16	5465.16	0.00
c202c15	6	7891.61	7891.61	0.00
c208c15	6	8210.68	8210.68	0.00
r102c15	6	5062.99	5113.62	1.00
r105c15	5	5826.06	5848.78	0.39
r202c15	7	8001.84	8112.29	2.63
r209c15	7	7251.46	7279.02	0.38
rc103c15	5	7560.69	7562.96	0.03
rc108c15	7	10440.30	10538.44	0.94
rc202c15	6	8770.42	8770.42	0.00
rc204c15	7	11213.68	11491.78	2.48
Average	N/A	7863.48	7924.72	0.70

4.4.4 Small Instances

In this section, we provide a comprehensive analysis of the results obtained from the tests conducted on the small modified benchmark instances derived from [Schneider et al. \(2014\)](#). These instances were solved using both the commercial solver Gurobi and the proposed SA/VNS method. The detailed results for each small instance are presented in Tables 4.6, 4.7, and 4.8.

Each table contains the following information: the instance names, the number of vehicles utilized, the energy consumption associated with the optimal solutions, and the gaps observed between the solutions obtained from Gurobi and SA/VNS when compared to the optimal solutions.

By examining these tables, we can gain insights into the performance of Gurobi and the proposed SA/VNS method on the small benchmark instances. The gaps reported in the tables provide an indication of the relative quality of the solutions obtained by each method compared to the optimal solutions.

Table 4.6 showcases the outcomes obtained for the five-customer instances, where both Gurobi and SA/VNS achieved optimal solutions. Similarly, Table 4.7 presents the results for the ten-customer instances, with Gurobi also attaining optimality for all cases. The optimality of these results is indicated by Gurobi successfully terminating within the specified time limit for each of the instances considered.

Moving on to Table 4.8, which presents the fifteen-customer instances, it is evident that Gurobi encountered challenges in maintaining its performance compared to SA/VNS, despite the relatively small problem size of fifteen customers. Out of the twelve instances with fifteen customers, only three were solved to optimality by Gurobi. Although certain average results from SA/VNS aligned with those of Gurobi, hinting at the possibility of an optimal solution, Gurobi's inability to reach a conclusive outcome within the time limit means that a conclusion cannot be drawn. SA/VNS, on the other hand, outperformed Gurobi in half of the instances, exhibiting an average deviation of 1.26% from Gurobi's results.

Table 4.6: 5-customer instances

BSF		Gurobi			SA/VNS		
<i>Instance</i>	<i>Vehicles</i>	<i>Energy</i>	<i>Energy</i>	<i>Gap_{BSF}%</i>	<i>Energy_{avg.}</i>	<i>Energy_{best}</i>	<i>Gap_{BSF}%</i>
c101c5	3	3662.75	3662.75	0.00	3662.75	3662.75	0.00
c103c5	3	2698.09	2698.09	0.00	2698.09	2698.09	0.00
c206c5	3	2704.75	2704.75	0.00	2704.75	2704.75	0.00
c208c5	3	4779.94	4779.94	0.00	4779.94	4779.94	0.00
r104c5	3	2134.89	2134.89	0.00	2134.89	2134.89	0.00
r105c5	2	1381.10	1381.10	0.00	1381.10	1381.10	0.00
r202c5	3	1568.07	1568.07	0.00	1568.07	1568.07	0.00
r203c5	3	2828.08	2828.08	0.00	2828.08	2828.08	0.00
rc105c5	4	5019.44	5019.44	0.00	5019.44	5019.44	0.00
rc108c5	3	5579.50	5579.50	0.00	5579.50	5579.50	0.00
rc204c5	4	5100.98	5100.98	0.00	5100.98	5100.98	0.00
rc208c5	3	2465.94	2465.94	0.00	2465.94	2465.94	0.00
Average	-	3326.96	3326.96	0.00	3326.96	3315.71	0.00

Table 4.7: 10-customer instances

BSF		Gurobi			SA/VNS		
<i>Instance</i>	<i>Vehicles</i>	<i>Energy</i>	<i>Energy</i>	<i>Gap_{BSF}%</i>	<i>Energy_{avg.}</i>	<i>Energy_{best}</i>	<i>Gap_{BSF}%</i>
c101c10	5	7754.12	7754.12	0.00	7754.12	7754.12	0.00
c104c10	5	5776.82	5776.82	0.00	5776.82	5776.82	0.00
c202c10	5	6853.08	6853.08	0.00	6853.08	6853.08	0.00
c205c10	4	6004.50	6004.50	0.00	6004.50	6004.50	0.00
r102c10	5	4516.26	4516.26	0.00	4516.26	4516.26	0.00
r103c10	4	3082.25	3082.25	0.00	3082.25	3082.25	0.00
r201c10	5	3844.80	3844.80	0.00	3844.80	3844.80	0.00
r203c10	4	3511.19	3511.19	0.00	3511.19	3511.19	0.00
rc102c10	5	6451.89	6451.89	0.00	6451.89	6451.89	0.00
rc108c10	4	5371.85	5371.85	0.00	5371.85	5371.85	0.00
rc201c10	4	5376.41	5376.41	0.00	5376.41	5376.41	0.00
rc205c10	5	5841.67	5841.67	0.00	5841.67	5841.67	0.00
Average	-	5365.40	5365.40	0.00	5365.40	5365.40	0.00

Table 4.8: 15-customer instances

<i>Instance</i>	<i>Vehicles</i>	BSF	Gurobi			SA/VNS	
		<i>Energy</i>	<i>Energy</i>	<i>Gap_{BSF}%</i>	<i>Energy_{avg.}</i>	<i>Energy_{best}</i>	<i>Gap_{BSF}%</i>
c103c15	7	8666.84	8666.85	0.00	8666.84	8666.84	0.00
c106c15	4	5465.16	5465.16	0.00	5465.16	5465.16	0.00
c202c15	6	7891.61	8051.07	2.02	7891.61	7891.61	0.00
c208c15	6	8210.68	8329.90	1.45	8210.68	8210.68	0.00
r102c15	6	4934.03	5235.34	6.11	5062.99	4934.03	0.00
r105c15	5	5826.06	5826.06	0.00	5826.06	5826.06	0.00
r202c15	7	8001.84	8001.84	0.00	8001.84	8001.84	0.00
r209c15	7	7251.46	7251.46	0.00	7251.46	7251.46	0.00
rc103c15	5	7560.69	7726.32	2.19	7560.69	7560.69	0.00
rc108c15	7	10235.80	10555.89	3.13	10440.30	10235.80	0.00
rc202c15	6	8770.42	8791.27	0.24	8770.42	8770.42	0.00
rc204c15	7	11213.68	11213.68	0.00	11213.68	11213.68	0.00
Average	-	7835.69	7926.24	1.26	7863.48	7835.69	0.00

To provide a visual comparison of the results, we present Figure 4.1, which focuses on the instance c202C15. Notably, the disparity between the two solutions is minimal, as the sole difference lies in the relocation of node 12 from route 0, 12, 15, 6, 1 to route 0, 19, 14, 4.

The disparity between SA/VNS and Gurobi becomes evident when considering their execution times. Table 4.9 provides the run times, measured in seconds, for each of the small instances using both methods. While both approaches performed great on the smallest instances, the difference became significant when dealing with ten-customer instances. On average, Gurobi required approximately 100 seconds to solve these instances, whereas SA/VNS achieved the same results in just eight seconds. Instances featuring fifteen customers posed a particularly challenging task for Gurobi, as only three instances were solved to optimality, and the remaining instances reached Gurobi’s time limit of 1800 seconds before termination. The gap in execution time between Gurobi and SA/VNS, coupled with Gurobi’s difficulty in larger instances, renders Gurobi unsuitable for extensive deployment. Additionally, it is worth noting that SA/VNS operates as a single-thread application, whereas Gurobi utilizes a multi-threaded implementation.

4.4.5 Large Instances

The largest instances in Schneider et al. (2014) comprise one hundred customers. Each instance has twenty CSs, including the depot that can also function as a CS. To demonstrate the efficacy of the SA component in the SA/VNS algorithm, results with and without SA are compared. In both cases, the number of initial solutions remains constant at half the number of customers. The maximum number of iterations, which controls the cooling rate in SA/VNS and serves as a duration limit for plain VNS, is set to $iter_{max} = 5000$.

Table 4.10 presents the average results of ten runs for each instance. The first three columns indicate the instance name, the number of EVs, and the energy consumption for the BSF. The subsequent three columns display the results for plain VNS, while the final three columns depict

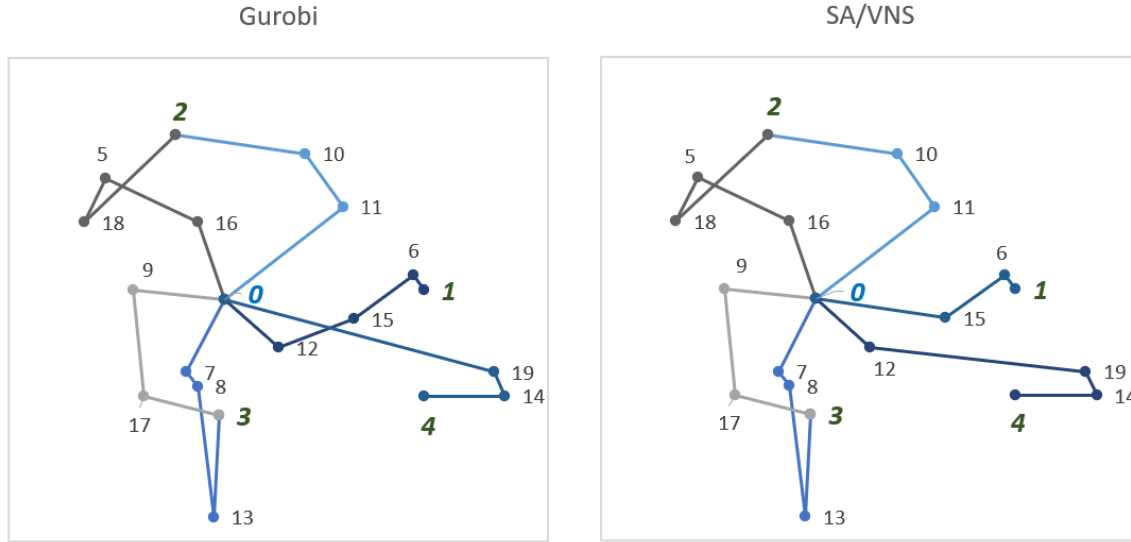


Figure 4.1: Comparison of the results for instance c202C15.

Table 4.9: Execution time for small instances (in seconds).

5-customers			10-customers			15-customers		
Instance	Gurobi	SA/VNS	Instance	Gurobi	SA/VNS	Instance	Gurobi	SA/VNS
c101c5	0.8	0.4	c101c10	37.2	7.8	c103c15	1800.0	27.9
c103c5	1.1	0.3	c104c10	19.1	5.3	c106c15	1800.0	37.8
c206c5	1.6	0.2	c202c10	604.3	6.5	c202c15	1800.0	41.5
c208c5	3.9	0.2	c205c10	97.0	8.6	c208c15	1800.0	35.8
r104c5	0.9	0.2	r102c10	4.0	4.9	r102c15	1800.0	39.0
r105c5	0.8	0.2	r103c10	29.0	11.1	r105c15	1340.0	57.7
r202c5	0.9	0.5	r201c10	4.0	8.0	r202c15	130.6	15.7
r203c5	1.1	0.4	r203c10	204.0	11.6	r209c15	440.6	40.3
rc105c5	1.1	0.2	rc102c10	4.0	1.1	rc103c15	1800.0	50.1
rc108c5	1.8	0.3	rc108c10	19.0	7.5	rc108c15	1800.0	24.3
rc204c5	1.2	0.2	rc201c10	109.0	10.2	rc202c15	1800.0	51.0
rc208c5	0.8	0.5	rc205c10	126.0	6.9	rc204c15	1800.0	38.5
Average	1.3	0.3	Average	104.7	7.5	Average	1509.26	38.3

the results for SA/VNS. The execution time is reported in seconds, ranging from approximately 55 seconds to around 145 seconds.

It is evident that SA/VNS outperforms plain VNS while maintaining a comparable execution time. SA/VNS successfully attained all of the BSFs. The smallest gap between VNS and the BSF, and subsequently SA/VNS, was observed for the first instance in the table. The largest gap was observed for instance r111. On average, the integration of SA and VNS yielded an improvement of approximately 5.7%.

4.5 Conclusions

This section introduces the Close-Open Electric Vehicle Routing Problem along with its mathematical formulation. The COEVRP addresses the key limitations of EVs, namely energy and payload capacity, and presents an alternative routing methodology where EVs are not permitted to recharge between deliveries but only after completing all deliveries. This approach is particularly suitable for city logistics, offering a more realistic solution for EV adoption in supply chains, especially in last-mile logistics. Given the current limitations of battery technology and the inadequate infrastructure of charging stations, the proposed model acknowledges the challenges in relying solely on EVs and the existing charging infrastructure for efficient routing operations.

The initial solutions for COEVRP are generated using a construction algorithm inspired by the construction phase of the GRASP. To enhance these solutions, a hybrid algorithm that combines Simulated Annealing and Variable Neighborhood Search is developed for solving COEVRP. Unlike the original VNS algorithm, which only allows moves that immediately improve the solution, the SA/VNS hybrid algorithm incorporates non-optimal moves, providing greater diversification and exploration of the solution space. The SA/VNS hybrid algorithm is tested on modified instances from the literature, with smaller instances also compared to the Gurobi Optimizer. Three Local Search operators, namely 1-1 Intra-route Swap, 1-1 Inter-route Swap, and 1-0 Relocate, are included in the algorithm.

The energy consumption results of SA/VNS and Gurobi for five and ten-customer instances exhibit similar outcomes, while SA/VNS outperforms Gurobi in half of the fifteen-customer instances. However, the most significant difference between the two methods lies in their execution time. Gurobi takes significantly longer, with ten-customer instances requiring more than ten times the time of SA/VNS, and fifteen-customer instances taking on average forty times longer to solve. Consequently, the larger one hundred-customer instances are exclusively solved using SA/VNS. Comparisons between SA/VNS and VNS without the SA component reveal that SA/VNS reduces energy consumption by 5.71%.

Furthermore, several tests are conducted on the operators and variables of SA/VNS. The number of initial solutions is set to twenty times the number of nodes in each instance. The cooling time of the SA component, determined by the number of SA/VNS iterations, is tested with four different values, demonstrating that three thousand iterations yield the best results. The maximum number of LS moves generated in each iteration is also considered, with a maximum of seventy-five moves proving to be optimal. Finally, the LS operators of SA/VNS are tested, highlighting the necessity of all LS operators to achieve desired results.

Future research in COEVRP should focus on incorporating additional realistic elements and considering more parameters. Different energy consumption functions could be explored, while maintaining a balance between energy expenditure and the number of vehicles, considering the substantial investment required for EVs. Conducting small-scale real-life tests would provide more

Table 4.10: 100-customer instances

Instance	Veh.	BSF	VNS			SA/VNS		
		Energy	Energy	Time	$Gap_{BSF}\%$	Energy	Time	$Gap_{BSF}\%$
c101	16	68836.8	71283.0	75.8	3.55	68836.8	78.8	0.00
c102	16	69113.8	71659.8	69.8	3.68	69113.8	69.4	0.00
c103	17	68366.7	71314.6	67.6	4.31	68366.7	67.5	0.00
c104	16	69178.8	71809.0	65.6	3.80	69178.8	69.4	0.00
c105	16	69219.2	72106.4	68.3	4.17	69219.2	70.2	0.00
c106	17	68392.7	71261.7	59.0	4.19	68392.7	71.2	0.00
c107	16	68832.4	71972.0	70.7	4.56	68832.4	72.2	0.00
c108	16	68936.4	72138.3	67.3	4.64	68936.4	74.9	0.00
c109	16	69068.2	71706.5	73.4	3.82	69068.2	75.9	0.00
c201	17	71201.6	75133.1	131.1	5.52	71201.6	131.8	0.00
c202	17	71342.6	74944.2	116.4	5.05	71342.6	125.4	0.00
c203	17	71648.6	75454.5	141.0	5.31	71648.6	131.3	0.00
c204	17	71384.2	74901.6	130.9	4.93	71384.2	130.3	0.00
c205	16	72197.7	75900.4	137.0	5.13	72197.7	146.6	0.00
c206	17	71491.2	75106.0	128.9	5.06	71491.2	117.1	0.00
c207	17	71391.6	74858.5	122.7	4.86	71391.6	141.3	0.00
c208	17	72008.2	74885.6	131.6	4.00	72008.2	139.9	0.00
r101	14	53334.3	56729.1	51.8	6.37	53334.3	60.2	0.00
r102	13	54713.9	58509.0	63.5	6.94	54713.9	69.2	0.00
r103	13	54460.6	58572.6	60.3	7.55	54460.6	63.3	0.00
r104	13	54306.9	58489.8	60.7	7.70	54306.9	62.7	0.00
r105	13	54437.4	58577.4	58.0	7.61	54437.4	65.0	0.00
r106	13	54305.6	58023.9	59.4	6.85	54305.6	61.7	0.00
r107	13	54468.5	58792.9	68.6	7.94	54468.5	64.6	0.00
r108	14	53323.3	56402.1	52.5	5.77	53323.3	54.1	0.00
r109	13	54305.3	57653.8	62.7	6.17	54305.3	70.0	0.00
r110	14	53082.0	56398.0	49.0	6.25	53082.0	56.3	0.00
r111	13	54049.2	58551.7	59.4	8.33	54049.2	63.9	0.00
r112	13	54279.8	58130.0	62.2	7.09	54279.8	63.6	0.00
r201	14	53451.0	56765.3	76.2	6.20	53451.0	96.5	0.00
r202	13	54215.9	58469.4	108.0	7.85	54215.9	100.1	0.00
r203	13	54702.3	58386.1	108.7	6.73	54702.3	103.6	0.00
r204	14	53801.6	57011.3	83.0	5.97	53801.6	96.4	0.00
r205	14	52960.3	57107.3	84.3	7.83	52960.3	85.1	0.00
r206	13	54661.2	58673.1	100.1	7.34	54661.2	112.8	0.00
r207	13	54516.5	58189.6	101.6	6.74	54516.5	94.2	0.00
r208	13	54560.2	58900.1	99.5	7.95	54560.2	105.8	0.00
r209	13	54542.8	58403.0	107.4	7.08	54542.8	110.8	0.00
r210	13	54490.3	58794.9	104.7	7.90	54490.3	108.9	0.00
r211	13	54633.8	58391.5	112.5	6.88	54633.8	101.8	0.00
rc101	17	74572.2	78098.7	80.9	4.73	74572.2	85.9	0.00
rc102	17	74132.9	78155.6	82.8	5.43	74132.9	86.9	0.00
rc103	17	74675.6	78812.9	83.8	5.54	74675.6	93.6	0.00
rc104	18	73519.7	77770.0	74.8	5.78	73519.7	78.7	0.00
rc105	17	74918.4	77982.1	85.7	4.09	74918.4	87.5	0.00
rc106	17	74436.9	78307.5	84.2	5.20	74436.9	87.4	0.00
rc107	17	74253.5	78265.9	81.2	5.40	74253.5	83.3	0.00
rc108	18	73430.2	77108.8	74.5	5.01	73430.2	71.6	0.00
rc201	17	74585.2	78400.5	116.1	5.12	74585.2	134.9	0.00
rc202	17	74108.2	77916.7	116.7	5.14	74108.2	124.2	0.00
rc203	18	73240.6	76708.1	112.4	4.73	73240.6	105.5	0.00
rc204	17	74243.8	78361.3	134.9	5.55	74243.8	124.8	0.00
rc205	17	74514.4	77956.5	133.6	4.62	74514.4	125.9	0.00
rc206	17	74459.7	77794.3	127.1	4.48	74459.7	130.1	0.00
rc207	17	74650.9	78467.7	136.5	5.11	74650.9	113.6	0.00
rc208	17	74759.5	77982.3	121.3	4.31	74759.5	83.0	0.00
Average	N/A	64762.8	68365.1	91.0	5.71	64762.8	92.9	0.00

accurate energy consumption estimates. Furthermore, adapting the COEVRP model for Multi-Depot problems, incorporating an objective function that considers vehicle distribution, would be a valuable extension to the literature.

Chapter 5

The Close Open Mixed Fleet Electric Vehicle Routing Problem

5.1 Introduction

The consideration for a mixed fleet of owned and rented EVs is the natural evolution of the CO-EVRP that was discussed in detail in the previous section of this thesis. While EVs offer numerous environmental and operational advantages, the initial acquisition cost of an EV is generally higher compared to an equivalent ICE vehicle. This cost difference often leads business owners to hesitate when it comes to adopting EVs for their fleet updates. However, with the increasing popularity of EVs, many rental companies are starting to offer EVs as part of their fleet, providing an opportunity for logistics operators to test and evaluate EVs before committing to a full transition. This rental option allows businesses to use EVs on an occasional basis, further exploring the feasibility and benefits of incorporating EVs into their operations.

In this research, we consider a specific scenario in which a logistics company decides a transition to an EV fleet but faces financial constraints that prevent them from fully subsidizing the complete transition. As a result, the company opts to acquire a smaller fleet of EVs and supplement their fleet with rented EVs as needed. This scenario accurately reflects the dynamics of last-mile logistics operations, where flexibility and adaptability are crucial to meet the varying demands of urban delivery services.

