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DEPARTMENT OF
ELECTRICAL AND COMPUTER ENGINEERING

UNLOCKING VALUE FROM DEMAND-SIDE FLEXIBILITY IN POWER SYSTEMS

DOCTOR OF PHILOSOPHY DISSERTATION

VENIZELOS VENIZELOU

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VENIZELOS VENIZELOU

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The present Doctoral Dissertation was submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy at the ***Department of Electrical and Computer Engineering*** *and was approved on the 08/07/2021 by the members of the* ***Examination Committee****.*

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The present doctoral dissertation was submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy of the University of Cyprus. It is a product of original work of my own, unless otherwise mentioned through references, notes, or any other statements.

Venizelos Venizelou

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ABSTRACT (GREEK)

Οι πρωτόγνωρες αλλαγές διαταράσσουν τα σημερινά δρώμενα στο τομέα της ηλεκτρικής ενέργειας, δημιουργώντας νέες προκλήσεις στους διαχειριστές ηλεκτρικών συστημάτων και σε κυβερνήσεις σε όλο τον κόσμο. Η εξισορρόπηση της διαλείπουσας παραγωγής και η αύξηση της μέγιστης ζήτησης, καθώς και η ενσωμάτωση ανανεώσιμων πηγών ενέργειας για την επίτευξη των κλιματικών στόχων καθιστά την εξισορρόπηση παραγωγής και ζήτησης δυσκολότερη και ακριβότερη από ό, τι στο παρελθόν.

Ένας από τους πιο καλά ερευνημένους τομείς της ευελιξίας του συστήματος ηλεκτρικής ενέργειας είναι η Διαχείριση Ενεργειακής Ζήτησης (Demand Side Management), η οποία στοχεύει στη βελτίωση της ευελιξίας από την πλευρά των ενεργειακών καταναλωτών. Η Διαχείριση Ενεργειακής Ζήτησης μπορεί να εφαρμοστεί με δύο τρόπους: μέσω Ενεργειακής Απόδοσης ή Απόκρισης Ζήτησης (Demand Response), η οποία αναφέρεται σε προγράμματα που ενθαρρύνουν τους τελικούς χρήστες να κάνουν βραχυπρόθεσμες μειώσεις στη ζήτηση ενέργειας.

Η συμβολή αυτής της διατριβής έγκειται στην εισαγωγή μιας καθολικά εφαρμοσμένης μεθοδολογίας για την ανάπτυξη ενός οικονομικά αποδοτικού συστήματος Διαχείρισης Ενεργειακής Ζήτησης που εστιάζει στην εξαγωγή ευελιξίας μέσω κινήτρων στη μορφή δυναμικής ενεργειακής τιμολόγησης. Αυτή η διατριβή εξετάζει περαιτέρω την πιθανή μεγιστοποίηση της ευελιξίας παρουσιάζοντας ένα καινοτόμο πλαίσιο Απόκρισης Ζήτησης που στοχεύει στην ελαχιστοποίηση του κόστους Σωρευτικής Εκπροσώπησης (Aggregation) λαμβάνοντας υπόψη τεχνικές παραμέτρους αλλά και παραμέτρους απόδοσης. Το προτεινόμενο πλαίσιο Απόκρισης Ζήτησης λειτουργεί ως ένα ολιστικό πλαίσιο το οποίο είναι έτοιμο να εφαρμοστεί σε χώρες όπου οι κανόνες της αγοράς ηλεκτρικής ενέργειας και οι τεχνολογίες αυτοματισμού είναι ώριμες και προηγμένες.

Το προτεινόμενο σύστημα Διαχείρισης Ενεργειακής Ζήτησης μαζί με το αναπτυγμένο πλαίσιο Απόκρισης Ζήτησης αποσκοπούν στο να ξεκλειδώσουν πλήρως τη διαθέσιμη ανεκμετάλλευτη ευελιξία φορτίου με βάση τις δομικές ιδιαιτερότητες της ηλεκτρικής αγοράς που εφαρμόζεται.

ABSTRACT

Profound changes are disrupting the electricity sector, bringing about new challenges for utilities, system operators and governments around the world. Balancing intermittent generation and increasing peak demand while integrating renewables to meet climate goals make balancing supply and demand harder and more expensive than it used to be. One of the most well-researched fields of electricity system flexibility is Demand Side Management (DSM), which aims to improve flexibility on the consumer side. DSM can be implemented in two ways: through Energy Efficiency or Demand Response (DR), which refers to programs that encourage end users to make short-term reductions in energy demand.

The contribution of this work lies in the introduction of a universally-applicable methodology for deploying a cost-effective DSM scheme that focuses on flexibility extraction through price incentives. This thesis delves further into flexibility potential maximization by presenting an innovative framework for DR that aims to minimise the Aggregator's cost by considering technical and performance parameters. The proposed DR framework serves as a holistic framework that is ready to be applied in countries where the electricity market rules and automation technologies are mature and advanced.

The proposed DSM scheme along with the developed DR framework aim to fully unlock the available untapped flexibility potential based on the market structure specificities of each area of deployment.

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After an intensive period of five years of both professional and personal development, I would like to reflect and acknowledge the people who accompanied me during the time of this endeavor and helped shape me as the person, researcher and colleague I am today.

Firstly, I would like to appreciate not only the unwavering support, motivation, guidance, and expertise my supervisor, Professor George E. Georghiou, has provided me during the completion of this research but also the challenges and ideas he has presented me in order for me to succeed in this endeavor.

Finally, there are no words to express the deep gratitude and great affection I feel towards my parents, Ioannis and Mary, for their undying support and continuous encouragement during this time.

"If you need inspiring words, don't do it."

Elon Musk

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Acronyms and Abbreviations

AFI	Absolute Fairness Index
aFRR	Automatic Frequency Restoration Reserves
ANN	Artificial Neural Network
BESS	Battery Energy Storage System
BRP	Balance Responsible Party
CBA	Cost-Benefit Analysis
CCSA	Conservative Convex Separable Approximation
CDH	Cooling degree hours
CES	Constant elasticity of substitution
CFI	Capacity Fairness Index
CIM	Common Information Model
CPP	Critical Peak Pricing
CRSE	Clustered robust standard errors
DDT	Distributed dynamic tariff
DER	Distributed energy resources
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operators
EAC	Electricity Authority of Cyprus
EV	Electric Vehicle
FI	Fairness Index
GPRS	General Packet Radio Service
HDH	Heating degree hours
ICT	Information and communications technology
IHD	In House Display
IT	Information Technology
LF	Load Factor
LS	Load Shifting
MAPE	Mean absolute percentage error
MDMS	Meter Data Management System
mFRR	Manual Frequency Restoration Reserves
MMA	Method of Moving Asymptotes
OLS	Ordinary least squares
OPF	Optimal Power Flow
PAM	Partition Around Medoids
PCC	Pearson correlation coefficient
PLC	Power-line communication
PPIS	Python programmed integrating script
PV	Photovoltaic
PVTL	Photovoltaic Technology Laboratory
RES	Renewable Energy Sources
RI	Reliability Index
RMSE	Root mean square error
RTP	Real Time Pricing

SMs	Smart Meters
ToU	Time-of-Use
TSO	Transmission System Operator
UCY	University of Cyprus
UFTP	USEF Flexibility Transfer Protocol

Publications led to this Thesis

Peer-reviewed Journal Publications

[1] V. Venizelou, N. Philippou, M. Hadjipanayi, G. Makrides, V. Efthymiou, and G. E. Georghiou, "Development of a novel time-of-use tariff algorithm for residential prosumer price-based demand side management," *Energy*, vol. 142, pp. 633 – 646, 2018.

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Chapter 1

Introduction

International energy landscapes are evolving rapidly as the increasing deployment of decentralized and intermittent resources pose several energy management challenges to system operators. Increasing shares of intermittent distributed energy resources (DER), such as Photovoltaic (PV) systems, along with the transition to deregulated organizational systems and market-oriented approaches initiate the loss of centralization in the management and control of electrical power systems as well as the need for balancing supply with demand. Unlocking flexibility at the demand-side, instead of investing in new non-renewable transmission-connected generation capacity introduces a more pro-active and effective approach for embracing this energy transition. The need for exploiting the available untapped flexibility is more important than ever, now that the large shares of DERs in the distribution network render prosumers as the predominant class of electricity customers. Demand Side Management (DSM), which is defined as the utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e. time pattern and magnitude of a utility's load, is a promising method for balancing supply and demand in power systems with a high share of variable renewable energy generation.

1.1 Motivation and Research Objectives

The lack of research on a comprehensive methodology for creating cost-effective incentives for prosumers for altering their consumption patterns has led to the development of a consistent and universally-applicable methodology to derive effective price-based DSM schemes for the residential sector. The proposed methodology was verified through statistical analysis and validated on a pilot-network comprising of 300 prosumers with roof-top PV systems. The methodology addresses the technological challenges related to price-based DSM design such as the optimum number of Time-of-Use (ToU) block periods, evaluation of the impact of the proposed scheme, training of the consumers and prosumers, active participation and rewarding, development of a pilot network and cost-benefit analysis of deploying such schemes.

As electrical smart grid technologies are increasingly developed and electricity markets are maturing, exceptional opportunities for more complex electrical supply and demand interactions that used to be historically unilateral, are now offered. These opportunities mainly rely on exploiting the flexibility available at the demand-side. However, strict market and grid-related regulations exclude single small-scale electricity customers to participate in the provision of such services, thus third parties such as Aggregators must undertake the role of summing those multiple flexibility volumes. Aggregators are being lauded as critical entities in providing these valuable electricity services, acting as intermediates between the small / medium scale consumers and the electricity market stakeholders at higher levels, such as the Distribution System Operators (DSOs) [1, 2]. The most common approach for extracting these flexibility volumes is through Demand Response (DR), which is a program that is established to change the demand-side electric use from normal consumption patterns in response to changes in the price of electricity, or incentive payments [3]. To achieve optimal Aggregation, a holistic DR framework for optimal cooperation between a DSO and an Aggregator is developed. The proposed DR framework can be seen as a key for enhancing the DSO-Aggregator coordination as well as a pathway for facilitating the role of the Aggregator in a fully liberalized electricity market.

1.2 Key Contributions to Knowledge

This research provides important contributions to the research community as well as to power system operators and policymakers by expanding the knowledge on DSM- and DR-related aspects through the introduction of consistent and transparent methodologies that will help promote effective flexibility extraction. This thesis initially presents a comprehensive and universally-applicable methodology for developing and implementing a cost-effective price-based DSM scheme which is directly deployed from the DSO to the end-users. The proposed methodology introduces steps for replacing the costly large-scale deployment of

PV meters as well as the development and implementation of optimum ToU tariffs on a real pilot-network comprising of 300 prosumers with roof-top PV systems. Part of the novelty of the algorithm for developing the optimum ToU tariffs is its capability to adjust the tariff structure (period and rate) in order to be applicable to both consumers and prosumers by utilizing net-load energy profiles. The methodology, proposed in this thesis, introduces a detailed evaluation stage that includes methods for verifying and validating the effectiveness of the developed price-based DSM scheme based on technical and economic performance data.

More specifically, the first part of this thesis introduces a coherent methodology for developing, implementing and evaluating optimum price-based DSM schemes, where an optimization algorithm, based on net-load, for developing cost-effective ToU tariffs for both consumer and prosumer classes is utilised. Moreover, within the scope of this work, a real pilot-network consisting of 300 prosumers with various demographic characteristics, which can act as a test-bed for newly introduced energy policies and electricity pricing schemes is established. Additionally, the results emanating from this work provide useful knowledge in the fields of energy behavioural patterns and flexibility potential of prosumers that can be vital instruments for policy makers to direct and encourage the implementation of DSM schemes at a larger scale.

The results of applying the proposed methodology on the pilot-network highlighted that DSM schemes that offer price incentives to the electricity customers are considered as an easy pathway for deferring investments for network reinforcement and incorporating higher levels of DERs. Additionally, it is proven that domestic electricity customers can be a significant source of demand-side flexibility. It is believed that more pro-active and smart approaches for the future Smart Grid energy transactions can fully enable the demand-side flexibility exploitation in both small and medium scale consumers. To this end, the System Operators are shifting their attention towards DR events that can effectively unlock the available flexibility on short notice through instantaneous signals. The establishment of DR events is also accelerated with the advancement of technology that facilitates real-time monitoring of both supply and demand as well as identification of any grid violations, while enabling automated DR request and flexibility activation. Compensations offered to the electricity customers, for participating in a DR event, can be combined with other DSM scheme rewards in order to offer higher price incentives that can fully unlock the available untapped flexibility. However, flexibility maximization depends on the optimal DR distribution on the demand-side. The role of enabling small-scale electricity customers in participating in such DR events is undertaken by the Aggregator who is responsible for summing the multiple flexibility volumes available at the demand-side.

By extending the first part of this thesis and to address the above-mentioned upcoming electricity market changes, a holistic DR framework for DSO-Aggregator coordination and optimal DR distribution is developed. The key added value is the utilisation of a novel bi-level constrained objective optimisation function which minimises the flexibility aggregation costs through optimal segmentation of customer groups based on performance indices, while maintaining the distribution grid balancing. Even though the focus of this work is the Aggregator, other market players could also employ the framework, such as Utilities, Flexibility traders, etc. Moreover, the proposed DR framework, and subsequently the developed optimisation function, can be applied to any type of contracts (dynamic and/or static) between the DSO and Aggregator as well as between the Aggregator and its customers, while the technical parameters utilised in the optimisation function enable the exploitation of the developed framework for any network topology. The proposed DR framework serves as a holistic framework that is ready to be applied in countries where the electricity market rules and automation technologies are mature and advanced.

The proposed DSM scheme along with the developed DR framework aim to fully unlock the available untapped flexibility potential based on the market structure specificities of each area of deployment.

1.3 Thesis Structure

The thesis starts with a review of existing research on the subject matter and identified objectives. Each research objective was addressed in its own chapter that provides objective specific results, discussion and conclusion sections. The concluding chapter reviews the outcomes for each objective before determining the overall implications of the research, including further potential research areas. The rest of this thesis is structured as follows: Chapter 2 provides the main contextual knowledge for this thesis. Theoretical background information regarding the general principles of the power system, the increasing integration of distributed renewable generation and the transition towards smart grids is provided. The context and necessity of DR, the distinction between implicit and explicit DR, as well as the role of the Aggregator are also presented. Additionally, this chapter reviews existing literature focusing on summarising known information about each research objective and the knowledge gaps that are addressed by this work. Chapter 3 addresses the first objective by proposing a three-stage methodology for developing and deploying a cost-effective price-based DSM scheme that focuses on the deployment of Implicit DR. More specifically, this chapter presents the activities and results obtained from the implementation of ToU tariffs on a real pilot-network comprising of 300 prosumers, in Cyprus, with roof-top PV systems. Outcomes and lessons learned from the work conducted in Chapter 3 revealed that more pro-active and smart approaches are needed to fully unlock the untapped demand-side flexibility. To this end, Chapter 4 introduces a holistic DR framework for DSO-Aggregator coordination that exploits a bi-level constrained-objective optimisation function which minimises the flexibility aggregation costs through optimal segmentation of customer groups based on performance indices, while maintaining the distribution grid balancing. The followed methodology and the verification results of the proposed DR framework are presented in detail in this chapter. Chapter 5 covers the overall conclusions as well as future work.

The following figure provides a schematic representation of the thesis structure to illustrate how the chapters and content are organised.

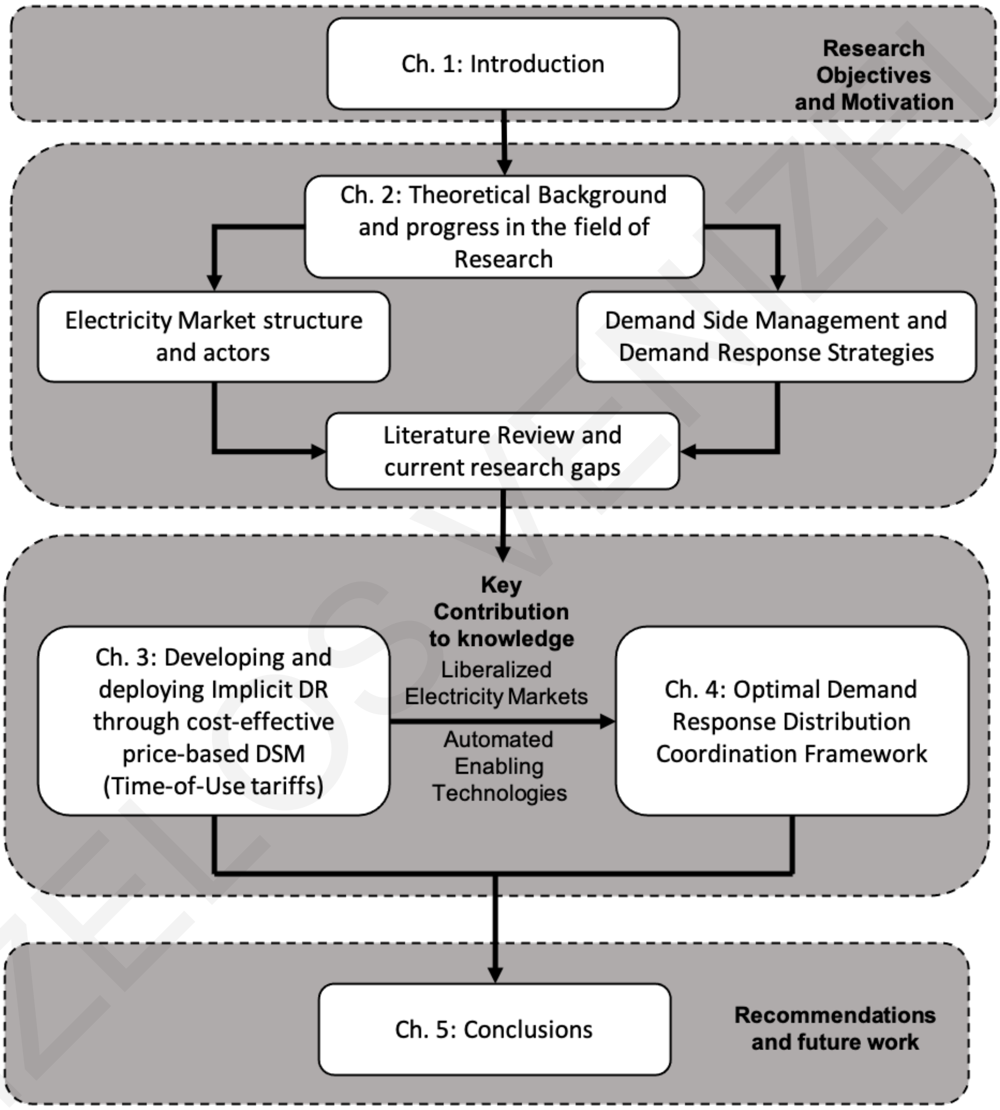


Figure 1.1: Schematic overview of the structure of the Thesis.

Chapter 2

Theoretical Background and Progress in the Research Field of Flexibility Provision

The recent drive towards decarbonization in the electricity sector entails increased investment in breakthrough technologies and low carbon energy sources such as Renewable Energy Sources (RES). However, integrating RES without jeopardizing security of supply and economic operation of the power system is quite a challenge. The load growth accommodation and the problems of ageing infrastructure render the situation even more challenging. The aforementioned drivers imply a growing need for distribution system flexibility at the demand side as well as customer engagement and empowerment in order to maintain an affordable energy system. A prominent method to provide flexibility is through DSM, which involves schemes established to provoke changes in electricity demand by end-use consumers and to encourage lower electricity use at periods of high market price. DSM activities can be classified into Energy Efficiency and DR (price and incentive-based DR). Energy Efficiency focuses on strategies aiming at reducing the power usage to perform the same tasks. This involves a permanent reduction of demand by using more efficient load-intensive appliances (e.g. water heaters, refrigerators, or washing machines), while DR refers to a wide range of actions which can be taken at the end-user side of the electricity meter in response to particular conditions within the electricity system (such as peak period network congestion or high prices). Lately, DR strategies have been gaining more attention in power system operations, driven by growing interest in the smart grid concept. Specifically, time-varying electricity pricing incentives such as ToU tariffs or peak demand charging for residential consumers, offer a way for financial gains and improved perception about their energy consumption profiles and costs. Changes in consumption patterns, including time-variable electricity prices or incentive payments, can be achieved by consumers/prosumers themselves or through aggregation. Aggregation is mainly necessary if small scale production and DR are to participate in the market. Aggregators can be divided into different types, according to the DERs they aggregate (be it DR or distributed generation resources). The authors of [4] define three types of aggregators: production, demand and commercial Aggregators. Production Aggregators group together small generators in order to generate economies of scale in accessing the markets (e.g. Virtual Power Plants). Demand Aggregators act as intermediaries between small consumers, while commercial Aggregators buy and supply electricity that is locally generated and at the same time are responsible for maintaining the balance of the grid. Essentially, Aggregators are considered DR enablers for end-users who want to participate but cannot meet minimum programme requirements. Additionally, Aggregators are considered as the connection point for transferring flexibility, in the form of DR, from lower electricity market levels (demand-side, producers) to higher electricity levels (system operators). The existing electricity market actors have been described in the harmonized role model established by entso-e [5]. This Role Model has been developed in order to facilitate dialogue between the market participants from different countries through an agreed terminology and the designation of a single name for each role and domain that are prevalent within the electricity market. The major actors participating in DR are:

- **Transmission System Operator (TSO):** Is responsible for a stable power system operation through a transmission grid in a geographical area. The System Operator will also determine and be responsible for cross border capacity and exchanges. If necessary, it may reduce allocated capacity to ensure operational balancing. More specifically, TSOs must guarantee that adequate network transmission capacity is available for energy to flow freely between its producers and its end users, while maintaining system balancing. Moreover, the TSO safeguards the system's long-term ability to meet electricity transmission demands while being responsible for maintaining the system's balancing by deploying regulating capacity, reserve capacity, and incidental emergency capacity.

- **Distribution System Operator (DSO):** Is responsible for operating, ensuring the maintenance of and, if necessary, developing the distribution system in a given area and, where applicable, its interconnections with other systems and for ensuring the long-term ability of the system to meet reasonable demands for the distribution of electricity. The DSO provides network access to the rest of the actors, while is contracted to supply or purchase energy for and from the demand-side.

- **Balance Responsible Party (BRP)**: The "Winter Energy Package" defines a BRP as a market participant or its chosen representative responsible for its imbalances in the electricity market [6]. Given that the market participants have an implicit responsibility to balance the electricity system, the BRPs are financially responsible for keeping their own position balanced over a given timeframe (the Imbalance Settlement Period), thus are considered as the link between TSOs and DSOs. The remaining short and long energy positions in real-time are described as the BRPs' negative and positive imbalances, respectively. As described by entso-e in 2013 [5], in order to be balanced or help the system to be balanced according to the provision defined by the terms and conditions of each TSO, each BRP shall be entitled to change its Position in the Intraday timeframe until the Intraday Cross Zonal Gate Closure Time basing on rules and criteria defined by its Connecting TSO. The aforementioned imbalances are usually dealt by purchasing flexibility and energy from the demand-side and producers, respectively and offering it to the TSOs in the form of Ancillary Services.

- **Aggregator:** Aggregators can provide services to aggregate energy production from different sources, including local aggregation of power demand and power supply from consumers/prosumers. In some cases, the Aggregators have contracts with local producers for purchasing energy at price determined in the contract.

- **Prosumer:** A prosumer is a new entity that consumes but also can produce or store electricity. Prosumers are able to own and operate small or large parts of the power grid and obtain revenues according to their energy utilization.

- **Consumer:** A consumer is an entity that requests electricity. Small consumers are connected to the distribution system and they buy electricity from a retailer. Large consumers can, on the other hand, either buy electricity directly from the electricity market by bidding for purchase.

- **Producer:** A party that produces electricity either through conventional ways or renewable sources.

- **Policy makers / Regulator:** The regulator is the governmental body assigned with the duty to ensure a fair and efficient operation of the electricity sector and participants. It defines the prices of the services and products offered by the entities having monopolies, while establishing rules for the energy market and examining cases in which market power may be misused.

The following figure illustrates the position of each actor in the electricity market chain.

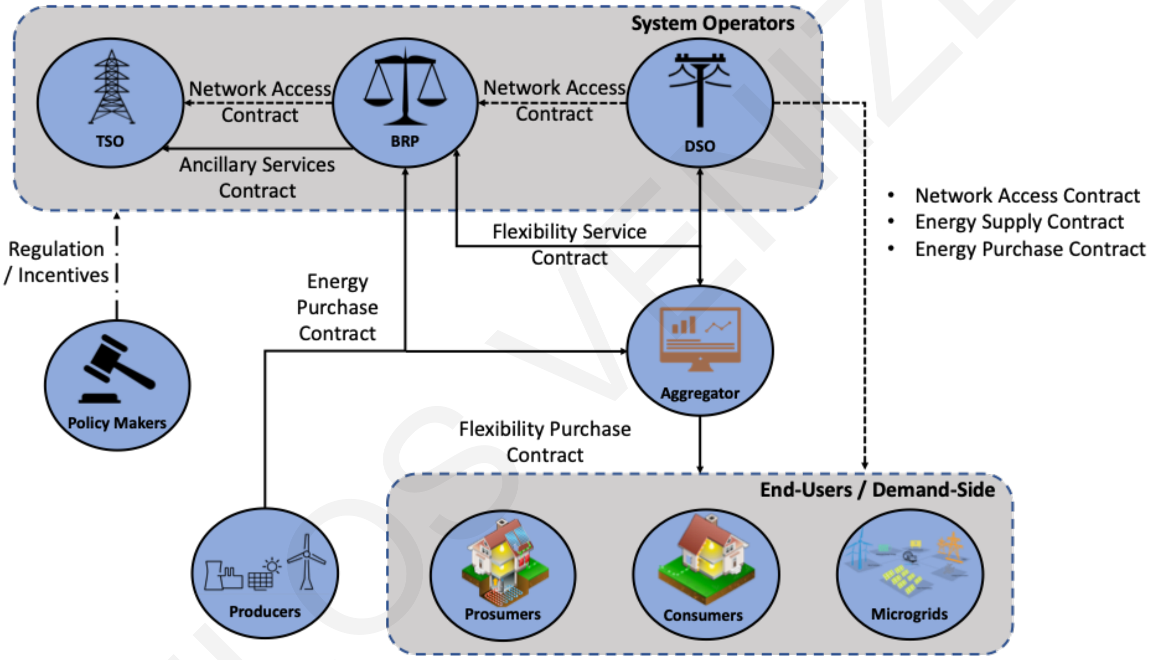


Figure 2.1: Overview of electricity market operations.

The purchase and sale of electricity to resellers is done in the wholesale market, while the purchase and sale of electricity to consumers is done in the retail market. Therefore, Aggregators typically buy and sell flexibility, in the form of DR, in the wholesale market. The integration of DR programs in the planning and operation of electricity systems from a time horizon point of view is demonstrated in Fig. 2.2.

In all market structures, the management of electric power systems is largely shaped by two important physical properties of electricity production. First, mismatches in supply and demand can threaten the integrity of the electrical grid within seconds and second, generation and transmission system investments are large projects with expected economic lifetimes of several decades that often take many years to develop, site and construct. These features of

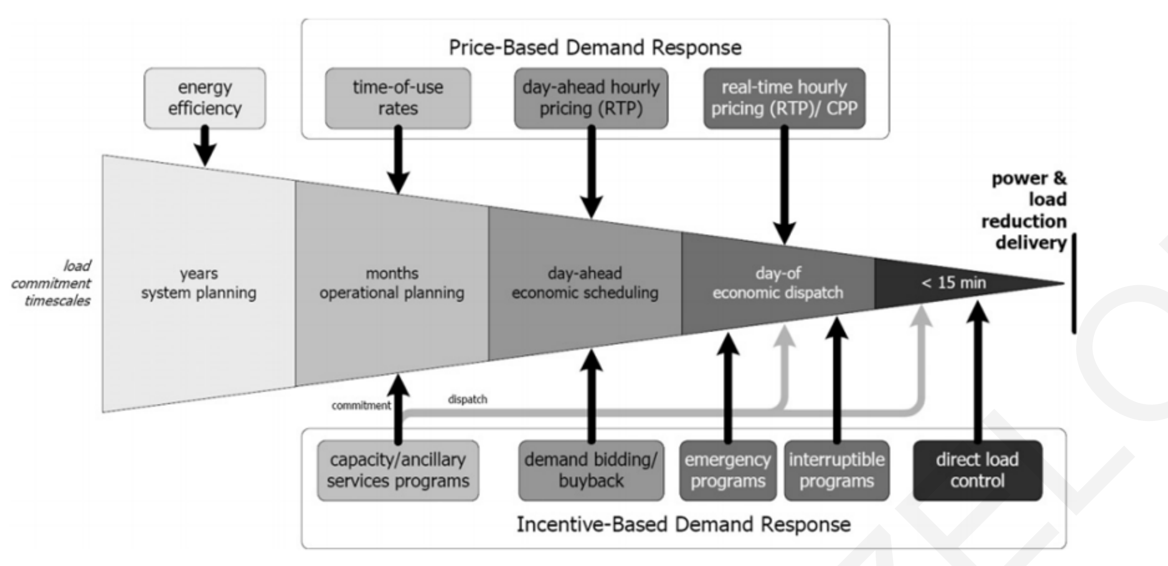


Figure 2.2: DR in electric system planning and operations [7].

electric power systems necessitate management of electricity for a range of timescales, from years for generation and transmission planning and construction, to seconds for balancing power delivery against fluctuations in demand. Decisions are made at several junctures along this timeframe. Details of the timeframes, as illustrated in Fig. 2.2, are provided below.

Capacity and operations planning include long-term investment and planning decisions. Capacity planning (years system planning) involves assessing the need for and investing in new generation, transmission and distribution system infrastructure over a multi-year time horizon. Operations planning (months operational planning) involves scheduling available resources to meet expected seasonal demand and spans a period of months.

Operations scheduling refers to the process of determining which generators operate to meet expected near-term demand. This typically involves making day-ahead economic scheduling based on the next day's forecasted demand, with adjustments made in a period of hours down to 15 minutes to account for any unexpected generation plant outages or transmission line problems in day-of economic dispatch.

System balancing refers to adjusting resources to meet last-minute (< 15 mins) fluctuations in power requirements. In regions with organized wholesale markets, resources offer ancillary services to support electrical grid operation. All DR strategies fall into the category of "Capacity and operation planning" and can participate in the capacity market, while all DR strategies that fall into the categories "Operations scheduling" and "System balancing" can participate in the Balancing Market. At a high level, DR can first be clustered into two major categories, namely: Implicit (price-based) and Explicit (incentive-based) DR. Another important demand side resource that can be considered independently, but not necessarily disconnected from the implicit and explicit DR programs, is the energy efficiency. However, energy efficiency focuses on the capacity planning and the reinforcement of the grid, which require years of planning and therefore is out of the context of this work. The two major DR categories and their respective strategies are described in the two following sections.

2.1 Implicit (Price-based) Demand Response

Implicit DR is the application of tariffs in which the price of electricity is dependent on the time of use. There are many approaches to these tariffs, from a set two-point peak/off-peak tariff system to a real-time system responding to changes in the wholesale market and informing customers with little notice. A middle ground approach is found with critical peak pricing whereby a standard rate tariff is adjusted by pre-set amounts at peak times. For these programmes to be offered, the electricity consumption metering device of the customer must be capable of providing verified meter readings with at least the same frequency/time segregation which is used for the tariff. The resolution of such meters tends to range from hourly to quarter-hourly, depending on the market. Retailers must also be allowed to adjust their settlement processes – so that they no longer purchase electricity according to averaged profiles but rather according to actual consumption. There are a wide variety of varying ToU tariffs operating on different time frames and with different relative payments for each. Daily time varying tariffs are common to discourage use in peak events. Seasonal tariffs are utilised to mitigate against elevated usage mostly from weather related demand variation. Some markets operate with multiple tariffs and tariffs can be found as compounded tariffs over various time frames, such as daily and seasonal multiples. The main Implicit DR techniques are described below:

- **Time-Of-Use Tariff (ToU):** This strategy of management uses different types of tariffs to encourage customers to eliminate consumption during peak periods. ToU is designed to reflect the utility cost structure where rates are higher during peak periods and lower during off peak periods. ToU tariffs based on peak load pricing have been introduced in recent years, having proved to be one of the most efficient strategies in load management. Both the supplier and the end-user benefits from successfully designed ToU rates.

- **Real Time Pricing (RTP)** is the programme most closely aligned with situations where supply as well as demand are variable or 'unbiddable', meaning that a significant portion of national capacity is sourced from intermittent renewable generation. RTP is a means by which retail prices follow wholesale prices from day to day, hour to hour or even minute by minute. Spot pricing can be linked with automation to lower demand whenever wholesale market prices go over a certain pre-set amount.
- **Critical Peak Pricing (CPP)** is a programme usually developed for both residential and commercial consumers that involves raising prices or offering financial incentives to cut demand for a set number of hours on days when critical peaks in consumption are expected, often triggered by changes in weather conditions. Both the numbers of days on which a peak can be called and the number of hours are known beforehand and usually regulated at a regional or national level. By their nature, they occur at irregular intervals in either winter or summer and come under the heading of dynamic peak shifting.

