DEVELOPMENT AND APPLICATION OF STACKELBERG GAME-BASED STRATEGIES FOR ENERGY SHARING MANAGEMENT OF MICROGRIDS

Dissertation

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Dissertation

Department of Electrical and Electronics Engineering
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FINAL APPROVAL FOR THESIS

This thesis titled **“Development and Application of Stackelberg Game-Based Strategies for Energy Sharing Management of Microgrids"** has been prepared and submitted by **Özge EROL** in partial fullfillment of the requirements in “Eskişehir Technical University Directive on Graduate Education and Examination" for the Degree of Doctor of Philosophy (PhD) in Department of Electrical and Electronics Engineering has been examined and approved on 17/01/2023.

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SUPERVISOR APPROVAL

PhD student Özge EROL, whom I supervise, has completed this thesis titled **"Development and Application of Stackelberg Game-Based Strategies for Energy Sharing Management of Microgrids"**. According to my inspections, the work is scientifically and ethically appropriate for the student to take the thesis defense exam.

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ABSTRACT

Development and Application of Stackelberg Game-Based Strategies for Energy Sharing Management of Microgrids

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Department of Electrical and Electronics Engineering
Programme in Electrical Installation Systems
Eskişehir Technical University, Institute of Graduate Programs, January 2023

Supervisor: Assoc. Prof. Dr. Ümmühan BAŞARAN FİLİK

The main objective of this thesis is to develop energy sharing management strategies for microgrids. In accordance with this purpose, the problem of energy sharing management of a microgrid including photovoltaic - wind turbine prosumers with energy storage systems, and plug-in electric vehicle charging stations is modeled as a single-leader multi-follower Stackelberg game. The proposed game provides several significant contributions to literature. Firstly, the roles of prosumers can dynamically change as buyers or sellers according to the pricing policy of the leader in each time interval. Secondly, prosumers can take an active role in the microgrid by shaping their energy consumption strategies with their specified decision parameters. Thirdly, the energy demands of plug-in electric vehicle charging stations are determined as variable demands based on the operational characteristics of charging stations, considering an integer programming problem. Fourthly, by the necessary modifications identified for the presented approach, the microgrid can operate independently from the utility grid and satisfy the requirements of islanded mode. Finally, a proper billing scheme is designed to eliminate the negative effects caused by uncertainties, and thus, to increase the robustness of the game approach on real-time applications. In addition to these contributions, the proposed Stackelberg game approach is extended to solve the problem of energy sharing management between microgrids. To demonstrate the effectiveness of the developed strategies, case studies are performed on MATLAB software and results are presented.

Keywords: Stackelberg game, microgrid, energy management, islanded mode.

ÖZET

Mikro Şebekelerin Enerji Paylaşım Yönetimi için Stackelberg Oyun Tabanlı Stratejilerin Geliştirilmesi ve Uygulanması

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Bu tezin temel amacı, mikro şebekeler için enerji paylaşım yönetimi stratejileri geliştirmektir. Bu amaç doğrultusunda, enerji depolama sistemlerine sahip fotovoltaik - rüzgar türbini üreten tüketicileri ve elektrikli araç şarj istasyonlarını içeren bir mikro şebekenin enerji paylaşım yönetimi problemi, tek-liderli çok-takipçili Stackelberg oyunu olarak modellenmiştir. Önerilen oyun, literatüre birkaç önemli katkı sağlamaktadır. İlk olarak, üreten tüketicilerin rolleri, her bir zaman aralığında liderin fiyatlandırma politikasına göre alıcı veya satıcı şeklinde dinamik olarak değişebilmektedir. İkincisi, üreten tüketiciler, enerji tüketim stratejilerini belirledikleri karar parametreleri ile şekillendirerek mikro şebekede aktif rol alabilmektedir. Üçüncüsü, elektrikli araç şarj istasyonlarının enerji talepleri, bir tamsayı programlama problemi dikkate alınarak, şarj istasyonlarının çalışma özelliklerine dayalı değişken talepler olarak belirlenmektedir. Dördüncüsü, sunulan yaklaşım için tanımlanan gerekli değişikliklerle, mikro şebeke ağ şebekesinden bağımsız olarak çalışabilmekte ve ada modu gereksinimlerini karşılayabilmektedir. Son olarak, belirsizliklerin neden olduğu olumsuz etkileri ortadan kaldırmak ve böylece oyun yaklaşımının gerçek zamanlı uygulamalar üzerindeki gürbüzlüğünü arttırmak için uygun bir faturalandırma şeması tasarlanmıştır. Bu katkılara ek olarak, önerilen Stackelberg oyun yaklaşımı, mikro şebekeler arasındaki enerji paylaşım yönetimi problemini çözmek için genişletilmiştir. Geliştirilen stratejilerin etkinliğini göstermek için MATLAB yazılımında vaka çalışmaları yapılmış ve sonuçlar sunulmuştur.

Anahtar Sözcükler: Stackelberg oyunu, mikro şebeke, enerji yönetimi, ada modu.

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Özge EROL

17/01/2023

17/01/2023

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis, and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with “scientific plagiarism detection program" used by Eskişehir Technical University, and that “it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

Özge EROL

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ABBREVIATIONS

CS	: Charging Station
DER	: Distributed Energy Resource
ES	: Energy Storage
ESP	: Energy Sharing Provider
MAPE	: Mean Absolute Percentage Error
MGO	: Microgrid Operator
PEV	: Plug-in Electric Vehicle
PV	: Photovoltaic
RER	: Renewable Energy Resource
SOC	: State of Charge
WT	: Wind Turbine