To solve the proposed Close Open Mixed Fleet Electric Vehicle Routing Problem (COMF-EVRP), two meta-heuristic algorithms are developed and compared against each other. These meta-heuristics belong to the category of Swarm Intelligence (SI) algorithms, which are specifically designed for tackling discrete optimization problems rather than continuous ones. The first meta-heuristic employed is the Bee Colony Optimization (BCO), a nature-inspired algorithm that mimics the foraging behavior of bees to find optimal solutions. The second meta-heuristic utilized is the Ant Colony Optimization (ACO) algorithm, another nature-inspired approach that emulates the behavior of ant colonies to efficiently explore solution spaces. In the case of ACO, two variations are explored: the Ant Colony System (ACS) and the Max-Min Ant System (MMAS), which introduce different mechanisms and strategies to enhance the exploration and exploitation capabilities of the algorithm.

By considering the mixed fleet scenario and developing these SI-based meta-heuristics, this re-

search aims to provide valuable insights into the practical adoption of EVs in logistics operations. The study recognizes the financial constraints faced by businesses and explores alternative strategies to incorporate EVs in a cost-effective manner. Through this comprehensive analysis, the research aims to provide decision-makers with valuable guidance and support in navigating the complexities of adopting EVs in mixed ownership fleet configurations for last-mile logistics operations.

In the following subsection, the mathematical formulation of the COMF-EVRP, as well as the proposed meta-heuristics and the experimental results, are presented.

5.2 Problem Description

The proposed COMF-EVRP offers several positive aspects from a business standpoint. It involves satisfying the company's average daily operations and budget constraints through the owned fleet while renting additional EVs from an external EV rental business as needed. Furthermore, the plan allows for flexibility in routing, as the owned fleet EVs have the option to conclude their routes either at Charging Stations (CSs) or at the company's depot. From a business standpoint, this approach offers potential advantages such as cost efficiency and scalability. Renting additional EVs instead of owning a larger fleet upfront can result in cost savings, allowing the company to manage its budget effectively. Moreover, the flexibility in routing provides an opportunity to optimize operational logistics, reduce idle time, and enhance overall efficiency. In addition, the plan aligns with environmental sustainability goals by utilizing EVs as the primary mode of transportation. This approach addresses the growing demand for eco-friendly practices and positions the logistics company favorably in attracting environmentally conscious customers. By reducing carbon emissions through the use of EVs, the company can contribute to a greener transportation ecosystem and enhance its brand image.

However, the plan also presents certain negative aspects that should be considered. One major concern is the dependency on the availability and reliability of the external EV rental business. Any disruption in the supply or service quality from the rental business could lead to operational challenges, potentially impacting customer satisfaction and overall business performance. Subsequently, having many rental business partners would be essential.

Additionally, the plan assumes the existence of adequate charging infrastructure at the CSs. In reality, there may be limitations in the charging infrastructure, such as insufficient capacity or congestion during peak times, which could hinder the smooth operation of the logistics company. This is the risk that motivated the move of charging to the end of the operations. Moreover, in case the fleet size expands, the logistics company will face increased maintenance and long-term costs. Proper planning, maintenance partnerships, and budget allocation will be necessary to address these potential challenges effectively.

The return strategy for owned EVs that conclude their trips at a CS is a critical aspect that warrants attention within the framework of efficient operations. Different companies can have different strategies, such as considering charging stops that offer drivers the ability to rest before returning to the depot to restock their vehicles, or opt to consider only fast CSs that would enable them to return to the depot after charging for only a few minutes.

The formulation of a return strategy for owned EVs that terminate their journeys at a CS is an essential element that requires careful consideration. Companies may adopt different approaches to tackle this issue, depending on the available infrastructure. Some examples are incorporating charging stops that provide drivers with an opportunity to rest prior to returning to the depot to

reload the vehicles and continue, or they may consider only fast CSs that would enable a quick return to the depot following a short charging stop.

Lastly, with the continuous advancement of technology and as economies of scale progress, it becomes necessary for companies following this model to regularly reassess their requirements and make necessary adjustments to their fleets.

5.2.1 Mathematical Formulation

The formulation of the Close-Open Electric Vehicle Routing Problem with Mixed Fleets closely resembles that of the COEVRP, as discussed in the preceding section of this thesis. The primary objective of COMF-EVRP remains the same: to fully satisfy customer demand while not violating to the payload and energy capacity constraints of EVs. However, the key distinction of COMF-EVRP lies in the incorporation of rented EVs to augment the existing fleet as required.

The following assumptions are made in COMF-EVRP:

- All EVs have the maximum energy at the start of the trip.
- Customers are visited precisely once.
- There is an available charger at all times in each CS.
- Owned EVs end their trips at the closest possible location (depot or CS).
- Rented EVs end their journey at the closest CS.

It is important to highlight the prevalent assumption in VRPs that the routing of rented vehicles concludes once the last customer on the route has been visited. However, in the context of EVs, an additional consideration arises due to their reliance on battery power and associated limitations. To ensure the EV's operational viability, it becomes necessary to maintain a sufficient battery level that allows for a visit to the closest CS.

The presented COMF-EVRP formulation is influenced by the work of [Liu and Jiang \(2012\)](#) that introduced the Close-Open VRP variant and from the model of [Jie et al. \(2019\)](#).

Table 5.1 presents a comprehensive list of all the sets, decision variables, and other parameters of the formulation.

Objective Function:

$$\min : \sum_{k \in K_2} \sum_{j \in V} x_{0jk} + \left(\sum_{i \in V} \sum_{j \in V} \sum_{k \in K} (1 + f_{ijk}) \times d_{ij} \times x_{ijk} \right) / E \quad (5.1)$$

Subject to:

$$\sum_{k \in K} \sum_{j \in V} x_{ijk} = 1, \forall i \in V_C, i \neq j \quad (5.2)$$

$$\sum_{j \in V} x_{ijk} = \sum_{j \in (V_C \cup V_D)} x_{jik}, \forall i \in V_C, k \in K, i \neq j \quad (5.3)$$

$$\sum_{j \in V_C} x_{0jk} \leq 1, \forall k \in K \quad (5.4)$$

$$\sum_{i \in V_C} x_{i0k} = 0, \forall k \in K_2 \quad (5.5)$$

Table 5.1: Notation used for the COMF-EVRP formulation.

Sets	
V_D	Set of Depots (one depot in this case), $V_D = \{v_D\}$
V_C	Set of customers to serve, $V_C = \{v_{C1}, v_{C2}, \dots, v_{Cn_c}\}$
CS	Set of Charging Stations, $CS = \{CS_1, CS_2, \dots, CS_{n_{cs}}\}$
V_E	Set of ending nodes (Depot and CSs), $V_E = V_D \cup CS$
V	Superset of all previous sets, $V = V_D \cup V_C \cup CS$
K_1	Set of owned EVs, $K_1 = \{k_{o1}, k_{o2}, \dots, k_{n_o}\}$
K_2	Set of rented EVs, $K_2 = \{k_{r1}, k_{r2}, \dots, k_{n_r}\}$
K	Set of both owned and rented EVs $K = K_1 \cup K_2$
Characteristics	
d_{ij}	Distance from node i to node j
n_c	Total number of customers
n_{cs}	Total number of Charging Stations (CS)
n_o	Total number of owned electric vehicles
n_r	Total number of rented electric vehicles
n_{ev}	Total number of electric vehicles
q_i	Demand of customer i
Q	Maximum load capacity for each electric vehicle
E	Maximum energy capacity for each electric vehicle
Decision Variables	
f_{ijk}	Saves the payload of EV k traveling from i to j .
x_{ijk}	If arc (i, j) is crossed, $x_{ijk} = 1$, otherwise $x_{ijk} = 0$.

$$\sum_{j \in (V_C \cup V_D)} \sum_{k \in K} f_{jik} - \sum_{j \in V} \sum_{k \in K} f_{ijk} = q_i, \forall i \in V_C, i \neq j \quad (5.6)$$

$$q_j \times x_{ijk} \leq f_{ijk} \leq (Q - q_j) \times x_{ijk}, \forall i \in V, j \in V, k \in K \quad (5.7)$$

$$\sum_{i \in V} \sum_{j \in V} (1 + f_{ijk}) \times d_{ij} \times x_{ijk} \leq E, \forall k \in K \quad (5.8)$$

$$x_{ijk} = 0, \forall i \in V_D, j \in V_E, k \in K \quad (5.9)$$

$$x_{ijk} \in \{0, 1\}, \forall i \in (V_C \cup V_D), j \in (V_C \cup V_E), k \in K, i \neq j \quad (5.10)$$

The proposed model is a Nonlinear Mixed-Integer Programming model. Similar to the formulation of COEVRP, the objective function (5.1) of COMF-EVRP comprises of two parts, one referring to the number of vehicles and the other to the energy. The first part aims to minimize the total number of rented EVs, in contrast to the total number of EVs for COEVRP. The second part remains the same, dividing the energy consumption of all the EVs by the energy capacity of a single EV to bring the number to the same order of magnitude as the number of vehicles. In contrast to COEVRP, no coefficients were used, as initial testing showed it was not necessary for the instances solved; however, it may be for different instances. This scalarized approach allows for the simultaneous consideration of the two objectives and enables the optimization process to find a single solution that balances the trade-offs between these objectives.

Constraints (5.2) force the number of incoming arcs to each customer to one. Constraints (5.3) pair the incoming arc of a customer with an outgoing one, meaning that no route may end at a customer location. Constraints (5.4) limit the outgoing arcs for each vehicle from the depot to not

exceed one, subsequently, each vehicle may be deployed once. Constraints (5.5) prevents non-owned vehicles from returning to the depot. Constraints (5.6) enforce payload restrictions. When vehicle k departs from customer i , the demand of the customer must be subtracted from the load of the vehicle. The load of each vehicle is capped by constraints (5.7) at each customer node. When vehicle k does not travel on arc (i, j) , the decision variable $x_{i,j,k} = 0$, meaning the load is also zero. The maximum energy spent by each vehicle is limited by constraints (5.8). Constraints (5.9) remove any direct connection from the depot to CSs. The binary constraints for the decision variable $x_{i,j,k}$ are found in constraints (5.10). The definition prevents unwanted connections from any node to itself, and prohibit direct connections originating from CSs to any other node, given that a CS may be visited after the completion of the deliveries.

The objective function and constraints described in Equation (4.8) exhibit non-linear characteristics. It is important to highlight that the commercial solver utilized in this study automatically generates a piecewise-linear approximation for these non-linear components. As a result, the detailed explanation and inclusion of this approximation have been omitted from the current discussion. Equation (4.8) is necessary as it limits the energy consumption of each vehicle, while the objective function ensures that the energy consumption is minimized.

5.3 The proposed Bee Colony Optimization algorithm

The concept of emulating the behavior of bees in optimization algorithms was first introduced in Lucic and Teodorovic (2001). In later research, Teodorovic and Dell’Orco (2005) presented the initial variant of the BCO algorithm. In the context of this research, the variant proposed by Wong et al. (2008) is explored, which builds upon the BCO implementation of Teodorovic and Dell’Orco (2005).

BCO is a population-based metaheuristic algorithm in which each agent, representing a bee in this case, provides a complete solution. In the context of COMF-EVRP, the bees represent a population of solutions. Each bee starts its journey from the depot and sequentially visits the customers until no more visits are feasible. The bee then either returns to the depot or stops at a charging station to complete the current trip, depending on ownership considerations. This process is repeated until all customers have been served. If any constraint violations occur during the construction of a solution, it is discarded.

Algorithm 3 outlines the pseudo-code for the BCO implementation. It is important to note that BCO itself does not generate initial solutions; thus, a mechanism similar to the one employed in the COEVRP, inspired by GRASP, is utilized to create initial solutions. Subsequently, each bee generates a new solution based on the initial solution. If a newly generated solution is better than the current best solution, the bee performs a waggle dance, indicating its discovery of a superior solution. Once each bee has generated a solution, the VNS algorithm selects the overall best solution and aims to further optimize it. This iterative process is repeated for a specified number of BCO iterations (BCO_{it}), with the final outcome being the globally best solution achieved.

5.3.1 Transition Rules

To determine the possibility of moving from the current node to another one, the transition rules given in Eq.(5.11) are used. The calculations are based on two parameters that correspond to the randomness of the selection and the greediness, namely λ , and β .

Algorithm 3: Bee Colony Optimization algorithm

Data: Instance, BCO_{it} , λ, β
Result: Global best solution

```

1 Initialize  $\lambda, \beta$  ;
2 Generate random initial solution ;
3 for each iteration of  $BCO_{it}$  do
4   for each bee in Bees do
5     Observe the waggle dances of previous bees ;
6     Initialize new solution ;
7     while termination criteria not met do
8       Select a customer;
9       if the selected customer can be serviced then
10        | Add selected customer to the solution;
11        | Update termination criteria;
12       if the solution quality allows a waggle dance then
13        | Perform waggle dance;
14   Find the best bee of the iteration;
15   Apply VNS;
16   if the current solution is better than the global best then
17     | Re-apply VNS;
18     | Set current solution as the global best;
19 return Global best solution;

```

$$p_{ij} = \begin{cases} \frac{[\rho_{ij}][\frac{1}{d_{ij}}]^\beta}{\sum_{l \in L_i} [\rho_{il}][\frac{1}{d_{il}}]^\beta}, & \text{if } j \in L_i \\ 0, & \text{otherwise} \end{cases} \quad (5.11)$$

L_i represents all the unserved customers, and ρ_{ij} represents the value of $arc(i, j)$ given in Eq.(5.12):

$$\rho_{ij} = \begin{cases} \lambda, & \text{if } j \in F_i \\ \frac{1 - \lambda \cdot |L_i \cap F_i|}{|L_i| - |L_i \cap F_i|}, & \text{otherwise} \end{cases} \quad (5.12)$$

F_i is the best candidate to move to next, according to the information of the waggle dance, and $\lambda \in (0, 1)$.

5.3.2 Waggle Dance

The waggle dance plays a crucial role in the BCO method. It occurs after each bee completes its solution and serves to communicate the quality of the achieved solution to other bees, particularly

if it is deemed good. The evaluation of the solution's quality is based on a comparison with the personal best solution obtained by each bee.

The bees that observe the waggle dance must make a decision regarding whether they should adopt the solution provided by the waggle dancing bee or continue with their own solution. This decision is based on the objective function value, with a preference for solutions that yield lower objective function values, as the objective is to minimize it. Each alternative has a selection probability, denoted as SC , which is inversely proportional to the objective function value, i.e., $SC_{bee} = \frac{1}{\text{cost}(S_{bee})}$. The scoring rules, as presented in Wong et al. (2008), are provided in Table 5.2. The population score is calculated as the average of the selection probabilities of all bees in the colony, represented by $\bar{SC}_{colony} = \sum_{bee \in bees} SC_{bee} / \text{numBees}$.

Table 5.2: Score Rules

Score	$P_{followed}$
$SC_{bee} < 0.5\bar{SC}_{colony}$	0.60
$0.5\bar{SC}_{colony} \leq SC_{bee} < 0.65\bar{SC}_{colony}$	0.20
$0.65\bar{SC}_{colony} \leq SC_{bee} < 0.85\bar{SC}_{colony}$	0.02
$0.85\bar{SC}_{colony} \leq SC_{bee}$	0.00

5.4 The proposed Ant Colony Optimization algorithms

The foraging behavior of ants has served as a source of inspiration for the development of the Ant Colony Optimization (ACO) family of algorithms. In their natural environment, ants utilize pheromone trails as a means of communication to convey information about the quality of food sources. Rather than direct communication, ants leave pheromone trails on the ground, which can be detected by other ants. This form of communication is known as stigmergy. Ants are more inclined to follow paths with higher concentrations of pheromone, while the pheromone on less favorable paths tends to evaporate more quickly. As a result, the ant colony gradually converges on the best path, leading to the formation of the lines of ants observed in nature.

Dorigo et al. (1996) introduced the concept of using ant colony behavior for optimization. Since this original publication, numerous variations and adaptations of ACO algorithms have been proposed. The ACS and the MMAS, which are the focus of this study, were introduced in Dorigo and Gambardella (1997), and Stützle and Hoos (2000), respectively.

ACS incorporates both local and global pheromone updates during the solution construction phase, aiming to encourage exploration of the solution space. On the other hand, MMAS maintains the pheromone levels within a specific range of values to foster a diverse population of solutions throughout the solution process, and employs only a global update mechanism.

In the context of the current application, similar to the BCO approach where each bee represents a solution, each ant represents a solution. Each ant constructs a complete solution by starting from the depot, visiting customers, returning when it can no longer serve any more customers, and repeating this process until all customers have been served. For both ACS and MMAS, a solution is accepted only if it is feasible. More detailed explanations of each method are provided in the subsequent subsections.

5.4.1 Ant Colony System

Parameter q_0 is used by ACS to control the greediness, which determines the next node to be added to the route, as presented in Eq. (5.13). Greater q_0 values improve the likelihood that the ant will pick the most favorable route. The proportional importance of the heuristic information η is controlled by the parameter β . L_i represents the unvisited customers, and τ_{ij} represents the trail between nodes i , and j .

$$j = \begin{cases} \arg \max_{l \in L_i} [\tau_{il}] [\eta_{il}]^\beta, & \text{if } q \leq q_0 \\ Z, & \text{otherwise} \end{cases} \quad (5.13)$$

q is a generated random number between zero and one, and Z is the customer with highest probability, according to (5.14).

$$p_{ij} = \begin{cases} \frac{[\tau_{ij}] [\eta_{ij}]^\beta}{\sum_{l \in L_i} [\tau_{il}] [\eta_{il}]^\beta}, & \text{if } j \in L_i \\ 0, & \text{otherwise} \end{cases} \quad (5.14)$$

The pheromone trails in the ACS implementation are updated in two points within the solution process. As a new solution is constructed, pheromone gets removed from the trails, making the other ants less likely to follow the same path. This local update mechanism offers additional exploratory properties to the algorithm. To calculate the pheromone levels, Eq. (5.15) is used:

$$\tau_{ij}^{new} = (1 - \rho) \tau_{ij}^{old} + \rho \tau_0 \quad (5.15)$$

$$\tau_0 = 1 / (n \times C^{IS}) \quad (5.16)$$

τ_0 is the initial pheromone, C^{IS} the initial solution cost, and n is the number of customers.

When an iteration of the ACS is over, it is time to perform the global update, the second place an update can be made within the ACS algorithm. The ant with best overall solution updates the pheromone levels in this case, as described in Eq. (5.17).

The second pheromone update mechanism utilized by the ACS is the global update. In each iteration, the BSF ant updates the pheromone levels by laying pheromone inversely proportional to cost, as seen in Eq. (5.18). Algorithm 4, presents the described solution generation method.

$$\tau_{ij}^{new} = (1 - \rho) \tau_{ij}^{old} + \Delta \tau_{ij}^{BSF} \quad (5.17)$$

$$\Delta \tau_{ij}^{BSF} = 1 / C^{BSF} \quad (5.18)$$

C^{BSF} is the cost of the best found solution, and ρ is the pheromone evaporation rate.

5.4.2 Max-Min Ant System

The MMAS shares one of its parameters, β , with ACS. β controls once again the relative importance of the heuristic information. The other parameter, Q_0 , helps set the lower limit for quantity of pheromone on the trails. In this case, the chance of an ant selecting to traverse $arc(i, j)$ is calculated by eq. (5.19).

Algorithm 4: ACS+LS

Data: Instance, $ACSiters$, $NumAnts$, q_0 , ρ , β , $LSiters$
Result: S^{BSF}

```

1 Initialize  $\tau, \eta$  ;
2 for  $iter \leftarrow 1$  to  $ACSiters$  do
3   for  $ant \leftarrow 1$  to  $NumAnts$  do
4      $S_{ant} \leftarrow \text{ConstructACSsolution}(\tau, \eta, q_0, \beta)$ ;
5     LocalPheromoneUpdate( $\tau, \rho, S[ant]$ ) ;
6     if  $cost(S_{ant}) < cost(S^{IB})$  then
7        $S^{IB} \leftarrow S_{ant}$ ;
8   LocalSearch( $S^{IB}, LSiters$ );
9   if  $cost(S^{IB}) < cost(S^{BSF})$  then
10     $S^{BSF} \leftarrow S^{IB}$ ;
11  GlobalPheromoneUpdate( $\tau, \rho, S^{BSF}$ ) ;
12 return  $S^{BSF}$ ;

```

$$p_{ij} = \begin{cases} \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in L_i} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, & \text{if } j \in L_i \\ 0, & \text{otherwise} \end{cases} \quad (5.19)$$

α represents the importance of pheromone.

The pheromone levels are constrained in the MMAS implementation and the values fall between $[\tau_{min}, \tau_{max}]$. This method keeps less appealing arcs relevant throughout the solving process. At the start of the solution, the amount of pheromone is maximized over all arcs to allow the same chance of visiting all nodes. To determine the range of allowed pheromone amounts, Equations (5.21) and (5.20) are employed. Algorithm 5, presents an outline of the proposed method.

$$\tau_{max} = 1/\rho C^{IS} \quad (5.20)$$

$$\tau_{min} = \tau_{max}/Q_0 \quad (5.21)$$

Equation (5.22) presents the pheromone update rule that is used by the best overall ant at the end of each iteration.

$$\tau_{ij}^{new} = (1 - \rho)\tau_{ij}^{old} + \Delta\tau_{ij}^{BSF} \quad (5.22)$$

$$\Delta\tau_{ij}^{BSF} = 1/C^{BSF} \quad (5.23)$$

ρ represents the pheromone evaporation rate, as in ACS.

