*Cost of energy optimisation for the operation of microgrids based on Demand Response techniques*


*Nikolaos Kampelis*

School of Environmental Engineering

Technical University of Crete


This dissertation is submitted for the degree of

*Doctor of Philosophy*

May 2020

# Ph.D. Dissertation Committee

*Associate Professor Dionyssia (Denia) Kolokotsa*

*Professor Kostantinos Kalaitzakis*

*Professor Georgios Karatzas*

*Professor Michael Lazaridis*

*Professor Theocharis Tsoutsos*

*Associate Professor Fotios Kanelos*

*Associate Professor Eftychios Koutroulis*

# Acknowledgments

I would first of all like to express my sincere appreciation and gratitude to my supervisor Associate Professor Denia Kolokotsa. Her consistent guidance and support during this Ph.D. research has been vital and it could not have been materialised otherwise. Furthermore, I owe special thanks to Dr. Cristina Cristalli and Loccioni Group for providing us access to Leaf Community in the framework of Smart GEMS Marie Curie H2020 Project. Working with the people in Loccioni has been motivational and a great experience overall. Moreover, I would like to thank Prof. Kostas Kalaitzakis for his precious time in overseeing the progress of this work and thoughtful suggestions. In addition, I would like to express many thanks to Associate Professor Eftychios Koutroulis, Professor Theocharis Tsoutsos and all members of the dissertation committee for their valuable recommendations and comments. Also, I would like to thank all the members of the EMBER lab for the fruitful collaboration, the team work which really enabled this research– and much more - to take place. In specific I would like to thank my colleague and good friend Dr. Kostas Gobakis who has advised and assisted me in dealing with many technical issues. Also, I would like to thank Mrs. Aggeliki Mavrigiannaki for her excellent (!) support in the course of Smart GEMS research and management activities. In addition, I ought to thank Mrs. Elisavet Tsekeri and Mr. Nikos Sifakis for their hard and high-quality collaborative work. Last but not least, I would like to say a very big thank you to all my family and especially my wife Ermioni, my daughter Georgia and my son Stavros for being patient when I was absent.

Finally, I dedicate this work to my parents and sister for all they have done for me…

# Περίληψη

Η παρούσα διδακτορική διατριβή αφορά την ανάπτυξη και αξιολόγηση προηγμένων τεχνικών απόκρισης ζήτησης σε κτιριακές εγκαταστάσεις σχεδόν μηδενικής ενεργειακής κατανάλωσης και μικροδίκτυα.

Στο παραπάνω πλαίσιο, έγινε κατ΄αρχήν λεπτομερής διερεύνηση και ανάλυση της ενεργειακής απόδοσης ενός πρότυπου κτιρίου κατοικιών και ενός πρότυπου κτιρίου βιομηχανικής χρήσης (/γραφείων). Τα κτίρια Leaf House και Leaf Lab που μελετήθηκαν, χαρακτηρίζονται ως σχεδόν μηδενικής ενεργειακής κατανάλωσης (near-zero energy buildings), καθώς συνδυάζουν αποτελεσματικά συστήματα διαχείρισης ενέργειας με μία ευρεία γκάμα αυτοματισμών, τεχνολογίες ΑΠΕ και αποθήκευση ενέργειας. Για την αξιολόγηση της ενεργειακής απόδοσης των κτιρίων αυτών αναπτύχθηκε και χρησιμοποιήθηκε μεθοδολογία η οποία περιελάμβανε τη λήψη και αξιοποίηση μετρήσεων συνθηκών εσωτερικού και εξωτερικού περιβάλλοντος, ενεργειακών καταναλώσεων και ηλεκτροπαραγωγής από ΑΠΕ. Επιπρόσθετα, αναπτύχθηκαν μοντέλα δυναμικής προσομοίωσης των κτιριακών εγκαταστάσεων με χρήση των λογισμικών Open Studio / EnergyPlus, για τα οποία έγινε επαλήθευση βάσει των παραπάνω μετρήσεων. Η ανάλυση ανέδειξε την αναγκαιότητα επαλήθευσης και ανάλυσης της πραγματικής ενεργειακής απόδοσης των κτιριακών εγκαταστάσεων καθώς και της ενδεχόμενης απόκλισης (performance gap) από την «θεωρητική» απόδοση που προκύπτει βάσει υπολογιστικών μοντέλων που χρησιμοποιούνται συνήθως κατά τον σχεδιασμό ή την ενεργειακή αναβάθμιση ενός κτιρίου.

Η δημιουργία επαληθευμένων μοντέλων ενεργειακής απόδοσης των κτιρίων αποτελεί απαραίτητη προϋπόθεση για την ανάπτυξη της μεθοδολογίας

αξιολόγησης προηγμένης τεχνικής απόκρισης ζήτησης όπως περιγράφεται στη συνέχεια.

Ειδικότερα, αξιοποιώντας τα αποτελέσματα της πρώτης φάσης, αναπτύχθηκε μεθοδολογία για την μελέτη και αξιολόγηση της δυνατότητας μετατόπισης φορτίου του συστήματος θέρμανσης, μηχανικού αερισμού, κλιματισμού (HVAC) του κτιρίου βιομηχανικής χρήσης Leaf Lab. Η εν λόγω προσέγγιση, αφορά τον καθορίσμό της ωριαίας τιμής του θερμοστάτη χώρου από μοντέλο γενετικού αλγόριθμου. Τα σενάρια που αναπτύχθηκαν και αξιολογήθηκαν αφορούν μεταβλητό ανά ώρα κόστος προμήθειας ηλεκτρικής ενέργειας που βασίσθηκε σε δεδομένα από την αγορά ενέργειας της περιοχής ενδιαφέροντος. Το μοντέλο βελτιστοποίησης λαμβάνει υπόψη τη διακύμανση του κόστους κατανάλωσης ηλεκτρικής ενέργειας και του δείκτη θερμικής άνεσης Predicted Mean Vote (PMV). Με βάση τα αποτελέσματα προκύπτει σημαντικό περιθώριο εξοικονόμησης ενέργειας και μείωσης του ενεργειακού κόστους κατανάλωσης ηλεκτρικής ενέργειας διατηρώντας τα επίπεδα θερμικής άνεσης και μεταβολής της τιμής του θερμοστάτη χώρου εντός των ορίων που θέτουν τα σχετικά διεθνή πρότυπα.

Παράλληλα, αναπτύχθηκε μέθοδος βραχυχρόνιας πρόβλεψης (με χρονικό ορίζοντα 24 ώρες) των ηλεκτρικών καταναλώσεων καθώς και της ηλεκτροπαραγωγής ενέργειας από ΑΠΕ με χρήση μοντέλων Τεχνητών Νευρωνικών Δικτύων. Η μέθοδος χρησιμοποιήθηκε για την εξαγωγή και αξιολόγηση αποτελεσμάτων τόσο σε επίπεδο κτιρίου όσο και σε επίπεδο μικροδικτύου. Τα αποτελέσματα που εξήχθησαν εμφανίζουν υψηλά επίπεδα συσχέτισης (Pearson's coefficient, MBE, MAPE) μεταξύ των προβλεπόμενων και πραγματικών τιμών. Εν συνεχεία, αναπτύχθηκε 2-στοχικό μοντέλο βελτιστοποίησης ΓΑ για τη μετατόπιση φορτίου (load shifting) και μείωση του κόστους ηλεκτρικής ενέργειας της επόμενης ημέρας σε επίπεδο κτιρίου και μικροδικτύου. Η παραπάνω συνδυαστική μέθοδος ΤΝΔ/ΓΑ ελέγχθηκε ενδελεχώς και χρησιμοποιήθηκε επιτυχώς για την εξαγωγή ισορροπημένων λύσεων μείωσης του κόστους ηλεκτρικής ενέργειας και της μετατόπισης φορτίων σε επίπεδο ομάδας κτιρίων και μικροδικτύου.

# Abstract

This Ph.D. thesis focuses on the development and evaluation of advanced demand response techniques for Near-Zero Energy Buildings (NZEB) and microgrids.

In this context, the energy performance of a residential and an industrial (/office) NZEB was investigated and analysed. The Leaf House (residential) and Leaf Lab (industrial/office) buildings are characterised as NZEB as they effectively integrate energy management systems with a wide range of automation, renewable energy sources, and energy storage. For the evaluation of the energy performance of these buildings, a method was developed and deployed which involved the collection and exploitation of measurements concerning the indoor and outdoor environment, energy consumption and renewable energy production. In addition, dynamic Open Studio / EnergyPlus models of the energy performance of buildings were created and subsequently validated with the aid of the aforementioned measurements and data. The analysis highlighted the importance of evaluating the "performance gap" of buildings as the actual energy performance of buildings can significantly deviate from the "theoretical" values typically used when designing or renovating a building.

Creating validated and dynamic building energy models was a prerequisite for the development and testing of the advanced HVAC demand response methodology described hereafter.

In this context, a novel methodology, for investigating and evaluating the potential HVAC load shifting based on temperature setpoint adjustment, was developed and deployed for the industrial building (Leaf Lab). This approach concerns the determination of the hourly temperature set point by a Genetic Algorithm optimisation model. The scenarios that were developed for testing the GA model

take into account variable hourly electrical energy prices based on real data by the Day-Ahead market of the building's region. The optimisation model takes into account variation of the cost of the HVAC's electrical energy consumption and the Predicted Mean Vote (PMV) index of thermal comfort. Results revealed significant margins of energy and cost savings while comfort levels and temperature setpoint drift are kept in line with regulations defined by well-established international standards.

In parallel, a method for short-term (24 hours ahead) prediction of the electrical consumption and Renewable Energy Sources' production was developed based on Artificial Neural Network models. The method was effectively tested using various datasets to produce results of a high correlation between the real and predicted values, both at building and at the microgrid level, as justified by various indicators (Pearson's coefficient, MBE, MAPE). Furthermore, a double goal Genetic Algorithm optimisation model of the electrical energy cost and load shifting for the day ahead was developed and thoroughly tested. Day-ahead ANN-based predicted data are used as input for the GA optimisation model to produce balanced solutions for cost savings and load shifting at both building and microgrid level.

# Publications

The following articles have been published in the context of this doctoral dissertation:

### Publications in scientific journals directly related to the PhD thesis

- N. Kampelis, K. Gobakis, V. Vagias, D. Kolokotsa, L. Standardi, D. Isidon, C. Cristalli, F. M. Montagnino, F. Paredes, P. Muratore, L. Venezia, M. Kyprianou Dracou, A. Montenon, A. Pyrgou, Theonni Karlessi, Mat Santamouris., "Evaluation of the Performance Gap in Industrial, Residential & Tertiary Near-Zero Energy Buildings" Energy and Buildings (IF: 4.457, 5-year IF:4.779 148), (2017).
- N. Kampelis, E.Tsekeri, D. Kolokotsa, K. Kalaitzakis, D. Isidori, C. Cristalli, Development of Demand Response energy management optimisation at building and district level using Genetic Algorithm and Artificial Neural Network modeling power predictions, Energies (IF: 2.676, 5-year IF: 3.045), 2018
- N. Kampelis, N. Sifakis, D. Kolokotsa, K. Kalaitzakis, K. Gobakis, D. Isidori, C.Cristalli, Genetic HVAC Optimisation Algorithm for Industrial Near-Zero Energy Building Demand Response, Energies (IF: 2.676, 5-year IF: 3.045), 2019

### Publications in scientific journals not directly related to the PhD thesis

- Kampelis, N.; Papayiannis, G.I.; Kolokotsa, D.; Galanis, G.N.; Isidori, D.; Cristalli, C.; Yannacopoulos, A.N. An Integrated Energy Simulation Model for Buildings. *Energies* 2020, *13*, 1170.
- D. Kolokotsa, N. Kampelis, A. Mavrigiannaki, M. Gentilozzi, Filippo Paredes, Fabio Montagnino, Luca Venezia, On the integration of the energy storage in smart grids: Technologies and applications, Energy Storage, Wiley, 2019
- D. Kolokotsa, K.Gobakis, S.Papantoniou, C.Georgatou, N. Kampelis. K.Kalaitzakis, K. Vasilakopoulou, M. Santamouris., "Development of a web-based energy management system for University Campuses: The CAMP-IT platform" Energy and Buildings (IF: 4.457, 5-year IF: 4.779 148), vol. 123, pp. 119–135, Jul. 2016.

## Publications in international scientific conferences

- Kolokotsa Denia, Mavrigiannaki Angeliki, Kampelis Nikos, Paredes Filippo, Montagnino Fabio Maria. Development of ANN algorithms for forecasting Fresnel thermal power production. IAPE 2019, Oxford, UK

- Theoni Karlessi, Nikos Kampelis, Denia Kolokotsa, Mat Santamouris, Laura Standardi, D. Isidori, C. Cristalli., "The Concept of Smart and NZEB Buildings and the Integrated Design Approach". International High- Performance Built Environment Conference – A Sustainable Built Environment Conference 2016 Series (SBE16), iHBE 2016.

- N. Kampelis, K. Gobakis, D. Kolokotsa, A. Ferrante, K. Kalaitzakis., "Energy management optimization in camp it infrastructure based on a demand response perspective". In Proceedings CRETE 2016, Fifth International Conference on Industrial & Hazardous Waste Management Chania – Crete – Greece, September 2016.

- Theoni Karlessi, Nikos Kampelis, Denia Kolokotsa, Margarita Assimakopoulos, Mat Santamouris, "Towards sustainable and smart communities: integrating energy-efficient technologies into buildings through a holistic approach", 9th International Conference Improving Energy Efficiency in Commercial Buildings and Smart Communities, At Frankfurt, March 2016.

- Angeliki Mavrigiannaki, Nikos Kampelis, Denia Kolokotsa, Daniele Marchegiani, Laura Standardi, Daniela Isidori, Cristina Christalli., "Development and testing of a micro-grid excess power production forecasting algorithm", 9th International Conference on Sustainability in Energy and Buildings, SEB-17, 5-7 July 2017, Chania, Crete, Greece.

- N. Kampelis, A. Ferrante, D. Kolokotsa, K. Gobakis, L. Standardi, C.Cristalli, "Thermal comfort evaluation in HVAC Demand Response control", 9th International Conference on Sustainability in Energy and Buildings, SEB-17, 5-7 July 2017, Chania, GREECE.

## Contents

## Nomenclature

### Acronyms

| | |
|---|---|
| AC Alternating Current | ESCO Energy Service Company |
| AMI Advanced Metering Infrastructure | FC Fuel Cell |
| ANN Artificial Neural Network | GA Genetic Algorithm |
| ARC Aggregators or Retail Customers | HVAC Heating Ventilation Air Conditioning |
| ANN Artificial Neural Network | HRES Hybrid Renewable Energy System |
| AS Ancillary Services | ID Integrated Design |
| BEMS Building Energy Management System | IoT Internet of Things |
| biPV Building Integrated Photovoltaic | IPMVP International Performance |
| CHP Cogeneration of Heat and Power | Measurement and Verification Protocol |
| CO2-eq Carbon Dioxide equivalent emissions | MAPE Mean Average Percentage Error |
| COP Coefficient of Performance | MBE Mean Bias Error |
| CSP Curtailment Service Provider | MILP Mixed Integer Linear Programming |
| Cv Coefficient of Variance | MINLP Mixed Integer Non-Linear |
| CPP Critical Peak Pricing | Programming |
| DA Day-Ahead | MIP Mixed Integer Programming |
| DARTP Day-Ahead Real Time Pricing | MPPT Maximum Power Tracking |
| DC Direct Current | MT Micro-Turbine |
| DEMS District Energy Management Systems | NARX Nonlinear Autoregressive ANN with |
| DER Distributed Energy Resources | Exogenous Input |
| DG Diesel Generator | NIST National Institute of Standards and |
| DHW Domestic Hot Water | Technology |
| DR Demand Response | NZEB Near Zero Energy Building |
| DRP Demand Response Providers | OpenADR Open Automated Demand Response |
| DSM Demand Side Management | PSO Particle Swarm Optimisation |
| DSO Distribution System Operator | RES Renewable Energy Sources |
| EED Energy Efficiency Directive | RTO Regional Transmission Operator |
| EER Energy Efficiency Ration | RTP Real Time Pricing |
| EMS Energy Management System | PMV Predicted Mean Vote |

| | |
|---|---|
| PPD Percentage of People Dissatisfied | SDG Sustainable Development Goal |
| PV Photovoltaic | ToU Time of Use |
| R Pearson's coefficient | VEN Virtual End Node |
| RH Relative Humidity | VTN Virtual Transfer Node |
| RMSE Room Mean Squared Error | WT Wind Turbine |
| SaaS Software as a Service | ZEB Zero Energy Buildings |

# Symbols

| | |
|---|---|
| $C_i$ day ahead price per hour for hours 1 to 24<br>$C_T$ Total energy bill (€)<br>$C_E$ Total energy charges (€)<br>$C^h_{E\_unit}$ is the day-ahead hourly unit cost of energy in each building (€/kWh)<br>$C_T$ Total tax charges (€)<br>$C_S$ Energy procurement cost (€)<br>$C_N$ Network services cost (€)<br>$C_{S,F}$Energy procurement fixed cost component (€/kWh)<br>$C_{EDD}$ Daily excise duty on electricity and taxes (€)<br>$C_{v,u}$ Various costs normalized per kWh (€/Wh)<br>$C_F$ Fixed cost component (€)<br>$C_{Pmax}$Maximum power cost component (€/kW)<br>$C_{AT}$ Active energy cost component (€/kWh)<br>$C_{A-UC}$ Fixed cost for up to 4GWh per month (€/kWh)<br>$C_{EDH}$ Excise duty per kWh (€/kWh)<br>$C_{FAA}$ Parameter to account for F, AT and A-UC components (€/kWh)<br>$C_{Pmax,F}$ Maximum power fixed cost component (€/kW)<br>Icl Clothing insulation in ($m^2K/W$);<br>IVA Value added tax (€)<br>$Load_{Shift}$ is the daily load shift (kWh) | M Metabolic rate in $W/m^2$<br>$P_i$is hourly average power consumption of the HVAC in kW (equivalent to kWh)<br>$T_{s\,i=1}^{\,24}$hourly temperature set points of the HVAC system the next day<br>$Cost_E$ is the daily energy operating costs (€)<br>$Cost_{E\_Lab}$ is the daily energy operating costs of Leaf Lab (L4) building (€)<br>$Cost_{E\_Summa}$ is the daily energy operating costs of Summa (L2) building (€)<br>$Cost_{E\_Kite}$ is the daily energy operating costs of Kite (L5) building (€)<br>$DA_h$ Day-ahead market prices (€/kWh)<br>$DA_{N,h}$ DA price flexible factor per hour $h$ (€/kWh)<br>RH Relative humidity (%).<br>Tair Air temperature (Tair) in (°C);<br>Tr Mean radiant temperature (Tr) in (°C);<br>Vair Relative air velocity in (m/s);<br>W Effective mechanical power in $W/m^2$;<br>$w_c$ weighting coefficient for the daily operational cost of energy for the HVAC<br>$w_{pmv}$ weighting coefficient for the daily thermal comfort<br>$X^h_E$ is the hourly value of total energy consumption in each building (kWh) |

| | |
|---|---|
| $X_{E_{opt}}^{h}$ is the GA optimised hourly electrical energy (kWh) at building or building group level | $X_{E_{baseline}}^{h}$ is the Baseline hourly electrical energy (kWh) based on day-ahead Neural Network predictions |

# 1. Introduction and state of the art

In broad terms, DR refers to retail customers participating in electricity markets by responding to varying prices over time [1]. Demand Response (DR) is otherwise defined as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized"[2]. On the other hand, DR is inextricably linked with smart grids since an optimum response to real-time signals or any kind of dynamic information requires interoperability, embedded intelligence and advanced controls working harmonically in the same direction.

In parallel, energy consumption in the building sector calls for innovations, effective policies and regulations to enable a new technological paradigm for new and renovated dwellings. In particular, the design and construction of smart and zero energy buildings as well as smart communities is a primary objective that needs to be met as part of the smart grid evolution. Aggregating energy consumption in buildings may, under certain conditions, provide a valuable resource allowing indirect participation in energy markets.

Smart communities can be formed in various physical configurations. Connecting building facilities together to form semi-independent small subdivisions of the main electrical distribution grid offers significant advantages i.e. exploiting on-site energy generation by applying advanced control, intelligence and storage at the local level. The microgrid paradigm fits well with the smart community concept especially with respect to the basic local interconnecting infrastructure and the overall management of energy consumption, renewable energy production and storage. In specific, the microgrid concept is bound to the necessary operations for monitoring, storing and controlling energy flows between smart buildings and other facilities i.e. storage so that renewable energy is optimally deployed.

In this framework, the state of the art in the fields of smart and zero energy buildings is presented first. Recent advances in DR at building and district level are explored with a specific focus of DR in microgrids.

## 1.1 Smart and Zero Energy Buildings

The smart building is a fundamental entity of the smart grid concept. Nonetheless, providing demand flexibility and operational responsiveness in a smart building remains a challenge since it requires a high level of intelligence along with the integration and optimisation of users' actions and decisions. The smart building combines advanced energy management systems overseeing the operation of a range of elegant and multifunctional intelligent equipment to control various building systems such as HVAC, lighting and shading. The smart building user is informed of the building's energy flows and provided with the tools for the dynamic management of systems installed e.g. to adjust indoor environment conditions according to his/r preferences or specific needs, control devices remotely etc. Furthermore, tools assisting users to optimise the energy performance of a smart building and at the same time minimise the cost of the energy bills are envisioned.

In this context, the goal of the efficient exchange of energy and information between the building and the grid in a way that is mutually beneficial must be facilitated. At the distribution level, the energy demand in buildings forms an important asset in terms of the collective power flexibility potential.

Aligned with the smart building, the (Near-) Zero Energy Building concept constitutes a technological paradigm of unquestionable importance since it incorporates the necessary measures for minimising the net energy inflow from the main grid. The NZEB is inherently associated with Integrated Design (ID), high-end energy conservation measures, advanced controls as well as on-site renewable energy generation and exploitation. The NZEB concept resembles the evolution of building design and construction in a holistic way to ensure the true and actual sustainable levels of energy performance.

The concepts of Smart and Zero Energy Buildings have attracted the interest of the scientific community, policy organisations and the industry worldwide. Special attention is paid to coupling integrated design, energy efficiency and renewable energy in new and renovated buildings. From a policy perspective, this is being pursued via strategic energy and environmental objectives, policy initiatives, regulatory reforms and financial incentives. In this regard, the EU has placed a special weight on the reduction of the high energy consumption in the building sector using various policy tools and directives including, among other, the EU 2020 targets, the Energy Performance Building Directive (EPBD), the climate change adaptation and mitigation strategies and the low carbon economy roadmap 2050 [3], [4].

EPBD Recast (2010), imposed member states to ensure all public buildings (or buildings used by public organisations), as well as new buildings, comply with near-zero energy consumption since 2018 and by 2020 respectively. Under this legislative framework, Member States are responsible to report on the detailed progress with respect to Near-Zero Energy Buildings' (NZEBs) agenda implementation in practice so as it needs to be adjusted to reflect national, regional or local conditions.

The NZEB is conceptualised in the EPBD and characterised by a very high energy performance, a very low amount of required energy and a very significant contribution of RES to cover the remaining energy use. Very high energy performance is translated into buildings integrating passive and active systems and falling into the top categories of the energy certification process.

A clear universal definition of a Zero Energy Building is, however, somewhat of a challenge and usually linked to the framework of the analysis i.e. whether carried out for new construction, energy efficiency evaluation or classification, specific research, development of policy tools or another purpose. Definitions may vary according to the metric and period of balance, type of energy use and balance, renewable supply options, connectivity with the grid, requirements, etc. [5]. Apart from the EPBD, linking energy performance to annual normalised primary energy consumption (in kWh/m$^2$/year), various definitions have been proposed including net zero site energy, net zero source energy, net zero energy cost and net zero energy emissions depending on the metric (energy, cost, $CO_{2\text{-eq}}$ emissions) and domain (site or source). Where applicable, a net-zero site energy benchmark is considered most appropriate as it is fully verifiable through on-site measurements and cannot be affected by external factors (i.e. related to the operation of the main grid or the energy market) which may vary according to the dimensions of time, space and territory.

It is noteworthy that quantitative targets linked to zero or near-zero energy performance are dispersed between 0-270 kWh/m$^2$/year of primary energy consumption. Higher figures in this range are associated with hospitals or non-residential buildings [6]. For NZE residential buildings the average targets vary from 33kWh/m$^2$/year in Croatia and 45-50 kWh/m$^2$/year for the many EU member states (Belgium, Estonia, France, Ireland ) while some countries use nondimensional values or an energy performance class (e.g. A++ in Lithuania) [7]. In Italy, the regulation for new dwellings requires a minimum energy efficiency of 65-70kWh/m$^2$ [8]. In Cyprus, the threshold for NZEB is 100 kWh/m$^2$/year of primary energy for new and existing residential buildings and 125 kWh/m$^2$/year of primary energy for non-residential buildings [6].

ZEB or NZEB currently in operation or even those in development stages primarily use fossil fuel based energy sources coupled with renewables such as solar, wind, geothermal or biomass to attain "nearly-zero energy" behaviour[7],[9]. The transition to smart ZEBs from an industrial point of view, depends to some extend on the adoption of common communication protocols, standards and interfaces to enable interoperability of systems, subsystems and the bi-directional flow of energy and information [10]. Coupling existing building energy systems with modern monitoring and control equipment is often a barrier for renovating the existing building infrastructure.

Discussions in this direction expand towards the challenges of NZEB integration in smart grids with the aid of evolving technologies [11], [12]. Various efforts have dealt with optimising the design and operation of building integrated renewables, thermal or electrical storage and holistic energy management using a broad range of techniques. Attention has also been drawn in developing tools for user/customer engagement, increasing transparency of grid operations with the aid of Advanced Monitoring Infrastructure (AMI) and enabling Demand Response (DR) within the Internet of Things (IoT) applications [13].

In many occasions, the actual operating performance of buildings significantly deviates from the designed target. This 'performance gap' is associated to a) the design and construction processes of the building envelope and systems otherwise referred to as the 'design and construction phase 'or b) the management of the building and its facilities or the 'operational phase'. In the design and construction phase, the performance gap is often related to the assumptions / inputs or misuse of calculation methodologies and tools utilised. Furthermore, the performance gap may be linked to the lack of consideration or expertise about the deployment of Integrated Design (ID) principles impacting energy consumption, indoor comfort and health conditions. Performance gap issues are also evident during the construction phase due to improper installation of building envelope components (i.e. insulation, glazing etc.) which may be a result of inadequate training, time limitations, cost-cutting constraints or barriers related with resistance to change [14], [15]. Such phenomena may have as a consequence the occurrence of thermal bridges and high infiltration rates eventually leading to energy losses, high total energy consumption and unhealthy or uncomfortable indoor conditions. Last but not least, energy management and operational inefficiencies are critical to the observed gap in buildings' energy performance, depending on the specificities of each case. This may be due to lack of appropriate maintenance and service, misuse of energy systems' operation or suboptimum performance in systems' integration. However, often there is a valid potential for bridging the 'gap' of underperformance in the buildings' operational phase which can be effectively addressed via a mixture of technological, organisational and training actions.

In terms of the technological progress, indoor environmental quality control and Building Energy Management Systems (BEMS) have evolved considerably in the last decades, in parallel with the growing concern about energy efficiency requirements and the demand for environment friendly buildings. Modern customised building energy management solutions can be exploited to enable better visual, thermal comfort and air quality control. Research efforts in this direction focus on advanced BEMS which can implement sophisticated algorithms capable of predicting and evaluating a range of alternatives in the way buildings exchange energy with the ambient environment and the grid. State of the art BEMS techniques nowadays offer the potential for applying predictive control which may contribute to 20-30% in the reduction of energy consumption [16]–[18] and equivalent operational cost savings. Prediction of energy demand is becoming increasingly effective as part of an overall energy management optimisation process which could be deployed in the near future [16], [17]. Simultaneously, researchers are providing new scientific evidence on how the prediction of renewable energy production can increase its utilisability in building integrated applications and deal with the volatility of Decentralised Energy Resources (DER) and the future microgrids.

Furthermore, smart metering, data processing and interpretation provide useful steps for going deeper into understanding buildings energy behaviour [19]. This is especially important when such knowledge can be developed to inform decisions about the systems' operational strategies based on scientifically sound methodologies and technologically robust processes. In this direction, Demand Response (DR) techniques have been applied in various settings to optimise the operation of building energy systems (i.e. HVAC), to perform active load management and to minimise energy from the grid as well as the respective costs on the demand side [20], [21]. Accordingly, data monitoring i.e. the provision of meaningful information along with practical tools for managing energy consumption, combined with specific incentives provide the fundamentals for actively engaging users in realising the potential of DR wide scale environmental and social benefits. This transition requires targeted investments both in grid infrastructure and at the users' side as well as a transparent, open and attractive regulatory framework to create the supporting framework for innovations which will transform the market in this field.

With respect to renewables, advanced solutions such as concentrating solar thermal technologies have emerged to offer attractive options in meeting the cooling demand during the summer season and reduce heating demand from the grid during winter time. The real challenge with such systems concerns the design of a suitable and cost efficient solution utilizing maximum heat from the sun to fulfil the required energy demand [22].

Other commercially available solutions include building-integrated Photovoltaics (biPV) and small wind turbine systems offering a broad range of designs and technical attributes. Such systems are coupled with inverters normally equipped with Maximum Power Point Tracking (MPPT) and controls for providing energy to the power grid, microgrid or autonomous installations [23]–[25]. Recently, building integrated combined Solar and Wind driven energy systems have entered the market promising to be a cost viable breakthrough technology.

## 1.2 Demand Response and Smart Grids

Storage of electricity is subjected to technical and economic barriers making absorption of excess electricity by renewable energy sources feasible through a demand following generation concept [26]. Demand response (DR) refers to ways of altering the power consumption of buildings, settlements, or other facilities, within a specific time frame, for economic return [27]. It implies regulatory, technological, and market changes affecting the way energy is transacted and exploited. DR is strongly interlinked with the smart grid technological paradigm. By definition, in DR, consumers are able to adjust their power purchasing patterns according to the dynamic exchange of information, incentives, and disincentives

[28]. In the case of a power system integrating multiple energy carriers the concept of Integrated Demand Response (IDR) is used along with the Energy Internet (EI) to provide a wider framework of DR features and complementarity between the various energy sources [29].

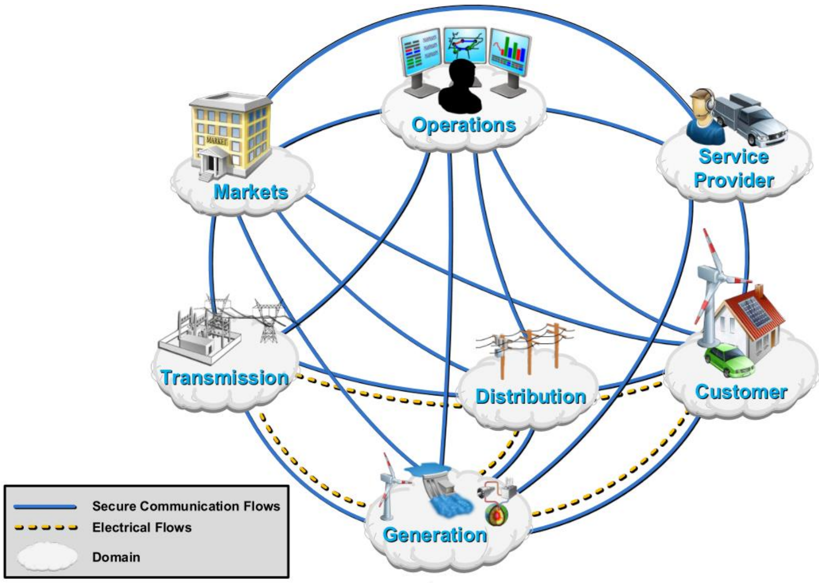


Figure 1: Smart Grid NIST conceptual model

The smart grid is defined by the National Institute of Standards and Technology of the U.S. Department of Commerce to be comprised of seven domains as shown in Figure 1. In the market domain, trading of grid assets and resources such as electricity, $CO_2$ allowances, gas, coal, etc. takes place while the operations domain concerns the overseeing of energy management and the smooth control of the power grid transmission and distribution networks by regulating authorities. The Service Provider domain is linked to the business functions between power system producers, DSOs and customers such as billing and customer account management but also hosts more advanced services supporting energy management and generation. Furthermore, the Generation domain is associated with the conversion and supply of electricity from various energy carriers such as gas, coal, pumped hydro, wind, solar, geothermal etc. New requirements include greenhouse emissions control, an increase of RES and provision of storage to deal with RES intermittency. The Transmission domain is dealing with the reliable transfer of electrical power from generation to distribution substations. The Distribution domain, refers to the link between the Customer and the Transmission domains which takes place through various network configurations (radial, looped, meshed). Finally, the Customer domain is segmented to differentiate between homes, commercial buildings and industrial facilities. The energy services interface is part of the customer domain for establishing remote communication and applications control.

On the other hand, demand response is linked to sustainable development goal (SDG) 7 for ensuring access to affordable, reliable, sustainable, and modern energy for all [30]. DR is directly linked to targets for increasing the share of renewables and improving energy efficiency in smart grids. In addition, the wide implementation of DR is expected to be complementary to SDG 13 as part of the efforts to keep global warming to well below 2 °C above pre-industrial levels.

In this context, **Distributed Energy Resources (DER)** and **Demand Response (DR)** (sometimes the term **Demand Side Management** are used interchangeably**)** are gradually gaining ground with respect to their potential applications in (a) the reduction of peak loads, (b) grid balancing and (c) dealing with the volatility of renewable energy sources (RES). Maintaining grid balance is a primary ancillary service and a prerequisite for the provision of high-quality power utility services affecting everyday life, as well as social and economic progress.

According to Reference [31], **demand-side management (DSM)** measures can be categorized based on the timing and the impact of the measure into energy efficiency, time of use, demand response, and spinning reserve. Another definition of DSM measures is given in [32] as a way to induce a load shape change to obtain short and long term benefits (Figure 2).