NOTATION

λ_s^{PV}	: Export price between MGO and utility grid for PV energy
λ_s^{WT}	: Export price between MGO and utility grid for WT energy
λ_s^{m}	: Export price between ESP and utility grid
λ_b	: Import price between MGO and utility grid
λ_b^{m}	: Import price between ESP and utility grid
$\tilde{p}_s^{PV}$	: Forecasted internal selling price for PV prosumers
p_s^{PV}	: Internal selling price determined by MGO for PV prosumers
$\tilde{p}_s^{WT}$	: Forecasted internal selling price for WT prosumers
p_s^{WT}	: Internal selling price determined by MGO for WT prosumers
p_s^{m}	: Internal selling price determined by ESP for microgrids
$\tilde{p}_b$	: Forecasted internal buying price for prosumers and PEV CSs
p_b	: Internal buying price determined by MGO for prosumers and PEV CSs
p_b^{m}	: Internal buying price determined by ESP for microgrids
$\mathcal{G}$	: Set of prosumers
$\mathcal{B}$	: Set of buyers among prosumers
$\mathcal{S}$	: Set of sellers among prosumers
$\mathcal{S}^{PV}$	: Set of sellers among PV prosumers
$\mathcal{S}^{WT}$	: Set of sellers among WT prosumers
$\mathcal{V}$	: Set of PEV CSs
$\mathcal{M}$	: Set of microgrids
$\mathcal{M}_B$	: Set of buyers among microgrids
$\mathcal{M}_S$	: Set of sellers among microgrids
N	: Number of prosumers
N_B	: Number of buyers among prosumers
N_S	: Number of sellers among prosumers
N_S^{PV}	: Number of sellers among PV prosumers
N_S^{WT}	: Number of sellers among WT prosumers
N_V	: Number of PEV CSs
N_M	: Number of microgrids
$\tilde{E}_n^{g}$	: Forecasted energy generated by n^{th} prosumer

E_n^g : Energy generated by n^{th} prosumer

$\tilde{E}_l^m$: Forecasted energy generated by l^{th} microgrid

E_l^m : Energy generated by l^{th} microgrid

$\tilde{x}_n$: Forecasted energy consumed by n^{th} prosumer

x_n : Energy consumed by n^{th} prosumer

x_n^a : Actual energy consumed by n^{th} prosumer

$\tilde{x}_l^m$: Forecasted energy consumed by l^{th} microgrid

x_l^m : Energy consumed by l^{th} microgrid

$\tilde{L}_i$: Forecasted load of i^{th} PEV CS

L_i : Load of i^{th} PEV CS

L_i^a : Actual load of i^{th} PEV CS

R : Profit of MGO

R^a : Actual profit of MGO

R_{upd}^a : Updated actual profit of MGO

R_{ESP} : Profit of ESP

$U_n^{PV,ES}$: Utility of n^{th} PV prosumer with an ES system

$U_n^{WT,ES}$: Utility of n^{th} WT prosumer with an ES system

U_i^{CS} : Utility of i^{th} PEV CS

U_l : Utility of l^{th} microgrid

a_n : Elasticity coefficient of energy consumption of n^{th} prosumer

b_n^b : Relative benefit from energy consumption of n^{th} buyer prosumer

$b_n^{s,PV}$: Relative benefit from energy consumption of n^{th} seller PV prosumer

$b_n^{s,WT}$: Relative benefit from energy consumption of n^{th} seller WT prosumer

b_n^{ss} : Relative benefit from energy consumption of n^{th} self-sufficient prosumer

f_i : Preference parameter of i^{th} PEV CS

$\tilde{d}_{p_n}$: Forecasted exchanging energy of ES system of n^{th} prosumer

d_{p_n} : Exchanging energy of ES system of n^{th} prosumer

$c_{d_{p_n}}$: Life loss cost of ES system of n^{th} prosumer

SOC_{p_n} : State of charge of ES system of n^{th} prosumer

η_{p_n} : Charging/discharging efficiency of ES system of n^{th} prosumer

E_n^{avl} : Available capacity of ES system of n^{th} prosumer

ζ^{χ} : Subsidy of generated PV or WT energy

δ_n : Hourly deviation of net energy of n^{th} prosumer

δ_i^{PEV} : Hourly deviation of load of i^{th} PEV CS

$\beta_{i,j}$: The weight of the edge (i, j)

α_l^s : Seller weighted average factor

α_l^b : Buyer weighted average factor

k_l : Preference parameter of l^{th} microgrid

1. INTRODUCTION

In Section 1.1, the background and existing literature about the content of this thesis are overviewed. In Section 1.2, the motivation and objectives of this thesis are presented. In Section 1.3, the outline of the subsequent chapters is given.

1.1. Background and Literature Overview

Microgrids have emerged as an important platform for evolving the existing power grid to a future smart grid in line with the growing demand for enhanced energy efficiency, reduced greenhouse gas emissions, and improved power reliability and quality [1, 2]. With the ongoing developments and innovations in distributed generation, advanced power electronics [3], energy storage (ES) [4], and modern communication technologies [5], microgrids facilitate the effective management and operation of complex and critical infrastructures. Microgrids are an ideal solution for ensuring secure energy distribution in small communities and industrial areas. They can adequately meet local energy demands by utilizing renewable energy generation, ES facilities, and upgraded energy policies in distribution networks [6, 7]. Thus, microgrids improve the efficiency of power systems, supply electricity that is highly reliable as well as cost-effective, and reduce transmission/distribution losses with the physical proximity of distributed energy resources (DERs) and loads [8].

In a typical microgrid architecture, different types of renewable energy resources (RERs) (such as photovoltaic (PV) panels and wind turbines (WTs)), loads, and ES systems are connected to the utility grid with proper monitoring, communication, protection, and control systems [9]. A microgrid can operate in either grid-connected mode or islanded mode, and it can switch seamlessly between these two modes according to the requirements and operational characteristics of the network [10, 11]. In normal conditions, a microgrid is connected to the utility grid through a point of common coupling [12] and acts as a subsystem of distribution systems. In this mode, local loads inside the microgrid are supplied by distributed generation units located near the loads [13]. The connection to the utility grid is aimed to transfer power between the microgrid and utility grid if there is demand or excessive energy. Thus, during the grid-connected mode, a microgrid reaps the advantages of power trading with the utility grid. However, for the time intervals in which an outage or a failure occurs in the utility grid, the microgrid disconnects from the utility grid and shifts its operation from grid-connected mode to islanded mode to ensure the system's stability and reliability [14]. In islanded mode, it is capable of ensuring continuous supply to demands by efficient operational integration of DERs, demand response, and load shedding. Not all microgrids have two modes of operation, some microgrids fully operate as islanded microgrids because they do not have access to the utility grid.