2.2 Explicit (Incentive-based) Demand Response

Explicit DR requires active participation of end users responding to requests from within an existing framework agreement, therefore are technically more difficult to achieve. Explicit DR can be divided into the following schemes:

- **Direct Load Control (DLC):** Typically for small commercial and residential consumers. Direct control of specific appliances is given to utilities, predominantly temperature regulation devices and occasionally lighting. The control mechanism is generally given as simple on/off commands. Notice of control events is given but the timeframe for notice is small (of the order of minutes). The most common market approach for participation is fixed scheduled payments in the form of utility bill credits and additional participation payments.
- **Load Curtailment Requests:** Typically managed by Aggregators. Load curtailment requests are similar to direct load control mechanisms although they typically involve greater user interaction for confirmation of participation and longer notice periods (of the order of hours or day ahead). The curtailment options are integrated into retail

tariffs that provide a rate discount or bill credit for agreeing to reduce load during system contingencies. Given that the typical framework for operation is to pay for availability as well as to provide additional payments for participation, penalties are given to entities that do not participate when called upon as this effectively breaks the availability agreement. Penalties vary in severity but must at least cover the cost of the availability and participation payment to alternative curtailment providers. The reward structures are widely varying; although, given the greater need for human interaction and the requirement for baselining submissions, payments are often focused on participation with some capacity payment structures available for reliable users. Interruptible programs have traditionally been offered only to the largest industrial (or commercial) customers.

- **Demand Reduction Bidding:** A mechanism by which entities can sell load reduction, either directly as a large consumer or indirectly via an Aggregator for smaller consumers. Typically, this occurs as a bidding process followed by the establishment of a merit order for dispatch to equilibrium. Demand Reduction Bidding is typically only offered to large ($>$ 1 MW) customers. In the case of bidding to capacity markets, customers offer load curtailments as system capacity to replace conventional generation or delivery resources. Customers typically receive day-ahead notice of events. Incentives usually consist of up-front reservation payments, and face penalties for failure to curtail when called upon to do so.

- **Ancillary Service Provision:** For ancillary service provision, entities bid into markets ran by system or regional transmission operators. The ancillary services market is organised to negotiate energy loads to ensure reliability and energy quality through four key paths: system restarts, frequency control, voltage control, and balance control. Frequency reserve and operating reserve services are the most common form of distributed ancillary service provision. Frequency response is a quick (order of minutes) load adjustment (either decrease or increase) triggered by real time signals to rebalance grid frequency to the operational set-point. Operating reserves are dispatchable power generators able to respond rapidly to signals in order to correct under generation conditions caused, for example, by generator failure or prediction errors. Payment schemes tend to be by capacity commitment. Frequency control, which is the most commonly implemented ancillary service is divided into three types:

– Primary reserve – close to real-time actuation, it allows an automatic regulation of load to place frequency within bounds in a matter of seconds;

– Secondary reserve – after the primary reserve is successfully implemented and frequency is within bounds, the secondary automatic reserve is activated to place frequency at a target/standard value, as primary reserve returns to its previous level;

– Tertiary reserve – similar to what secondary reserve performs for primary reserve, this reserve implicates manual changes to the load that guarantee frequency stability and adequate value, as secondary reserve returns to its previous level as mentioned before for primary. Further differentiation is made between automatically activated (aFRR) and manually activated (mFRR) services. aFRR is more deeply integrated with the TSO systems, while mFRR is activated manually in both a discrete and "close to" continuous manner by TSOs. Payment is given for availability to accepted bids and entities are obliged to be on standby for operation. Further payment is given, typically at the spot market price, for participation if called upon to act for ancillary service provision.

- **Emergency Response:** Emergency Response programmes are agreements to limit consumption to a specified level when there is a grid level threat. There are typically predefined timeframes for required availability that reflect potential critical grid scenarios, primarily around peak load times. Participants are paid for availability and effectively join the merit order for dispatch, penalties are given if participants fail to produce when called upon.

It is clear that the flexibility volume as well as the extraction method is directly related to the electricity market structure of each country. In locations where the electricity market is not liberalised and dominated by vertically integrated utilities that own all levels of the supply chain, DSM schemes offering price incentives to the electricity customers are considered as an easy pathway for deferring investments for network reinforcement. However, for locations where the electricity market is mature, all the involved actors see DSM programmes and DR in particular as a business opportunity that can benefit all sides. Major focus is given to the Aggregator, who is directly involved or interested in all DR strategies and therefore can be considered as the major bonding actor that maximizes and transfers flexibility from lower levels (demand-side, producers) to higher levels (system operators).

2.3 Literature Review

Lately, DSM schemes and DR strategies have been gaining more attention in research and industry, driven by growing interest of power system operators to avoid expensive network reinforcement through cheap and effective solutions. This section focuses on the recent research and real applications conducted in this field, broken-down into the different aspects and highlighting the respective specific gaps.

Research on the development of price-based DSM schemes

Prosumers and especially residential prosumers are often perceived as a very difficult target group for DSM programmes because of the large scale and diversity of energy behaviour. In addition, a major barrier for enabling DSM rollout is the unavailability of daily electrical consumption and production profiles, since spatiotemporal profiles are not normally available from existing electromechanical meters and non-modernized grid networks [8]. In this domain, testing and validating developed DSM schemes on representative consumer samples is the most appropriate method to provide useful insights for establishing new energy policies. Over the past years, several research programmes were set out to acquire knowledge on how current and future changes in supply and demand energy patterns can be addressed [9–13]. The programmes focused on the energy behaviour of households, adaptation of consumer preferences, enforcement of new tariffs (price-based DSM schemes) and endorsement of technologies that impact grid management. The main outputs included the reduction in the electricity bill of the active consumers, utilisation of DSM at a variety of scales (local, regional and national), improved use of storage by consumers and widespread use of automated energy management systems [9, 10].

In particular, the emphasis of [14] is to analyse impacts of price-based DSM schemes in relation not only to socio-demographics but also time of activities. These are analysed by socio-demographic groups (household type and income) and clusters based on similarities in time use activities during peaks. The socio-demographic characteristics in each cluster do not point to any significant dominant parameter being able to explain the shape or intensity of energy-related activities during peak periods. This means that income and household structure, for instance, are not as powerful as activity-based clusters in describing changes in demand across the day because regardless of socio-demographic parameters different households might carry out very similar activities at peak time, experience the same peak to off-peak ratios and consequently face equivalent financial losses or gains due to the introduction of the price-based DSM scheme. The activity-based clusters feature distinctive patterns in density and timing of energy-related activities in the morning. Clustering by activities represents a powerful way to appraise groups of people who might be either advantaged or disadvantaged from the introduction of the price-based DSM scheme. This has conceptual implications for framing flexibility and its effects. Approaches which do not take as starting points either the socio-demographics of consumers or the flexible attributes of practices are better suited for understanding the complexities of demand-side flexibility. Instead, the results on clustering of activities at peak time suggest that the effects of DSM schemes are better understood through analytical efforts to place time at the centre of research on flexibility. The main advantage of inferring flexibility through the attributes of practices consists of being able to directly assume what can be flexed. However, assumptions around the flexibility of practices risk being void of their temporal arrangements. Findings show that socio-demographic distribution did not demonstrate any significant dominant parameter. Instead, clustering based on similarities in the timing of activities has provided distinctive patterns and can shed light on groups of people who might be either advantaged or disadvantaged from the introduction of the price-based DSM scheme.

Recent research outcomes from large-scale DSM experimental studies conducted in the UK [15, 16], highlight issues related to participation in price-based DSM programmes and more specifically the voluntary commitment endorsement of cost-reflective tariffs which is likely to be fairly low across the population. Moreover, research investigations focusing on consumer participation designated that a distinctive subset of consumers chose cost-reflective pricing due to favourable consumption patterns [17–21]. However, contrary evidence also exists suggesting that consumers that willingly choose time-varying pricing do not tend to have different patterns of consumption [22–24]. Nevertheless, most studies conclude that consumers are willing to adopt a ToU tariff and change their consumption when properly trained on how to increase their potential savings in compensation for their discomfort [25]. Other DSM pilot programmes that provided forecasting and information services for possible flexibility provision demonstrated that constant feedback is a valuable tool for the effective deployment of a price-based DSM scheme [11, 26]. In this context, training the consumers on how to grasp the benefit of a time-varying electricity pricing scheme is essential.

Another survey study based on a pilot programme enrolled by Entergy New Orleans demonstrated the issue of energy savings variation among the treatment groups [13]. More specifically, 78% to 90% of the participants believed that they saved money as a result of the programme, even though the data indicated that only 58% to 67% of customers were active and actually saved energy. This outcome further highlights the significance of evaluating active participation in DSM scheme deployment. Overall, most price-based DSM pilot studies include an evaluation period to assess the most important issue of price-based DSM which is the impact of the applied scheme on electricity usage. In order to explore whether the initial goals set by the utility are met, a comparative analysis of the energy behaviour (load shifting and energy conservation) must be initiated between the baseline and the implementation year, before and after the pilot-application of DSM scheme, respectively. A study that investigated the impact of price-based DSM scheme in peak demand, carried out at the Canadian province of Ontario, showed a 3% reduction in peak usage which was slightly lower than the provincial estimation [12]. A method for obtaining the anticipated DSM targets is to provisionally evaluate and refine the DSM scheme during the implementation period in order to correct any oversights occurring at the planning stage.

An efficient load scheduling based DSM scheme for the objective of peak load reduction is proposed in [27]. Two heuristic algorithms, named G-MinPeak and LevelMatch, which are based on the generalized two-dimensional strip packing problem are utilised. In this approach each of the appliances has their specific timing requirements to be fulfilled. The authors propose some improvement schemes that try to modify the resulted schedule from the initial heuristic algorithms to reduce the peak. All the proposed algorithms and improvement schemes are experimented using benchmark datasets for performance evaluation. Simulation studies are conducted using practical data to evaluate the performance of the algorithms in real life. The results obtained show that all the proposed methodologies are effective in reducing peak load, resulting in smoother load profiles. Specifically, for the benchmark datasets, the deviation from the optimal values is approximately 6% and 7% for LevelMatch and G-MinPeak algorithms respectively and by using the improvement schemes the deviations are further reduced up to 3% in many cases. For the practical datasets, the proposed improvement schemes reduce the peak by a percentage between 5.21 and 7.35% on top of the peaks obtained by the two proposed heuristic algorithms without much computation overhead. The results show high levels of peak reduction, however the results are obtained in a simulated environment that does not consider the unpredictable behaviour of electricity customers.

The work conducted in [28] projects the long-term density of the daily peak demand with the goal of understanding its growing pattern and ultimately reducing the resulting burden on the power grid. The approach accounts for the changes both in temperature due to climate change and in the socio-economic variables. Specifically, the proposed daily peak temperature model with a non homogeneous generalized extreme value framework allows the authors to adjust the possible biases in the global climate model projections while keeping their temporal variation. The expected population growth (or decay) pattern and the building demand saving from DSM programs are formulated with the logistic growth model and Bass diffusion model, respectively. The presented approach is validated in a case study with actual data collected in the south-central region of Texas. The results provide useful insights into how the daily peak demand densities would change over time, in response to climate change, population growth and participation in DSM activities. While this study provides a generic framework for characterizing the progression of peak loads in the long-term, it has limitations, because the results are obtained with limited data. In particular, DSM activities for buildings could substantially affect the peak load. Although actual building data are used, the authors do not consider that the electricity usage patterns change as DSM programs evolve over time.

A methodology to extract valuable information from a large volume of data is proposed in [29]. The methodology is based on clustering methods applied on questionnaire results conducted before and after a trial of various tariff structures including ToU. The pre- and post-trial questionnaires offer insights into the consumers' values, motivational factors and needs, as well as their perspective and perceived behaviour regarding consumption. The pre-trial questionnaire showed mixed views in terms of household flexibility in decreasing and changing electricity usage, and a low interest in environmental issues. While smaller households with older members proved to be the least flexible, larger, younger families with more children are more motivated and had higher expectations of the trial. By contrast, the post-trial questionnaire portrays a positive, homogenous attitude, as well as an improved energy literacy and increased overall awareness thanks to the conducted trial. Using NoSQL and machine learning, the authors analyse the impact of the non-optimised ToU tariff structure and highlight that a 3,89% financial loss on average for the entire lot of consumers is yielded. This led the authors to conclude that some incentive-based rates may increase the bill, while optimum ToU tariffs and other optimally designed incentives are good opportunities for behavioural change if they are fully understood and bring benefits to consumers.

A robust distributed algorithm for modelling a system of interconnected smart energy hubs has been proposed in [30]. The work describes how users can participate in integrated demand-side management. A non-cooperative congestion game model was used in which users independently optimize their energy consumption and storage schedule. To evaluate the performance of the proposed algorithm, a benchmark case with five hubs equipped with storage devices was investigated. In this model, users can take part in the program both by shifting their load demand (using storage devices) or by switching their energy sources. In order to verify the effectiveness of the proposed algorithm, two different signaling schemes (i.e. price-based and load-based setup) have been introduced and compared. Both of these setups are categorized as a price-based DSM program in which the prices of energy carriers are the driving signals. Simulation results for the load-based and price-based setup, respectively, show a 27.1% and 24.4% reduction of the peak load only in the electricity networks. Furthermore, the daily energy bill is reduced by 11.9% and 15.5% in the load-based setup and price-based setup, respectively. However, the price-based setup shows more instability because of price fluctuations. Even though the results are promising, several assumptions have been made with regards to the users' response to the prices.

Based on a large sample of the German population, the authors of [31] use a choice experiment with ToU tariffs to estimate the effect of different peak time schemes on private consumers' "willingness to accept". These tariffs allow for additional services during peak times, i.e., controlling electricity consumption of specific appliances. The authors used Mixed Logic models for unobserved heterogeneity. The results showcased that a significant share of respondents always neglects inconveniences of peak time pricing while a smaller share reacts only to discounts. The authors expect that utility companies will face serious difficulties to incentivize customers to choose ToU tariffs. Still, they identify 70% of the selected sample as potential ToU tariff purchasers of which 36% never chose a fixed rate tariff. The results suggest that most consumers demand high compensational payments to accept ToU tariffs but might benefit from a control of appliances. Therefore, the authors recommend electricity providers to offer ToU tariffs including those benefits, and suggest decision-makers to force smart meter roll out and to encourage purchases of smart appliances. An increasing share of consumers purchasing ToU tariffs could lead to a significant shift in electricity consumption from peak times to off-peak times, and therefore a cost reduction in redispatch. A limitation of this analysis might be the consideration of the same appliances for households. The authors mention that future studies should use questionnaires that would allow to incorporate the specific devices that the responding household is using. Furthermore, the authors state that future studies should also investigate sources of heterogeneity in more detail by applying qualitative methods to a larger series of focus groups.

The study conducted by the authors of [32] aims to identify the dominant household factors from houses in relation to daily electricity consumption patterns so that potential DSM strategies can be indicated. Time-segmented regression analysis is employed to identify the factors that dominate at different timeslots across the day. The method that was applied to a limited dataset reveals that the dominant factors responsible for residential electricity demand variation are the number of major electrical appliances and the number of occupants in the household. Furthermore, the number of occupants is found to be the dominant factor during electricity grid peak hours only. Additionally, the results reveal that there is a potential interplay between one or more dominating factors during peak hours, for instance, the interplay between number of occupants and major electrical appliances. The authors highlight the fact that a real monitoring campaign could provide more insight on the energy patterns and how the DSM-related policy-making should be adjusted.

Furthermore, to determine the success of the potential large-scale rollout of any developed price-based DSM scheme, a detailed Cost-Benefit Analysis (CBA) for planning and implementing the price-based DSM scheme nationally should be carried out. CBAs for planning and implementing price-based DSM schemes in Germany [33] and France [34], showed that for end-users with low levels of annual consumption the costs of a smart metering system would far outweigh the average potential annual energy savings. The CBA outcomes indicated the importance of conducting a CBA in cases where the impact of the proposed price-based DSM scheme must be verified.

Despite the aforementioned successful implementation of price-based DSM schemes at pilot areas, there are still many challenges to be overcome and numerous issues that must be taken into consideration when designing an effective price-based DSM scheme. A concrete and universally-applicable methodology for developing, implementing and evaluating a DSM scheme is missing in recent literature. Additionally, it's clear that the applied ToU tariff structure has a major impact on the effectiveness of a price-based DSM schemes.

Research on the development of optimum ToU tariff structure

Even though the flexibility-enabling technologies are progressing, the development and implementation of optimum ToU tariffs remains a research question for more recent studies. A two-stage optimisation model applied to complete households is described in [35]. The model incorporates multiple potential flexibility provision functions that have been widely reported within the literature; including electric vehicles, rooftop PV and time of use tariffs. This work demonstrates the potential beneficial impacts that the combination of ToU tariffs and PVs can have both for the customer in terms of financial savings and for the community at large through the reduction in greenhouse gas emissions. Minimal uptake enabled savings is exhibited by all engaged customers, showing that there is scalability in the integration of these methodologies and is not dependent on a significant initial uptake. Financial savings within this study are dependent on the use of EVs, with lower flexibility event participation (20%) and electric vehicle ownership at 10% receiving the greatest financial savings of 37%, compared to 28% and 27% respectively for the 40% and 60% participation rates. However, this study does not take into consideration the embedded cost of the flexibility-enabling technologies, which are at present exogenous to the model inputs.

One of the most important challenges when defining the periods of tariff structures is to address the problematic herding phenomenon which arises when consumers shift large amounts of their consumption to low-price periods and create new load peaks [36].

Another main challenge involves the modification of the applied time-varying tariff based on the energy behaviour of the end-users. A typical example of a region that overhauls the way it generates, transmits and uses electricity is California whereby eleven million residential utility customers were fully converted to ToU tariffs [37]. In this case, ToU tariffs were applied to motivate load shifting and to reduce regressive consumer cross-subsidies that arise with the growth of the residential sector self-generation due to PV systems, highlighting the importance of adjusting tariff structures based on the specific energy profiles of the area of application [37].

An additional challenge addressed in previous studies considers the fact that a ToU tariff structure that is revenue-neutral at the class level may not be neutral at the individual prosumer level. Prosumers with peak consumption shares that are lower than the typical peaks will achieve bill reductions without changing their load profiles. In general, a major aspect of a price-based DSM scheme is to prevent the creation of "free riders" that will create revenue loss not offset by cost savings [38, 39].

The authors of [40] introduce a Bi-level model of the interaction between a retailer and consumers in the electricity retail market, including shiftable, interruptible and thermostatic loads, which can be controlled by an energy management system. The aim is to determine the optimal dynamic ToU electricity prices to be established by a retailer to maximize profits in face of consumers' demand response to minimize costs considering comfort requirements of time slots for shiftable load operation. The Bi-level model is dealt with a hybrid approach based on a particle swarm optimization algorithm that calls a mixed-integer programming solver to deal with the consumer's problem of appliance scheduling for a given instantiation of electricity prices (upper level decision variables). Since only optimal solutions to the lower level problem are feasible to the Bi-level problem, non-optimal solutions to the lower level problem may lead to misleading solutions to the problem. For this purpose, the authors propose an approach to compute lower/upper estimates for the optimal solution of the Bi-level problem when a computational budget should be considered to obtain solutions to the lower level problem. However, the impact of the developed ToU electricity prices in energy conservation is not tested and verified in this study.

The methodology proposed and described in [41] is applied to different PV and battery scenarios so that economic indicators are determined and later compared to the results of other alternatives to establish useful parameters for guiding investment decisions. At each step of the methodology, the variables that allow the economic evaluation of investments is determined, namely all the costs, the revenues and the variables that are important for the projection of the cash flow for the entire project life, as well as the impact of the variation of these parameters. For the simulated system options, a ToU tariff is used. The sensitivity analysis carried out shows that the initial equipment cost is the main impact factor in the profitability when including PV generation, while the lifetime and ToU tariff structure are the main factors for profitability in terms of storage systems. The authors highlight that policies to encourage the adoption of distributed generation and energy storage technologies should focus on adjusting tariffs to lead to a more attractive environment, while the declining costs of PV and storage follow their path and financing modalities of systems with attractive interest rates become more available. The residential ToU tariff is the only factor controlled by the distribution utility, and it is, therefore, a major factor influencing the economic attractiveness for the adoption of storage systems. Because there is no obligation to adopt a ToU tariff, residential consumers might see no reason to migrate to a new tariff structure that might increase their energy bill in the event of high consumption at peak hours, in case there are large differences between on- and off-peak-hour tariffs. The results could be more promising in case that the ToU tariff structure was optimised.

Based on the above studies it's very evident that static forms of price-based DSM schemes, such as ToU tariffs, can lead to negative profiling effects when coupled with intermittent renewable generation and not optimally developed. Hence, the development of an optimum ToU tariff structure should consider numerous parameters and redesigned regularly based on the outcomes of its application.

Transitioning from DSM to DR

Exploiting the demand flexibility, instead of investing in new non-renewable transmission-connected generation capacity introduces a more pro-active and effective approach for the energy transactions. However, strict market and grid-related regulations exclude single small-scale electricity customers to participate in the provision of such services, thus third parties such as Aggregators must undertake the role of summing those multiple flexibility volumes. Aggregators are being lauded as critical entities in providing these valuable electricity services, acting as intermediates between the small / medium scale consumers and the electricity market stakeholders at higher levels, such as the DSOs [1, 2]. The most common approach for extracting these flexibility volumes is through DR, which is a program that is established to change electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high electricity market prices [3].

Research on the development of DR frameworks

Many recent studies focus on facilitating the role of Aggregators into the distribution-level electricity market to improve market efficiency, while emphasizing the role of DR [42–47]. In this context, various DR frameworks can be found in the literature such as the hierarchical control DR framework, presented in [48]. The framework enables support of multiple aggregation entities, with different capacities and objectives, towards delivering cooperative flexibility services. Employing a sequential optimisation approach for the participation of two separate Aggregators is explored, presenting interesting insight into the revenue acquired from both sides. However, in the scenarios explored, the interaction between the Aggregators and their customers was not considered.

Similarly, in [49] a set of Aggregators provides their flexibility to the DSO under a fair and incentive compatible flexibility mechanism which is based on a max-min fair formulation, so that network constraints are satisfied in a fair way. Nevertheless, the proposed framework tackles the participation of Aggregators to flexibility markets and not DR mechanisms, whereas the fairness aspect refers to the Aggregator and not the end customers.

The various proposed DR frameworks, utilise a diversity of optimisation approaches that mainly focus on the Aggregator's costs or balance of the distribution network [50–53]. A cost focused bi-level optimisation model for determining the pricing parameters of Time-and-Level-of-Use tariffs, maximizing the supplier revenue while anticipating an optimal reaction of the customer is presented in [54]. The reaction of the customer to the proposed pricing is integrated in the supplier decision problem, thus turning the customer-supplier interaction into a Stackelberg game. Even though promising results are demonstrated, the actual effectiveness of the proposed methodology is unclear.

In recent times, the scope of DR has been expanded to include system expenditure reduction as well as the balance improvement of the distribution network [55]. The balance of the distribution networks directly falls to the DSOs, who ensure the normal operation by sending appropriate DR signals to the flexibility providers.

In the future, it is expected that DSOs will have a broader role as neutral market facilitators offering equal opportunities to all Aggregators to sell their services [56]. The approach proposed in [57] uses an integrated strategy for the day ahead market, which may result in the provision of reserve and in consumption deviations, depending on the dispatch events. Using accurate forecasts of dispatch events, the Aggregator can optimize its participation in the markets by allocating the flexible resources to the periods when tertiary reserve is required by the system. The proposed methodology consists in two steps: (1) an analytical method to calculate the market expected value of each individual availability profile; (2) a heuristic method, based on a merit order, in order to find the high valuable and less risky bids from the combinations of flexibility profiles in the Aggregator portfolio. The advantage of the heuristic approach is to avoid a combinatorial problem with infeasible dimensions for larger groups of consumers. The methodology is applied to a sample of 1500 residential consumers, while considering the Portuguese tertiary reserve market conditions. The results demonstrate the capability of the heuristic methodology to find a significant number of non-dominated bidding solutions leading to higher remuneration for the Aggregator.

The authors of [58] propose an emergency DR scheme for microgrid autonomous operation based on local frequency measurements. The active participation of microgrid loads can contribute to ensure the balance of the microgrid in the moments subsequent to islanding, taking into account the frequency behaviour and available energy in storage units. The proposed control strategy is supported by an online tool integrated into the microgrid central controller, which is responsible for periodically defining the most adequate technical solution for managing responsive loads, following an unplanned event and taking into account the microgrid operating conditions. Centralized strategies at the microgrid controller level are used to define the new active and reactive power set-points for the controllable sources, taking into consideration the overall microgrid operating state. Secondary control includes additional synchronization loops for a smooth re-connection to the main grid after islanding. The test cases evaluated through the conducted dynamic simulations, demonstrate the quality and the feasibility of the proposed tool when dealing with this problem.

The work conducted in [59] focuses on the use of a Virtual Energy Plant, which aggregates the decentralized multi-energy resources. Aimed at the difficulty of access and regulation of the decentralized multi-energy resources in the local area, considering the energy purchase from external markets and the energy retail to internal users of virtual plant, a grading dynamic aggregation model is incorporated into the optimal scheduling of the virtual plant. A decentralized multi-energy resources aggregation model based on bi-level interactive transactions is established. The study results highlight that the aggregation and invocation of the proposed model mainly pertain to the load peak, and this realization can reduce the energy purchasing cost of the virtual plant, improve the energy retail revenue and expand the profit space. The peak energy retail price is offset from the peak real-time price to enhance the market competitiveness, while the offset period is at least 1 h. By the proposed method, it is beneficial for the virtual plant to integrate and utilize the decentralized multi-energy resources to participate in the market and to maximize the economic benefits of its operations. Compared with other methods such as the fixed polymerization, the economic benefits are increased by 6.52%.

The authors of [60] propose a Home Energy Management System that optimizes the load demand and distributed energy resources. The optimal demand/generation profile is presented while considering utility price signal, customer satisfaction, and distribution transformer condition. The electricity home demand considers electric vehicles, Battery Energy Storage Systems, and all types of non-shiftable, shiftable, and controllable appliances. Additionally, PV-based renewable energy sources are utilized as sources of generated power during specific time intervals. In this model, customers can only perform DR actions with contracts with utility operators. A multi-objective demand/generation response is proposed to optimize the scheduling of various loads/supplies based on the pricing schemes. The customers' behaviour comfort level and a degradation cost that reflects the distribution transformer Loss-of-Life are integrated into the multi-objective optimization problem. Simulation results demonstrate the mutual benefits that the proposed Management System provides to customers and utility operators by minimizing electricity costs while meeting customer comfort needs and minimizing transformer Loss-of-Life to enhance operators' assets. The results show that the electricity operation cost and demand peak are reduced by 31% and 18%, respectively, along with transformer Loss-of-Life which is reduced by 28% compared with the case when no DR was applied.

A recovery DR mechanism considering personalized electricity reliability under outage conditions to improve network resilience is presented in [61]. Novel customer classification and a market clearing mechanism are proposed to adapt the trend of privatization and demand-side participation. Customers are classified by internal information such as income, age, house type, children number etc. and external information such as electricity usage habit. Then the proposed bidding mechanism that takes full account of dynamic elasticity and reliability level service is applied to each group. After receiving warning level information, customers can choose to participate in trading to satisfy private reliability level. Corresponding market clearing mechanism is applied to facilitate customers' transactions. The authors propose a group double side auction method for trading and market clearing mechanism under outage conditions with an islanding-operation for microgrids. Under this mechanism, the price for DERs will likely be higher than the retail price providing more incentive for customers to participate. The proposed model acts as a bidding mechanism that allows customers with higher reliability requirements to maintain their desired consumption with corresponding higher price. And customers who pursue higher interests can also gain higher benefits through transactions. The model mainly solves three problems. First, the trading mechanism is triggered by an early warning failure possibility for power outages. Customers with different requirements for reliability levels and economic benefits can be satisfied in the model. Second, dynamic elasticity replaces fixed elasticity by a stochastic process to better simulate the user's real-time preferences. Third, Group double side auction for market clearing mechanism was applied to auction private reliability services.

The authors of [62] propose a bi-level integrated DR framework for alleviating congestion in coupled networks. At the upper level, an independent system operator aims to alleviate congestion by imposing the lowest possible traffic tolls and electricity tariffs. At the lower level, electric vehicle owners schedule their routes and departure times according to traffic tolls and traffic conditions, yielding a multi-period user equilibrium state in which the generalized travel cost of users cannot be decreased by unilaterally changing routes or departure times. Simultaneously, load Aggregators schedule flexible power demands according to electricity tariffs to minimize total energy costs. The overall bi-level programming is reformulated into a single-level mathematical program with a complementarity constraint problem, which is efficiently solved as a sequence of relaxed non-linear programming problems by a specially designed algorithm. Numerical results demonstrate the effectiveness of the proposed DR framework in alleviating congestion and reducing total procurement costs.

The work presented in [63] uses the Weber–Fechner law and a clustering algorithm to construct quantitative response characteristics models. The deep Q network is used to build a dynamic subsidy price generation DR framework for load Aggregators. The study focuses on DR aggregation for electric heating applications combined renewable energy utilization. Through simulation analysis based on the evolutionary game model of a project in a rural area in Tianjin, China, the authors conclude that, through the proposed model, the regenerative electric heating users can save up to 8.7% of costs, power grid companies can save 56.6% of their investment. The framework proposed in this study considers user behaviour quantification of DR participants and the differences among users.

Even though the aforementioned studies present promising results, there is no clear consideration of how the performance of end-users in DR events can potentially affect the Aggregator's strategies.

Research on DR framework for restoring the normal operation of the grid

Many approaches can be found in the literature focusing on the interactions between the DSOs and Aggregators that aim in identifying and resolving grid constraints, with the most important being the methodology specified in the USEF Flexibility Transfer Protocol (UFTP) [64, 65]. In this methodology, USEF addresses congestion management or grid-capacity management through Congestion Points that are published by the DSOs and exploited by the Aggregators.

The work conducted in [66] introduces a model to optimize energy consumption in buildings, aiming at minimizing costs while satisfying the technical constraints of the power network. The model is capable of controlling a wide variety of loads taking into account the flexibility that their owners are willing to provide. This flexibility can be used for technical matters, such as for improving the network operation or economic purposes. The proposed model is applied in a test network to quantify and compare the capability of only electrical buildings and Multi-Energy System buildings to offer flexibility. Analyzing the grid technical problems, in a scenario with only electrical buildings, there are a number of undervoltage problems detected in the network that cannot be entirely solved even when flexibility is activated through DR programs. These stressful operating conditions are not verified in the Multi-Energy Systems scenarios, where no technical problems were detected. In the only electrical buildings scenarios, the voltage problems detected were greatly reduced after the activation of the DR program. More specifically, the number of buses with voltages below 0.9 p.u. was reduced from 54 to 14, representing a 74% reduction, thus concluding that DR programs are an important tool for system operators as they can enable important changes in the load profiles to avoid voltage problems or overloaded branches.

Other approaches found in the literature, include the distributed dynamic tariff (DDT) method for congestion management in distribution networks that is presented in [67]. This method employs a decomposition based optimisation method to have Aggregators explicitly participate in congestion management. By establishing an equivalent overall optimisation, it is proven that the DDT method is able to minimize the overall energy consumption cost and line loss cost.

Another energy allocation mechanism that is considered efficient while respecting grid constraints has been proposed in [68]. At the DSO level, the auction price is heterogeneous among Aggregators, while the lower level auction price is uniform among home agents. The upper level agent allocates power to the Aggregators that in turn conduct their separate Aggregator level auction to establish market equilibrium conditions locally within their agents. Even though the proposed mechanism is able to maximize the revenues for the stakeholders, the authors have not considered any behavioural parameters of the Aggregatror's customers.

Several risk measures (e.g. variance, shortfall probability, expected shortage and stochastic dominance) investigated in [69], highlighted that there is a trade-off between anticipated profit and its variability. When dealing with small scale customers and local communities, their reliability to the DR request from different perspectives must be researched. A Reliability Rate has been introduced in [70] towards identifying trustworthy customers for a specific DR target. Even though the results indicated that rating customer participation can lead to more successful DR programs, the grid technical parameters are not considered.

It's clear that full or partial visibility of the distribution network, will enable Aggregators and DSOs to improve flexibility procurement for more economically efficient grid management and strengthen the resilience of the distribution network [71].

Research on DR framework complementary functionalities

Besides the exploitation of various optimisation functions, modern electricity frameworks necessitate the consideration of complementary factors such as communication and security. Semantic interoperability, i.e., the ability of systems to exchange and consume data transparently among them, resolves issues that stem from the fragmentation of standards regarding building and/or energy management systems, energy marketplaces and the ever increasing penetration of IoT devices in the energy domain, while security ensures that transactions between stakeholders are executed in a trustworthy and verifiable fashion. Recent studies have focused on cyber-security in energy and power systems, with blockchain technologies being one of the most recent trends in research efforts. Offering data integrity, confidence, efficiency, control and security in terms of information exchange, blockchain technologies have gain a lot of attention and multiple applications have appeared [72].

A sustainable microgrid design problem by leveraging blockchain technology to provide the real time-based DR programmes is presented in [73]. Three sustainable objectives (economy, environment, and society) are formulated by a multi-objective mixed integer-linear programming model. A robust fuzzy multi-objective optimization approach is proposed to determine the optimal number, location, and capacity of renewable distributed generation units as well as the equilibrium supply and dynamic pricing decisions under uncertain demand, capacity, and economic, environmental, and social parameters. The proposed model and solution approach are then applied to a case study in Vietnam. The blockchain technology-based sustainable microgrid can result in a 1.68% and 2.61% increase of profitability and consumer satisfaction, respectively, and a 0.97% reduction of environmental impacts.