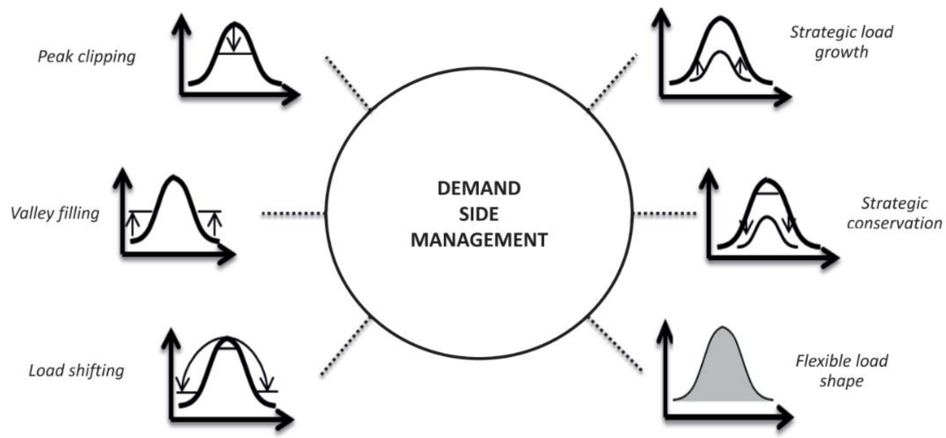


**Figure 2: DSM power profile change objectives** [32]

The following list provides a brief explanation of power profile change objectives presented in Figure 2 to be pursued in DSM:

- Peak clipping refers to the reduction of system peak load using direct load control.
- Valley filling concerns the exploitation of energy during low utilization periods to improve the ratio between the peak and minimum load of the system.
- Load shifting is related to rewarding end users for time shifting their consumption in order to reduce system peak levels.
- Strategic load growth is connected to establishing objectives that will lead to higher electrical energy consumption such as providing tax incentives for e-mobility.
- Strategic conservation is associated with total lower energy consumption due to higher overall efficiency.

- Flexible load shape is linked to the activation of loads' flexibility in real time to optimise demand and supply.

Demand response is otherwise classified into (i) incentive-based, including direct load control, interruptible/curtailable rates, emergency DR, capacity market programs, and demand bidding programs, and (ii) time-based, such as time of use (ToU) rates, critical peak pricing (CPP), and real-time pricing (RTP). In CPP, a high rate is imposed on the customer in the case of critical events of high wholesale market prices [33]. In RTP, end customers are forwarded wholesale market prices a day or an hour before energy delivery. One of the main challenges in RTP is associated with the requirement for robust and continuous real-time communication between the energy provider and customers [34]. Prices in RTP fluctuate as a consequence of wholesale market price variation and design aspects. Several RTP structures were assessed by utilities [34]. Other pricing structures such as Inclined Block Rate whereby tariffs vary based on consumption level thresholds have been exploited in order to promote energy conservation, load balancing and reduction of peak load [35].

In this framework, the idea of an open and transparent smart grid accommodating participants on a fair and inclusive basis is tied with (a) the allocation of actual costs for the generation, transmission, and distribution to the various stakeholders, and (b) the transition to a very high share of clean energy resources in the electricity generation mix. Undoubtedly, the smart grid of the next decade needs to ensure very high penetration of RES, as well as gradual replacement of fossil fuels and other power sources associated with high environmental risks. Grid energy efficiency is currently related, among others, with requirements for significant levels of spinning reserves and low-efficiency generators compromising environmental sustainability. In DR, consumers are incentivized to control their consumption in time to follow high RES production, contribute to the decrease of demand peaks and lead to improved overall energy efficiency at the grid level.

The potential benefits of DR for customers, system operation, market efficiency, and reliability of the power system were critically evaluated based on different innovative technologies, real case studies, and research projects [28], [36], [37]. The long term impact of DR in the Portuguese electric system is investigated in [38]. In all of the scenarios studied DR was found to lead in reduction of the total costs and of the total capacity as well as an increase of RES penetration. Also, high variable RES power generation is reflected to changes in models dealing with optimisation of the power system [39]. In this context, short-term operations become increasingly important with respect to integrating renewables, power generation flexibility, interregional transmission of energy, energy storage and DR.

On the contrary, several factors are slowing down the widespread implementation of DR such as human intrinsic, economic, social, technological, and regulatory aspects as discussed in References [40]–[42]. In terms of the infrastructure modernization necessary for DR to take place, smart meters and advanced metering infrastructure (AMI) have a fundamental role to play. Advanced metering infrastructure, such as smart meters, is an essential part of the smart grid for utilities to be able to monitor and control any point of energy consumption/production or distribution in the grid. AMI and smart meters are also essential for consumers to be able to monitor their consumption and react to information about prices or DR events in real time. Moreover, AMI constitutes the necessary infrastructure for collection of load profiles which can be exploited by utilities or aggregators using clustering to identify common patterns of energy consumption, design appropriate tariffs and target groups of customers for participating in DRP [43].

Various forms of possible DR program types and interactions between stakeholders involved such as utilities, aggregators, and resources are defined in the Open ADR standard [44]. In specific, DR program types of Critical Peak Pricing, Capacity Bidding, Thermostat / Direct Load Control, Fast DR Dispatch / Ancillary Services, Electric Vehicles and DER are defined. According to the OpenADR 2.0, a resource for a utility in a DR program can be anything from a single customer load or an aggregator down to as specific as a thermostat.

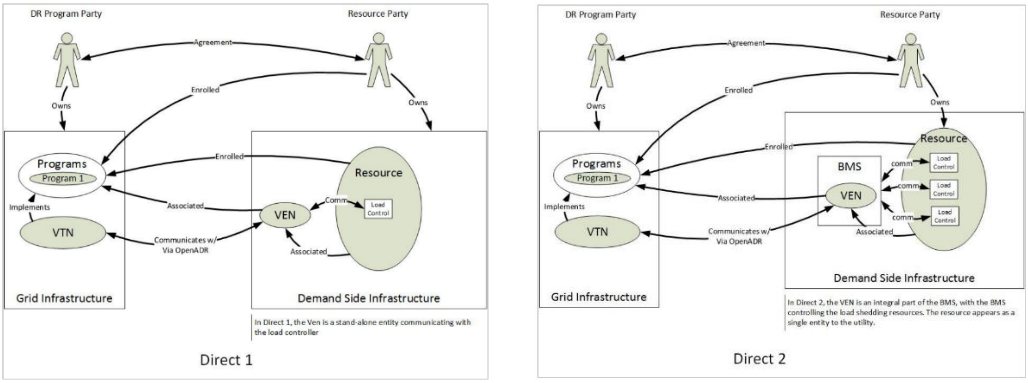


**Figure 3: Open ADR 2.0 simple DR deployment scenario (Direct 1&2,** [44]**)**

In Figure 3, two simple DR deployment scenarios are presented. When a resource is enrolled in a DR program, the utility may dispatch an 'EiEvent' message to the Virtual End Node (VEN), serving as mean of communication for the resource, specifying the resource to be targeted. If such a target qualifier is not included then all resources behind a VEN are specified. In this case, the relationship between the DR Program Party and the Resource Party is direct. The Direct 1 scenario applies to commercial and industrial buildings with a VEN gateway translating the incoming signal to a load controller based on a specific protocol. In the Direct 2 scenario, the VEN is part of a BMS and the resource is composed of large building facilities such as HVAC, lighting, industrial processes etc.

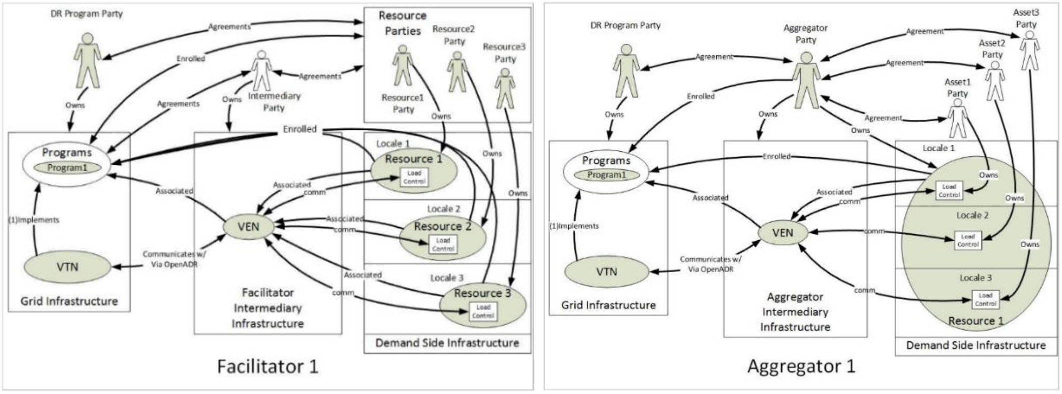

**Figure 4: Open ADR 2.0 facilitator and aggregator DR deployment scenarios (Facilitator 1, Aggregator 1,** [44]**)**

In Figure 4, two more complicated scenarios, employing a facilitator (left) and an aggregator (right), are presented. The facilitator is an intermediary assisting asset parties in managing their resources. Resources are directly enrolled in DR programs and remain in direct communication with the DR Program Party. The VEN, in this case, sometimes offered as a cloud based Software as a Service (SaaS), resides within the Facilitator who is acting as a gateway for OpenADR actions. When a DR signal is sent by the DR Program Party (VTN) to the Facilitator (VEN), it is forwarded to a specific resource for some DR logic to take place or converted to load control commands for several load controllers. A company managing the facilities of a large commercial or industrial company, Energy Service Companies (ESCOs) or cloud based equipment management i.e. smart thermostat services are different example applications which fall in this category. In the second scenario of Figure 4, the Resources are not directly engaged with the DR Program Party but with the Aggregator instead. The aggregator enrolls resources forming various portfolios managed in response to DR signals received by the DR Program Party.

The DR Party has no knowledge of the resources the Aggregator is managing. Instead, the Aggregator is the only point of reference for the Resources in this scenario.

### 1.2.1 DR and congestion management

One of the challenges related to the smart grid transition is congestion management. The high penetration of DER in the distribution grids may in some cases cause congestion issues thus creating the need for new approaches to deal with such a constraint. DER coordination, flexibility and consumer active demand are the basis for the next generation efficient and reliable distribution grid [45]. Dynamic pricing can be exploited in this context to relief congestion and reduce line losses in distribution networks. Such an approach is proposed in [46] to facilitate the high penetration of electric vehicles. The cost of flexible loads along with the line losses cost due to the network's topology form a single objective function to address the cost of congestion management and yield realistic and optimal results.

Moreover, in [47] a local flexibility market trial has been implemented under real conditions and addressed a lot of important issues from the different perspectives of the stakeholders involved. In particular, the authors in [47] present a thorough approach for baseline flexibility services and capacity limitation services. In this framework the DSO creates flexibility requests based on the forecasting of congestion risk in the distribution network. Long term forecasting in this context uses load scenarios which do not predict the electric load for each node over time but provide a probabilistic network evaluation based on historical data and a decomposition approach. The risk of congestion management is translated into operational cost (i.e. reduced transformer life cycle, cost of non-provision of services to customers) and compared to the cost of activating flexibility services alleviating this risk. In case the cost of alleviating the risk of congestion is lower than activating flexibility services, the DSO issues a flexibility services list and the maximum price for each of the services in the list. The aggregators may respond to the DSO by sending their bids and ultimately one bid may be accepted to be activated for each flexibility service in the list. The scope of the local flexibility market is to operate in parallel and provide complementary services to the wholesale markets by optimizing the operation of the distribution grid in the presence of increased DERs.

### 1.2.2 DR and ancillary services

Although most balancing in the power system takes place through energy scheduling, real time contingencies such as the loss of a generator or of a major transmission line requires a different level of response referred to as AS. Ancillary Services (AS) in the power system include frequency control, voltage control, spinning reserve, standing reserve, operating reserve, black start capability, remote generation control, grid loss compensation and emergency control actions [48]. The value of AS is associated with the capability of the grid to respond in a fast and reliable way and maintain balance. AS requirements vary from 1% of the load in wide interconnected systems to 5-7% in smaller systems with wind and solar generation. DR resources are able to offer significant and in some cases superior AS to the grid [49]. In fact, curtailing loads can be faster than varying the rotational speed of large scale equipment such as in conventional power generation plants. Furthermore, integrating DR resources in AS opens up the controllable reliability options for system operators and enables greater system flexibility thus allowing improved penetration of RES such as wind or solar generation.

In particular, activating DR actions in short time has been identified as suitable in providing contingency and operating reserves. HVAC systems are considered controllable loads which can be exploited in this way since a) they are installed in most residential and commercial buildings and consume a high share of their electric load, b) their operation is linked with the building's thermal inertia therefore allowing a margin for operational control within a range of set-points which is not directly translated to a deviation from the acceptable thermal comfort levels of occupants and c) they are coupled with EMSs. Also, Thermostatically Controlled Loads (TCLs) such as refrigerators and water heaters have been considered in studies investigating the potential of DR in connection with AS. In this context, the DR control signal entails a request for resetting the temperature set point of a TCL, as an action related to frequency regulation or to a change in power consumption. In organized wholesale markets, transmission providers procure AS via cost based contracts and AS costs are defined through a regulated process to include a bid and an opportunity component. AS providers are compensated for their marginal costs (including maintenance and operational costs i.e. fuel) on the basis of the bid component and in case of energy sale a lost opportunity cost based on the difference between the market clearing price and the AS provider energy market bid. In this context, DR resources can be exploited to provide AS at a different frequency and duration compared to current DR deployment experience. For instance, in the case of emergency and economic load shedding, DR is triggered a limited number of times in a year (10-15) for a duration of 4-8 hours each time. Instead, AS such as contingency reserve in particular are deployed at a frequency between once every two days and once every two weeks for a duration of up to 30 minutes each time.

Demand fluctuations is a significant cost factor driving ancillary costs to supplier higher. This is expected to become more significant as RES penetration rises and poses certain challenges for the conventional power generation units. In [50], the ancillary costs are modelled with respect to demand variability. A dynamic pricing mechanism is proposed that motivates customers to adjust their energy consumption while they provide a balanced demand response. Results through a dynamic game theoretic approach indicate that demand variability and requirements for peaking plants can ultimately both be significantly reduced.

### 1.2.3 DR Programs

Adding flexibility in power consumption provides a sound basis for improving the grid's environmental performance. Reduction of peak loads at grid level could lead to a lower level of operation for generation plants of high running cost, low efficiency, and low environmental performance. DR potential in the United States (US) alone could lead to peak load reductions of 150 GW, an equivalent of approximately 2000 peaking plants [51].

A thorough review of existing DR programs available to US commercial and residential customers by numerous independent system operators (ISOs) and regional transmission organizations (RTOs) was provided in Reference [52]. Such programs include real-time demand, real-time price (RT-Price), day-ahead load response (DALRP), day-ahead demand response program (DADRP), and more. In RT-Price programs, consumers can choose to reduce their load in real time as a response to prices exceeding a certain value. A detailed classification and survey of DR programs in smart grids with respect to pricing and optimization algorithms is available in Reference [53]. In day-ahead real-time pricing (DARTP) programs, the predicted next day's real-time prices are announced to customers and used for billing their consumption. DARTP is reported as one of the solutions which was tested and found effective in achieving flatter demand, reduction of losses, shorter peak-to-peak distance, and a higher load factor.

### 1.2.3 Building level Demand Response

In DR, the consumer becomes a prosumer with an important active role in the transaction of energy on a day-to-day basis. This transition calls for higher environmental and social awareness as well as new tools and services to allow for dynamic interoperable bidirectional flow of data. Hence, DR is identified as an important field for technological and market innovations aligned with climate change mitigation policies and the transition to sustainable smart grids in the near future.

In this direction, a wide range of demand response techniques was applied and documented according to the type of the loads and the installed facility equipment [54], [55]. Customers can change their electricity pattern and participate in DR by reducing their use of electricity, by shifting consumption to another time period, and by self-generating electricity [56]. In this context, at the building level, the adjustment of the heating, ventilation, and air conditioning (HVAC) temperature set points is reported as an effective way to exploit the thermal mass of the building in order to reduce peaks or shift loads. Changing thermostat settings or reducing the operational time of HVAC systems as well as decreasing artificial lighting levels are some of the main load curtailment techniques [54], [56].

HVAC is among the major energy loads of the building sector [57]. The performance of the HVAC system is of great importance with respect to the energy efficiency of a building overall. HVAC efficiency depends on the technical attributes of the technology employed and on the way systems are controlled, i.e., settings and embedded intelligence, which in turn define its actual operational performance and indoor comfort conditions. Many researchers investigated the potential of applying advanced controls and optimization techniques to improve energy HVAC efficiency [16], [58]–[64]. In [65], the case of CHP combined with thermal and electrical storage is explored in an RTP DR setting for a 12-storey large office building equipped with two 1,300kW water cooled chillers and a gas boiler for cooling and heating (including DHW) respectively. Savings of 7% are established due to the operation of the thermal storage. Despite the fact that the RTP scheme can be exploited using the EES to store energy during off-peak periods and reduce consumption during peak periods, the high investment cost associated with it is a barrier for its adoption. Furthermore, a multi-objective optimisation approach is utilized to investigate the trade-off between the aggregator and smart apartment residents offered RTP in Japan [66]. A total of 100 smart apartments equipped with PV and batteries used for storage, heat pumps (flexible loads) assisted by solar thermal collectors and EVs are used as an aggregator's portfolio for indirect optimisation through the identification of real time pricing profiles to promote load curtailment and load shifting. Optimum results of leveled profits for the aggregator and the apartment residents were obtained and analysed.

A mixed-integer linear problem (MILP) for real-time cost optimization of HVAC operation at building level was proposed by Risbeck et al. [67]. This study focuses on the optimization of equipment usage in HVAC commercial systems. In their study, building temperature dynamics were either considered linear and used to estimate cooling or heating loads, or assumed to be available as a forecast of hot and cold water demand. Pompeiro et al. applied dynamic programming and genetic algorithm (GA) optimization to maximize thermal comfort and minimize the HVAC cost with photovoltaic (PV) production and storage in an experimental facility [68]. Their approach concentrated mainly on the exploitation of energy from PV and storage. The operation of the HVAC was controlled based on indoor temperature measurements and its performance was restricted in low, medium and high levels. A Time of Use (ToU) pricing scheme of three tariffs was used in the optimization of a small experimental room. An experimental evaluation of an HVAC system under variable pricing was conducted in Reference [69]. A linear model of temperature evolution was developed by correlating past values of temperature with HVAC modules turned on/off at any instance in time. The approach was validated in an experimental facility, demonstrating reduced cost with respect to a normal thermostat in two different ToU pricing schemes. In Reference [70], a MIP configuration was proposed to optimize HVAC operation based on a comfort/cost trade-off. The approach determined when each one out of a set of many HVAC units was turned on and off based on common goals. Cost reductions of 4.73%, 4.5%, 11.2%, and 8.5% in two different scenarios were achieved. In Reference [71], direct load control and set point regulation of aggregated HVAC systems for frequency regulation in smart grids were investigated. A simplified HVAC model was used to evaluate temperature evolution and power consumption. Results demonstrated acceptable variations of temperature and on/off operations associated with smaller tracking errors compared to direct load controls and sliding-mode control strategies. In Reference [72], a model predictive control framework, was proposed, to determine optimal control profiles of HVAC systems in a demand response context. This approach used a non-linear autoregressive neural network configuration to model the thermal behaviour of the building zone and to simulate HVAC control strategies as a response to a demand response signal. The optimal control problem was formed as a mixed-integer non-linear problem (MINLP), taking into account on-site energy storage and energy generation systems with night set-up, demand-limiting and pre-cooling HVAC control strategies. Results for a day in August indicated reliable prediction levels for zone temperature and power. Cost savings, in the case of a varying pricing signal, of 14.25% to 15.26% for demand-limiting and optimal control without energy generation and storage were achieved. In the case of optimal control combined with energy generation and storage, cost savings of 30.95% were obtained. Particle swarm optimization was used in Reference [73] to optimize the operation of residential HVAC systems based on a multi-objective scheduling problem taking into account day-ahead (DA) electricity price, outdoor temperature forecast and user preferences. A cooling scenario with DA pricing was demonstrated where a decrease in HVAC energy consumption of 6.54% and a reduction of 18.71% in electricity cost were achieved.

Furthermore, a bi-level optimisation approach is proposed in [74] with respect to energy management in a residential setting to determine the day ahead energy quantity bid at the upper level by minimising energy uncertainty cost while ensuring optimal operation of building loads, DERs and storage. According to the authors, the proposed approach outperforms non-optimal inflexible scheduling methods by up to 51% and deterministic optimization based methods by 22%.

### 1.2.4 District level Demand Response and Microgrids

Hybrid Renewable Energy Systems (HRES) have been implemented in various configurations to combine two or more renewable and non-renewable sources in order to deal with the intermittency of renewable energy sources, such as solar or wind. HRES have important attributes which make them increasingly attractive as alternatives to conventional fossil fuel energy sources in numerous applications [75]–[79]. Microgrid optimal energy management can be highly complex and challenging especially in the case of hybrid systems combining a wide range of renewable and non-renewable technologies. In [80] optimal dispatch strategy of a hybrid microgrid connecting PV, WT, FC, MT, DG and batteries operating both in standalone and grid-connected operation is investigated through a multi-objective mixed integer linear programming approach for a particular Demand Response program. Results show a 51.6% reduction of CO2 emissions in standalone operation. In [81] stability in MGs in the case of communication interruption is dealt by a hybrid prediction-based DR energy management approach. PSO is used to optimize microgrid operation including a WT, a PV, a MT, ES, FC, interruptible, flexible and fixed loads. Results demonstrate cost reductions of up to 57.89%.

Aligned with HRES, the concept of the microgrid as a semi-autonomous system of increased flexibility and manageable energy resources, including renewable energy generation, storage, backup systems and flexible demand, is of particular importance when it comes to supporting grid stability and decentralized control [82]. A comprehensive critical review on the energy management systems of microgrids, connected to the level of maturity of real world applications, is conducted by Zia et al. [83].

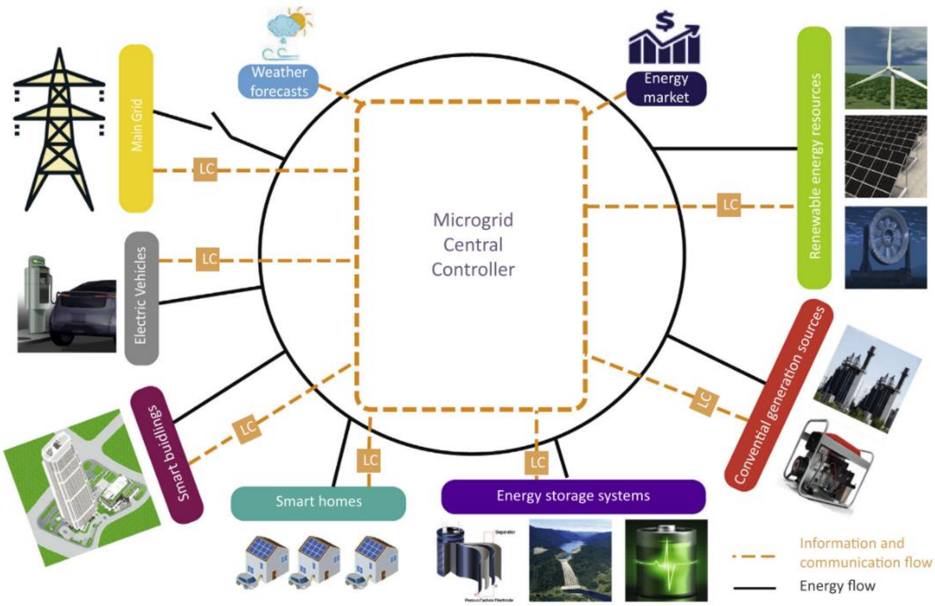


Figure 5: Microgrid conceptual architecture [83]

Communication issues, control technologies and architectures, deployment costs, energy management strategies, optimisation, objectives and limitations, are addressed. An auto-configuration function using a multi-agent approach is proposed by Bui et. al. [84] to establish automatic connection or disconnection of DER at microgrid level, capable of dealing with system faults and re-optimising the new configuration as necessary. Unsymmetrical and ground faults analysis in microgrids distribution systems is proposed by Ou in [85], [86]. Hirsch et al. in [87] surveyed technologies and key drivers of microgrid implementation and research, at the international level. Reported drivers in this context include extreme weather related concerns, cascading outages, cyber and physical attacks, deferral of infrastructure expansion costs, reduced line losses, efficiency improvements, savings, responsiveness, balancing loads, RE generation, etc. In [88], the authors present a residential microgrid day-ahead planning approach to accommodate appliance scheduling by modelling, among other aspects, inter-phase delay duration and time preference, in order to take advantage of shiftable loads and energy storage charging/discharging time. In [89], multi-microgrid configurations are presented and analyzed by means of the power line technology (AC, DC), layout (series, parallel, mixed), and interconnection technology (transformer, converter). A comparison of architectures based on cost, scalability, protection, reliability, stability, communications and business models is performed. Energy management and DR of multi-microgrids based on a hierarchical multi-agent approach by introducing adjustable power is proposed by Bui et al. [90]. Different operation modes are evaluated according to a two-level management cooperative multi-microgrid MILP-based model for day-ahead scheduling. In [91] MILP is used to formulate a cooperative market mechanism for energy transactions in a multi-microgrid setting. A RTP DR program is considered and each MG interconnects DGs, WTs, PVs, flexible and critical loads as well as ESS. Scenarios are generated in a stochastic way to account for market uncertainty and renewable energy generation. Various scenarios are investigated to include grid-connected operation, island mode and different connection levels between participating MGs. Results showed the effectiveness of this approach in lowering market prices and enhancing reliability in the case of increased power transaction capacity. Towards the application of state of the art, a microgrid energy management a Genetic Algorithm

(GA) approach is applied in [92] to optimize cost strategies for scheduling distributed energy resources. A quasi-static artificial bee colony approach is used to optimize a multi-objective DR problem, based on the cost of energy and peak demand at the building level [93], including PV, Combined Heat and Power (CHP), batteries, electrical energy from the grid, and natural gas. Particle swarm optimisation is used in [94] to solve a bi-level problem modelling the interaction between the retailer and consumers. The energy hub is explored in [95] to develop a multi-carrier Demand-Side Management Time of Use (DSM ToU) optimization balancing energy import, conversion, and storage. A multicarrier energy system of thermal, electrical and hydrogen loads is optimised using a fully decentralized multi-agent approach [96]. Comparing a case of responsive loads to a case without responsive loads via simulations led to the observation that DR could provide added value to the social welfare of the system and individual profit of agents.

Furthermore, a GA approach using present and day-ahead data was tested by Ferrari et al. [97] with respect to the management of loads of an experimental plant case study in Italy. The analysis involves PV, wind generation, a micro-CHP with a gas boiler, and an absorption chiller coupled with thermal storage.

In addition, game theory is widely explored in formulating the interaction between consumers and utilities in DR. In [98], this interaction is formed as a Bayesian game where the Bayesian Nash Equilibrium is changed according to the regulation price set by the utility. Results indicate that this approach is effective in balancing energy and demand. Gong et al [99] developed a game-theoretic approach to test a distributed control strategy for large scale DR consisting of high populations of EVs and storage devices. These flexible loads react to prices by optimizing their own objective functions in an agent-based framework. Prices are settled by solving a power flow dispatch optimisation problem and results are presented to demonstrate optimality of each individual's objective function and of social welfare for the system overall. According to this approach full control is maintained at customer side since it does not need to be transferred to the aggregator's side.

Abuelnasr et. al. used a GA approach to evaluate the impact of different microgrid topologies on EMS operations considering energy losses, energy from the main grid and $CO_2$ emissions [100]. Microgrid topologies consisted of networks, loads, biomass generation, PV and storages. More specifically a GA optimisation model is used to examine the influence of different microgrid topologies in energy management from the perspective of objective functions of energy loss, energy import and $CO_2$ emissions minimized individually. The participating microgrids are comprised of 26 load points, ten PV DGs half of which of 200kW and half of 500kW and a storage unit of 250kW and 1000kWh as well as biomass DGs. Eleven controls are employed in the energy management optimisation including four DR controls for loads above 50kW, two 3-phase dispatchable DGs, output power controls, three single phase shunt capacitors control switches, one 3-phase capacitor control switch and storage control. Three different configurations were investigated to identify optimal decisions and demonstrate the effectiveness of the proposed approach. A regional integrated energy system is modelled to optimise the operation of a system comprising of wind power, concentrating solar power, gas power generation, thermal and electric power storage while meeting electric and thermal loads on the demand side [101]. The optimisation model addresses a) the total operational costs, b) the system environmental cost and c) the system economic benefits due to participation in DR. The impact of different DR modes on system operation are considered using simulation. Results indicate that Integrated Demand Response can lead to a cost saving of 7.86% and a reduction of pollutants emissions of 18.37%. Furthermore, Alharbi and Kankar [102] present a stochastic EMS model to investigate several short term dispatch probabilistic scenarios for isolated microgrids integrating wind and solar generation with EVs and DR.

### 1.2.5 ANN based short term power forecasting

ANN models are designed to imitate biological nervous system information processing and evolution. They have been used for years in different areas of engineering, science, and business to deal with highly complex and nonlinear data sets. The ANN models assimilate the natural bonds of neurons and their high level interconnection to model complex systems. Artificial Neural Networks (ANN)-based short term power forecasting is practiced to estimate day-ahead loads and renewable energy production.

In the case of short-term predictions, the ANN models can be more effective compared to statistical, linear, or non-linear programming techniques. They encompass capabilities such as adaptive learning, self-organization, real time operation, fault tolerance, and the approximation of complex nonlinear functions. Kalaitzakis et al. in [103] tested advanced neural network short-term load forecasting using data from the electric power grid of the island of Crete in Greece. Various structures and configurations were assessed in their study and a parallel processing approach for a 24 h-ahead prediction was demonstrated to be the most effective. ANN architectures for forecasting demand in electric power systems are presented in [104] by Tsekouras et al. A case study of the Greek electric power grid is used to explore the performance of different ANN configurations and factors, including period length and inputs for training, confidence interval, and more. Moreover, short term power forecasting is of particular value for prosumers to model, understand, and predict their consumption profiles, as well as to apply effective scheduling and control. A framework for district-level energy management and ANN forecasting at the building level was investigated by Hu et al. in [105], evaluating the performance for 6 buildings of different occupancy routines. Hybrid Short Term Load Forecasting ANN combined with techniques such as Fuzzy Logic, GA, and Particle Swarm Optimisation are briefly discussed in [106]. Furthermore, a 24h ahead prediction of excess power at microgrid level is proposed by Mavrigiannaki et al. [107], testing 3 different configurations, as a fundamental part of an advanced microgrid energy management strategy. Finally, an overview of load forecasting, dynamic pricing, and demand side management techniques in smart grid research applications reveals their potential for operational cost reductions between 5–25% [108].

## 1.3 Problem statement & innovation of the research

Following the description of the state of the art, the problem statement and innovativeness of the research of the present PhD thesis is analysed below.

- A comprehensive approach for evaluating the **performance gap of Smart / Near-Zero Energy buildings** including industrial and residential case studies is developed. Dynamic energy models are developed, validated upon real data and exploited to explore key aspects of the operational behaviour of buildings and systems. The developed approach provides an innovative, complete and transparent framework for analysing the energy efficiency of buildings during their operational phase.

- **At the building level**, a novel **demand response GA based HVAC optimization scheme** is developed. According to this scheme an optimisation problem is formed to include the **cost of energy** and **predicted mean vote (PMV)** as the two criteria merged into one objective function. HVAC hourly set points are used as the variables of the optimization. A Genetic Algorithm is used to identify dominant HVAC set point patterns based on dynamic energy prices, actual weather conditions and preferences with regard to indoor conditions. The developed approach constitutes a powerful assessment and decision tool which can be used to identify and ultimately apply dominant HVAC set point patterns based on dynamic conditions. The GA optimization algorithm is coupled with the validated dynamic thermal model of the building enabling the assessment of energy cost, energy savings, and thermal comfort for a wide range of temperature set point patterns and RTP schemes. The developed approach is explored to assess RTP schemes based on **real DA market information** on the basis of price fluctuations reflecting current market operations. This approach constitutes a significant contribution to the literature of HVAC energy management based on a demand response perspective. According to the best of the author's knowledge, previous attempts to investigate this problem are limited to oversimplified mathematic models of the building HVAC operation. In addition, the innovation of the developed approach is justified by the fact that solutions are assessed against dynamic pricing profiles which have been constructed based on real market data.

- **At the district level,** a **DR energy management GA-based optimisation** approach **based on day ahead ANN generated prediction models** is proposed. The developed GA algorithm incorporates **load shifting for the day ahead (24 h period)** and evaluates possible alternatives based on cost and assumptions related to the practicality of the obtained solutions. The practical benefits of the proposed approach are linked to the development of a valuable tool for the evaluation of the potential rewards and risks of engagement in DR.
- The contribution of this work, at the district level, is related to linking ANN short-term electric forecasting and GA multi-objective optimization as a tool for generating and evaluating alternative day-ahead load shifting solutions.

In the case studies that follow, Time of Use and DA Real Time pricing schemes are assessed.

## 1.4 Thesis outline and objectives

The thesis structure and objectives are outlined below. In the second chapter, the description of the facilities under investigation is provided. At the building level, these include Leaf House and Leaf Lab, a residential and an industrial smart and zero energy buildings respectively. At the district level, the Leaf community, a microgrid which includes several buildings (including the Leaf Lab), various renewable energy systems as well as thermal and electrical storage. In the third chapter, a thorough analysis of the performance gap in one residential and one industrial smart near zero energy buildings is conducted. The analysis is based on the comparison of actual measured energy consumption during a full year period, with the energy performance according to the initial design considerations and a new developed dynamic simulation model. The model is developed based on the – as built – plans and a detailed building/systems audit. Subsequently, in situ measurements were obtained to record indoor temperature in representative thermal zones and use them in validating the building energy model. In the fourth chapter, the validated building energy model of Leaf Lab was exploited in a novel DR HVAC GA optimisation scheme. The optimisation approach entailed the hourly temperature set point as a chromosome (decision variable) for the GA. The goal of the developed optimisation model is to minimize daily HVAC energy cost while adhering to comfort standards. Day ahead real time pricing profiles were created based on DA market information and results demonstrated significant margins of energy and cost savings throughout the year especially when the daily variation of the pricing profiles allowed for adequate levels of load shifting between adjacent working hours. In Chapter 5, a new method for assessing DR energy management potential at district levels is presented. The method was developed and successfully tested to predict energy demand and optimize load shifting options to evaluate cost savings for the same energy consumption levels. ANN based algorithm is used for predicting day ahead consumption and a GA approach was implemented to provide balanced and cost optimum load shifting solutions.

Chapter 6 encompasses a critical reflection on key considerations and the main conclusions stemming from this thesis. An overview of the limitations and constraints of the developed approaches is included along with future prospects recommendation for further work.

# 2. DR in Smart and Near Zero Energy Buildings: The Leaf Community

Leaf Community is an industrial settlement owned and managed by Loccioni Group for conducting research and innovation in the sectors of energy, environment, automotive, aerospace, robotics and other. The Leaf Community is a unique blend of inspired qualified personnel where the preservation of the natural environment, RES, and worldwide R&D meets education, local culture, and society. Mainly, industrial buildings in the Leaf Community, located in Angeli di Rosora of Ancona in Italy, are the key loads part of a microgrid interconnecting various Photovoltaic (PV) installations, electric and thermal storage, micro-hydroelectric plants and electric vehicles (EV). The climate in Ancona is mediterranean with dry hot summers and mild winters. The warm season starts in June and lasts till mid-September with an average high temperature of 29°C and an average low temperature of 19°C. The cold season starts in November and ends in March with an average high temperature below 12°C [109].