Microgrids may face some challenges in meeting local energy demands with the energy provided by DERs. This is caused by the stochastic, uncertain, and intermittent nature of RERs, which highly depend on environmental factors, and also uncertainties in load demands and schedules [15]. Considering the increasing incorporation of RERs, the effective coordination of energy sharing inside a microgrid plays a significant role in satisfying system constraints in either grid-connected mode or islanded mode. In conventional microgrids, a central entity ensures energy sharing within the microgrid, aiming to minimize the total cost. The end-users generally exhibit passive behaviors while supplying their energy needs from the microgrid [16]. However, in microgrids consisting of multi-parties, each party may have a different aim for selling, buying, consuming, or even storing energy depending on the adopted role. These parties can include prosumers, active end users with flexible loads, etc., which are assumed as rational and autonomous. Thus, the energy sharing in these microgrids can not be conducted considering only cost minimization [17]. In this regard, as microgrids become more complex, the key factor for the development and reliable operation of such microgrids is based on the definition of a robust energy management framework [18–20].

Energy sharing management maintains the supply-demand balance of a smart microgrid by adjusting power from/to the utility grid, DERs, and loads. The DERs and loads have the capability to communicate with the central unit and even directly with each other in a dynamic manner, enabling centralized, decentralized, or distributed optimization of microgrid operations [21]. Thus, the microgrid can operate as a self-controlled system dynamically interacting with different entities to optimize energy utilization based on individual rationality [22]. However, it may be challenging to perform energy management algorithms due to the unpredictable nature of renewable power generation and inconsistencies in load demands as well as rational or autonomous behaviors of active end-users [23, 24]. Considering these factors, researchers have directed their attention towards the energy management of microgrids with the aim of ensuring consistent, sustainable, and cost-effective operation of microgrids, while satisfying specified operational objectives and system constraints [25].

In the existing literature, there are many decision-making strategies and their solution methods applied for energy management of microgrids [26–28], including linear [29–34], nonlinear [35–38], dynamic [39–44], stochastic [45–51], and robust [52–55] programming techniques, metaheuristic approaches [56–60], fuzzy logic [61–63], neural network [64–67], and game theory [68–71]. Among these methods, game theory is an analytical as well as a conceptual framework with a set of mathematical tools enabling the study of complex interactions among independent rational agents [72]. This theory attempts to mathematically capture the behavior of individuals in strategic situations, in which an individual's success in making choices depends on the choices of others. More precisely, a game consists of a set of players, a set of moves (or strategies) available to those players, and a specification of payoffs for each combination of moves [73]. It is well-known that game theory is a powerful tool for representing interactions among self-interested players/agents and predicting their choices of strategies [74]. In game theory, there are several types of solutions, such as Nash, Stackelberg, and Bayesian [71].

Stackelberg games are a special kind of non-cooperative games, in which there exists a hierarchy among players. In a two-level game, players are classified as leaders and followers [75]. In the original work of Heinrich von Stackelberg given in 1934, the Stackelberg model applies to monopolistic conditions where a number of small firms follow the behavior of a large dominant firm, which is the case including a single leader and multiple followers [76]. Note that, in the literature of game theory, the Stackelberg model has been also extended to the case including multiple leaders and multiple followers [77]. In general, each player in a Stackelberg game is rational and selfish, aiming to maximize its utility. In addition, the leaders are in a position to enforce their strategies on the followers [78]. Hence, the leader takes action first, and then the follower responds to the leader's decisions in a rational manner [79]. It is assumed that the leader is aware that the follower will observe its decisions, and the leader possesses full knowledge of how the follower will react to its decisions. Once the decisions have been made, the leader must commit to them; that is, the leader cannot reverse its actions [80]. The leader is believed to have certain advantages that enable it to act first, such as the structural advantage of being a manufacturer over suppliers and customers. These advantages result in greater profits for the leader as compared to the follower. However, the leader must provide a certain level of incentives to the follower, or the follower may decline to participate in the supply chain. This scenario could render the leader's strategic plan infeasible or unprofitable [81].