Those studies indicate that the use complementary functionalities, such as security between the engaged stakeholders, can result to a self-enforceable and tamper-proof framework that removes intermediaries and reduces transacting, contracting, enforcement and compliance costs [74].

Addressing the Research gaps on DSM and DR

All the aforementioned studies have managed to significantly contribute in the research field of demand-side flexibility, however as the DSM and DR programmes evolve over the years there are still several research gaps that need to be addressed.

Even though the results of those studies are promising, the majority of the analyses are conducted in simulated environments. A real monitoring campaign could provide more insight into the impact of DSM schemes as well as how the DSM-related policy-making should be adjusted. Through a real implementation, the various sources of heterogeneity and the unpredictable behaviour of electricity customers would be considered. An additional

challenge that needs to be addressed is the fact that most of those studies consider that the electricity customers consist exclusively of consumers. However, it is expected that in the near future distributed renewable generation will be one of the main sources of the total electricity supply [75]. Therefore, pricing schemes that are revenue-neutral at the consumer class level may not be neutral at the individual prosumer level. Furthermore, despite all the identified advantages that ToU tariff schemes offer, the effectiveness of such tariff schemes must be verified prior to implementation because of the eminent high risk of a new peak appearing through load shifts at cheaper price periods, posing negative effects on the optimal operation of system.
All the aforementioned studies have also exhaustively explored DR approaches, while considering customer behaviour and have established a solid foundation for the significant potential of participating in the flexibility market. However, as power flows are expected to become bi-directional, real-time grid management as well as activation of procured flexibility necessitate a more coordinated approach between the DSOs and the Aggregators. This new paradigm creates not only challenges but also great opportunities. DSOs may use the flexibility provided by the Aggregators to solve voltage problems or manage congestion at the distribution network, while the Aggregators can optimally exploit the available flexibility of their customers to participate in DR events at minimum cost. Nevertheless, the expected costs of the Aggregator may come with a high level of variability, depending on the reliability of his customers. The response of a customer in modifying his consumption pattern is not certain so there is a requirement of studying DR considering the uncertainty associated with it. Additionally, a fair distribution of flexibility requests to all the customers, will enlarge the portfolio of the specific Aggregator due to the increased willingness of other customers to enroll. These cost and performance aspects combined with the grid technical constraints, while considering security and communication aspects, are yet to be thoroughly investigated. The DR-related research field lacks a framework that considers both the performance of electricity customers as well as the the distribution grid balancing.

To this end, as DSM schemes evolve from the research stage to deployment and the integration of PV systems is rapidly increasing, a universally-applicable and robust methodology for developing optimum price-based DSM schemes must be established. Moreover, as the electricity markets are maturing, the introduction of new electricity stakeholders as well as the facilitation of DR in electricity services are inevitable. Subsequently, a holistic framework that addresses these upcoming changes must be established. Considering these past endeavours and aiming to bridge the identified research gaps, this work provides a universally-applicable methodology for deploying a cost-effective DSM scheme that focuses on flexibility extraction through price incentives. The proposed methodology is applicable to both consumers and prosumers as the optimization algorithm utilizes net-load energy profiles. This thesis delves further into flexibility potential maximization by presenting an innovative framework for DR that aims to minimise the Aggregator's cost by considering technical and performance parameters. The proposed DR framework serves as a holistic framework that is ready to be applied in countries where the electricity market rules and automation technologies are mature and advanced. The proposed DSM scheme along with the developed DR framework aim to fully unlock the available untapped flexibility potential based on the market structure specificities of each area of deployment.

Chapter 3

Developing and Deploying Implicit Demand Response in the Form of Price-Based Demand Side Management

3.1 Introduction

The evolution of DSM schemes from the research stage to deployment, along with the increasing integration of PV systems that will eventually render prosumers as the main class of residential electricity customers, creates a need for a universally-applicable and robust methodology for developing optimum price-based DSM schemes. The scope of this chapter is to provide a consistent and universally-applicable methodology to derive effective price-based DSM schemes for the residential sector that was verified through statistical analysis and validated on a pilot-network comprising of three hundred prosumers with roof-top PV systems. The proposed methodology for deriving the optimum ToU tariffs is applicable to both consumers and prosumers as the optimization algorithm utilizes net-load energy profiles. The methodology further addresses the technological challenges related to price-based DSM design such as the optimum number of ToU block periods, evaluation of the impact of the proposed scheme, training of the consumers and prosumers, active participation and rewarding, development of pilot network and CBA. Finally, the results emanating from this work provide useful knowledge in the fields of energy behavioural patterns and flexibility potential of prosumers that can be vital instruments for policy makers to direct and encourage the implementation of DSM schemes at a larger scale.

3.2 Methodology

The cost-optimum price-based DSM methodology for residential prosumers is divided into the planning, implementation and evaluation stages, as illustrated in Fig. 3.1. The designed methodology was applied and validated on a pilot-network of three hundred residential prosumers with installed roof-top PV systems, within the distribution grid of Cyprus.

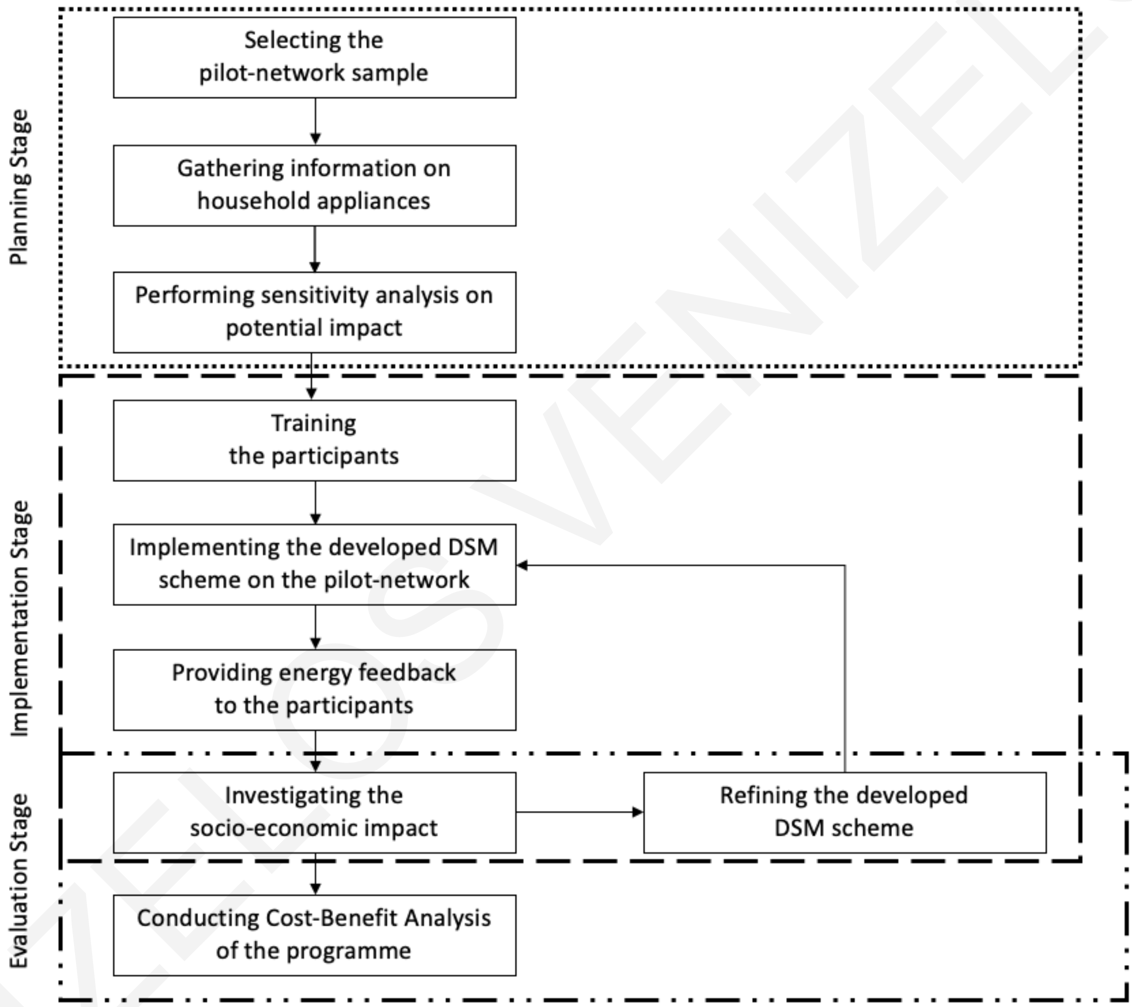


Figure 3.1: Methodology for developing effective DSM scheme.

3.2.1 Planning Stage

The first step for establishing price-based DSM schemes that are capable of persuading participants to alter their energy patterns and achieve desired peak demand reduction, was to develop an optimum ToU tariff structure that represents the characteristics of the electricity consumption both in terms of electricity demand as well electricity price variation. The development of a ToU structure is typically a two-step approach that includes the establishment of the ToU block periods and then the respective rates.

Establishment of the ToU block periods

In an attempt to encompass seasonal variations in the development of the ToU tariff structure, the electricity consumption of the participants was divided between winter, middle and summer periods and a clustering analysis was performed in order to derive the optimum block periods of each season. The goal of the clustering analysis is to partition (or group) a set of instances into clusters such that each cluster indicates a group of instances that are more strongly associated with each other than with those in different clusters. Clustering is one of the unsupervised learning methods in machine learning and at the individual domestic customer level it has many potential uses for energy companies. The clustering method was utilized for this study as (i) it allows the adjustment of the results to reflect biases in the selected sample, (ii) it can identify which characteristics correlate with energy behavioural use and (iii) it can result in more suitable tariffs by comparing different groups in intra-day behaviour. The partitioning-based clustering approach performs partitioning on a set of instances into non-overlapping subsets called clusters. Most classical partitioning based algorithms include K-means and PAM (Partitioning Around Medoids). The main assumption is that n objects described by the attribute vectors $\{x_1,x_2, \ldots, x_n\}$ are partitioned into k clusters, where $k \leq n$. Let m_i be the mean of the vectors in the cluster i. An object o_j belongs to the cluster i if the distance between o_j and m_i is the minimum. The K-means algorithm is known for its efficiency in clustering large datasets, but is limited to datasets involving only interval-scaled attributes. To avoid this deficiency, PAM uses medoids rather than centroids to represent clusters. The medoid of a cluster is the most centrally located object in a cluster and it is considered to be a representative object of the data set as its average dissimilarity to the rest of the objects in the cluster is minimal. The PAM algorithm finds k clusters in n objects by first calculating a representative object for each cluster. Once k medoids have been selected, each non-selected object is classified into the closest medoid according to a distance measure. Subsequently, it repeatedly tries to make a better choice by substituting a medoid m_j with a non-selected object o_h as long as such substitution improves the quality of the clustering (i.e., reduces the average distance between an object and its closest medoid). Assume D is the dataset to cluster (with n objects), M is the set of medoids, $rep(M, o_i)$ returns a medoid in M that is closest to the object o_i, and $d(o_i, o_k)$ is the distance between objects o_i

and o_k. The cost (i.e., average distance between an object and its closest medoid) of M is:

$$\text{Cost(M,D)} = \frac{\sum_{j=1}^{n} d(o_i, rep(M, o_i))}{n} \tag{3.1}$$

The effect of substituting a medoid is:

$$\text{TC} = \text{Cost(M',D)-Cost(M,D)} \tag{3.2}$$

where *M'* is the new set of medoids after substituting a medoid in *M* with an object o_h not in *M*. When *TC* is greater than zero, this means that replacing the medoid with another would result in a greater average distance between an object and the medoid of its cluster. Thus, if *TC* is greater than zero, o_h will not be selected to replace the medoid. For performing a clustering analysis, it is essential to first decide the optimum number of clusters. For this purpose, hierarchical clustering was employed. Hierarchical clustering represents data by building a cluster tree (a dendrogram), where each group (or "node") is linked to two or more successor groups. As shown in Fig. 3.2, the results of employing the hierarchical clustering method indicated that the optimum number of clusters is equal to three.

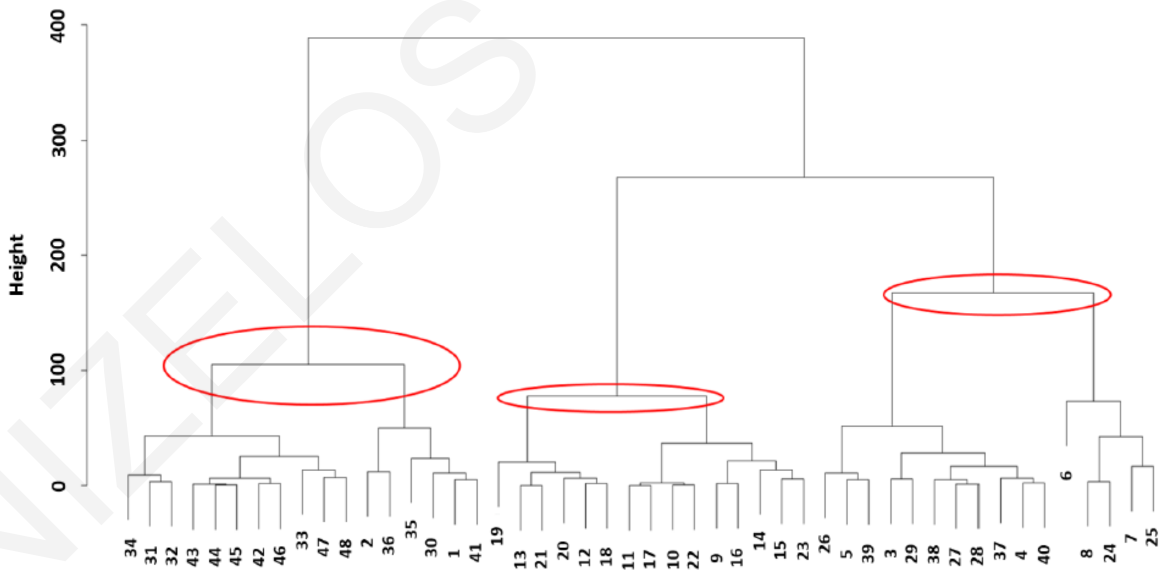


Figure 3.2: Cluster dendrogram showing the possible clusters for the winter season.

The derived number of clusters demonstrates the presence of three distinct segments representing the off-peak and peak periods as well as a third period. This time period represents the transitional (shoulder) period that can be used by prosumers to cover their needs that can be shifted from the peak periods but cannot wait until the off-peak period.

Establishment of the optimum ToU rates

Besides the identification of the ToU block periods the estimation of the applicable ToU rates for the corresponding periods is essential. The optimized ToU rates were calculated using an optimization algorithm which can derive a constrained minimum of a scalar function of several variables starting from initial conditions and are subject to nonlinear multivariable constraints and bounds. General nonlinear optimization problems can be written in the form of:

$$\begin{aligned} \min f(x) \forall x \in R^n \\ \text{subject to:} \\ g(x) \leq 0 \\ h(x) = 0 \\ lb \leq x \leq ub \end{aligned} \tag{3.3}$$

where *f* is the objective function to be minimized and *x* represents the *n* optimization parameters. This problem may optionally be subject to the bound constraints (also called box constraints), *lb* and *ub*. For partially or totally unconstrained problems the bounds can be taken to be *-Inf* or *Inf*. One may also optionally have nonlinear inequality constraints (sometimes called a nonlinear programming problem), which can be specified in *g(x)*, and equality constraints that can be specified in *h(x)*. The methodology followed for solving the optimization function was based on an improved Conservative Convex Separable Approximation (CCSA) algorithm [76] of the original MMA (Method of Moving Asymptotes) algorithm, published by Svanberg in 1987 [77]. At each point *x*, MMA forms a local approximation using the gradient of *f* and the constraint functions, plus a quadratic "penalty" term to make the approximations "conservative" (upper bounds for the exact functions). The main point is that the approximation is both convex and separable, making it trivial to solve the approximate optimization by a dual method. Optimizing the approximation leads to a new candidate point *x*. The objective and constraints are evaluated at the candidate point. If the approximations were indeed conservative, then the process would be restarted at the new *x*. Otherwise, the approximations are made more conservative and re-optimized. More specifically, in our study, the ToU rates were calculated based on the following optimization function:

$$\min\left\{ \sum_{i=1}^{3}(\sum_{j=1}^{N} R_{j,i} \cdot C_{j,i}) - \sum_{i=1}^{3} \cdot(R_{\text{Flat}} \cdot (\sum_{j=1}^{N} C[j,i])) \right\} \tag{3.4}$$

where *R* and *C* represent the rates and consumption levels, respectively, while the current flat electricity rate is represented by R_{Flat}. The index j = *1,...,N* represents the number of time blocks as derived from the PAM clustering method, where *N* is the total number of periods and the index i = *1,2,3* specifies the three seasons. The objective of the optimization function was to minimize the difference between the proposed ToU and the flat tariff annual electricity cost. The function ensured that the proposed rates can fully cover the electricity costs for the baseline profiles. The selected boundary conditions assured that the proposed ToU rates will be higher that the marginal electricity costs (*mc*) which are the costs experienced by utilities for the last kilowatthour (kWh) of electricity produced. In order to increase the total number of investigated combinations of rates, a relatively high upper bound was selected by limiting the lowest rate up to the standard flat rate and the highest rate up to twice the flat rate. The upper and lower boundaries were set as:

$$\begin{aligned} &lb : [R_{j,i}] \geq [mc, mc, mc] \\ &ub : [R_{j,i}(\text{highest}), R_{j,i}(\text{lowest})] \geq [2 \cdot R_{\text{Flat}}, R_{\text{Flat}}] \end{aligned} \tag{3.5}$$

In parallel with the surveying questionnaires, focus groups were performed in order to identify consumer preferences towards load shifting. The focus groups showed that pilot-network prosumers were motivated to shift consumption whenever the rate between the time blocks of applied ToU tariff was higher than 20%. To achieve this, the following constraints were used:

$$R_{j+1,i} \geq 1.2 \cdot R_{j,i} \tag{3.6}$$

Pareto dominance of the developed tariff

When developing ToU tariff schemes it is crucial to investigate the difference between the total amount that consumers are willing and able to pay for electricity and the total amount that they actually do pay, as well as how a change in electricity prices affects the welfare of the utilities and their customers. In conventional economic theory these matters are commonly handled through the concept of consumer's surplus and Pareto superiority. By definition, an outcome is Pareto superior to another, or Pareto dominates it, if the second is a Pareto improvement over the first. A Pareto improvement is defined as any change which leaves everyone at least as well off, or someone strictly better off without negatively affecting the other [78]. To establish that the developed ToU tariff scheme is profitable, the Pareto superiority of the design was investigated by following the methodology proposed by other authors [38, 76, 79]. The profitability of the ToU design can be evaluated by applying the flat and the time-varying rates on the demand curves. The demand curves provide all the information that is used to determine a customer's ToU consumption and his choice between ToU and standard rates. The demand curves of each consumer are assumed to be linear [80], with a y-intercept and a slope for describing the customer's demand curve. The y-intercept denotes the level of demand, while the slope denotes the price responsiveness of the customer. A consumer's demand curve measures how much the consumer would pay for the first kWh consumed, and the second, and so on. Generally the more consumed, the less would be paid for the next kWh. The difference between the maximum a consumer would pay as revealed by the consumer's demand curve and what the consumer actually does pay is the consumer's surplus. For the case of Cyprus, the flat rate is a quantity-weighted average of the marginal costs of generation in each time period by including all the fixed and fuel adjustment costs. Assume that m_O and m_P are the marginal costs in off-peak and peak periods, respectively. Also, C_O and C_P are the off-peak and peak percentage of the total consumption (initial scenario), then the flat rate is equal to:

$$F = m_o \cdot C_o + m_P \cdot C_P \tag{3.7}$$

During the shoulder period, consumers will see no change in their electricity bill since the shoulder rate is equal to the flat rate thus the shoulder percentage is neglected in the analysis. Consider the demand-supply curve shown in Fig. 3.3, which shows the demand for off-peak electricity. Prior to the implementation of ToU tariffs, the consumer paid a flat tariff F per kWh and consumed $x_{F,O}$ kWhrs per month. At the new off-peak rate O, where $O<F$, the electricity customer now consumes quantity x_O.

After the ToU tariff implementation he pays a price O for every unit consumed. But according to the original demand, he would be willing to pay a slightly higher price for slightly less consumption. But he receives these marginal units of consumption at rate O instead of F. Thus, the consumer benefits by a surplus value which is represented by the amount A + C. Otherwise the shaded area (price units), represents a real gain in the

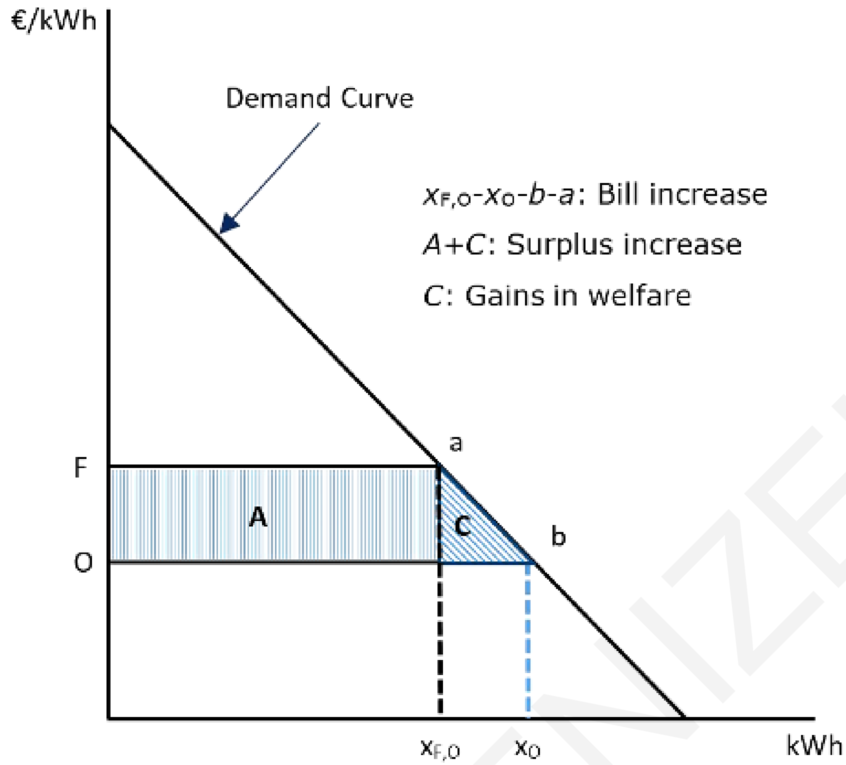


Figure 3.3: Comparison between flat and off-peak rate on a typical electricity Demand-Supply curve.

consumer's welfare. Similarly, Fig. 3.4 illustrates the case where the peak period price is increased from the flat rate F to the peak rate P. Since this is a higher price, the consumer will reduce his consumption down to x_P kWhrs compared to $x_{F,P}$. Using the same heuristic approach as before, the change in the consumer's surplus is represented by the area *L (F-P-d-h)*.

Therefore the consumer's surplus, due to the implementation of ToU tariffs, can be given by:

$$\Delta CS = -[\Delta O \cdot (\frac{x_O + x_{F,O}}{2}) + \Delta P \cdot (\frac{x_P + x_{F,P}}{2})] \tag{3.8}$$

where $\Delta P = P - F$ and $\Delta O = O - F$.

From the power utility's viewpoint, assuming that the demand is inelastic, it will lose revenue by reducing the price from F to O during the off-peak period. This is equal to the amount $Ox_O - Fx_{F,O}$ for a change in production costs of $O(x_O - x_{F,O})$. This will result in a net loss (negative quantity) equal to:

$$-F \cdot x_{F,O} + O \cdot x_{F,O} = \Delta O \cdot x_{F,O} \tag{3.9}$$

Following the same approach, by assuming that demand is inelastic, during the peak period

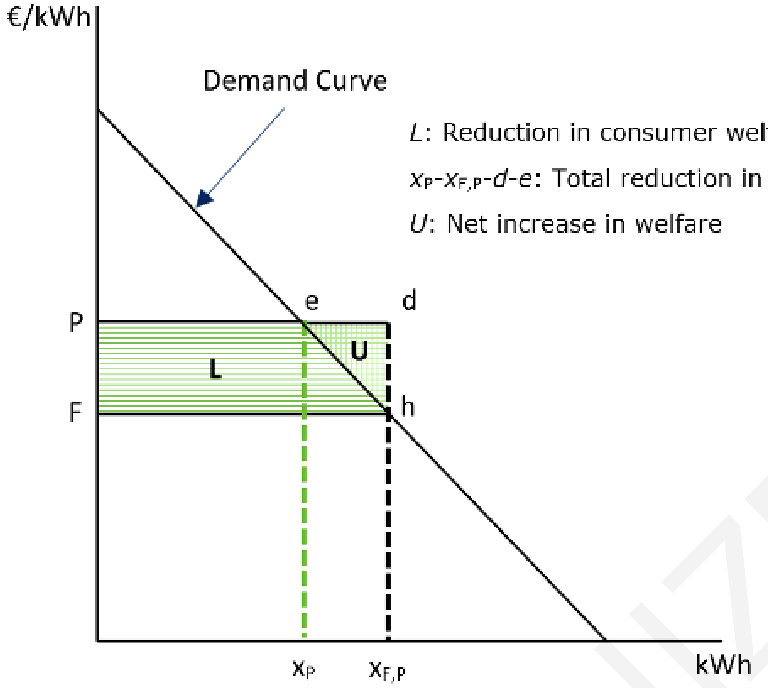


Figure 3.4: Comparison between flat and peak rate on a typical electricity Demand-Supply curve.

the utility's revenues are increased by raising the price from *F* to *P*. For the utility, this will result in a net gain equal to $\Delta P x_{F,P}$. In sum the net revenue for the producer is:

$$\Delta NR = \Delta O \cdot x_{F,O} + \Delta P \cdot x_{F,P} \tag{3.10}$$

Therefore, the change in welfare that occurs due to the adoption of a ToU tariff scheme is equal to:

$$\begin{aligned} \Delta W =& \Delta CS + \Delta NR \\ &= -[\Delta O \cdot (\tfrac{x_O + x_{F,O}}{2}) + \Delta P \cdot (\tfrac{x_P + x_{F,P}}{2})] + \Delta O \cdot x_{F,O} + \Delta P \cdot x_{F,P} \\ &= -\frac{1}{2}[\Delta O \cdot (x_o - x_{F,O}) + \Delta P \cdot (x_P - x_{F,P})] \\ &= -\frac{1}{2}[\Delta O \cdot \Delta LS_o + \Delta P \cdot \Delta LS_P] \end{aligned} \tag{3.11}$$

where, ΔLS_O and ΔLS_P is the kWh load shifted in off-peak and peak period respectively. This sum is equivalent to the sum of the areas *C* and *U* shown in Fig. 3.3 and 3.4, respectively. At the initial consumption levels, if the consumer participates in the ToU tariff scheme, the electricity bill will change by:

$$\Delta \text{Bill}_0 = \Delta O \cdot x_{F,O} + \Delta P \cdot x_{F,P} \tag{3.12}$$

Whether this number is positive or negative will depend on how

$$\frac{x_{F,O}}{x_{F,O} + x_{F,P}} \text{ and } \frac{x_{F,P}}{x_{F,O} + x_{F,P}} \tag{3.13}$$

are compared to the off-peak and peak percentage of the total initial consumption (C_O and C_P). Considering that consumers who participate in the ToU tariff scheme will shift loads, the final bill change is equal to:

$$\Delta \text{Bill} = \Delta \text{Bill}_0 + O \cdot \Delta LS_O + P \cdot \Delta LS_P \tag{3.14}$$

For a representative consumer, one whose consumption levels during peak and off-peak period are proportional to C_O and C_P, the bill changes $\Delta Bill_0$ are equal to zero. In this case, the representative consumer's bill increases by an amount equal to the area x_F,O-x_O-b-a, while the surplus has increased by the area A + C. The area C represents the net increase in welfare. Similarly, for the peak period the consumer's bill is reduced by the amount x_P-$x_{F,P}$-d-e, whereas the surplus is reduced by the area G. The net effect is a gain equal to the area U. On the contrary, for a non-representative consumer, one who consumes electricity proportionally different to C_O and C_P, the bill changes are not equal to zero. Therefore, if a non-representative consumer keeps his consumption levels the same as the baseline, before the implementation of ToU tariffs, there will be a shift in revenue either to the consumer or the power utility. In other words, the developed optional ToU tariff scheme Pareto dominates the prevailing flat rates and will result in sufficiently more welfare in the case where the electricity customers are persuaded that their DSM adoption will offer them economic gains.

Sensitivity analysis on the potential impact of the developed ToU tariffs

To verify the effect of the developed time-varying tariffs, before their real application, a sensitivity analysis based on the Load Factor (LF) was performed. More specifically, statistical analysis of the appliances listed in the completed questionnaire, was undertaken in order to identify the flexibility potential of each load. Increasing the LF can be recognized as an outcome of the load shifting technique that could diminish the average unit cost (demand and energy) of the kWh and therefore lead to substantial savings for the power utility and subsequently for the consumers. The LF is defined as the average load divided by the peak load in a specified time period:

$$LF = \frac{\text{Energy Generated in a given period}}{\text{Maximum Load x Period}} \tag{3.15}$$

This was achieved by exploiting the following optimization function:

$$\max f(x) = \frac{\sum_{i=1}^{48} x_i}{\max(x) \cdot 48} \tag{3.16}$$

subject to:

$$\sum_{i=1}^{48} x_{i,\text{before DSM}} = \sum_{i=1}^{48} x_{i,\text{after DSM}} \tag{3.17}$$

$$\max(x)_{\text{before DSM}} > \max(x)_{\text{after DSM}} \tag{3.18}$$

where, x is the power at time interval i, $x_{i,before\ DSM}$ and $x_{i,after\ DSM}$ the power before and after applying the DSM technique respectively. The main objective was to maximize the *LF* of the total residential load profile by shifting the usage time of the selected deferrable appliances, from peak to off-peak hours, by a predefined percentage (5-20%).

Pilot-implementation of the developed ToU tariffs

After the verification of the developed tariff structure through the sensitivity analysis, the proposed DSM scheme was implemented for the participants of the pilot-network for a period of one year in order to measure the real electricity demand flexibility of prosumers as a result of the price-based DSM scheme. It is worth noting that this was the first time that residential prosumers in Cyprus were exposed to a real time-varying electricity price. The approach followed was to transfer all prosumers to the time-varying tariff ("smart bill") but to simultaneously provide them bill protection during the first year of implementation as a transitional period. In this respect, at the end of each billing period a "shadow bill" was issued based on the prevailing flat-rate tariff. In case the flat bill was higher than the ToU bill, participants were compensated the difference. In order to control "free riders", the active participation of the prosumers was determined by correlating the baseline and implementation energy profiles at the end of each billing period. More specifically, a participant was assumed to be "active" if at least one of the following criteria were met:

- Peak consumption percentage was decreased compared to the baseline profile of the respective period;

- Off-peak Consumption percentage was increased, and peak consumption percentage remained unaffected, compared to the baseline profile for the respective period.

The aforementioned rules effectively removed any inadvertent losses created by any possible "free riders". Training the participants was also considered a key aspect of the implementation stage. In this respect, personal meetings with the participants were held at their households in order to train, guide and engage them with the programme, as well as to answer all their possible questions and address their concerns. Besides training, a key factor that drastically improves the response from end-users is the In House Display (IHD) which offers feedback in various forms [81–83]. For the purposes of our pilot, a less costly option in the form of a custom web and an android application was developed and offered exclusively to the participants.

3.2.2 Evaluation Stage

The evaluation stage began at the same time as the pilot implementation. The changes in their energy behaviour were investigated by comparing the consumption levels recorded before (baseline year) and after the application (implementation year) of the developed tariff scheme. The consumption levels of both periods (baseline and implementation year) were normalized to the exhibited daily peak demand in order to facilitate easier comparison. After the first six months of the programme and an extensive analysis of the results of each individual participant, several prosumers gained a significant financial benefit, not by improving their energy performance or applying any DSM technique but due to the nature of those consumers who are also energy producers through their installed PV systems. This necessitated the re-evaluation and re-design of the applied tariff structure to depend on the net-load profile which is the total energy imported to the grid minus the total excess energy produced that was exported to the grid and not on the total consumption. Furthermore, the impact on the power network was assessed by estimating the percentage reduction of the peak demand as well as the LF of the aggregated load profile.

Estimation of the peak kWh reduction due to possible various ToU price ratios

In order to estimate the peak kWh reduction due to possible various ToU price ratios the constant elasticity of substitution (CES) was utilized as an expenditure function. In economic terms, the elasticity of substitution measures the shape of the indifference curves that underlie the consumer's utility function. It is related to the own price and cross price elasticities of demand through the Slutsky equation in microeconomics [84]:

Own price elasticity of demand = compensated own price elasticity of demand + (income elasticity of demand × budget share of commodity in question)

In the case of electricity demand, this measures the percentage shift in consumption across time periods (such as peak to off-peak) in response to price changes that alter the price relationship between the two time periods (e.g. changing the price ratio). For example, in the case of a ToU rate, the peak to off-peak elasticity of substitution represents the percentage change in the ratio of peak to off-peak usage that occurs in response to a given change in the ratio of peak to off-peak prices while all other factors are held constant.