The Leaf community (Figure 6) consists of 5 industrial buildings (L3-AEA, L4-Leaf Lab, L5-Kite Lab, L6), one office building (L2-Summa), and a building used mainly for meetings (Leaf Farm). All buildings (except the Leaf Farm) are equipped with rooftop photovoltaics (PV) of total power 629.2 kWp, and ground water heat pumps. In addition, a 2-axis solar tracker of 18 kWp, a 48 kWp micro-hydro plant, a 224 kWh battery storage, and a 523.25 kWh/K thermal storage are connected to the microgrid, which also features electric vehicle charging stations. Buildings, renewable energy systems (PVs, micro-hydro), and storage systems are all coupled and connected to the main power grid via a single interconnection line (point of delivery).


**Figure 6. The Leaf Community map.**

## 2.1 The Leaf Lab industrial building, AEA Italy

The Leaf Lab (Figure 7) is an industrial building of rectangular shape and floor area of approximately 6,000m$^2$ located in the Leaf Community [110], one of the very well established smart microgrids in Europe. The Leaf Lab incorporates the newest technology making it exceptionally tolerant to external weather conditions. This reduces to the minimum the amount of energy needed for heating, cooling, ventilation and lighting. The Leaf Lab is a Near-Zero Energy Building (NZEB) combining passive systems, energy efficient technologies, integrated monitoring and control as well as renewable energy production. Renewable energy is exploited with the use of PV systems, thermal storage and heat pumps. Thermal storage is exploited to optimize HVAC performance and minimize dependency on energy imported from the main grid.

**Figure 7. The Leaf Lab**

The building envelope of Leaf Lab consists of highly insulated external walls with U-value of 0.226 $W/m^2K$ and double glazed windows with U-value between 1.793-3.194 $W/m^2K$. The HVAC system installed in Leaf Lab is comprised of heat pumps with a heating COP of 4.8 and cooling EER of 6.2-7. A thermal storage water tank of 400$m^3$ is coupled to the HVAC system of the building to reduce peak power and improve the efficiency of the HVAC system during heating and cooling periods throughout the year [26]. This is implemented using energy excess from the PV i.e. during weekends, holidays etc. to operate the heat pumps and store heating or cooling energy in the thermal tank.  Stored energy is then used to optimise the HVAC efficiency by reducing peak demand and imported energy consumption during working hours. The HVAC is controlled with digital thermostats distributed in the various thermal zones satisfying the set-point limits of the CEN 15251 (20-24°C for heating, 23-26°C for cooling). Set-points for industrial and office spaces in heating mode are 21°C and 22°C whereas in cooling more set points are 25°C and 26°C respectively.

Illuminance sensors, controlling artificial lighting in the indoor spaces of the Leaf Lab, activate dimmable LED lights when levels due to natural lighting fall below 500 lux. Furthermore, automated shading is installed in the vast majority of the windows and operated according to the altitude of the sun. This allows for natural light to be adequately levelled for visual comfort throughout clear sky days while minimising energy consumption for artificial lighting and avoiding glare. Finally, as shown in Figure 7, a rooftop photovoltaic system of 236.5 kWp is installed in Leaf Lab.

The energy efficiency of the Leaf Lab as recorded in the energy certificate was A+ associated with net primary energy consumption of 4.11 kWh/m$^3$ (equivalent to 26.91 kWh/m$^2$).

## 2.2 Leaf House Residential building AEA /Italy

The Leaf House (Figure 8) is a residential building of exceptional bioclimatic design and smart technologies [111]. It consists of six highly insulated apartments with a total floor area of approximately 470m$^2$, a ventilated roof, solar tubes, smart monitoring, and controls, building integrated photovoltaics, geothermal air preconditioning with heat pumps, solar thermal collectors, electrical storage and a user-friendly energy management system for residents. The number of residents in Leaf House varies as it accommodates both employees of Loccioni Group [112] and short term visitors of the Leaf Community [113].

**Figure 8: The Leaf House**

The building envelope of the Leaf House is composed of external walls with a U-value of 0.41 W/m$^2$K and windows of total U-value between 0.73-1.49 W/m$^2$K. The HVAC system installed in Leaf House is comprised of three heat pumps with geothermal air preconditioning and heat recovery connected to a radiant floor distribution system. The heating COP of the heat pumps is in the range from 2.9 to 4.6 while the cooling EER varies between 1.9 and 3.6. Seven solar thermal collectors of a total area of 19 m$^2$ are connected to a 1m$^3$ thermal storage boiler of 15kW electrical power for domestic hot water and space heating. Moreover, 115 PV panels and a total peak power of 20kWp covering a total area of 150m$^2$ are integrated into the Leaf House's rooftop as depicted in Figure 8Figure 13. The energy produced by the photovoltaic system is mainly exploited to power the geothermal heat pumps and reduce overall power consumption. According to the energy certificate of the Leaf House, its normalised annual primary energy consumption is 19.66 kWh/m$^2$ corresponding to an energy efficiency class of A+. The apartments in the Leaf House are equipped with a touch display providing access to an energy management interface for observing indoor conditions, energy-related data as well as for managing HVAC, lights, window shutters etc. Also, an extensive database of measurements for each apartment in the Leaf House including power related data is accessible online restricted to authorised use only through MyLeaf platform.

# 3. Performance Gap in Industrial and Residential Near-Zero Energy Buildings Demand Response

In this chapter, a comprehensive approach for evaluating the performance of one industrial and one residential Smart / Near-Zero Energy building is presented. Initially, the buildings are audited for a detailed investigation of their construction characteristics, installed systems and controls. Subsequently, holistic data from advanced metering and sensor equipment is explored for verifying energy demand and actual performance. Dynamic energy models are developed, validated and tested to explore key aspects of the operational behaviour of buildings and systems and draw essential knowledge about their performance. A comparison of measured data with dynamic modelling results and the initial design energy efficiency certification study is explored to address the actual performance gap, reflect on the limitations of each approach and highlight important conclusions stemming from this work.

## 3.1 Materials and Methods

The research activities performed and presented hereafter target to the estimation and evaluation of the performance gap between the design and operational phase of zero energy buildings.

The steps followed are:

1. Selection of the case study buildings: Two case studies are analysed to cover industrial and residential building use. The Leaf Lab and Leaf House envisage unique building designs for minimizing net energy consumption. This is achieved through a variety of measures including responsive building envelope applications, efficient HVAC systems coupled with storage, intelligent controls,

renewable energy systems and integrated energy management. The initial design target of the two buildings to operate as near-zero energy is established based on their energy certification process and is used throughout the text as a working definition serving qualitative assessment purposes.

2. The second step involves an analysis of the buildings and their systems' design, assessment of power and energy requirements through dynamic thermal simulation models.
3. The third step is the data collection while the buildings are in operation to test and evaluate:
    a. The performance gap between the developed dynamic simulation models and actual operation.
    b. The performance gap between the initial zero energy targets and buildings' actual operation.
4. The fourth step includes a comparison of the results of the buildings and the extraction of useful remarks and conclusions.

In our analysis, a combination of metrics including primary energy consumption and end-use net consumption (absolute and normalised) as well as $CO_{2\text{-}eq}$ emissions is deployed. The period of balance is annual to account for yearly representative thermal loads and renewable energy production. Renewable supply in the considered cases is on-site and building integrated. Of the examined cases, the residential building is directly connected to the power distribution grid and the industrial one as part of the Leaf Community microgrid.

### 3.1.1 Energy simulation model

EnergyPlus is the simulation engine software used to conduct an integrated simulation of the building, system, and plant whereby supply and demand are matched based on successive iteration substitution following Gauss–Seidel updating [114]. Open Studio is used as the API software for developing and parameterizing the model following the principles outlined by Brackney et al. [115]. Ambient temperature, relative humidity, solar radiation, and wind speed data was obtained from local meteorological equipment and converted to yearly weather file. Data of total HVAC energy consumption is exploited for providing the baseline against which model based results are evaluated.

The simulation model contains, on the one hand, the geometry, construction components and materials of the building under study. For opaque material thickness (m), thermal conductivity (W/mK), density (kg/$m^3$), and thermal absorptance (dimensionless) properties are edited. For transparent materials, such as glass in windows and sky windows thickness (m), thermal conductivity (W/mK) and optical properties, such as solar, visible, and infrared transmittance, are inserted. On the other hand, a model of the HVAC system is designed based on the installed technologies and adjusted accordingly to the actual key performance heat pump technical parameters such as Coefficients of Performance (COP), fan maximum flow power ($m^3$/s), pressure rise, and efficiency. Other parameters such as rated total heating/cooling capacity, and rated and maximum air flow rated are automatically sized based on the software's calculations. Furthermore, with respect to the operation of the major installed systems, the simulation model takes into account the temperature set points of the HVAC system, ventilation, and infiltration rates ($ACH^{-1}$) and a number of schedules to determine artificial lighting, electric equipment, and occupancy. Subsequently, an intensive search of the parameters that affected the daily, monthly, and annual power distribution profiles is followed to improve the initial results of the model based by minimizing deviation from HVAC power consumption data. Through the trial and error various combinations and fine-tuning of the all of the above parameters is carried out to reach the optimum results when assessing intra-day, monthly, and annual deviation levels.

EnergyPlus simulation is based on heat balance calculations solved simultaneously with the aid of on an integration solution manager, which includes surface heat balance, air heat balance, and building systems simulation blocks. The heat balance of outside surfaces is calculated based on the equation:

$$q''_{asol} + q''_{LWR} + q''_{conv} - q''_{ko} = 0 \quad (3.1)$$

where

$q''_{asol}$ is the absorbed direct and diffuse solar (short wavelength) radiation and heat flux $q''_{LWR}$ is the net long wavelength (thermal) radiation flux exchange with the air and surroundings $q''_{conv}$ is the convective flux exchange with the outside air $q''_{ko}$ is the conduction heat flux (q/A) into the wall

Clearly, $q''_{asol}$ is influenced by parameters such as location, surface angle and tilt, surface material, and weather conditions. $q''_{LWR}$ is determined by radiation exchange between the surface and the ground, sky and air. It is dependent on the absorptivity and emissivity of the surface; the temperature of the surface, sky, ground, and air; and corresponding view factors. Assumptions such that each surface is at uniform temperature and energy flux leaving a surface is evenly distributed are considered reasonable for building energy simulation. Using the Stefan–Boltzmann Law in the above equation yields:

$$q''_{LWR} = \epsilon\sigma F_{gnd}\left(T_{gnd}^4 - T_{surf}^4\right) + \epsilon\sigma F_{sky}\left(T_{sky}^4 - T_{surf}^4\right) + \epsilon\sigma F_{air}\left(T_{air}^4 - T_{surf}^4\right) \quad (3.2)$$

where

$\epsilon$ is the long-wave emittance of the surface

$\sigma$ is the Stefan–Boltzmann constant

$F_{gnd}$ is the view factor of wall surface to ground surface temperature

$F_{sky}$ is the view factor of wall surface to sky temperature

$F_{air}$ is the view factor of wall surface to air temperature

$T_{surf}$ is the outside surface temperature

$T_{gnd}$ is the ground surface temperature

$T_{sky}$ is the sky temperature

$T_{air}$ is the air temperature

The above equation is converted by introducing linear radiative heat transfer coefficients such that:

$$q''_{LWR} = h_{r,gnd}\left(T_{gnd} - T_{surf}\right) + h_{r,sky}\left(T_{sky} - T_{surf}\right) + h_{r,air}\left(T_{air} - T_{surf}\right) \tag{3.3}$$

where

$$h_{r,gnd} = \epsilon\sigma F_{gnd}\left(T_{surf}^4 - T_{gnd}^4\right)/(T_{surf} - T_{gnd})$$

$$h_{r,sky} = \epsilon\sigma F_{sky}\left(T_{surf}^4 - T_{sky}^4\right)/(T_{surf} - T_{sky})$$

$$h_{r,air} = \epsilon\sigma F_{air}\left(T_{surf}^4 - T_{air}^4\right)/(T_{surf} - T_{air})$$

Exterior convection is modelled using equation:

$$q''_{conv} = h_{c,ext}A(T_{surf} - T_{air}) \tag{3.4}$$

where

$q''_{conv}$ is the rate of exterior convective heat transfer

$h_{c,ext}$ is the exterior convection coefficient A is the surface area

$T_{surf}$ is the surface temperature

$T_{air}$ is the outdoor air temperature

Conduction heat fluxes are modelled based on equation:

$$q''_{ko}(t) = \sum_{j=0}^{\infty} X_j T_{0,t-j\delta} - \sum_{j=0}^{\infty} Y_j T_{i,t-j\delta} \tag{3.5}$$

where

$q''_{ko}(t)$ is the conductive heat flux for the current time step

$T$ is temperature, $i$ indicates the internal element of the building $o$ indicates the external element of the building $X, Y$ are the response factors

In more detail, Conduction Transfer Functions (CTFs) as shown below are used to estimate the heat fluxes on either side of the building elements based on previous temperature values of interior and exterior surfaces as well as previous interior flux values.

$$q''_{ki}(t) = -Z_o T_{i,t} - \sum_{j=1}^{nz} Z_j T_{i,t-j\delta} + Y_o T_{o,t} + \sum_{j=1}^{nz} Y_j T_{o,t-j\delta} + \sum_{j=1}^{nz} \Phi_j q''_{ki,t-j\delta} \tag{3.6}$$

$$q''_{k0}(t) = -Y_o T_{i,t} - \sum_{j=1}^{nz} Y_j T_{i,t-j\delta} + X_o T_{o,t} + \sum_{j=1}^{nz} X_j T_{o,t-j\delta} + \sum_{j=1}^{nz} \Phi_j q''_{ko,t-j\delta} \tag{3.7}$$

where

$X_j$ is the outside CTF coefficient, j = 0 ,1,...nz

$Y_j$ is the cross CTF coefficient, j = 0 ,1,...nz

$Zj$ is the inside CTF coefficient, j = 0 ,1,...nz

$\Phi_j$ is the flux CTF coefficient, j = 0 ,1,...nq

$T_i$ is the inside surface temperature

$T_o$ is the outside surface temperature

$q''_{k0}$ is the conduction heat flux on the outside face

$q''_{ki}$ is the conduction heat flux on the inside face

In addition, for each thermal zone EnergyPlus simulation is based on an integration of energy and moisture balance as shown in the equation below:

$$C_z \frac{dT_z}{dt} = \sum_{i=1}^{N_{sl}} \dot{Q}_i + \sum_{i=1}^{N_{surfaces}} h_i A_i (T_{si} - T_z) + \sum_{i=1}^{N_{surfaces}} m_i C_p (T_{zi} - T_z) + m_{inf} C_p (T_\infty - T_z) + \dot{Q}_{sys} \quad (3.8)$$

where

$\sum_{i=1}^{N_{sl}} \dot{Q}_i$ is the sum of convective heat transfer from the zone surfaces

$\sum_{i=1}^{N_{surfaces}} h_i A_i (T_{si} - T_z)$ is the convective heat transfer from the zone surfaces

$m_{inf} C_p (T_\infty - T_z)$ is the heat transfer due to infiltration of outside air

$\sum_{i=1}^{N_{surfaces}} m_i C_p (T_{zi} - T_z)$ is the heat transfer due to interzone air mixing

$\dot{Q}_{sys}$ is the air systems output

$C_z \frac{dT_z}{dt}$ is the energy stored in zone air

$T_\infty$ is the fluid temperature (K)

and

$$C_z = \rho_{air} C_p C_T \quad (3.9)$$

where

$\rho_{air}$ is the zone air density

$C_p$ zone air specific heat

$C_T$ sensible heat capacity multiplier

Infiltration is outdoor air unintentionally entering the building due to the opening of doors as well as air leakage through windows and other openings. Infiltrated air is mixed with air in the various thermal zones of the building. Determining infiltration (or air tightness) values contains significant uncertainty, as it requires a complex and elaborate procedure often referred to as blower door test. Infiltrated air is commonly modelled as the number of air changes per hour ($ACH^{-1}$) and taken into account in the air heat balance at temperature equal to that of ambient air. In EnergyPlus, infiltration is modelled based on the equation:

$$Infiltration = (I_{design})(F_{schedule})[A + B|(T_{zone} - T_{odb})| + C(Windspeed) + D(Windspeed^2)] \quad (3.10)$$

where

$I_{design}$ is the user defined infiltration value ($ACH^{-1}$)

$T_{zone}$ is the zone air temperature at current conditions (°C)

$T_{odb}$ is the outdoor air dry-bulb temperature (°C)

$F_{schedule}$ is a user defined schedule value between 0 and 1 A is the constant term coefficient

$B$ is the temperature term coefficient

$C$ is the velocity term coefficient

$D$ is the velocity squared coefficient

Similarly, ventilation can be modelled using a schedule, maximum and minimum values, as well as delta temperature values, and is determined by the equation:

$$Ventilation = (V_{design})(F_{schedule})[A + B|(T_{zone} - T_{odb})| + C(Windspeed) + D(Windspeed^2)] \tag{3.11}$$

where

$V_{design}$ is the user defined ventilation value (ACH$^{-1}$)

$T_{zone}$ is the zone air temperature at current conditions (° C)

$T_{odb}$ is the outdoor air dry-bulb temperature (° C)

$F_{schedule}$ is a user defined schedule value between 0 and 1 A is the constant term coefficient

$B$ is the temperature term coefficient

$C$ is the velocity term coefficient

$D$ is the velocity squared coefficient

Furthermore, the energy provided to each thermal zone by the HVAC system, $\dot{Q}_{sys}$ is given by:

$$\dot{Q}_{sys} = \dot{m}_{sys} C_p (T_{sys} - T_z) \tag{3.12}$$

Equations (3.8) and (3.12) can be transformed to yield zone air temperature as shown in equation (3.12) below.

$$T_z^t = \frac{\sum_{i=1}^{N_{sl}} \dot{Q}_i^t + \dot{m}_{sys} C_p T_{supply}^t + \left(C_z \frac{T_z}{\delta t} + \sum_{i=1}^{N_{surfaces}} h_i A_i T_{si} + \sum_{i=1}^{N_{zones}} \dot{m}_i C_p T_{zi} + \dot{m}_{inf} C_p T_\infty\right)^{t-\delta t}}{\frac{C_z}{\delta t} + \left(\sum_{i=1}^{N_{surfaces}} h_i A_i + \sum_{i=1}^{N_{zones}} \dot{m}_i C_p + \dot{m}_{inf} C_p + \dot{m}_{sys} C_p\right)} \quad (3.12)$$

## 3.2 Energy performance analysis

### 3.2.1 Leaf Lab

The aim of the present section is to analyse Leaf Lab's energy performance and compare modelling results with real-time data. Modeling and simulation for the

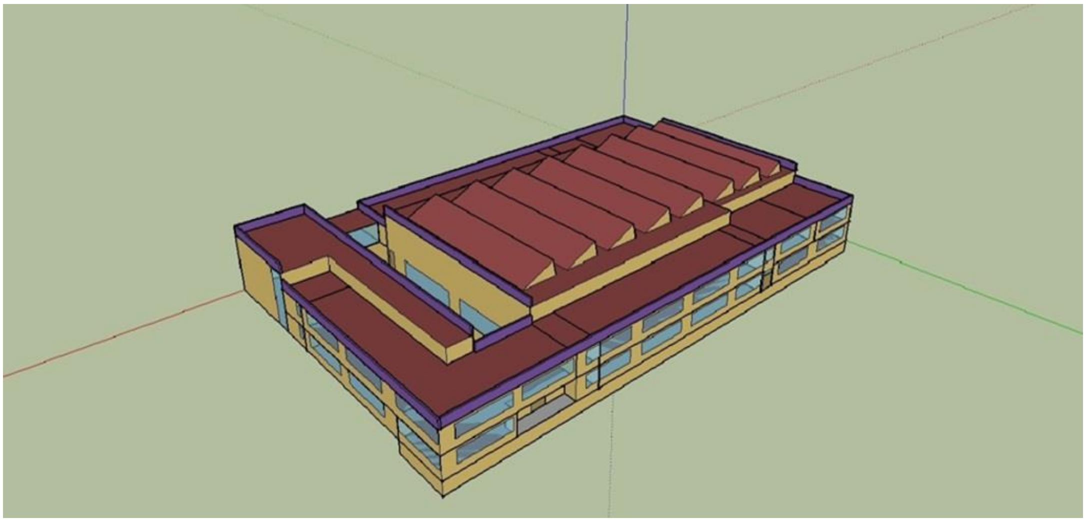

**Figure 9: The model of the Leaf Lab in Google SketchUp**

Leaf Lab are carried out using Google SketchUp [116] as the graphical user interface for 3D modelling, Open Studio plugin and standalone application [117] for editing the various model parameters and EnergyPlus [118] as the simulation engine. The model is depicted in Figure 9. Architectural drawings are used to design the building structure and envelope as well as to convert the several spaces into thermal zones. Electro-mechanical and implemented HVAC system designs are taken into consideration. Moreover, the physical and thermal characteristics of the external and internal walls, roof, ground floor and ceiling, alongside with similar information about the external windows are collected. The lights of each space, approximate number of persons in each space as well as equipment information are recorded for the estimation of the internal thermal gains and electrical energy consumption.

Energy consumption and production data from measurements is collected, analysed and processed to serve the scope of the analysis. The validation of the model is then performed using data recorded temperature and relative humidity sensors installed carefully in selected representative thermal zones of the building taking into consideration size, orientation, use and contact with the ground or outdoor air. Additional, data is extracted by MyLeaf [119], a specialised Loccioni Group proprietary web-based Energy Management System (EMS), providing reliable and user-friendly representation of any energy related monitored parameter such as ambient and indoor environment conditions, power consumption, production and storage over time. The open MyLeaf architecture allows the integration of advanced energy management and control applications in building and microgrid (district) level.

Specifically, the collected data from MyLeaf is: (a) Building total and HVAC power demand and (b) power production by the photovoltaic system.

As it can be observed in Figure 10 and Figure 11, the simulated indoor temperature versus the measured one is less than 1 K at all times. The same applies to the reception area as well as all the rooms monitored indicating high levels of agreement between the simulated and measured data.

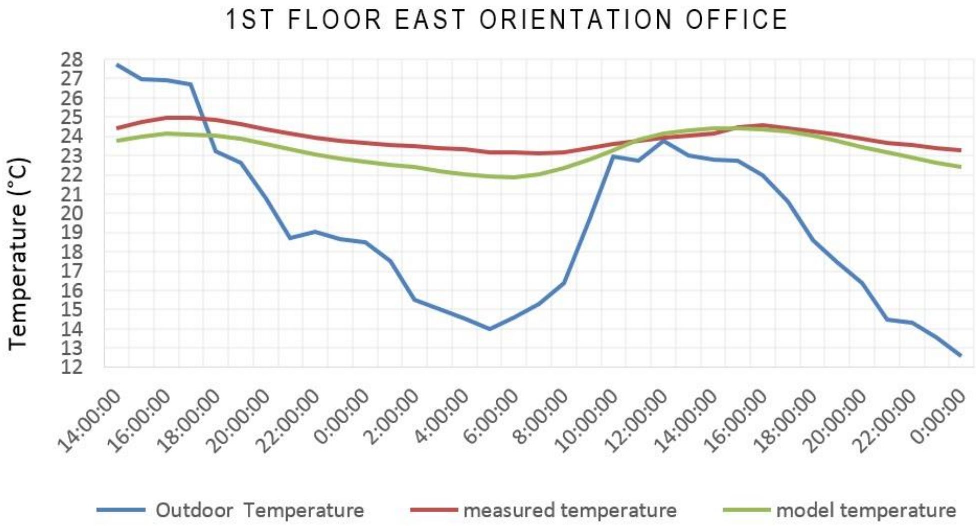


**Figure 10: 1st Floor East Office measured and simulated indoor temperature**

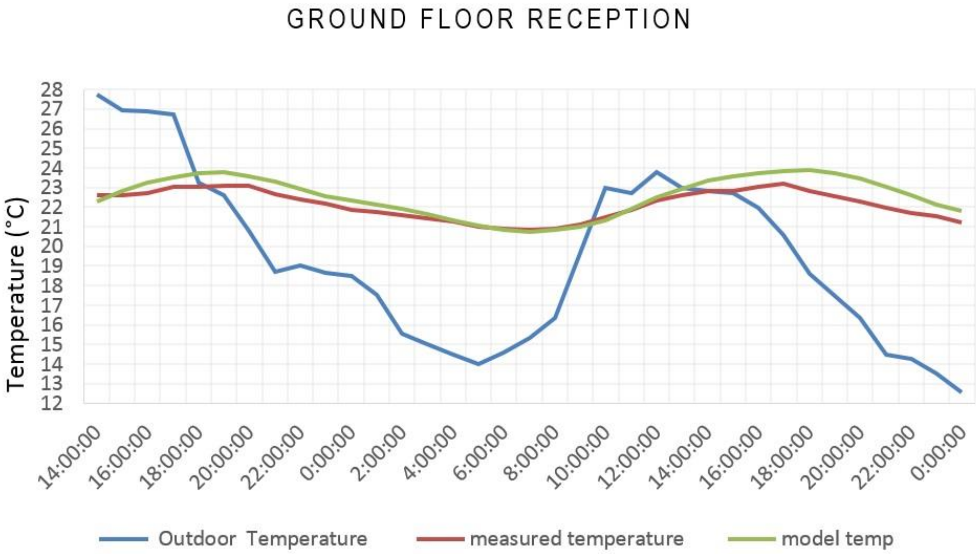


**Figure 11: Ground floor, Leaf Lab reception measured and simulated indoor temperature**

A comparison of the measured and simulated energy consumption is tabulated in Table 1. It is observed that the difference in energy consumption between the various categories is of 1.4% for artificial lighting, 0.6% for HVAC, 0.4% for equipment (including industrial processes) and 0.1% in total, demonstrating a strong correlation between simulation results and the actual behaviour of the building during its operational phase.

**Table 1: Validation of the Leaf Lab Model based on data from MyLeaf**

| Leaf Lab (Industrial) | | Artificial Lighting | HVAC | Industrial / Office Equipment | Total |
|---|---|---|---|---|---|
| **Monitored data** | Electrical Energy Consumption (kWh) | 35,467.3 | 227,176.1 | 297,366.1 | 560,009.5 |
| | Normalised Electrical Energy Consumption (kWh/m²) | 5.9 | 37.9 | 49.6 | 93.3 |
| | Energy Consumption (%) | 6.3% | 40.6% | 53.1% | 100.00% |
| | Normalised Primary Energy Consumption (kWh/m²) | 11.0 | 70.4 | 92.2 | 173.6 |
| | Energy Production by the PV (kWh) | | | | 275,942 |
| | Normalised PV energy (kWh/m²) | | | | 46 |
| **Simulated data** | Energy Consumption (kWh) | 34,985.5 | 225,838.3 | 298,604.2 | 559,428.0 |
| | Normalised Electrical Energy Consumption (kWh/m²) | 5.8 | 37.6 | 49.8 | 93.2 |
| | Energy Consumption (%) | 6.3% | 40.4% | 53.4% | 100.0% |
| **Difference** | Energy Consumption (kWh) | 481.8 | 1,337.8 | -1,238.1 | 581.5 |
| | Energy Consumption (%) | 1.4% | 0.6% | 0.4% | 0.1% |

As indicated, in Table 1, the energy consumption share of the industrial/office operations in the Leaf Lab is the highest between the categories accounting for 53.1%. This is of particular importance when one considers the energy balance (especially given the PV electrical energy production of 46 kWh/m$^2$) as it reveals, HVAC and lighting systems electrical energy consumption being equal to 43.8 kWh/m$^2$. For the conversion of electrical energy to primary energy consumption, a factor of 1.86 is used based on internationally reported calculations for the energy mix and power grid efficiency of Italy [120]. Taking into account energy production from the PV plant, it is concluded that the Leaf Lab is a Near-zero Energy Industrial Building with total net electrical energy consumption of 47.3 kWh/m$^2$ and normalized total net primary energy consumption of 127.6 kWh/m$^2$.

The correlation of the Leaf Lab model and the measured HVAC power demand on a monthly basis as presented in Figure 12 demonstrates part of the validation process according to standardized measurement and verification principles [121]. In the examined case, the Coefficient of Variation ($C_v$) of the Root Mean Square Error (RMSE) of 14.8% satisfies the International Performance Measurement and Verfication Protocol (IPMVP) acceptable monthly tolerance levels.

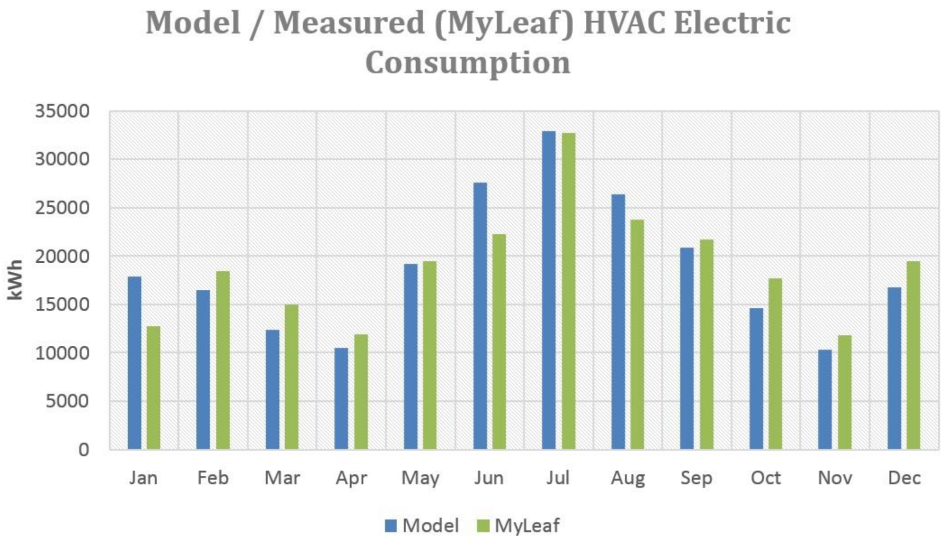


**Figure 12: HVAC system validation based on monthly electrical energy consumption**

### 3.2.2 Leaf House

Modeling and analysis of the Leaf House as in the case of Leaf Lab is carried out using Google SketchUp [116] as the graphical user interface for 3D modelling, Open Studio [117] plugin and standalone application for editing the various model parameters and EnergyPlus [118] as simulation engine. The developed 3D model is depicted in Figure 13. The thermal zone division is performed with a large attention to detail to best capture differences in indoor comfort leading to every room being considered a separate thermal zone.

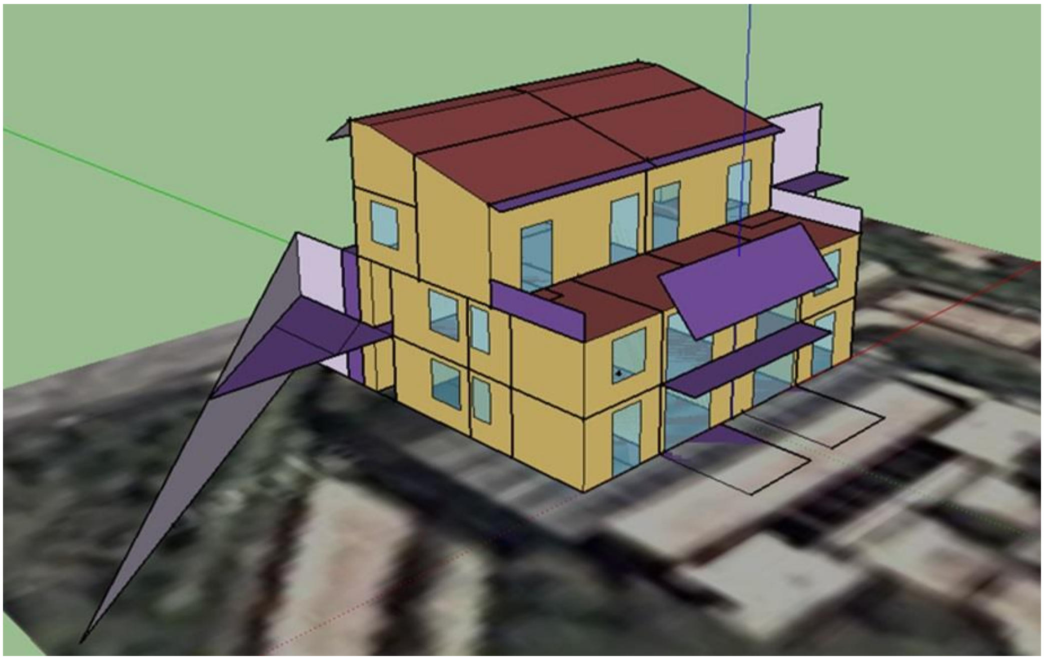

**Figure 13. The Leaf house and its thermal energy model using Open Studio plugin**

Energy performance in Leaf House according to 2015 data from MyLeaf is summarized in Table 2. In the measurements, it is observed that Leaf House is a Near-Zero Energy Building since its normalized primary energy consumption is 54.4 kWh/m$^2$. The PV system energy production accounts for 63.1% of the building energy demand and $CO_{2\text{-eq}}$ emissions reduction of 11.32 t on a yearly basis (Figure 14).