Algorithm 5: MMAS+LS

Data: Instance, $MMASiters$, $NumAnts$, Q , ρ , α , β , $LSiters$, $NBS = \{NB_1, NB_2, \dots\}$
Result: S^{BSF}

```

1 Initialize  $\tau, \eta, \tau_{max}, \tau_{min}$  ;
2 for  $iter \leftarrow 1$  to  $MMASiters$  do
3   for  $ant \leftarrow 1$  to  $NumAnts$  do
4      $S_{ant} \leftarrow \text{ConstructMMASSolution}(\tau, \eta, \alpha, \beta)$ ;
5     if  $cost(S_{ant}) < cost(S^{IB})$  then
6        $S^{IB} \leftarrow S_{ant}$  ;
7   LocalSearch( $S^{IB}$ ,  $LSiters$ );
8   if  $cost(S^{IB}) < cost(S^{BSF})$  then
9      $S^{BSF} \leftarrow S^{IB}$  ;
10  EvaporatePheromone( $\tau_{min}, \rho$ ) ;
11  ApplyPheromone( $\tau_{max}, S^{BSF}$ );
12 return  $S^{BSF}$ ;
```

5.5 Local search

To enhance the performance of BCO, ACS, and MMAS algorithms and obtain improved solutions, the VNS method was employed in a manner similar to its usage in COEVRP. VNS consists of three main phases: shaking, LS, and move. In the shaking phase, a solution is randomly selected, and LS operators are applied to generate potential moves. Finally, a move is selected for further exploration.

In the COEVRP variant, three LS operators were employed: *1-1 Inter-route Swap*, *1-1 Intra-route Swap*, and *1-0 Relocate*. In the COMF-EVRP, an additional operator, the *k-Opt* operator, was introduced. A brief explanation of each operator is provided below:

- *k-Opt*: This operator randomly selects two different customers within the same route. The visiting order starting from one of the selected customers and up to the other is reversed. This requires a feasibility calculation as the distribution of the weight over each arc changes, affecting the energy consumption.
- *1-1 Inter-route Swap*: two randomly selected customers from two different vehicles exchange their places.
- *1-1 Intra-route Swap*: two randomly selected customers from the same vehicle exchange their places.
- *1-0 Relocate*: a randomly selected customer is removed from his original vehicle and placed in a different one.

5.6 Computational Experiments

To ensure the effectiveness of the proposed BCO algorithm, several experiments were conducted, comparing its results to those obtained using the Gurobi Optimizer (version 9.1.2). The BCO algorithm was implemented in C++ (C++20 standard) and compiled using Microsoft Visual Studio 2019 (community edition). On the other hand, the Gurobi Optimizer model was developed using

Python (version 3.9.1). The experiments were performed on a computer with an Intel Core i3-8130u processor running at 2.20GHz and equipped with 12 GB of DDR4 RAM operating at 2400MHz.

The problem instances for COMF-EVRP were identical to those used in COEVRP, except for the maximum energy capacity of each vehicle in the larger instances, which was set to 15000 energy units. Additionally, the number of owned vehicles was specified. In this case, a total of ten EVs were available, with three vehicles designated as owned. This configuration was selected as most of the smaller instances could be effectively solved using three vehicles.

The computational experiments for COMF-EVRP are presented in the following subsection, along with insightful observations. It should be noted that while the reported number of vehicles represents the total number of vehicles utilized, it is essential to emphasize that for the calculation of the objective function, only the number of rented vehicles is considered.

Table 5.3 provides a comprehensive overview of all the relevant parameters employed by the BCO, ACS, and MMAS algorithms.

Table 5.3: Parameter description and settings		
Parameter	Description	Values Tested
BCO		
<i>Bees</i>	Total population of bees	10
λ	Moderates the greediness in the construction phase	$\{0.1, \dots, 0.9\}$
β	Moderates the effect of the heuristic data	$\{1, \dots, 9\}$
ACS		
<i>Ants</i>	Total population of ants	10
q_0	Moderates the greediness in the construction phase	$\{0.1, \dots, 0.9\}$
β	Moderates the effect of the heuristic data	$\{1, \dots, 9\}$
ρ	Pheromone evaporation rate	0.01
MMAS		
<i>Ants</i>	Total population of ants	10
Q_0	Moderates the greediness in the construction phase	$\{300, 600, 900\}$
β	Moderates the effect of the heuristic data	$\{1, \dots, 9\}$
ρ	Pheromone evaporation rate	0.02
α	Moderates the pheromone significance	1
Other		
VNS_{it}	Total VNS iterations	25000
K_1	Number of owned vehicles	3

5.6.1 Small Instances

This subsection, presents the results of the smaller benchmark instances. These instances were solved with Gurobi, as well as with the meta-heuristics.

The results of Gurobi for five and ten-customer instances are the same to these of the proposed meta-heuristic algorithms, and are shown in Tables 5.4 and 5.5. The first column in each table displays the name of the instance, while the following three columns reveal the BSF, which consists of the objective function, and next its two components, the number of EVs and the total energy consumption.

Table 5.6 follows the same format as the previous two tables, with the addition of four columns to display the gap between Gurobi and the proposed algorithms to the BSF.

Based on the analysis performed, the following can be deduced:

- The number of EVs used by all solution methods was consistent across all instances.

Table 5.4: 5-customer instances

Instance	BSF		
	Objective	Vehicles	Energy
c101c5	1.57	3	3662.75
c103c5	1.16	3	2698.09
c206c5	1.16	3	2704.75
c208c5	2.05	3	4779.94
r104c5	1.17	3	2134.89
r105c5	0.63	3	1153.61
r202c5	0.86	3	1568.07
r203c5	1.56	3	2828.08
rc105c5	2.50	3	5832.05
rc108c5	2.39	3	5579.50
rc204c5	2.39	3	5584.75
rc208c5	1.00	3	2330.96
Average	1.54	3	3404.79

Table 5.5: 10-customer instances

Instance	BSF		
	Objective	Vehicles	Energy
c101c10	2.12	5	7754.12
c104c10	2.38	4	6411.92
c202c10	3.04	4	8215.19
c205c10	1.26	4	6004.50
r102c10	2.28	4	4864.67
r103c10	3.01	3	3469.88
r201c10	2.77	4	4342.45
r203c10	1.47	3	4170.31
rc102c10	1.33	4	7741.89
rc108c10	0.96	4	5371.85
rc201c10	1.08	3	6027.02
rc205c10	2.79	4	6493.61
Average	2.04	3.83	5905.62

Table 5.6: 15-customer instances

Instance	BSF			Gap(BSF)			
	Objective	Vehicles	Energy	Gurobi	BCO	ACS	MMAS
c103c15	6.24	5	9886.41	0.00%	0.00%	0.00%	0.00%
c106c15	3.34	4	5465.16	0.00%	0.00%	0.00%	0.00%
c202c15	5.70	5	8638.77	0.30%	0.00%	0.00%	0.00%
c208c15	5.61	5	8414.41	0.00%	0.00%	0.00%	0.00%
r102c15	4.30	4	5991.06	0.00%	0.00%	0.00%	0.00%
r105c15	5.20	5	5826.06	0.00%	0.00%	0.00%	0.00%
r202c15	7.50	6	8174.28	0.34%	0.00%	0.00%	0.00%
r209c15	7.06	6	7379.29	0.00%	0.00%	0.00%	0.00%
rc103c15	5.27	5	7630.15	0.00%	0.00%	0.00%	0.00%
rc108c15	8.09	6	11867.36	0.00%	0.00%	0.00%	0.00%
rc202c15	6.05	5	9454.51	0.00%	0.00%	0.00%	0.00%
rc204c15	8.07	6	11839.63	0.00%	0.00%	0.00%	0.00%
Average	6.04	5.17	8380.59	0.05%	0.00%	0.00%	0.00%

- When the results differed from the BSF, the number of EVs was the same and only their routing was different.
- Gurobi solved all of the five-customer instances and three of the ten-customer instances to optimality.
- Two of the solutions by Gurobi on the fifteen-customer instances were worse than the BSF.
- In two of the fifteen-customer instances, Gurobi failed to reach the BSF.
- BCO, ACS, and MMAS, were able to solve all small instances, and matched the results of Gurobi in optimally solved solutions.

The Gurobi Optimizer attained optimal solutions for all instances with five customers and three instances with ten customers. However, for instances in which the optimization process exceeded the time limit of 900 seconds, Gurobi could not guarantee optimality. Notably, Gurobi exhibited an average deviation of 0.05% from the BSF in the larger fifteen-customer instances.

One significant factor influencing the execution times is the utilization of computational resources. Gurobi takes advantage of all four CPU threads, whereas the C++ implementations of BCO, ACS, and MMAS are single-threaded applications. Consequently, the execution times between Gurobi and the meta-heuristics are not directly comparable.

The three meta-heuristics efficiently solved each instance and generated solutions that were comparable to or even superior to those obtained using Gurobi. As anticipated, Gurobi exhibited fast solving times for the smaller instances with five customers. However, as the instance size increased, the execution time of Gurobi also escalated, necessitating the application of meta-heuristics for solving larger instances. Table 5.7 presents the average execution times of Gurobi and BCO for producing a single solution. The results for ACS and MMAS are excluded from the table, as their execution times were consistently below ten milliseconds for all instances. The longer computational times of BCO are attributed to the initial solution generation stage.

Table 5.7: Execution time for small instances (in seconds).

5-customers			10-customers			15-customers		
Instance	Gurobi	BCO	Instance	Gurobi	BCO	Instance	Gurobi	BCO
c101c5	1.1	1.1	c101c10	900.0	1.1	c103c15	900.0	1.8
c103c5	1.0	1.8	c104c10	900.0	1.3	c106c15	900.0	1.8
c206c5	1.1	1.3	c202c10	900.0	1.4	c202c15	900.0	1.6
c208c5	1.2	0.8	c205c10	900.0	1.4	c208c15	900.0	1.5
r104c5	1.7	1.2	r102c10	900.0	1.2	r102c15	900.0	2.1
r105c5	2.9	1.2	r103c10	64.4	1.6	r105c15	900.0	1.7
r202c5	2.8	1.6	r201c10	900.0	1.3	r202c15	900.0	1.4
r203c5	1.2	0.9	r203c10	72.3	1.5	r209c15	900.0	1.2
rc105c5	0.6	0.8	rc102c10	900.0	1.2	rc103c15	900.0	1.6
rc108c5	0.5	0.6	rc108c10	900.0	1.3	rc108c15	900.0	1.6
rc204c5	1.7	0.9	rc201c10	20.1	1.5	rc202c15	900.0	1.8
rc208c5	1.2	1.4	rc205c10	900.0	1.4	rc204c15	900.0	1.4
Average	1.4	1.1	Average	688	1.3	Average	900.0	1.6

5.6.2 Large Instances

Table 5.8 provides a summary of the optimal results obtained for each instance with one hundred customers. The table includes the instance name, the objective function value, and the number of EVs associated with the best solution found. The following six columns present the gaps between the objective function values and the number of EVs used for BCO, ACS, and MMAS, respectively. These gap values are calculated by comparing the results of each method to the corresponding best found value.

5.6.3 Result Analysis

Further analysis was carried out on the larger instances to examine the behavior of the parameters used by each meta-heuristic.

The instances in this study can be categorized into three types based on the distribution of customers: clustered ('c'), random ('r'), and a combination of both ('rc'). There are a total of 17 instances of type 'c', 23 instances of type 'r', and 16 instances of type 'rc'.

Among the three meta-heuristics, ACS achieved the highest number of BSFs with 37 instances, followed by MMAS with 10 instances, and BCO with 9 instances. ACS demonstrated superiority across all customer distribution types, providing the most BSFs. The average gap between ACS solutions and the BSF was 0.17%, while MMAS had an average gap of 0.99%, and BCO had the largest average gap of 2.05%. In all cases, ACS used the same number of vehicles as the BSF, while MMAS utilized an extra vehicle in three instances, and BCO required an additional vehicle in 14 instances. It is noteworthy that all algorithms employed the same number of vehicles as the BSF in instances with a combination of clustered and random customer distribution.

Table 5.9 presents the average results per instance type and per algorithm. It can be observed that instances with customers clustered together required a higher average number of vehicles, whereas instances with randomly distributed customers necessitated fewer vehicles on average. This

Table 5.8: Results for 100-customer instances

	BSF		BCO		ACS		MMAS	
Instance	Objective	Veh.	$Gap_{obj.}$	$Gap_{veh.}$	$Gap_{obj.}$	$Gap_{veh.}$	$Gap_{obj.}$	$Gap_{veh.}$
c101	11.53	10	0.00%	0	0.02%	0	0.22%	0
c102	11.55	10	0.25%	0	0.00%	0	0.12%	0
c103	11.54	10	0.54%	0	0.00%	0	0.07%	0
c104	11.53	10	0.37%	0	0.00%	0	0.08%	0
c105	11.53	10	0.00%	0	0.05%	0	0.21%	0
c106	11.54	10	0.13%	0	0.00%	0	0.06%	0
c107	11.54	10	0.11%	0	0.00%	0	0.01%	0
c108	11.54	10	0.23%	0	0.00%	0	0.14%	0
c109	11.53	10	0.35%	0	0.00%	0	0.28%	0
c201	9.62	7	6.99%	+1	0.00%	0	1.86%	0
c202	9.72	7	2.40%	0	0.00%	0	3.07%	0
c203	9.81	7	5.16%	+1	0.00%	0	0.46%	0
c204	9.67	7	6.66%	+1	0.00%	0	6.09%	+1
c205	9.71	7	5.79%	+1	2.44%	0	0.00%	0
c206	9.68	7	6.24%	+1	0.63%	0	0.00%	0
c207	9.93	7	3.74%	+1	0.01%	0	0.00%	0
c208	9.79	7	3.78%	0	1.97%	0	0.00%	0
r101	8.90	8	0.23%	0	0.00%	0	0.88%	0
r102	8.86	8	0.12%	0	0.00%	0	0.88%	0
r103	8.87	8	0.15%	0	0.00%	0	0.40%	0
r104	8.85	8	0.00%	0	0.60%	0	0.65%	0
r105	8.89	8	0.30%	0	0.00%	0	0.49%	0
r106	8.90	8	0.36%	0	0.00%	0	0.39%	0
r107	8.90	8	0.00%	0	0.30%	0	0.05%	0
r108	8.85	8	1.38%	0	0.00%	0	1.20%	0
r109	8.83	8	0.65%	0	0.00%	0	0.72%	0
r110	8.90	8	0.68%	0	0.01%	0	0.00%	0
r111	8.91	8	0.05%	0	0.27%	0	0.00%	0
r112	8.89	8	0.44%	0	0.11%	0	0.00%	0
r201	7.61	6	7.73%	+1	0.00%	0	3.48%	0
r202	7.60	6	0.00%	0	1.20%	0	7.27%	+1
r203	7.75	6	1.95%	0	0.00%	0	0.30%	0
r204	7.69	6	0.00%	0	0.08%	0	0.10%	0
r205	7.67	6	7.68%	+1	0.00%	0	5.55%	+1
r206	7.74	6	5.88%	+1	0.00%	0	1.14%	0
r207	7.70	6	6.96%	+1	0.00%	0	2.12%	0
r208	7.71	6	6.88%	+1	0.00%	0	1.54%	0
r209	7.72	6	5.22%	+1	0.00%	0	2.28%	0
r210	7.75	6	4.99%	+1	0.00%	0	1.15%	0
r211	7.64	6	7.78%	+1	0.00%	0	2.06%	0
rc101	11.57	9	0.51%	0	0.00%	0	1.12%	0
rc102	11.59	9	2.37%	0	0.00%	0	0.03%	0
rc103	11.59	9	1.32%	0	0.00%	0	0.58%	0
rc104	11.53	9	2.10%	0	0.03%	0	0.00%	0
rc105	11.53	9	0.00%	0	0.60%	0	1.09%	0
rc106	11.56	9	1.02%	0	0.11%	0	0.00%	0
rc107	11.55	9	0.00%	0	0.24%	0	1.17%	0
rc108	11.61	9	0.50%	0	0.00%	0	0.52%	0
rc201	10.45	8	0.05%	0	0.27%	0	0.00%	0
rc202	10.41	8	0.82%	0	0.00%	0	1.08%	0
rc203	10.38	8	1.36%	0	0.00%	0	0.38%	0
rc204	10.42	8	0.00%	0	0.45%	0	0.72%	0
rc205	10.45	8	0.05%	0	0.00%	0	0.59%	0
rc206	10.45	8	0.23%	0	0.00%	0	1.13%	0
rc207	10.41	8	0.68%	0	0.00%	0	0.58%	0
rc208	10.41	8	1.79%	0	0.00%	0	1.32%	0
Average	9.80	7.93	2.05%	+0.25	0.17%	0.00%	0.99%	+0.05

discrepancy may be attributed to the varying number of customer clusters in different instances, compared to instances with randomly placed customers. Furthermore, regardless of the customer distribution type, BCO consistently required the highest number of vehicles, while ACS required the fewest.

Table 5.9: Average results per instance type

	BCO		ACS		MMAS		
Distribution	Obj_{avg}	Veh_{avg}	Obj_{avg}	Veh_{avg}	Obj_{avg}	Veh_{avg}	Avg.
c	10.94	9.13	10.72	8.80	10.77	8.87	8.93
r	8.51	7.43	8.32	7.13	8.42	7.22	7.26
rc	11.08	8.38	11.01	8.25	11.07	8.25	8.29
Average	10.18	8.31	10.02	8.06	10.08	8.11	N/A

Figures 5.1, 5.2, and 5.3 depict the average objective function value in relation to the parameter settings for instances solved using the BCO, ACS, and MMAS meta-heuristics, respectively.

Figure 5.1 illustrates the impact of the parameters λ and β utilized by BCO. Here, λ represents the level of randomness in the node selection process, while β indicates the degree of greediness. It is evident that lower randomness coupled with higher greediness yielded better solutions. For values of $\beta \geq 6$ the change is very limited, with randomness having seemingly no effect on the results.

The parameter analysis for the ACS algorithm is presented in Figure 5.2, where the parameter q regulates the balance between exploration and exploitation, and β determines the significance of the heuristic information. ACS exhibited less sensitivity to parameter settings compared to BCO. It is worth noting that for values of $\beta \geq 0$, any changes in the results become negligible; however, the best results were achieved with $q_0 = 0.8$. Interestingly, for lower values of β , $q_0 = 0.9$ is the better option.

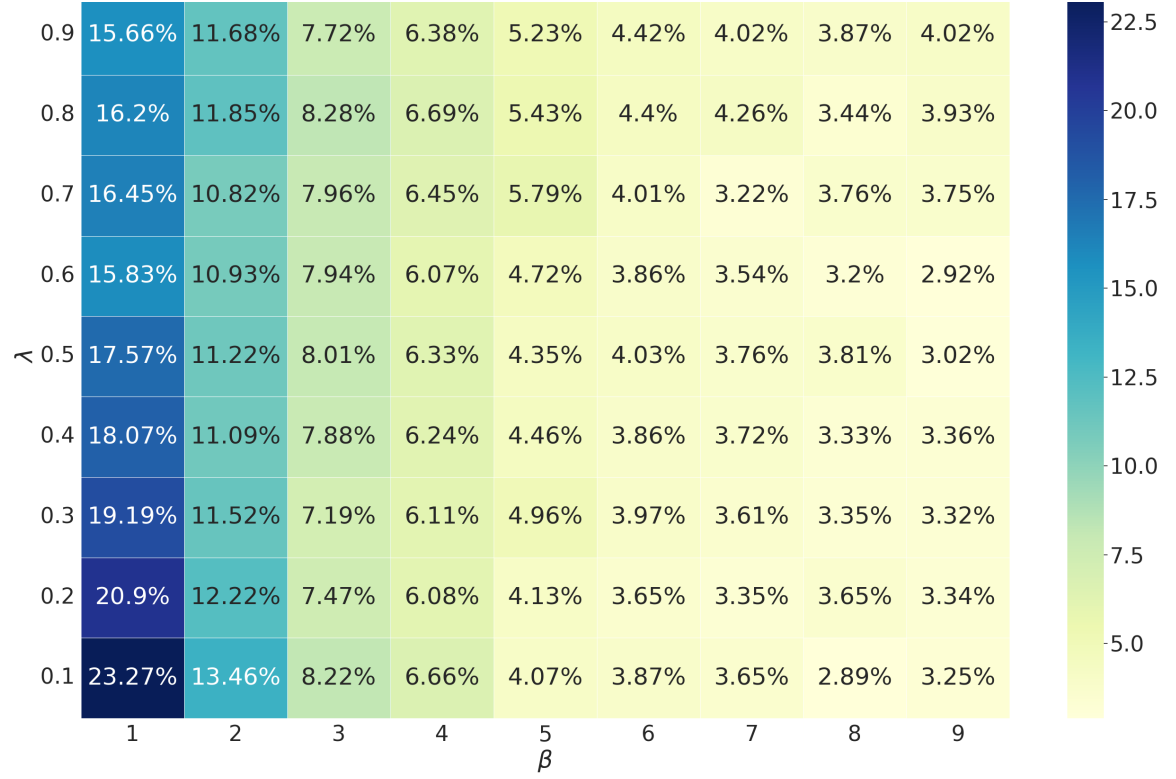
Lastly, Figure 5.3 explores the parameter settings of MMAS, with Q determining the lower bound of pheromone levels to prevent rapid convergence. In this case, the results were primarily affected by the value of β , which similar to ACS controls the importance of the heuristic data. For $\beta \geq 5$, the percentage change was insignificant regardless of Q .