When the previous works are considered, it is observed that Stackelberg games are effectively utilized to develop energy management strategies, particularly for energy trading between service providers and users, through the use of a leader-follower framework [82, 83]. Tushar et al. proposed a non-cooperative game and achieved a unique Stackelberg equilibrium to provide energy management of a smart grid consisting of a shared facility controller and multiple residential units [84]. Liu et al. proposed a game approach with a single leader and multiple followers to coordinate energy sharing in a microgrid including PV prosumers [85]. Ma et al. introduced a leader-follower game model for the energy management of a grid-connected microgrid including PV prosumers, and combined heat and power [86]. Bu and Yu proposed a game-theoretic scheme, in which real-time pricing based demand-side management is used, to coordinate the interactions between the electricity retailer and customers [87]. Maharjan et al. formulated a Stackelberg game that involves end-users and utility companies, intending to maximize the benefits of both parties, specifically the payoff of each user and the revenue of each utility company [88]. Meng and Zeng presented a Stackelberg game approach aiming for the maximization of a utility company's profit and minimization of its customers' payment bills [89]. Chen and Zhu provided a Stackelberg game-based framework to model the interactions between microgrids and generators by considering not only the physical constraints of the grid but also the economic factors [90]. Tushar et al. developed a single-leader multi-follower Stackelberg game approach to coordinate energy management between the central power station and consumers [91]. The proposed optimal distributed solution aims to minimize the total cost of the power station and maximize the benefits of end-users. Li et al. proposed a cooperative Stackelberg game model that captures the interaction between a retailer and several prosumers, with the retailer acting as the leader to coordinate peer-to-peer energy transactions among the prosumers through the pricing strategies [92]. Liu et al. introduced a leader-follower game model for the multiparty energy management of combined heat and power-based microgrids with thermal and electricity demand responses [93]. Yin et al. presented a two-stage Stackelberg game model for the energy management of aggregate prosumers in a virtual power plant considering the uncertainties of renewable energy output and market price [94]. Anoh et al. developed a multi-leader multi-follower game-based framework to optimize energy sharing in a virtual microgrid consisting of consumers and producers [95]. Shen et al. established a single-leader multi-follower game to formulate the interactions among a DER aggregator, day-ahead energy and reserve markets, and distribution system, considering the security check [96]. Liu et al. proposed a game model that enables energy sharing between PV prosumers in two different modes as direct sharing, and buffered sharing which involves the ES system [97]. Matamala and Feijoo proposed a two-stage stochastic Stackelberg game with a chance constraint approach to model microgrid operations considering the uncertainty of renewable power generation and electricity prices [98]. Erol and Başaran Filik presented a Stackelberg game approach to coordinate energy sharing in a microgrid that includes PV and WT prosumers [99]. The authors also proposed a leader-follower game model aiming to provide flexibility to end-users by addressing the problem given in [99] more comprehensively with the inclusion of ES systems and plug-in electric vehicle (PEV) charging stations (CSs) in the microgrid [100]. Jiang et al. established a Stackelberg game-based planning approach to formulate the interactions in an integrated community energy system, aiming to maximize the profit of the energy server and minimize the energy bill of the energy consumer [101]. Huang et al. designed a dynamic pricing model based on the Stackelberg game, in which the energy service provider optimizes the planned output strategy and load curve of users considering both its profit and the interests of users [102]. Zhang et al. constructed a non-cooperative Stackelberg game framework with the aim of optimizing the power transaction between the integrated energy system operator and integrated energy systems [103]. The framework utilizes dynamic pricing to achieve optimal energy efficiency and economic benefits while taking into account costs. Cai et al. proposed a day-ahead optimal scheduling model for a hybrid AC/DC multi-energy microgrid considering uncertainties and Stackelberg game-based integrated demand response [104]. Li et al. proposed a Stackelberg game-based framework for the optimal scheduling of integrated energy systems through coordinating renewable energy generations and integrated demand response [105]. He et al. presented a leader-follower game to model the interaction between the retailer and consumers by designing customized prices based on consumption patterns and occupancy status of different consumers [106]. Luo et al. formulated a multi-leader multi-follower Stackelberg game model for the energy scheduling of a three-level integrated energy system including electricity and natural gas utility companies, smart energy hubs, and users [107]. Li et al. constructed a leader-follower-based stochastic scheduling for the energy management of multi-community integrated energy systems in an uncertain environment [108]. Tang et al. established a Stackelberg game model to coordinate energy management among multiple microgrids by determining optimal bus routes, where a plug-in electric bus (a special type of PEV) operator is the leader and microgrid operators (MGOs) are the followers [109].

1.2. Motivation and Objectives

In light of the aforementioned works, the main objective of this thesis is to propose energy sharing management strategies for microgrids. Motivated by this objective, the problem of energy sharing management of a microgrid including PV-WT prosumers with ES systems, and PEV CSs is discussed. Following the formulation of the problem, a single-leader multi-follower Stackelberg game approach is proposed considering the flexibility as well as behavioral/operational characteristics of end-users, and requirements of the network. The proposed approach designates the MGO as the leader responsible for managing energy sharing within the microgrid by establishing a pricing scheme, with PV-WT prosumers and PEV CSs acting as followers. Prior to the start of the game, a decision-making strategy for day-ahead ES scheduling covering a 24-hour time period is presented to determine the amount of charging or discharging energy required for each prosumer's ES system. Since the proposed game approach requires the exact implementation of the strategy determined by the leader, it is of great importance to deal with the uncertainties of renewable energy generation, charging/discharging energy of the ES systems, and energy consumption. Thus, possible negative effects of these uncertainties on the outcome are minimized by designing a billing scheme within the scope of this thesis. After implementing the energy sharing management for a single microgrid, the problem is extended to address the management of energy sharing between microgrids.

Briefly, the contributions of this study to the existing literature can be outlined as

- The problem of energy sharing management of a microgrid is addressed comprehensively, including two typical types of prosumers equipped with ES systems, and PEV CSs. By the proposed single-leader multi-follower Stackelberg game approach, the energy management problem of the microgrid is discussed from the perspective of the MGO, aiming to coordinate energy sharing to attain the highest profit while considering the interests of all prosumers and PEV CSs.

- In the existing studies, seller and buyer roles owned by prosumers are determined based on their forecasted energy production and consumption values at the beginning of each time interval, and these roles remain fixed even if a change in the role could lead to greater benefits according to updated prices. In the proposed approach, after the game is performed for each time slot, the roles of prosumers can change from seller to buyer or buyer to seller in response to the prices set by the MGO. Therefore, prosumers have the flexibility to switch their roles based on the final prices, rather than being constrained to their initial roles. This enables greater adaptability and potential for increased benefits.
- In the previous studies, the chosen utility functions of prosumers do not incorporate prosumer-based parameters that can enhance the energy sharing problem of the MGO in prosumers' interests. However, in this study, the decision parameters of prosumers, which can be specified in accordance with their preferences, are included in the utility functions. Together with these decision parameters, the behavioral characteristics of prosumers are integrated into the problem and considered in the solution. As a result, the energy management strategies of prosumers can be obtained based on their specified parameters reflecting the behavioral characteristics, which allows for a more active role of prosumers in the problem.
- Consumption limits of prosumers are defined in the problem as non-linear constraints. In addition, state of charge (SOC) limits of ES systems are integrated into the ES planning of prosumers. By including these constraints in the non-linear programming problem discussed, the distribution of prosumers to buyer, seller, and self-sufficient sets can be made more accurately.
- In similar studies, PEV CSs are considered as regular consumers like buyer prosumers that supply their energy demands from the microgrid as total loads independent from vehicle numbers and charging levels. In the hereby approach, while designing the energy management algorithm of the microgrid, the problem of planning the energy demands of PEV CSs has been transformed from a non-linear programming problem into an integer programming problem. Relevant changes have

been made so that the problem of determining loads of PEV CSs is handled as determining the number of vehicles over the specified vehicle charge levels. This vehicle-based planning provides the consideration of operational characteristics of PEV CSs during problem-solving, which improves the real-time application of the approach.