**Table 2: Leaf House energy consumption data for 2015 (MyLeaf)**

| Leaf House | Total | Total Net (consumption minus production) |
|---|---|---|
| Annual Electrical Energy Consumption (kWh) | 37,196.0 | 13,746.0 |
| Normalized Annual Electrical Energy Consumption (kWh/m$^2$) | 79.1 | 29.2 |
| Primary Annual Energy Consumption (kWh) | 69,184.6 | 25,567.6 |

| | | |
|---|---|---|
| Normalized Annual Primary Energy Consumption (kWh/m$^2$) | 147.2 | 54.4 |
| Annual $CO_{2\text{-}eq}$ emissions (kg) | 17965.7 | 6639.3 |

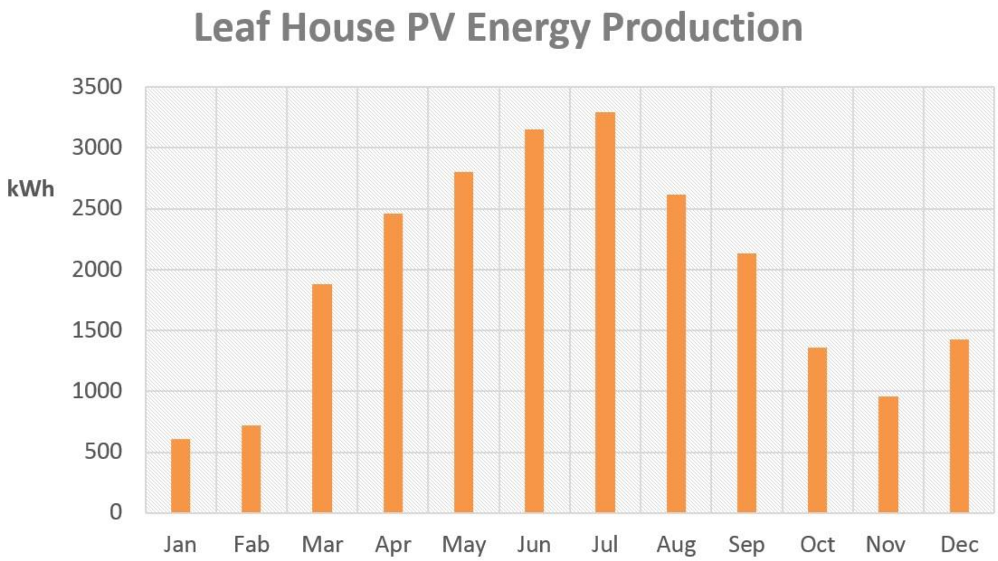


**Figure 14: Leaf House PV System Monthly Energy Production for 2015 (MyLeaf)**

## 3.3 Discussion

In the selected case studies the performance gap is finally assessed by comparing design and operational primary energy consumption in Table 3:

**Table 3: Normalised primary energy consumption in the design and operational phase**

| Pilot case study | Normalised Primary Energy Consumption in Design Phase (kWh/m$^2$) | Normalised Net Primary Energy Consumption in Operational Phase (kWh/m$^2$) |
|---|---|---|
| Leaf Lab | 26.9 | 35.4 |
| Leaf House | 19.6 | 54.4 |

With regards to the Leaf Lab, the net normalised primary energy in the operational phase is calculated by deducing energy dissipated for industrial purposes as this is not taken into consideration in the corresponding design value. According to the results, there is a relatively low difference of 8.5 kWh/m$^2$ in primary energy consumption which is not considered particularly significant.

In the case of the Leaf House the performance gap is of higher magnitude and in specific 34.8 kWh/m$^2$ of primary energy consumption. A possible explanation for - at least - part of this performance gap is that the energy classification process in Italy (as well as in other countries) does not take into account energy for lighting or other appliances as it depends on residents' behaviour or other factors that cannot be standardised and applied as a common assessment framework. One issue that may also be related to the performance gap, in this case, is associated with the operation of the hydronic underfloor heating in the Leaf House. The system is characterised by high thermal inertia which is slow in responding to weather changes. In this regard, it would be interesting to evaluate alternative advanced controls (i.e. predictive control) effectiveness in improving energy efficiency and indoor comfort levels. Another critical consideration with respect to the performance gap in the Leaf House concerns the engagement of residents in terms of their capability in controlling building systems, their understanding of the actual potential in saving energy and their motivation in this direction. Despite the fact that residents of Leaf Lab enjoy an elaborate monitoring and control interface, it has not been adequately explored if a performance gap may be linked to a lack of capability in using the elegant controls provided or a low commitment in addressing energy savings. An important parameter in this direction is that residents in the Leaf Lab are often visitors who do not permanently reside in the building but in an ad-hoc fashion.

Overall, in the examined cases, the performance gap is either not particularly significant or it can be possibly addressed by technical improvements or factors related to human activity. In the case of the Leaf Lab and the Leaf House, this is largely due to the integrated initial design, involving implementation of state of the art techniques, technologies and know-how for achieving Near-Zero energy goals. In the case of the Leaf House, technical measures such as predictive control could possibly provide a smart solution in avoiding energy waste and improving indoor conditions. On the other hand training about available controls, behavioural change and active engagement can be especially important for residents to become proactive in reducing energy consumption to even lower levels. Behavioural change can be achieved in a number of ways including raising awareness, gamification i.e. competitions between apartments or enrolment in rewarding (future) Demand Response programs.

### 3.4 Conclusions

In this chapter, the operational performance of industrial and residential buildings has been investigated, analysed and optimized with the use of dynamic simulation tools. Energy efficient technologies, renewable energy technologies, storage, as well as smart monitoring and controls have been audited to evaluate their significance for smart near-zero energy buildings of different utilization. Various performance indicators have been used in this analysis including normalized electrical and primary energy consumption. Smart monitoring and indoor conditions' measurements have been exploited to allow the extraction of robust results and the validation of dynamic building energy models. The above analysis reveals the significance in evaluating the actual performance gap in NZEBs and provide the basis for decision making and smart adjustments as necessary. In both cases, apart from the high quality building envelopes, the Near-Zero target is largely pursued by renewable energy technologies and the implementation of advanced monitoring and controls. Furthermore, in the aforementioned cases, there is a systematic and continuous approach in establishing near-zero energy targets through research and innovation activities. In this direction, predictive control, behavioural change and proactive users' engagement through gamification and enrolment in demand response programs have been identified as potential areas for addressing energy efficiency improvements in the future.

# 4. HVAC Optimisation Genetic Algorithm for Industrial Near-Zero Energy Building Demand Response

Demand response offers the possibility of altering the profile of power consumption of individual buildings or building districts, i.e., microgrids, for economic return. There is a significant potential for demand response in enabling flexibility via advanced grid management options, allowing higher renewable energy penetration and efficient exploitation of resources. Demand response and dynamic management of distributed energy resources are gradually gaining importance as valuable assets for managing peak loads, grid balance, renewable energy source intermittency and energy losses. In this chapter, the potential for operational optimization of a heating, ventilation and air conditioning (HVAC) system in a smart near-zero-energy industrial building is investigated with the aid of a genetic algorithm. The analysis involves the validated building energy model of Leaf Lab presented in chapter 3, a model of energy cost and an optimization model for establishing HVAC optimum temperature set points. Optimization aims at establishing the trade-off between the minimum daily cost of energy and thermal comfort. The predicted mean vote is integrated into the objective function to ensure thermal comfort requirements are met.

The purpose of this chapter is to propose a GA optimisation approach and investigate its effectiveness in HVAC temperature set point control, based on day-ahead pricing information, for realizing profits as a reward for exploiting flexibility. Cost of energy is used as one of the two optimization criteria and is naturally, as well as in this case, a function of energy consumption over time. Using energy consumption as the optimization criterion instead, would lead to suboptimum performance with respect to cost, which is the main incentive behind changes in power consumption. Most importantly, minimizing on-site energy consumption measured at the point of consumption does not guarantee optimum environmental performance, since it does not take into account where, when, and how energy is generated. On the other hand, having the cost of energy as one criterion in the objective function provides an indirect way to account for operational aspects of the power grid, provided that the energy market is transformed to allow the penetration of demand response resources as well as distributed renewable energy generation. Reduction of energy on-site consumption is, also in this case, however, considered as an indirect goal and evaluated, since it is acknowledged as a well-established measure providing necessary information on the energy efficiency of buildings and cannot be neglected.

## 4.1 Methodology

The framework presented hereafter concerns optimization of the HVAC temperature set point hourly schedule based on a genetic algorithm incorporating daily operational cost and the mean predicted mean vote (PMV) as the two criteria of the objective function. Operational cost refers to the cost of energy on the basis of the given day-ahead hourly pricing profile and the HVAC hourly energy consumption obtained by the simulation of the building's validated model. The building thermal model is validated based on annual HVAC energy consumption and measurements of indoor temperature [122]. The validated thermal model of the building provides a reliable basis for this kind of investigation, as it takes into consideration the physical aspects of the building (geometry, materials), operational aspects, and climate conditions in a dynamic way. The baseline scenario is a reliable benchmark against which the optimized scenario is compared. Therefore, operational effects are kept constant to account for the fact that user behaviour, natural ventilation, and industrial operations are difficult to model and are in most cases not monitored. On the other hand, inducing changes in the temperature set points of the HVAC system makes it imperative to evaluate any solution on the basis of the building users' thermal sensation and the heat exchange of the human body with the surrounding indoor environment. This balance of energy fluxes is influenced by physical activity, clothing, and the following indoor conditions; air temperature, mean radiant temperature, air velocity, and relative humidity (RH). Internal comfort is evaluated in this work using the PMV index as developed by Fanger in 1972 and adopted by ISO 7730 to account for human heat generation and exchange with the surrounding environment [123]. PMV is converted to the Percentage of People Dissatisfied (PPD) to provide an estimate of the share of people feeling uneasy with certain thermal conditions. Decision variables in the optimization process are the hourly HVAC temperature set points. Controlling HVAC temperature set points has, as a consequence, variations in the operation, power consumption and running cost of the HVAC system. Naturally, this will impact indoor thermal conditions, thereby imposing the need for including thermal comfort as a criterion into the optimization process and compliance with established standards.

The methodology followed is depicted in Figure 15. Firstly, the building (Leaf Lab) three-dimensional (3D) thermal model was developed in Open Studio based on the technical information of the building (i.e., drawings, datasheets of systems installed) and site audits. Secondly, the model was validated using measurements of weather conditions, indoor (air temperature, RH) conditions and HVAC power consumption. Details on the building modelling and validation procedures are available in Reference [122]. Thirdly, a new weather file was constructed for the year of interest by merging together weather measurements including dry and wet bulb temperature (°C), atmospheric pressure (kPa), relative humidity (%), dew point temperature (°C), global, normal and diffuse solar irradiance (Wh/m$^2$), and wind speed (m/s). The validated 3D thermal model of the building was set up to receive an input the temperature setpoints from an external source (Matlab in this case) when simulating the building's energy performance and provide HVAC power demand ($P_{HVAC}$, kW), indoor air temperature ($T_{air}$, °C), indoor radiant temperature ($T_{rad}$, °C), and relative humidity (RH, %) as an output. Fourthly, day-ahead pricing information was used to create the DARTP model required for the optimization. Day-ahead energy prices (€/MWh) for the region of central–northern Italy were used as the main component for the formulation of the energy pricing scheme used in the optimization. Additional costs related to transmission/distribution, as well as other costs and taxes, were included to define the final energy pricing profile. Fifthly, a genetic algorithm was constructed to optimize the objective function composed by (a) the daily sum of the hourly cost of energy, and (b) the daily average of hourly PMV values for the working hours of the building and specifically from 9:00 a.m. to 6:00 p.m. In the developed GA optimization scheme, HVAC temperature set points were used as the discrete decision variables subject to upper and lower boundaries which differed between the heating and cooling seasons. Lastly, simulation of the validated building thermal model was executed in an iterative process using the set points selected by the GA until convergence criteria were met. Output values of HVAC power simulation, indoor air temperature, radiative temperature and relative humidity were used to evaluate energy cost and the PMV at each iteration.

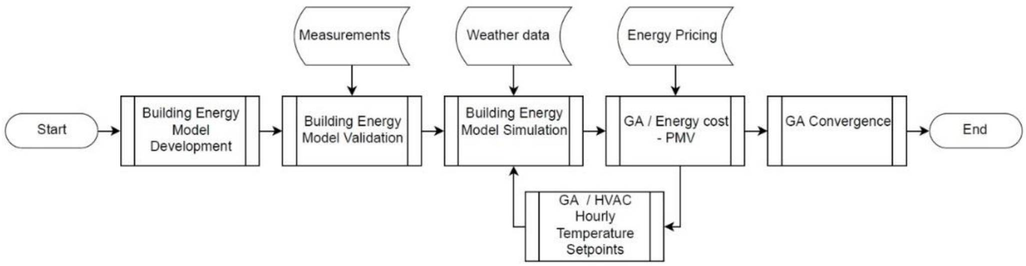


**Figure 15: Genetic algorithm (GA)-based heating, ventilation, and air conditioning (HVAC) temperature set point optimization scheme**

## 4.2 GA optimisation model

The generic objective function of the GA optimization process is given by equation 4.1 below.

$$[min]f\left({T_s}_{i=1}^{J}\right) = w_c \times \frac{\sum_{i=1}^{J} C_i \times P_i}{\sum_{i=1}^{J} C_i \times P_{i_{baseline}}} + w_{pmv} \times \frac{\sum_{i=1}^{J} |PMV_i|}{PMV_{max} \times J} \tag{4.1}$$

subject to $|PMV_i| \leq 1$.

$P_i$ is the HVAC power obtained as an output by the simulation of the building's thermal model and varies according to the building load and temperature set points $({T_s}_{i=1}^{J})$.

$PMV_i$ varies from −3 (cold) to +3 (hot) with zero being the optimum neutral value according to which internal heat production is equal to the loss of heat to the environment. PMV is calculated according to ISO 7730 based on the following parameters:

Metabolic ($M$) rate in W/m$^2$

Effective mechanical power ($W$) in W/m$^2$;

Clothing insulation ($I_{cl}$) in (m²K/W);

Air temperature ($T_{air}$) in (°C);

Mean radiant temperature ($T_r$) in (°C);

Relative air velocity ($V_{air}$) in (m/s);

For the calculation of the PMV hourly values ($PMV_i$), air temperature, radiant temperature and relative humidity were obtained as an output from the simulation of the building, while certain other parameters such as $M$, $W$, $f_{cl}$, and $p_a$, were considered to be constant. In the developed approach, the normalized daily average of PMV hourly absolute values was used to search for optimal near-zero, positive, or negative values. Furthermore, the actual values of the PMV are also assessed to reject solutions associated with extreme changes in thermal comfort from one hour to another. This is also prevented based on standards' constraints for set point temperatures drift as explained later in this chapter.

The genetic algorithm developed to optimize the objective function as expressed in Equation (4.1) was based on chromosomes of 24 discrete values (genes) each, corresponding to the temperature set points of the HVAC for hours 1–24 of the day. Chromosome values were subjected to upper and lower constraints depending on the season of the year. In heating season, genes $T_{s}{}_{i_h=8}^{18}$ during the working hours of the building (9:00 a.m. to 6:00 p.m.) had a lower boundary of 18 °C and an upper boundary of 24 °C. In cooling season, genes $T_{s}{}_{i_c=8}^{18}$ during working hours of the building had a low boundary of 20 °C and an upper boundary of 26 °C. This is mathematically expressed in the following constraints:

$$18 \leq T_{s}{}_{i_h=9}^{18} \leq 24$$

$$20 \leq T_{s}{}_{i_c=9}^{18} \leq 26$$

For the two hours prior to the working hours of the building and the two hours after, the following constraints were applied to consider preheating and the impact of the extended operation of the HVAC system:

$$17 \leq Ts_{i_h=7}^{8} \leq 24;$$

$$17 \leq Ts_{i_h=19}^{20} \leq 24;$$

For two hours prior to the working hours of the building and two hours after, the following constraints were applied to consider precooling and the impact of the extended operation of the HVAC system:

$$20 \leq Ts_{i_c=7}^{8} \leq 27$$

$$20 \leq Ts_{i_c=19}^{20} \leq 27$$

## 4.3 Model of energy cost

According to the utility bills of the Leaf Community in 2018, the average unit cost of energy varied monthly between 0.1507 €/kWh and 0.1749 €/kWh, as shown in Figure 16. Furthermore, it is evident from the graph that the energy consumed outside the peak hours is significant and equal to 35.8%. The two-zone (peak/off-peak) ToU pricing scheme, however, offers low incentives for managing loads during daytime mainly as a consequence of monthly peak power charges.

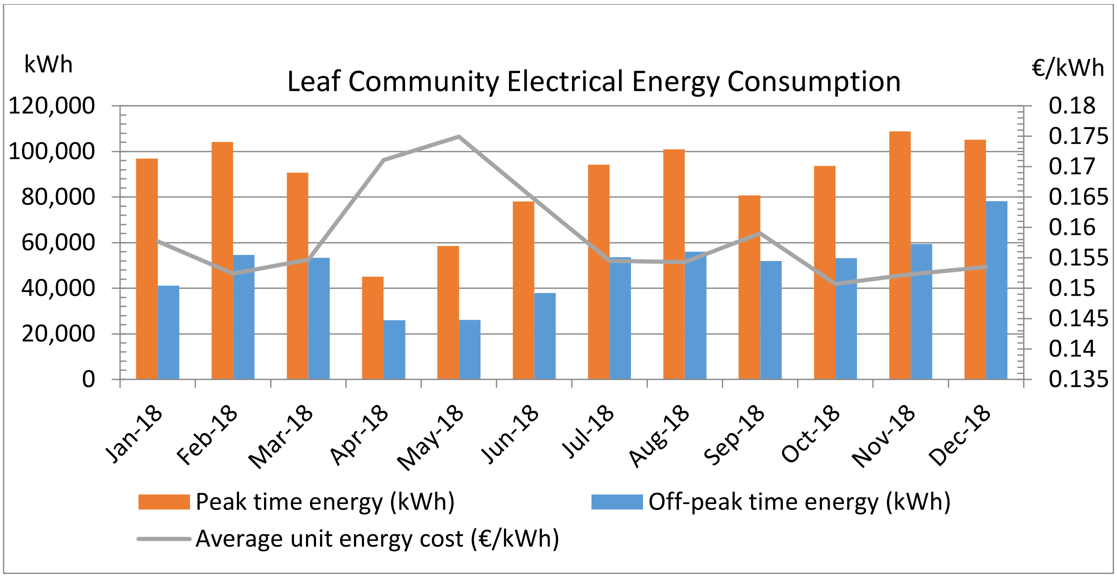


Figure 16: Leaf Community electrical energy consumption and unit cost of energy in 2018.

The cost of energy model of the Leaf Community was developed in Matlab as described below. Based on current charges related to energy consumption as identified through energy bills for 2018, basic components were adjusted to incorporate day-ahead hourly price fluctuations in a DARTP scheme and to formulate the case study for dynamic HVAC energy management. Overall, the developed hourly pricing scheme contains costs related to the consumption of energy, maximum power, grid services, taxes and levies. Due to the fact that, in the current pricing scheme, a high share of the costs are determined by fixed charges, these costs were allocated a dynamic parameter to account for network flexibility and stability. The mathematical model of the energy cost is presented in the equations below.

$$C_T = C_{E,T} \times (1 + IVA); \tag{4.2}$$

$$C_{E,T} = C_S + C_N + C_{EDD}; \tag{4.3}$$

$$C_S = \sum_{h=0}^{J} E_{hvac,h} \times (DA_h + C_{S,F})\,; \tag{4.4}$$

$$C_N = C_F + C_{Pmax} + C_{AT} + C_{A-UC}; \tag{4.5}$$

$$C_F + C_{AT} + C_{A-UC} = \sum_{h=0}^{J} E_{hvac,h} \times DA_{N,h} \times C_{FAA}\,; \tag{4.6}$$

$$C_{Pmax} = \max(P_{hvac,h}) \times C_{Pmax,F}; \tag{4.7}$$

$$C_{EDD} = \sum_{h=0}^{J} E_{hvac,h} \times DA_{N,h} \times C_{EDH}. \tag{4.8}$$

## 4.4 Results and discussion

The generic GA optimization scheme analysed in the previous section was applied to include working hours (9:00 a.m. to 6:00 p.m.) plus two hours before (7:00–9:00 a.m.) and two hours after (6:00–8:00 p.m.). This is considered essential in order to study the effects of preheating or precooling of the building and to maintain internal conditions at comfortable limits for some time after working hours to account for the fact that some people may still occupy the building. Optimization was conducted for the main industrial thermal zone of the building, which occupies a total area of 1,327 $m^2$ and a height of 8 m surrounded by various other spaces including offices, meeting rooms and other facilities on two floors. Following a number of trials, the population size of the GA was set to 50, the crossover fraction was set to 0.8 and the maximum number of iterations was set to 4,600 in order to examine a wide range of different solutions. All solutions obtained during the optimisation are stored and the top solutions are filtered to assess the set point patterns associated with optimum levels of energy and cost savings, as well as compliance with well-established standards of thermal comfort and temperature set point drift. The approach is designed to evaluate energy cost on a 24-h time frame. Representative results for four winter days, two days for autumn, one for summer and one for spring are presented to account for different seasonal climatic conditions, heating and cooling modes as well as DA pricing profiles.

**Scenario 1: 25 January 2018 (winter)**

Results from the GA HVAC optimization on 25 January 2018 are presented in Figure 17 below. In the optimized scenario of this case, set points during working hours were selected, on an hourly basis, to be between 18 °C and 22 °C, as shown in Figure 17a, and the energy of the HVAC was reduced from 759.88 kWh to 570.13 kWh, a reduction of 25% (Figure 17c). Energy cost (Figure 17d) was decreased from €159.3 to €121.03, which is equal to 25.0% savings. The HVAC power was kept lower in the optimized scenario, except during hours 6:00 and 8:00 p.m. At the baseline scenario, the PMV varied from −0.36 to 0.13, while, at the optimized scenario, from −0.78 to −0.05 (Figure 17b). The average PMV varied from −0.14 to −0.38, which corresponds to a PPD increase from 6.28% to 9.13% between the baseline and optimized scenario. In this case, a trade-off between thermal comfort and energy consumption was found to be associated with significant cost savings at times of high pricing rates but also during low pricing zones.

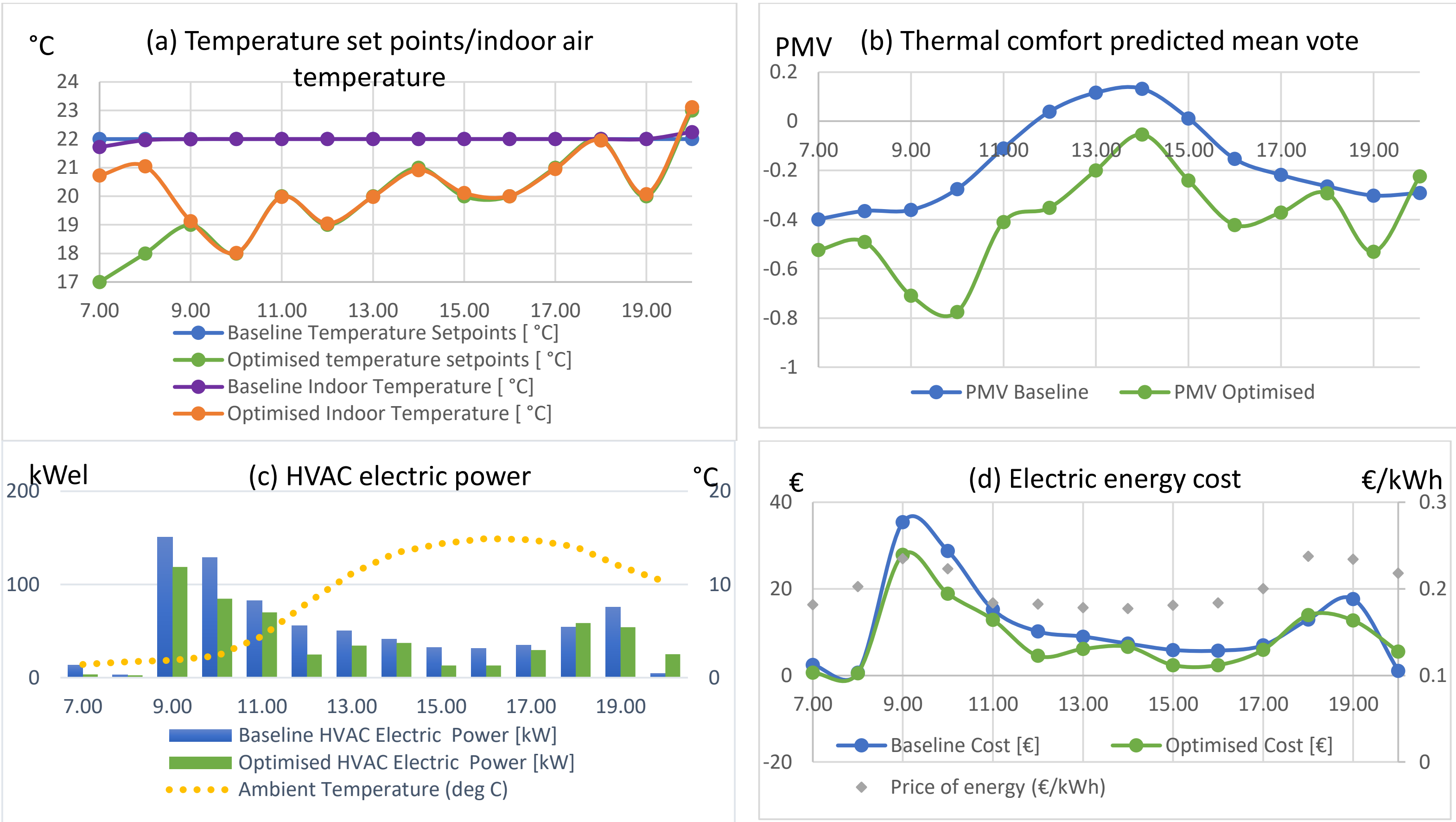


**Figure 17: GA HVAC optimization results for 25 January 2018 (winter).**

**Scenario 2: 27 March 2018 (spring)**

Results from the GA HVAC optimization on 27 March 2018 are presented in Figure 18 below. In the optimized scenario of this case, set points were dynamically altered between 19 °C and 22 °C within working hours (Figure 18a), and the energy of the HVAC was reduced from 610.91 kWh to 463.43 kWh (Figure 18c), a reduction of 24.1%. Energy cost (Figure 18d) was decreased from €121.02 to €94.05, which is equal to 22.3% savings. The HVAC power was lower in the optimized scenario, except during hours 10:00 a.m. and 8:00 p.m. (outside working hours). At the baseline scenario, the PMV varied from −0.39 to −0.02, while, at the optimized scenario, PMV varied from −0.65 to −0.18 (Figure 18b). The average PMV varied from −0.2 to −0.41, which corresponds to a PPD increase from 6.47% to 9.28% between the baseline and optimized scenario. Similarly, in this case, cost savings occurred mostly early in the morning and late in the evening when prices were relatively high. Some savings were also observed around 12:00–1:00 p.m. just before prices got to the lowest level of that particular day.

**Scenario 3: 15 August 2018 (summer)**

Results from the GA HVAC optimization on 15 August 2018 are presented in Figure 19 below. In the optimized scenario, temperature set points varied, on an hourly basis, from 26 °C to 24 °C, within working hours (Figure 19a), whereas the energy of the HVAC (Figure 19c) was reduced from 1447.83 kWh to 1175.93 kWh, a reduction of 18.8%. Energy cost (Figure 19d) was decreased from €295.26 to €238.57, which is equal to 19.2% savings. The mean PMV for working hours was improved from −0.2 to −0.007, and the PPD was decreased from 6.42% to 5.03%. In the optimized solution, HVAC power was lower during all hours except 2:00, 5:00, and 6:00 p.m. following the set points changing from higher to lower values down to 24

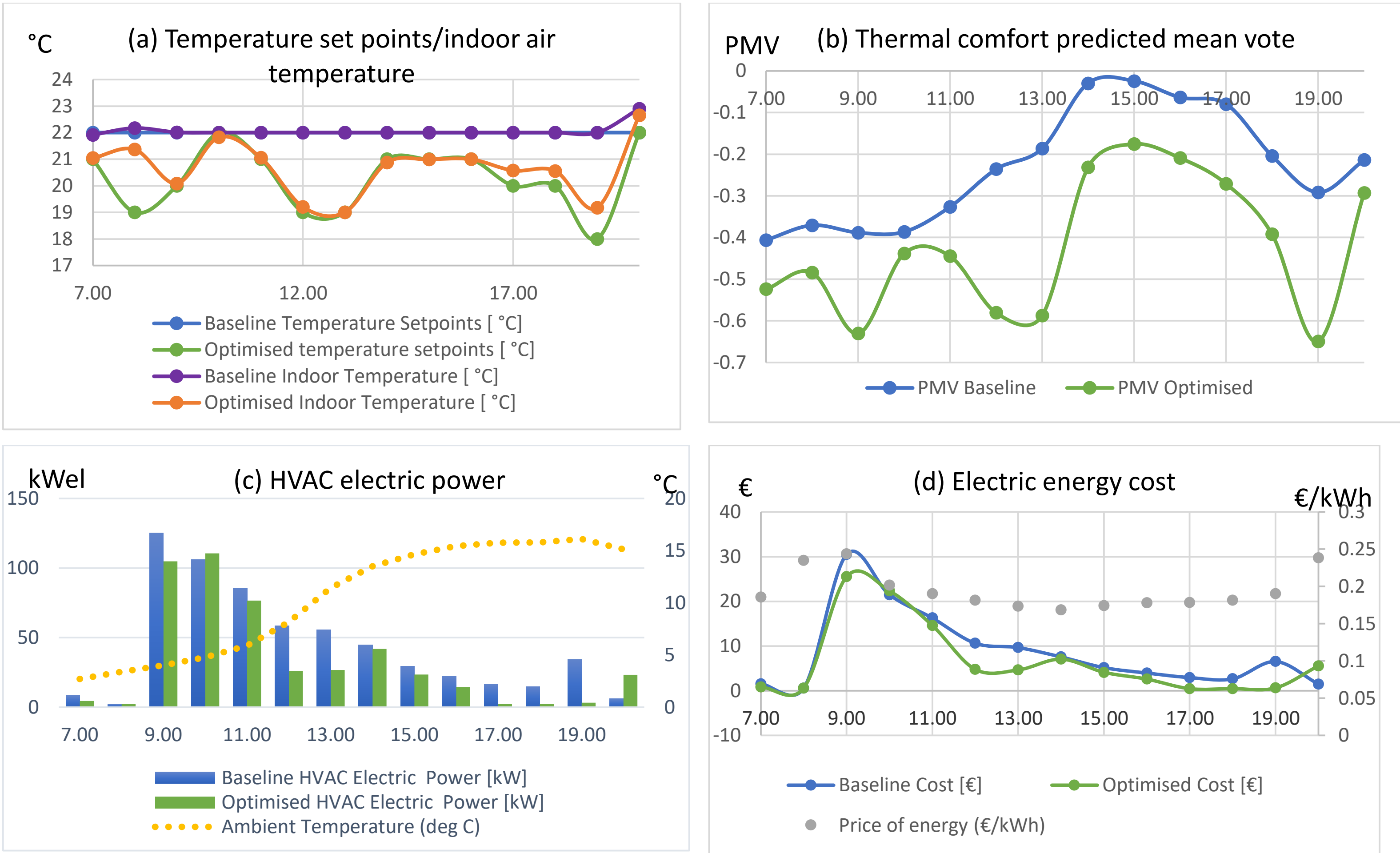


**Figure 18: GA HVAC optimization results for 27 March 2018 (spring).**

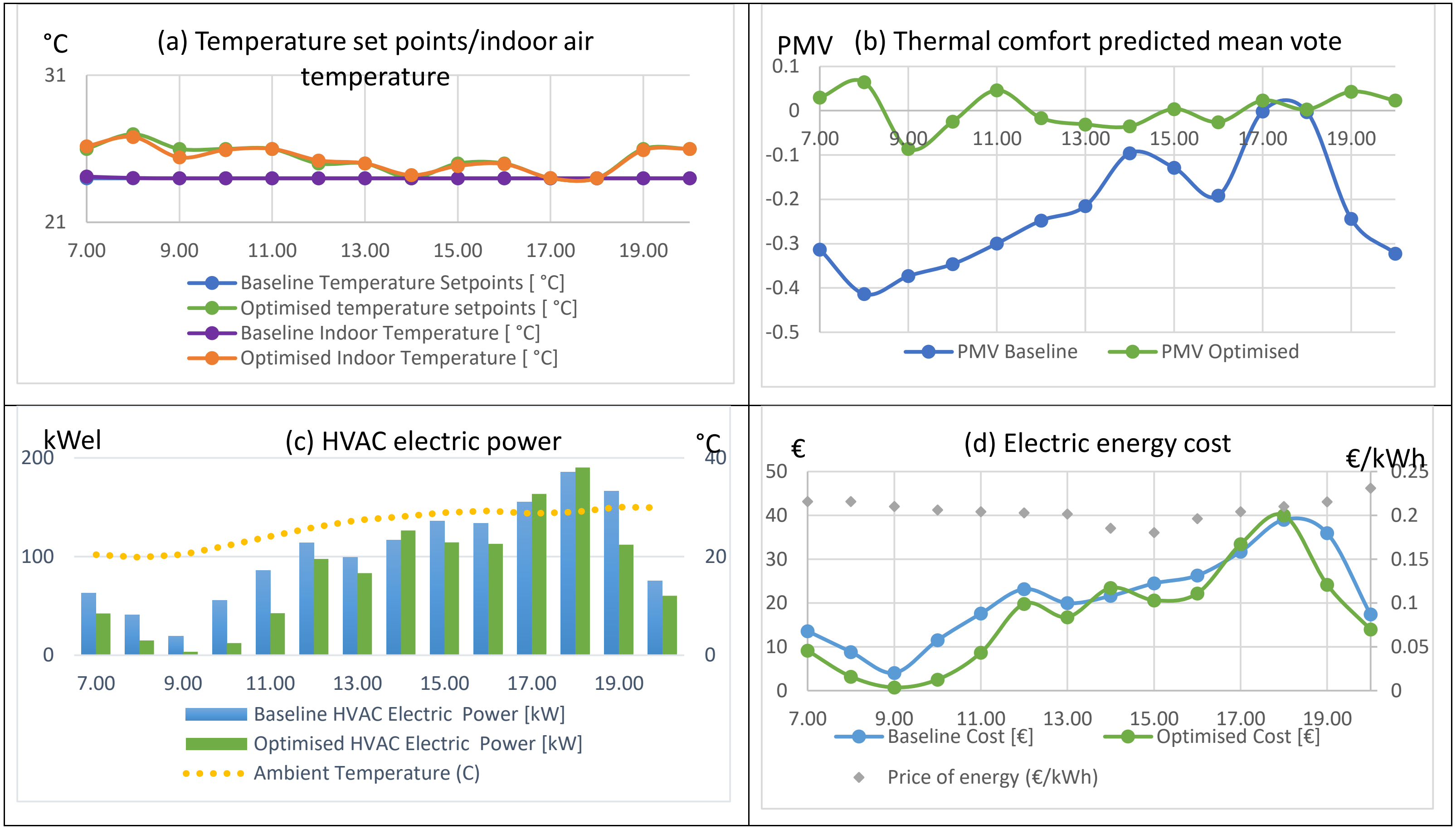


**Figure 19: GA HVAC optimization results for 15 August 2018 (summer)**

°C. In this scenario, cost savings occurred throughout the day, while they were more evident during hours of high prices compared to neighbour regions. The PMV was improved as the fixed cooling set point caused thermal discomfort and unnecessary high energy consumption levels for most hours during the day (Figure 19b).