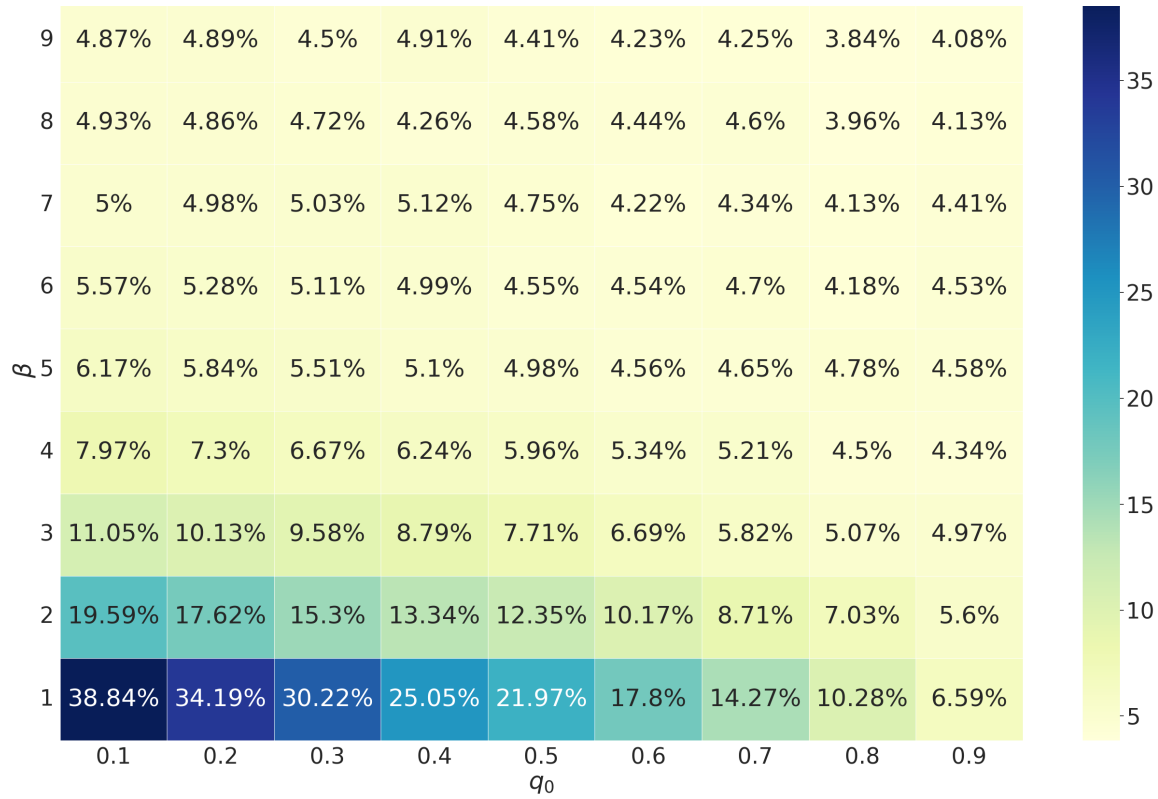
In general, ACS achieved the most successful outcomes, generating 37 out of the 56 BSFs, and exhibiting less sensitivity to parameter settings. ACS and MMAS possessed an advantage over BCO as they are capable of generating solutions from scratch, whereas BCO relies on an initial solution provided by the GRASP initial solution mechanism. This distinction may account for BCO having a higher average number of vehicles compared to ACS and MMAS. ACS outperformed MMAS due to its intermediate local pheromone update stage, which provides faster feedback compared to MMAS where evaporation occurs only after the completion of a full solution.

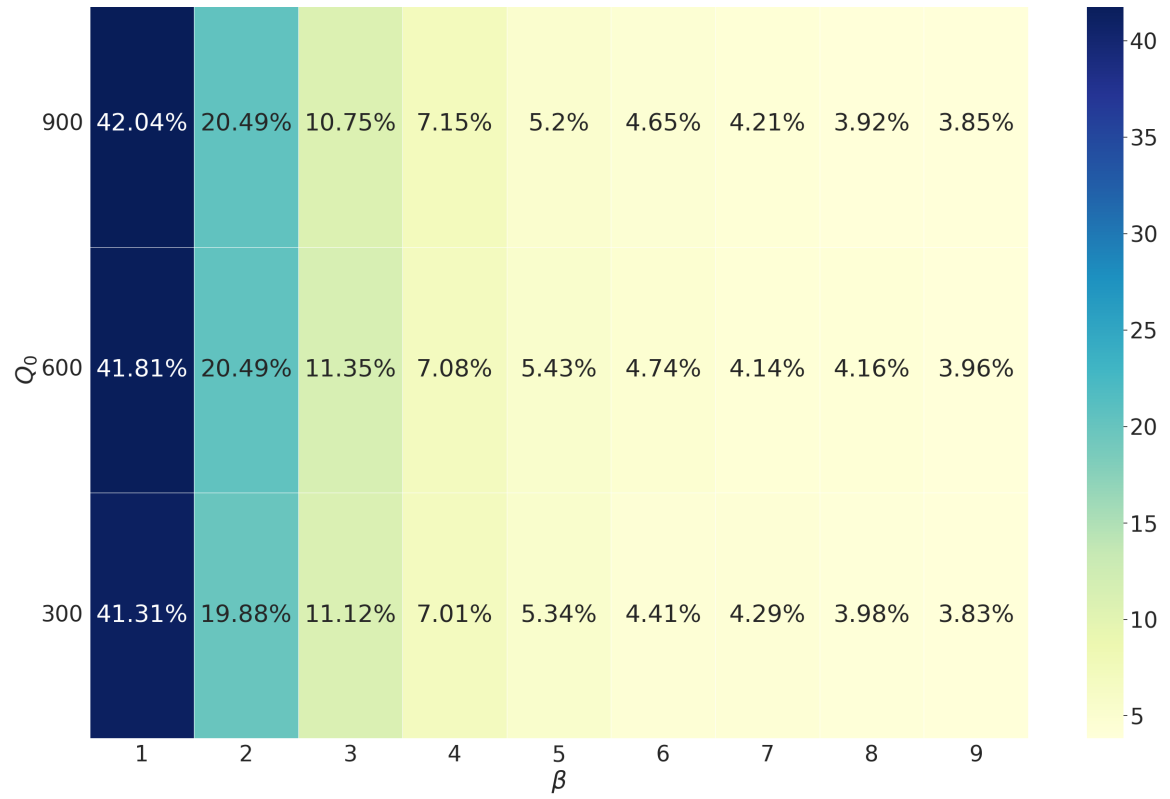
5.7 Conclusions

Electric Vehicles have experienced a significant rise in popularity and market share in recent years. However, certain drawbacks, such as limited range, slow recharge speed, and high initial costs, continue to hinder widespread adoption. These challenges also impact the logistics sector.

One of the major obstacles faced by EV drivers is the availability and reliability of CSs. CSs may be out of order or occupied, making it unrealistic to rely on their availability in the middle of logistics operations. To address this issue, a new operational concept for logistics companies is

Figure 5.1: Mean of average BCO solutions $GAP_{avg}(Objective_{avg})\%$ to BSF

Figure 5.2: Mean of average ACS solutions $GAP_{avg}(Objective_{avg})\%$ to BSF

Figure 5.3: Mean of average MMAS solutions $GAP_{avg}(Objective_{avg})\%$ to BSF

proposed in this study. Specifically, it considers a logistics company that owns a small fleet of EVs for daily operations. When the owned fleet is unable to meet the demand, additional EVs are rented, and these rented EVs end their trips at CSs. The owned EVs may also visit CSs after completing their trips to recharge.

This scenario is modeled as the Close-Open Mixed-Fleet Electric Vehicle Routing Problem (COMF-EVRP). The mathematical formulation of COMF-EVRP incorporates all the vehicle constraints and the proposed charging strategy. It combines the Close-Open Mixed-Fleet variant with EVs, along with a novel charging approach that leads to more reliable delivery plans.

To solve small instances of COMF-EVRP, both the commercially available software Gurobi Optimizer and swarm intelligence algorithms were employed. However, due to high CPU times, Gurobi was not suitable for larger instances. For hundred-customer COMF-EVRP instances, Bee Colony Optimization, Ant Colony System, and Max-Min Ant System meta-heuristics were developed. A VNS algorithm was subsequently applied, incorporating four LS operators: *k-Opt*, *1-1 Intra-route Swap*, *1-1 Inter-route Swap*, and *1-0 Relocate*. Instances from the literature were adapted for COMF-EVRP with minimal modifications, ensuring easy replication.

Results for five and ten-customer instances were identical between Gurobi and the meta-heuristics, but the meta-heuristics achieved them in significantly less CPU time despite utilizing a single CPU thread compared to Gurobi's multi-threaded implementation. All five-customer instances were solved optimally, while only three out of twelve ten-customer instances reached optimality. For fifteen-customer instances, the meta-heuristics outperformed Gurobi in two out of twelve instances, as Gurobi reached the maximum time limit for all fifteen-customer instances.

The meta-heuristics exclusively solved hundred-customer instances due to their superior performance and faster computation compared to Gurobi. Average results were presented, followed by an extensive parameter analysis. Among the three methods, ACS proved to be the most effective, providing 37 BSFs, while MMAS provided 10 and BCO provided 9. MMAS and BCO collectively accounted for one-third of the BSFs. A parameter sensitivity analysis was conducted for all three methods.

In future research, attention could be directed towards incorporating additional factors into the problem model to achieve more realistic representations of routing scenarios. This includes considering weather conditions (given their impact on battery efficiency), variable speed profiles that accommodate kinetic energy recovery systems, and other factors. Moreover, the procurement and presentation of realistic instances would be a valuable contribution. Exploring alternative objective functions to achieve different goals and testing different meta-heuristics or LS algorithms are also areas worth investigating.

Chapter 6

The Electric Vehicle Routing Problem with Drones

6.1 Introduction

The adoption of EVs in logistics operations has introduced new and complex challenges in delivery planning. These challenges arise from the combination of two significant factors: the limited energy capacity and the time-consuming nature of their charging process. These limitations make it imperative to explore innovative approaches to overcome these setbacks and ensure efficient and sustainable delivery operations.

In recent years, researchers and practitioners have turned their attention to the integration of drones, also known as UAVs, as a promising direction for addressing many logistics challenges, ranging from disaster response, to farming, surveillance, and deliveries. Despite the above, the combination of EVs and drones for logistics operations has not been previously proposed, and it holds great potential in revolutionizing the way deliveries are conducted. The integration of electric vans and drones is rooted in the shared characteristics of these vehicles. Both electric vans and drones face similar constraints, such as limited energy capacity and a strong dependence on payload for energy consumption. By exploiting the complementary strengths of these vehicles, it becomes possible to optimize delivery operations and achieve the best possible outcomes. They also share some advantages such as zero local emissions and great potential of technology integration.

To formalize the proposed delivery operation scheme, the concept of the Electric Vehicle Routing Problem with Drones (EVRPD) is introduced. In this scheme, electric vans are assigned the crucial task of transporting drones to strategically chosen locations within the delivery area. These locations, called satellites, are carefully designated to ensure that the electric vans can park without obstructing traffic flow while awaiting the return of the drones. Once launched, the drones efficiently cover shorter distances to serve customers, effectively reducing the overall travel distance and energy consumption of the electric vans. Moreover, the utilization of drones is not limited solely by their State of Charge (SoC). They can perform multiple deliveries per flight, thereby enhancing efficiency and optimizing resource utilization. This multifaceted approach involving electric vans and drones presents a promising solution to overcome the limitations of electric vehicles in logistics operations.

To tackle the EVRPD, four solution approaches are devised, each leveraging different optimiza-

tion techniques. The first approach utilizes the Bee Colony Optimization method, which has shown promise in addressing complex routing problems in various domains. Furthermore, the Ant Colony Optimization method is employed, incorporating two novel hybrid algorithms in addition to the existing ones outlined in Section 5. Additionally, two variants of the GRASP method are integrated into the solution approaches. Lastly, a Simulated Annealing approach, known for its effectiveness in finding near-optimal solutions, is employed with three distinct cooling rates.

To further enhance the performance of these solution approaches, a Variable Neighborhood Descent framework is applied. This framework introduces the concept of exploring different neighborhoods of the solution space to refine and optimize the obtained results. By combining these diverse techniques, robust and efficient algorithms are developed, capable of solving the EVRPD and effectively optimizing the proposed integration of both electric vans and drones in delivery planning.

The proposed integration of electric vans and drones in the field of logistics operations opens up a new avenue for research and innovation. It offers the potential to revolutionize the way deliveries are conducted, addressing the challenges associated with energy limitations and charging times of electric vans. As this field continues to evolve, further research and advancements in optimization algorithms and practical implementation will play a pivotal role in shaping the future of sustainable and efficient delivery operations.

The following subsections offer a closer look to the proposed problem, the solution approaches, and the conclusion of the research on EVRPD.

6.1.1 Payload

One of the primary elements that require attention when drones are integrated into delivery operations pertains to their maximum carrying capacity, which encompasses both the quantity and weight of items. Table 6.1 illustrates the three weight classes utilized in this research, illustrating the respective weight ranges associated with each class, as well as the weight utilized for energy consumption calculations. All values are expressed in standardized units of weight. It is noteworthy that the calculations employ the maximum weight value within each class, thereby accommodating a potential buffer of energy since not all packages will attain the maximum weight allowance within their respective classes.

Table 6.1: Weight classes of packages

Class	Weight	Accounted Weight
C1	$(0.0 \rightarrow 1.0]$	1.0
C2	$(1.0 \rightarrow 2.0]$	2.0
C3	$(2.0 \rightarrow 3.0]$	3.0

In addition to the classification of items based on weight classes, an important aspect to consider is the maximum number of items that can be simultaneously accommodated by a drone. In the present study, drones are capable of accommodating a maximum of three containers, with their collective weight limited to a maximum of four units of weight. Table 6.2 provides an overview of all conceivable loading scenarios for a drone, wherein each container corresponds to one customer.

Table 6.2: Drone payload combinations

Case	Containers			Quantity & Weight	
1	C1	-	-	1	1.0
2	C1	C1	-	2	2.0
3	C1	C1	C1	3	3.0
4	C1	C2	-	2	3.0
5	C1	C1	C2	3	4.0
6	C2	-	-	1	2.0
7	C2	C2	-	2	4.0
8	C3	-	-	1	3.0
9	C3	C1	-	2	4.0

6.1.2 Energy

Energy consumption constitutes a crucial aspect for both vehicle types under consideration. The rate at which energy is consumed can be influenced by a multitude of external and internal factors, although the weight being carried is the most significant, particularly for drones, given their limited battery capacity. Thus, ensuring an optimized routing strategy for both vehicle types becomes imperative in order to minimize the combined energy expenditure.

In the context of the EVRPD, the determination of energy expenditure is predicated on the energy minimizing VRP, which was originally introduced by [Kara et al. \(2007\)](#). This approach, while uncomplicated, exhibits a high degree of realism, as it solely considers the mechanical work entailed in transporting the objects for delivery, as shown in equations 6.1.

$$Work = Force \times Distance \quad (6.1)$$

As expected, an increase in the weight of an item or items necessitates a greater amount of work to transport them across a given distance. Likewise, the longer the distance, the higher the amount of work required to move an item of certain weight. Based on equation 6.1, the energy consumption formula, as depicted in equation 6.2, incorporates a fundamental distinction in the form of an additional unit of weight. This inclusion ensures that energy consumption remains nonzero when an empty vehicle returns to its origin.

$$Energy = Distance \times (1 + weight) \quad (6.2)$$

Subsequently, the computation of the overall energy consumption summarizes the energy consumption values of each individual electric van and drone across all their respective trips. This constitutes the objective function, which serves as the target to be minimized. One important characteristic of this formulation is that any alteration in the direction of a trip leads to a corresponding adjustment in energy consumption. Consequently, certain segments of the route may only be feasible when traversed in a specific direction, thus exhibiting directional dependency.

6.1.3 Assumptions

The formulation of the EVRPD necessitates the incorporation of certain assumptions, given the inherent limitations in representing all parameters in a realistic manner. The following assumptions have been taken into consideration:

- Only drones may be used for deliveries.
- The demand of each customer is assumed to be a single item.
- Satellites may not be revisited by the same EV.
- EVs launch the drones and remain stationary until they return.
- The drones may be re-deployed if their energy capacity allows it.
- Each EV may simultaneously deploy many drones.
- No obstructions are considered in the drone routes.
- The energy consumption for take-off is the same as for gliding.
- The available vehicles (EVs, and drones) are sufficient.
- The time to deploy and collect the drones is negligible.

The assumption regarding exclusive drone deliveries offers substantial energy savings for the electric vans involved. Although the take-off energy required for drones is notably higher, this is mitigated by considering the worst-case scenario within the weight classes, partially counterbalancing the energy expenditure difference.

6.2 Mathematical Formulation

The payload weight is a crucial component within the EVRPD, having a pivotal factor in minimizing the collective energy consumption. Conceptually, the EVRPD can be likened to a two-echelon problem, wherein the drones are conveyed to designated launch or retrieval sites by the EVs acting as mobile depots or satellite locations. The formulation explicitly considers both the weight and quantity of the payload, incorporating them as constraints to optimize the overall solution.

Let V_D, V'_D the Depot set, $V_D = \{v_D\}$ and its dummy $V'_D = \{v'_D\}$. V_S, V'_S denote the Satellites set, $V_S = \{v_{S1}, v_{S2}, \dots, v_{S n_s}\}$ and its dummy $V'_S = \{v'_{S1}, v'_{S2}, \dots, v'_{S n_s}\}$. Let V_C , the set of Customers, $V_C = \{v_{C1}, v_{C2}, \dots, v_{C n_c}\}$.

A_1 denotes the first echelon arcs set, $A_1 = \{(i, j) | i \in V_D \cup V_S, j \in V'_D \cup V_S, i \neq j\}$ and A_2 denotes the second echelon arcs set, $A_2 = \{(i, j) | i \in V_C \cup V_S, j \in V_C \cup V'_S, i \neq j\}$.

With K^{EV} and K^D the sets of Electric Vehicles (EVs) and drones are denoted, respectively. k_{EV} and k_d are the corresponding number of each vehicle type. Q^{EV} and Q^D are the maximum payload quantity capacity of EVs and drones, respectively. Likewise, W^{EV} and W^D are the respective maximum payload weight capacities, and E^{EV} , E^D the respective maximum energy capacity of each vehicle type.

Each pair of nodes (i, j) is associated with a distance d_{ij} and each node i has payload weight demand p_i . Decision variable x_{ijk} describes whether or not EV k traverses the arc (i, j) , while z_{ijsk} describes whether or not drone k traverses the arc (i, j) , beginning from satellite s . w_{ik} is the payload weight delivered to satellite i by vehicle k , f_{ijk}^1 is the payload weight in EV k that arrives from i to j and f_{ijsk}^2 is the payload weight in drone k that arrives from i to j , beginning from satellite s . Binary variables TD_{ijs+} and TD_{ijs-} denote the arrival and departure of EV i at satellite s transporting drone j , respectively.

The following model represents the described EVRPD:

$$\begin{aligned} \min f = & \sum_{(i,j) \in A_1} \sum_{k \in K^{EV}} (d_{ij} \times (1 + f_{ijk}^1) \times x_{ijk}) \\ & + \sum_{(i,j) \in A_2} \sum_{k \in K^D} \sum_{s \in V_S} (d_{ij} \times (1 + f_{ijsk}^2) \times z_{ijsk}) \end{aligned} \quad (6.3)$$

Subject to:

$$\sum_{j \in (V_D' \cup V_S)} x_{ijk} = \sum_{j \in (V_D' \cup V_S)} x_{jik}, \forall i \in (V_S \cup V_D), k \in K^{EV} \quad (6.4)$$

$$\sum_{j \in (V_C \cup V_S')} z_{ijsk} = \sum_{j \in (V_C \cup V_S')} z_{jisk}, \forall i \in V_C, s \in V_S, k \in K^D \quad (6.5)$$

$$\sum_{k \in K^D} \sum_{s \in V_S} \sum_{j \in (V_C \cup V_S')} z_{ijsk} = 1, \forall i \in V_C \quad (6.6)$$

$$\sum_{i \in (V_S \cup V_D)} x_{isk} \leq 1, \forall s \in V_S, k \in K^{EV} \quad (6.7)$$

$$\sum_{j \in (V_S \cup V_D')} x_{v_djk} = 1, \forall k \in K^{EV} \quad (6.8)$$

$$\sum_{i \in (V_D \cup V_S)} x_{iv_dk} = 1, \forall k \in K^{EV} \quad (6.9)$$

$$w_{ik} = \sum_{j \in (V_D' \cup V_S)} f_{jik}^1 - \sum_{j \in (V_D' \cup V_S)} f_{ijk}^1, \forall i \in V_S, k \in K^{EV} \quad (6.10)$$

$$0 \leq f_{ijk}^1 \leq W^{EV} \times x_{ijk}, \forall (i,j) \in A_1, k \in K^{EV} \quad (6.11)$$

$$\sum_{i \in (V_C \cup V_S)} \sum_{j \in V_C} z_{ijsk} \leq Q^D, \forall s \in V_S, k \in K^D \quad (6.12)$$

$$\sum_{i \in (V_D \cup V_S)} \sum_{j \in V_S} x_{ijk} \leq Q^{EV}, \forall k \in K^{EV} \quad (6.13)$$

$$p_i = \sum_{j \in (V_C \cup V_S')} f_{jis}^2 - \sum_{j \in (V_C \cup V_S')} f_{ijsk}^2, \forall i \in V_C, s \in V_S, k \in K^D \quad (6.14)$$

$$0 \leq f_{ijsk}^2 \leq W^D \times z_{ijsk}, \forall (i,j) \in A_2, s \in V_S, k \in K^D \quad (6.15)$$

$$\sum_{k \in K^D} \sum_{(i,j) \in A_2} p_i \times z_{ijsk} \times TD_{lks+} = w_{sl}, \forall s \in V_S, l \in K^{EV} \quad (6.16)$$

$$\sum_{i \in V_S} \sum_{j \in V_C} \sum_{k \in K^D} z_{ijsk} \times TD_{lks+} \leq k_d, \forall s \in V_S, l \in K^{EV} \quad (6.17)$$

$$\sum_{i \in (V_D \cup V_S)} \sum_{j \in (V_C \cup V_S')} (1 + f_{ijk}^1) \times d_{ij} \times x_{ijk} \leq E^{EV}, \forall k \in K^{EV} \quad (6.18)$$

$$\sum_{(i,j) \in A_2} \sum_{s \in V_S} (1 + f_{ijsk}^2) \times d_{ij} \times z_{ijsk} \leq E^D, \forall k \in K^D \quad (6.19)$$

$$\sum_{i \in (V_S \cup V'_S)} \sum_{j \in (V_S \cup V'_S)} z_{ijsk} = 0, \forall s \in V_S, \forall k \in K^D \quad (6.20)$$

$$TD_{ijs+} = TD_{ijs-}, \forall i \in K^{EV}, j \in K^D, s \in V_S \quad (6.21)$$

$$\sum_{i \in K^{EV}} TD_{ijs+} = 1, \forall j \in K^D, s \in V_S \quad (6.22)$$

$$TD_{ijs+} = TD_{ijs'+}, \forall i \in K^{EV}, j \in K^D, s \in V_S, s' \in \{V_S | s' \neq s\} \quad (6.23)$$

$$TD_{ijs+}, TD_{ijs-} \in \{0, 1\}, \forall i \in K^{EV}, j \in K^D, s \in (V_S \cup V'_S) \quad (6.24)$$

$$x_{ijk} \in \{0, 1\}, \forall (i, j) \in A_1, k \in K^{EV} \quad (6.25)$$

$$z_{ijsk} \in \{0, 1\}, \forall (i, j) \in A_2, s \in V_S, k \in K^D \quad (6.26)$$

Constraints (6.4) require that each node has the same number of incoming and outgoing arcs for EVs. Constraints (6.5) enforce the same requirement on drones. Constraints (6.6) enforce the no split-delivery policy. In addition, each of the satellites may be visited at most once by the same EV, represented by constraints (6.7). Constraints (6.8) and (6.9) set the number of outgoing and incoming arcs to the depot per EV to be exactly one.