- Game-theoretic approaches are generally performed aiming for the maximization of profit while reducing the energy exchange with the grid. However, because of some situations such as planned outages or maintenance, it is crucial for a microgrid to disconnect from the utility grid, and therefore, to eliminate the energy need over the grid by moving away from the goal of profit maximization. In this regard, necessary modifications to the underlying approach are presented in this study to enable the transition from grid-connected mode to islanded mode in some situations where it is beneficial or necessary for the microgrid to be in islanded mode.
- Game-theoretic approaches highly depend on forecasted energy values, and the accuracy of the forecasting directly affects the output of end-game strategies on real-time applications. Considering this point, the possible negative effects caused by the forecasting errors or the mismatches between determined and actual energy values are eliminated by designing a billing scheme under twelve different cases for the problem addressed in this thesis. Thus, with the billing procedure established for such a comprehensive problem, it is aimed to contribute to the literature.
- The game approach proposed for energy sharing management of a single microgrid has been extended to address the problem of energy sharing management between multiple microgrids. With this extension, it becomes possible to create a comprehensive solution capable of efficiently managing the distribution of energy across a broader network of microgrids while considering the preferences and constraints of individual microgrid owners.

1.3. Outline

A brief outline of the thesis is given in this section. A detailed outline of subsequent chapters is given at the beginning of each chapter. In Chapter 2, the problem of energy sharing management of a microgrid is introduced along with the game-based methodology proposed to address this problem. In Chapter 3, the billing mechanism, which is designed for eliminating the negative effects caused by uncertainties, is presented. In Chapter 4, the problem of energy sharing management between microgrids is described, together with the game approach proposed as a solution. In Chapter 5, real-like microgrid simulations are presented to show the effectiveness of the developed energy sharing management strategies. Finally, in Chapter 6, the key findings of the thesis are highlighted, and possible research objectives for the future are discussed.

2. ENERGY SHARING MANAGEMENT OF A MICROGRID

In Section 2.1, the formulation of energy sharing management problem is presented, which includes utility models of prosumers and PEV CSs, and profit model of the MGO. In Section 2.2, the definition of the proposed Stackelberg game model is given. In Section 2.3, the procedure for solving the considered problem is explained based on the day-ahead ES scheduling, the implementation steps for the Stackelberg game approach, and defined modifications associated with islanded mode.

2.1. Problem Statement

The problem of energy sharing management of a microgrid including prosumers and PEV CSs is addressed. Prosumers considered in this problem can be smart houses, buildings, or factories that contain either PV systems or WT systems, capable of both producing and consuming energy during specific periods [110]. In addition, prosumers are equipped with ES systems that enable them to charge or discharge energy based on a predetermined ES strategy. Thus, they can act as buyers or sellers in the microgrid depending on their produced energy from PV panels or WTs, consumed energy, and charging/discharging energy. Unlike the prosumers, PEV CSs only behave as buyers in the problem. As a centralized coordinator, MGO is responsible for conducting the optimization of energy sharing inside the microgrid. While the MGO aims to maximize its profit, both prosumers and PEV CSs prioritize their utilities. In this context, utility refers to the level of satisfaction attained or discomfort avoided as a consequence of an economic act.

In order to coordinate the energy sharing, internal selling price (p_s) and internal buying price (p_b) are, simultaneously, set by the MGO. When the amount of energy produced does not meet the energy need or there is surplus energy in the microgrid, the MGO can trade energy with the utility grid. This energy trading ensures the balance between supplied and demanded energy. According to the price tariff of Turkey in 2021, the prices of exported and imported energy between the MGO and utility grid are

- Export price (λ_s): PV energy: 0.133 USD/kWh
  WT energy: 0.073 USD/kWh on- and off-shore
- Import price (λ_b): 2.22 USD/kWh.

For each time slot t, internal prices $p_s[t]$ and $p_b[t]$ are determined by the MGO under the constraint $\lambda_s \leq p_s[t] < p_b[t] \leq \lambda_b$. As can be seen, the internal selling price is expected to be more than (or at least equal to) the export price (i.e., $\lambda_s \leq p_s[t]$) in order to make the energy sales of seller prosumers to the MGO more (or at least equally) profitable than the direct sales to the utility grid. Similarly, the internal buying price is expected to be less than (or at least equal to) the import price (i.e., $p_b[t] \leq \lambda_b$) in order to make energy purchases of buyer prosumers and PEV CSs from the MGO more profitable (or at least equally) than direct purchases from the utility grid. In short, with the defined pricing relation, both prosumers and PEV CSs can get more benefits from trading energy with the MGO instead of the utility grid directly. This encourages local consumption of renewable energy, and therefore, reduces the grid dependency of the microgrid.

As stated by the price tariff, the export prices for PV energy and WT energy are different, so these prices can be denoted as λ_s^{PV} and λ_s^{WT}, respectively. Accordingly, the internal selling price should also be expressed separately as $p_s^{PV}[t]$ and $p_s^{WT}[t]$ depending on the type of the prosumer.[1] Considering these definitions, the constraint on internal prices can be extended to $\lambda_s^{PV} \leq p_s^{PV}[t] < p_b[t] \leq \lambda_b$ and $\lambda_s^{WT} \leq p_s^{WT}[t] < p_b[t] \leq \lambda_b$. The pricing scheme of the microgrid is shown in Figure 2.1.