The most commonly used [85–88] CES electricity expenditure function is the following:

$$C(P_1, P_2, E) = [aP_1^{\rho} + (1-\alpha)P_2^{\rho}]^{\frac{1}{2}} \cdot F(E) \tag{3.19}$$

where,
P_1 = peak price,
P_2 = off-peak price,
F(E) = a scalar function of electricity services E (e.g. heating, cooling, lighting etc), the parameter ρ determines the elasticity of substitution and *a* is a weight.

Using the Shephard's Lemma yields [89], the least-cost peak and off-peak electricity demands are equal to:

$$\frac{\partial C}{\partial P_1} = X_1 = \alpha P_1^{\rho-1} G^{\frac{1}{\rho}-1} F(E) \tag{3.20}$$

$$\frac{\partial C}{\partial P_2} = X_2 = (1 - \alpha P_2^{\rho-1} G^{\frac{1}{\rho}-1}) F(E) \tag{3.21}$$

where,

$$G = [\alpha P_1^{\rho} + (1-\alpha)P_2^{\rho}] \tag{3.22}$$

Although *F(E)* is unobservable, we can use the ToU price ratios and consumption data to estimate the following equation:

$$\ln\left(\frac{X_1}{X_2}\right) = \beta_0 + \beta \ln\left(\frac{P_1}{P_2}\right) \tag{3.23}$$

where,

$$\beta_0 = \ln\left[\alpha(1-\alpha)\right] \tag{3.24}$$

In econometric analysis, the elasticity at a certain range can be estimated from a typical linear regression model using the slope coefficients, the price and quantity estimates. However, in practice it is more convenient to estimate these elasticities by applying a log-linear form, as the elasticities (which will be constant) can be estimated directly from the slope coefficients. Additionally, it is known that:

$$\sigma \equiv \frac{\partial \ln(\frac{X_1}{X_2})}{\partial \ln(\frac{P_1}{P_2})} \tag{3.25}$$

therefore $\sigma \equiv -\beta$.

Since $ln(X_1/X_2)$ varies between participants and seasons, we assume that the intercept β_0 is a linear function that represents the pre-pilot consumption. For the regression model, we used a modified version of the regression model proposed by C.K. Woo et al. [59]:

$$\begin{aligned}\ln(\frac{X_{1kt}}{X_{2kt}}) = \gamma + \theta \ln(Q_{kt}) + \beta \ln(\frac{P_{1kt}}{P_{2kt}}) + \phi_1 \ln(H_{kt}) + \phi_2 \ln(C_{kt}) \\ + \sum_m \mu_m M_{mt} + \omega_1 W_{dt} + \omega_2 W_{et} + \epsilon_{kt}\end{aligned} \tag{3.26}$$

The model describes the variation in participant *k*'s peak to off-peak ratio on day *t* where, γ is an intercept, ϵ_{kt} is a random-error, $ln(Q_{kt})$ is the pre-pilot consumption and $ln(P_{1kt}/P_{2kt})$ is the peak to off-peak price ratio whose coefficient is $\beta = -\sigma$.

Additionally, the weather is accounted for by $ln(H_{kt})$ and $ln(C_{kt})$ which is the natural logarithm of daily heating and cooling degree hours respectively. Daily heating degree hours (*HDH*) is the daily sum of *max(20°C – hourly temperature, 0)* for the winter and autumn season, while the daily cooling degree hours (*CDH*) were estimated by the daily sum of *max(hourly temperature – 20°C, 0)* for the summer and spring season. The ambient temperature datasets were acquired from the installed weather stations. Based on the results of the questionnaire, the primary space-heater of the participants is electric and therefore the variable that distinguishes electric to oil heater owners was not considered.

Furthermore, to capture the effect of each month on the consumption ratio, twelve month-of-the-year binary indicators were used. The variable M_{mt} is equal to unity if day t is in month m and zero otherwise, where $m = 1,\ldots,12$ for each month of the year. Similarly, two binary indicators, W_{dt} and W_{et}, were utilized in order to capture the effect of the weekdays and weekends on the consumption ratio.

To estimate the regression coefficients three methods were employed. The first one is the ordinary least squares (OLS), which is one of the most commonly used methods to produce initial results [90, 91]. For the second method, the clustered robust standard errors (CRSE) were used for gauging the coefficient estimates' precision and p-values [92]. Finally, due to the huge sample size, panel-data analysis was also performed. To implement this a) a fixed-effects and b) a random effects model was employed. CRSE were used for both the aforementioned models.

The hourly peak kW reduction was estimated using the methodology that was proposed by [93] and was based on [94]. By considering $ln(X_1/X_2) = Z$ as the non-random portion of the regression line and by using simple algebraic manipulation we can write the peak kWh usage *(S)* as:

$$S = \frac{X_1}{X} = \frac{e^Z}{(1+e^Z)} \tag{3.27}$$

where X is equal to X_1+X_2 and represents the daily total consumption. This implies that the peak consumption is given as:

$$X_1 = SX \implies \ln(X_1) = \ln(S) + \ln(X) \tag{3.28}$$

Furthermore, the changes in peak consumption can be derived in percentage by using:

$$\Delta X_1/X_1 = \Delta S/S + \Delta X/X = \text{load shifting effect + Total consumption effect} \tag{3.29}$$

However, as indicated by the author of [95], for a "revenue-neutral" time-varying tariff, such as the one developed in our study, the total consumption effect is close to zero. For this reason the total consumption effect was neglected and the peak consumption reduction was based solely on the load shifting effect. Since load shifting depends on the pre-pilot profile and the price-ratio, the $\Delta S/S$ value was estimated by utilizing the regression equation using different price ratios that range from 2:1 to 12:1 for all three seasons (winter, middle, summer).

Cost-Benefit Analysis for Smart Metering and time-varying pricing deployment

The final aspect of the evaluation stage involved the CBA. The CBA was performed to investigate whether benefits resulting from the programme outweighed the capital investment costs. The CBA should encompass both the direct monetary and wider societal costs and benefits of a large-scale rollout of the programme. In this scope, the guidelines for conducting a CBA for smart grid projects that are proposed by JRC [96], were followed. In order to estimate the benefits, the assets (i.e. SMs) involved in the pilot-implementation along with their functionalities (i.e. regular remote meter reading) must be first identified. Subsequently, those functionalities must be mapped to their respective benefits (e.g. reduced consumption and related costs, etc). It should be noted that the focus of the conducted CBA was on quantifiable costs and benefits only, in the direction of protecting the robustness of the CBA. These benefits and costs are broken down into various elements to describe the consumption and peak demand decrease; the meter reading; the meter tampering; bad depts; the reduction in call volume; and the capital and operational costs associated with the programme rollout from the perspective of networks. The main benefits for the consumers largely come from the possible electricity bill reductions, if peak demand is moved to adjacent hours or if the overall consumption is reduced through informed decisions and effective application of time-varying electricity pricing. Benefits linked with reduction in meter reads include the reduction in manual meter reading labour costs, associated Information Technology (IT) costs and transportation costs. Additionally, smart metering will significantly aid in the early detection of meter tampering and energy theft. By exploiting the high frequency SM readings, the detection of abnormal patterns of energy resulting from theft and tampering can be exposed. Furthermore, smart metering infrastructure can be used to perform a remote disconnect and re-connect based on the regulatory timeframe allowed thus reducing costs associated with uncollectible expense/bad debt. The implementation of smart metering can also provide utilities the ability to quickly identify dead or stopped meters that can no longer measure electricity due to meter failure. This early identification helps utilities rapidly take steps towards repairing or replacing the dead meter, thereby reducing potential revenue losses occurring due to this kind of interruptions. Another benefit is the cost savings achieved through efficiency improvements in customer call services. Elimination of meter reading errors along with consumer education will increase customer adoption of self-service leading to an overall reduction in call volume. Capital expenditure includes the SM cost as well as the data transmission and management costs. The net cost of SMs was estimated by subtracting the cost of a conventional meter from the cost of a SM, as conventional meters would have been installed in any case due to regulatory requirements. As a result, the incremental cost was considered. Power-line communication (PLC) was assumed as the preferred method for transmitting data and electric power in urban areas, while General Packet Radio Service (GPRS) technology for use in rural areas. In addition, the long-term data storage and management for data delivered by SMs is expected to be performed by a Meter Data Management System (MDMS). Apart from the capital expenditure, two main operational expenses were exploited, which are directly linked with their corresponding Capex items. First one being the GPRS Opex subscription, which is the product of the estimated subscription cost and the proportion of rural residential users expected to install a GPRS modem. While the second one is the MDMS operational cost and was calculated based on the annual cost and the total population of residential consumers. The allocation of costs and benefits to the stakeholders differs per cost-benefit item. For electricity savings, the benefits were allocated to the consumer while deferred (missed) income was attributed to the supplier/DSO. The cost for procurement and installation of the SMs was allocated to the DSO. However, the reduction of bad debts, theft and interruptions benefit the supplier/DSO [97].

3.3 Results

The proposed three stages of planning, implementation and evaluation for deploying an effective price-based DSM scheme were applied for the period of one year on the pilot-network of three hundred residential prosumers with installed PV systems on their rooftops. The results obtained during the three stages as well as a comparative assessment of the suggested guidelines are presented in this section.

3.3.1 Planning Stage

The pilot-network

The type, power, usage season and duration of the typical residential household appliances as derived from the questionnaire are presented in Table 3.1.

After acquiring energy data for the period of one year, the identified baseline profile was compared to the aggregated residential consumption of Cyprus. As shown in Fig. 3.5, the comparison indicated that the selected sample was representative since the Pearson correlation coefficient (PCC) was equal to 96.73%, 97.81% and 96.13% for the summer, middle and winter season, respectively. This demonstrated that the selected prosumer sample (residential sector pilot-network) is representative of the whole island. In addition, PV production datasets that were calculated by applying machine learning techniques for prosumers without SM, were compared with actual production profiles measured by reference PV system SMs. The annual average PCC between the calculated and measured PV production was found to be 98.5%, demonstrating that weather stations, which are geographically spread throughout the implementation area, can be a sufficient replacement for the costly large-scale deployment of PV meters and can be utilized to accurately calculate PV production profiles.

Table 3.1: Typical types, power and usages of residential household appliances.

	Appliance	Number in the household	Power (W)	Usage Season	Usage Period / Duration
White Appliances	Fridge / Freezer	1	250	Year-round	00:00 – 23:30 / 10 h
	Dishwasher	1	1100	Year-round	18:00 – 19:30 / 1.5 h
	Washing Machine	1	500	Year-round	18:00 – 19:30 / 1.5 h
	Clothes Dryer	1	3100	Year-round	19:00 – 21:30 / 1.5 h
	Oven	1	2700	Year-round	11:00 – 13:30 / 1.5 h
	Dehumidifier	1	350	Year-round	11:00 – 13:30 / 1.5 h
	Microwave	1	800	Year-round	12:30 – 14:00 / 30 min
Other Appliances	TV	3	170	Year-round	14:00 – 00:00 / 5 h
	Computer Desktop	1	180	Year-round	17:00 – 21:00 / 4 h
	Computer Monitor	1	50	Year-round	17:00 – 21:00 / 4 h
	Laptop	2	35	Year-round	17:00 – 21:00 / 4 h
	LED Lights	22	65	Year-round	19:00 – 00:00 / 2.5 h
	Printer	1	100	Year-round	17:00 – 21:00 / 5 min
	Router WiFi	1	22	Year-round	00:00 – 23:30 / 24 h
	Coffee Machine	1	1300	Winter / Middle	06:30 – 08:00 / 15 min
	Electric kettle	1	2000	Winter	06:30 – 08:00 / 30 min
	Hair Blow Dryer	2	1250	Year-round	20:00 – 20:30 / 10 min 07:00 – 07:30 / 10 min
	Clothing Iron	1	1150	Year-round	16:00 – 17:00 / 1 h
	Swimming Pool Pumps	1	1800	Summer	07:00 – 17:00 / 8 h
Heating/ Cooling	Air conditioner - Heating	4	1000	Winter / Middle	19:00 – 05:00 / 5 h
	Air conditioner - Cooling	4	400	Summer / Middle	16:00 – 07:00 / 10 h
	Portable Fan	2	100	Summer / Middle	19:00 – 21:00 / 2 h
	Portable Heater	2	1400	Winter / Middle	16:00 – 20:00 / 2 h
	Water Heater	1	2500	Winter / Middle	06:00 – 07:00 / 45 min 18:00 – 20:00 / 45 min

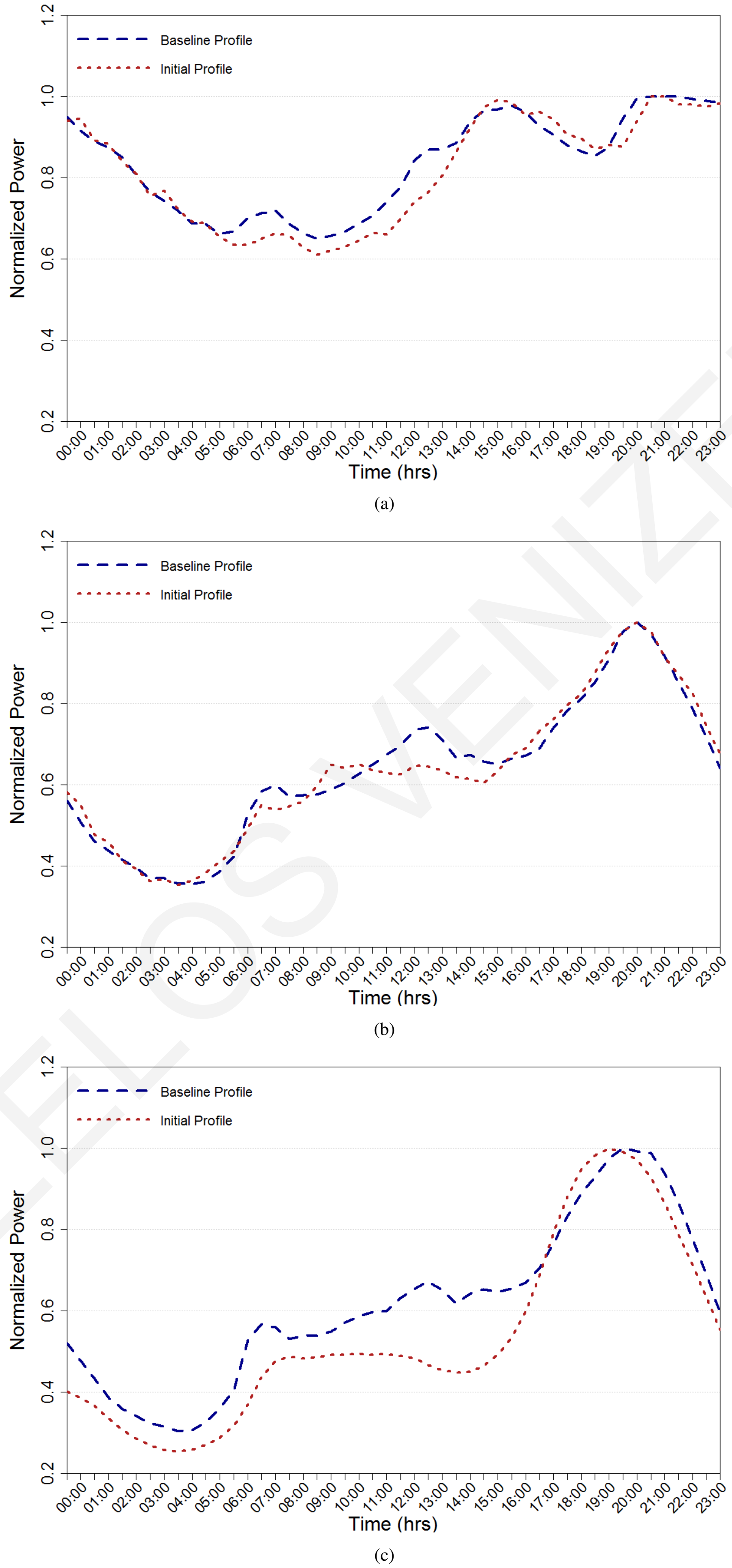


Figure 3.5: Comparison between the normalized initial and the baseline scenario for: (a) summer, (b) middle and (c) winter season.

3.3.2 Implementation Stage

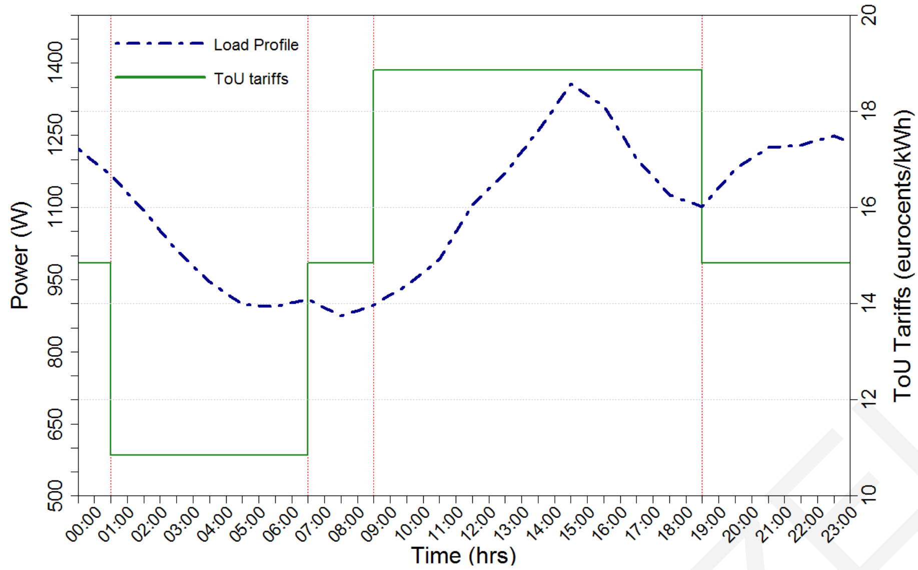
The developed ToU tariff structure

The developed ToU tariff structure including the duration of each block and the respective rates are summarized in Table 3.2 [98, 99]. The calendar year was divided into three seasons representative of different load profiles (winter, summer and middle season). The daily profile was divided into the peak, shoulder and off-peak periods with 18.85, 14.85 and 10.85 €cents/kWh, as the proposed respective rates. The average value of the prevailing electricity rate (flat tariff) was equal to 14.75 €cents/kWh. The peak, shoulder and off-peak time periods were seasonally dependent. A major factor that proved to be vital is the inclusion of a shoulder period. Prosumers could take advantage of this period by meeting their energy demands that can be shifted away from peak hours but cannot be postponed until the off-peak hours. Moreover, this transitional period could prevent the potential relocation of the peak demand that could occur in the case that only two periods were available as a result of the herding phenomenon.

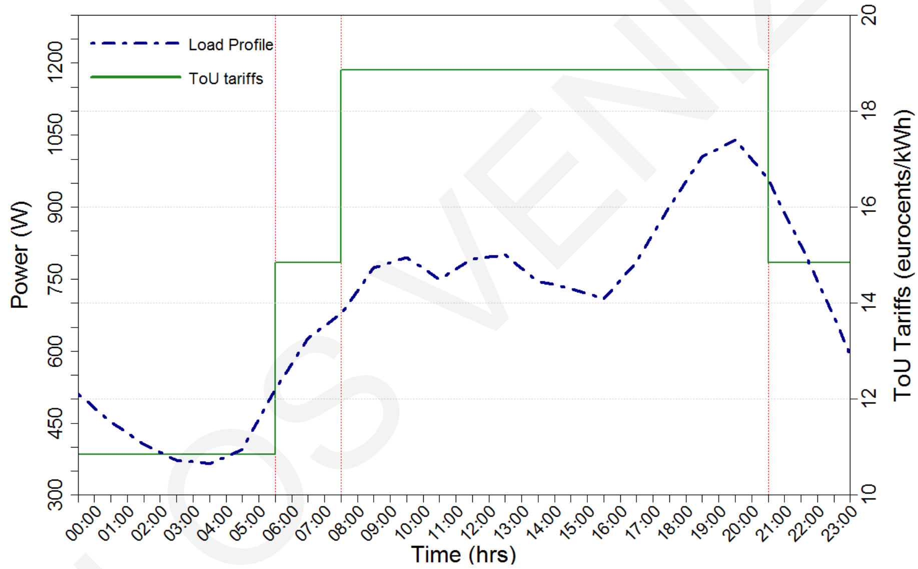
Table 3.2: Developed ToU tariff structure per season (based on the consumption profile).

Block	**Rate (€cents/kWh)**	**Winter Season (Dec – Mar)**	**Summer Season (Jun – Sep)**	**Middle Season (Apr, May, Oct, Nov)**
Peak	18.85	16:00 – 21:59	09:00 – 18:59	08:00 – 20:59
Shoulder	14.85	06:00 – 15:59 22:00 – 23:59	07:00 – 08:59 19:00 – 00:59	06:00 – 07:59 21:00 – 23:59
Off-peak	10.85	00:00 – 05:59	01:00 – 06:59	00:00 – 05:59

The summer, middle and winter season ToU tariffs obtained from the optimization method applied to the seasonal load curves and the average load profile of the participating prosumers are presented in Fig. 3.6 (a), (b) and (c), respectively. All plots clearly show three distinct segments for the off-peak, shoulder and peak period.



(a)



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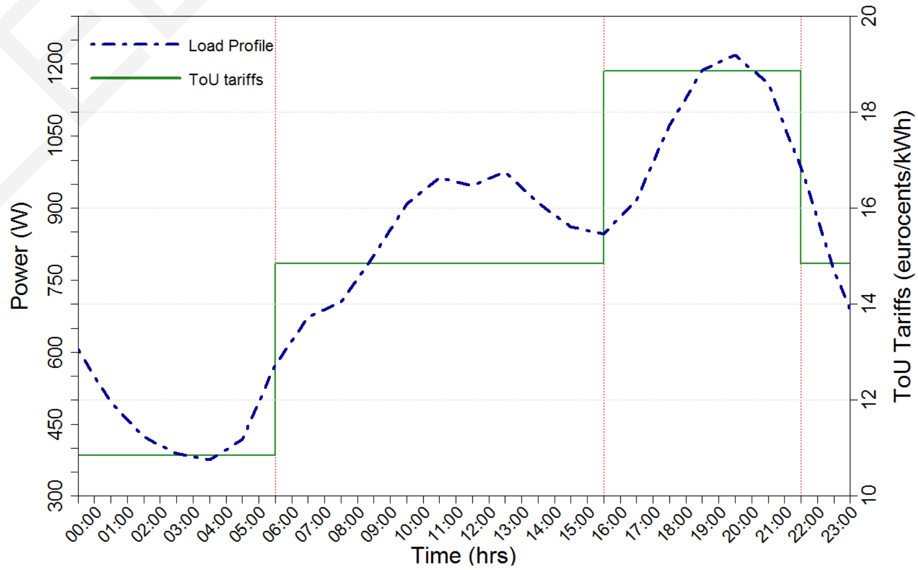


(c)

Figure 3.6: Derived ToU tariffs and average load profiles of participating prosumers for: (a) summer, (b) middle and (c) winter season.

Sensitivity analysis based on the Load Factor

To evaluate the impact of the developed ToU tariffs, a sensitivity analysis based on the LF was carried out. More specifically, the seasonal average load profile of the participants was divided into a number of main load type categories. The percentage of each category was estimated by conducting a statistical analysis on the listed appliances included in the questionnaire completed by the participants. A load shifting (LS) technique was applied for percentiles between 5 - 20% (in steps of 5%) exclusively on the category of the listed deferrable loads. The participants should be able to shift the electricity consumption of these appliances from peak periods to lower rate periods, usually through timers, and therefore minimize their electricity cost. The sensitivity analysis included two scenarios: i) shifting deferrable loads mainly to off-peak periods ii) shifting deferrable loads mainly to shoulder periods. The sensitivity analysis performed to emulate the response of the pilot network of prosumers to the imposed ToU tariffs, yielded important results on the potential improvement of the average residential load profile. The resulting average load profiles of the residential prosumers, after deferring load segments from the peak to the off-peak periods, for the all three seasons, are demonstrated in Fig. 3.7.

The results highlight that overall the derived load profiles were improved due to the load increase occurring mainly during the off-peak hours, however, this does not apply for the summer season. As shown in Fig. 3.7, during the summer season and for the case of shifting 20% of deferrable load, the demand was significantly reduced during the peak hours (15:00 pm) and increased during the off-peak hours (00:00 am), which resulted in a transfer of the peak demand from peak period to off-peak period. Additionally, a slight increase in demand during the transition of off-peak to shoulder period (06:00-07:00 am) was observed for all the investigated cases of the summer season. This is more evident during the summer season due to the difference between the peak and the lowest demand being the minimum of all three seasons and thus implying that the summer load profile is flatter compared to the winter and middle seasons. Therefore, shifting a relatively high percentage of consumption load can lead to the displacement of the peak demand. In addition to the summer profile being flatter, the low duration of the shoulder period following-up the off-peak period caused the small increase of the demand during that transition period. This occurred due to the lack of time to potentially shift the usage time of the appliances. In order to evaluate the impact of shifting segments of deferrable loads to the off-peak period, the average residential LF for each one of the cases was calculated.

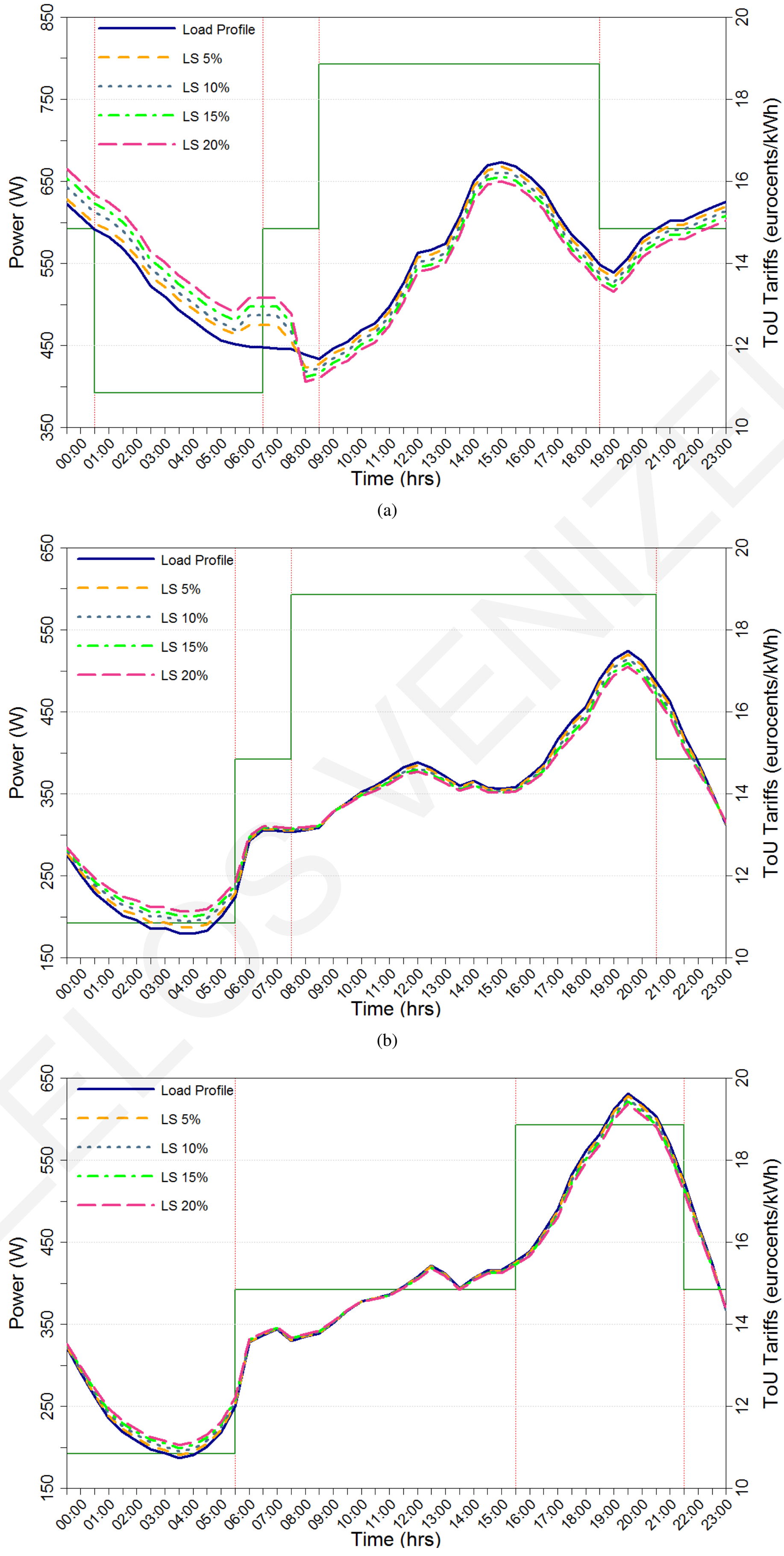


Figure 3.7: Load Shifting (LS) of deferrable loads from peak to off-peak periods for: (a) summer, (b) middle and (c) winter season.

As shown in Table 3.3, the results verified that the implementation of the proposed scheme can contribute to the electricity cost reduction by improving the LF for all the examined cases [100].

Table 3.3: Residential Load Factor (LF) for the Load Shifting (LS) technique (off-peak period scenario) per season.

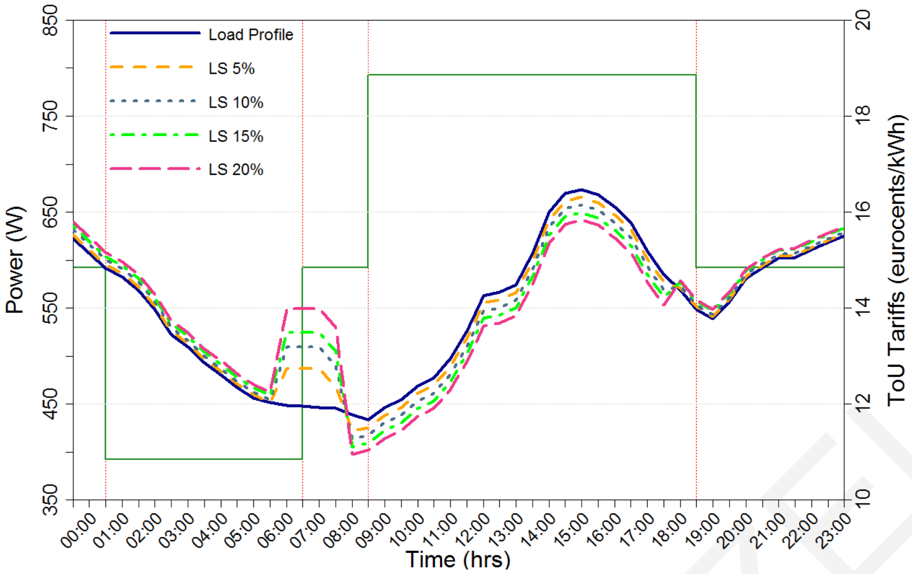
	Summer Season		**Middle Season**		**Winter Season**	
	LF (%)	Improvement	LF (%)	Improvement	LF (%)	Improvement
Baseline profile	40.65	-	32.94	-	32.48	-
LS 5%	41.29	0.64	33.34	0.40	32.69	0.21
LS 10%	41.79	1.14	33.48	0.54	32.9	0.42
LS 15%	42.30	1.65	33.36	0.42	33.12	0.64
LS 20%	42.83	2.18	33.21	0.27	33.33	0.85

The same approach was conducted to analyse the impact of shifting deferrable loads mainly to the shoulder periods. The resulting average load profiles of the residential prosumers, for the load shifting technique, are demonstrated in Fig. 3.8.

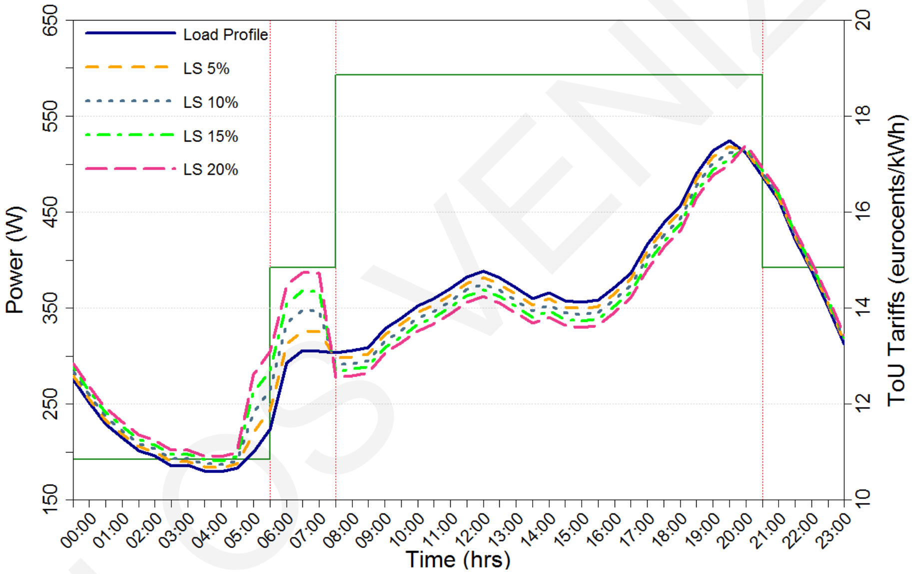
The sensitivity analysis results showed that shifting loads to the shoulder periods for the summer and middle season can potentially lead to the creation of a second peak demand during a specific period as shown in Fig. 3.8a and b. This can be considered as an outcome of the low duration of the shoulder period that follows immediately after the off-peak period. However, this is not the case for the winter season as shown in Fig. 3.8c, where the respective shoulder period is longer compared to the one of summer and middle season and therefore participants are able to disperse the usage time of their appliances in a more convenient way. Finally, the changes that occurred on the LF by shifting loads due to the ToU tariffs to the shoulder segments, are summarized in Table 3.4. The obtained results indicated that the average residential load profile can benefit from the specific DSM technique as the LF is increased in all cases.