To keep track of the payload movement from the depot to the satellite location constraints (6.10) are used. To keep track of the following payload movement by the drones to the delivery site, constraints (6.11) are used. For both constraints (6.10), and (6.11), if the arc is not traversed, the payload is going to be zero. The quantity of items being transported by the EV is controlled by constraints (6.12), while constraints (6.13) control the quantity for the drones. The weight of items being transported by the drones is controlled by constraints (6.14), and (6.15). To synchronize the weight carried by the drones and that carried by the EVs, constraints (6.16) are used. Each EV may carry up to a certain number of drones, enforced through constraints (6.17).

The energy expenditure is monitored through constraints (6.18) for the EVs, and through constraints (6.19) for the drones.

Moving from a set of locations to its dummy counterpart is not allowed; therefore, constraints (6.20) have to be put in place.

Constraints (6.21) synchronize the movement of EVs and drones at satellites by balancing their unique incoming and outgoing arcs, constraints (6.22) ensure each of the drones is used at each satellite, and (6.23) balance the original and the dummy satellite location variables used for the synchronization.

Lastly, the variables used in the formulation are restricted by constraints (6.24) to (6.26).

6.3 The Proposed Solution Algorithms

Addressing instances of the EVRPD poses significant challenges due to the inclusion of a constraint on energy consumption, the impact of vehicle weight on energy usage, and the intricate interdependence between two distinct vehicle types that necessitate meticulous planning. This study focuses on the generation of solutions through the utilization of heuristics and meta-heuristics. Two methods, namely ACO and BCO, have been proposed in Section 5 and have been adapted for the EVRPD.

Two additional methods have been devised, one draws inspiration from a SA approach presented in Section 4, and the last method is GRASP, an effective solution method for many VRPs. Each of these methods has been chosen for its unique characteristics, aimed at evaluating the efficacy of diverse approaches in tackling the EVRPD.

6.3.1 Ant Colony Optimization

The Ant Colony framework is the first to be explored. The two variations introduced in the context of COMF-EVRP, namely ACS and MMAS have been adapted for the EVRPD, in addition to a hybrid variant for each of them, based on the research presented in Kyriakakis et al. (2021), where these hybrid methods exhibited promising outcomes when applied to a different routing problem.

The differentiating factor between the hybrid variants and their non-hybrid counterparts lies in the adoption of a single solution based on the Ant Colony Optimization (ACO) formula, which is modified through the incorporation of neighborhood structures. This modification leads to reduced computational requirements. Short descriptions of these algorithms have already been presented in Section 5, where they were employed to solve COMF-EVRP.

6.3.2 Bee Colony Optimization

The Bee Colony Optimization framework was initially introduced in Section 5 of this study. In the present application, the same solution process is employed, utilizing initial solutions generated through the mechanism employed by the GRASP method to ensure a diverse set of initial solutions.

In contrast to the COMF-EVRP formulation, this particular application incorporates two distinct types of vehicles that are assigned to different types of routes. The EVs are routed to satellite locations, while each drone is responsible for delivering items. Additional EVs and drones are introduced until all customers have been visited.

The transition rules and fitness function calculation remain unchanged in this application. For the EVs, the next node to visit can either be the depot or a satellite location, whereas for the drones, it can be either the EV itself or the next customer to serve. The bees' waggle dance mechanism is also applied in a similar manner as in previous implementations.

6.3.3 Simulated Annealing

The Simulated Annealing method was initially introduced and discussed in Section 4, where it was utilized as the selection criteria for a modified variant of the VNS algorithm to address the COEVRP. However, in the context of the EVRPD, the solution methodology exhibits several notable differences from the previous implementation.

One key advantage of the SA algorithm lies in its ability to evaluate all solutions based on their performance, even those that are inferior to the incumbent solution. The selection criterion for accepting or rejecting a solution is determined by a combination of the current temperature and the cost of both the incumbent solution and the proposed solution. The cooling schedule employed in the SA algorithm plays a critical role in influencing its performance. It determines the trade-off between exploration and exploitation during the search for an optimal solution. In this particular case, three distinct cooling methods are tested to evaluate their impact on the algorithm's performance.

The proposed methodology entails the generation of multiple solutions through the utilization of a variant of the Nearest Neighbor (NN) algorithm. This variant selects customers at random from a pool that includes the nearest ones. In each step of the SA process, a neighborhood operator is

applied to each available solution in order to explore the solution space. The operator identifies the best neighboring solution, which then replaces the current solution based on probabilities determined by the SA algorithm. A comprehensive outline of the SA implementation is presented in Algorithm 6.

Algorithm 6: Simulated Annealing outline

Data: $instance_data, N = \{n_1, n_2, ..n_{k_{max}}\}, T_0, \alpha, Iter_{max}, Pop_{max}$

```

1  $T \leftarrow T_0$  /* Initialize Temperature */
2 ;
3  $P \leftarrow \emptyset$ ;
4  $i \leftarrow 0$ ;
5 while  $i \neq Pop_{max}$  do
6    $s \leftarrow \text{RandomizedNearestNeighbor}(instance\_data)$ ;
7    $P \leftarrow P \cup s$ ;
8    $i \leftarrow i + 1$ ;
9  $s_{best} \leftarrow \arg \min\{s | Cost(s), s \in P\}$ ;
10  $iter \leftarrow 0$ ;
11 while  $iter \neq Iter_{max}$  do
12   forall  $s \in P$  do
13      $n \leftarrow \text{RandomlySelectNeighborhoodOperator}(N)$ ;
14      $s' \leftarrow \text{ApplyNeighborhoodOperator}(instance\_data, s, n)$ ;
15      $\Delta Cost \leftarrow Cost(s') - Cost(s)$ ;
16     if  $\Delta Cost \leq 0$  then
17        $s \leftarrow s'$ ;
18     if  $Cost(s') < Cost(s_{best})$  then
19        $s_{best} \leftarrow s'$ ;
20     else if  $\text{rand}(0, 1) < \exp(-\Delta Cost/T)$  then
21        $s \leftarrow s'$ ;
22    $iter \leftarrow iter + 1$ ;
23  $T \leftarrow \text{UpdateTemperature}(iter, T_0, \alpha)$ ;
```

Initial Solution Construction The Randomized Nearest Neighbor (RNN) algorithm is a variant of the NN heuristic, which introduces an element of randomness in the selection of the next customer. Unlike NN, which always selects the closest node, RNN randomly selects the next customer from a list of the k -closest nodes. Consequently, RNN yields varying routing solutions compared to NN's consistent routing solution.

The step-wise construction mechanism of RNN is applied at the depot and at satellites and progressively incorporates additional nodes, such as satellites or customers, until a constraint violation occurs. In such cases, the vehicle in use returns to its origin to finalize the route. This iterative process continues until all customers have been serviced.

Algorithm 7: Randomized Nearest Neighbor

Data: *instance_data*, *k*, *U*

```

1  $R \leftarrow \{0\};$ 
2 while  $U \neq \emptyset$  do
3    $V \leftarrow \text{GetKNearestNodes}(\text{instance\_data}, k);$ 
4    $j \leftarrow \text{RandomChoice}(V);$ 
5   if  $\text{IsInsertFeasible}(\text{instance\_data}, R, j)$  then
6      $U \leftarrow U / \{j\};$ 
7      $R \leftarrow R \cup j;$ 
8   else
9     return  $R, U$ 
10 return  $R, U ;$ 

```

Neighborhood Operators In order to enhance the quality of solutions within the population, a collection of neighborhood operators is employed. These operators are utilized to manipulate individual drone routes, multiple routes belonging to a specific drone, routes associated with different drones, as well as electric van routes.

The operators follow the Best Acceptance criterion, whereby they return the best possible solution within the neighborhood of the current solution, regardless of whether it represents an improvement or not. This differs from LS operators, which exclusively accept solutions that demonstrate improvement over the current solution.

Let n represent a specific neighborhood operator. This operator expands the current solution to generate a set of neighboring solutions denoted as $N_n(s)$. Subsequently, the operator identifies the best feasible solution, denoted as s_{BN} , from this set. The probability of replacing the current solution with its best neighboring solution is determined through the utilization of Equation (6.27). A more detailed description of the aforementioned task is presented in Algorithm 8.

$$p_{\text{accept}} = e^{-(c' - c)/T} \quad (6.27)$$

where c' is the cost of the candidate solution and c the cost of the current solution.

Algorithm 8: Best Acceptance Neighborhood Operator

Data: *instance_data*, *s*, *n*

```

1  $s_{BN} \leftarrow s;$ 
2  $c_{BN} \leftarrow INF;$ 
3 for  $\text{All } s' \in N_n(s)$  do
4    $c' \leftarrow \text{Cost}(s');$ 
5   if  $\text{is\_feasible}(s')$  and  $c' < c_{BN}$  then
6      $c_{BN} \leftarrow c';$ 
7      $s_{BN} \leftarrow s';$ 
8 return  $s_{BN} ;$ 

```

Temperature Reduction The cooling rate serves as a crucial parameter in the implementation of the SA algorithm, as previously discussed. In the context of the COEVRP implementation, a linear cooling rate was employed. However, for the current implementation, two additional cooling rates were explored in addition to linear, namely exponential, and logarithmic. Consequently, three variants of the SA algorithm were devised: SA-LIN, SA-EXP, and SA-LOG.

The key distinction among these variants lies in the temperature reduction stage, where the calculation of the next temperature to be considered occurs. Equations (6.28), (6.29), and (6.30) correspond to the linear, exponential, and logarithmic implementations, respectively. Here, T_i represents the temperature at the i -th SA iteration, T_0 denotes the starting temperature, and α denotes the cooling parameter.

$$T_t = \arg \max\{0, T_0 \times (1 - \frac{\alpha * t}{T_0})\} \quad (6.28)$$

$$T_t = \alpha^t \times T_0 \quad (6.29)$$

$$T_t = \frac{\alpha \times T_0}{\log(1 + t)} \quad (6.30)$$

6.3.4 Greedy Randomized Adaptive Search Procedure

The Greedy Randomized Adaptive Search Procedure (GRASP, [Feo and Resende \(1995\)](#)) represents a two-phase optimization technique characterized by the utilization of a randomized greedy approach to generate an initial feasible solution in the first phase, followed by an iterative improvement process aimed at identifying a local minimum in the second phase. This iterative process continues until a predefined stopping criterion, such as reaching the maximum number of iterations, is satisfied. Throughout the optimization process, GRASP maintains a record of the best solution encountered.

During the initial phase of the GRASP algorithm, a combination of greedy and random characteristics is employed to construct solutions. This procedure involves incrementally augmenting an incomplete solution by adding nodes, selected from a list of potential nodes referred to as the Restricted Candidate List (RCL). The RCL is constructed using a greedy strategy, including the best candidate nodes. However, the algorithm introduces an element of randomness by randomly selecting one of the top candidates for addition to the solution. This integration of randomness in the solution construction process ensures diversity while still maintaining a focus on creating good solutions.

The heuristic component of the GRASP method is adaptive in nature, as it dynamically updates the benefits associated with each element during each iteration of the construction phase. This adaptability allows the algorithm to produce a range of diverse solutions.

The LS phase begins with the solution generated during the construction phase and progressively replaces the current solution with improved neighboring solutions until no further enhancements can be achieved. The overall structure of the proposed algorithm is presented in Algorithm 9.

For the EVRPD, two variations of the GRASP algorithm are introduced. The first variant, GRASP-VL, adopts a value-based criterion to construct the RCL, which is based on the disparity between the best and worst candidate solutions. The second variant, GRASP-CRD, utilizes a cardinality-based criterion to construct the RCL by including the top n candidates in the list. The selection of customers from the RCL is performed randomly.

Algorithm 9: GRASP Outline

Input: *instance, parameters*
Result: S_{best}

```

1 while Stop criterion not satisfied do
2    $S \leftarrow \text{ConstructGRASPSolution}(\text{instance}, \text{parameters});$ 
3    $S_{improved} \leftarrow \text{LocalSearch}(S);$ 
4   if  $\text{Cost}(S_{improved}) < \text{Cost}(S_{best})$  then
5      $S_{best} \leftarrow S_{improved};$ 
6 return  $S_{best};$ 

```

GRASP-VL RCL construction The GRASP-VL method employs a parameter, denoted as $\alpha \in [0, 1]$, to determine the selection of nodes for inclusion in the RCL. The eligibility of customers to join the RCL is determined based on the distances between the previous node and the nearest potential node (d_{min}) as well as the furthest potential node (d_{max}). The acceptance criterion for a candidate node l is defined in equation (6.31), which determines whether customer l is considered for inclusion in the RCL. More specifically, if the distance between the current node i and node l is less than or equal to the value specified in the right-hand side of the equation, then customer l is included in the RCL. The proposed method is described in further detail in Algorithm 10.

$$d_{il} \leq d_{min} + \alpha(d_{max} - d_{min}) \quad (6.31)$$

Algorithm 10: Value-based RCL construction

Data: d, i, α, L
Result: RCL

```

1  $d_{min} \leftarrow \min\{d_{il} | l \in L\};$ 
2  $d_{max} \leftarrow \max\{d_{il} | l \in L\};$ 
3  $RCL \leftarrow \{\};$ 
4 for  $l$  in  $L$  do
5   if  $d_{il} \leq d_{min} + \alpha(d_{max} - d_{min})$  then
6      $RCL \leftarrow RCL \cup \{l\};$ 
7 return  $RCL;$ 

```

GRASP-CRD RCL construction In the case of the GRASP-CRD approach, the size of the RCL is determined by a parameter denoted as n , independent of the distances involved. If the number of remaining available nodes is less than n , then all of these nodes are included as candidates in the RCL. The nodes chosen for the RCL are specifically those that are closest to the last node in the route. The described method is explained in detail in Algorithm 11.

Algorithm 11: Cardinality-based RCL construction

Data: d, i, n, L
Result: RCL

```

1  $RCL \leftarrow \{\}$ ;
2 for  $k \leftarrow 1$  to  $\min(|L|, n)$  do
3    $d_{min} \leftarrow \min\{d_{il} | l \in L\}$ ;
4    $l_{min} \leftarrow \{l \in L | d_{il} = d_{min}\}$ ;
5    $RCL \leftarrow RCL \cup \{l_{min}\}$ ;
6    $L \leftarrow L - \{l_{min}\}$ ;
7 return  $RCL$ ;

```

6.3.5 Variable Neighborhood Decent

In order to enhance the existing solution methods, a Variable Neighborhood Descent (VND) framework is introduced. The VND framework is a deterministic approach derived from the well-known VNS algorithm. The VND framework, initially presented in Mladenović and Hansen (1997), employs a systematic change of neighborhoods to optimize a solution. In this study, the Pipe-VND (P-VND) methodology is adopted, where the algorithm remains in the same neighborhood as long as improvements can be made. The P-VND terminates when no further improvements are achievable within the current neighborhood.

The algorithmic details of the employed approach are provided in Algorithm 12. The set $N = \{N_1, N_2, \dots, N_{k_{max}}\}$ represents the operators that map a solution to a specific neighborhood structure $N_k(S)$.

Algorithm 12: Pipe-VND

Data: $S, N = \{N_1, N_2, \dots, N_k\}, VNDiters$
Result: S'

```

1 for  $iter \leftarrow 1$  to  $VNDiters$  do
2   for  $k \leftarrow 1$  to  $k_{max}$  do
3      $improved \leftarrow True$ ;
4     repeat
5        $S' \leftarrow N_k(S)$ ;
6       if  $cost(S) < cost(S')$  then
7          $S \leftarrow S'$ ;
8       else
9          $improved \leftarrow False$ ;
10    until  $improved = False$ ;

```

A set of LS operators were developed for use in the EVRPD and are presented in the following list:

- **Intra-EV-Intra-Drone** The following three operators are concerned with only one EV and only one drone.

1-1 Intra-route Swap: Two nodes are selected from one drone route, and their positions are swapped. (Fig. 6.1)

1-1 Inter-route Exchange: Two nodes are selected from two drones routes of the same drone, and their positions are exchanged. (Fig. 6.2)

1-0 Inter-route Relocation: One node is selected from a drone route and is moved to another route of the same drone. (Fig. 6.3).

- **Intra-EV-Inter-Drone** The following two operators are concerned with only one EV and all of its drones.

1-1 Inter-route Exchange: Two nodes are selected from two different drones, and their positions are exchanged. (Fig. 6.4)

1-0 Inter-route Relocation: One node is selected from a drone route and is moved to drone route of a different drone. (Fig. 6.5)

- **Inter-EV-Inter-Drone** The following two operators are concerned with all EVs and drones.

1-1 Inter-route Exchange: Two nodes are selected from two different drones, deployed from two different EVs, and their positions are exchanged.

1-0 Inter-route Relocation: One node is selected from a drone route and is moved to drone route of a different drone, deployed from a different EV.

- **EV-route** The following operator is concerned with the satellites that a single EV will visit.

2-Opt Intra-route: Two satellites from the route of a single EV are selected, and the route between them is reversed. (Fig. 6.6)

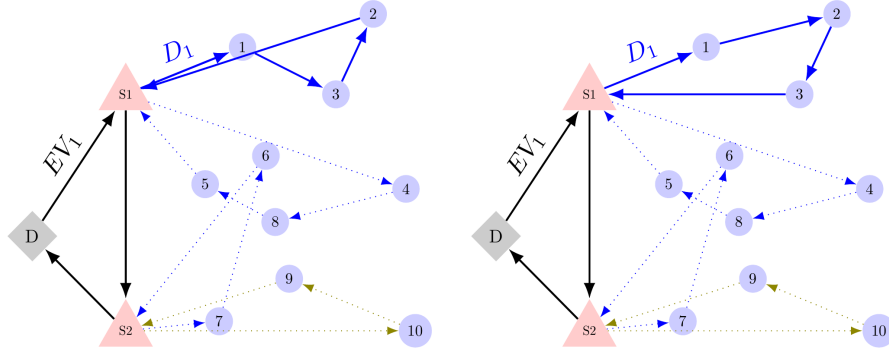


Figure 6.1: 1-1 Intra-route Swap (Intra Drone)

6.4 Computational Experiments

Due to the novelty of the EVRPD, no benchmark datasets exist. To facilitate the evaluation and comparison of the proposed solution methods, a new set of benchmarks was generated. These benchmarks were developed based on the second instance set introduced by [Perboli et al. \(2011\)](#) for the two-echelon variant of the VRP. The selection of this instance set was motivated by the diverse range of customers and the presence of satellite locations.