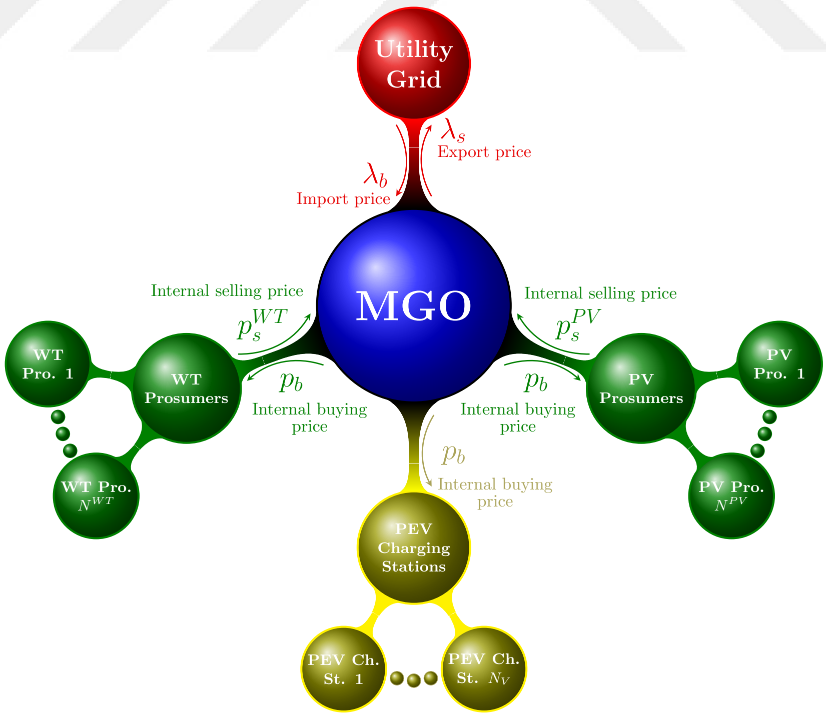

Figure 2.1. *Pricing scheme of the microgrid.*

[1] $p_s^{PV}[t]$ and $p_s^{WT}[t]$ denote internal selling prices, respectively, for PV prosumers and WT prosumers.

2.1.1. Utility models of prosumers with ES systems

Given the varying power profiles of prosumers, ES systems can serve as buffers to facilitate energy sharing when prosumers experience either a shortage or excess of energy. As ES technologies continue to advance, prosumers are increasingly adopting ES systems to save the electrical energy that is generated but not immediately utilized and to improve their energy management plans [111]. While it may be challenging to outfit every prosumer with an ES system, many prosumers incorporate at least small-scale ES systems to enhance the reliability of their overall power supply. Thus, the focus of this thesis is to tackle the problem of energy sharing among prosumers that possess self-supervised ES systems.

Let $\mathcal{G}$ denote the set of prosumers in the microgrid, and let $\mathcal{G}^{PV}$ and $\mathcal{G}^{WT}$ be, respectively, the set of PV prosumers and the set of WT prosumers.[2] Let $\mathcal{B}$ and $\mathcal{S}$ denote, respectively, the set of buyers and the set of sellers among the prosumers. Also, let $\mathcal{S}$ be partitioned into $\mathcal{S}^{PV}$ and $\mathcal{S}^{WT}$ such that they denote, respectively, the set of sellers among PV prosumers and the set of sellers among WT prosumers. Let $N = |\mathcal{G}|$ indicate the number of prosumers such that $N = N_B + N_S$ where $N_B = |\mathcal{B}|$ is the number of buyers and $N_S = |\mathcal{S}|$ is the number of sellers among the prosumers. Also, let $N_S^{PV} = |\mathcal{S}^{PV}|$ and $N_S^{WT} = |\mathcal{S}^{WT}|$ such that $N_S = N_S^{PV} + N_S^{WT}$.

For a time slot t, prosumers can behave as sellers or buyers, or they can be self-sufficient with balanced net energy. Considering the cost associated with the buffering process of the ES system, the utility perceived by n^{th} prosumer is modeled as a piecewise function:

$$U_n^{\chi,\text{ES}}\big(x_n[t]\big) = \begin{cases} \begin{array}{c} -a_n[t]\dfrac{\lambda_s^\chi}{p_s^\chi[t]}(x_n[t]-\tilde{x}_n[t])^2 + \lambda_s^\chi \dfrac{\lambda_b}{p_b[t]} b_n^{s,\chi}[t] x_n[t] \\ +p_s^\chi[t]\Delta_n[t] + \zeta^\chi E_n^g[t] - c_{d_{pn}}\big|d_{p_n}[t]\big| \end{array} & , \Delta_n[t] > 0 \\ \\ \begin{array}{c} -a_n[t]\dfrac{p_b[t]}{\lambda_b}(x_n[t]-\tilde{x}_n[t])^2 + \lambda_b \dfrac{\lambda_s^\chi}{p_s^\chi} b_n^b[t] x_n[t] \\ +p_b[t]\,\Delta_n[t] + \zeta^\chi E_n^g[t] - c_{d_{pn}}\big|d_{p_n}[t]\big| \end{array} & , \Delta_n[t] < 0 \\ \\ \begin{array}{c} -a_n[t](x_n[t]-\tilde{x}_n[t])^2 + b_n^{ss}[t] x_n[t] \\ +\zeta^\chi E_n^g[t] - c_{d_{pn}}\big|d_{p_n}[t]\big| \end{array} & , \Delta_n[t] = 0 \end{cases} \tag{2.1}$$

[2] $\mathcal{G} = \mathcal{G}^{PV} \cup \mathcal{G}^{WT}$.

where χ indicates either PV or WT depending on the type of n^{th} prosumer. For each prosumer n in a given time slot t, $a_n[t]$ is the elasticity coefficient of energy consumption; $b_n^{s,\chi}[t]$, $b_n^b[t]$, and $b_n^{ss}[t]$ are the coefficients of relative benefit from energy consumption for the seller (depending on the prosumer's type), buyer, and self-sufficient prosumer, respectively; $x_n[t]$ is the energy consumption; $\tilde{x}_n[t]$ is the forecasted energy consumption; $E_n^g[t]$ is the energy generation; $d_{p_n}[t]$ is the charging/discharging energy of the ES; $\Delta_n[t] = E_n^g[t] - x_n[t] - d_{p_n}[t]$ is the amount of energy sharing; $c_{d_{pn}}$ is the life loss cost of the ES; ζ^χ indicates the subsidy of PV or WT energy generation[3]. Considering the type of the prosumer, $p_s^\chi[t]\Delta_n[t]$ is the revenue of n^{th} prosumer from selling the excessive energy to the MGO at an internal selling price of $p_s^\chi[t]$. Meanwhile, $p_b[t]\Delta_n[t]$ is the negative revenue of n^{th} prosumer from purchasing the required energy from the MGO at an internal buying price of $p_b[t]$.