Table 3.4: Residential Load Factor (LF) for the Load Shifting (LS) technique (shoulder period scenario) per season.

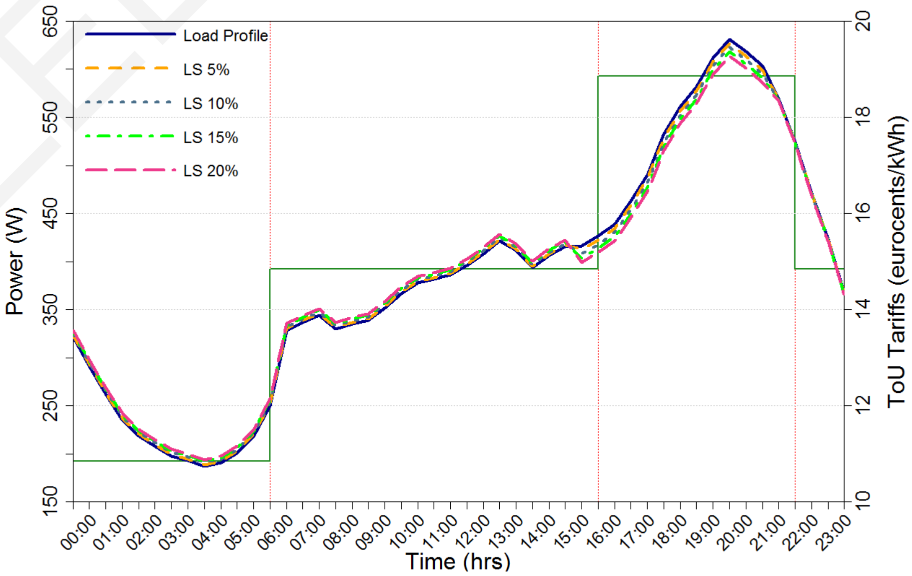
	Summer Season		**Middle Season**		**Winter Season**	
	LF (%)	Improvement	LF (%)	Improvement	LF (%)	Improvement
Baseline profile	40.65	-	32.94	-	32.48	-
LS 5%	41.15	0.5	33.25	0.31	32.64	0.16
LS 10%	41.51	0.86	33.56	0.62	32.8	0.32
LS 15%	41.88	1.23	33.88	0.94	32.97	0.49
LS 20%	41.92	1.27	34.21	1.27	33.13	0.65



(a)



(b)



(c)

Figure 3.8: Load Shifting (LS) of deferrable loads from peak to shoulder periods for: (a) summer, (b) middle and (c) winter season.

The comparative assessment of the LF results, when shifting load segments to the shoulder or off-peak periods, further showed that there is a slight improvement in the LF when shifting loads mainly to off-peak periods compared to shoulder periods. Additionally, the sensitivity analysis proved that the application of the developed ToU tariffs can benefit the electricity utility by improving the LF for all the investigated cases.

3.3.3 Evaluation Stage

Re-design of the developed ToU tariff structure

Creating a time-varying electricity tariff structure for prosumers is more complicated than typical consumers due to the dual energy usage nature (producing and consuming energy) which can provide significant revenues to prosumers as they are credited for any excess produced energy at a peak rate. This creates a substantial positive monetary gain if the tariff structure is not optimal. The positive monetary gain, which is the difference between the calculated "shadow" and "smart" bill, can be considered as an outcome of either successful load shifting or the sale of excess PV production at a profitable price. Nevertheless, the main objective of an effective DSM is to provide price incentives for changes in energy consumption patterns and not to reward excess production that can lead to cross-subsidies between prosumers and consumers. During the first six months of the evaluation period, the prosumers managed to grasp this positive monetary gain and therefore reduced their electricity bills. However, more than 50% of those revenues were obtained mainly from selling their excess production at peak price while the rest was due to successful load shifting. The re-designed ToU tariff structure, shown in Table 3.5, was based on the net-load profile and accomplished to reduce the percentage of revenues gained due to selling the exported energy below 35% of the positive monetary gain.

Table 3.5: Re-designed ToU tariffs per season (based on the net-load profile).

Block	**Rate (€cents/kWh)**	**Winter (Dec – Mar)**	**Summer (Jun – Sep)**	**Middle (Apr, May, Oct, Nov)**
Peak	17.42	16:00 – 21:59	11:00 – 20:59	16:00 – 20:59
Shoulder	14.07	06:00 – 15:59 22:00 – 23:59	07:00 – 10:59 21:00 – 00:59	06:00 – 15:59 21:00 – 23:59
Off-peak	10.85	00:00 – 05:59	01:00 – 06:59	00:00 – 05:59

Load shifting and energy conservation results

The percentage of the total consumption corresponding to each ToU block per season is depicted in Table 3.6.

Table 3.6: Consumption percentage comparison between the baseline and implementation year.

Season	Time Block	Baseline Year	Implementation year	Difference
Summer (%)	Peak	42.70	39.51	- 3.19
	Shoulder	24.01	25.66	1.65
	Off-peak	33.29	34.82	1.53
Middle (%)	Peak	36.11	35.08	- 1.03
	Shoulder	15.12	16.87	1.75
	Off-peak	48.77	48.05	- 0.72
Winter (%)	Peak	61.02	59.62	- 1.40
	Shoulder	22.89	23.33	0.44
	Off-peak	16.08	17.05	0.97

The consumption percentage comparison between the baseline and implementation year clearly demonstrated that the applied price-based DSM scheme has led to peak demand reduction equal to 3.19%, 1.03% and 1.40% for the summer, middle and winter season, respectively. Moreover, it is important to note that the peak demand was not shifted to different hours compared to the baseline year. This led to the conclusion that the proposed methodology has successfully motivated the prosumers to alter their usual energy patterns in an effort to reduce their electricity bills [101].

An additional energy metric that can be used for evaluating the performance of the sample is the LF. Increasing the energy to maximum power ratio reduces electricity marginal costs for dispatch and leads to savings for the supplier that can be passed to its consumers. The comparison between the baseline and the implementation year showed that the annual LF had risen from 40.65% to 41.43%. Moreover, the effectiveness of the developed methodology was examined by correlating the annual consumption of the participants with the entire residential sector population of Cyprus. In this scope, a second sample (typical sample) of residential prosumers with comparable consumption levels to the pilot-network (smart sample) was populated using information acquired by the DSO. In order to remove any consumption deviations occurring due to climate or national economy changes, a range of ±10% of the average consumption of the smart sample was considered for the creation of the typical sample. A margin of error equal to 0.98% was also considered for populating the typical sample. The annual average consumption for the baseline and the implementation year for both samples as well as the respective consumption ratios are presented in Table 3.7. The outcome of this comparison has demonstrated a considerable decrease of 2.17% in the annual energy consumption of the participants as compared to the typical sample. This overall behavioural change signifies that the developed price-based DSM schemes not only incentivised profile shifting, but also the reduction of consumption levels compared to the typical use case. Energy conservation has a major role in alleviating potential grid reinforcements. As concluded by the Electric Power Research Institute, a 2.5% reduction in electricity demand state-wide could reduce wholesale spot prices in California by as much as 24% while a 10% reduction in demand might reduce wholesale price spikes by half [102].

Table 3.7: Annual consumption comparison between the Baseline and Implementation year for the two samples.

	Average Consumption Baseline Year	**Average Consumption Implementation Year**	**Energy Difference between years (%)**
Smart Sample	6864.11 kWh	7138.98 kWh	4.00 %
Typical Sample	6785 kWh	7204 kWh	6.17 %
Deviation between samples (%)	1.012 %	0.99 %	-2.17 %

Estimation of the peak kWh reduction due to possible various ToU price ratios

For the regression model, the two ToU tariff schedules (original and re-evaluated) were utilized for estimating the regression coefficients while the sample size was equal to 109,500 (300 prosumers × 365 days). The OLS method has the drawback of being very sensitive to the presence of outliers or high-leverage points [103] and therefore outliers were removed when using this method. Although this led to a reduction of the sample size by approximately 0.07%, it is in line with the approach followed in similar studies [91, 93]. The *p-value* for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low *p-value* (< 0.05) indicates that the null hypothesis can be rejected. In other words, a coefficient that has a low *p-value* is likely to be a meaningful addition to a model because changes in the coefficient's value are related to changes in the response variable. The regression results, based on the model (3.26) that is described in the methodology section, for the winter, middle and summer season are presented in Table 3.8, 3.9 and 3.10, respectively.

The low R^2 value indicates that the estimated regression explains 6.89, 4.17 and 6.91% of the variance in the natural logarithm of the consumption ratio for the winter, middle and summer period respectively for the OLS method. Similar observations are obtained when CRSE were included in the regression. Additionally, the obtained results highlight that all coefficients are statistically significant (*p-value* < 0.05) with one exception: the coefficient estimates yielded from the panel-data analysis with fixed effects were statistically insignificant (*p-value* > 0.05), even with the use of the CRSE.

Table 3.8: Regression results based on the developed tariffs for the Winter period. The p-value for each coefficient is included in the parenthesis.

Winter Period								
	Ordinary Least Squares (OLS)		Clustered Robust Standard Errors (CRSE)		Fixed Effects with CRSE		Random Effects with CRSE	
R^2	0.0689		0.0666		-		-	
Intercept: γ	3.0539	(.0001)	2.8939	(.0001)	2.8974	(.0001)	2.9657	(.0001)
$ln(Q_{kt})$: ϑ	-0.0788	(0.0230)	-0.0770	(0.0180)	-0.0769	(0.0702)	-0.0773	(0.0140)
$ln(P_{1kt}/P_{2kt})$: β	-0.1646	(0.0350)	-0.1628	(0.0120)	-0.1618	(0.0310)	-0.1499	(.0001)
$ln(\mathrm{H}_{kt})$: φ_1	-0.0047	(0.0087)	-0.0049	(0.0082)	-0.0027	(0.0456)	-0.0156	(0.0115)
$ln(C_{kt})$: φ_2	0.0037	(0.0030)	0.0031	(.0001)	0.0042	(0.0690)	0.0015	(0.0266)
$M_{12t} = 1$ if t in December; 0, otherwise: μ_{12}	0.0584	(0.0048)	0.0563	(.0001)	0.0561	(0.0687)	0.0537	(.0001)
$M_{01t} = 1$ if t in January; 0, otherwise: μ_{01}	0.0552	(0.0034)	0.0597	(.0001)	0.0545	(0.0368)	0.0529	(.0001)
$M_{02t} = 1$ if t in February; 0, otherwise: μ_{02}	0.0468	(0.0050)	0.0414	(.0001)	0.0482	(0.0209)	0.0530	(.0001)
$M_{03t} = 1$ if t in March; 0, otherwise: μ_{03}	0.0761	(0.0027)	0.0732	(.0001)	0.0766	(0.0234)	0.0698	(.0001)
$W_{dt} = 1$ if t in weekdays; 0, otherwise: ω_1	0.0397	(.0001)	0.0318	(.0001)	0.0235	(0.0650)	0.0326	(.0001)
$W_{et} = 1$ if t in weekends; 0, otherwise: ω_2	0.0312	(.0001)	0.0248	(.0001)	0.0128	(0.0753)	0.0278	(.0001)

Table 3.9: Regression results based on the developed tariffs for the Middle period. The p-value for each coefficient is included in the parenthesis.

Middle Period								
	Ordinary Least Squares (OLS)		Clustered Robust Standard Errors (CRSE)		Fixed Effects with CRSE		Random Effects with CRSE	
R^2	0.0417		0.0358		-		-	
Intercept: γ	3.2568	(.0001)	3.2725	(.0001)	3.2678	(.0001)	3.2304	(.0001)
$ln(Q_{kt}) : \vartheta$	-0.0891	(0.0212)	-0.0874	(0.0097)	-0.0871	(0.0460)	-0.0867	(0.0101)
$ln(P_{1kt}/P_{2kt}) : \beta$	-0.0704	(0.0110)	-0.0732	(0.0021)	-0.0729	(0.0661)	-0.0726	(0.0270)
$ln(\mathrm{H}_{kt}) : \varphi_1$	-0.1051	(0.0081)	-0.1086	(.0001)	-0.1058	(0.0674)	-0.1149	(.0001)
$ln(C_{kt}) : \varphi_2$	-0.0523	(0.0013)	-0.0502	(.0001)	-0.0602	(0.0460)	-0.0585	(0.0360)
$M_{10t} = 1$ if t in October; 0, otherwise: μ_{10}	0.0213	(0.0035)	0.0197	(.0001)	0.0185	(0.0510)	0.0192	(0.0197)
$M_{11t} = 1$ if t in November; 0, otherwise: μ_{11}	0.0264	(0.0022)	0.0255	(.0001)	0.0325	(0.0590)	0.0320	(0.0296)
$M_{04t} = 1$ if t in April; 0, otherwise: μ_{04}	0.0297	(0.0029)	0.0303	(.0001)	0.0343	(0.0420)	0.0281	(0.0173)
$M_{05t} = 1$ if t in May; 0, otherwise: μ_{05}	0.0465	(0.0011)	0.0420	(.0001)	0.0510	(0.0421)	0.0421	(.0001)
$W_{dt} = 1$ if t in weekdays; 0, otherwise: ω_1	0.0302	(.0001)	0.0310	(.0001)	0.0312	(0.0243)	0.0317	(.0001)
$W_{et} = 1$ if t in weekends; 0, otherwise: ω_2	0.0271	(.0001)	0.0284	(.0001)	0.0254	(0.0187)	0.2444	(.0001)

Table 3.10: Regression results based on the developed tariffs for the Summer period. The p-value for each coefficient is included in the parenthesis.

Summer Period								
	Ordinary Least Squares (OLS)		Clustered Robust Standard Errors (CRSE)		Fixed Effects with CRSE		Random Effects with CRSE	
R^2	0.0691		0.0625		-		-	
Intercept: γ	2.7782	(.0001)	2.7375	(.0001)	2.7342	(.0001)	2.2888	(.0001)
$ln(Q_{kt}) : \vartheta$	-0.0345	(0.0247)	-0.0380	(0.0126)	-0.0389	(0.0650)	-0.0412	(0.0045)
$ln(P_{1kt}/P_{2kt}) : \beta$	-0.1385	(0.0190)	-0.1309	(0.0030)	-0.1302	(0.0521)	-0.1298	(.0001)
$ln(\mathrm{H}_{kt}) : \varphi_1$	0.0000	(0.0000)	0.0000	(0.0000)	0.0000	(0.0000)	0.0000	(0.0000)
$ln(C_{kt}) : \varphi_2$	0.0769	(0.0046)	0.0720	(.0001)	0.0530	(0.0360)	0.0697	(0.0210)
$M_{06t} = 1$ if t in June; 0, otherwise: μ_{06}	0.0533	(0.0041)	0.0569	(.0001)	0.0497	(0.0502)	0.0521	(0.0002)
$M_{07t} = 1$ if t in July; 0, otherwise: μ_{07}	0.0598	(0.0038)	0.0611	(.0001)	0.0552	(0.0471)	0.0578	(.0001)
$M_{08t} = 1$ if t in August; 0, otherwise: μ_{08}	0.0528	(0.0072)	0.0510	(.0001)	0.0567	(0.0688)	0.0564	(.0001)
$M_{09t} = 1$ if t in September; 0, otherwise: μ_{09}	0.0317	(0.0065)	0.0349	(.0001)	0.0298	(0.0428)	0.0335	(.0001)
$W_{dt} = 1$ if t in weekdays; 0, otherwise: ω_1	0.0355	(.0001)	0.0375	(.0001)	0.0315	(0.0587)	0.0368	(0.0160)
$W_{et} = 1$ if t in weekends; 0, otherwise: ω_2	0.0246	(.0001)	0.0267	(.0001)	0.0235	(0.0535)	0.0253	(0.0005)

As depicted, the coefficient for $ln(P_{1kt}/P_{2kt})$ is negative and relatively high for all seasons and methods, implying that participant responsiveness to the time-varying prices is adequate and that the developed ToU tariff structure is a major driver in the reduction of the consumption ratio. Similarly, the coefficient estimates of θ that correspond to $ln(Q_{kt})$ are negative, supporting that total consumption has a compelling role in the peak kWh reduction. The coefficient estimates for the daily *HDH* $ln(H_{kt})$ are negative, thus indicating that falling temperatures tend to reduce the participants' consumption ratio. However, the coefficient estimates for the daily *CDH* $ln(C_{kt})$ are positive, supporting that rising temperatures tend to increase the participants' consumption ratio. This is understandable as the results from the questionnaire showed that space-cooling units and swimming pool pumps are two of the most commonly used major electric loads during the summer period. This can also be verified by the month-of-the-year binary indicators. The coefficient estimates revealed that during the warmest month of each investigated season, the participants' consumption ratio is the highest. Furthermore, the day-of-the-week indicators (W_{dt}, W_{et}) demonstrate that during the weekdays the ratio of peak to off-peak consumption is higher. This was expected as the participants spent more time at their residence during the weekends and therefore it is easier to shift the usage-time of their appliances from peak to either shoulder or off-peak periods. Using the regression coefficient estimates shown in Table 3.9 through 3.10, the percentage kWh reductions by price ratio were computed. The mean percentage kWh reduction by price ratio and the lower and upper bounds (=mean ± 2.5 standard deviations) for the three seasons are illustrated in Fig. 3.9. The results confirm the percentage peak reductions estimated by the average seasonal profiles (Table 3.6).

Both of the applied ToU tariff ratios lie within the range of 1.5 and 2 (in particular 1.73 for the first and 1.6 for the re-evaluated design) and it is obvious that higher ratios can potentially lead to higher peak reductions. However, applying a higher ratio to the selected sample is not an easy task due to the fact that the off-peak price is close, and in some periods equal, to the lowest price that the power utility can provide electricity. Consider the two following cases that result in higher price ratios:

- The off-peak rate remains constant while the peak rate increases: This will have two potential outcomes. Firstly, consumers will not be willing to participate in the optional ToU tariffs due to the high peak rate and therefore they will tend to stay on the flat tariff. Secondly, consumers will voluntarily participate on the optional ToU tariffs and in their attempt to reduce their electricity bills they will shift a relatively high percentage of peak kWh either to the shoulder or the off-peak period thus moving the peak consumption to these periods.

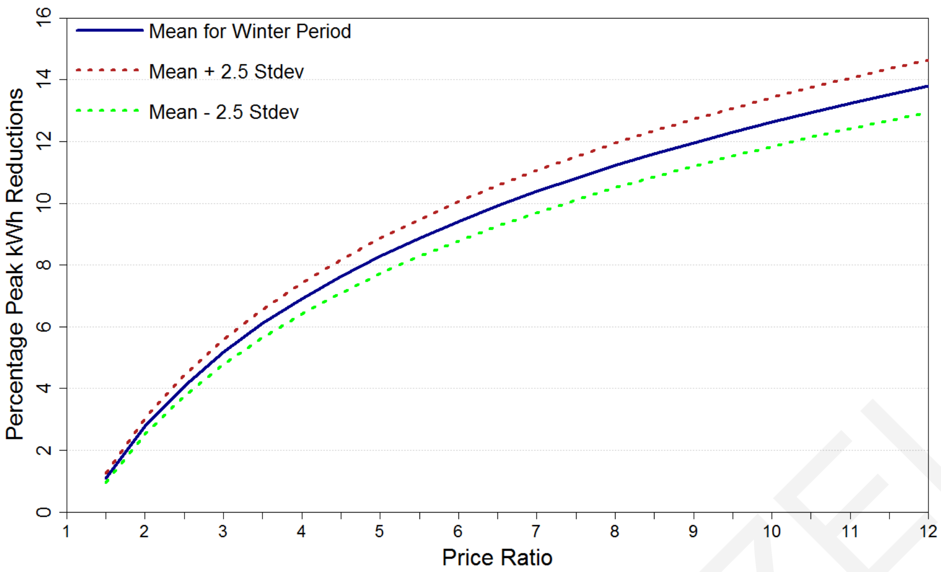
- The off-peak rate increases and the peak rate increases: In this case, the off-peak rate will be close to the prevailing flat rate while the peak rate will be too high compared to the flat rate. Therefore, since at this early stage of introducing ToU tariffs it is optional for the consumers to participate, they will prefer to stay on the current flat tariffs.

For the aforementioned reasons, at this moment it is difficult to investigate a ratio that is higher than 2.

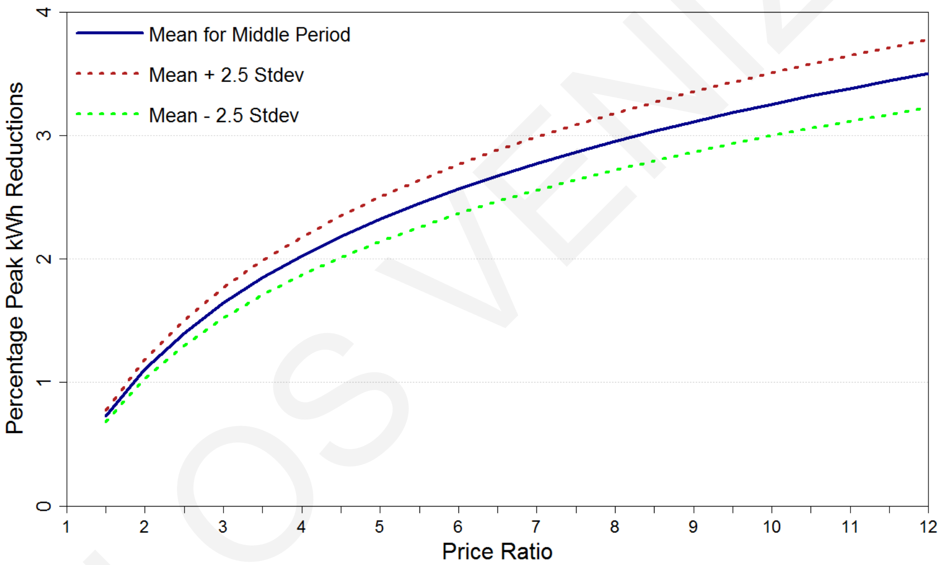
Furthermore, when evaluating ToU tariff schemes it is crucial to investigate how a change in the electricity prices affects the household welfare. By utilizing the CES unit expenditure function (3.26), the welfare improvement indicator I is equal to:

$$I = \frac{\text{CES expenditure function}_{ToUrates}}{\text{CES expenditure function}_{Flatrate}} \tag{3.30}$$

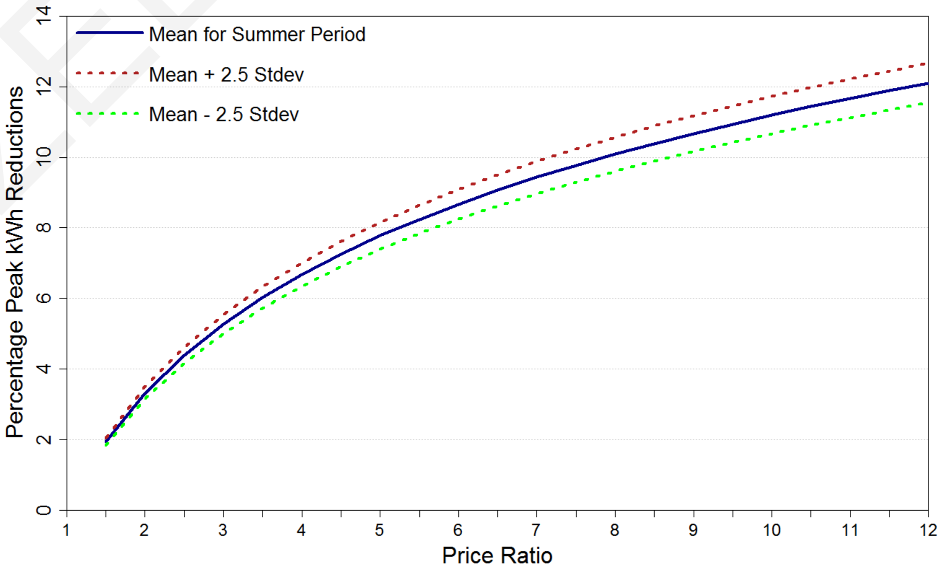
where for the flat rate, $P_{1kt} = P_{2kt}$. When applying (3.30) the results highlight that the cost index I is less than one, for the whole sample, thus proving that the developed ToU tariff is welfare improving [104].



(a)



(b)



(c)

Figure 3.9: Estimation of peak kWh reduction due to various ToU price ratios for the: (a) winter, (b) middle and (c) summer season.

Cost-Benefit Analysis for Smart Metering and time-varying pricing deployment

Reducing the peak demand either through load shifting or energy conservation can also have a positive impact on the CBA. Effective deployment of a price-based DSM scheme can potentially lead to avoidance or deferment of new investments and network capacity expansion as energy savings translate to less fuel required for generation. Results highlight that the percentage of consumption during the peak hours of the implementation year is reduced by 3.19%, 1.03% and 1.40%, compared to the baseline year, for the summer, middle and winter season, respectively. Peak load transfer benefits both the prosumers and the power utility. Prosumers gain financial benefit by consuming more energy during periods with lower electricity rates thus reducing their electricity bills, while the utility benefits by the fact that a more streamlined demand curve will lead to a more streamlined production curve and therefore reduced operating costs. Additionally, the energy behaviour change was investigated by comparing the average annual consumption of the smart prosumers with a second set of domestic consumers with similar consumption levels populated from the rest of Cyprus. The results of this comparison have indicated a sizable reduction of 2.17% in the energy consumption of the "smart" prosumers as compared to the rest of Cyprus domestic consumers. Assuming this decrease will also be reached on a national scale rollout for all domestic consumers, the overall reduction in consumption (extrapolated) is estimated at approximately 32 GWh per year (based on historical data provided by the Electricity Authority of Cyprus-EAC). The overall benefit to the society at large, from the decreased consumption, is the avoided cost associated with the estimated reduced consumption. In order to be able to monetize this benefit, the EAC's average cost of production during the pilot implementation period was initially determined. The average cost of production for the implementation period was 6.7 €cents, hence the producer's saving is estimated at €2.152.895. In Cyprus, the fuel costs per kWh are very high compared to other European countries. Therefore the effect of energy savings is also very high on the positive side of the CBA, since every kilowatt-hour of saved energy means less fuel is necessary for the generation. In order to monetize the benefits, in terms of consumption reduction, the seasonal consumption as well as the seasonal ToU price weights were utilized. The seasonal consumption weights were estimated by dividing the total seasonal energy consumption (kWh) to the total annual energy consumption (kWh) i.e. weight for baseline year: 22.21 / (22.21 + 14.64 + 17.82) = 0.41. The results for the summer, middle and winter period are summarised in Tables 3.11, 3.12 and 3.13, respectively.

Table 3.11: Average Daily consumption (kWh) and weights for the Summer season.

	Summer	
	Baseline year	**Implementation year**
Peak	9.48	8.77
Shoulder	5.33	5.69
Off-Peak	7.39	7.73
Total	**22.21**	**22.19**
Season Weight	**0.41**	**0.39**

Table 3.12: Average Daily consumption (kWh) and weights for the Middle season.

	Middle	
	Baseline year	**Implementation year**
Peak	5.29	5.10
Shoulder	2.21	2.45
Off-Peak	7.14	6.99
Total	**14.64**	**14.55**
Season Weight	**0.27**	**0.26**

Table 3.13: Average Daily consumption (kWh) and weights for the Winter season.

	Winter	
	Baseline year	**Implementation year**
Peak	10.87	11.87
Shoulder	4.08	4.65
Off-Peak	2.86	3.40
Total	**17.82**	**19.92**
Season Weight	**0.33**	**0.35**

The steps followed to derive the weighted ToU average price for each year are depicted in Table 3.14. The rates for each of the three tariffs were multiplied by their corresponding seasonal consumption percentage and the tariff weights for each season and year. For instance, the weighted average price of the implementation year was derived by:

- Multiplying each tariff's weight with the corresponding tariff rate i.e. (42.70% x 17.42) + (24.01% x 14.07) + (33.29% x 10.85) = 14.43;
- Then multiplying the average price per season by the corresponding season i.e. 14.43 * 0.41 = 5.86.

Then, the weighted average for each year can be calculated by repeating this calculation for each season in each year. In conclusion, the weighted average prices are 14.51 and 14.39 €cents/kWh for baseline and implementation year, respectively.

Table 3.14: Weighted Average ToU price for the baseline and implementation year.

Description	Baseline Year			Implementation Year		
	Summer	Middle	Winter	Summer	Middle	Winter
Peak	42.70%	36.11%	61.03%	39.52%	35.08%	59.62%
Shoulder	24.01%	15,12%	22.89%	25.66%	16.87%	23.33%
Off-Peak	33.29%	48.77%	16.08%	34.82%	48.05%	17.05%
Average Price per Season	**14.43**	**13.71**	**15.60**	**14.43**	**13.71**	**15.60**
Weighted Price per Season	**5.86**	**4.47**	**4.18**	**5.59**	**4.82**	**3.98**
Annual Weighted Average		**14.51**			**14.39**	

The total savings that occurred due to consumption reduction were derived by comparing 2015's total consumption in € per kWh with the corresponding 2016 consumption, i.e. (1,475,972,000 kWh x €0.1451) – (1,475.972 x (1-2.17%) x €0.1439) = €6,382,066, as depicted in Table 3.15.

Table 3.15: Energy savings due to energy conservation.

Description	Baseline Year	Implementation Year
Smart Sample Savings		2,17%
Total Domestic Consumption	1,475,972,000	1,443,929,611
Average ToU price (€)	0.1451	0.1439
Total	214,163,537	207,781,471
Monetized reduction		**€6.382.066**

Even though the saving in energy by the consumer is lost by the producer, the producer is saving the cost of producing the reduced energy and therefore the consumption related element creates an overall societal benefit. On the other hand, the price related element has effectively no net impact on society at large. This is because the money that is saved by consumers is effectively lost by the producer. An additional saving is related to losses savings. Based on information obtained from the EAC, the average system losses amount to approximately 6% of the total energy consumed, leading to an equivalent amount of energy savings. The reason this saving is not attributed to the producer, is because these losses are charged to the consumers and therefore not to the EAC. As a result, this is effectively a saving to consumers and to society at large. The efficiency losses savings are depicted in Table 3.16.

Further savings are associated with load shifting. To calculate the financial benefits (FB_{LS}) yielded from shifting demand from peak to shoulder and off-peak rates, were estimated

Table 3.16: Efficiency losses savings.

Description	Amount
Energy Saved	32,132,835
Efficiency Losses	6%
Additional energy saved	**1,927,970**
Avoidance rate (€)	0.067
Savings to the society due to efficiency losses avoided	**€129,174**

using:

$$FB_{LS} = (\Delta(\text{Margin Peak}) - \text{Non Peak Rates}) \cdot PLT \cdot TC \tag{3.31}$$

where,

Δ*Margin Peak - Non Peak rate* = wholesale margin difference between peak and non-peak generation

PLT = Peak load transfer percentage

TC = Total Energy Consumption

The annual average peak load transfer was derived based on the load demand data-sets that were collected during the baseline and the implementation year, while the Δ*Margin Peak* is the difference between the peak price and the marginal electricity cost which was provided by EAC. The total savings that resulted due to load shifting action are shown in Table 3.17.

Table 3.17: Energy savings due to load shifting.

Description	ΔMargin	Peak Load Transfer	Total
Peak – Shoulder	0.0165	3.84%	915,970
Peak – Off Peak	0.0183	1.78%	471,343
Total			**€1,387,313**

Additionally, the introduction of smart metering in Cyprus, through the potential enrollment of a DSM-scheme, will most likely eliminate the cost currently incurred by the EAC for read-outs (Table 3.18) as well as a decrease in electricity theft equal to 50% (Table 3.19), up to 0.4% decrease in bad debts (Table 3.20), approximately 30% reduction of power interruptions (Table 3.21) and a reduction in telephone calls by 0.5% (Table 3.22). Those are indirect benefits that are associated with the large-scale deployment of a DSM-scheme.

A breakdown of the capital and operational expenditure used in the investigated CBA analysis is shown in Table 3.23 and 3.24, respectively.

The parameters and the respective values used for the capital and operational expenditure as well as the indirect benefits were selected based on an economic analysis conducted by the Energy advisory company DNV KEMA, which is subcontracted by the national DSO, the EAC [105].

Table 3.18: CBA: Read-outs.

Parameter	Unit	Value	Commentary
Number of yearly Read-Outs	#	30%	This benefit is derived by multiplying the annual cost of Read-outs per customer and the baseline year total residential consumers.
Cost per Read Out	€	2	
Yearly Read-Outs cost	€	25,746	
Number of residential consumers	#	442,293	
Expected Saving	**€**	**2,653,758**	

Table 3.19: CBA: Electricity theft.