**Scenario 4: 10 September 2018 (autumn)**

Scenario 4 results from the GA HVAC optimization on 10 September 2018 are presented in Figure 20 below. In this case, the energy of the HVAC (Figure 20c) was reduced from 1268.47 kWh to 1136.29 kWh, a reduction of 10.4%, while energy cost (Figure 20d) was decreased from €311.59 to €280.68, a reduction of 9.9%. The slight difference in the mean PMV for working hours from −0.144 to −0.073 corresponds to a PPD decrease by 1.1%. The PMV at the baseline scenario varied from −0.56 up to 0.11, while, in the optimized scenario, PMV varied from −0.39 to 0.06 (Figure 20b). HVAC power values (Figure 20c) in the optimized scenario exceeded their respective values in the baseline scenario at times of low prices with respect to the neighbouring regions and specifically from 12:00–3:00 p.m. Baseline energy consumption was unnecessarily high during morning hours as it coincided with significant negative PMV levels, while efficient performance was observed in the optimized scenario where the set point was kept at the highest allowed level. Indoor temperature (Figure 20a) deviated from the set point temperature for both the baseline and the optimized scenario between 9:00 and 10:00 a.m. In the optimized scenario, the HVAC energy consumption remained at low levels due to the negative PMV levels during the same time period. Another interesting observation was that the PMV in the baseline scenario significantly increased over time during the day, despite the fact that the indoor temperature was kept constant, which was mainly due to the effect of radiative temperature on thermal comfort.

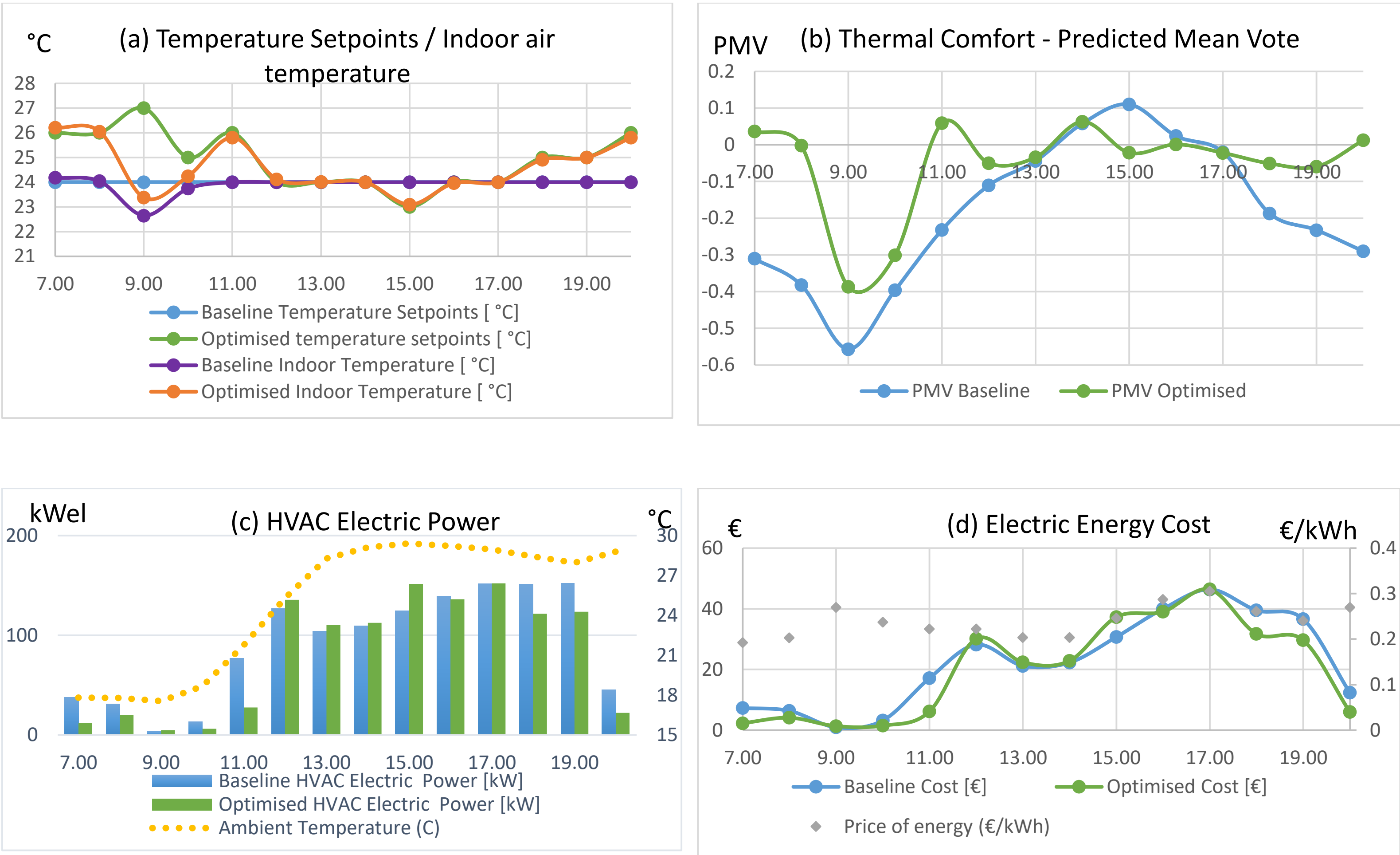


**Figure 20: GA HVAC optimization results for 10 September 2018 (autumn)**

**Scenario 5: 21 September 2018 (autumn)**

Results from the GA HVAC optimization on 21 September 2018 are presented in Figure 21 below. In the optimized scenario, set points within working hours fluctuated between 26 °C and 24 °C (Figure 21a), while the energy of the HVAC was reduced from 1248.69 kWh to 1078.16 kWh (Figure 21c), a reduction of 13.7%. Energy cost (Figure 21d) was decreased from €298.07 to €253.79, which is equal to savings of 14.9%. The mean PMV for working hours was improved from −0.172 to −0.056, and the respective PPD was decreased from 6.4% to 5.4%. In this case, the optimized PMV (Figure 21b) reflected improved thermal conditions, since it oscillated in the region −0.40 to 0.05 in the optimized scenario, while, in the baseline scenario, it varied between −0.56 and 0.05. Energy savings were achieved by keeping the temperature set points at higher levels, while the PMV was at negative levels during early morning and late afternoon working hours. Slightly higher HVAC power levels (Figure 21c) were observed during hours 12:00–3:00 p.m., coinciding with the lowest energy prices during the day.

**Scenario 6: 20 November 2018 (winter)**

Results from the GA HVAC optimization on 20 November 2018 are presented in Figure 22 below. Temperature set points in the optimized scenario were dynamically controlled from 17 °C to 23 °C (18 °C to 22 °C within working hours; Figure 22a). In the optimized scenario, the energy of the HVAC was reduced from 923.75 kWh to 756.67 kWh, a reduction of 18.1% (Figure 22c). Energy cost, shown in Figure 22d, was decreased from €217.33 to €177.66, which is equal to savings of 17.4%. PMV in the optimized scenario varied from −0.50 to −0.10, whereas, in the baseline scenario, it varied between −0.07 and −0.05 (Figure 22b). The mean PMV for working hours was increased from −0.055 to −0.276, and the respective PPD was

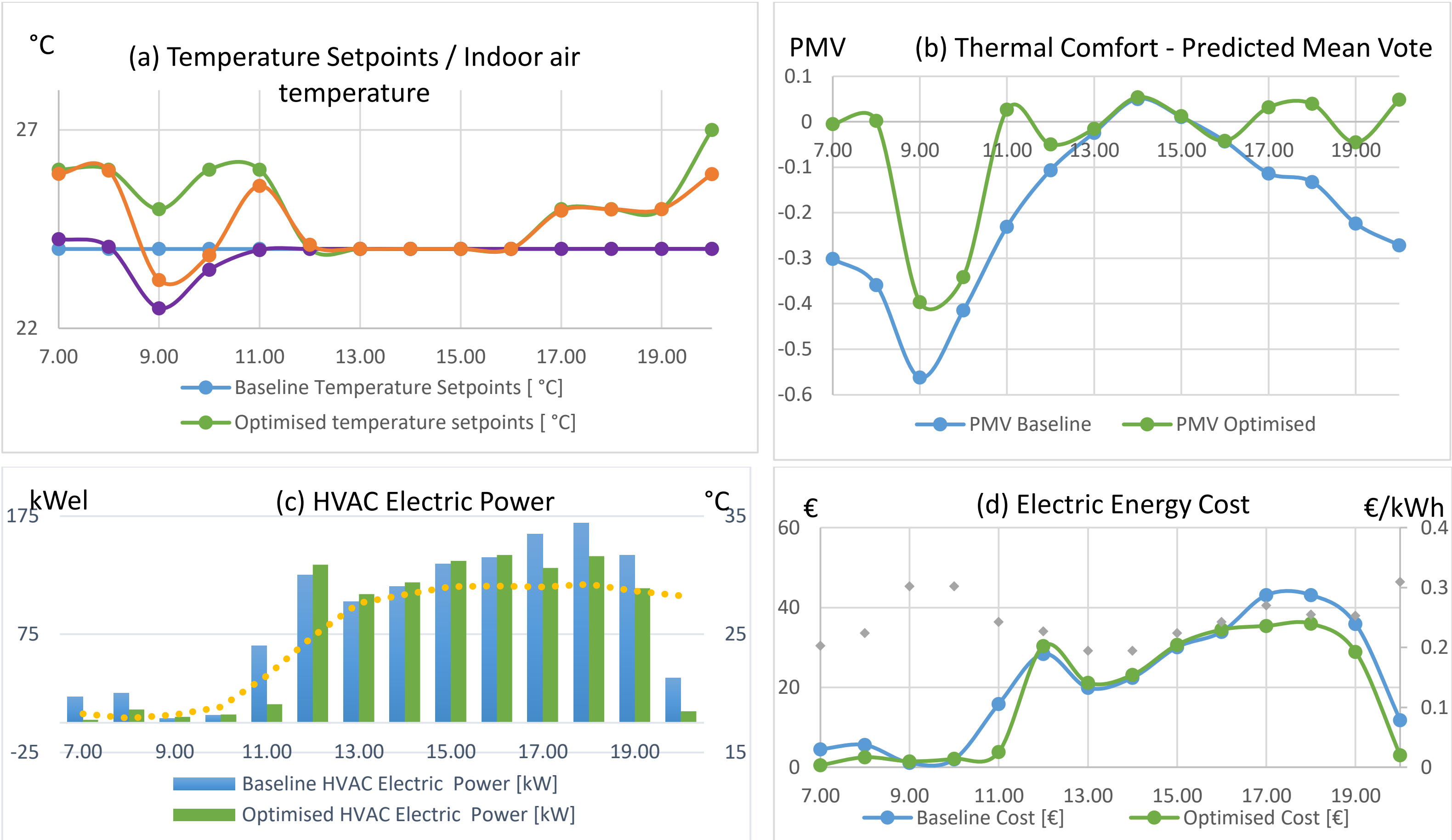


**Figure 21: GA HVAC optimization results for 21 September 2018 (autumn)**

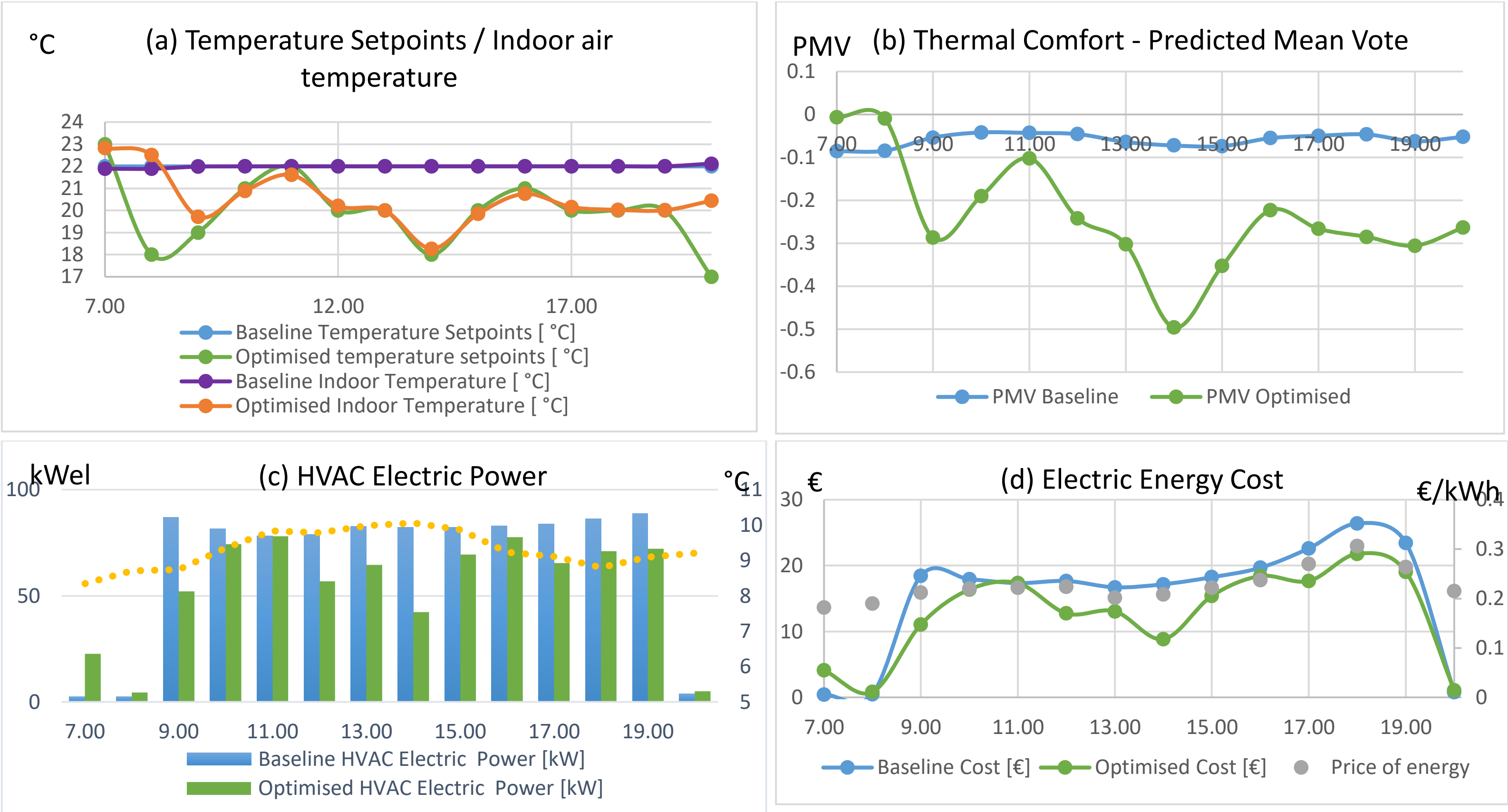


**Figure 22: GA HVAC optimization results for 20 November 2018 (winter)**

increased by 1.4%. PMV was kept at small negative values and above −0.3 for most hours, except for 2:00 and 3:00 p.m., where PMV was −0.49 and −0.35, respectively. HVAC power in the optimized scenario was kept at lower levels compared to the baseline for all working hours (except early morning hours).

**Scenario 7: 22 November 2018 (winter)**

Results from the GA HVAC optimization on 22 November 2018 are presented in Figure 23 below. Optimized temperature set points, as presented in Figure 23a, varied from 19 °C to 22 °C. In the optimized scenario, the energy of the HVAC was reduced from 717.77 kWh to 631.61 kWh, a reduction of 12.0% (Figure 23c). Energy cost (Figure 23d) was decreased from €179.59 to €159.01, which is equal to savings of 11.5%. PMV in the optimized scenario (Figure 23b) varied between −0.25 and −0.01 and, in the baseline scenario, PMV varied between −0.03 and −0.01. The mean PMV for working hours was increased from −0.016 to −0.110, and the respective PPD was increased by 0.4%. Significant energy savings occurred during hours of high prices, corresponding to hours 9:00 a.m., 1:00 p.m., and 3:00–6:00 p.m., while the PMV was kept at small negative levels down to −0.25.

**Scenario 8: 25 November 2018 (winter)**

Optimization results for HVAC optimization on 25 November 2018 are available in Figure 24. Temperature set points varied from 18 °C to 22 °C in the optimized solution (Figure 24a). In this scenario, HVAC energy consumption (Figure 24c) was reduced from 944.85 kWh to 776.17 kWh, a decrease of 17.9% compared to the baseline. Daily cost (Figure 24d) was reduced from €199.52 to €164.26, a reduction of 17.7%. The mean PMV was decreased from −0.244 in the baseline scenario to −0.478, which is equivalent to a PPD increase of 4.2% (Figure 24b). HVAC

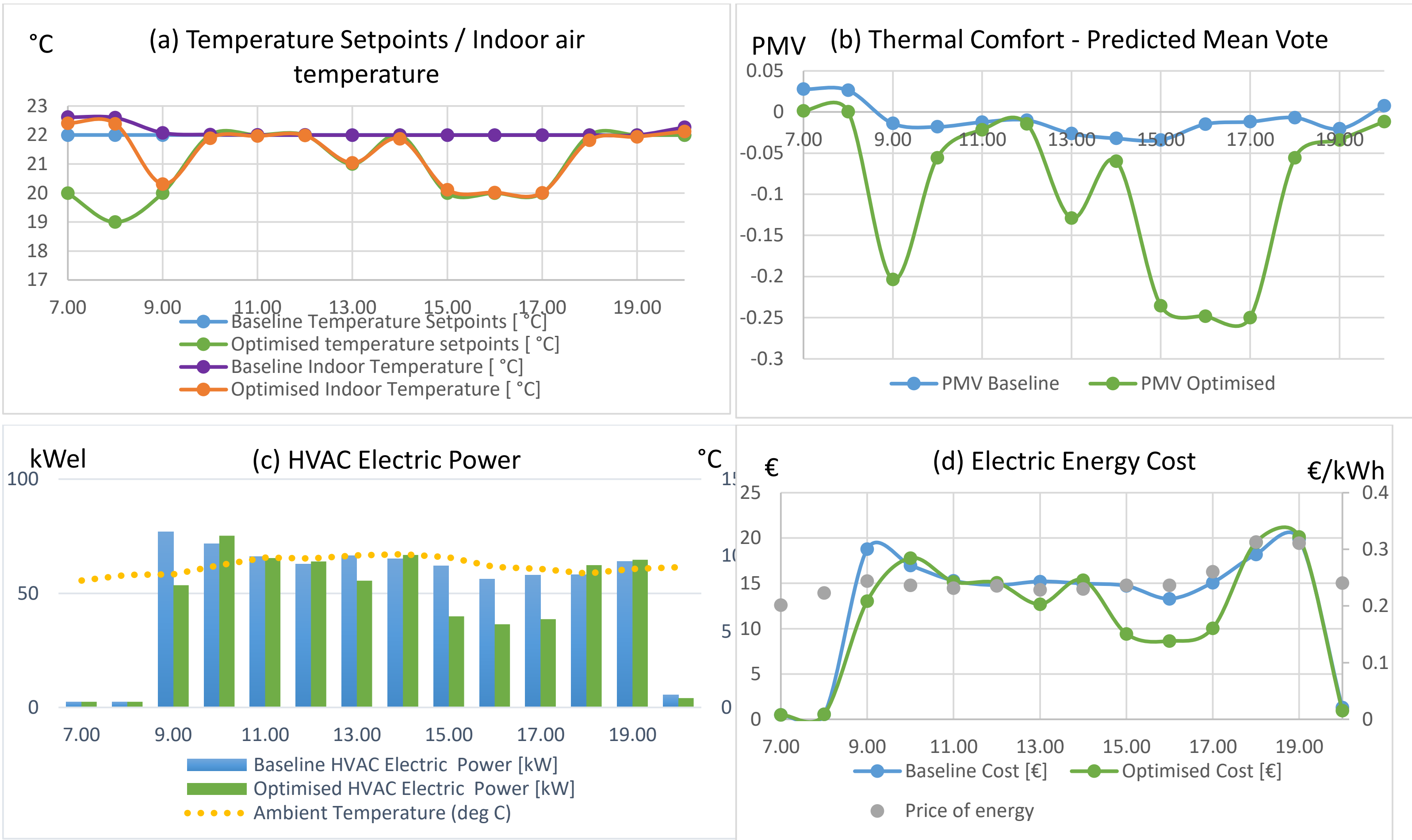


**Figure 23: GA HVAC optimization results for 22 November 2018 (winter)**

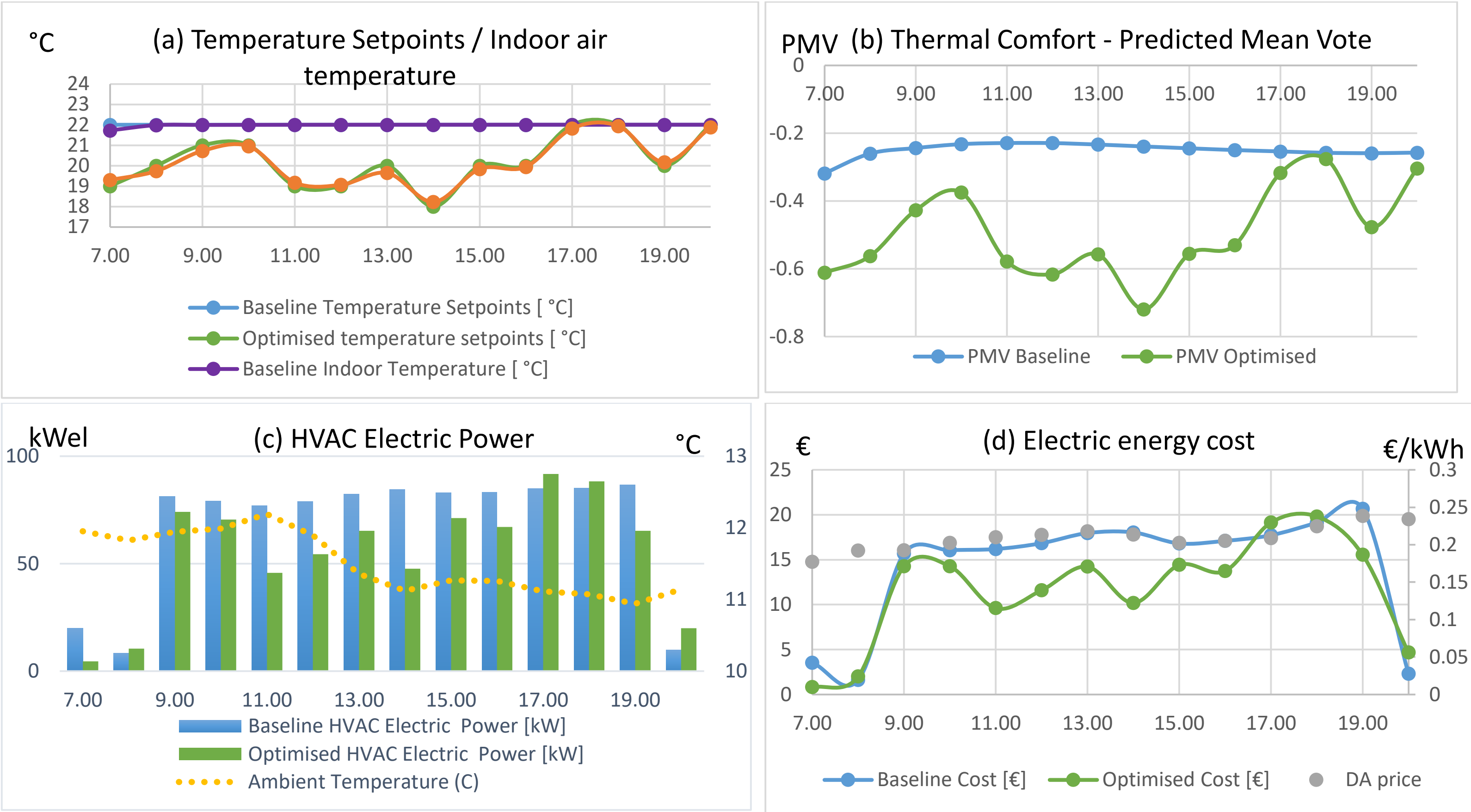


**Figure 24: GA HVAC optimization results for 25 November 2018 (winter)**

consumption in the optimized scenario exceeded the baseline levels slightly during hours 8:00 a.m., and 5:00 and 6:00 p.m. A compromise between maintaining comfort within tolerable levels while maximizing cost savings was reached.

### 4.5 Conclusions and future steps

The developed approach provides an optimization assessment framework for HVAC energy management in day-ahead real-time pricing demand response programs. In this framework, a GA-based approach was developed to investigate DR implementation for a near-zero-energy industrial building located in the region of Marche in Italy. Results indicate that there is significant potential for energy and cost savings by controlling indoor conditions within acceptable levels of thermal comfort as evaluated according to predicted mean vote. Several scenarios were analyzed to demonstrate a realistic potential of cost of energy reductions in the range between 9.9% and 25%, whereas the reduction of HVAC energy consumption varied between 10.4% and 25%. Presented solutions within established standard requirements for indoor comfort and indoor temperature drift rate were selected for evaluation from a wide range of available solutions. The proposed demand response approach is applicable in a wide range of building energy optimization assessment schemes due to the fact that it deploys temperature set point levels for HVAC control. It can be applied to establish optimal control of thermal zones in buildings of various uses and sizes controlled by single or distributed thermostatic controls. Results demonstrate that there is an unexplored potential for HVAC dynamic control associated with demand response RTP schemes which could intelligently be embedded in the operation of such systems in the years to come. The computational cost of the proposed approach was significant, as, at this stage of the research, a high number of iterations (4,600) were performed to ensure the search was as extensive and deep as possible. However, based on the results obtained, there is great potential for reducing the time for GA convergence, since satisfactory near-optimal results were, in most cases, obtained in the first day of the run (total average time for a conventional personal computer (PC) was approximately two days). Furthermore, a careful adjustment of optimization parameters and constraints combined with weather predictions, along with the evolution of computer resources and microprocessor capabilities, can make the proposed approach real time deployable in the near future. In addition, future research could involve the investigation of a typology of HVAC near-optimal set point configurations in response to patterns in ambient conditions. Experimental research could entail the testing of optimal set point patterns in real conditions as a next step toward the actual implementation of the developed methodology.

# 5 Smart grid / community load shifting GA optimization based on day-ahead ANN Power Predictions

Preparation for the transition from conventional power grids to next generation, so-called “smart” grids, is a worldwide trend nowadays. The goal for stakeholders in the domains of operations, generation, transmission, distribution, and service provision [124] is to offer more and higher quality services while improving operational capabilities, flexibility, and energy efficiency. In this context, a higher-level utilisation of smart grid resources is targeted by grid modernisation and enhanced dispersed dynamic measurements at local, regional, and wider levels. Various forms of communication equipment and protocols allow smart metering, monitoring, and controls in an interoperable unified system often described as Advanced Metering Infrastructure (AMI). Several architectures and network topologies have been proposed to accommodate a reliable and efficient exchange of bidirectional flow of energy and information. In [125] consumer demand is prioritized and DR data throughput is optimized enabling a faster reaction.

Smart metering and AMI are widely recognized as a necessity for the reliable and fast exchange of data in smart grids [126]. It is expected that nodal analysis of power measurements in the power grid will provide valuable information for utilities to control multi-directional flows of energy and improve dispatching, addressing vulnerabilities and constraints. In this sense, it is foreseen that a variety of technological solutions will emerge to balance the high volatility and power quality issues of the miscellaneous intermittent loads and renewable energy sources.

On the market side, reforms are required to leverage innovation in services and new business models which will upgrade existing operations. In this context, Demand Response constitutes a variety of services which have transformed the electric grid and energy markets operations during the past decades. Significant progress has been made in the US, where DR programs have been designed and implemented for years, and span across the full range of dispatchable (reliability, economic) and non-dispatchable (time sensitive pricing; ToU, CPP, RTP) demand side management options [127]. Demand side management is a valuable prospect for consumers and utilities—if used properly—for the use of assets to decrease losses in transmission and distribution as well as to reduce avoidable costs. In this context, DR, along with the demand-side management of distributed energy resources, expand the boundaries for near future scientific and technological advances.

In the European Union, the Energy Efficiency Directive (EED), 2012/27/EU foresees the elimination of barriers for Demand Response (DR) in balancing and ancillary services markets [128]. Among the EU Member States (MS), considering the progress in DR, Belgium, France, Ireland, and the UK, are in the leading group. Significant steps have also been taken in this direction by Germany, the Nordic countries, the Netherlands, and Austria. Generally, DR programs are differentiated (a) explicitly, i.e., where DR participants transact directly in the energy market, and (b) implicitly, i.e., where participation through a third party is facilitated [129].

The overall framework of smart grids with regards to DR is presented and analyzed by Siano in [130]. Important aspects are defined, and a description of the possibilities created by DR for utilities and customers are analyzed. Load curtailment, shifting energy consumption, and using onsite energy generation, thus reducing the dependence on the main grid, are the main mechanisms for customers to participate in DR. Customer participation in wholesale markets via intermediaries, such as curtailment service providers (CSP), aggregators, or retail customers (ARC), demand response providers (DRPs), or local distribution companies, is documented in [130]. Moreover, a review of DR and smart grids with respect to the potential benefits and enabling technologies is provided. Considering system operation, contingency issues can be dealt with through DR implementation, resulting in a reduction of electrical consumption at critical hours, and avoiding serious impacts due to failure of power services provision. Considering energy efficiency, it is ascertained that effective management of aggregated loads can lead to a reduction of the overall cost of energy, due to the reduction and operating-time-shortening of conventional power generation equipment. Avoiding network upgrades at the local level, or postponing investments in new capacity, reserves or peaking units at the system level is another important potential benefit linked to high level implementation of DR. Modelling of incentive-based DR focusing on interruptible/curtailable service and capacity market programs is investigated by Aalami et al. in [131]. Price elasticity of demand, and a customer benefit function, are used to develop an economic model. Several scenarios are simulated and evaluated according to different strategies, improvement of the load curve (peak reduction, load factor, peak to valley), the benefit of customers, and reduction of energy consumption.

Wholesale electricity market design considerations with regards to major challenges, aiming at increasing renewable energy penetration, are explored in [132]. Various dynamic energy pricing models have been proposed to compensate for market uncertainty and risks [133], [134]. A residential DR based on adaptive consumption pricing is proposed by Haider [135], allowing utilities to manage aggregate load, and customers to lower their energy consumption. The proposed pricing scheme adapts energy costs to customers' consumption levels, thus encouraging active enrolment in the DR program. Cost and comfort optimisation of load scheduling under different pricing schemes has been investigated using various techniques including linear, convex, PSO, MINLP [136]. Furthermore, technology readiness, opportunities, and requirements for the deployment of DR in buildings and blocks of buildings are addressed by Crosbie et al. in [137], [138].

On the other hand, buildings worldwide are responsible for over 40% of total energy consumption, gas emissions, and global warming [139]. The role of smart grids for near- and zero-energy building communities is investigated by researchers to test new approaches, identify critical aspects, and tackle challenges emerging when dealing with design and operational problems [19], [140]. On the demand side, a wide variety of developed scientific tools influence the dynamics of advances in energy performance and energy management in buildings [17], [122], [141], [142]. Such tools are embedded in data monitoring applications, such as innovative web-based energy management platforms [10], [143] to enable improved analysis, decision making, and dynamic controls. Moving from Building Energy Management Systems (BEMS) [144], [145] to District Energy Management Systems (DEMS) [146] entails the dynamic exchange and hierarchical processing of data streams between various components and systems, as in the Internet of Things (IoT) paradigm [147], [148]. Various techniques and tools have been investigated for dealing with challenges in various fields pertaining to smart grids: smart metering data analysis and dynamic processing [149], power demand forecasting [106], [150], Distributed Energy Resources (DER) management optimisation [78], users' engagement [151], etc.

Demand Response (DR) is a fundamental aspect of the smart grid concept as it refers to the necessary open and transparent market framework linking energy costs to the actual grid operations. DR allows consumers to directly or indirectly participate in the markets where energy is being exchanged. One of the main challenges for engaging in DR is associated with the initial assessment of the potential rewards and risks under a given pricing scheme. In this chapter, a Genetic Algorithm (GA) optimisation model, using Artificial Neural Network (ANN) power predictions for day ahead energy management at building and district level, is proposed. Individual building and building group analysis are conducted to evaluate ANN predictions and GA generated solutions. ANN based short term electric power forecasting is exploited in predicting day ahead demand and form a baseline scenario. GA optimisation is conducted to provide balanced load shifting and cost of energy solutions based on alternative pricing schemes. Results demonstrate the effectiveness of this approach for assessing DR load shifting options based on Time of Use and DARTP pricing schemes. Through the analysis of the results, the practical benefits and limitations of the proposed approach are addressed.

The chapter is organised as follows. In section 5.1, the infrastructure and the applied methodology are presented. The proposed day-ahead GA approach for the cost of energy and load shifting optimization based on ANN hourly power predictions is analysed in section 5.2. Results of ANN power predictions and GA load shifting optimisation based on a ToU pricing scheme are presented in section 5.3 while results of ANN power predictions and GA load shifting optimisation based on a DARTP scheme are provided in section 5.4. Further discussion on ANN power predictions and GA based obtained solutions are provided in section 5.5. Finally, in section 5.6, conclusions and recommendations for future work are summarised.

## 5.1 Infrastructure and methods

The proposed novel approach was developed and tested on the basis of data available from the MyLeaf platform which monitors and controls the Leaf Community buildings. The buildings in the Leaf Community are highly thermally insulated and are equipped with automations for controlling the HVAC systems, as well as the natural and artificial lighting by means of adjustable external louvers and luminance sensors. The primary annual energy consumption for the Leaf Lab is rated at 35.4 kWh/m$^2$ (including the PV power production and subtracting industrial consumption) [122] based on year round measurements while the L6 is estimated at 46.85 kWh/m$^2$. Table 4 summarises the basic components of the building envelopes and systems installed at the Leaf Community buildings under consideration. A detailed description of the Leaf Community is provided in section 2.

**Table 4. Pilot buildings in the Leaf Community**

| Pilot Case Studies | Sky windows | Automatic shading | Illuminance/ presence light controls | LED | Ground water heat pumps | biPV | Thermal storage | Electrical Storage |
|---|---|---|---|---|---|---|---|---|
| L2: Summa – Offices/Warehouse (1,037m$^2$) | | | • | • | • | • | | • |
| L4: Leaf Lab – Industrial (6,000m$^2$) | • | • | • | • | • | • | • | • |
| L5: Kite Lab (3,514m$^2$) - Offices, Laboratories | • | | • | • | • | • | | • |

The methodology developed comprises of several steps, as shown in Figure 25.