To reflect the principles of n^{th} prosumer according to possible internal prices, the coefficients of a_n and b_n should be determined based on the prosumer's characteristics [113]. However, these parameters are weighted appropriately depending on the prosumer's type and role, as they are determined on possible internal prices and their effects on the utility function should vary with changes in internal pricing. The parameter a_n that weights the elasticity of the consumption according to the forecasted consumption varies with respect to the ratio of the internal buying or selling prices to the corresponding utility grid prices, depending on the prosumer's role. This aims to increase elasticity at advantageous pricing. In addition, the parameter b_n is weighted according to an internal pricing that may be advantageous in the cross role. The objective here is to be able to direct role changes by reflecting the effect of advantageous pricing in the cross role.

For a specified $p_s^\chi[t]$ and $p_b[t]$ in a given time slot t, if $E_n^g[t] - x_n[t]$ is positive, n^{th} prosumer is producing more energy than it is consuming, resulting in excess energy. Conversely, if $E_n^g[t] - x_n[t]$ is negative, n^{th} prosumer is consuming more energy than it is producing, resulting in an energy deficit. In either case, the ES system is responsible for determining how to utilize surplus energy or address the energy deficit of the prosumer. According to a predetermined schedule, the ES system can be charged to store the excess energy or discharged to meet the prosumer's demand. If $d_{p_n}[t] > 0$, the ES system is

[3] In Turkey, local-content bonus on export price is 0.006-0.067 USD/kWh for PV energy and 0.006-0.037 USD/kWh for WT energy [112].

charged from the surplus energy $E_n^g[t]-x_n[t]$ or additional energy bought from the MGO. If $d_{p_n}[t] < 0$, the ES system is discharged generally to reduce the amount of energy purchased from the MGO when the production of n^{th} prosumer is insufficient to meet its consumption. Following the implementation of the ES strategy, if $\Delta_n[t] > 0$, n^{th} prosumer sells energy to the MGO. Otherwise, if $\Delta_n[t] < 0$, n^{th} prosumer purchases energy from the MGO.

The n^{th} prosumer needs to strike a balance between its revenue and convenience to maximize its utility $U_n^{\chi,\text{ES}}\big(x_n[t]\big)$. Each prosumer n optimizes its consumption $x_n[t]$ based on dynamic prices set by the MGO, utilizing a predefined ES strategy and required parameters. Therefore, it is important to note that $x_n[t]$ represents the decision variable for n^{th} prosumer and can be classified into two categories: baseload and flexible load. The term "baseload" refers to the minimum amount of demand that must always be fulfilled for prosumers, whereas the "flexible load" refers to the power demand that can be adjusted within certain limits based on the load type and the characteristics of prosumers. Accordingly, lower and upper bounds on the power consumption of n^{th} prosumer can be specified as $x_n^{\min}[t] \le x_n[t] \le x_n^{\max}[t]$. Since the prosumer's utility function is continuously differentiable with respect to the consumption $x_n[t]$, the extremum of $x_n[t]$ is

$$x_n[t] = \begin{cases} \tilde{x}_n[t] + \dfrac{p_s^{\chi}[t]}{\lambda_s^{\chi}} \left(\dfrac{\lambda_s^{\chi} \dfrac{\lambda_b}{p_b[t]} b_n^{s,\chi}[t] - p_s^{\chi}[t]}{2a_n[t]} \right), & \Delta_n[t] > 0 \\ \tilde{x}_n[t] + \dfrac{\lambda_b}{p_b[t]} \left(\dfrac{\lambda_b \dfrac{\lambda_s^{\chi}}{p_s^{\chi}[t]} b_n^{b}[t] - p_b[t]}{2a_n[t]} \right), & \Delta_n[t] < 0 \\ \tilde{x}_n[t], & \Delta_n[t] = 0 \end{cases} . \tag{2.2}$$

The internal prices $p_s^{PV}[t]$, $p_s^{WT}[t]$, and $p_b[t]$ can be initially assigned as λ_s^{PV}, λ_s^{WT}, and λ_b, respectively, for each time slot t ($t \in \{1, \ldots, 24\}$). Prosumers can increase their energy sales by reducing their consumption as the internal selling price rises. They can also sell the energy stored in their ES systems to the MGO. On the other hand, prosumers can increase their energy purchases by consuming more energy as the internal buying price declines. They can even purchase energy to charge their ES systems. However, it should be noted that the main priority of the ES system is to minimize the energy exchange of the respective prosumer.