Parameter	Unit	Value	Commentary
Electricity theft	%	1.50%	Electricity theft reduction benefit is estimated by multiplying the product of current electricity theft percentage (1.5%) and baseline residential sales by the estimated reduction.
Residential revenue	€	225,536,197	
Total	€	3,383,043	
Estimated reduction	%	50%	
Expected Saving	**€**	**2,653,758**	

Table 3.20: CBA: Bad debts reduction.

Parameter	Unit	Value	Commentary
Residential bad debts	%	0.40%	The reduction in residential bad debts (0.2%) was multiplied by the product of debt collection per bad debt (€30)
Bad debt reduction	%	50%	
Expected bad debts reduction	%	0.2%	
Bad debt collection cost	€	30	
Number of residential consumers	#	442,239	
Total cost	€	13,268,790	
Expected Saving	**€**	**26,538**	

Table 3.21: CBA: Reduction in interruptions.

Parameter	Unit	Value	Commentary
Reduction interruptions	%	30%	This benefit is estimated by multiplying the product of revenue per hour and the forecasted reduction in interruptions, by the cost per unserved kWh
Average interruption	hours	2	
Expected reduction	hours	0,6	
Residential revenue	€	225,536,197	
Hours in the year	hours	8,760	
Revenue per hour	€	25,746	
Cost per unserved kWh	€	1.6	
Expected Saving	**€**	**24,716**	

Table 3.22: CBA: Reduction in telephone calls.

Parameter	Unit	Value	Commentary
Number of annual calls	#	20,014	This benefit is derived by multiplying product of total hourly cost and the total call hours per year by the estimated percentage reduction of 0.5%.
Time per call	mins	4	
Total call time	hours	1,334	
Societal cost per hour	€	4.7	
Call center cost per hour	€	18.8	
Administration cost per hour	€	25	
Total hourly cost	€	48.5	
Estimated telephone calls cost	€	64,712	
Expected Reduction in telephone calls	%	0.50%	
Expected Saving	**€**	**324**	

Table 3.23: CBA: Capital expenditure.

Parameter		Driver				
Description	Value	Description	Value	Adjustment factor	Total (€)	Commentary
Capex smart E-Meter (€/unit)	65	Number of consumers	442,293	-	28,749,045	CapEx for meters was estimated by subtracting the cost of a conventional E-meter from the cost of a smart E-meter. The sum of these numbers was then multiplied by the baseline year number of residential consumers in Cyprus.
Less: Capex conventional E-Meter (€/unit)	20	Number of consumers	442,293	-	(8,845,860)	
Total					19,903,185	
PLC Communication (€/unit)	25	Number of consumers	442,293	85%	9,398,726	PLC Communication was estimated by multiplying the cost per unit (25) by the baseline year total number of residential consumers. This product was then discounted by 15% in order to reflect the mix of residential to rural users.
Capex GPRS Modem (€/unit)	40	Number of consumers	442,293	15%	2,653,758	CapEx GPRS was estimated by multiplying the cost per modem (40) by the baseline year total residential consumers. Their product was then multiplied by 15% which is the percentage of users estimated that will have this modem installed.
MDM Initial cost (€)	6,500,000	-	-	78%	5,070,000	MDM CapEx was estimated by discounting the initial cost required by the 2016 residential consumers' weight.
Total CapEx					**37,025,669**	
Annual CapEx				15	**2,468,378**	Derived by dividing the total CapEx by the useful years of smart E-meters.

Table 3.24: CBA: Operational expenditure.

Parameter		Driver				
Description	Value	Description	Value	Adjustment factor	Total (€)	Commentary
Opex subscription (€/year)	10	Number of consumer	442,293	15%	663,440	The OpEx subscription by multiplying the cost per subscription by the total number of residential users during the baseline year. This product was then multiplied by 15% as this is the proportion of consumers expected to install the GPRS modem.
MDM Annual Cost (€/year)	400,000	-	-	78%	312,000	MDM CapEx was estimated by discounting the initial cost required by the baseline year residential consumers' weight.
Total OpEx					**975,440**	

As shown in Table 3.25, the CBA results demonstrated that the overall net-benefit to society from a potential nationwide rollout of smart metering is approximately €4mln over a 15-year period. The results also indicated that the parameters used for the CBA are variable and highly dependent on the exact deployment area and the principal difficulty in performing the CBA is the internalization of these cost and benefits. However, increasing the lifetime and the scale of the pilot programme can minimize the uncertainties of the parameters and therefore improve the CBA outcome. Hence, a one-size-fits-all CBA model is not sufficient.

Table 3.25: CBA: Overall benefit arising from a potential large-scale rollout.

Description	Cost	Benefit
Consumption reduction		
Energy consumption reduction / avoided production cost – Benefit to the power utility		€2.152.895
Power losses savings		€129.174
Load shifting		
Shifting loads away from peak hours – Benefit to the power utility		€1.387.313
Indirect Benefits		
Read-outs costs		€2.653.758
Electricity theft reduction		€1.691.521
Bad debts reduction		€26.538
Quickly identify dead / stopped meters		€24.716
Customer call services		€324
Capital expenditure (Capex)		
Capex smart meter	€1.326.879	
Power-line communication	€626.582	
General Packet Radio Services (GPRS)	€176.917	
Meter Data Management System (MDMS) Capital Cost	€338.000	
Operational expenditure (Opex)		
General Packet Radio Service (GPRS) – subscription	€663.440	
Meter Data Management System (MDMS) Annual Cost	€312.000	
Total Annual Cost	**€3.443.817**	**€8.066.239**
Net Annual Cost		**€4.622.421**

3.4 Concluding Remarks

The aim of this chapter is to present a universally-applicable methodology for effective deployment of implicit DR in the form of a price-based DSM scheme. The proposed methodology was applied and verified on a real smart pilot-network in Cyprus comprising of three hundred prosumers with PV systems installed on their rooftops. The resulted peak reduction in the range of 1% and 3.2% as well as the reduction of the overall consumption by approximately 2% proved that the application of the proposed scheme incentivised the participants to change their energy behaviour and minimize the need for electricity network reinforcement. The effectiveness of the proposed price-based DSM scheme was also verified by the regression analysis results as all coefficients appeared to be significant (below 5% level) and with the expected signs. Furthermore, the proposed methodology can be applied to both prosumers and consumers since the utilization of the net-load profile was found to reduce the percentage of unintended revenues below 35%. The overall net benefit to the society is further proved as the results of the performed cost benefit analysis showed a gain of €4.62mln in the case of large-scale deployment of the proposed scheme. An assessment of the impact of the individual measures for the effective deployment of DSM, including their level of impact and cost as well as their various strengths and weaknesses, is presented in Table 3.26 [106].

Based on the gained experience and knowledge, populating a pilot-network consisted of a large sample of residential prosumers whose consumption patterns are representative of the aggregate residential consumption and are equipped with the required technology for enabling time-varying electricity pricing is of utmost importance. Therefore, the establishment of an appropriate pilot-network of prosumers has the highest impact on the development of an effective price-based DSM scheme and should be employed regardless of the high implementation cost. Measures such as data acquisition, information feedback and re-evaluation of the developed scheme have high importance and medium to low implementation cost, hence should be employed. Conducting a questionnaire survey, training the participants and performing a CBA have medium impact on the development of a price-based DSM scheme and can be applied in all cases where the cost is relatively low. Finally, a sensitivity analysis that can verify the effectiveness of the proposed DSM scheme, should also be undertaken.

Table 3.26: Assessment of the impact of the individual measures for the effective deployment of DSM.

Measure	Impact	Cost	Strengths	Weaknesses
Establishing Pilot-network	High	High	+ Diversity will provide more accurate results + Candidates will be informed on DSM even if they don't participate + Provide information for larger-scale rollout + Weather Stations can help understand variations of demand due to weather conditions	- Hawthorne effect must be taken into account - Different socio-economic classes and geographical diversity is difficult to achieve - Must be relatively large - Installing weather stations is costly
Questionnaire	Medium	Low	+ List of the available appliances is important for future investigations + Understanding what motivates behavioural changes + Recommendations from the participants	- If completed incorrectly can be misleading
Technology	High	High	+ Enabling technologies help to achieve better results + Smart Meters aid data collection and feedback stages	- Extremely high capital cost to fully equip all households
Data Acquisition	High	Low	+ Provides historical feedback to the participants + Helpful for future evaluations + Critical success factors for benchmarking	- At least one year of data collection is necessary to incorporate seasonal trends
Sensitivity Analysis	Low	Low	+ Understanding the impacts of the developed ToU tariffs + Indication to what extent participants can be involved	- Data extending over a sufficient time is required - List of the available appliances is required
Training	Medium	Medium	+ Ensure successful rollout of ToU tariffs + Communication channels between the power utility and prosumers + Prosumer energy education	- Requires continuous and diligent education - Marketing campaign costs
Information Feedback	High	Medium	+ Can lead to consumption reductions + Self-trained prosumers + Raise prosumer awareness on energy profiles and electricity costs	- Appropriate technology is necessary
Re-evaluation	High	Low	+ Refinement will lead to optimal schemes and substantive impacts	- Iterative process - Proper feedback from the prosumer is required
Cost Benefit Analysis	Medium	Low	+ A good indicator of the potential benefit + A positive result can lead to accelerated large-scale rollout	- Final outcome is extremely sensitive to small changes due to uncertainties

Regression analysis results highlighted that there is still a lot of potential for flexibility provision in the residential sector. This is mainly due to the low reward provided to residential customers for altering their energy behaviours in exchange of their comfort levels. The appeal of DSM schemes could be increased with the inclusion of explicit DR offerings, such as availability payments that support equipment installation and reward customers for the full benefit they provide. Moreover, advancements in the energy market structure so that the residential sector can contribute in more services (e.g. ancillary services) could potentially provide incentives for DR participation. Furthermore, a general lesson learnt from the experimental work is that many residential customers could have easily contributed to flexibility provision, however they were not overly fond of the idea of waiting until midnight hours to do the house chores just to take advantage of the cheaper electricity price. This means that appliances using automation technologies are very important in maximising the flexibility potential. This leads to the conclusion that countries where the electricity market is mature, additional relevant stakeholders are established, and the available technology is well advanced can greatly benefit from a DR framework that enables optimal flexibility dispatch.

Chapter 4

Optimal Demand Response Distribution Coordination Framework Towards Reliable, Fair, and Secure Flexibility Dispatch

4.1 Introduction

As electricity markets and technological advancements are progressing, more DSM program offerings are available. Many enabling technology end-uses have technical capabilities that allow the end-users to achieve multiple DSM objectives including automated DR. Deployment of "smart" technologies (real-time, automated, interactive technologies that optimize the physical operation of appliances and consumer devices) for metering, communications concerning grid operations and status, and distribution automation as well as increased use of digital information and controls technology to improve reliability, security, and efficiency of the electricity grid have all led to "smarter" electricity networks also known as "Smart Grids". The Smart Grid encompasses the integration of power, communications, and information technologies for an improved electric power infrastructure that serves loads while providing for an ongoing evolution of end-use applications. Automated DR has a major role in the smart grid concept as the primary enabler for optimum energy management. However, in order to maximise flexibility extraction in a fully automated fashion, third parties such as Aggregators must undertake the role of summing those multiple flexibility volumes by considering various parameters in relation to the performance of their customers as well as the impacts on the grid balancing. All previous studies presented in Section 2.3 have exhaustively explored DR approaches, while considering customer behaviour and have established a solid foundation for the significant potential of participating in the flexibility market. However, as power flows are expected to become bi-directional, real-time grid management as well as activation of procured flexibility necessitate a more coordinated approach between the DSOs and the Aggregators. This new paradigm creates not only challenges but also great opportunities. DSOs may use the flexibility provided by the Aggregators to solve voltage problems or manage congestion at the distribution network, while the Aggregators can optimally exploit the available flexibility of their customers to participate in DR events at minimum cost. Nevertheless, the expected costs of the Aggregator may come with a high level of variability, depending on the reliability of his customers. The response of a customer in modifying his consumption pattern is not certain so there is a requirement of studying DR considering the uncertainty associated with it. Additionally, a fair distribution of flexibility requests to all the customers, will enlarge the portfolio of the specific Aggregator due to the increased willingness of other customers to enroll. These cost and performance aspects combined with the grid technical constraints, while considering security and communication aspects, are yet to be thoroughly investigated. The scope of this chapter is to present a holistic DR framework for DSO-Aggregator coordination that exploits a bi-level constrained-objective optimisation function, which minimises the flexibility aggregation costs through optimal segmentation of customer groups based on performance indices, while maintaining the distribution grid balancing. The holistic approach is concluded with the inclusion of complementary functionalities such as open protocols and blockchain methods that establish the interoperability and increased security capabilities of the proposed DR framework [107].

The rest of this chapter is structured as follows: Section 2 presents an overview of the proposed DR framework including a detailed description of the two levels of the optimisation function as well as the horizontal complementary functionalities. The results of testing the proposed DR framework on a modified IEEE 33-bus radial distribution system are presented in Section 3. Important concluding remarks appear in Section 4 of this chapter.

4.2 Methodology

In the problem of enabling optimal flexibility provision, a holistic DR framework that enables interoperable and secure DR activation for DSO-Aggregator coordination is developed. The backbone of the proposed framework is a bi-level optimisation function that aims to minimize the Aggregator's costs while ensuring the normal operation of the distribution network through technical constraint evaluation. As illustrated in Fig. 4.1, the proposed DR framework for DSO-Aggregator coordination operates between the two stakeholders, utilizing information data from both sides. More specifically, the proposed DR framework exploits information regarding the distribution network topology, offered by the DSO, as well as the portfolio data of the Aggregator. Both sets of data are used as inputs to derive a decision about the optimal combination of customers and their flexibility volume based on each DR signal and the activities of the Aggregator in the electricity market. After a DR signal is initiated by the DSO, a preliminary check that the total flexibility volume of the Aggregator can meet the total requested flexibility is performed. In that case, the optimisation function procedure runs. Otherwise the DR signal is rejected. The two levels of the optimisation function, utilised by the proposed DR framework, simultaneously address both cost and customer performance parameters as well as the distribution network technical criteria. Doing so, not only does the risk associated with the DR customer selection lowers, but also risk-averse bidding strategies, occurring due to various grid violations, are foreseen and avoided. The decision about the optimal combination of customers that can participate in the current DR signal is then fed as an output to the Aggregator. A DR signal activation ends with the flexibility extraction from the customers, followed by the flexibility provision to the DSO. As added-value, the proposed DR framework ensures communication interoperability as well as secure interaction between all the involved energy stakeholders through the exploitation of its horizontal complementary functionalities, the OpenADR standard [108] and blockchain technology. Even though the focus of this work is the Aggregator, other market players could also employ the framework, such as Utilities, Flexibility traders, etc. Moreover, the proposed DR framework, and subsequently the developed optimisation function, can be applied to any type of contracts (dynamic and/or static) between the DSO and Aggregator as well as between the Aggregator and his customers, while the technical parameters utilised in the optimisation function enable the exploitation of the developed framework for any network topology.

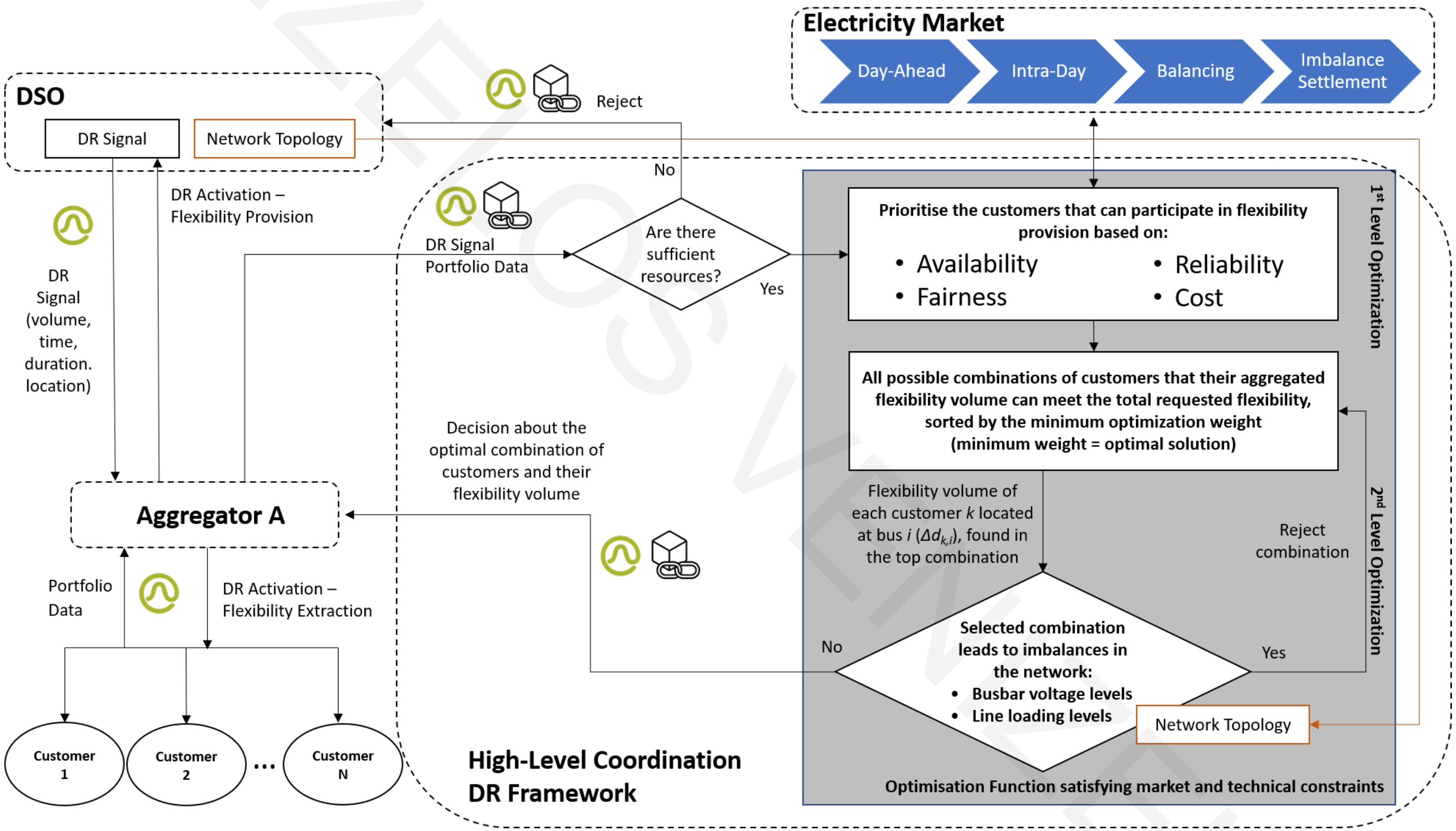


Figure 4.1: Decision flow diagram of the proposed DR framework for DSO-Aggregator coordination.

An overview of the assumptions made for the proposed DR framework as well as a detailed description of the two optimisation levels and the horizontal complementary functionalities are presented in the following sections.

4.2.1 DR Framework Assumptions

The proposed DR framework aims to optimise flexibility provision in an electricity landscape where a DSO-Aggregator coordination mechanism is already established. Even though sharing a network topology in real-world applications is not easy, following the EC Third Package [6] suggestions for the creation of equal opportunities for all stakeholders to enter the electricity markets, it is believed that in the near future the network visibility will be increased. As of today, many countries are using the USEF Flexibility Trading Protocol specifications [65]. In this protocol, USEF recommends declaring congestion points at the lowest possible level in the grid as this allows for detailed insight about local congestion while simultaneously, through aggregation, safeguarding the reliability of the grid safety analysis. To this end, it is assumed that a similar approach will eventually be adopted in other European countries as well as the rest of the world, where a DR framework that will operate between the DSO and Aggregator layer will render the network topology observable. The visibility level will surely depend on the regulations of each country. The System Operators and the Aggregators will not necessarily have access to all the data flows and information exploited by the proposed framework but only to the inputs and outputs related to their role in the electricity market. In this context, both the DSO and Aggregator must coordinate within the DR framework for safeguarding the balance of the distribution network in a manner where the DSO sends a direct signal to an Aggregator to address a local congestion problem related to gird balancing. The Aggregator, who alleviates the problem through flexibility provision, is compensated based on a direct bilateral contract price agreed with the DSO. Moreover, the proposed DR framework enables the Aggregator to concurrently participate in other flexibility markets, besides congestion management, while considering the balance of the distribution network coverage.

4.2.2 DR Framework: First Level of the Optimisation Function - Cost and Performance Aspects

To address the cost and customer performance variability in flexibility aggregation, the first level of the optimisation function utilised by the developed DR framework introduces two new indices: the Fairness Index (FI) and Reliability Index (RI). The FI and RI represent the equal distribution of DR signals to all customers as well as their reliability to flexibility commitment, respectively. The two proposed indices act as risk management mechanisms by prioritizing the group of customers that can reliably participate in a DR event by meeting the requested flexibility volume, while ensuring that the Aggregator utilises all the customers within his portfolio. The two proposed indices are integrated in the first level of the optimisation function along with the typical cost and availability indices. The first one facilitates the minimization of the total cost of the Aggregator, while the latter ensures that the selected customers are not scheduled to participate in the electricity market throughout the day, thus their available flexibility volume can be exploited. At this level the optimisation function derives all the available possible combinations with which their aggregated flexibility volume can meet the total requested flexibility, while resulting in a fair and reliable solution.

4.2.3 DR Framework: Second Level of the Optimisation Function - Technical Aspects

To maintain the balance of the distribution network, the proposed optimisation function considers flexibility aggregation, scheduling and disaggregation capabilities under the constraints of maintaining the balance of the distribution network at all times. The aim of this component is to allow Aggregators to optimally access the energy flexibility market services and exploit DR without affecting the balance and adaptation capacity of the distribution network and at the same time to avoid congestion and operate within prescribed voltage, frequency and power margins. This entails the identification of any voltage or line loading issues, including time and specific location, occurring within the investigated network topology along with the required flexibility for restoring the voltage and line loading levels back to nominal.

4.2.4 DR Framework: Optimisation Function Model Formulation

The proposed objective function considers the minimization of the total cost of the Aggregator, constrained by the technical parameters of the distribution network that are obtained through Optimal Power Flow (OPF) analysis.

Suppose that customer k can change his demand from $d_{k,0}(t)$ [kWh] (initial value) to $d_k(t)$ [kWh] during the t^{th} hour where a DR event occurs, based on the value which is considered for the incentive and the penalty included in the contract. Then the change in the demand, or equally the estimated flexibility provided by each customer is calculated using:

$$\Delta d_k(t) = |d_k(t) - d_{k,0}(t)| \tag{4.1}$$

If $I(t)$ [€/kWh] is paid as incentive to the customer in t^{th} hour for each kWh flexibility, as part of the contract with the Aggregator, then the total compensation of the customer for participating in DR signals will be as follows:

$$P(\Delta d_k(t)) = I_k(t) \cdot \Delta d_k(t) \tag{4.2}$$

If the customer who has been enrolled in the mentioned DR programs does not commit to his obligations according to the contract, he will be faced with a penalty. If the penalty price for inadequate flexibility provision is denoted by $pen_k(t)$ [€/kWh], then the potential total penalty cost is equal to the difference between the requested flexibility for the current DR event, $\Delta d_k(t)$, and the average flexibility volume ($AvgFlex_k(t\text{-}1)$) that the customer k offered in all previous events (t-1).

$$\begin{aligned} &PEN(\Delta d_k(t)) = \\ &pen_k(t) \cdot \Big[\Delta d_k(t) - AvgFlex_k(t-1)\Big] \end{aligned} \tag{4.3}$$

In this case, the total revenue for the customers who participate in the DR is calculated as follows:

$$P(\Delta d_k(t)) = I_k(t) \cdot [d_{k,0}(t) - d_k(t)] - PEN(\Delta d_k(t)) \tag{4.4}$$

In order to prioritise those who are reliable and offer the exact amount of requested flexibility on a regular basis, a reliability index (RI) depends on the data recorded until the previous DR event (*t-1*) and is estimated based on the following equation:

$$\begin{aligned} RI_k(t) =& RI_k(t-1) - \frac{ReqFlex_k(t-1) - \Delta d_k(t-1)}{TotalFlex(t-1)} \\ &+ PI_k(t-1) \cdot \frac{\Delta d_k(t-1)}{TotalFlex(t-1)} \end{aligned} \tag{4.5}$$

where $ReqFlex_k(t\text{-}1)$ [kWh] is the last requested flexibility volume, *PI* is a binary indicator used for identifying if the customer participated in the last DR event, while *TotalFlex(t-1)* [kWh] is the total flexibility volume provided by all *N* customers for all past DR requests, and can be estimated by:

$$TotalFlex(t-1) = \sum_{k}^{N} ReqFlex_k(t-1) \tag{4.6}$$

The higher the RI index, the better reliability performance of the executed DR. In order to evenly distribute DR requests among customers, an Absolute Fairness Index (*AFI*) per customer is introduced, which is defined as the ratio of the total number of requests sent to customer *k* to the total number of requests for all customers.

$$AFI_k(t) = \frac{TotalReq_k(t-1)}{\sum_k^N TotalReq_k(t-1)} \tag{4.7}$$

In addition to the *AFI*, a Capacity Fairness Index (*CFI*) is considered, in order to fairly assign the requested flexibility volume based on the maximum (*MaxFlex*) and minimum (*MinFlex*) flexibility capacity that each customer *k* can realistically provide and the average flexibility volume (*AvgFlex*) he has offered in all previous requests. This index aims to exploit the flexibility volume of each asset at its maximum offered capacity.

$$CFI_k(t) = 1 - \frac{MaxFlex_k - AvgFlex_k(t-1)}{MaxFlex_k - MinFlex_k} \tag{4.8}$$

All variables related to the DR participation of each customer *k* (i.e. *ReqFlex*, *TotalReq*, *AvgFlex*) are stored and updated for each time interval that the proposed DR framework is executed. The values of the maximum and minimum available flexibility are defined in the contract based on the deferrable loads of each customer.

First level optimisation

Considering the above, the proposed optimisation function that aims to minimize the total cost of the Aggregator by allocating all available assets based on total cost and reliability of his customers as well as a fair approach that will help the participants become more actively engaged can be defined as:

$$Optimisation\ weight = min \left\{ \sum_{k}^{N} \left(P(\Delta d_k(t)) \cdot \frac{1}{RI_k(t)} \cdot \frac{1}{AFI_k(t)} \cdot \frac{1}{CFI_k(t)} \right) \right\} \tag{4.9}$$

The result of the optimisation function (*Optimisation weight*) is a value that represents the effect of each combination of customers on the Aggregator's costs. The lower the weight is, the lower the expected cost will be. In order to achieve optimal DSO-Aggregator coordination, several technical constraints must be considered. To this end, the developed optimisation function (4.9) is subject to constraints that ensure voltage as well as active and reactive power at both bus- and line- levels at all times. The variable that relates the optimisation function with the technical constraints is the available flexibility of customer *k*, $\Delta d_k(t)$.

Second level optimisation

The bus-level active and reactive power balance are maintained through:

$$PD_i(t) - PC_i(t) + \sum_{i'} P_{i,i'}(t) = 0 \qquad \forall i, i' \in I, \forall t \in T \tag{4.10}$$

$$QD_i(t) - QC_i(t) + \sum_{i'} Q_{i,i'}(t) = 0 \qquad \forall i, i' \in I, \forall t \in T \tag{4.11}$$

The above constraints retain a balance between the active and reactive loads at bus *i* and time *t* [$PD_i(t)$, $QD_i(t)$] with the respective changes resulted due to flexibility provision [$PC_i(t)$, $QC_i(t)$]. The total active load, $PD_i(t)$, at bus *i* is equal to the total consumption of all customers connected to that bus:

$$PD_i(t) = \sum_{k}^{N} d_{k,i}(t) \tag{4.12}$$

while the total active power provision, $PC_i(t)$, at bus i is equal to the total flexibility (upwards or downwards) provided by all customers connected to that bus:

$$PC_i(t) = \sum_{k}^{N} \Delta d_{k,i}(t) \tag{4.13}$$

Active and reactive line flows are calculated as:

$$\begin{aligned} P_{i,i'}(t) = G_{i,i'}V_i^2(t) + V_i(t)V_{i'}(t)G_{i,i'}cos[\delta_i(t) - \delta_{i'}(t)] \\ +V_i(t)V_{i'}(t)B_{i,i'}sin[\delta_i(t) - \delta_{i'}(t)] \\ \forall i, i' \in I, \forall t \in T \end{aligned} \tag{4.14}$$

$$\begin{aligned} Q_{i,i'}(t) = -B_{i,i'}V_i^2(t) + V_i(t)V_{i'}(t)G_{i,i'}sin[\delta_i(t) - \delta_{i'}(t)] \\ -V_i(t)V_{i'}(t)B_{i,i'}cos[\delta_i(t) - \delta_{i'}(t)] \\ \forall i, i' \in I, \forall t \in T \end{aligned} \tag{4.15}$$

where $G_{i,i'}$ and $B_{i,i'}$ represent the real and imaginary parts, between the bus i and i', of the respective element in the bus admittance matrix. The voltage magnitude and phase angle at bus i and time t are described by $V_i(t)$ and $\delta_i(t)$, respectively. The real and imaginary parts $G_{i,i'}$ and $B_{i,i'}$ as well as the voltage magnitude and phase angle at bus i are estimated based on the inputs provided through the Network Topology. In addition, the power factor at load points should remain constant when the load is curtailed or shifted:

$$PD_i(t)QC_i(t) = QD_i(t)PC_i(t) \qquad \forall i \in I, \forall t \in T \tag{4.16}$$

The bus voltage is one of the most essential and significant safety and service quality indices. In this case, the bus voltage limits are maintained through:

$$\underline{V} \leq V_i(t) \leq \overline{V} \qquad \forall i \in I, \forall t \in T \tag{4.17}$$

where $V_i(t)$ is the voltage magnitude of the i^{th} bus, while $\underline{V}$ and $\overline{V}$ are the allowed lower and upper voltage magnitudes, respectively. All utilised voltage values are in p.u.

Line flow capacity limits are ensured as:

$$\overline{-S_{i,i'}} \leq S_{i,i'}(t) \leq \overline{S_{i,i'}} \qquad \forall i, i' \in I, \forall t \in T \tag{4.18}$$

where

$$S_{i,i'}(t) = \sqrt{P^2_{i,i'}(t) + Q^2_{i,i'}(t)} \qquad \forall i, i' \in I, \forall t \in T \tag{4.19}$$

while load change at each time is limited by the consumption load:

$$0 \leq PC_i(t) \leq PD_i(t) \qquad \forall i \in I, \forall t \in T \tag{4.20}$$

The required flexibility for restoring the bus voltage to normal operating conditions is based on a voltage sensitivity analysis performed on the flexibility provision, $PC_i(t)$. More specifically the flexibility value provided by each customer is marginally deviated within the range of the minimum and maximum flexibility volume so that voltage limits are maintained. In this sense, this sensitivity analysis gives an indication of the extent of the influence the variation of active power on a node has on voltage.

In case where a line overloading occurs, then the total required flexibility for restoring the network's normal operation is estimated by:

$$TotalFlex_{i,i'}(t) = \frac{Violation_{i,i'}(t) - 100}{100} P_{i,i'}(t) \tag{4.21}$$

where $Violation_{i,i'}(t)$ is the load percentage of the line between the bus *i* and *i'* and is calculated based on the Network Topology inputs. Subsequently, to avoid a line violation event, the aggregated flexibility of bus *i*, $PC_i(t)$, should be equal to the $TotalFlex_{i,i'}(t)$.
The outcome of the objective function is the optimal combination of customers along with their respective flexibility volume that can meet the total flexibility request with the minimum cost and without affecting the balance of the distribution network.

4.2.5 DR Framework: Horizontal Complementary Functionalities

To further support the viability of the proposed methodology, two added-value functionalities also have been implemented, towards presenting an interoperable and secure framework. A twofold approach is employed in order to provide semantic interoperability. First, an ontology based on the OpenADR standard has been used [109] for formal data validation and integration with other standards. Second, a communication component [110] that interconnects systems with heterogeneous communication protocols, formats and data models is utilised. By employing semantic web technologies, the ontology allows transparent exchange and consumption of data. Collectively, these two pillars are referred to as the

Common Information Model (CIM) and provide for a semantically interoperable ecosystem within the proposed DR framework.

Facilitating the growth of (future) marketplaces and incentivizing the participation of all energy stakeholders necessitates a decentralized and trustworthy infrastructure that must provide, at minimum, financial settlement of DR-related transactions. A permissioned blockchain-based platform is employed, based on Hyperledger Fabric [111], which is maintained and operated by multiple, distinct administrative domains. These entities participate in an authenticated, byzantine fault-tolerant consensus algorithm, which is decentralized by design and provides for tamper-resilience and liveness in the presence of (arbitrary) failures. Moreover, to promote fully automated contractual agreements among participants of DR schemes in the context of different marketplaces in a trustworthy and verifiable fashion, we leverage the power and expressiveness of smart contracts. These are automated agents that "live" in the blockchain and play an integral part of the proposed DR framework [112] as they mediate and monitor transactions, provide transparency, as well as, enforcement of contractual clauses by regulating energy supply, payments and potentially incurred penalties. As the algorithms and rules upon which these contractual agreements are formed reside on the blockchain, end-to-end verifiability, transparency and financial settlements are achieved.