The transformation process for the benchmarks primarily focused on adjusting the customer demands. Each customer's demand was categorized into one of three weight classes provided. The

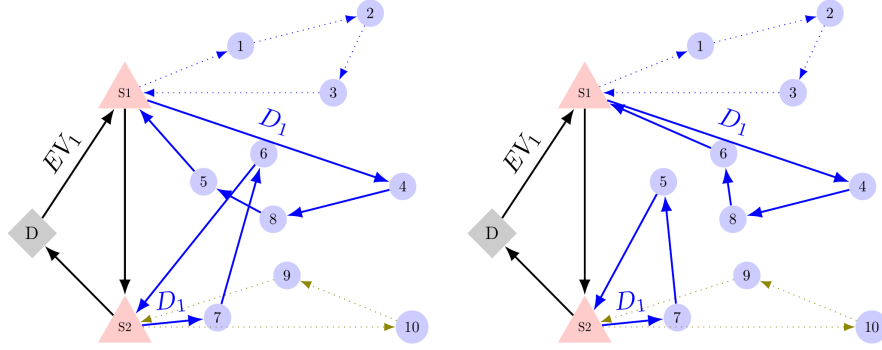


Figure 6.2: 1-1 Inter-route Exchange (Intra Drone)

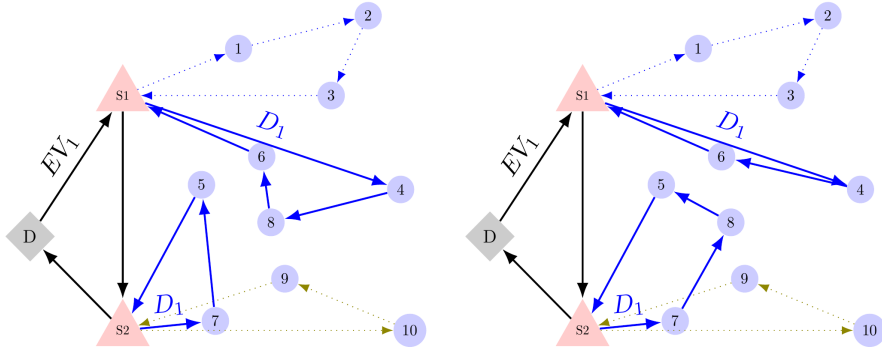


Figure 6.3: 1-0 Inter-route Relocation (Intra Drone)

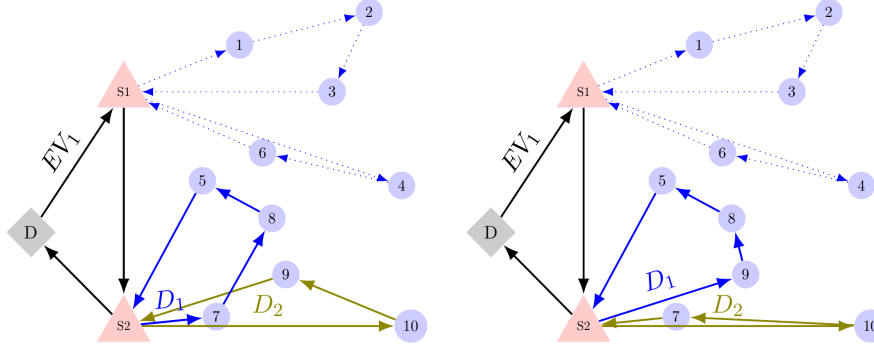


Figure 6.4: 1-1 Inter-route Exchange (Inter-Drone)

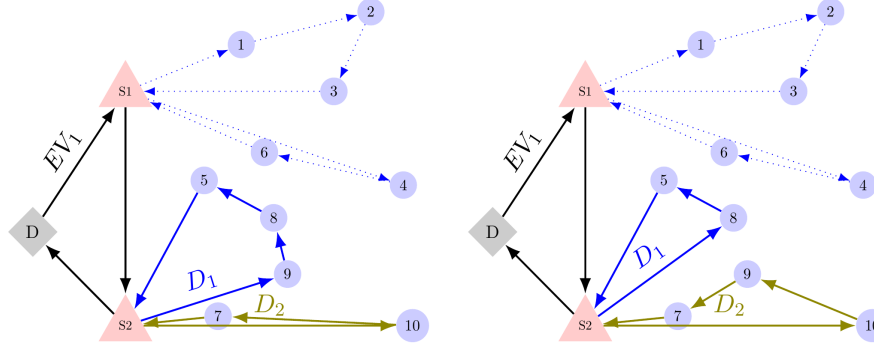


Figure 6.5: 1-0 Inter drone route Relocation (Inter-Drone)

geographical coordinates of all nodes within the instances remained unchanged. The fleet sizes for the electric vans and drones were customized according to the specific characteristics of each benchmark instance. The number of electric vans deployed varied between two and three, while two to four drones were assigned to each van.

6.4.1 Ant Colony Optimization

All experiments were carried on an Intel®Core i7-4770 clocked at $3.40GHz$, equipped with 7.7GB of available RAM. All of the proposed algorithms were implemented in C++, using the GCC 11 compiler. Table 6.3, presents and describes the parameters used for all of the ACO implementations, with each test being carried 15 times.

Setting the appropriate parameters holds considerable significance as they directly impact the efficacy of the algorithms. Consequently, this study examines the sensitivity of the four implemented algorithms to key parameters, namely β and q_0 for ACS and HACS, and β for MMAS and HMMAS. Subsequently, ACS and HACS were tested with $\beta \in \{0.85, 0.90, 0.95\}$, and $q_0 \in \{1.0, 2.0, 3.0\}$. Similarly, MMAS and HMMAS were tested with $\beta \in \{1.0, 2.0, 3.0, 4.0, 5.0\}$.

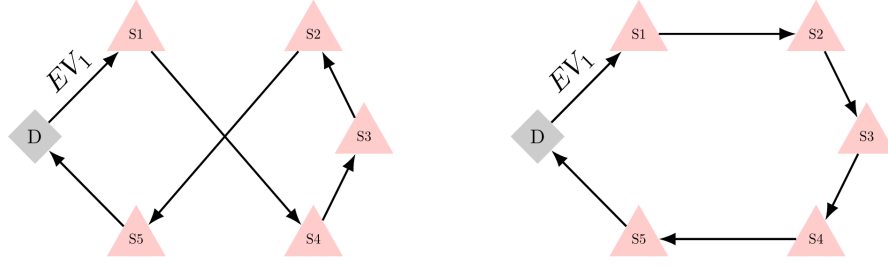


Figure 6.6: 2-Opt Intra EV route

Table 6.3: Parameter description and settings

Parameter	Description	Values Tested
<u>ACS, HACS</u>		
<i>ACOiters</i>	Number of iterations	10000
ρ	Pheromone evaporation factor	0.1
q_0	Controls exploitation during solution construction	{0.85, 0.90, 0.95}
β	Controls the importance of heuristic information	{1.0, 2.0, 3.0}
<i>VNDiters</i>	Number of the LS iterations	50
<u>MMAS, HMMAS</u>		
<i>ACOiters</i>	the number of iterations	10000
Q_0	Used to set the τ_{min} value.	300
ρ	Pheromone evaporation factor	0.02
α	Controls the importance of pheromone trails	1.0
β	Controls the importance of heuristic information	{1.0, 2.0, 3.0, 4.0, 5.0}
<i>VNDiters</i>	Number of the LS iterations	50

Figure 6.7, and Figure 6.8, present the sensitivity results for ACS, and MMAS variants, respectively. Each figure presents the average percentage gap of the best solutions attained for different parameter combinations from the BSF, employing Equation 6.32 to calculate the gaps.

$$Gap(x) = (x - BSF)/BSF\% \quad (6.32)$$

The findings reveal that, in the case of ACS and HACS, employing parameter values of $q_0 = 0.85$ and 0.90 , along with $\beta = 1$, yield the highest average solution quality. Notably, increased randomness positively impacts performance, and the two methods demonstrate very similar performance levels.

Regarding sensitivity, the gap range for ACS is 0.45 , while for HACS, it is 0.28 , suggesting that HACS displays lower sensitivity towards parameter adjustments. As for MMAS and HMMAS, the best average results are attained when setting $\beta = 1$, with only a marginal deviation observed for $\beta = 2$. The gap range for MMAS and HMMAS was 0.21 and 0.17 , respectively, indicating that the hybrid variant exhibits diminished susceptibility to parameter variations.

Further analysis was carried out and is presented in Fig. 6.9. The four presented plots illustrate the 95% confidence interval of the gaps, over all parameters, arranged in ascending order from the worst to the best.

One of the first visual cues for the difference between ACS and HACS is the presence of a few extreme outlier values for HACS, but for some of the worst parameter combinations. Both ACS and HACS obtained the best results with $\beta = 1$ and $q_0 = 0.85$. The difference between MMAS and

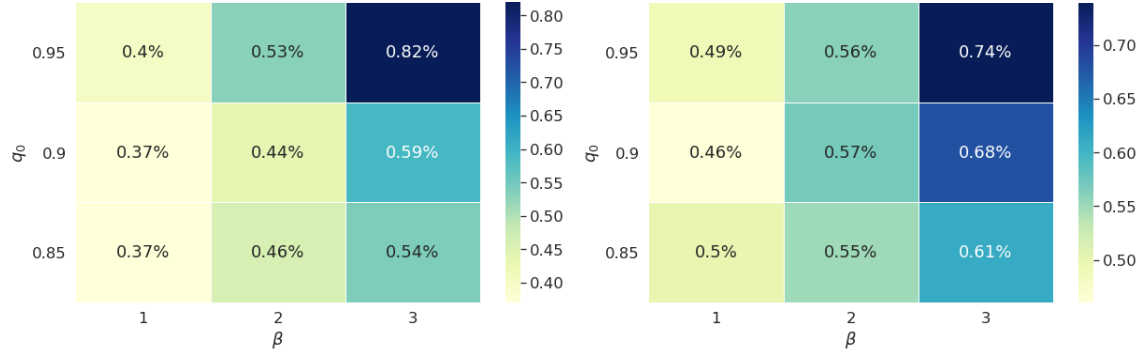


Figure 6.7: $Gap_{Avg}(Cost_{Best})\%$ to BSF: ACS on the left, HACS on the right.

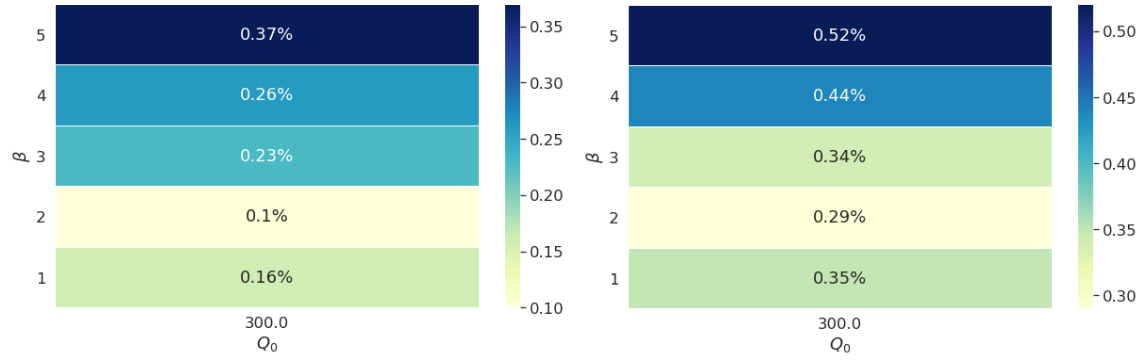


Figure 6.8: $Gap_{Avg}(Cost_{Best})\%$ to BSF: MMAS on the left, HMMAS on the right.

HMMAS are subtle as well. Once again, both of them achieved the optimal results with the same parameter value, $\beta = 2$

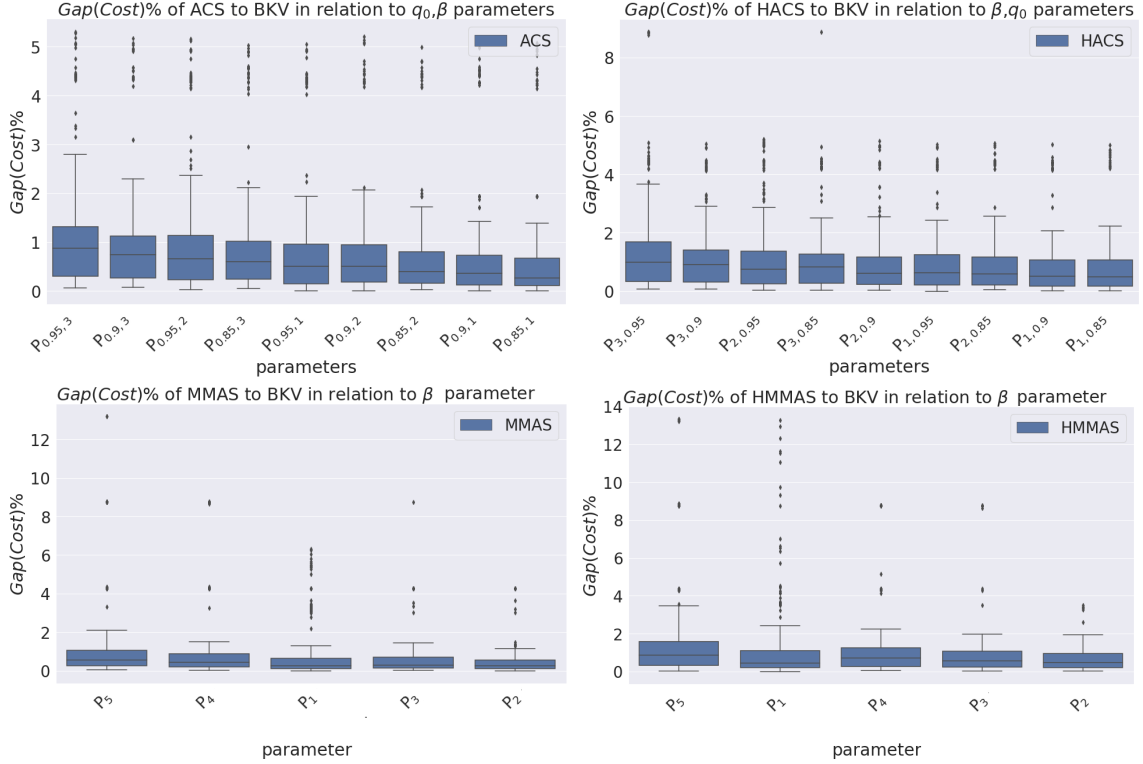


Figure 6.9: Gap(Cost)\% to BKV for ACO implementation for all parameters.

The findings of the computational experiments are presented in Table 6.4. The first column of both tables provides the instance name, along with the number of satellites, drone capacity of each EV, and the EV fleet size. The following three columns report the best solutions obtained by ACS, the gap between these solutions and the overall BSF, and the average cost.

Overall, ACS and MMAS demonstrated significantly superior performance compared to the hybrid variants. Among them, MMAS outperformed the others by achieving the highest number of BSFs and exhibiting the best average performance. The average gap between the best solutions of MMAS and the BSFs was a mere 0.16%, indicating minimal deviation. Following MMAS, HMMAS achieved the second-best gap at 0.31%, while ACS ranked third at 0.39%, and HACS performed the least favorably with a gap of 0.47%.

In general, the performance of all four variants can be characterized as satisfactory. Although HMMAS exhibited a better gap than ACS, ACS reached four BSFs, while HMMAS only reached one. MMAS successfully reached the BSFs for seven of the small instances. HACS outperformed HMMAS in all instances of size $n51$, while the reverse was observed for the small instances $n22$ and $n33$, with two exceptions.

Based on the results, ACS appears to be more suitable for larger instances, while MMAS demon-

strates better performance for smaller ones. This difference can possibly be attributed to the distinct feedback mechanisms employed.

The primary factor driving the dominance of ACS and MMAS over the hybrids is the element of randomness. As the hybrids are based on a single solution, whereas the traditional variants generate multiple solutions, the latter approach enables a broader exploration of the solution space. This theory aligns with the results obtained from the parameter analysis and the observed correlation between randomness and solution quality.

Table 6.4: Computational results for ACO

Instance	ACS		HACS		MMAS		HMMAS	
	$Cost_{best}$	$Cost_{avg}$	$Cost_{best}$	$Cost_{avg}$	$Cost_{best}$	$Cost_{avg}$	$Cost_{best}$	$Cost_{avg}$
n22-k4-s10-14	1144.28	1149.75	1145.37	1158.12	1144.28	1152.62	1145.37	1162.67
n22-k4-s11-12	1403.94	1438.99	1406.06	1418.46	1404.22	1438.10	1405.84	1422.19
n22-k4-s12-16	1243.38	1252.32	1244.10	1258.47	1241.16	1246.51	1240.95	1248.07
n22-k4-s6-17	1627.76	1640.91	1627.93	1648.49	1610.70	1627.89	1614.12	1632.96
n22-k4-s8-14	1191.20	1199.01	1194.06	1207.12	1191.20	1218.75	1194.06	1227.59
n22-k4-s9-19	1878.84	1884.06	1874.20	1883.43	1874.20	1879.37	1876.74	1880.37
n33-k4-s1-9	3599.67	3604.23	3600.27	3606.09	3599.16	3601.95	3599.75	3604.30
n33-k4-s14-22	4035.51	4040.06	4035.65	4040.50	4033.19	4037.81	4034.78	4039.27
n33-k4-s2-13	3429.00	3433.03	3429.00	3435.44	3428.85	3432.84	3429.00	3435.03
n33-k4-s3-17	3440.19	3459.68	3443.84	3456.86	3307.26	3319.26	3313.89	3334.94
n33-k4-s4-5	3795.70	3799.08	3796.16	3799.74	3795.61	3800.70	3796.47	3802.41
n33-k4-s7-25	3819.82	3826.87	3821.10	3827.77	3819.62	3825.91	3819.62	3827.03
n51-k5-s11-19	3061.89	3086.29	3067.14	3094.27	3067.40	3117.85	3084.38	3147.20
n51-k5-s11-19-27-47	1916.57	1928.39	1920.91	1931.76	1917.73	1925.49	1921.28	1932.76
n51-k5-s2-17	2891.04	2921.97	2902.64	2928.88	2909.18	2936.29	2907.18	2946.38
n51-k5-s2-4-17-46	2895.94	2922.84	2902.34	2929.37	2897.17	2938.39	2916.73	2953.09
n51-k5-s27-47	1918.45	1928.85	1921.03	1931.61	1917.50	1925.20	1921.10	1930.25
n51-k5-s32-37	4918.59	4924.44	4920.40	4927.77	4921.56	4939.19	4925.68	4955.94
n51-k5-s4-46	4170.25	4181.72	4171.78	4184.86	4171.00	4179.80	4176.14	4187.83
n51-k5-s6-12	2545.84	2561.59	2543.61	2568.61	2540.91	2554.11	2546.96	2567.47
n51-k5-s6-12-32-37	2545.90	2561.04	2546.75	2568.80	2543.73	2554.55	2549.05	2570.68
Average	2736.85	2749.77	2738.78	2752.69	2730.27	2745.36	2734.24	2752.78

The average computational time required for each instance is presented in Table 6.5. MMAS and HMMAS exhibit similar average elapsed times, with MMAS being slightly faster overall. On the other hand, HACS generally requires more time compared to HMMAS, although this disparity can be primarily attributed to the instance *n51-k5-s32-37*, where the algorithm became trapped in an infeasible region of the solution space. This characteristic is even more pronounced in ACS, which exhibits outlier computational times in three instances, resulting in an average running time nearly four times longer than that of MMAS implementations.

Based on the presented results, the MMAS approach is recommended for solving small to medium instances of the EVRPD. For instances with more than 50 customers, ACS is capable of obtaining

the highest number of BSFs, closely followed by MMAS. However, due to the uncertainty in regards to performance on even larger instances, a confident conclusion cannot be made at this time.

Table 6.5: Average cpu time for the ACO algorithms in seconds.

Instance	ACS	HACS	MMAS	HMMAS
n22-k4-s10-14	24.39	24.63	23.46	24.75
n22-k4-s11-12	22.03	23.73	21.81	23.78
n22-k4-s12-16	23.82	24.80	21.76	24.58
n22-k4-s6-17	23.68	24.99	21.82	23.93
n22-k4-s8-14	23.33	24.11	22.16	24.06
n22-k4-s9-19	23.48	23.03	19.62	22.46
n33-k4-s1-9	45.74	43.50	39.76	41.41
n33-k4-s14-22	41.04	43.34	40.71	42.65
n33-k4-s2-13	45.93	43.25	37.57	40.41
n33-k4-s3-17	87.59	47.35	39.86	41.10
n33-k4-s4-5	411.43	75.04	36.53	38.12
n33-k4-s7-25	42.95	40.12	37.49	39.26
n51-k5-s11-19	76.96	60.21	57.25	59.11
n51-k5-s11-19-27-47	57.51	58.27	58.40	59.13
n51-k5-s2-17	68.52	57.94	56.15	59.25
n51-k5-s2-4-17-46	69.62	58.45	56.31	57.99
n51-k5-s27-47	58.34	58.31	57.80	59.09
n51-k5-s32-37	2181.76	851.37	59.89	60.03
n51-k5-s4-46	85.50	57.63	56.21	56.17
n51-k5-s6-12	57.28	58.94	56.21	56.81
n51-k5-s6-12-32-37	56.99	59.13	56.11	57.17
Average	167.99	73.72	41.75	43.39

6.4.2 Bee Colony Optimization

All experiments were carried on an Intel®Core i7-4770 clocked at $3.40GHz$, equipped with 7.7GB of available RAM. All of the proposed algorithms were implemented in C++, using the GCC 11 compiler. Table 6.6, presents the parameters used for the BCO.

Table 6.6: BCO Algorithm Parameters

Parameter	Description	Values Tested
BCO_{iters}	Maximum BCO iterations	10000
$numBees$	Number of bees	10
λ	Parameter of greediness	{0.7, 0.8, 0.9}
β	Parameter for heuristic importance	{1.0, 2.0, 3.0}
LS_{iters}	Maximum Local Search iterations	50

In Figure 6.10, a sensitivity analysis of the BCO parameters β , and λ is presented. Each of the nine cells contains the average gap of the best solution found for each set of parameters to the overall BSF. It is observed that higher values of β provide better results, while the best results were

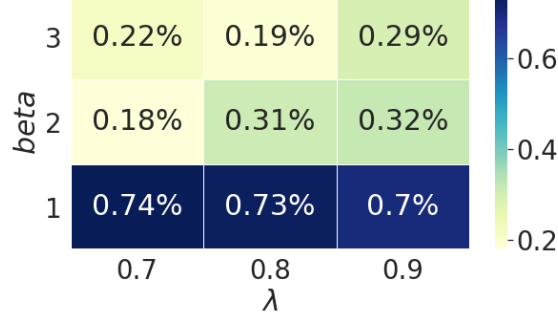


Figure 6.10: Objective function sensitivity analysis: $Gap_{Avg}(Cost_{Best})\%$ to BSF.

observed for $\beta = 2$, and $\lambda = 0.7$. Overall, the algorithm is more sensitive to the changes of β . It should be noted that these values are an average from all the instances and each instance was solved ten times.