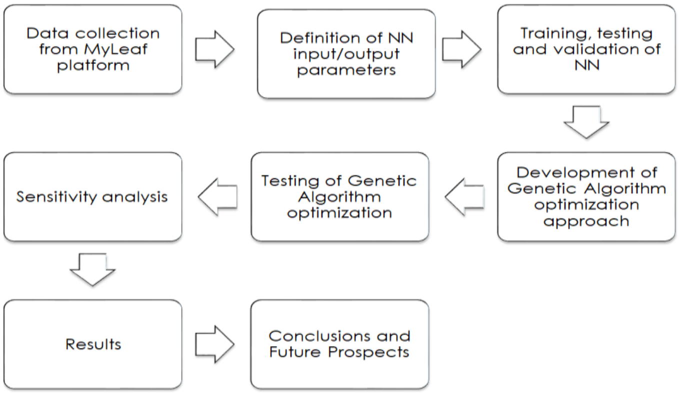


**Figure 25. Methodological framework**

**1. Collection of data:** All data from measuring equipment, sensors and actuators in Leaf Community is collected, organised and made remotely available through the MyLeaf platform [33]. In this case, the MyLeaf platform is used to collect data of ambient temperature, irradiance and power demand of the buildings considered in the analysis.

**2. Development and testing of ANN models:** ANN models are developed and exploited to perform day-ahead predictions of consumption power using Matlab. For the 24h ahead prediction of consumption power, the day of the week, the time, irradiance and the external temperature are used as inputs, while the 24 hours ahead net electrical power is used as the target. Trial of various combinations for the ANN model parameterisation is performed, considering the structure, the algorithm, the number of hidden layers and the delays. A Lavemberg-Marquardt algorithm was deployed in a Nonlinear Autoregressive ANN structure with Exogenous Input (NARX), with 3 hidden layers and a delay of 1.

**3. GA load shifting approach:** A genetic algorithm (GA) optimisation scheme was developed and tested in Matlab, in order to provide alternative solutions for load shifting. The GA optimisation scheme is based on the developed mathematical model analysed in section 5.2. The objective function encounters of the criteria of energy and load shifting. Market information is used to construct the hourly pricing profiles used in the optimisation process. Weighting coefficients are applied to both normalized criteria to enable consideration of several alternatives, depending on several priorities and energy management capabilities. Weighting coefficients are used to provide a trade-off between cost and load shift. The role of weighting coefficients is to allow a decision maker to investigate a set of solutions and obtain solutions which better match his/r preferences. Preferences differ based on the decision maker's knowledge and understanding but may also be influenced by other factors priorities during various time periods. For example, cost savings could be considered to be the "default" priority but during certain periods minimisation of load shifting could be upgraded to become the dominant factor in the optimisation process.

**4. Sensitivity analysis and evaluation of results:** Sensitivity analysis is performed by changing the GA parameters, such as crossover, population size, mutation rate, tolerance etc. Furthermore, since load shifting is related to changes in the operation of building systems (HVAC, lighting, etc.) and operations (industrial, office), it needs to be also minimized, in order to avoid significant intervention in the buildings' use. On the other hand, the cost of energy is minimized when load shifting occurs from hours of high prices to hours of low prices. The solutions are hence evaluated considering the hourly/daily cost of energy and load shifting preferences.

The developed approach is illustrated with the aid of the flowchart of Figure 26.

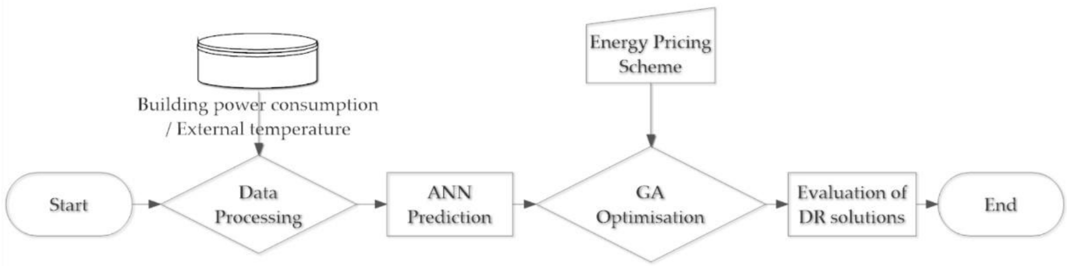


**Figure 26. Flowchart of the developed approach**

## 5.2 Day-ahead GA cost of energy/load shifting optimization based on ANN hourly power predictions

The GA optimisation scheme is based on the developed mathematical model presented hereafter. The two criteria, namely the normalised cost of energy and load shifting, form the objective function as shown in eq. 5:

$$f = \min\left(w_1 \frac{Cost_E}{Cost_{E_{max}}} + w_2 \frac{Load_{Shift}}{Load_{Shift\_max}}\right) \tag{5}$$

At the building group level, the cost term of the objective function in eq. 5, is given by equation 5.1.

$$Cost_E = \sum_{b}^{B} Cost_E^b \tag{5.1}$$

where

$b$ is used to denote each building which belongs to the group.

The energy cost of each building in eq. 5.1 is calculated based on equation 5.1.1 as shown below:

$$Cost_E^b = \sum_{h=1}^{H} X_{E\_b}^h \times C_{E\_unit}^h \tag{5.1.1}$$

Whether the optimisation concerns a building, or a building group analysis, for the evaluation of the GA based results, a comparison to baseline consumption, as obtained by the Artificial Neural Network day ahead prediction, is conducted. The cost linked to the genetic algorithm optimised solution is compared to the cost of the baseline scenario, is given by the generic equations 5.1.2 and 5.1.3 respectively:

$$Cost_{E\_opt} = \sum_{h=1}^{H} (X_{E_{opt}}^{h} \times C_{E_{unit}}^{h}) \tag{5.1.2}$$

$$Cost_{E\_baseline} = \sum_{h=1}^{H} (X_{E_{baseline}}^{h} \times C_{E_{unit}}^{h}) \tag{5.1.3}$$

At the building group level, the load shifting term of the objective function in eq. 5 is calculated by equations 5.2 and 5.2.1 as shown below:

$$Load_{Shift} = \sum_{b}^{B} Load_{Shift}^{b} \tag{5.2}$$

where:

$$Load_{Shift}^{b} = \sum_{h=1}^{H} |X_{E_b}^{h} - X_{E_{b_{baseline}}}^{h}| \tag{5.2.1}$$

The constraint in equations 5.2.2 is applied to ensure there is no deviation between the total daily energy consumed between baseline and optimized solutions for each building:

$$\sum_{h=1}^{H} X_{E_b}^{h} - \sum_{h=1}^{H} X_{E_{b_{baseline}}}^{h} = 0 \tag{5.2.2}$$

Finally, constraints on the hourly energy consumption of the optimised solution are applied to enable preferences or limitations in shifting loads from one time period within the day to another as shown in eq. 5.2.3.

$$X_{Emin_b}^{h} \leq X_{E_b}^{h} \leq X_{Emax_b}^{h} \tag{5.2.3}$$

## 5.3 Application in Time of Use pricing scheme

### 5.3.1 ANN based predictions

The results of ANN based net electrical power predictions for the period from 1/2/2017 to 28/4/2017 (1st period), from 2/5/2017 to 1/8/2017 (2nd period) and from 2/8/2017 to 29/11/2017 (3rd period) for L2 (Summa), L4 (Leaf Lab) and L5 (Kite Lab), are presented in Figure 27, Figure 27 and Figure 28 respectively. The day ahead predicted values correspond to a Pearson's correlation for L2 ranging from 0.91-0.97, L4 close to 0.4 and L5 between 0.97-0.98 for training, validation, testing and overall. Furthermore, the ANN based predictions of net electrical energy consumption of the buildings under study versus the actual measured values for a working week in the summer from 24/7/17-28/7/17 (left) and a working week in the winter from 20/11/17 to 24/11/17 (right) are illustrated in Figure 30. It is observed that predicted obtained time series largely coincide with measured (actual) values for both periods and all three buildings under investigation.

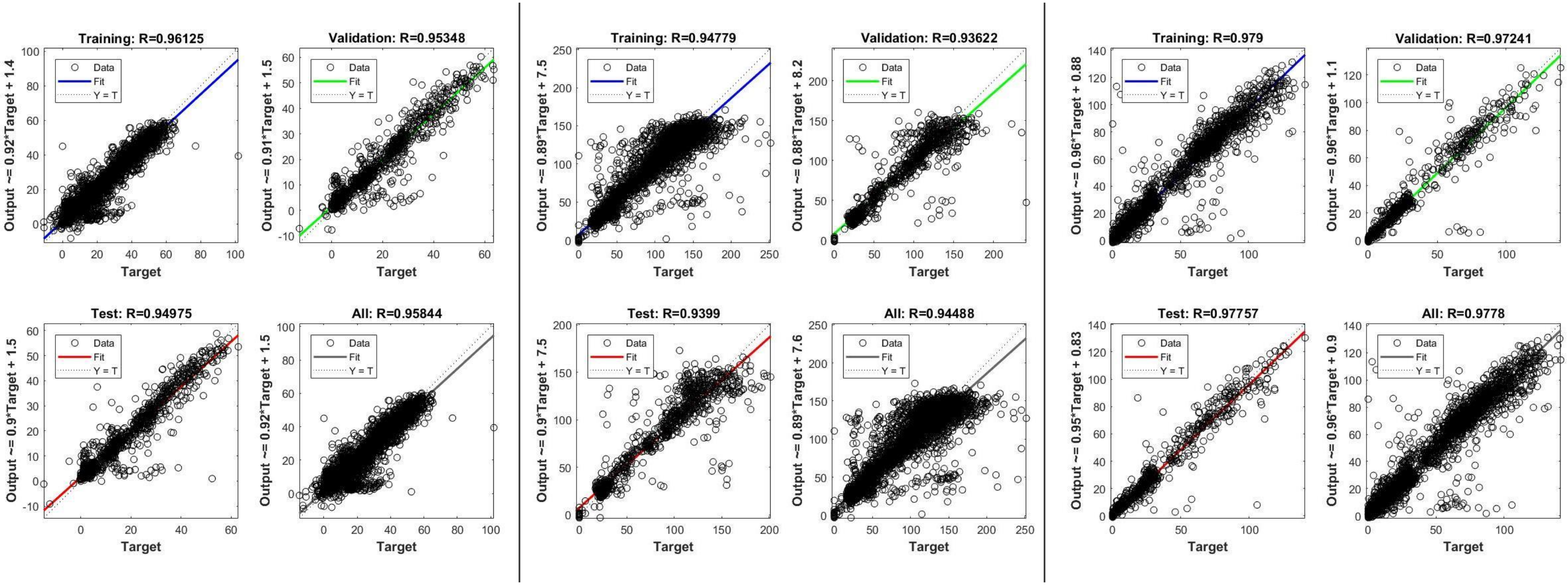


Figure 27. Prediction of net electrical power consumption power of L2, L4 and L5 for the 1st period of 2017

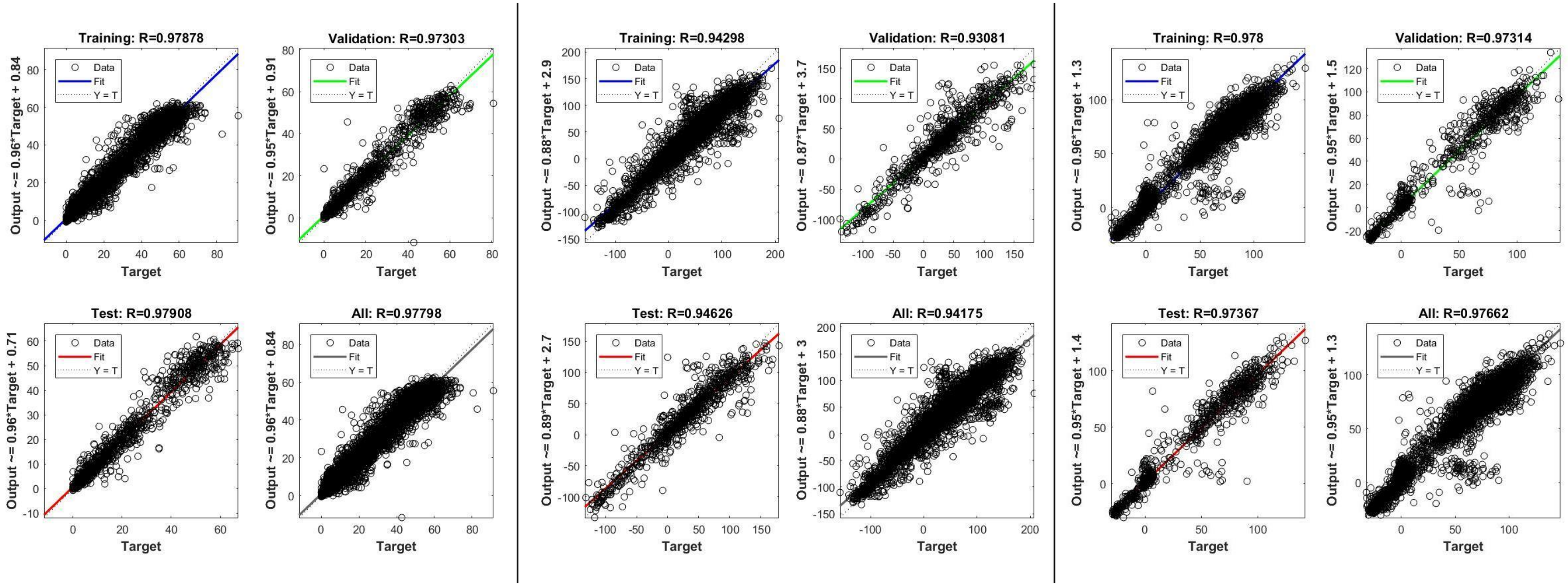


Figure 28. Prediction of net electrical power consumption of L2, L4 and L5 for the 2nd period of 2017

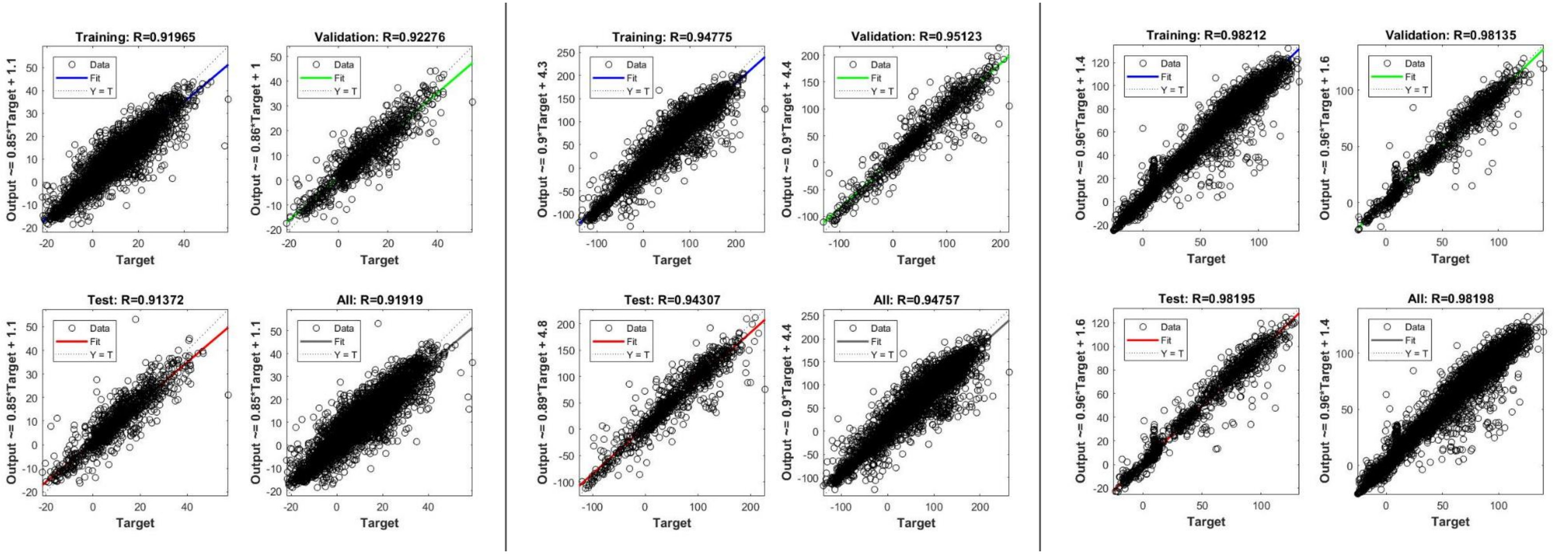


Figure 29. Prediction of net electrical power consumption of L2, L4 and L5 for the 3rd period of 2017

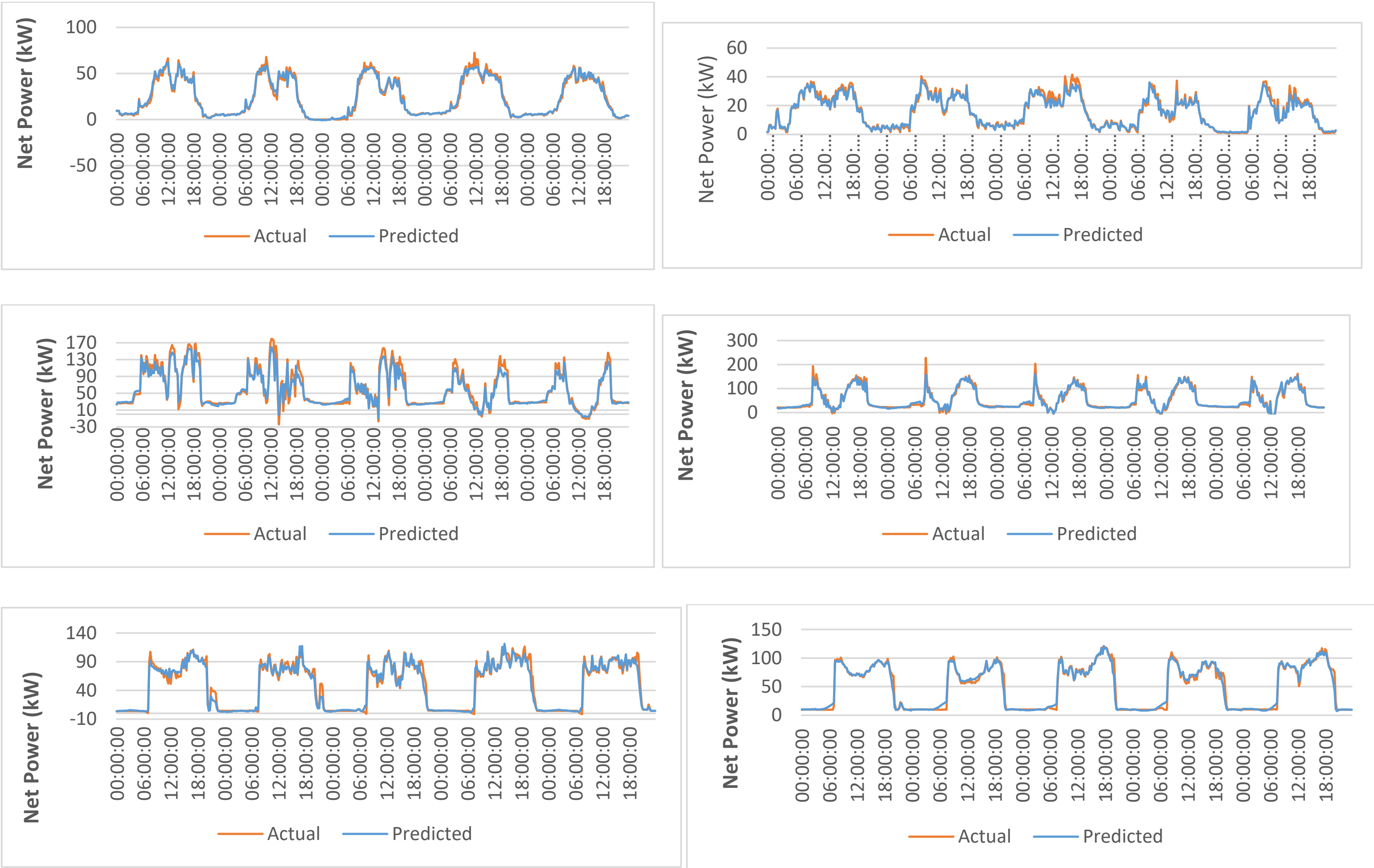


Figure 30. Prediction of net electrical power consumption for L2, L4 and L5 from 24/7/2017 to 28/7/2017 (left) and from 20/11/2017 to 24/11/2017 (right)

Mean Bias Error (MBE) and Mean Absolute Percentage Error (MAPE) values for the ANN predicted versus actual values for the periods from 24/7/2017 to 28/7/2017 and from 20/11/2017 to 24/11/2017 for Summa, Leaf Lab and Kite Lab are presented in Table 5. MAPE values in Table 5 are notably increased by a range of ratios of actually low numerator differences divided by denominators which approximate to zero.

Table 5. MBE and MAPE for ANN predictions

| ANN prediction | 24/7/2017 to 28/7/2017 | | 20/11/2017 to 24/11/2017 | |
|---|---|---|---|---|
| | MBE | MAPE (%) | MBE | MAPE (%) |
| L2: Summa | 0.21 | 32.62 | -0.52 | 12 |
| L4: Leaf Lab | -3 | 29 | -0.40 | 20.73 |
| L5: Kite Lab | -0.94 | 35.32 | -0.01 | 11 |

### 5.3.2 Genetic Algorithm optimization results

In this section, GA optimisation results for 24/7/2017 and 20/11/2017 are presented and analysed for the weighting coefficient values $w_1 = w_2 = 0.5$. For the baseline scenario, a flat tariff at 0.28 €/kWh is used (Flat 1, Figure 31). The optimized scenario is calculated taking into account a 2-zone tariff ToU pricing scheme of 0.2 €/kWh from 8 a.m. to 6 p.m. and 0.30 €/kWh from 6 p.m. to 8 a.m. (ToU1, Figure 31).

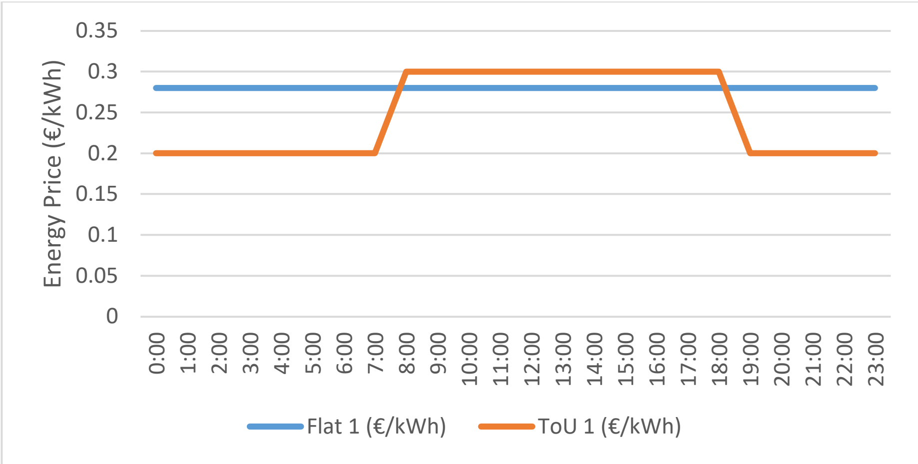


Figure 31. Energy pricing profiles used in the baseline and optimised scenarios


Figure 32. GA optimisation power and cost results for the L2, L4 and L5 on 24/7/2017

In Figure 32, the results of the developed GA optimisation approach are presented. The charts on the left columns of these figures illustrate the ANN based power forecast as the baseline scenario. In the same charts, the GA optimised power profiles demonstrate load shifting solutions. The related costs are depicted in the right columns of the Figures. The baseline costs are calculated based on the flat tariff of Figure 31, while the GA optimised costs are based on the 2-zone tariff of the same figure.

With respect to the net electrical consumption of the L2 building, it is observed in Figure 32 that load shifting occurs from the high price to low price hours. This is also reflected, in terms of the cost profile, to the day which accounts for a reduction of 15.08% from € 173.49 to €147.32. Likewise, the net electrical consumption in L4 is shifted outside the high price region, with the baseline daily cost of €515.71 being decreased down to €420.06, a reduction of 13.73%. Similarly, shifting of net electrical energy consumption in L5 occurs from the high tariff zone towards the early morning and the evening hours, without a reduction in total energy consumption. In this case, the baseline cost is €321.29 and the optimized total cost is €271.74 which is equal to a reduction of 15.42%.

The analysis of the winter results is displayed in Figure 33. The shift for the L2 net electrical power profile leads to a cost reduction of 17.3% from €123.26 in the baseline scenario down to €101.92.

Load shifting throughout the 24h occurs in L4 in a way that changes the overall power profile especially with respect to the early hours of the day. This transition of loads, corresponds to 18.09% of costs savings, reflecting also the differences between the flat and the 2-zone tariff pricing scheme.

With respect to the daily power in L5 during the winter, changes between baseline and optimised scenarios appear to take place in a harmonic way from high to low price hours. In this case, a 17.55% cost saving is achieved, since the baseline daily cost is €331.53 compared to the optimized daily cost of €273.33.

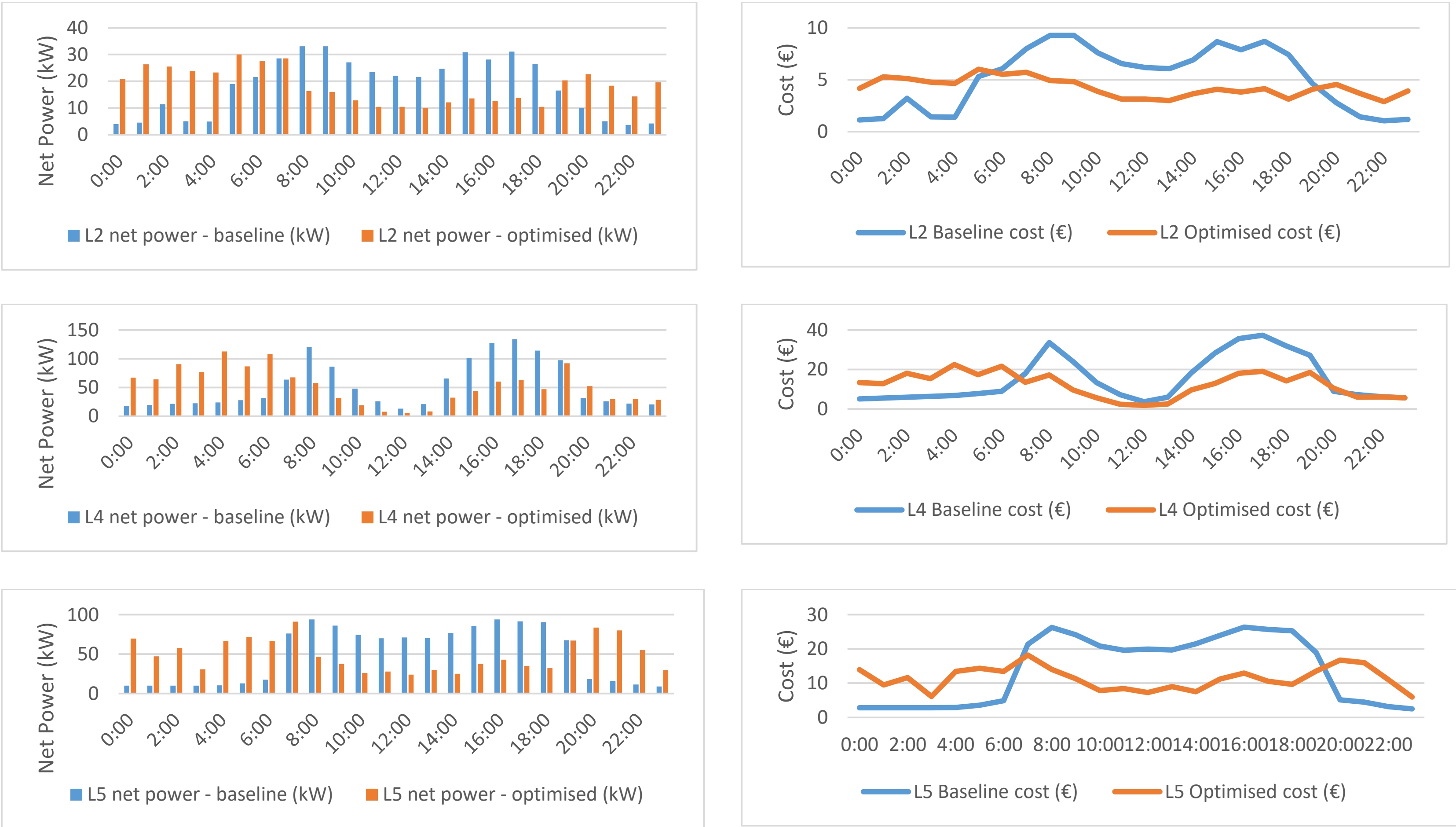


Figure 33. GA optimisation power and cost results for the Leaf Lab, the Summa and the Kite Lab during 20/11/2017

In Figure 34, the total power consumption of the 3 buildings is illustrated. In the first case, the high power consumption according to the baseline power is shifted from working hours towards early morning and late evening hours. In terms of cost, the total baseline cost at the district level is 1009.67 € and the total optimized cost is €835.55 which corresponds to a reduction of 17.24%.

With respect to the winter period, the hourly district level GA optimised power values for equal weighting coefficients undergo a significant differentiation with respect to the baseline. The district level total baseline cost is €814.51 and the total optimized cost is €683.05, leading to a reduction of 16.13%.


Figure 34. GA optimisation power and cost results for the total power on 24/7/2017 (up) and 20/11/2017 (down)

According to Table 6, regarding the Summa building (L2), the results for each case prove that the optimization is successful, bearing in mind that the baseline cost is €172.67 and the optimized values range from €145.79 to €147.23, a maximum operational costs percentage reduction of 15.56%. For the Leaf Lab (L4), the optimized cost for each pair of weights is lower than the baseline cost of €515.71 and varies between €414.18 and €422.05. The percentage reduction, in this case, reaches 19.68% Furthermore, the optimisation for the Kite Lab revealed that the GA produces better results compared to the baseline cost of €321.29 for all pairs of weights ranging from €269.85 down to €271.83. The percentage reduction, in this case, is up to 16.01%. The last column of the table represents the optimised cost for the group of buildings which is lower than the baseline cost of €1009.67 for all pairs of weighting coefficients varying from €835.15 to €841.70. The maximum percentage reduction, in this case, is 15.39%.

Table 6. Results of the optimization on 24/7/2017 during the summer period.

| w1 : Cost | w2: Load Shifting | Summa (L2) cost (€) | Leaf Lab (L4) cost (€) | Kite Lab (L5) cost (€) | District level cost (€) |
|---|---|---|---|---|---|
| 0 | 1 | 146.59 | 421.03 | 269.85 | 836.16 |
| 0.1 | 0.9 | 147.18 | 422.05 | 270.93 | 836.45 |
| 0.2 | 0.8 | 147.23 | 420.30 | 270.35 | 839.13 |
| 0.3 | 0.7 | 146.42 | 421.67 | 270.45 | 836.70 |
| 0.4 | 0.6 | 146.30 | 414.18 | 271.83 | 839.59 |
| 0.5 | 0.5 | 147.33 | 420.06 | 271.75 | 835.56 |
| 0.6 | 0.4 | 147.00 | 419.09 | 270.63 | 837.96 |
| 0.7 | 0.3 | 147.19 | 419.03 | 270.50 | 840.83 |
| 0.8 | 0.2 | 146.69 | 418.24 | 269.54 | 839.05 |
| 0.9 | 0.1 | 145.79 | 418.88 | 270.73 | 841.70 |
| 1 | 0 | 146.51 | 415.33 | 270.34 | 835.15 |

Table 7, includes the results of optimisation for each pair of weighting coefficients in both, building and district level, for the winter period. The results for the Summa (L2), depict the optimized cost for all weights combinations. As it is observed, in all cases, the optimized cost varies between €100.21 to €101.92 which is lower than the baseline cost of €123.26 in this case and accounts for a percentage reduction of up to 18.70%. Moreover, the optimisation for the Leaf Lab (L4) building revealed genetic algorithm solutions with costs from €289.95 to €294.94, a maximum percentage reduction of 19.39% compared to the baseline cost of €359.71 in this case. Subsequently, in the Kite Lab, the optimized cost is from €277.66 down to €273.31, equal to a percentage reduction of up to 17.56% lower than the baseline cost of €331.53. The last column represents the optimized cost in the group of buildings during the winter, varying from €684.77 to €682.33 leading to a maximum percentage reduction of 16.22% compared to the baseline cost of €814.51.

Table 7. Results of the optimization on 20/11/2017 during the winter period.

| $w_1$ | $w_2$ | Summa (L2) cost (€) | Leaf Lab cost (€) | Kite Lab cost (€) | District level Cost (€) |
|---|---|---|---|---|---|
| 0 | 1 | 101.46 | 293.21 | 276.71 | 683.95 |
| 0.1 | 0.9 | 101.53 | 289.95 | 276.36 | 684.77 |
| 0.2 | 0.8 | 100.85 | 291.78 | 275.95 | 683.48 |
| 0.3 | 0.7 | 100.88 | 294.94 | 277.35 | 682.33 |
| 0.4 | 0.6 | 101.50 | 293.35 | 277.66 | 684.50 |
| 0.5 | 0.5 | 101.92 | 294.64 | 273.33 | 683.06 |
| 0.6 | 0.4 | 101.65 | 292.97 | 276.87 | 683.47 |
| 0.7 | 0.3 | 100.45 | 294.85 | 277.30 | 684.69 |
| 0.8 | 0.2 | 100.99 | 293.46 | 275.64 | 684.56 |
| 0.9 | 0.1 | 101.35 | 290.87 | 273.31 | 684.34 |
| 1 | 0 | 100.21 | 293.68 | 275.31 | 683.37 |

## 5.4 Application in DA Real Time Pricing Scheme

### 5.4.1 ANN based predictions

Artificial Neural Network (ANN) models are conceived on the basis of biological nervous systems to imitate information processing and evolution. ANNs assimilate the natural bonds of neurons and their high level interconnection to model complex systems. In the case of predictions, ANNs can be more effective compared to statistical, linear or non-linear programming techniques. ANN models have been used for years in different areas of engineering, science and business to deal with complexity and nonlinearity of data sets. They present capabilities such as adaptive learning, self-organisation, real time operation, fault tolerance and approximation of complex nonlinear functions. The mathematical model of a neuron is presented in Figure 35 [152].

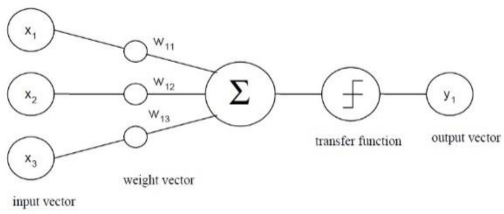


**Figure 35: Mathematical model of a neuron**

Various ANN architectures for forecasting demand in electric power systems are presented in [104] by Tsekouras et al. A case study of the Greek electric power grid is used to showcase the performance of different ANN configurations and factors including period length and inputs for training, confidence interval and more. Hybrid Short Term Load Forecasting ANN with techniques such as Fuzzy Logic, GA and Particle Swarm Optimisation are briefly discussed in [106].