4.3 Results

4.3.1 Test Case Description

In this section, the performance of the proposed DR framework is evaluated based on a hybrid test network comprised of a physical microgrid and nanogrid network connected to a simulated distribution network. The reason for creating this hybrid test network is to investigate the applicability and effectiveness of the proposed DR framework under real-conditions where a microgrid is interacting with a nanogrid and their joint operation directly affects a nearby distribution network connected to the same Primary Substation. Both the microgrid and nanogrid are physical parts of the University of Cyprus (UCY) campus where full monitoring and control capabilities are enabled. The inability to control the nearby connected physical distribution network is addressed through the utilisation of a simulated IEEE 33-bus test system that is modified to represent the unavailable physical distribution network.

The physical microgrid is comprised of 14 tertiary buildings that span a broad variety of typologies and uses (educational facilities, office building, restaurants, sports and health centres, etc.) along with large shares of DERs, such as PVs. Similarly, the physical nanogrid (PVTL nanorgid) includes PVs, Battery Energy Storage System (BESS) and Electric Vehicles (EVs). The modified IEEE 33-bus test system includes both domestic and commercial electricity customers. To consider the effect of RES integration in the distribution network, the domestic customers are equally divided to consumers and prosumers.
In order to be able to evaluate the impacts of both the physical and simulated parts of the hybrid test network in a unified environment at the same time, the topology of the microgrid, nanogrid and modified IEEE 33-bus test system were modelled in a power system analysis software application, DIgSILENT. The modelled test network provided the additional ability of testing various distribution network imbalance issues that otherwise would be impossible to physically create. The characteristics for the microgrid and nanogrid models are based on their physical counterparts, while the consumption and production datasets as well as BESS and EV profiles for the modelled microgrid and nanogrid are fed in real-time to the models through the installed SMs across the UCY campus. Deferrable loads such as the chillers, dimming lights, smart AC split-units that can be exploited as sources of flexibility for participating in the DR events are also considered and controlled in real-time. The load profiles for the IEEE-bus test system were based on previous studies [100, 113]. The modelled hybrid test network, used for the evaluation of the proposed DR framework is illustrated in Fig. 4.2. As can be seen in the figure, the test network consists of the Primary substation, where two feeders (Feeder 1 and 2) are delivering electricity to the physical microgird and nanogrid as well as a third feeder (Feeder 3) that connects the modified IEEE 33-bus test system.

The line loading as well as the Low Voltage levels, under normal operating conditions are illustrated in Fig. 4.3 and 4.4, respectively. It can be seen that the line loading remains below 100% of the line capacity, while the voltage levels at the buses are maintained between 0.9 and 1.1 p.u. of the nominal voltage.

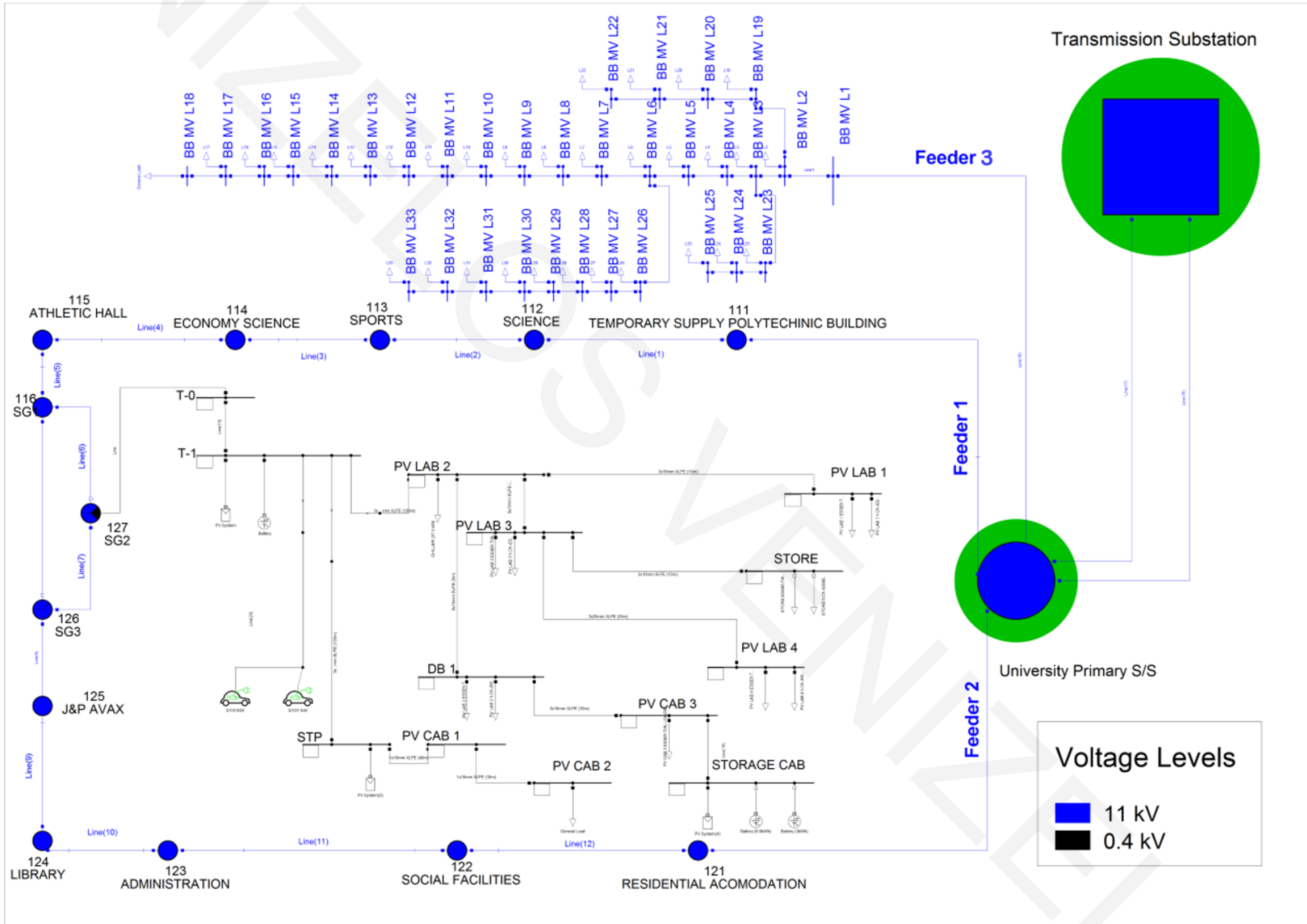


Figure 4.2: Modified IEEE 33-bus test system for evaluating the proposed framework.

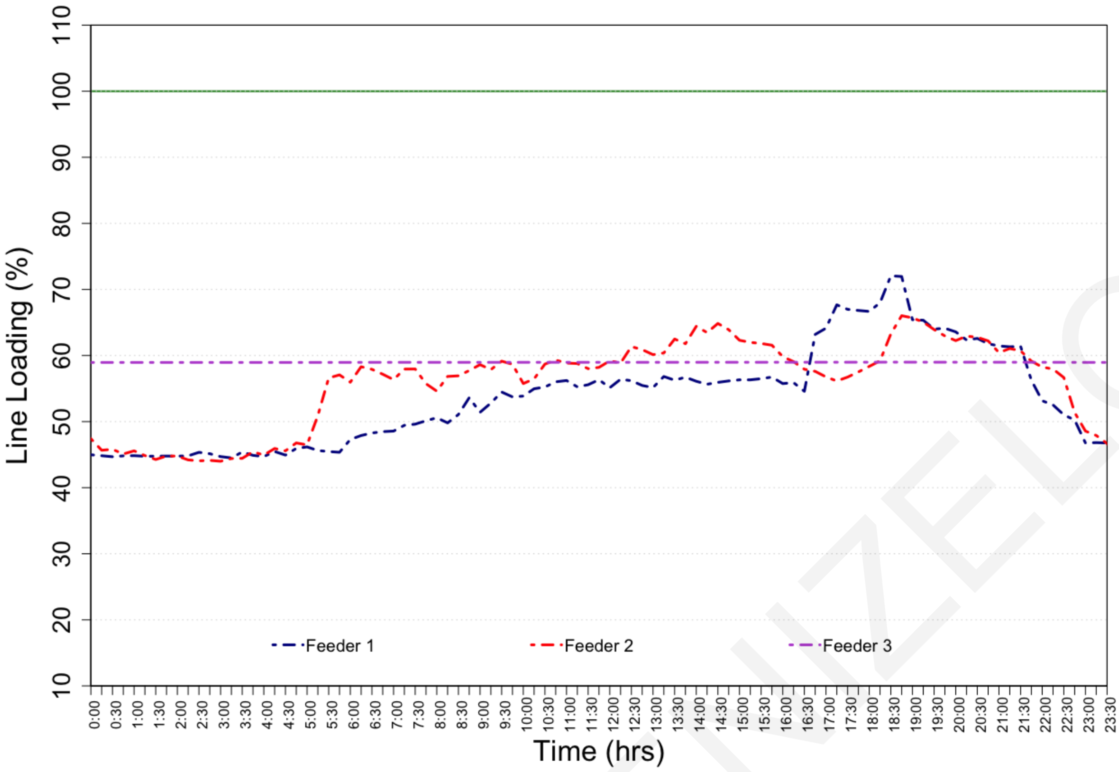


Figure 4.3: Line loading levels under normal operating conditions.

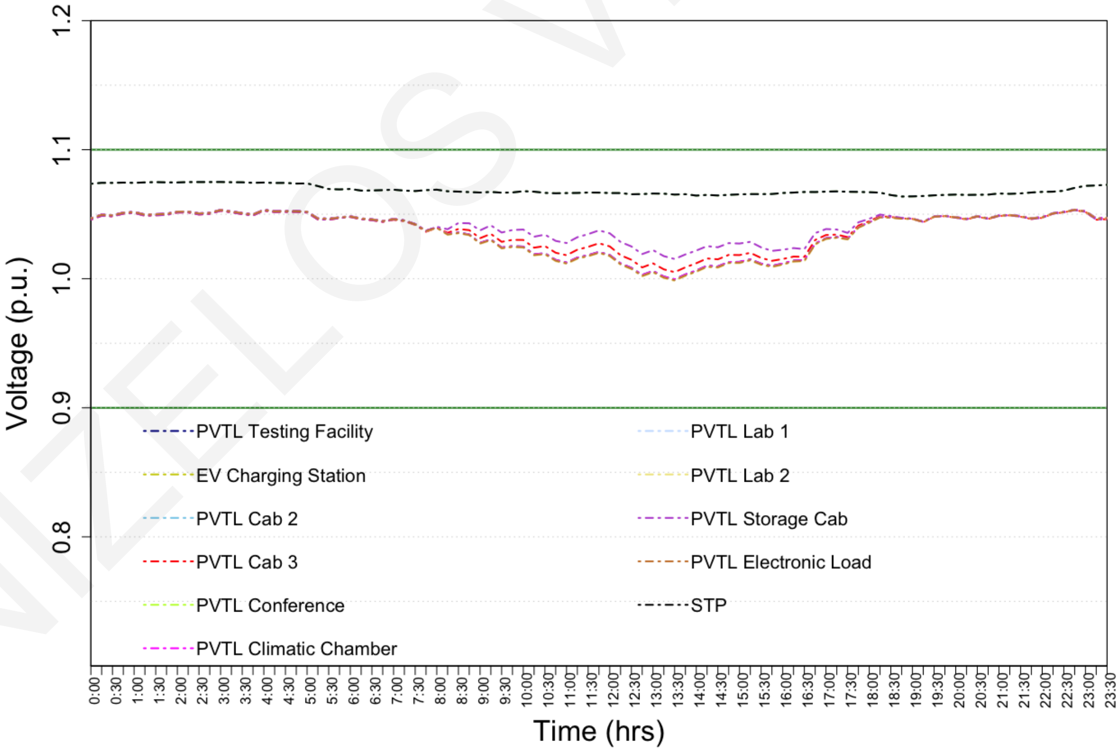


Figure 4.4: Low-voltage busbar levels under normal operating conditions.

The integration of a Python programmed integrating script (PPIS) is developed in order to integrate the proposed DR framework, the test case as well as the interactions between the DSO and Aggegator in one unified environment. In this way, any control strategy applied to the modelled microgrid and nanogrid components is carried out to their respective physical ones through the PPIS. This resembles a Hardware-in-the-loop approach which enables the testing of the functionalities the proposed DR framework in a semi-real environment where the embedded physical parts are capable of interacting with the simulated ones, thus rendering the evaluation results more accurate. In addition, the developed PPIS allows the demonstration of the interoperable and secure functionalities of the proposed DR framework.

4.3.2 Test Case Modelling Parameters and Assumptions

In this Test Case, it is assumed that the DSO takes the role of the price-maker who compensates the Aggregator at a contracted price for alleviating distribution grid violations at his area of responsibility. The contracted price between the DSO and the Aggregator is based on a CBA conducted by the national DSO, the EAC [114]. The CBA indicates that the congestion in an MV Feeder is expected due to either increased load demand (during the winter period) or increased generation of RES (during the summer period). Based on this CBA, the price that the DSO is willing to pay for each unit of Flexibility Energy [MWh] is related to the total flexibility energy units required for congestion avoidance. Following the CBA results, in this Test Case it is assumed that the flexibility events can be divided into the categories depicted in Table 4.1.

Table 4.1: Flexibility event categories.

Flexibility Level	Feeder Congestion (of nominal capacity)	Occurrence Frequency	Price (/€MWh)
Critical Flexibility	120%	10%	157.99
Normal Flexibility	105 -119%	40%	110.67
Non-critical Flexibility	95-104%	50%	94.54

In this Test Case it is also assumed that the Aggregator is a price-taker with respect to the DSO, but by contrast a price-maker with respect to the flexibility price he offers to his customers. The Aggregator's business model, of course, is based on sharing a percentage of the achieved savings from the optimized portfolio with the participating customers. However, to persuade a customer to participate in flexibility programmes that will affect his thermal or visual comfort levels, an attractive incentive must be offered. Hence, it is expected that the earnings for the provider of the flexibility (customer) will be higher than the Aggregator's. In this respect, it is assumed that the Aggregator will compensate his customers with a percentage between 60 and 90% of the flexibility price, offered by the DSO, for each successful DR activation. The sharing percentage level that the Aggregator offers to his customers is assumed to vary based on their:

- Maximum Flexibility Capacity: Max. amount of flexible power [MW]
- Maximum Duration: Max. time the load capacity can be shed/shifted [h]
- Frequency: Max. number of events over a period [N/year]
- Notice time: Time before the event is actually triggered [h]
- Recovery time: Max. time energy has to be recovered [h]

Therefore, it is assumed that customers who can provide flexibility for long periods of time will be compensated less (lower sharing portion) than the ones who can provide flexibility for short periods. This assumption is backed up by the fact that the customers who can participate for longer periods have a higher chance to be selected for a DR event. The flexibility price is considered to consist of two parts: the contract reservation and the activation price. The first price stipulates the cost paid by the Aggregator for periods during which the Aggregator can manage flexibility devices, while the latter price stipulates the fee when the Aggregator activates DR. Non or insufficient delivery may result in a penalty. Penalty calculations need to be differentiated depending on the market and the risk posed. In this study, a penalty equal to 1/6 of the contractual fee is assumed.

Considering the aforementioned assumptions, a flexibility price and the respective penalty is assigned to each customer/asset (building or facility) of the physical microgrid and nanogrid based on their availability periods (max duration and frequency) as well as the maximum Flexibility Capacity. The contract details per portfolio asset for the critical, normal and non-critical flexibility provision, as defined for the purposes of this Test Case, are summarized in Table 4.2, 4.3 and 4.4, respectively.

Table 4.2: Contract details per portfolio asset for Critical Flexibility, as defined for the Test Case.

Asset ID - Building	Feeder	Critical Flexibility	
		Flexibility Price [/€kWh]	Penalty [/€kWh]
111CA - Polytechnic School	Feeder 1	0,1102	0,0184
112CA - Faculty of Science - Incomer 1	Feeder 1	0,1160	0,0193
112CB - Faculty of Science - Incomer 2	Feeder 1	0,1285	0,0214
113CA - Sport Fields	Feeder 1	0,1264	0,0211
114CA - Faculty of Economics and Business	Feeder 1	0,1195	0,0199
115CA - Sports Centre Power	Feeder 1	0,1080	0,0180
116CA - Energy Center 1a	Feeder 1	0,1065	0,0178
116CB - Energy Center 1b	Feeder 1	0,1101	0,0184
121CA - Residential Accommodation	Feeder 2	0,1202	0,0200
121PA - Residential Accommodation - PV System	Feeder 2	0,1154	0,0192
122CA - Social Facilities	Feeder 2	0,1085	0,0181
122PA - Social Facilities - PV System	Feeder 2	0,1213	0,0202
123CA - Administration	Feeder 2	0,1073	0,0179
123PA - Administration - PV System	Feeder 2	0,1207	0,0201
124CA - Library - Incomer 1	Feeder 2	0,0925	0,0154
124CB - Library - Incomer 2	Feeder 2	0,1192	0,0199
125CA - JP AVAX	Feeder 2	0,1176	0,0196
126CA - Energy Center 2	Feeder 2	0,0936	0,0156
127CA - Energy Center 3	Feeder 2	0,1272	0,0212
EV1 - nanogrid	Feeder 2	0,0989	0,0165
EV2 - nanogrid	Feeder 2	0,1110	0,0185
PVTL Climatic Chamber	Feeder 2	0,1077	0,0180
PVTL Indoor Testing 1	Feeder 2	0,1179	0,0197
PVTL Conference FLEX	Feeder 2	0,1128	0,0188
PVTL Conference BASE	Feeder 2	0,1026	0,0171
PVTL Offices 1 FLEX	Feeder 2	0,0959	0,0160
PVTL Offices 1 BASE	Feeder 2	0,1161	0,0194
PVTL Indoor Testing 2 FLEX	Feeder 2	0,0960	0,0160
PVTL Indoor Testing 2 BASE	Feeder 2	0,1050	0,0175
PVTL Offices 2 FLEX	Feeder 2	0,1198	0,0200
PVTL Offices 2 BASE	Feeder 2	0,0985	0,0164
PVTL Storage CAB	Feeder 2	0,1042	0,0173
PVTL CAB 3	Feeder 2	0,1173	0,0196

Table 4.3: Contract details per portfolio asset for Normal Flexibility, as defined for the Test Case.

Asset ID - Building	Feeder	Normal Flexibility	
		Flexibility Price [/€kWh]	Penalty [/€kWh]
111CA - Polytechnic School	Feeder 1	0,0893	0,0149
112CA - Faculty of Science - Incomer 1	Feeder 1	0,0905	0,0151
112CB - Faculty of Science - Incomer 2	Feeder 1	0,0900	0,0150
113CA - Sport Fields	Feeder 1	0,0948	0,0158
114CA - Faculty of Economics and Business	Feeder 1	0,1016	0,0169
115CA - Sports Centre Power	Feeder 1	0,0842	0,0140
116CA - Energy Center 1a	Feeder 1	0,0767	0,0128
116CB - Energy Center 1b	Feeder 1	0,0892	0,0149
121CA - Residential Accommodation	Feeder 2	0,0926	0,0154
121PA - Residential Accommodation - PV System	Feeder 2	0,0900	0,0150
122CA - Social Facilities	Feeder 2	0,0760	0,0127
122PA - Social Facilities - PV System	Feeder 2	0,0873	0,0146
123CA - Administration	Feeder 2	0,0841	0,0147
123PA - Administration - PV System	Feeder 2	0,0845	0,0141
124CA - Library - Incomer 1	Feeder 2	0,0777	0,0130
124CB - Library - Incomer 2	Feeder 2	0,1013	0,0169
125CA - JP AVAX	Feeder 2	0,0976	0,0163
126CA - Energy Center 2	Feeder 2	0,0768	0,0128
127CA - Energy Center 3	Feeder 2	0,0890	0,0148
EV1 - nanogrid	Feeder 2	0,0781	0,0130
EV2 - nanogrid	Feeder 2	0,0777	0,0130
PVTL Climatic Chamber	Feeder 2	0,0862	0,0144
PVTL Indoor Testing 1	Feeder 2	0,0955	0,0159
PVTL Conference FLEX	Feeder 2	0,0880	0,0147
PVTL Conference BASE	Feeder 2	0,0739	0,0123
PVTL Offices 1 FLEX	Feeder 2	0,0710	0,0118
PVTL Offices 1 BASE	Feeder 2	0,0824	0,0137
PVTL Indoor Testing 2 FLEX	Feeder 2	0,0682	0,0114
PVTL Indoor Testing 2 BASE	Feeder 2	0,0882	0,0147
PVTL Offices 2 FLEX	Feeder 2	0,0899	0,0150
PVTL Offices 2 BASE	Feeder 2	0,0808	0,0135
PVTL Storage CAB	Feeder 2	0,0854	0,0139
PVTL CAB 3	Feeder 2	0,0891	0,0149

Table 4.4: Contract details per portfolio asset for Non-critical Flexibility, as defined for the Test Case.

Asset ID - Building	Feeder	Non-critical Flexibility	
		Flexibility Price [/€kWh]	Penalty [/€kWh]
111CA - Polytechnic School	Feeder 1	0,0518	0,0086
112CA - Faculty of Science - Incomer 1	Feeder 1	0,0498	0,0083
112CB - Faculty of Science - Incomer 2	Feeder 1	0,0549	0,0091
113CA - Sport Fields	Feeder 1	0,0550	0,0092
114CA - Faculty of Economics and Business	Feeder 1	0,0569	0,0095
115CA - Sports Centre Power	Feeder 1	0,0505	0,0084
116CA - Energy Center 1a	Feeder 1	0,0460	0,0077
116CB - Energy Center 1b	Feeder 1	0,0526	0,0088
121CA - Residential Accommodation	Feeder 2	0,0602	0,0100
121PA - Residential Accommodation - PV System	Feeder 2	0,0531	0,0089
122CA - Social Facilities	Feeder 2	0,0494	0,0082
122PA - Social Facilities - PV System	Feeder 2	0,0507	0,0084
123CA - Administration	Feeder 2	0,0502	0,0084
123PA - Administration - PV System	Feeder 2	0,0473	0,0079
124CA - Library - Incomer 1	Feeder 2	0,0490	0,0082
124CB - Library - Incomer 2	Feeder 2	0,0638	0,0106
125CA - JP AVAX	Feeder 2	0,0547	0,0091
126CA - Energy Center 2	Feeder 2	0,0476	0,0079
127CA - Energy Center 3	Feeder 2	0,0561	0,0093
EV1 - nanogrid	Feeder 2	0,0508	0,0085
EV2 - nanogrid	Feeder 2	0,0466	0,0078
PVTL Climatic Chamber	Feeder 2	0,0526	0,0088
PVTL Indoor Testing 1	Feeder 2	0,0563	0,0094
PVTL Conference FLEX	Feeder 2	0,0493	0,0082
PVTL Conference BASE	Feeder 2	0,0414	0,0069
PVTL Offices 1 FLEX	Feeder 2	0,0426	0,0071
PVTL Offices 1 BASE	Feeder 2	0,0470	0,0078
PVTL Indoor Testing 2 FLEX	Feeder 2	0,0429	0,0072
PVTL Indoor Testing 2 BASE	Feeder 2	0,0556	0,0093
PVTL Offices 2 FLEX	Feeder 2	0,0557	0,0093
PVTL Offices 2 BASE	Feeder 2	0,0525	0,0088
PVTL Storage CAB	Feeder 2	0,0517	0,0082
PVTL CAB 3	Feeder 2	0,0508	0,0085

In most distribution systems, the DSO enters into contracts with DERs that are mandated to provide reactive power requirement approved by the grid code, and hence, the Distributed Generation (DG) units must operate between a mandatory leading and lagging power factor at every operating point. Although the grid codes for reactive power are considered as part of the constraints in the proposed optimisation function, incentive payments for reactive power provision are not investigated in this study. In this respect, the variables $QD_i(t)$ and $QC_i(t)$ utilized in (4.11) were predefined based on the real network information.

4.3.3 Test Case Scenario and Results

In order to verify the integrated functionalities of the proposed DR framework, a real possible scenario for flexibility provision is investigated. More specifically in this scenario, a real flexibility request is initiated from the national DSO, the EAC, due to congestion problem occurring within the area of the UCY campus. The role of the Aggregator in the investigated scenario is undertaken by the UCY, where the various facilities and buildings located within the physical microgrid as well as the nanogrid are considered to be the DR customers. Each customer is represented by the available flexibility (either static or range based on the flexibility source) that can serve specific energy markets and the compensation price of those services with the respective penalty prices, as derived from the contracts.

In this investigated scenario, a virtual congestion problem is created by increasing the electricity demand of two simulated buildings implemented in the modelled test network. The two simulated buildings represent the physical Library and Residential Building Blocks located in the microgrid network. This scenario is practically possible as a congestion problem could arise due to potential electricity demand increase of the Library and Residential Building Blocks that typically appears during the mid-day hours, where students return to their dorms or visit the library facilities during lecture breaks. The increased demand of those two buildings will overload the line of Feeder 2 to which those buildings are connected. As shown in Fig. 4.5, a line loading violation occurs at the second Feeder of the microgrid between 14:15 and 14:30. The line loading rises to 106.09% and 105.69%, at 14:15 and 14:30, respectively. These line violation incidents fall under the category of congestion problems in the distribution network and must be addressed locally through flexibility provision.

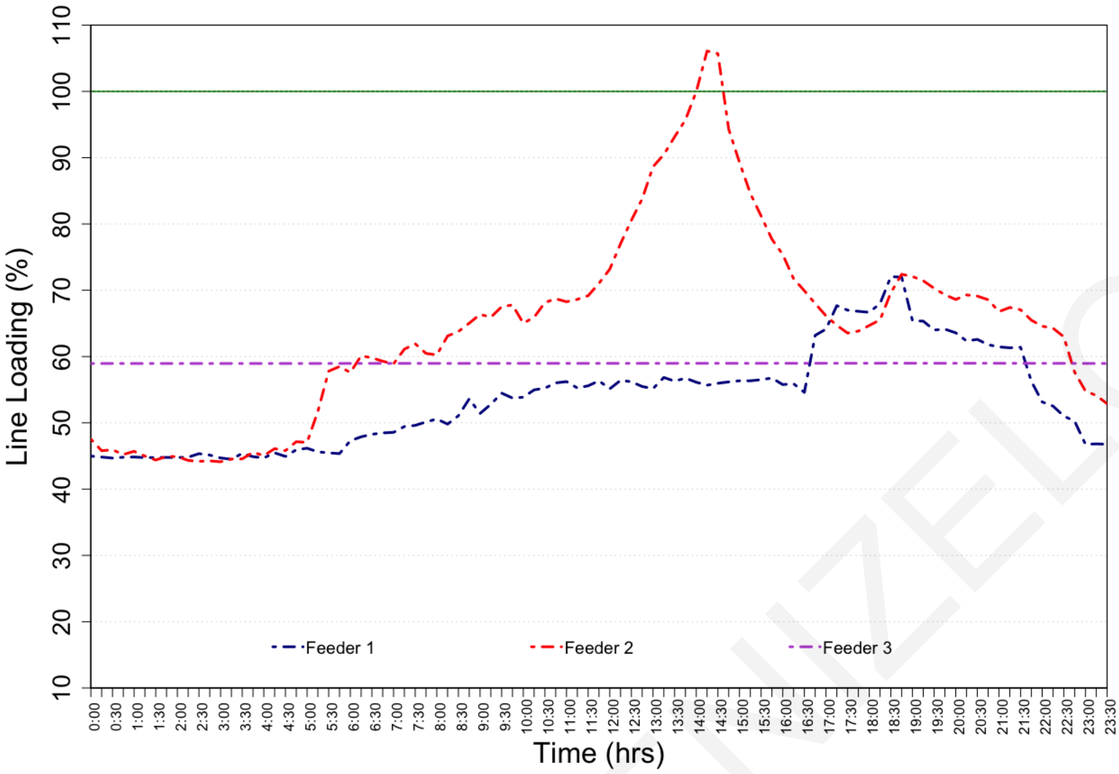


Figure 4.5: DR event due to line loading violation at Feeder 2.

Following the proposed DR framework, a DR request is initiated by the DSO (EAC) to the local Aggregator (UCY). Both violation levels correspond to a Normal Flexibility event. The proposed DR framework identifies the available and applicable customers who can participate during the specific time of the DR event. Only the assets connected to the second feeder can effectively contribute in this particular DR event, as it is a local congestion problem. It is important to note that DERs generators are not eligible to participate in this scenario as reducing the active power set-point can only contribute in restoring overvoltage events. An overview of the associated assets, including the available flexibility volume, the contracted prices as well as the performance indices, is presented in Table 4.5. As already indicated the minimum and maximum flexibility volume is defined in each contract, while the average flexibility volume and the performance indices are estimated based on historical DR events participation.

Table 4.5: Overview of assets associated with the local congestion event.

						Performance Indices (%)		
Asset ID	Flexibility Price [/€kWh]	Penalty [/€kWh]	Minimum Flexibility Volume [kWh]	Maximum Flexibility Volume [kWh]	Average Flexibility Volume [kWh]	Reliability	Absolute Fairness	Capacity Fairness
121CA	0,0926	0,0154	28	32	32	0.55	0.77	0.82
122CA	0,0760	0,0127	25	30	29	0.67	0.62	0.72
123CA	0,0841	0,0147	41	45	43	0.73	0.69	0.73
124CA	0,0777	0,0130	38	44	42	0.81	0.73	0.69
124CB	0,1013	0,0169	52	59	58	0.59	0.81	0.53
125CA	0,0976	0,0163	25	27	26	0.66	0.59	0.52
126CA	0,0768	0,0128	33	37	33	0.71	0.79	0.69
127CA	0,0890	0,0148	28	28	28	0.68	0.83	0.72

The first level of the optimisation function will identify all the possible combinations of customers who can participate in this DR event, while the optimisation weight of each combination is estimated based on the flexibility volume, price and the performance indices. The second level of the optimisation function identifies all combinations that will ensure the stable operation of the whole distribution test network. The minimum required flexibility for restoring the line loading below the nominal level, while maintaining the distribution network balancing is estimated to be 138 kWh for the whole period of the violation. The outcome of the bi-level optimisation function is the optimal combination (minimum optimisation weight) of assets (customers) accompanied by the individual flexibility volume that each asset must provide. The aggregated value of all individual flexibility volumes is equal to the total required flexibility.
For comparison reasons, Table 4.6 summarizes the thirty different combinations of assets that can meet the requested flexibility volume, while satisfying the grid constraints. As depicted in the table, even though the third combination is the most profitable for the Aggregator, as it would cost the least (€10.91) for triggering, the results of the optimisation function demonstrate that the first combination of assets (122CA, 124CA, 126CA,127CA) is the optimum selection as it would result in a more reliable and fair option, while the cost for triggering is marginally (€10.95) higher than the most profitable option.

As can been seen in Fig. 4.1, every transaction between the proposed framework and the external stakeholders (i.e. DSO and Aggregator) is based on the OpenADR standard and is issued to the blockchain, establishing interoperability, security and integrity. More specifically, after the identification of the optimal solution, the Aggregator proceeds to the extraction of the flexibility from the selected customers. Based on the proposed DR framework, this transaction is issued to the blockchain. The visualization of the transactions is presented via the Hyperledger Blockchain Explorer [115] tool. As shown in Fig. 4.6, a transaction is defined by a coded ID, a validation code and its its payload hash. Those are followed by the creator and endorser of the flexibility request, in this case the UCY which takes the role of the Aggregator. The chaincode name, the type as well as the time of the issuance is also included in the transaction. The read set portion of the read-write set is used for checking the validity of a transaction, while the write set portion of the read-write set is used for updating the versions and the values of the affected keys. As depicted in Fig. 4.6, the DR request from the Aggregator (vtnID) is directed towards the "Energy Center 3" customer (targetID). This information is included as part of Write Key #5 along with the flexibility

Table 4.6: Combination of the Aggregator's Assets.