Table 6.7 presents the solutions of the BCO algorithm on the EVRPD instances. The first column lists the instance names, the second lists the BSFs, the third and fourth columns list the best and average solution values obtained by the BCO, and the last column presents the average computational time required by the BCO.

The BCO approach contributed a single new BSF, specifically for the instance *EVRPD-n22-k4-s9-19*. Despite this limited achievement, the average gap between the best BCO solutions and the BSFs stood at 0.41%. Moreover, the average CPU time required for BCO implementation was just under one minute. One of the key distinctions between BCO and ACO is the absence of memory components in BCO. This fundamental difference explains both the variation in execution time between ACS and MMAS compared to BCO, as well as the disparities in the results obtained.

While BCO exhibited a faster average execution time, its overall average performance was inferior to all ACO implementations. However, in terms of best cost, BCO outperformed HACS. Additionally, the gap between the best solutions of BCO and the BSFs was smaller for small instances, suggesting better performance for such scenarios. This observation aligns with expectations, as the absence of memory promotes greater randomness in solution generation, which tends to be advantageous for small instances.

6.4.3 Simulated Annealing

All experiments were carried on an Intel®Core i5-11400F, equipped with 16GB of available RAM. All of the proposed algorithms were implemented in C++, using the GCC 12.1 compiler. Each of the experiments was carried ten times.

The Simulated Annealing algorithm relies on two critical parameters: the cooling rate and the initial temperature setting. Figure 6.11 illustrates the performance of all three variants with respect to these parameters. Similar to previous plots, the combinations of parameters are presented in ascending order from worst to best. Notably, the results demonstrate that higher initial temperatures correlate with poorer performance.

In Figure 6.12, an additional analysis is presented, showcasing the optimal gap to the BSFs of this algorithm for each parameter combination across all variants.

Table 6.7: BCO algorithm tests on EVRPD

Instance	$Cost_{best}$	$Cost_{avg}$	T_{avg}
n22-k4-s10-14	1139.10	1146.98	24.32
n22-k4-s11-12	1406.06	1412.19	23.87
n22-k4-s12-16	1241.12	1246.34	24.58
n22-k4-s6-17	1604.59	1621.69	22.90
n22-k4-s8-14	1191.20	1199.60	23.72
n22-k4-s9-19	1873.95	1877.78	22.45
n33-k4-s1-9	3601.61	3608.19	40.85
n33-k4-s14-22	4035.32	4038.20	41.36
n33-k4-s2-13	3430.99	3439.99	38.58
n33-k4-s3-17	3312.22	3331.69	40.64
n33-k4-s4-5	3797.89	3802.25	40.21
n33-k4-s7-25	3820.01	3827.62	39.34
n51-k5-s11-19	3084.43	3141.16	60.94
n51-k5-s11-19-27-47	1922.41	1935.76	60.55
n51-k5-s2-17	2926.24	2968.56	58.93
n51-k5-s2-4-17-46	2937.20	2982.40	58.75
n51-k5-s27-47	1920.97	1935.56	59.66
n51-k5-s32-37	4923.96	4955.67	62.51
n51-k5-s4-46	4181.82	4315.67	58.81
n51-k5-s6-12	2571.65	2620.27	59.34
n51-k5-s6-12-32-37	2572.56	2634.08	57.60
Average	2737.87	2763.89	43.81

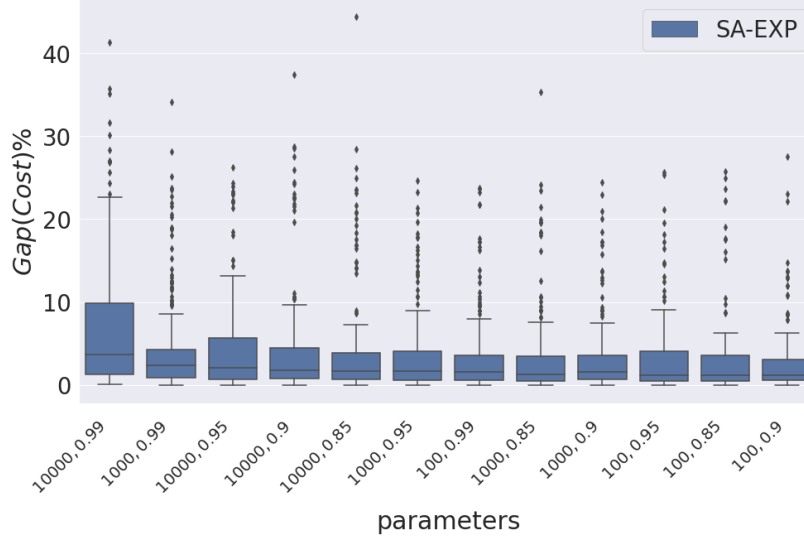
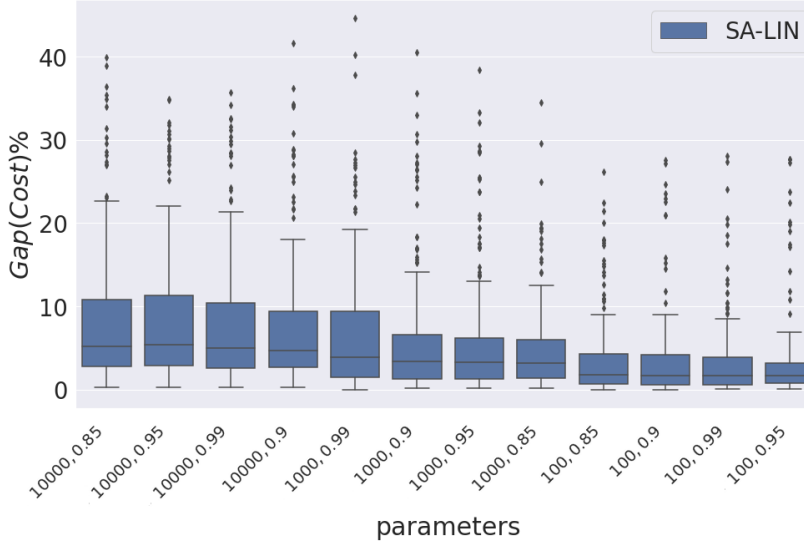
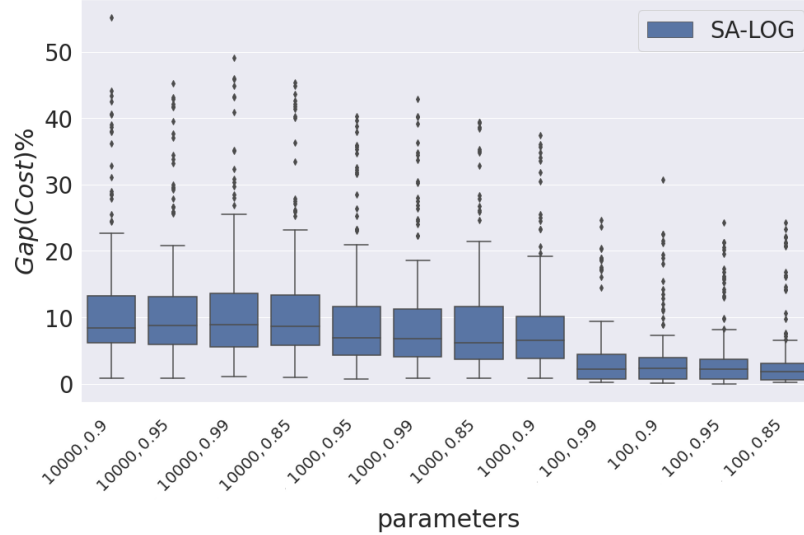
Gap(Cost)% of SA-EXP per scenario tested in relation to T_0 , a parametersGap(Cost)% of SA-LIN per scenario tested in relation to T_0 , a parametersGap(Cost)% of SA-LOG per scenario tested in relation to T_0 , a parameters

Figure 6.11: Percentage gap of objective to BSF for different parameter combinations.

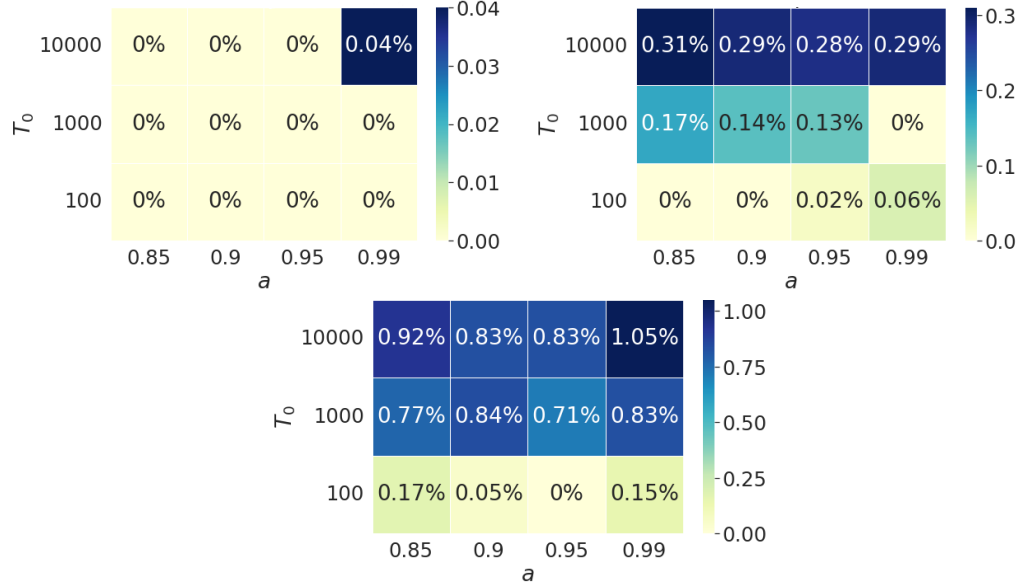


Figure 6.12: $Gap_{best}(Cost_{Best})\%$ to BSF for different parameters (left: exponential, right: linear, bottom: logarithmic).

The exponential cooling rate exhibited the best performance among the SA variants, with only one non-zero gap value observed for an initial temperature setting of $T_0 = 10000$. In contrast, the linear cooling rate was primarily influenced by the initial temperature and to a lesser extent by the cooling rate. For the logarithmic variant, both parameters held greater importance compared to the previous two implementations. The best gap was achieved with an initial temperature of $T_0 = 100$ and a cooling rate of $\alpha = 0.95$, with $\alpha = 0.90$ coming in a close second.

Table 6.8 presents the results of the computational experiments carried out for all proposed SA variations. The first column provides the instance name, followed by the BSFs in the second column. The subsequent three columns present the best solution cost obtained by SA-EXP, the gap between this solution and the BSF, and the average solution cost. The same format is repeated in the remaining columns for SA-LIN and SA-LOG.

Among the three SA variations, SA-EXP, utilizing an exponential cooling rate, was the most successful. Overall, the SA implementations were able to generate three new BSFs and match two more. SA-EXP achieved all of the new BSFs and matched one more, while SA-LIN matched a different BSF. On the other hand, SA-LOG failed to match or generate any BSFs. The average gaps further highlight the superior performance of SA-EXP.

6.4.4 GRASP

All experiments were carried on an Intel®Core i7-4770 clocked at $3.40GHz$, equipped with 7.7GB of available RAM. Both of the proposed algorithms were implemented in C++, using the GCC 11.2 compiler. Each tested was carried a total of fifteen times.

Table 6.9 presents the parameters used for all of the following tests.

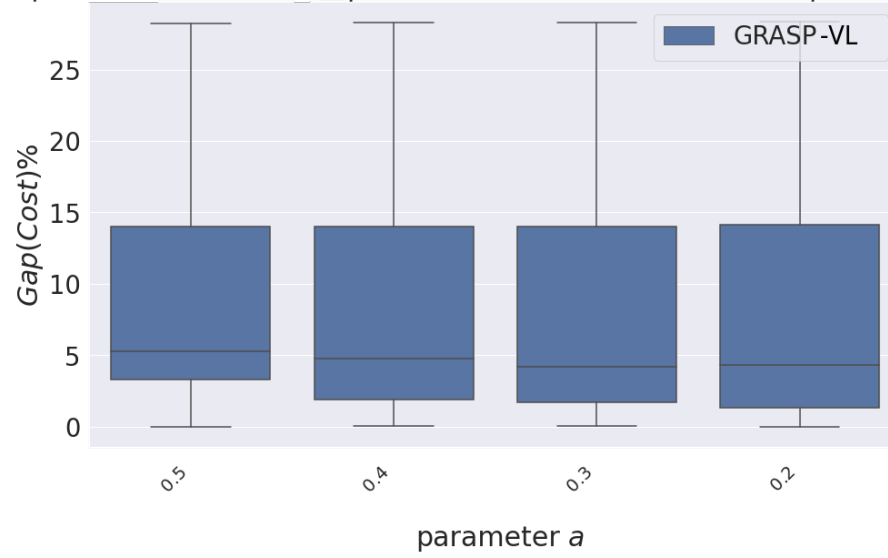
Table 6.8: Computational results of the SA variants for the EVRPD instances

Instance	SA-EXP		SA-LIN		SA-LOG	
	C_{best}	C_{avg}	C_{best}	C_{avg}	C_{best}	C_{avg}
n22-k4-s10-14	1144.28	1208.32	1147.08	1239.33	1147.08	1267.15
n22-k4-s11-12	1409.16	1455.14	1411.20	1480.12	1417.19	1491.53
n22-k4-s12-16	1247.67	1277.97	1252.41	1307.34	1253.74	1335.50
n22-k4-s6-17	1605.93	1668.61	1627.93	1709.09	1633.13	1726.20
n22-k4-s8-14	1194.06	1259.78	1198.11	1288.91	1201.79	1290.85
n22-k4-s9-19	1878.59	1908.09	1881.44	1925.44	1878.11	1937.06
n33-k4-s1-9	3600.17	3659.18	3608.69	3694.66	3610.94	3736.27
n33-k4-s14-22	4038.69	4073.56	4039.62	4114.41	4044.69	4116.46
n33-k4-s2-13	3429.30	3446.22	3428.85	3462.82	3437.79	3500.00
n33-k4-s3-17	3439.36	3536.57	3439.36	3627.16	3441.04	3635.18
n33-k4-s4-5	3795.91	3802.94	3797.08	3810.74	3802.61	3831.10
n33-k4-s7-25	3819.62	3875.39	3825.34	3913.27	3830.81	3961.73
n51-k5-s11-19	3042.83	3101.38	3054.67	3157.70	3072.59	3250.34
n51-k5-s11-19-27-47	1926.83	2167.37	1931.41	2296.24	1945.17	2348.74
n51-k5-s2-17	2885.02	2937.42	2896.10	2984.14	2924.40	3103.86
n51-k5-s2-4-17-46	2897.61	3002.60	2904.79	3048.13	2909.92	3177.27
n51-k5-s27-47	1929.08	2237.37	1931.47	2311.64	1933.00	2382.58
n51-k5-s32-37	4949.42	5124.06	4944.64	5151.16	5039.60	5212.26
n51-k5-s4-46	4169.82	4199.62	4171.21	4224.88	4189.62	4352.66
n51-k5-s6-12	2548.10	2583.91	2546.03	2619.57	2558.93	2783.87
n51-k5-s6-12-32-37	2548.72	2746.54	2566.38	2834.92	2573.90	2978.14
Average	2738.10	2822.48	2743.04	2866.75	2754.57	2924.70

Table 6.9: GRASP algorithm parameters tested

Parameter	Description	Values Tested
Max_{iter}	Maximum GRASP iterations	10000
LS_{iter}	Maximum LS iterations	50
GRASP-VL Parameter		
a	Controls RCL Greediness	{0.2, 0.3, 0.4, 0.5}
GRASP-CRD Parameter		
n	Controls RCL size	{2, 3, 5, 8}

$\text{Gap}(\text{Cost})\%$ of GRASP-VL per scenario tested in relation to parameter a



$\text{Gap}(\text{Cost})\%$ of GRASP-CRD per scenario tested in relation to parameter n

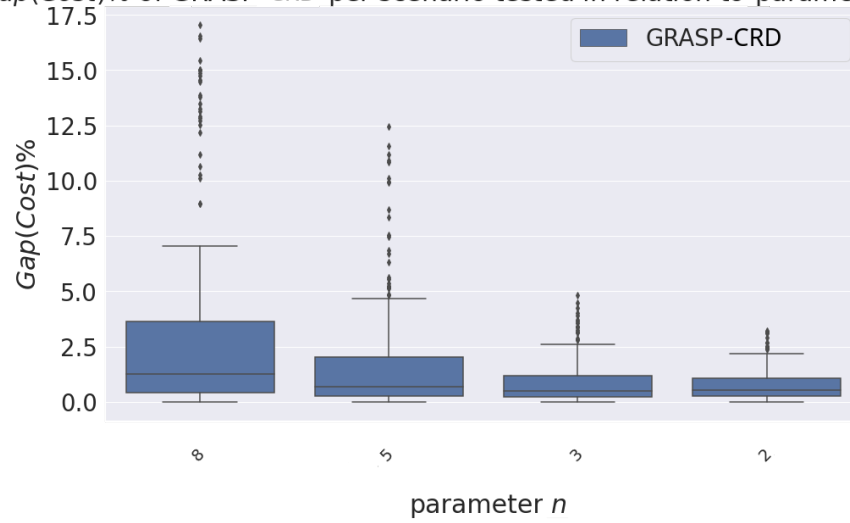


Figure 6.13: Percentage gap of objective to BSF for each algorithm.

Figure 6.13 illustrates the results of the sensitivity tests conducted for both GRASP variants. The first plot represents the sensitivity of GRASP-VL. It can be observed that the algorithm exhibited a limited sensitivity to parameter changes, with slightly improved results observed for lower levels of greediness. This behavior may be attributed to the algorithm's consideration of all good candidate solutions during the initial stages, coupled with the clustered distribution of nodes.

In contrast, the cardinality-based approach, which imposes a limit on the size of the RCL, demonstrated greater sensitivity to changes in the parameter n . This observation is expected, as a smaller RCL allows for a higher likelihood of selecting the optimal node for the subsequent visit.

Table 6.10 presents the results of the experimental analysis conducted for the GRASP variants. The first two columns provide the instance names and the BSFs. The subsequent three columns report the best solution costs, the gaps between these solutions and the BSFs, and the average solution costs for the GRASP-CRD variant. The final three columns present the same information for the GRASP-VL approach.

Table 6.10: Computational results of GRASP for the EVRPD instances

Instance	GRASP-CRD		GRASP-VL	
	$Cost_{best}$	$Cost_{avg}$	$Cost_{best}$	$Cost_{avg}$
n22-k4-s10-14	1136.29	1142.48	1293.90	1295.43
n22-k4-s11-12	1405.41	1410.21	1463.78	1464.55
n22-k4-s12-16	1239.74	1247.42	1421.66	1423.80
n22-k4-s6-17	1602.32	1617.77	2053.43	2054.62
n22-k4-s8-14	1189.32	1192.77	1293.83	1295.47
n22-k4-s9-19	1874.20	1879.94	2278.81	2279.25
n33-k4-s1-9	3615.09	3622.40	3793.41	3798.25
n33-k4-s14-22	4038.24	4049.83	4038.50	4046.52
n33-k4-s2-13	3434.82	3442.55	3461.27	3505.41
n33-k4-s3-17	3331.42	3375.77	3328.80	3366.99
n33-k4-s4-5	3810.39	3878.80	4591.91	4613.57
n33-k4-s7-25	3821.37	3830.03	3909.77	3922.74
n51-k5-s11-19	3104.68	3144.38	3300.97	3389.15
n51-k5-s11-19-27-47	1968.93	2089.22	1958.55	1992.22
n51-k5-s2-17	2953.84	3000.79	3038.33	3122.75
n51-k5-s2-4-17-46	2960.97	3028.70	3014.60	3089.14
n51-k5-s27-47	1975.07	2070.98	1950.62	1983.73
n51-k5-s32-37	4998.20	5074.82	4973.86	5030.61
n51-k5-s4-46	4205.47	4233.21	5066.18	5148.52
n51-k5-s6-12	2634.67	2674.66	2739.78	2769.80
n51-k5-s6-12-32-37	2582.77	2723.38	2609.31	2669.19
n22-k4-s10-14	1136.29	1142.48	1293.90	1295.43
Average	2756.34	2796.67	2932.44	2964.84

The GRASP-CRD variant demonstrated excellent performance by generating new BSFs for four small instances. This algorithm restricts the size of the RCL while including as many of the closest customers as possible.

On the contrary, the GRASP-VL algorithm constructs an RCL that accommodates all good nodes to visit next, potentially leading to an RCL that is too large and negating its intended benefits.

The unbiased node selection exacerbates this issue, resulting in suboptimal solutions. Given the highly constrained nature of the problem, where infeasible solutions are not accepted as intermediate solutions by the VND, it becomes challenging to escape from poor solutions. Nevertheless, GRASP-VL outperformed GRASP-CRD in four of the larger instances and exhibited better average solutions in six instances.

Similar to BCO, this implementation of GRASP does not incorporate any memory components. Consequently, GRASP-CRD demonstrated good performance for smaller instances but struggled with larger ones.

6.4.5 Results Summary

Table 6.11: Gap% of best results to BSFs.