For the 24h ahead prediction of consumption power, day, time and external temperature were used as inputs and electrical power as the target. The 24h prediction of energy produced by renewable energy sources, day, time and irradiance were used as inputs and electrical power as the target. The lavemberg-marquardt algorithm was deployed in a Nonlinear Autoregressive ANN structure with Exogenous Input (NARX).

A summary of ANN predictions Pearson's correlation coefficient R for a 15-minute timestep is provided in Table 8 below:

**Table 8: Summary of ANN predictions (Pearson's correlation coefficient R) for a 15-minute timestep**

| 2/2/17-29/4/17 | Pearson's coefficient R | Training | Validation | Test | Overall |
|---|---|---|---|---|---|
| 15mns timestep | L2 consumption | 0.96518 | 0.95361 | 0.96684 | 0.96376 |
| | L2 production | 0.95796 | 0.9325 | 0.94017 | 0.9513 |
| | L4 consumption | 0.95665 | 0.9553 | 0.95135 | 0.95568 |
| | L4 production | 0.98507 | 0.97854 | 0.97351 | 0.98236 |
| | L5 consumption | 0.98261 | 0.97911 | 0.9719 | 0.98058 |
| | L5 production | 0.98585 | 0.97547 | 0.98528 | 0.98426 |
| | microgrid consumption | 0.98529 | 0.98534 | 0.98593 | 0.98539 |
| | microgrid production | 0.98343 | 0.97897 | 0.98202 | 0.98254 |
| 2/5/17-1/8/17 | Pearson's coefficient R | Training | Validation | Test | Overall |
| 15mns timestep | L2 consumption | 0.95152 | 0.95341 | 0.95072 | 0.95166 |
| | L2 production | 0.95546 | 0.96012 | 0.95837 | 0.95656 |
| | L4 consumption | 0.97811 | 0.97871 | 0.97204 | 0.97729 |
| | L4 production | 0.98059 | 0.98496 | 0.97866 | 0.98096 |
| | L5 consumption | 0.98184 | 0.97779 | 0.97659 | 0.98048 |
| | L5 production | 0.98196 | 0.98104 | 0.9806 | 0.98162 |
| | microgrid consumption | 0.98982 | 0.99138 | 0.98869 | 0.98991 |
| | microgrid production | 0.9815 | 0.98103 | 0.98368 | 0.98177 |
| 2/8/17-29/11/17 | Pearson's coefficient R | Training | Validation | Test | Overall |
| 15mns timestep | L2 consumption | 0.95181 | 0.95267 | 0.95787 | 0.95281 |
| | L2 production | 0.95604 | 0.9486 | 0.95174 | 0.95427 |
| | L4 consumption | 0.97573 | 0.97283 | 0.97241 | 0.9748 |
| | L4 production | 0.97778 | 0.97099 | 0.97594 | 0.97648 |
| | L5 consumption | 0.98024 | 0.98066 | 0.98115 | 0.98044 |
| | L5 production | 0.9768 | 0.97723 | 0.97818 | 0.97707 |
| | microgrid consumption | 0.98955 | 0.98862 | 0.98863 | 0.98928 |
| | microgrid production | 0.97814 | 0.98149 | 0.98181 | 0.97918 |

Likewise, for timestep of one hour, correlation of training, validation, test and overall prediction with real values is presented in Table 9.

**Table 9: Summary of ANN predictions (Pearson's correlation coefficient R) for a timestep of one hour**

| 2/2/17-29/4/17 | Pearson's coefficient R | Training | Validation | Test | Overall |
|---|---|---|---|---|---|
| 1 hour timestep | L2 consumption | 0.96129 | 0.95094 | 0.9418 | 0.95685 |
| | L2 production | 0.95145 | 0.96731 | 0.96268 | 0.95534 |
| | L4 consumption | 0.94398 | 0.90304 | 0.91239 | 0.9332 |
| | L4 production | 0.9696 | 0.95827 | 0.95994 | 0.96635 |
| | L5 consumption | 0.97321 | 0.95967 | 0.95715 | 0.96859 |
| | L5 production | 0.9785 | 0.96903 | 0.96748 | 0.97536 |
| | microgrid consumption | 0.98456 | 0.97903 | 0.97272 | 0.98185 |
| | microgrid production | 0.97633 | 0.96367 | 0.97019 | 0.97358 |
| 2/5/17-1/8/17 | Pearson's coefficient R | Training | Validation | Test | Overall |
| 1 hour timestep | L2 consumption | 0.96568 | 0.95888 | 0.96533 | 0.9646 |
| | L2 production | 0.95845 | 0.94951 | 0.9684 | 0.95848 |
| | L4 consumption | 0.98329 | 0.97145 | 0.97276 | 0.97991 |
| | L4 production | 0.97867 | 0.97159 | 0.97193 | 0.97653 |
| | L5 consumption | 0.97935 | 0.97571 | 0.97412 | 0.97791 |
| | L5 production | 0.97842 | 0.97549 | 0.96029 | 0.97517 |
| | microgrid consumption | 0.99136 | 0.98762 | 0.98968 | 0.99051 |
| | microgrid production | 0.97754 | 0.97458 | 0.96684 | 0.97559 |
| 2/8/17-30/10/17 | Pearson's coefficient R | Training | Validation | Test | Overall |
| 1 hour timestep | L2 consumption | 0.95021 | 0.94759 | 0.93891 | 0.94792 |
| | L2 production | 0.97436 | 0.96261 | 0.96707 | 0.97168 |
| | L4 consumption | 0.96217 | 0.96687 | 0.9598 | 0.96251 |
| | L4 production | 0.9754 | 0.96104 | 0.98115 | 0.97429 |
| | L5 consumption | 0.98388 | 0.98042 | 0.97804 | 0.98241 |
| | L5 production | 0.9725 | 0.97069 | 0.97084 | 0.97193 |
| | microgrid consumption | 0.98987 | 0.98547 | 0.99004 | 0.98921 |
| | microgrid production | 0.9771 | 0.97756 | 0.97273 | 0.97643 |

| 2/11/17-30/12/17 | Pearson's coefficient R | Training | Validation | Test | Overall |
|---|---|---|---|---|---|
| 1 hour timestep | L2 consumption | 0.95817 | 0.95945 | 0.9479 | 0.95677 |
| | L2 production | 0.95075 | 0.9141 | 0.90309 | 0.93871 |
| | L4 consumption | 0.95108 | 0.94872 | 0.9343 | 0.94781 |
| | L4 production | 0.96894 | 0.9123 | 0.92778 | 0.95574 |
| | L5 consumption | 0.96995 | 0.95004 | 0.95726 | 0.96491 |
| | L5 production | 0.93863 | 0.95771 | 0.93775 | 0.94213 |
| | microgrid consumption | 0.98859 | 0.98068 | 0.98116 | 0.98624 |
| | microgrid production | 0.95557 | 0.94048 | 0.93984 | 0.95111 |

With respect to the quality of the prediction, one can identify differences due to various reasons. The timestep seems to be a factor slightly affecting the quality of the prediction according to R values in Table 8 and Table 9. Even not in all cases a 15 minutes timestep normally provides better prediction results compared to a timestep of one hour. This can be attributed to a higher resolution leading to improved training of the ANN model. Another observation is that power consumption of buildings L4, L5 and the microgrid are more predictable than L2. This is possibly related to the variability and stochastic nature of loads in L2. Finally, it is observed that the period of the analysis plays an important role with respect to the outcome of the prediction. For example in Table 8, the prediction of consumption in L4 during the period from 2/2/17-29/4/17 has an overall R value of 0.95568 whereas the same building in the period from 2/5/17-1/8/17 has an overall R value of 0.97729. The reason behind this difference could be the variability of loads linked to a higher variation in weather conditions. In some cases, quality of data is also an issue and this is not always easy to identify in R values or correlation plots but may become obvious when plotting time series data.

### 5.4.2 Combined ANN prediction / Genetic Algorithm optimisation results

*DA-RTP Scenario 1: Net microgrid level prediction and optimisation – 20/3/17*

In Figure 36 the real versus predicted power for the net electrical power withdrawn by the microgrid is presented. Daily actual net energy consumption, in this case, is 2875.21 kWh corresponding to a cost of according to the considered DA scheme €163.75. The equivalent predicted values are 2824.64 kWh and €161.94 respectively. The percentage difference between the predicted and actual energy on the day and between the cost of energy is 1.7% and 1.1% respectively.

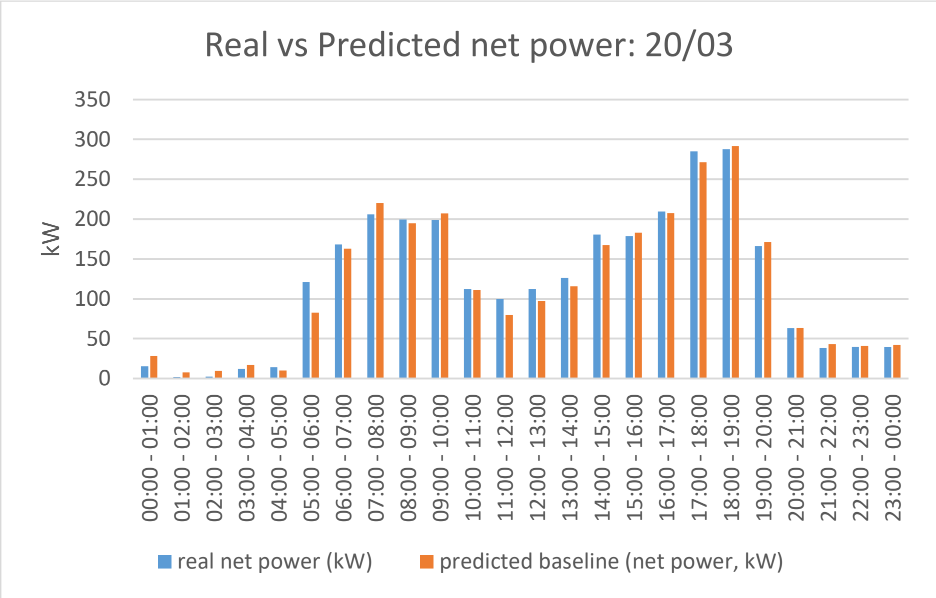


**Figure 36: Real versus predicted net microgrid electrical power on 20/3/17**

In Figure 37, the obtained GA obtained solution shown is associated with significant load shifting. In detail, load shifting occurs mainly in hours 5-6, 8-11 and 12-21. The daily cost of energy, in this case, is reduced from €161.75 to €152.73 and equal to a percentage cost reduction of 5.7%.

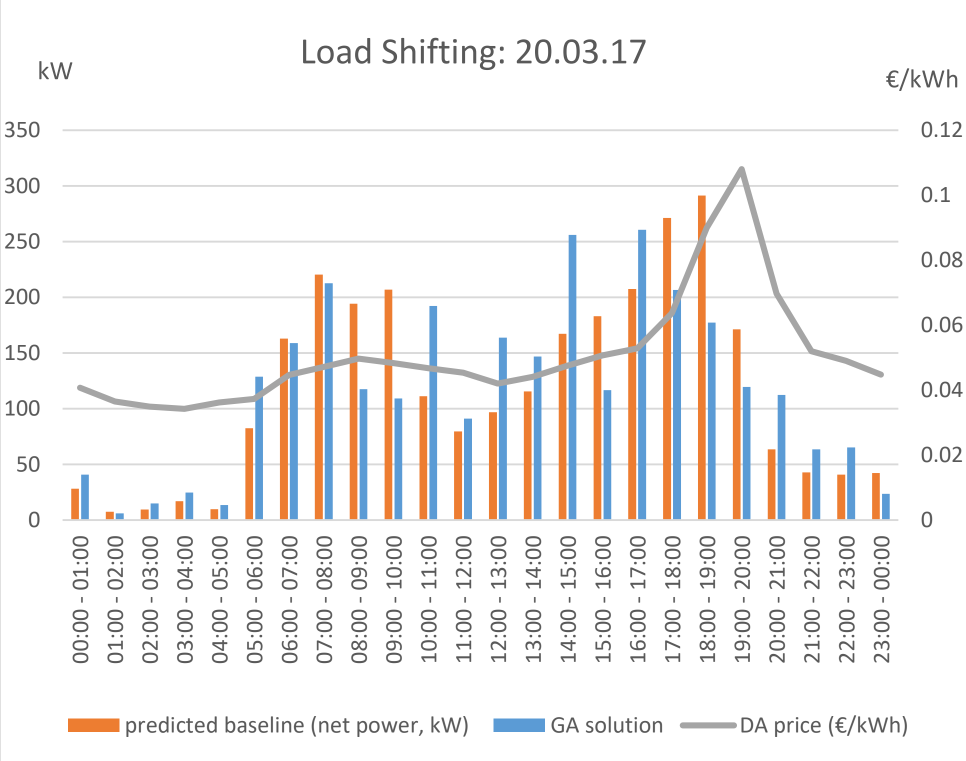


**Figure 37: GA obtained load shifting solution for 20.03.17**

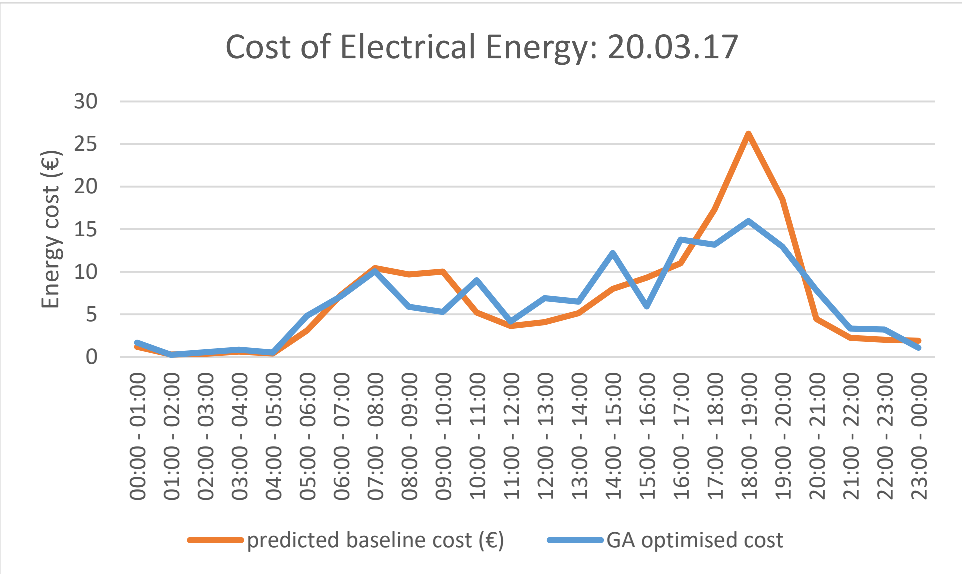


**Figure 38: Cost of electrical energy based on DA RTP scheme as obtained by the GA for 20.03.17**

In Figure 38 the graphical representation of the cost of electrical energy according to the examined scenario is displayed. It is illustrated that the higher cost savings occur during the hours of high energy prices and especially from 17:00-20:00.

**DA-RTP Scenario 2: Net microgrid level prediction and optimisation – 1/8/17**

In Figure 39, the real versus predicted power for the net electrical power withdrawn by the microgrid for 1/8/17 is presented. Daily actual net energy consumption, in this case, is 5,586.82

kWh corresponding to a cost of according to the considered DA scheme €389.37. The equivalent predicted values are 5,555.08 kWh and €387.26 respectively. The percentage difference between the predicted and actual energy on the day and between the cost of energy is 0.57% and 0.54% respectively.

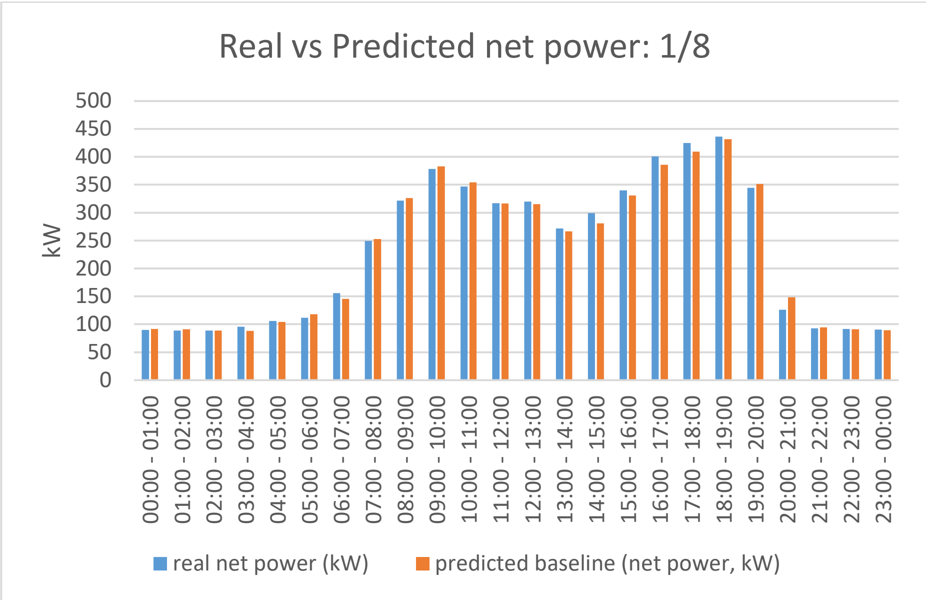


**Figure 39: Real versus predicted net microgrid electrical power on 01/8/17**

In Figure 40, the obtained GA obtained solution shown is associated with significant load shifting. In detail, load shifting occurs mainly in hours 5-8, 12-15, 14-20. The daily cost of energy, in this case, is reduced from €387.26 to €356.57 and equal to a percentage cost reduction of 7.9%.

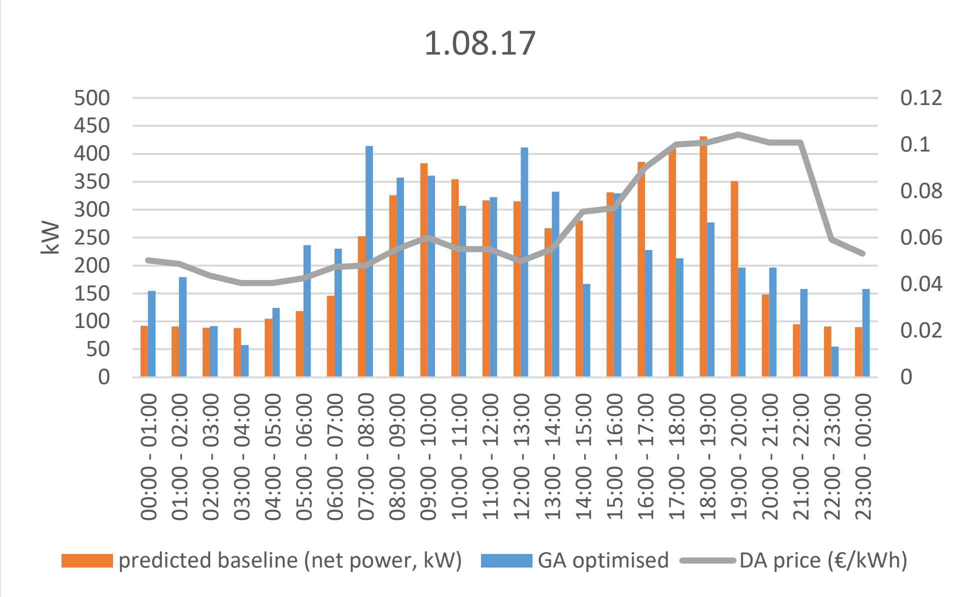


**Figure 40: GA obtained load shifting solution for 01.08.17**

In Figure 41, the graphical representation of the cost of electrical energy according to the examined scenario is displayed. It is illustrated that the higher cost savings occur during the hours of high energy prices and especially from 16:00-21:00.

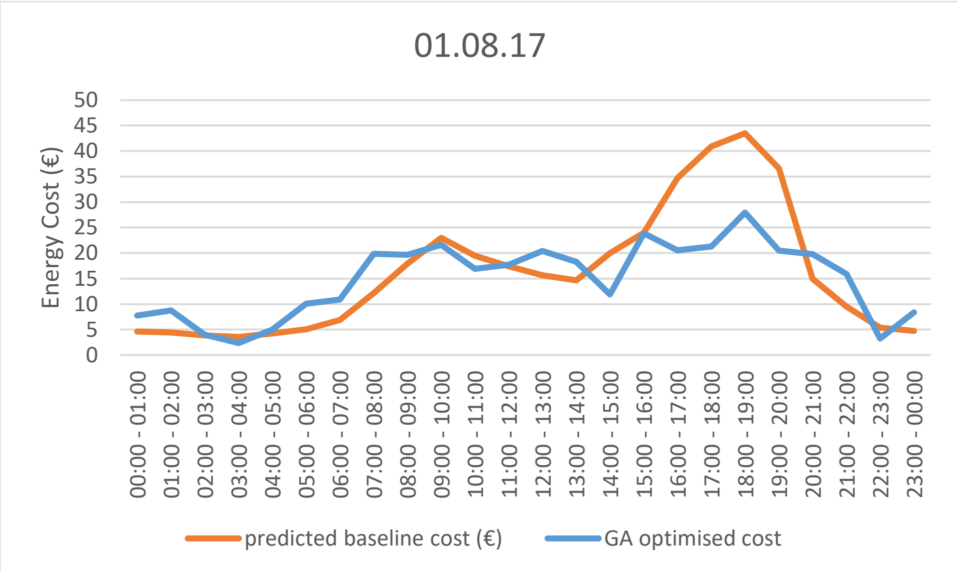


**Figure 41: Cost of electrical energy based on DA RTP scheme as obtained by the GA for 01.08.17**

**DA-RTP Scenario 3a: Net microgrid level prediction and optimisation – 14/11/17**

In Figure 42, the real versus predicted power for the net electrical power withdrawn by the microgrid for 14/11/17 is presented. Daily actual net energy consumption, in this case, is 5,907.70 kWh corresponding to a cost of according to the considered DA scheme €537.59. The equivalent predicted values are 5,812.38 kWh and €530.16 respectively. The percentage difference between the predicted and actual energy on the day and between the cost of energy is 1.6% and 1.38% respectively.

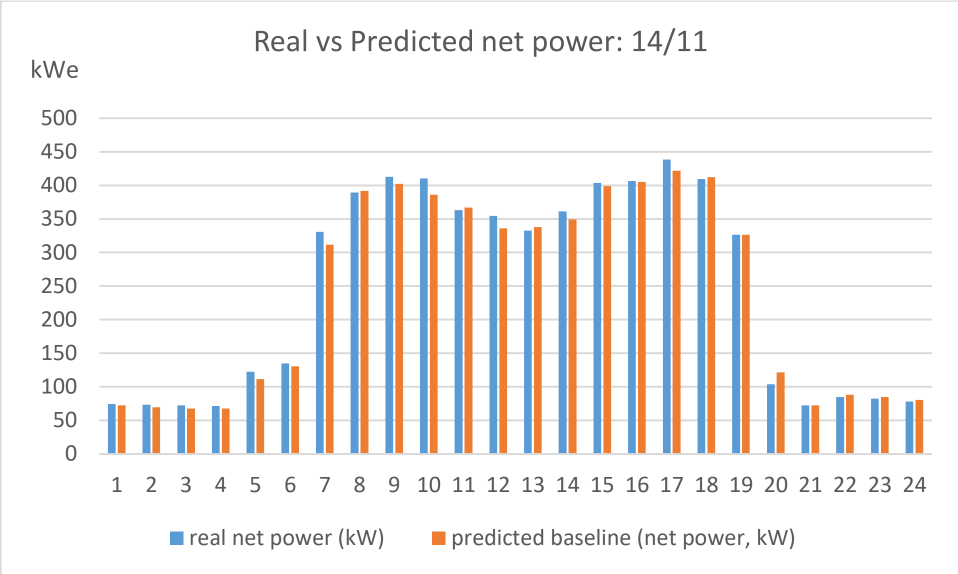


**Figure 42: Real versus predicted net microgrid electrical power on 14/11/17**

In Figure 43, the obtained GA obtained solution shown is associated with significant load shifting. In detail, load shifting occurs mainly in hours 6-7, 9-13, 18-21. The daily cost of energy, in this case, is reduced from €530.16 to €500.28 and equal to a percentage cost reduction of 5.6%.

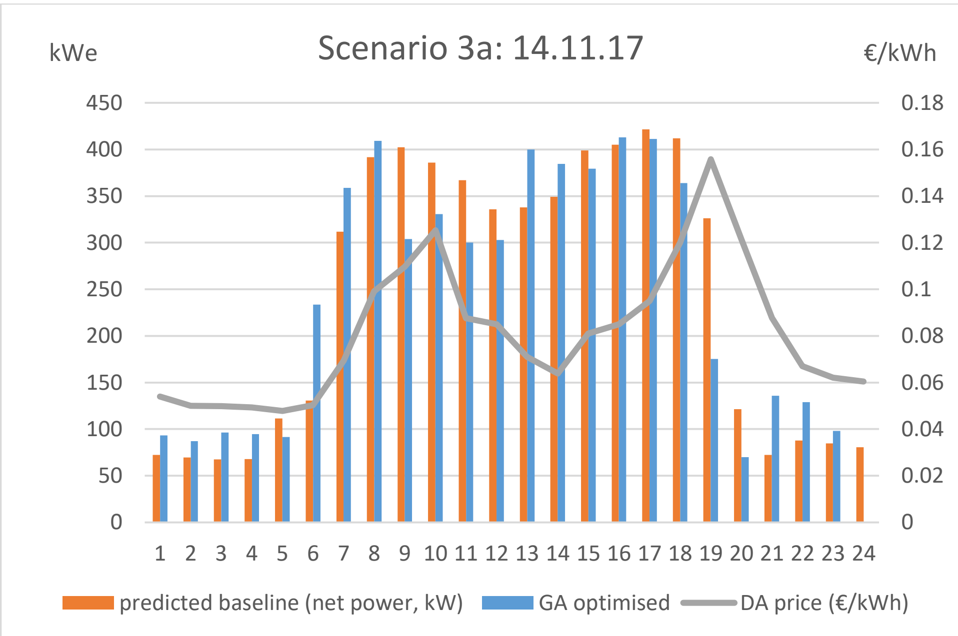


**Figure 43: GA obtained load shifting solution for 14.11.17**

In Figure 44, the graphical representation of the cost of electrical energy according to the examined scenario is displayed. It is illustrated that the higher cost savings occur during the hours of high energy prices and especially from 9:00-10:00 and from 18:00-21:00.

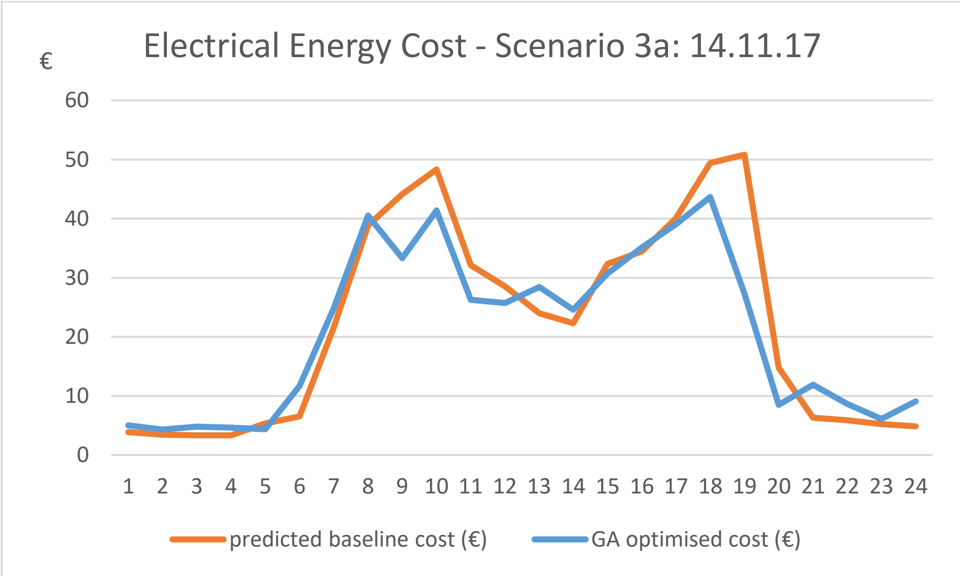


**Figure 44: Cost of electrical energy based on DA RTP scheme as obtained by the GA for 14.11.17**

**DA-RTP Scenario 3b: Net microgrid level prediction and optimisation – 14/11/17**

In Figure 45, the obtained GA obtained solution shown is associated with significant load shifting. In detail, load shifting occurs in hours 1, 3-5, 7, 11, 13-15, 17-19, 21, 23-24. The daily cost of energy, in this case, is reduced from €530.16 to €502.83 and equal to a percentage cost reduction of 5.1%.

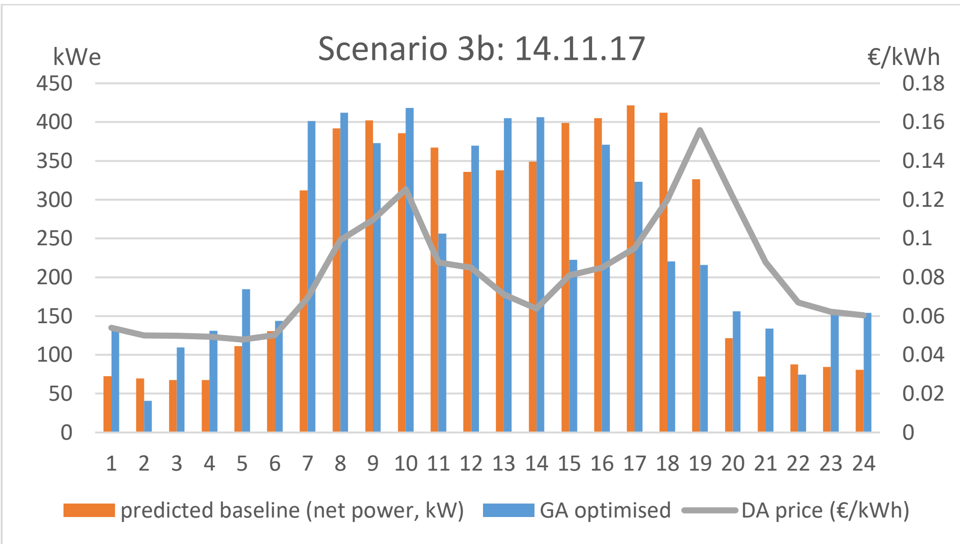


**Figure 45: GA obtained load shifting solution for 14.11.17**

In Figure 46, the graphical representation of the cost of electrical energy according to the examined scenario is displayed. It is illustrated that the higher cost savings occur mainly from 15:00-19:00.

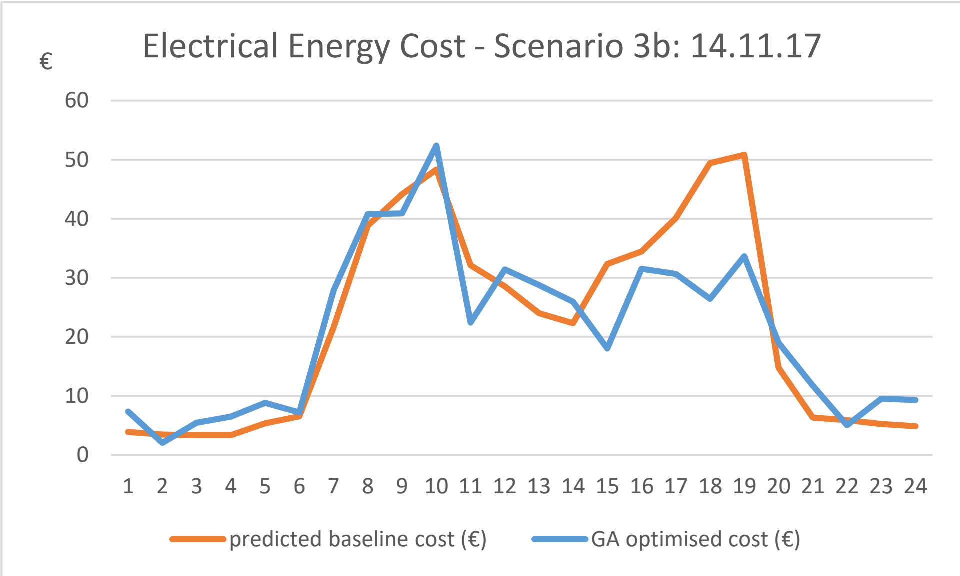


**Figure 46: Cost of electrical energy based on DA RTP scheme as obtained by the GA for 14.11.17**

### 5.5 Limitations of the proposed approach

The proposed approach entails some level of abstraction with respect to the load shift achievable within the capacity of individual systems and components. Evaluating load shift in conjunction to a pricing scheme requires deep knowledge and depends on the specificities of each case study. In this respect, load shift is determined by technical factors i.e. installed systems technical characteristics, control scheme etc. as well as organisational factors i.e. the potential shift of the industrial operations within each building. Detailed knowledge of the operation of each system in a building along with data i.e. power consumption profile is not available in most cases. This logic can be applied to some extend by using constraints to ensure that a specific percentage of the power at any time remains unchanged. Consequently, optimisation can be conducted based on the flexible share of the consumption power for every hour.

Also, the proposed approach is linked to the accuracy of the prediction which may vary according to the building under study and other factors i.e. type of loads, industrial operations, season etc. Therefore it is important to evaluate the risk associated with different prediction error levels according to the examined pricing scheme.

## 5.6 Conclusions

The main contribution of this work is related to linking ANN short term electric forecasting and GA multi-objective optimisation as a tool for generating and evaluating alternative day-ahead load shifting solutions. The first step of the proposed approach is exploiting Artificial Neural Network modelling for the prediction of the net power consumption in a period of 24 hours ahead. Predictions of net consumption power levels using the day of the week, time of day, irradiance and external temperature as inputs were obtained for each of the 3 buildings of Leaf Community (Summa, Leaf Lab and Kite Lab) as well as for the Leaf Community microgrid total energy consumption. Further predictions using the day of the week, time of day and irradiance were used to conduct 24h ahead ANN based power generation prediction at microgrid level. The results proved that a close correlation between predicted and actual values exists, during the studied summer and winter periods, as evaluated based on correlation coefficient R for the whole period, as well as Mean Bias Error (MBE) and Mean Average Predicted Error (MAPE) specific days used in the optimisation process.

The second step was to create an optimisation function to include energy cost and load shifting using appropriate variables and constraints. The objective function was minimized using a Genetic Algorithm to obtain solutions at individual building and building group level. Results demonstrated the effectiveness of this approach in considering alternative pricing schemes and load shifting possibilities, as a way to examine cost savings. With respect to the ToU pricing scheme examined, cost savings of levels between 14.67% and 19.68% at building level were associated with significant load shifting solutions obtained by the GA scheme in the two-zone ToU pricing scheme considered. At district level cost savings in the range of 15.92% and 17.24% were obtained. With respect to the DARTP scheme, balanced load shifting solutions associated with cost savings between 5.1 and 7.9% were obtained.