No	Combination of Assets	Flexibility volume per asset [kWh]	Total Cost [€]	Optimisation Weight
1	122CA, 124CA, 126CA, 127CA	29, 44, 37, 28	10.95	27.3924
2	121CA, 124CA, 126CA, 127CA	29, 44, 37, 28	11.43	27.5839
3	122CA, 123CA, 124CA, 126CA	25, 41, 38, 34	10.91	27.9267
4	121CA, 122CA, 124CA, 126CA	28, 29, 44, 37	11.05	28.4938
5	122CA, 123CA, 126CA, 127CA	28, 45, 37, 28	11.24	28.8458
6	122CA, 123CA, 124CA, 127CA	25, 41, 44, 28	11.25	28.8563
7	121CA, 123CA, 126CA, 127CA	28, 45, 37, 28	11.71	29.0307
8	121CA, 123CA, 124CA, 127CA	28, 41, 41, 28	11.71	29.2083
9	121CA, 122CA, 123CA, 126CA	28, 28, 45, 37	11.34	29.9472
10	121CA, 122CA, 123CA, 124CA	28, 25, 41, 44	11.35	29.9578
11	123CA, 124CA, 125CA, 126CA	41, 38, 25, 34	11.45	33.2902
12	122CA, 124CA, 125CA, 126CA	30, 44, 27, 37	11.17	34.1016
13	121CA, 124CA, 125CA, 126CA	30, 44, 27, 37	11.67	34.2996
14	123CA, 124CA, 125CA, 127CA	41, 42, 27, 28	11.83	34.7603
15	122CA, 123CA, 124CA, 125CA	25, 42, 44, 27	11.48	35.5433
16	122CA, 123CA, 125CA, 126CA	29, 45, 27, 37	11.46	35.5550
17	121CA, 123CA, 125CA, 126CA	29, 45, 27, 37	11.94	35.7464
18	121CA, 123CA, 124CA, 125CA	28, 41, 42, 27	11.93	35.8618
19	124CA, 124CB, 126CA	42, 59, 37	12.08	36.2374
20	122CA, 124CB, 126CA, 127CA	25, 52, 33, 28	12.19	36.9895
21	123CA, 124CB, 126CA	42, 59, 37	12.35	37.6459
22	123CA, 124CA, 124CB	41, 38, 59	12.37	37.9241
23	121CA, 122CA, 124CB, 126CA	28, 25, 52, 33	12.29	38.0909
24	121CA, 122CA, 124CB, 127CA	28, 25, 57, 28	12.75	39.9532
25	124CB, 125CA, 126CA, 127CA	52, 25, 33, 28	12.73	42.3530
26	122CA, 124CB, 125CA, 126CA	25, 52, 25, 36	12.37	43.0772
27	121CA, 124CB, 125CA, 126CA	28, 52, 25, 33	12.83	43.4545
28	121CA, 124CB, 125CA, 127CA	28, 55, 27, 28	13.29	45.4808
29	122CA, 124CB, 125CA, 127CA	25, 58, 27, 28	12.90	45.6934
30	121CA, 122CA, 124CB, 125CA	28, 25, 58, 27	13.00	46.7948

extraction signal of -28,000W (value) which is requested by the Aggregator for the specified 30 minute period (startTime, endTime). Finally, the payload encodes a reward (reward), which is equal to compensation, assuming that the "Energy Center 3" customer successfully dispatches the requested amount of flexibility over the DR signal's active period.

Following the issuance of a DR request, and upon its successful delivery, the status of the previously issued DR request transitions to an active status. The proposed DR framework concludes when the Aggregator, after the end of the request's active period, issues a completion transaction, which is also stored on the blockchain. Besides the status of the DR request that transitions to a completed status, the "Energy Center 3" is compensated

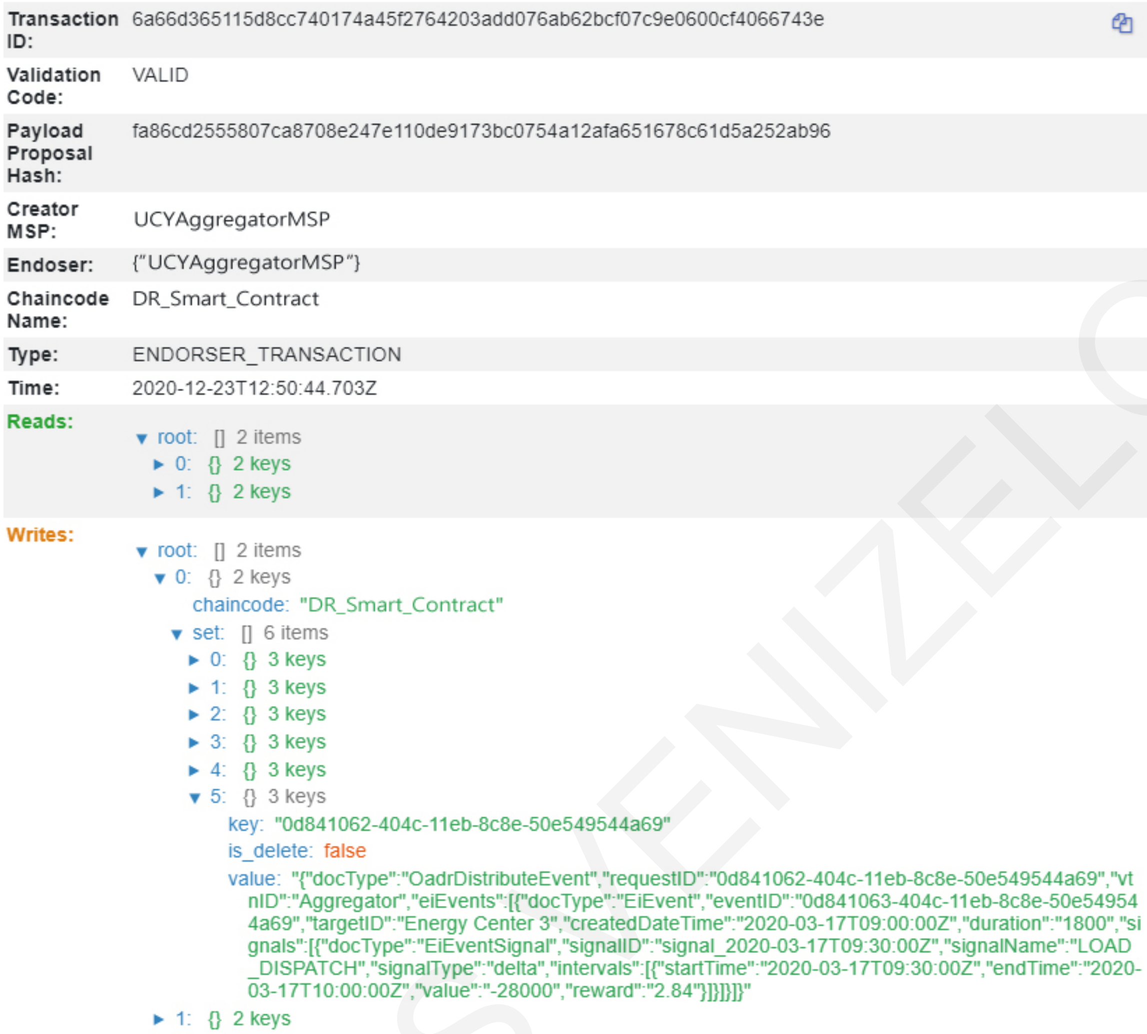


Figure 4.6: Issuance transaction of DR event containing a 30 minute load dispatch signal originating from the Aggregator and in which Energy Center 3 is specified as the target that should service it.

as indicated in the initial payload of the request. The transactions between the rest of the selected customers as well as the flexibility provision to the DSO, is executed in a similar manner.

The requested flexibility is physically extracted by the available deferrable loads of all the selected customers through hardware commands originated by the PPIS. The real consumption alteration, due to the flexibility provision, is measured by the SMs installed at each building and is fed back to test environment in order to verify that the operation of the proposed DR framework restored the grid back to normal operating conditions. As shown in Fig. 4.7, the line loading of all three feeders is below the nominal limit, highlighting the successful completion of the DR event, where the overloading violation at Feeder 2 is recovered and the balance of the distribution test network including the physical microgrid and nanogrid as well as the simulated distribution network is maintained.

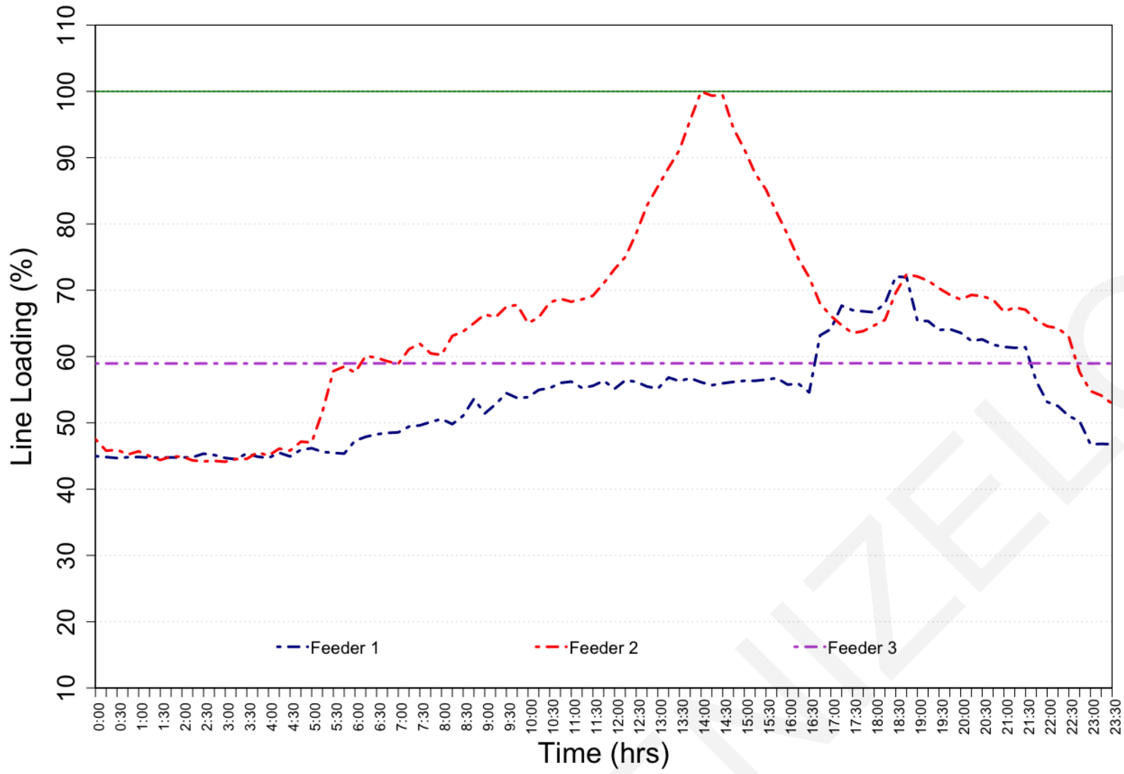


Figure 4.7: The combination of customers selected by the proposed DR framework restored the line loading level of Feeder 2 back to normal operating limits.

4.3.4 Computational Performance Evaluation of the Developed DR Framework

In order to gain helpful insights in the performance of the proposed DR framework, when applied in a real-life electricity market, a computational performance evaluation is undertaken. This evaluation focuses on the runtime of the proposed DR framework in an attempt to identify any potential bottlenecks related to the hardware used.

The computational performance evaluation is based on a 64-bit Windows 10 Professional operating system with an Intel Xeon E5-2650 v.4 CPU and 16 GB RAM. The CPU is clocked at 2.20 GHz. The modified IEEE 33-bus test system shown in Fig. 4.2 is used for the performance evaluation. The total number of busbars (low and medium voltage) and assets (consumption, production, storage) used in the investigated network are summarized in Table 4.7 and 4.8, respectively. The size of the dataset comprising the energy profiles of the investigated distribution network is relatively small (0.063 MB), while the internet connection bandwidth is very high at 1 Gbps meaning that there is no lag in the communication between the server and the equipment.

Table 4.7: Number of buses used in the investigated model.

	Low Voltage	Medium Voltage	
IEEE 33	33	-	
UCY micorgrid	13	13	
UCY nanogrid	10	-	
Total	**56**	**13**	**69**

Table 4.8: Total number of assets used in the investigated model.

	Consumption	Production	Storage	
IEEE 33	17	16		
UCY micorgrid	16	16		
UCY nanogrid	12	2	1	
Total	**45**	**34**	**1**	**80**

The evaluation is separated into seven scenarios, where the number of available assets that can participate in flexibility provision changes. The maximum number of available assets is limited to 8, as this is the maximum number of assets connected to a single feeder or busbar in the investigated distribution network. Each scenario is then divided into three sub-scenarios where the flexibility volume range offered by each asset changes between 2, 5 and 10 kWh. The evaluation considers all functions executed between the origination of a DR signal until its distribution to the final end-users/assets. The performance evaluation results are shown in the two following figures. The runtime tendency of the algorithm as the number of available assets and their flexibility volume range increases is exhibited in Fig. 4.8. For each one the three sub-scenarios, the linear as well as exponential trendline projection are added as a reference point for comparison. The runtime as a function of the flexibility volume for the scenarios where 2, 5 and 8 assets are available for flexibility provision is shown in Fig. 4.9. As expected, the runtime drastically increases with the increase of the investigated possible combinations that lead to the optimal solution. More specifically, for the first two sub-scenarios where the flexibility volume is tested at 2 and 5 kWh, it can be seen that the increase of the runtime is almost similar to the linear trendline projection. On the contrary, the runtime for the third sub-scenario, where the flexibility volume range per asset is 10 kWh, increases and gradually approaches the exponential trendline projection. The same conclusions can be derived by estimating the slopes of each curve. As shown in Fig. 4.8, the slope is 29.653, 63.476 and 121.19 for the 2, 5 and 10 kWh flexibility volume, respectively. The higher positive slope for the third sub-scenario verifies the steeper upward tilt to the curve, meaning that as the number of assets and the flexibility volume increases the higher the computational requirements.

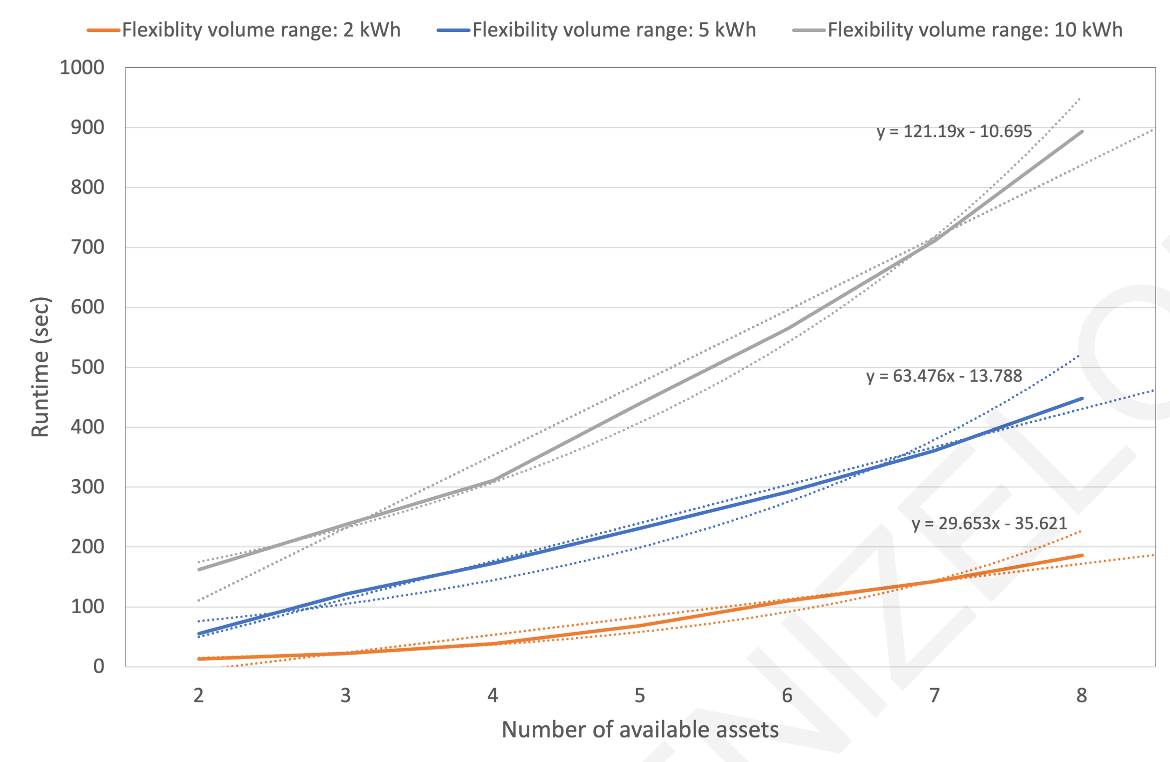


Figure 4.8: Runtime of the proposed DR framework as a function of the available assets.

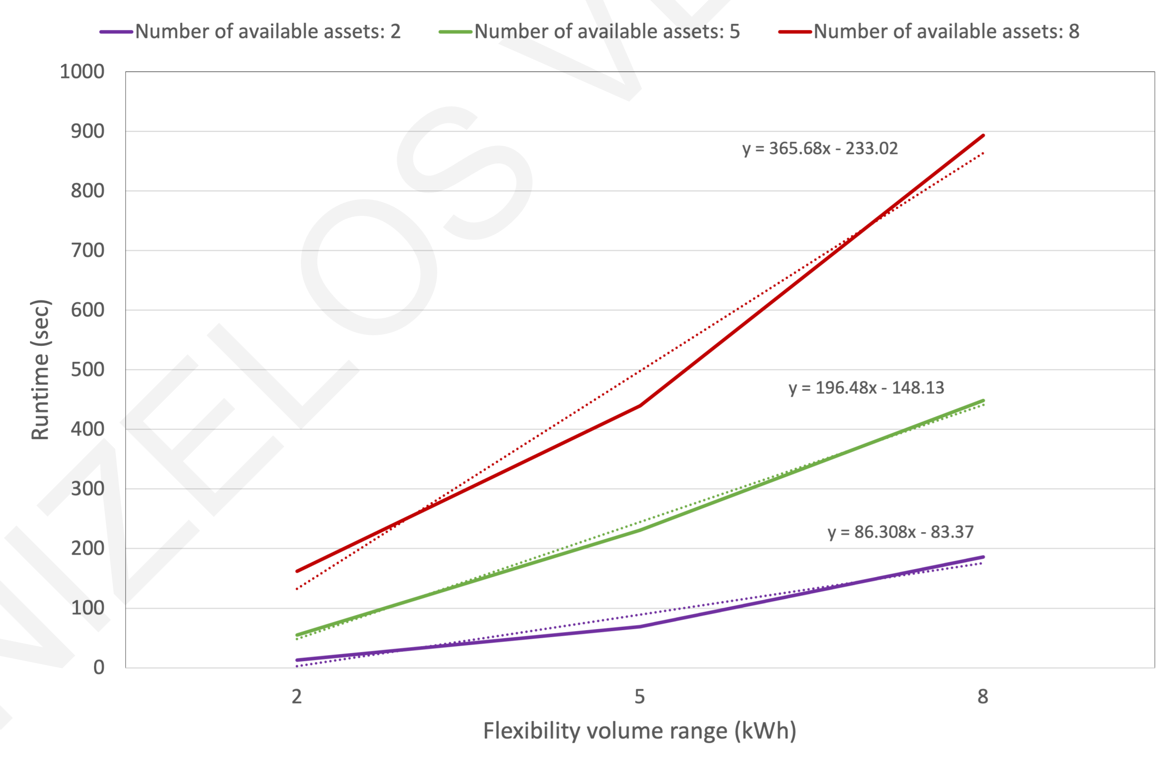


Figure 4.9: Runtime of the proposed DR framework as a function of the flexibility volume.

It is important to note that the results are indicative and concern the virtual machine and distribution network used for this performance evaluation. The specifications of the hardware used in this evaluation are low, leading to the very high runtime of approximately 15 minutes for the worst-case scenario (8 assets are available and each asset can offer up to 10 kWh of flexibility). It's obvious that in a real-life electricity market environment where assets are requested to participate in balancing market this level of runtime is prohibitive. However, this can be alleviated by utilising hardware with much higher specifications. This performance evaluation was undertaken to assess the runtime as a function of the different factors such as the power network characteristics, the available assets that can participate in an upcoming DR event as well as the flexibility volume that each asset can offer. For more credible results, benchmarking should be performed on various operating systems and hardware to properly identify the impact of higher-spec systems on the performance of the proposed DR framework.

4.4 Concluding Remarks

The immense introduction of Aggregators in the electricity markets will ultimately change how the DSOs manage their grids. In this chapter a novel DR framework for DSO-Aggregator coordination that utilises a constrained-objective optimisation function considering technical and energy market constraints to identify which assets should participate in each DR event, is presented. Aspects of the modern power systems, such as interoperability and security are also implemented. The performance of the proposed DR framework is evaluated based on a hybrid test network comprised of a physical microgrid and nanogrid network connected to a simulated distribution network. A real possible scenario where a line overloading problem is addressed through flexibility provision is investigated. The results highlighted that the proposed DR framework selects the optimal combinations of assets in terms of profitability, reliability and fairness while restoring the balance of the distribution network. The holistic approach followed by the proposed DR framework is showcased through the deployment of its OpenADR-inspired blockchain functionalities for all transactions held in the investigated scenario. The proposed DR framework can be seen as a key for enhancing the DSO-Aggregator coordination as well as a pathway for facilitating the role of the Aggregator, Utilities, Flexibility traders, etc. in a fully liberalized electricity market where security and interoperable communication is established at all scales of operation.

Chapter 5

Conclusions and Future Work

5.1 Conclusions and Achievements

In the future power grid, the penetration of DERs, such as energy storage, electric vehicles, roof-top photovoltaics, is expected to increase exponentially. Such modern power grids are facing many unprecedented challenges such as increased intermittency, operation uncertainties, and load consumption pattern shifts. From a market perspective, one could argue that, when the shares of renewables in the grid increase to high levels, their inherent fluctuations would cause more volatile spot market prices and higher imbalance prices, thus providing higher incentives, and possibly business models, for smart solutions. As the trend of investing on the supply-side alone to achieve reliable and secured grid operation will no longer be technically feasible or economically achievable, researchers in the power and energy community have shifted their efforts on developing a wide range of mechanisms to enable optimal energy management. With Demand-Side-Management (DSM) and Demand Response (DR), electricity customers can react to various incentives in order to alter their typical consumption patterns. Moreover, the objectives of DSM and DR are also broadened to unfold the full potential of customer-owned distributed energy resources (DERs) for providing a full range of grid services. These DER owners, also known as prosumers constitute one of the major classes of electricity customers.

Even though the research field of both DSM and DR is very rich with various studies, there are no concrete methodologies for optimally implementing such schemes that also consider the impact of prosumers, neither frameworks that can fully exploit the untapped demand-side flexibility. The contribution of this work lies in the introduction of a universally-applicable methodology for implementing and effectively deploying price-based DSM for residential prosumers. In support of this work, a pilot-network in Cyprus comprising of 300 prosumers with PV systems installed on their rooftops was established. The load profiles of the prosumers were recorded for one year (reference year). Using the collected datasets, the initial and baseline scenarios were defined in order to verify that an improvement on the participants' consumption profile will benefit the total aggregate consumption. In order to trigger a change in their typical energy habits, price incentives in the from of Time-of-Use (ToU) were offered to the prosumers. The derivation of the offered ToU tariff structure included the time blocks definition (peak and off-peak periods and the corresponding hours) and the respective rates. Initially, the seasonal average prosumer profiles were utilized in order to derive the daily ToU tariff time blocks by applying the Partitioning Around Medoid (PAM) clustering method. The respective ToU rates were calculated by exploiting an optimization function that maintained a neutral electricity bill in the case where the load profile remained unchanged. The optimization algorithm utilised in the proposed methodology is based on the net-load resulting in cost-effective ToU tariffs for both consumer and prosumer classes. Before applying the developed ToU tariffs to the pilot-network, a sensitivity analysis was conducted in order to estimate their potential impact. The main objective was to maximize the Load Factor (LF) of the seasonal residential load profile. For the summer and winter season, the maximum LF was 42.83% and 33.33% respectively and occurred when load was shifted mainly to the off-peak period. The developed ToU tariffs were approved by both the Electricity Authority of Cyprus and the Cyprus Energy Regulatory Authority and were applied to the prosumers of the pilot network for one year (implementation year). The results obtained, highlight that the ToU tariffs applied to the pilot network are effective to persuade the participants to shift loads from the peak to off-peak and shoulder periods. This was verified by observing the variation of the LF as well as the percentage of total consumption during peak hours when compared to the year before the real implementation of the derived ToU tariffs. More specifically, with respect to the reference year, the LF was increased from 40.65% to 41.43%, while the percentage of total consumption measured during peak hours was reduced by 3.19%, 1.03% and 1.40% for the summer, middle and winter season respectively. Additionally, the resulted seasonally dependent peak consumption reduction, which ranges between 1.03% and 3.19%, as well as the reduction of the overall consumption, by approximately 2%, proved that the application of the proposed scheme incentivised the participants to change their energy behaviour and minimize the need for electricity network reinforcement. The effectiveness of the proposed price-based DSM scheme was also verified by the regression analysis results as all coefficients appeared to be significant (below 5% level) and with the expected signs. Furthermore, the proposed methodology can be applied on both prosumers and consumers since the utilization of the net-load profile, and subsequently the refinement of the applied ToU structure, was found to reduce the percentage of unintended revenues below 35%. This led to the conclusion that the proposed price-based DSM scheme can be refined at regular intervals, by taking into consideration the new installed PV capacity and other relevant conditions in order to ensure that the optimum policies are reached. The overall net benefit to the society is further proved as the results of the performed cost-benefit analysis showed a large-scale deployment gain of €4.62mln, over a 15-year period, when considering also assumptions linked to the expected benefits as well as the values for the Capital and Operation Expenditure. While the above results represent important steps towards the realization of the proposed price-based DSM scheme, considerable investigation is required to analyse the potential risks related to costs and expected behavioural impacts. The results emanating from this work provide useful knowledge in the fields of energy behavioural patterns and flexibility potential of prosumers that can be vital instruments for policy makers to direct and encourage the implementation of a DSM scheme at a larger scale. The results of applying the proposed methodology on the pilot-network also highlighted that DSM schemes that offer price incentives to the electricity customers are considered as an easy pathway for deferring investments for network reinforcement and incorporating higher levels of DERs. In the end, the impact of various ToU price ratios on the peak kWh usage was investigated. Higher price ratio, than the one used, indicated higher peak kWh reductions. The regression results led to the conclusion that electricity customers are willing to sacrifice their thermal and visual comfort for a short period of time and offer the required flexibility in exchange for higher price incentives.

Subsequently and as worldwide electricity markets are maturing, the electricity prices will become more directly linked to the supply and demand equilibrium as well as to condition parameters related to the grid state. As both of the aforementioned factors dynamically, unpredictably and rapidly change, the System Operators are shifting their attention towards DR events that can effectively unlock the available demand-side flexibility on short notice. The application of DR signals is also accelerated with the advancement of technology that offers real-time monitoring of both supply and demand as well as identification of any grid violations, while enabling automated DR request and flexibility activation. Compensations offered to the electricity customers, for participating in a DR event, are generally accompanying a DSM scheme, thus offering higher price incentives that can fully unlock the available untapped flexibility. However, flexibility maximization depends on optimal DR distribution in the demand-side. The role of enabling small-scale electricity customers in participating in such DR events is undertaken by the Aggregator who is responsible for summing the multiple flexibility volumes available at the demand-side.

To address this, this thesis delves further into flexibility potential maximization by presenting an innovative framework for DR that aims to minimise the Aggregator's cost by considering technical and performance parameters. By extending the first part of this thesis, a novel DR framework for DSO-Aggregator coordination that utilises a constrained-objective optimisation function is proposed. The exploited optimisation function considers technical and energy market constraints to identify which assets should participate in each DR event. Aspects of the modern power systems, such as interoperability and security are also implemented. The performance of the proposed DR framework is evaluated based on a hybrid test network comprised of a physical microgrid and nanogrid network connected to a simulated distribution network. A real possible scenario where a line overloading problem is addressed through flexibility provision is investigated. The results highlighted that the proposed DR framework selects the optimal combinations of assets in terms of profitability, reliability and fairness while restoring the balance of the distribution network. The holistic approach followed by the proposed DR framework is showcased through the deployment of its OpenADR-inspired blockchain functionalities for all transactions held in the investigated scenario. The proposed DR framework, and subsequently the developed optimisation function, can be applied to any type of contracts (dynamic and/or static) between the DSO and Aggregator as well as between the Aggregator and his customers, while the technical parameters utilised in the optimisation function enable the exploitation of the developed framework for any network topology. To this end, the proposed DR framework can be seen as a key for enhancing the DSO-Aggregator coordination as well as a pathway for facilitating the role of the Aggregator, Utilities, Flexibility traders, etc. in a fully liberalized electricity market where security and interoperable communication is established at all scales of operation.

5.2 Future Work

Future work concerns the deeper analysis in self-learning algorithms and forecasting models that will capitalize on integrated multi-agent based, transactive energy matchmaking solutions, aiming to extend the current DR framework and propose new methods for DR-flexibility coordination that can be adopted in electricity markets in the next 5-10 years. More specifically, the future work aims to implement forecasting models both in terms of price and flexibility forecasting accompanied with comfort elasticity models that will lead to improved flexibility extraction and aggregation through clustering techniques.

The wholesale electricity market is approximated as a one-shot day-ahead market followed by a rescheduling in the balancing market. In reality, contracts for physical delivery of electricity range from years to seconds ahead depending on the type of product being sold, thus dynamically change throughout the days. To address this, the developed DR framework will be enhanced with an "Energy Price Emulator" component. This component will be responsible for the estimation of the price signal to be sent to each customer according to market conditions (e.g. wholesale price volatility) and building conditions (e.g. available demand flexibility and elasticity) in order to generate bespoke DR signals that will produce the desired, globally coordinated impact on the cumulative demand of the customers. Typical factors that influence electricity prices will be reviewed (such as season/day, weather, fuel prices, demand elasticity etc.) and price forecasting techniques will be employed (regression techniques, neural networks etc.). However, for use cases involving bilateral agreements and participation in e.g. capacity markets, the market price will be perceived as a known-constant value. The emulator will incorporate current and future price rate design approaches to enable exploration, investigation and evaluation of dynamic pricing schemes (e.g. Critical Peak Pricing, Real Time Pricing, ToU or novel ones potentially incentivising customers with above average and reliable demand flexibility) to stimulate the enrolment of risk averse customers, enhance protection of the energy poor as well as to bring the desired effect on the retailer's balance and finances.

Combining price along with demand elasticity forecasting will define the best aggregation strategies that will yield the maximum profit for all enrolled actors. To this end, a "Human-Centric Flexibility Extraction" component will be developed, whose purpose will be to analyse how occupants use loads and to create personal/group profiles that can quantitatively model their comfort preferences as well as their consumption and generation profiles.

External variables, e.g. weather or seasonal patterns, as well as internal variables, e.g. domestic habits, business processes, will be taken into account when generating comfort models. Furthermore, the comfort models will be used to estimate flexibility potential for the comfort-related loads – e.g. lighting, space heating, cooling – since typically comfort is achieved within parameter boundaries, not only at exact values. Using all the historical information collected about occupant behaviour, preferences and local demand and generation, this component will quantitatively estimate the comfort elasticity, which essentially represents how comfort preferences adapt to changing prices, e.g. consumers may be willing to give up some comfort when prices rise in order to avoid excessive energy bills. Comfort elasticity which involves comfort-related loads will be combined with demand elasticity to generate an aggregate elasticity model for the building that can be used to reproduce human behaviour to the extent possible. Furthermore, this component will be able to leverage local generation or storage capabilities in order to improve flexibility volume forecasts.

Both the demand elasticity and flexibility volume forecasts will be utilized for the creation of “Virtual Node Platform”. A “Virtual Node” is considered to be a neighborhood-based concept in which various customers are clustered based on various strategic possibilities. The clustering parameters will include not only their geographical locations but also their demand elasticity, flexibility forecasts as well as reliability and fairness indices that are already established in the proposed DR framework. When a customer alters one of these parameters (e.g. due to a renovation), he/she will be automatically reassigned to another cluster/Node. Each customer will be profiled and clustered within a node, and each node will be profiled and handled by the Aggregator with a node-specific DR strategy. The Aggregator will perceive each “Virtual Node” as a large prosumer with specific characteristics defined through an overall Node Profile. This segmentation will allow the Aggregator to further improve the flexibility aggregation by optimizing the use of his energy portfolio in terms of performance, grid balancing and capacity. Upon completion of the cluster, a “Virtual Node Platform” will undertake the role of creating profiles for every customer assigned to the Node, based on which, incoming DR signals will be distributed accordingly, following a top-down approach. On the other hand, when a Node produces or consumes more energy that it would normally do (and/or based on the Aggregator’s forecasting), a matchmaking algorithm will be activated towards identifying the best solution for the issue at hand. Initially, the “Virtual Node Platform” will try to optimally handle the assets belonging to the Node to absorb the problem internally, but in cases that this is found to be inadequate the matching process will be expanded to other Nodes. If then again the issue remains, the Node will dispatch a DR signal towards the Aggregator following a bottom-up approach and exploiting a bi-directional DR communication. Accordingly, if an imbalance issue is detected, the Node will follow the same approach by initially trying to balance the loads internally, then in coordination with other nodes (that have loads on the affected bus) and finally through the Aggregator.

Finally, the upgraded framework will be benchmarked on the already established pilot-network of 300 prosumers which will be upgraded with the required equipment as well as up-scaled to include feeders that represent real congestion points, so that all the functionalities can be tested and verified in real scenarios. The pilot-network will be upgraded in order to provide a heterogeneity of electricity customers as well as a number and capacity of intermittent generation. This will enable the testing of several different use cases and the concept of "Virtual Nodes". Similarly to the DSM-scheme, a holistic Cost-Benefit-Analysis (CBA) in full collaboration with the local Distribution System Operator will be conducted. The parameters for the CBA will include the improvement of energy efficiency in buildings, energy cost and emissions reduction, grid balancing (and investment deferral), security of energy supply, reduction of energy poverty, protection of vulnerable customers and enhanced market participation of energy consumers in order to evaluate the potential impact on the entire energy system. The CBA will also include the assessment and quantification of macro societal benefits, such as number of new jobs created, etc. Most of these social impacts will also be considered in the economic impact, monetizing the benefits provided.

The future DR framework will be simultaneously applied with the developed price-based DSM scheme in the upgraded pilot-network. This parallel operation will render the pilot-network as the ultimate test-bed that will enable various Stakeholders to benchmark future electricity market opportunities, thus developing future core solutions for DSM and DR toolkits with a scalability potential.

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