Instances	ACS	HACS	MMAS	HMMAS	BCO	SA	SA	SA	GRASP	GRASP
						EXP	LIN	LOG		
n22-k4-s10-14	0.70	0.80	0.70	0.80	0.25	0.70	0.95	0.95	0.00	13.87
n22-k4-s11-12	0.00	0.15	0.02	0.14	0.15	0.37	0.52	0.94	0.10	4.26
n22-k4-s12-16	0.29	0.35	0.11	0.10	0.11	0.64	1.02	1.13	0.00	14.67
n22-k4-s6-17	1.59	1.60	0.52	0.74	0.14	0.23	1.60	1.92	0.00	28.15
n22-k4-s8-14	0.16	0.40	0.16	0.40	0.16	0.40	0.74	1.05	0.00	8.79
n22-k4-s9-19	0.26	0.01	0.01	0.15	0.00	0.25	0.40	0.22	0.01	21.60
n33-k4-s1-9	0.01	0.03	0.00	0.02	0.07	0.03	0.26	0.33	0.44	5.40
n33-k4-s14-22	0.06	0.06	0.00	0.04	0.05	0.14	0.16	0.29	0.13	0.13
n33-k4-s2-13	0.00	0.00	0.00	0.00	0.06	0.01	0.00	0.26	0.17	0.95
n33-k4-s3-17	4.02	4.13	0.00	0.20	0.15	3.99	3.99	4.05	0.73	0.65
n33-k4-s4-5	0.00	0.01	0.00	0.02	0.06	0.01	0.04	0.18	0.39	20.98
n33-k4-s7-25	0.01	0.04	0.00	0.00	0.01	0.00	0.15	0.29	0.05	2.36
n51-k5-s11-19	0.63	0.80	0.81	1.37	1.37	0.00	0.39	0.98	2.03	8.48
n51-k5-s11-19-27-47	0.00	0.23	0.06	0.25	0.30	0.54	0.77	1.49	2.73	2.19
n51-k5-s2-17	0.21	0.61	0.84	0.77	1.43	0.00	0.38	1.36	2.39	5.31
n51-k5-s2-4-17-46	0.00	0.22	0.04	0.72	1.42	0.06	0.31	0.48	2.25	4.10
n51-k5-s27-47	0.05	0.18	0.00	0.19	0.18	0.60	0.73	0.81	3.00	1.73
n51-k5-s32-37	0.00	0.04	0.06	0.14	0.11	0.63	0.53	2.46	1.62	1.12
n51-k5-s4-46	0.01	0.05	0.03	0.15	0.29	0.00	0.03	0.47	0.85	21.50
n51-k5-s6-12	0.19	0.11	0.00	0.24	1.21	0.28	0.20	0.71	3.69	7.83
n51-k5-s6-12-32-37	0.09	0.12	0.00	0.21	1.13	0.20	0.89	1.19	1.53	2.58
Average	0.39	0.47	0.16	0.32	0.41	0.43	0.67	1.03	1.05	8.41

In this last section of the results, a summary of all the proposed algorithms is presented and their performance is compared. Table 6.11 presents the percentage gap of the best solutions of each algorithm to the BSF. All the algorithms are included.

As observed from the results, the MMAS algorithm demonstrated the highest level of performance, generating 9 BSFs and exhibiting the smallest average deviation from the BSF at just 0.36%. Following closely, HMMAS showcased the second-best average deviation, albeit only contributing one BSF to the results. In contrast, the ACS algorithm displayed a comparatively higher average gap from the BSF, yet it generated four BSFs.

The BCO algorithm managed to generate only one BSF, similarly to SA-LIN. However, the SA-EXP variant managed to generate four BSFs. The SA-LOG, along with HACS were the only two algorithms that did not generate any BSFs.

Table 6.12: Gap% of average results to average BSFs.

Instances	ACS	HACS	MMAS	HMMAS	BCO	SA	SA	SA	GRASP	GRASP
						EXP	LIN	LOG		
n22-k4-s10-14	0.64	1.37	0.89	1.77	0.39	5.76	8.48	10.91	0.00	13.39
n22-k4-s11-12	2.04	0.59	1.98	0.85	0.14	3.19	4.96	5.77	0.00	3.85
n22-k4-s12-16	0.48	0.97	0.01	0.14	0.00	2.54	4.89	7.15	0.09	14.24
n22-k4-s6-17	1.43	1.90	0.63	0.94	0.24	3.14	5.64	6.70	0.00	27.00
n22-k4-s8-14	0.52	1.20	2.18	2.92	0.57	5.62	8.06	8.22	0.00	8.61
n22-k4-s9-19	0.33	0.30	0.08	0.14	0.00	1.61	2.54	3.16	0.12	21.38
n33-k4-s1-9	0.06	0.11	0.00	0.07	0.17	1.59	2.57	3.73	0.57	5.45
n33-k4-s14-22	0.06	0.07	0.00	0.04	0.01	0.89	1.90	1.95	0.30	0.22
n33-k4-s2-13	0.01	0.08	0.00	0.06	0.21	0.39	0.87	1.96	0.28	2.11
n33-k4-s3-17	4.23	4.15	0.00	0.47	0.37	6.55	9.28	9.52	1.70	1.44
n33-k4-s4-5	0.00	0.02	0.04	0.09	0.08	0.10	0.31	0.84	2.10	21.44
n33-k4-s7-25	0.03	0.05	0.00	0.03	0.04	1.29	2.28	3.55	0.11	2.53
n51-k5-s11-19	0.00	0.26	1.02	1.97	1.78	0.49	2.31	5.32	1.88	9.81
n51-k5-s11-19-27-47	0.15	0.33	0.00	0.38	0.53	12.56	19.25	21.98	8.50	3.47
n51-k5-s2-17	0.00	0.24	0.49	0.84	1.59	0.53	2.13	6.22	2.70	6.87
n51-k5-s2-4-17-46	0.00	0.22	0.53	1.03	2.04	2.73	4.29	8.70	3.62	5.69
n51-k5-s27-47	0.19	0.33	0.00	0.26	0.54	16.21	20.07	23.76	7.57	3.04
n51-k5-s32-37	0.00	0.07	0.30	0.64	0.63	4.05	4.60	5.84	3.05	2.16
n51-k5-s4-46	0.05	0.12	0.00	0.19	3.25	0.47	1.08	4.14	1.28	23.18
n51-k5-s6-12	0.29	0.57	0.00	0.52	2.59	1.17	2.56	9.00	4.72	8.44
n51-k5-s6-12-32-37	0.25	0.56	0.00	0.63	3.11	7.52	10.98	16.58	6.61	4.49
Average	0.51	0.64	0.39	0.67	0.87	3.73	5.67	7.86	2.15	8.99

The GRASP-VL variant exhibited poor competitiveness in this study, failing to yield notable results. Interestingly, the GRASP-CRD variant demonstrated significant potential by generating four BSFs.

Overall, the performance evaluation of the proposed algorithms suggests that MMAS outperformed the other algorithms in terms of both the number of BSFs generated and the average gap from the BSF. ACS, SA-EXP, and GRASP-CRD showed promising performance in terms of contributing BSFs, albeit with slightly higher average gaps. On the other hand, GRASP-VL was deemed ineffective. These findings shed light on the relative strengths and weaknesses of the examined algorithms, providing valuable insights for future research and algorithm selection in the context of the problem under investigation.

The average performance of the algorithms is presented in Table 6.12. In this Table it is evident that the ACO algorithms outperformed the other algorithms on the larger instances, while BCO and GRASP-CRD provided the BSFs for the six small instances. The ACO and BCO implementations had an average gap from the optimal average performance lower than 1%, while the rest of the algorithms were unable to keep up. GRASP-VL was again the worst performer, with an average gap of almost 9%.

In order to assess and compare the performance of the algorithms and determine whether they exhibit statistically significant differences in their ability to generate results, a Wilcoxon signed-rank test was conducted. This non-parametric test was employed as it does not rely on any assumptions regarding the distribution of the data. All algorithms were compared against each other to evaluate their relative performance.

The results of the Wilcoxon signed-rank test, as presented in Table 6.13, aim to examine the

Table 6.13: Wilcoxon test for the average results of EVRPD algorithms

	ACS	HACS	MMAS	HMMAS	BCO	SA-EXP	SA-LIN	SA-LOG	GRASP-CRD
HACS	x								
MMAS	N	N							
HMMAS	N	N	x						
BCO	N	N	x	N					
SA-EXP	x	x	x	x	x				
SA-LIN	x	x	x	x	x	x			
SA-LOG	x	x	x	x	x	x	x		
GRASP-CRD	x	x	x	x	x	N	x	x	
GRASP-VL	x	x	x	x	x	x	N	N	x

null hypothesis (H_0) that the compared methods are capable of producing solutions of equal quality, with a maximum risk level of 5%. When the null hypothesis is rejected, denoted by an x, it indicates that there is insufficient evidence to support that the two tested methods yield results of equivalent quality. Conversely, when the null hypothesis is not rejected, indicated by **N**, it signifies that the statistical analysis does not provide enough evidence to reject the null hypothesis.

In this particular case, Table 6.13 provides insights based on the average values of the algorithms for each instance, thereby enabling a comprehensive evaluation of their overall performance. In the case of ACS, the null hypothesis is not rejected when compared to MMAS, HMMAS, and BCO. The same is true for its Hybrid variant as well. In addition, it was not rejected when comparing HMMAS and BCO, SA-EXP and GRASP-CRD, SA-LIN and GRASP-VL, and lastly SA-LOG and GRASP-VL. Subsequently, the superiority of the ACO methods is verified by this statistical test. On the other hand, SA and GRASP variants did contribute a number of BSFs; however, their average performance was inferior.

6.5 Conclusions

In conclusion, this thesis introduced the Electric Vehicle Routing Problem with Drones, a novel problem that combines the use of electric ground vehicles and drones to optimize energy consumption in logistics operations. The EVRPD leverages the common characteristics of drones and electric vans, such as zero emissions and low noise pollution, to create an eco-friendly and efficient delivery model, particularly suitable for urban areas.

The mathematical formulation of the EVRPD was proposed, incorporating elements from the EVRP, VRPD, and 2e-VRP variants. The emphasis was placed on minimizing energy consumption by optimizing the routing of vehicles, with a focus on payload weight as a key factor. Customer demands were categorized into three weight class categories, and drones were assigned maximum weight and item capacity.

To address the EVRPD, four different solution approaches were considered: Ant Colony Optimization with variations of Ant Colony System and Max-Min Ant System, Bee Colony Optimization, Simulated Annealing, and Greedy Randomized Adaptive Search Procedure. A Variable Neighborhood Descent algorithm was incorporated to enhance the solution quality.

The ACO methods demonstrated promising performance, with MMAS outperforming the hybrid versions in terms of both results and computational time. The Bee Colony method showed adequate performance for small instances but lagged behind in larger instances. The SA algorithm, specifically

the exponential variant, proved to be the best-performing among the three tested variants, achieving good results with low sensitivity to parameter changes. Two variations of GRASP, GRASP-VL and GRASP-CRD, were developed, with GRASP-CRD generating new best solutions on small instances.

Future research on the EVRPD could explore variants incorporating battery swaps for drones and EV recharging, as well as dynamic versions that respond to unpredictable changes in energy levels. Additional parameters affecting energy consumption, such as weather conditions and real-time battery updates, can be considered. Furthermore, the EVRPD can be expanded to account for more realistic factors and scenarios, including the use of drones for vehicle restocking. There are numerous opportunities for further research in the EVRPD, given the strong interest from the automotive and logistics industries.

Chapter 7

Conclusions

The race to catch up with the accelerating pace of climate change and its far-reaching consequences has prompted the reintroduction and widespread adoption of EVs. This shift in the automotive industry reflects a concerted effort to mitigate GhG emissions, reduce reliance on fossil fuels, and promote a sustainable and low-carbon transportation ecosystem. By promoting EVs as an alternative to conventional ICE vehicles, policymakers, researchers, and industry stakeholders are attempting to coordinate technological advancements, regulatory frameworks, and consumer preferences to meet the pressing challenges of decarbonization and green energy transition.

The objective of this thesis is to support the transition towards green mobility with an emphasis on logistics operations, a sector that poses significant challenges and necessitates a transformative shift. These challenges arise due to various factors, including the sheer scale of logistics operations, the reliance on conventional transportation modes, and the intricate network of supply chains. Additionally, the time-sensitive nature of logistics operations, coupled with the need to ensure cost-effectiveness and efficient delivery, introduces further complexity to the task of implementing sustainable practices.

Two prominent directions can be recognised in regards to the green mobility transition, infrastructure development and routing operations research, both of which were addressed in this study. The first direction, infrastructure development, encompasses the establishment of the physical and technological framework required to support the integration of sustainable transportation systems. In pursuit of this objective, this thesis makes a notable contribution with the development of a trip simulation model incorporating stochastic elements. The primary purpose of this model is to identify the road network edges that experience significant traffic volume, thereby identifying the areas that would derive the greatest advantage from the development of charging infrastructure. By incorporating stochastic elements into the simulation framework, the realism and accuracy of the analysis is enhanced, enabling a more robust assessment of the targeted locations for optimal infrastructure development.

The second direction revolves around routing operations research, with the primary goal of minimizing energy consumption. This involves the formulation of novel logistics operations schemes, taking into account the specific constraints posed by EVs and the corresponding transportation requirements. In this regard, this thesis introduces three novel variants of the VRP that address these considerations. Two of these variants concentrate on alternative charging strategies, aiming to optimize routing plans considering the operational requirements. The third variant explores the

integration of electric vans and drones within delivery operations, exploring the potential synergies and efficiencies that can be achieved through this hybrid approach. Collectively, these VRP variants contribute to the advancement of logistics operations by providing tailored solutions that accommodate the limitations and opportunities associated with EVs, while simultaneously catering to the evolving demands of transportation logistics. By leveraging meta-heuristic algorithms, data analytics, and simulation models, this research aims to enhance the operational efficiency and sustainability of transportation networks in light of the ongoing electric mobility revolution.

In summary, both infrastructure development and routing operations research have been examined in this thesis. The challenges, opportunities, and strategies associated with each direction are identified, shedding light on their interconnectedness and synergistic potential. By addressing these two key dimensions, the thesis contributes to the broader understanding of the green mobility transition and provides valuable insights for policymakers, industry stakeholders, and fellow researchers seeking to navigate the complex landscape of sustainable transportation. The following paragraphs of this section provide a detailed overview of the research conducted, outlining its key findings and implications, while also highlighting potential avenues for future investigations and advancements in the field.

The literature review section of this thesis offers a comprehensive and thorough examination of the various aspects related to the operation of EVs, focusing specifically on two key areas: charging infrastructure and route planning. By exploring the existing body of research and scholarly discourse in these domains, this section aims to present a well-rounded review that encompasses the current state of knowledge and identifies the gaps and challenges that exist. To begin with, the review delves into the topic of EV charging, examining the different types of charging stations available, such as public charging, and fast charging. It explores the advantages and limitations of each charging method, considering factors such as charging speeds, and environmental attributes. Furthermore, the review investigates the challenges associated with charging infrastructure, such as the distribution and availability of charging stations, as well as different applications. In addition the literature review also focuses on the significance of route planning for EVs. It explores the various factors that need to be considered when planning routes for EV travel, including distance, energy consumption, charging station availability, and time efficiency. The review examines existing approaches and algorithms for optimizing route planning for EVs, considering factors such as real-time traffic conditions, topography, and energy consumption models. Moreover, it highlights the importance of integrating route planning with charging station locations to ensure effective and efficient long-distance EV travel. Through an extensive review of the literature, this section not only provides an overview of the current knowledge on EV charging and route planning but also identifies the gaps and research opportunities that exist within these areas.

Section 3 presented a variant of the Charging Station Location Problem, focused on long distance trips. Previous formulations of the CSLP have predominantly concentrated on urban environments, where EVs have been utilized as environmentally friendly alternatives for city settings, and often associated with extremely limited driving ranges. This research aimed to address long-distance EV travel within the mainland of Greece, considering the current inadequate charging infrastructure in the country in combination with the rising EV market share. To determine the road segments that require fast CS deployment in order to enable long-distance journeys, a Monte-Carlo simulation was employed. A diverse range of popular EVs was subjected to testing using realistic energy consumption values, alongside a stochastic load generator. Additionally, two distinct temperature settings were evaluated during the experimentation phase. The outcomes of this study hold significant implications for policymakers, stakeholders, and individuals with an interest in EVs within Greece.

The findings can provide valuable insights to inform policy decisions and strategic planning, with the aim of enhancing the EV charging network and supporting the adoption of EVs in the country by enabling long-distance trips.

In Section 4, the novel Close Open Electric Vehicle Routing Problem was presented, as the first Close Open variant to consider EVs. The approach of this variant differs from the existing literature in the planning of charging stops, suggesting the removal of these stops from the middle of the operations and their introduction at the end of the delivery phase. This scenario provides carriers with the much needed assurance that all of their planned deliveries will take place without relying on finding an available and operational CS, which is common problem among EV users today. To provide a mathematical formulation as true to reality as possible, the objective function aimed to concurrently minimize the total energy consumption and the total number of EVs with a scalarized weighted objective function. The energy consumption was calculated based on both the distance to cover and the weight being carried. This is especially important to consider in the case of EVs. To provide solutions of adequate quality, initial solutions were generated with a method similar to that of the Restricted Candidates List of the GRASP. Then, they were improved using a VNS algorithm with Simulated Annealing selection criterion method. Instances from the EVRP literature were adapted for use in COEVRP, with smaller instances solved both by a commercial solver and the proposed solution algorithm. The results highlighted the effectiveness of the proposed hybrid algorithm and the benefit of the suggested selection criterion. The operators included in the VNS were also tested to ensure that no redundancies were introduced.

Section 5, presented the Close Open Electric Vehicle Routing Problem with Mixed Fleets, extending the COEVRP formulation to consider a Mixed Fleet of owned and rented EVs. COMF-EVRP assumes that a logistics company may initially own a small fleet of EVs, enough to cover their basic needs, and rent additional EVs when the demand requires them. Such an approach could become reality for companies that lack the funding to acquire a large fleet of EVs, since EVs tend to be more expensive, usually require the installation of charging equipment and may also include costs to upgrade the local grid connection to withstand the additional load from charging multiple EVs. The objective function in this case minimized the total energy consumption and the number of rented EVs. The same instances introduced in COEVRP were also used for COMF-EVRP; however, to provide solutions two Discrete Swarm Intelligence Algorithms were proposed. The first was the Bee Colony Optimization which is a memory-less approach that can provide better exploration of the search space, and the second was the Ant Colony Optimization with two variants being tested, the Ant Colony System and the Max-Min Ant System. ACO approaches have stronger intensification and are known to perform well. Another difference between the methods is in the initial solution construction as BCO relies on external solutions while ACO methods generate their own solutions. All methods were combined with a VNS framework, including four operators. ACS performed the best, providing 37 of the BSFs, MMAS provided 10, and BCO provided 9. On average, BCO used more vehicles than the ACO methods. Smaller instances were also solved with a commercial solver.

Section 6 presents the last topic of research, combining road EVs with Drones in the novel Electric Vehicle Routing Problem with Drones. This is the first formulation of VRP with Drones that considers EVs as road vehicles. Companies such as Mercedes-Benz and UPS are already researching this combinations of vehicles. In the formulation presented, all deliveries are made with drones, while road EVs are used as mobile depots for the drones, allowing both types of vehicles to travel less; thus, expanding the operational range of both. The objective function aimed to minimize the energy consumption of both EVs and drones, while considering the weight they carry. Instances from the Two-Echelon VRP were adapted for use in the EVRPD, with satellite locations used as

Designated parking spaces for the EVs. The energy capacity of the Drones was set to a tenth of the capacity of road EVs. The packages carried by the drones were assumed to belong in one of three weight classes, ranging from 1 to 3 kilograms each, with a maximum of 3 packages and 4 kilograms per drone. A number of heuristic and meta-heuristic algorithms were tested on the problem, namely, the two ACO formulations and the BCO presented in COMFEVRP, as well as three variants of SA similar to that presented in COEVRP, and two variants of GRASP with different methods for the creation of restricted candidates lists. ACO provided most BSFs, with SA matching a few of them. GRASP provided BSFs for four small instances, while BCO managed to provide only one BSF. All of them were combined with Variable Neighborhood Descent algorithm, including eight LS operators.

While new types of EVs have been introduced, their exploration and understanding in the context of logistics operations remain relatively uncharted territory. The present research, constrained within the scope of a PhD thesis, aims to shed light on these novel developments by formulating models that effectively leverage the potential of EVs and also help develop realistic infrastructure planning approaches. Numerous avenues for future research exist to advance the knowledge base pertaining to EVs. Firstly, the development of CSs warrants investigation at a localized level, as there is no universal approach that can singularly address this challenge. Thus, it is crucial to examine and understand the specific context of each location, considering factors such as infrastructure, demand patterns, and user requirements. Moreover, special attention should be devoted to accurately capturing and representing the preferences and needs of individuals, ensuring that charging station networks are designed and tailored to serve their users. In addition, there is a need to expand and extend the Vehicle Routing Problem to encompass a wider range of vehicles, encompassing various sizes, autonomy levels (ranging from fully autonomous to human-operated), and exploit their unique capabilities to the maximum extent possible. Researchers should prioritize the development of innovative routing strategies that integrate advanced levels of automation. By harnessing emerging technologies like artificial intelligence and machine learning, new routing algorithms can be devised, exhibiting exceptional adaptabilities, and foregoing the static solution methodologies employed in the past. Lastly, integrating real-world data into research methodologies holds the potential to enhance the precision and dependability of research findings. By incorporating data derived from EVs deployed in actual settings, researchers can analyze actual usage patterns, energy consumption profiles, and charging behaviors. This empirical approach will contribute to a more comprehensive understanding of EV performance while enabling the validation of simulation models and optimization algorithms.

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