Future steps in this work may involve: (i) extending research activities to focus more on renewable energy generation and storage capabilities, (ii) reforming the GA obtained solutions as to take into consideration actual loads (base, fixed, flexible), renewable energy production and storage and (iii) exploiting the potential for improvements in power predictions using ANN models.

# 6. Conclusions and recommendations

Targeting near-zero energy performance in buildings involves integrated design, energy efficiency measures, renewable energy, storage, advanced intelligence and systematic user engagement. In this thesis, the operational performances of a residential and an industrial NZEB have been investigated, analyzed and optimized with the use of measurements and dynamic energy modelling. The role of renewable energy systems, storage, smart monitoring and controls for the energy performance of NZEB and microgrid integration in smart grids has been qualitatively and quantitatively assessed. In specific, renewables and storage in buildings and microgrids are highlighted as of major importance to minimize energy demand and allow flexibility as a valuable resource asset. Smart monitoring and indoor conditions measurements have been deeply exploited to evaluate energy efficiency aspects and enable validation of the dynamic building energy models.

Subsequently, advanced and robust building energy models are used as the basis for real time energy management solutions to be designed, implemented and tested. In this framework, an optimization assessment framework for HVAC energy management in day-ahead real-time pricing demand response programs was developed. Results demonstrate a strong potential for energy and cost savings based on the provided optimized control of indoor conditions while indoor thermal comfort remains within prescribed levels. The scenarios examined are associated with potential levels of cost reductions in the order between 9.9% and 25% and HVAC energy reduction between 10.4% and 25%. The selected solutions fully comply with indoor comfort and indoor temperature drift rate standards. The developed approach can be widely used due to the fact that it deploys temperature set points for HVAC energy efficiency assessment and control. It allows expandability in establishing optimal control of thermal zones in buildings of various uses and sizes controlled by single or distributed thermostatic controls. A major conclusion stemming from this work is that HVAC dynamic control associated with demand response RTP schemes has high potential if intelligently integrated and explored along with the operation of smart buildings and smart grids in the near future.

ANN short term electric forecasting and GA multi-objective optimisation have been combined to create a tool for generating and evaluating alternative day-ahead load shifting solutions. Exploiting Artificial Neural Network modelling has been effective for the prediction of power consumption and production in a period of 24 hours ahead. Predicting hourly consumption, production and net consumption levels using appropriate input configurations has been proven effective at building and microgrid level. The results proved that a close correlation between predicted and actual values exists, as evaluated based on correlation coefficient R for the whole period, as well as Mean Bias Error (MBE) and Mean Average Predicted Error (MAPE) for specific days evaluated prior to the load shifting optimisation process.
Furthermore, a GA optimisation model was created to evaluate energy cost and load shifting of the ANN predicted consumption for several scenarios at building and microgrid levels. Power consumption and production predictions based on Artificial Neural Network models and GA optimisation models were tested and proven to be a robust technique for the implementation of load shifting strategies and evaluation of energy and cost savings. Results were used to provide thorough considerations regarding the effectiveness and limitations of this approach when considering alternative pricing schemes and load shifting possibilities in order to obtain cost savings. Cost savings between 14.67% and 19.68% and in the range of 15.92% and 17.24% were associated with significant load shifting solutions for building and district level respectively when a specific two-zone ToU scheme was considered. With respect to the DARTP scheme, cost savings between 5.1 and 7.9% were linked to relatively balanced net microgrid level optimised solutions.

Overall, the energy and cost optimization of the operational phase of buildings demands deep knowledge of components and performance over time coupled with intelligent advanced energy management systems. Throughout this research, a significant space of improvement in energy management both in terms of exploiting advanced control algorithms and demand response actions has been identified and demonstrated.

# 7. References


[1] "Benefits of demand response in electricity markets and recommendations for achieving them," 2006.

[2] A. Losi, P. Mancarella, and A. Vicino, Eds., *Integration of Demand Response Into the Electricity Chain*. ISTE Ltd / John Wiley & Sons, Inc., 2015.

[3] EU, "Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast)," *Off. J. Eur. Union*, pp. 13–35, 2010.

[4] "A Roadmap for moving to a compet itive low carbon economy in 2050," no. COM(2011) 112 final. EUROPEAN COMMISSION, Brussels, p. 16, 2011.

[5] A. J. Marszal *et al.*, "Zero Energy Building - A review of definitions and calculation methodologies," *Energy Build.*, vol. 43, no. 4, pp. 971–979, Apr. 2011.

[6] D. D 'agostino, P. Zangheri, B. Cuniberti, D. Paci, and P. Bertoldi, "Synthesis Report on the National Plans for Nearly Zero Energy Buildings (NZEBs)."

[7] S. M. Groezinger Jan, Boermans Thomas, Ashok John, Seehusen Jan, Wehringer Felix, "Overview of Member States information on NZEBs Working version of the progress report - final report," Cologne, 2014.

[8] P. Zangheri, L. Pagliano, and V. Bürger, "The challenges, dynamics and activities in the building sector and its energy demand in Italy D2.1 of WP2 from Entranze Project," 2012.

[9] M. E. Hemerlink Andreas, Schimschar Sven, Boermans Thomas, Pagliano Lorenzo, Zangheri Paolo, Armani Roberto, Voss Karsten, "Towards nearly zero - energy buildings, Definition of common principles under the EPBD, Final report – Executive Summary," Köln, 2013.

[10] D. Kolokotsa *et al.*, "Development of a web based energy management system for University Campuses: The CAMP-IT platform," *Energy Build.*, vol. 123, pp. 119–135, Jul. 2016.

[11] D. Kolokotsa, D. Rovas, E. Kosmatopoulos, and K. Kalaitzakis, "A roadmap towards

intelligent net zero- and positive-energy buildings," *Solar Energy*, vol. 85, no. 12. pp. 3067–3084, 2011.

[12] M. Karlessi, Theoni; Kampelis, Nikos; Kolokotsa, Denia; Santamouris, "Towards sustainable and smart communities: integrating energy efficient technologies into buildings through a holistic approach," in *9th International Conference Improving Energy Efficiency in Commercial Buildings and Smart Communities*, 2016, pp. 920–927.

[13] "Mapping Demand Response in Europe Today 2015," Brussels, 2015.

[14] P. De Wilde, "The gap between predicted and measured energy performance of buildings: A framework for investigation," *Autom. Constr.*, vol. 41, pp. 40–49, 2014.

[15] A. C. Menezes, A. Cripps, D. Bouchlaghem, and R. Buswell, "Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap," *Appl. Energy*, vol. 97, pp. 355–364, 2012.

[16] S. Papantoniou, D. Kolokotsa, and K. Kalaitzakis, "Building optimization and control algorithms implemented in existing BEMS using a web based energy management and control system," *Energy Build.*, vol. 98, 2015.

[17] D. Kolokotsa, C. Diakaki, E. Grigoroudis, G. Stavrakakis, and K. Kalaitzakis, "Decision support methodologies on the energy efficiency and energy management in buildings," *Advances in Building Energy Research*, vol. 3, no. 1. pp. 121–146, 2009.

[18] D. Kolokotsa, A. Pouliezos, G. Stavrakakis, and C. Lazos, "Predictive control techniques for energy and indoor environmental quality management in buildings," *Build. Environ.*, vol. 44, no. 9, pp. 1850–1863, 2009.

[19] D. Kolokotsa, "The role of smart grids in the building sector," *Energy Build.*, vol. 116, pp. 703–708, Mar. 2016.

[20] D. Gao and Y. Sun, "A GA-based coordinated demand response control for building group level peak demand limiting with benefits to grid power balance," *Energy Build.*, vol. 110, pp. 31–40, 2016.

[21] D. Gao, Y. Sun, and Y. Lu, "A robust demand response control of commercial buildings for smart grid under load prediction uncertainty," *Energy*, vol. 93, pp. 275–283, 2015.

[22] N. Kalkan, E. A. Young, and A. Celiktas, "Solar thermal air conditioning technology reducing the footprint of solar thermal air conditioning," *Renew. Sustain. Energy Rev.*,

vol. 16, no. 8, pp. 6352–6383, 2012.

[23] K. Koutroulis E , Kolokotsa D., Potirakis A., Kalaitzakis, “Methodology for optimal sizing of standalone photovoltaic /wind generator systems using genetic algorithm,” *Sol. Energy, 2006 80 107288*, vol. 80, no. 9, pp. 1072–1088, 2006.

[24] E. Koutroulis, D. Kolokotsa, and G. Stravrakakis, “Optimal design and economic evaluation of a battery energy storage system for the maximization of the energy generated by wind farms in isolated electric grids,” vol. 33, no. 1, pp. 55–81, 2009.

[25] E. Koutroulis and K. Kalaitzakis, “Design of a Maximum Power Tracking System for Wind-Energy-Conversion Applications,” *IEEE Trans. Ind. Electron.*, vol. 53, no. 2, 2006.

[26] D. Kolokotsa, N. Kampelis, and A. Mavrigiannaki, “On the integration of the energy storage in smart grids : Technologies and applications,” no. February, pp. 1–25, 2019.

[27] M. H. Albadi and E. F. El-Saadany, “A summary of demand response in electricity markets,” *Electr. Power Syst. Res.*, vol. 78, no. 11, pp. 1989–1996, Nov. 2008.

[28] P. Siano, “Demand response and smart grids - A survey,” *Renew. Sustain. Energy Rev.*, vol. 30, pp. 461–478, 2014.

[29] L. Cheng, Y. Wan, L. Tian, and X. Tian, “Integrated Demand Response under the Backgroud of Energy Internet: A Review and Outlook,” *2nd IEEE Conf. Energy Internet Energy Syst. Integr. EI2 2018 - Proc.*, pp. 1–6, 2018.

[30] D. Mccollum, L. Gomez, E. K. Riahi, and S. Parkinson, “A guide to SDG interactions: from science to implementation,” 2017. [Online]. Available: http://www.icsu.org/publications/a-guide-to-sdg-interactions-from-science-to-implementation.

[31] P. Palensky and D. Dietrich, “Demand side management: Demand response, intelligent energy systems, and smart loads,” *IEEE Trans. Ind. Informatics*, vol. 7, no. 3, pp. 381–388, 2011.

[32] E. Koliou, “Demand Response Policies for the Implementation of smart grids,” Delft University of Technology, 2016.

[33] H. Y. Song, G. S. Lee, and Y. T. Yoon, “Optimal operation of critical peak pricing for an energy retailer considering balancing costs,” *Energies*, vol. 12, no. 24, 2019.

[34] M. Doostizadeh and H. Ghasemi, “A day-ahead electricity pricing model based on smart metering and demand-side management,” *Energy*, vol. 46, no. 1, pp. 221–230,

Oct. 2012.

[35] F. Guang, Y. He, and L. Wen, "Impacts of hybrid time-varying tariffs on residential electricity demand: The case of Zhejiang Province," *Util. Policy*, vol. 61, no. July 2018, p. 100969, 2019.

[36] Y. Li *et al.*, "Optimal scheduling of isolated microgrid with an electric vehicle battery swapping station in multi-stakeholder scenarios: A bi-level programming approach via real-time pricing," *Appl. Energy*, vol. 232, pp. 54–68, 2018.

[37] Y. Li, Z. Yang, D. Zhao, H. Lei, B. Cui, and S. Li, "Incorporating energy storage and user experience in isolated microgrid dispatch using a multi-objective model," *IET Renew. Power Gener.*, vol. 13, no. 6, pp. 973–981, 2019.

[38] J. Anjo, D. Neves, C. Silva, A. Shivakumar, and M. Howells, "Modeling the long-term impact of demand response in energy planning: The Portuguese electric system case study," *Energy*, vol. 165, pp. 456–468, 2018.

[39] X. Deng and T. Lv, "Power system planning with increasing variable renewable energy: A review of optimization models," *J. Clean. Prod.*, vol. 246, p. 118962, 2019.

[40] N. Good, K. A. Ellis, and P. Mancarella, "Review and classification of barriers and enablers of demand response in the smart grid," *Renewable and Sustainable Energy Reviews*, vol. 72. 2017.

[41] M. Vallés, J. Reneses, R. Cossent, and P. Frías, "Regulatory and market barriers to the realization of demand response in electricity distribution networks : A European perspective," *Electr. Power Syst. Res.*, vol. 140, pp. 689–698, 2016.

[42] J. Torriti, M. G. Hassan, and M. Leach, "Demand response experience in Europe : Policies , programmes and implementation," *Energy*, vol. 35, no. 4, pp. 1575–1583, 2010.

[43] A. Satre-Meloy, M. Diakonova, and P. Grünewald, "Cluster analysis and prediction of residential peak demand profiles using occupant activity data," *Appl. Energy*, vol. 260, no. September 2019, p. 114246, 2020.

[44] "OpenADR 2.0 Demand Response Program Implementation Guide." OpenADR Alliance, pp. 1–91, 2014.

[45] C. ZHANG, Y. DING, N. C. NORDENTOFT, P. PINSON, and J. ØSTERGAARD, "FLECH: A Danish market solution for DSO congestion management through DER

flexibility services," *J. Mod. Power Syst. Clean Energy*, vol. 2, no. 2, pp. 126–133, 2014.

[46] S. Huang, Q. Wu, L. Cheng, and Z. Liu, "Optimal Reconfiguration-Based Dynamic Tariff for Congestion Management and Line Loss Reduction in Distribution Networks," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1295–1303, 2016.

[47] C. Heinrich, C. Ziras, A. L. A. Syrri, and H. W. Bindner, "EcoGrid 2.0: A large-scale field trial of a local flexibility market," *Appl. Energy*, vol. 261, no. December 2019, p. 114399, 2020.

[48] R. Yin *et al.*, "Quantifying flexibility of commercial and residential loads for demand response using setpoint changes," *Appl. Energy*, 2016.

[49] O. Ma *et al.*, "Demand response for ancillary services," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1988–1995, 2013.

[50] J. N. Tsitsiklis and Y. Xu, "Pricing of fluctuations in electricity markets," *Eur. J. Oper. Res.*, 2015.

[51] A. Faruqui *et al.*, "A national assessment of demand response potential," *FERC*. 2009.

[52] F. Shariatzadeh, P. Mandal, and A. K. Srivastava, "Demand response for sustainable energy systems : A review , application and implementation strategy," *Renew. Sustain. Energy Rev.*, vol. 45, pp. 343–350, 2015.

[53] J. Vardakas, N. Zorba, and C. Verikoukis, "A Survey on Demand Response in Smart Grids," *IEEE Trans. Ind. Informatics*, vol. 11, no. 3, pp. 1–8, 2015.

[54] N. Motegi, M. Piette, and D. Watson, "Introduction to commercial building control strategies and techniques for demand response," *… Lab. LBNL-59975*, no. 500, 2007.

[55] J. L. Mathieu, "Modeling, Analysis, and Control of Demand Response Resources," *Univ. Calif. Berkeley, PhD Diss.*, 2012.

[56] C. Goldman, M. Reid, R. Levy, and A. Silverstein, "National Action Plan for Energy Efficiency, Coordination of Energy Efficiency and Demand Response," 2010.

[57] L. Pérez-Lombard, J. Ortiz, and C. Pout, "A review on buildings energy consumption information," *Energy Build.*, vol. 40, no. 3, pp. 394–398, Jan. 2008.

[58] A. I. Dounis and C. Caraiscos, "Advanced control systems engineering for energy and comfort management in a building environment—A review," *Renew. Sustain. Energy Rev.*, vol. 13, no. 6–7, pp. 1246–1261, Aug. 2009.

[59] V. S. K. V. Harish and A. Kumar, "A review on modeling and simulation of building

energy systems," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 1272–1292, Apr. 2016.

[60] A. Afram and F. Janabi-Sharifi, "Review of modeling methods for HVAC systems," *Appl. Therm. Eng.*, vol. 67, no. 1–2, pp. 507–519, Jun. 2014.

[61] Z. Afroz, G. M. Shafiullah, T. Urmee, and G. Higgins, "Modeling techniques used in building HVAC control systems: A review," *Renew. Sustain. Energy Rev.*, vol. 83, no. February 2017, pp. 64–84, 2018.

[62] G. S. Okochi and Y. Yao, "A review of recent developments and technological advancements of variable-air-volume (VAV) air-conditioning systems," *Renew. Sustain. Energy Rev.*, vol. 59, pp. 784–817, Jun. 2016.

[63] S. Wang and Z. Ma, "Supervisory and Optimal Control of Building HVAC Systems: A Review," *HVAC&R Res.*, vol. 14, no. 1, pp. 3–32, Jan. 2008.

[64] H.-W. Lin and T. Hong, "On variations of space-heating energy use in office buildings," *Appl. Energy*, vol. 111, pp. 515–528, Nov. 2013.

[65] M. De Rosa, M. Carragher, and D. P. Finn, "Flexibility assessment of a combined heat-power system (CHP) with energy storage under real-time energy price market framework," *Therm. Sci. Eng. Prog.*, vol. 8, pp. 426–438, 2018.

[66] Y. Susowake *et al.*, "A Multi-Objective Optimization Approach towards a Proposed Smart Apartment with Demand-Response in Japan," *Energies*, vol. 13, no. 1, p. 127, 2019.

[67] M. J. Risbeck, C. T. Maravelias, J. B. Rawlings, and R. D. Turney, "A mixed-integer linear programming model for real-time cost optimization of building heating, ventilation, and air conditioning equipment," *Energy Build.*, vol. 142, pp. 220–235, May 2017.

[68] H. Pombeiro, M. J. Machado, and C. Silva, "Dynamic programming and genetic algorithms to control an HVAC system: Maximizing thermal comfort and minimizing cost with PV production and storage," *Sustain. Cities Soc.*, vol. 34, pp. 228–238, Oct. 2017.

[69] J. Serra, D. Pubill, M. Á. Vázquez, and C. Verikoukis, "Experimental evaluation of an HVAC system under dynamic pricing with comfort constraints," *2014 IEEE PES Innov. Smart Grid Technol. Conf. ISGT 2014*, 2014.

[70] M. Alhaider and L. Fan, "Mixed integer programming for HVACs operation," *IEEE*

*Power Energy Soc. Gen. Meet.*, vol. 2015-Septe, pp. 1–5, 2015.

[71] K. Ma *et al.*, “Switched Control Strategies of Aggregated Commercial HVAC Systems for Demand Response in Smart Grids,” *Energies*, vol. 10, no. 7, p. 953, Jul. 2017.

[72] Y. M. Lee, R. Horesh, and L. Liberti, “Simulation and optimization of energy efficient operation of HVAC system as demand response with distributed energy resources,” in *2015 Winter Simulation Conference (WSC)*, 2015, pp. 991–999.

[73] Y. Zhang, P. Zeng, and C. Zang, “Multi-objective optimal control algorithm for HVAC based on particle swarm optimization,” in *Fifth International Conference on Intelligent Control and Information Processing*, 2014, pp. 417–423.

[74] M. S. H. Nizami, M. J. Hossain, B. M. R. Amin, and E. Fernandez, “A residential energy management system with bi-level optimization-based bidding strategy for day-ahead bi-directional electricity trading,” *Appl. Energy*, vol. 261, no. December 2019, p. 114322, 2020.

[75] S. Guo, Q. Liu, J. Sun, and H. Jin, “A review on the utilization of hybrid renewable energy,” *Renew. Sustain. Energy Rev.*, vol. 91, no. March, pp. 1121–1147, 2018.

[76] S. M. Dawoud, X. Lin, and M. I. Okba, “Hybrid renewable microgrid optimization techniques: A review,” *Renew. Sustain. Energy Rev.*, vol. 82, pp. 2039–2052, Feb. 2018.

[77] T.-C. Ou, K.-H. Lu, C.-J. Huang, T.-C. Ou, K.-H. Lu, and C.-J. Huang, “Improvement of Transient Stability in a Hybrid Power Multi-System Using a Designed NIDC (Novel Intelligent Damping Controller),” *Energies*, vol. 10, no. 4, p. 488, Apr. 2017.

[78] S. Shinkhede and S. K. Joshi, “Hybrid Optimization Algorithm for Distributed Energy Resource,” no. November, 2014.

[79] T.-C. Ou and C.-M. Hong, “Dynamic operation and control of microgrid hybrid power systems,” *Energy*, vol. 66, pp. 314–323, Mar. 2014.

[80] V. V. S. N. Murty and A. Kumar, “Multi-objective energy management in microgrids with hybrid energy sources and battery energy storage systems,” pp. 1–20, 2020.

[81] D. Yuan, Z. Lu, J. Zhang, and X. Li, “A hybrid prediction-based microgrid energy management strategy considering demand-side response and data interruption,” *Int. J. Electr. Power Energy Syst.*, vol. 113, no. May, pp. 139–153, 2019.

[82] N. Hatziargyriou, H. Asano, R. Iravani, and C. Marnay, “Microgrids,” *IEEE Power Energy Mag.*, vol. 5, no. 4, pp. 78–94, Jul. 2007.

[83] M. F. Zia, E. Elbouchikhi, and M. Benbouzid, "Microgrids-energy-management-systems--A-critical-review-on-me_2018_Applied-E.pdf," *Appl. Energy*, no. 222, pp. 1033–1055, 2018.

[84] V.-H. Bui, A. Hussain, H.-M. Kim, V.-H. Bui, A. Hussain, and H.-M. Kim, "Optimal Operation of Microgrids Considering Auto-Configuration Function Using Multiagent System," *Energies*, vol. 10, no. 10, p. 1484, Sep. 2017.

[85] T.-C. Ou, "A novel unsymmetrical faults analysis for microgrid distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 43, no. 1, pp. 1017–1024, Dec. 2012.

[86] T.-C. Ou, "Ground fault current analysis with a direct building algorithm for microgrid distribution," *Int. J. Electr. Power Energy Syst.*, vol. 53, pp. 867–875, Dec. 2013.

[87] A. Hirsch, Y. Parag, and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues," *Renew. Sustain. Energy Rev.*, vol. 90, no. April, pp. 402–411, 2018.

[88] A. Mohseni, S. S. Mortazavi, A. Ghasemi, A. Nahavandi, and M. Talaei abdi, "The application of household appliances' flexibility by set of sequential uninterruptible energy phases model in the day-ahead planning of a residential microgrid," *Energy*, vol. 139, pp. 315–328, Nov. 2017.

[89] E. Bullich-Massagué, F. Díaz-González, M. Aragüés-Peñalba, F. Girbau-Llistuella, P. Olivella-Rosell, and A. Sumper, "Microgrid clustering architectures," *Appl. Energy*, vol. 212, no. December 2017, pp. 340–361, 2018.

[90] V.-H. Bui, A. Hussain, and H.-M. Kim, "A Multiagent-Based Hierarchical Energy Management Strategy for Multi-Microgrids Considering Adjustable Power and Demand Response," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1323–1333, Mar. 2018.

[91] R. Bahmani, H. Karimi, and S. Jadid, "Stochastic electricity market model in networked microgrids considering demand response programs and renewable energy sources," *Int. J. Electr. Power Energy Syst.*, 2020.

[92] Y. Wang *et al.*, "Energy management of smart micro-grid with response loads and distributed generation considering demand response," *J. Clean. Prod.*, vol. 197, pp. 1069–1083, 2018.

[93] H. Safamehr and A. Rahimi-Kian, "A cost-efficient and reliable energy management

of a micro-grid using intelligent demand-response program," *Energy*, vol. 91, pp. 283–293, 2015.

[94] P. Carrasqueira, M. J. Alves, and C. H. Antunes, "Bi-level particle swarm optimization and evolutionary algorithm approaches for residential demand response with different user profiles," *Inf. Sci. (Ny).*, vol. 418–419, pp. 405–420, 2017.

[95] M. Batić, N. Tomašević, G. Beccuti, T. Demiray, and S. Vraneš, "Combined energy hub optimisation and demand side management for buildings," *Energy Build.*, vol. 127, pp. 229–241, 2016.

[96] M. J. Shabani and S. M. Moghaddas-Tafreshi, "Fully-decentralized coordination for simultaneous hydrogen, power, and heat interaction in a multi-carrier-energy system considering private ownership," *Electr. Power Syst. Res.*, vol. 180, no. April 2019, p. 106099, 2020.

[97] L. Ferrari *et al.*, "Development of an optimization algorithm for the energy management of an industrial Smart User," *Appl. Energy*, vol. 208, no. July 2016, pp. 1468–1486, 2017.

[98] J. Yang, Z. Tian, and K. Ma, "A Demand-Side Pricing Strategy Based on Bayesian Game," *2018 15th Int. Conf. Control. Autom. Robot. Vision, ICARCV 2018*, pp. 146–150, 2018.

[99] X. Gong, A. De Paola, D. Angeli, and G. Strbac, "A game-theoretic approach for price-based coordination of flexible devices operating in integrated energy-reserve markets," *Energy*, vol. 189, p. 116153, 2019.

[100] M. Abuelnasr, W. El-Khattam, and I. Helal, "Examining the influence of micro-grids topologies on optimal energy management systems decisions using genetic algorithm," *Ain Shams Eng. J.*, vol. 9, no. 4, pp. 2807–2814, 2018.

[101] P. Jiang, J. Dong, and H. Huang, "Optimal integrated demand response scheduling in regional integrated energy system with concentrating solar power," *Appl. Therm. Eng.*, vol. 166, no. December 2019, p. 114754, 2020.

[102] T. Alharbi and K. Bhattacharya, "A Stochastic Energy Management System for Isolated Microgrids," *IEEE Power Energy Soc. Gen. Meet.*, vol. 2018-Augus, pp. 1–5, 2018.

[103] K. Kalaitzakis, G. S. Stavrakakis, and E. M. Anagnostakis, "Short-term load

forecasting based on artificial neural networks parallel implementation," *Electr. Power Syst. Res.*, vol. 63, no. 3, pp. 185–196, 2002.

[104] G. J. Tsekouras, F. D. Kanellos, and N. Mastorakis, *Computational Problems in Science and Engineering; Chapter 2 Short Term Load Forecasting in Electric Power Systems with Artificial Neural Networks*, vol. 343. 2015.

[105] J. Hu, V. C. M. Leung, G. Coulson, and D. Ferrari, *Smart Grid Inspired Future Technologies*, vol. 203. 2017.

[106] A. Baliyan, K. Gaurav, and S. Kumar Mishra, "A review of short term load forecasting using artificial neural network models," *Procedia Comput. Sci.*, vol. 48, no. C, pp. 121–125, 2015.

[107] A. Mavrigiannaki *et al.*, "Development and testing of a micro-grid excess power production forecasting algorithms," in *Energy Procedia*, 2017, vol. 134.

[108] A. R. Khan, A. Mahmood, A. Safdar, Z. A. Khan, and N. A. Khan, "Load forecasting, dynamic pricing and DSM in smart grid: A review," *Renewable and Sustainable Energy Reviews*. 2016.

[109] "Average Weather For Ancona, Italy - WeatherSpark." .

[110] E. Provata, D. Kolokotsa, S. Papantoniou, M. Pietrini, A. Giovannelli, and G. Romiti, "Development of optimization algorithms for the Leaf Community microgrid," *Renew. Energy*, 2015.

[111] G. Comodi *et al.*, "Multi-apartment residential microgrid with electrical and thermal storage devices: Experimental analysis and simulation of energy management strategies," *Appl. Energy*, vol. 137, 2015.

[112] "Loccioni Group." [Online]. Available: https://www.loccioni.com/en/. [Accessed: 13-Feb-2017].

[113] "Leaf Community | Loccioni Energy." [Online]. Available: https://www.loccioni.com/en/waves/leaf-community/.

[114] "Engineering Reference, EnergyPlus™ Version 9.1.0 Documentation." U.S. Department of Energy, p. 1748, 2019.

[115] L. Brackney *et al.*, *Building Energy Modeling with OpenStudio*. 2018.

[116] "3D modeling for everyone | SketchUp." [Online]. Available: http://www.sketchup.com/. [Accessed: 13-Feb-2017].

[117] "OpenStudio." [Online]. Available: https://www.openstudio.net. [Accessed: 13-Feb-2017].

[118] U.S. Department of Energy, "Building Technologies Office: EnergyPlus Energy Simulation Software," *Energy Efficiency and Renewable Energy*, 2015. [Online]. Available: http://apps1.eere.energy.gov/buildings/energyplus/. [Accessed: 13-Feb-2017].

[119] "MyLeaf Platform - Loccioni Group." [Online]. Available: https://myleaf2.loccioni.com. [Accessed: 26-Jul-2018].

[120] *Italian Energy Efficiency Action Plan*. 2014, p. 168.

[121] L. Webster *et al.*, "M&V Guidelines: Measurement and Verification for Performance-Based Contracts Version 4.0," 2015.

[122] N. Kampelis *et al.*, "Evaluation of the performance gap in industrial, residential & tertiary near-Zero energy buildings," *Energy Build.*, vol. 148, 2017.

[123] "EN ISO 7730 Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria (ISO 7730:2005)," *CEN*. 2006.

[124] C. Greer *et al.*, "NIST Framework and Roadmap for Smart Grid Interoperability Standards, Release 3.0," 2014.

[125] A. Jain, A. Mani, and A. S. Siddiqui, "Network architecture for demand response implementation in smart grid," *Int. J. Syst. Assur. Eng. Manag.*, vol. 10, no. 6, pp. 1389–1402, 2019.

[126] G. Rietveld *et al.*, "Measurement infrastructure for observing and controlling smart electrical grids," *IEEE PES Innov. Smart Grid Technol. Conf. Eur.*, pp. 1–8, 2012.

[127] NERC, "Demand Response Availability Data System (DADS): Phase I & II Final Report." North American Electric Reliability Corporation, 2011.

[128] European Parliament, *Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on energy efficiency*, no. October. 2012, pp. 1–56.

[129] P. Bertoldi, P. Zancanella, and B. Boza-Kiss, "Demand Response status in EU Member States," 2016.

[130] P. Siano, "Demand response and smart grids - A survey," *Renew. Sustain. Energy Rev.*, vol. 30, pp. 461–478, 2014.

[131] H. A. Aalami, M. P. Moghaddam, and G. R. Yousefi, "Demand response modeling considering Interruptible/Curtailable loads and capacity market programs," *Appl. Energy*, vol. 87, no. 1, pp. 243–250, Jan. 2010.

[132] A. Kusiak, F. Tang, and G. Xu, "Multi-objective optimization of HVAC system with an evolutionary computation algorithm," *Energy*, vol. 36, no. 5, pp. 2440–2449, 2011.

[133] M. A. F. Ghazvini, J. Soares, H. Morais, R. Castro, and Z. Vale, "Dynamic pricing for demand response considering market price uncertainty," *Energies*, vol. 10, no. 9, pp. 1–20, 2017.

[134] C. Triki and A. Violi, "Dynamic pricing of electricity in retail markets," *4or*, vol. 7, no. 1, pp. 21–36, 2009.

[135] H. T. Haider, O. H. See, and W. Elmenreich, "Residential demand response scheme based on adaptive consumption level pricing," *Energy*, vol. 113, pp. 301–308, Oct. 2016.

[136] K. M. Tsui and S. C. Chan, "Demand Response Optimization for Smart Home Scheduling Under Real-Time Pricing," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1812–1821, Dec. 2012.

[137] T. Crosbie, J. Broderick, M. Short, R. Charlesworth, and M. Dawood, "Demand Response Technology Readiness Levels for Energy Management in Blocks of Buildings," *Buildings*, vol. 8, no. 2, p. 13, 2018.

[138] T. Crosbie, M. Short, M. Dawood, and R. Charlesworth, "Demand response in blocks of buildings: opportunities and requirements," *Entrep. Sustain. Issues*, vol. 4, no. 3, pp. 271–281, 2017.

[139] M. Attia, N. Haidar, S. M. Senouci, and E. H. Aglzim, "Towards an efficient energy management to reduce CO2emissions and billing cost in smart buildings," *CCNC 2018 - 2018 15th IEEE Annu. Consum. Commun. Netw. Conf.*, vol. 2018-Janua, pp. 1–6, 2018.

[140] T. Karlessi *et al.*, "The Concept of Smart and NZEB Buildings and the Integrated Design Approach," in *Procedia Engineering*, 2017, vol. 180.

[141] C. Diakaki, E. Grigoroudis, and D. Kolokotsa, "Towards a multi-objective optimization approach for improving energy efficiency in buildings," *Energy Build.*, vol. 40, no. 9, pp. 1747–1754, Jan. 2008.

[142] C. Diakaki, E. Grigoroudis, N. Kabelis, D. Kolokotsa, K. Kalaitzakis, and G. Stavrakakis, “A multi-objective decision model for the improvement of energy efficiency in buildings,” *Energy*, vol. 35, no. 12, pp. 5483–5496, Dec. 2010.

[143] K. Gobakis, A. Mavrigiannaki, K. Kalaitzakis, and D.-D. Kolokotsa, “Design and development of a Web based GIS platform for zero energy settlements monitoring,” *Energy Procedia*, vol. 134, pp. 48–60, Oct. 2017.

[144] B. Zhou *et al.*, “Smart home energy management systems: Concept, configurations, and scheduling strategies,” *Renew. Sustain. Energy Rev.*, vol. 61, pp. 30–40, Aug. 2016.

[145] M. Shakeri *et al.*, “An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid,” *Energy and Buildings*, vol. 138. pp. 154–164, 2017.

[146] M. P. Fanti *et al.*, “A Control Strategy for District Energy Management,” *2015 IEEE Int. Conf. Autom. Sci. Eng.*, pp. 432–437, 2015.

[147] V. Marinakis and H. Doukas, “An advanced IoT-based system for intelligent energy management in buildings,” *Sensors (Switzerland)*, vol. 18, no. 2, 2018.

[148] G. Brusco, A. Burgio, D. Menniti, A. Pinnarelli, N. Sorrentino, and L. Scarcello, “An Energy Box in a Cloud-Based Architecture for Autonomous Demand Response of Prosumers and Prosumages,” *Electronics*, vol. 6, no. 4, p. 98, 2017.

[149] N. Lu, P. Du, X. Guo, and F. L. Greitzer, “Smart meter data analysis,” *Pes T&D 2012*, pp. 1–6, 2012.

[150] M. Q. Raza and A. Khosravi, “A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings,” *Renew. Sustain. Energy Rev.*, vol. 50, pp. 1352–1372, 2015.

[151] M. Goulden, B. Bedwell, S. Rennick-Egglestone, T. Rodden, and A. Spence, “Smart grids, smart users? the role of the user in demand side management,” *Energy Res. Soc. Sci.*, vol. 2, pp. 21–29, 2014.

[152] M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management; Chapter 2 Short-Term Load Forecasting*, vol. 9. John Wiley & Sons, Inc., 2002.