2.1.2. Utility models of PEV CSs

Let $\mathcal{V}$ denote the set of PEV CSs in the microgrid, and let $N_V = |\mathcal{V}|$ indicate the number of these PEV CSs. Also, let ψ_i be the levels of charging power available in i^{th} PEV CS given by $P_i = \left[P_i^1, \ldots, P_i^{\psi_i}\right]$ for $i \in \mathcal{V}$. For each time slot t, the state of i^{th} CS is defined as a vector $\Phi^i[t] = \left[\, \phi_1^i[t] \ \cdots \ \phi_{\psi_i}^i[t] \,\right]$, where $\phi_j^i[t]$ is the number of PEVs charging with power P_i^j for $j = 1, \ldots, \psi_i$ and $i \in \mathcal{V}$. Since each CS can accept a limited number of vehicles, let the vehicle capacity of i^{th} CS be ρ_i where $\phi_1^i + \cdots + \phi_{\psi_i}^i \leq \rho_i$. In this way, for a given time slot t, the load of i^{th} PEV CS can be calculated as [114]

$$L_i[t] = \left[\, P_i^1 \ \cdots \ P_i^{\psi_i} \,\right] (\Phi^i[t])^T \, . \tag{2.3}$$

The utility function of i^{th} CS can be given, for each time slot t, as

$$U_i^{CS}\big(L_i[t]\big) = f_i[t] \ln(1 + L_i[t]) - p_b[t] L_i[t] \tag{2.4}$$

where $f_i[t] \ln(1+L_i[t])$ is the utility that i^{th} CS obtains through the vehicles, and $p_b[t] L_i[t]$ is the negative revenue obtained by i^{th} CS with purchasing the required energy from the MGO. For a given $p_b[t]$, the extremum of $L_i[t]$ for i^{th} CS (which achieves maximum utility for U_i^{CS}) can be given as

$$L_i[t] = \frac{f_i[t]}{p_b[t]} - 1 \, . \tag{2.5}$$

The preference parameter f_i reflects the behavioral characteristics of i^{th} PEV CS into its utility function. If a PEV CS has a high f_i value, it indicates that the considered CS is tended to serve more vehicles or allow higher charging levels to obtain maximum utility as compared to a PEV CS that has a low f_i value. However, since the load of i^{th} CS is determined by the P_i and Φ^i vectors as given in (2.3), it is necessary to determine a state vector $\Phi^i[t]$ which results the nearest load $P_i(\Phi^i[t])^T$ to the $L_i[t]$ in (2.5). This problem can be reduced to an integer programming problem such as

$$\begin{aligned} \max_{\Phi^i[t]} \quad & \left[\, P_i^1 \ \cdots \ P_i^{\psi_i} \,\right] (\Phi^i[t])^T \\ \text{s.t.} \quad & \left[\, P_i^1 \ \cdots \ P_i^{\psi_i} \,\right] (\Phi^i[t])^T \leq \min\left(l_i^{\max}[t], \max\left(l_i^{\min}[t], \frac{f_i[t]}{p_b[t]} - 1 \right) \right) \\ & \Phi^i[t] \geq 0_{\psi_i \times 1} \\ & \phi_1^i[t] + \cdots + \phi_{\psi_i}^i[t] \leq \rho_i \end{aligned} \tag{2.6}$$

where $\phi_1^i[t], \ldots, \phi_{\psi_i}^i[t]$ are integers, and the constraint of lower and upper bounds of $P_i(\Phi^i[t])^T$ can be described as $l_i^{\min}[t] \leq L_i[t] \leq l_i^{\max}[t]$.

2.1.3. Profit model of the MGO

The MGO functions as a central unit that sets internal prices and manages the transfer of power between prosumers and CSs. In a particular time slot denoted as t, the total amount of energy traded between sellers and buyers can be expressed as

$$E_s^{PV}[t] = \sum_{n \in \mathcal{S}^{PV}} \big(E_n^g[t] - x_n[t] - d_{p_n}[t]\big), \quad E_s^{WT}[t] = \sum_{n \in \mathcal{S}^{WT}} \big(E_n^g[t] - x_n[t] - d_{p_n}[t]\big) \ , \tag{2.7}$$

$$E_b[t] = \sum_{n \in \mathcal{B}} \big(x_n[t] - E_n^g[t] + d_{p_n}[t]\big) + \sum_{i \in \mathcal{V}} \big(L_i[t]\big) \tag{2.8}$$

where E_s^{PV} and E_s^{WT} are, respectively, the total energy sold to the MGO by seller PV prosumers in set $\mathcal{S}^{PV}$ and seller WT prosumers in set $\mathcal{S}^{WT}$. Also, E_b is the total energy that buyer prosumers in set $\mathcal{B}$ and PEV CSs in set $\mathcal{V}$ purchase from the MGO. Let $E_s^{\text{Tot}}[t] = E_s^{PV}[t] + E_s^{WT}[t]$. Thus, the profit function of the MGO is given for $E_s^{\text{Tot}}[t] > E_b[t]$ as

$$\begin{aligned} R\big(p_s^{PV}, p_s^{WT}, p_b\big)[t] = p_b[t]E_b[t] &- (p_s^{PV}[t]E_s^{PV}[t] + p_s^{WT}[t]E_s^{WT}[t]) \\ &+ \lambda_s^{PV}(E_s^{PV}[t] - \gamma[t]E_b[t]) \\ &+ \lambda_s^{WT}(E_s^{WT}[t] - (1 - \gamma[t])E_b[t]) \end{aligned} \tag{2.9}$$

and for $E_s^{\text{Tot}}[t] \leq E_b[t]$ as

$$\begin{aligned} R\big(p_s^{PV}, p_s^{WT}, p_b\big)[t] = p_b[t]E_b[t] &- (p_s^{PV}[t]E_s^{PV}[t] + p_s^{WT}[t]E_s^{WT}[t]) \\ &- \lambda_b(E_b[t] - E_s^{\text{Tot}}[t]) \end{aligned} \tag{2.10}$$

where the variable $\gamma[t]$ represents the priority parameter for selling PV and WT energy to the utility grid during a specific time slot t, with its value ranging between 0 and 1 (i.e., $0 \leq \gamma[t] \leq 1$). If $E_s^{\text{Tot}}[t] > E_b[t]$, the MGO sells excess energy to the utility grid. In this case, the MGO must ensure that the energy requirements of buyers are satisfied by utilizing energy from PV prosumers and WT prosumers at the rates determined by $\gamma[t]$ and $1 - \gamma[t]$, respectively. Considering the price tariff for PV and WT energy, it can be clearly seen that priority should be given to the use of energy generated by WT prosumers to meet the energy demands of buyers. In cases where the generated WT energy fails to fulfill the total energy demand, the remaining energy required can be supplied to buyers using the energy generated by PV prosumers. Thus, if $E_s^{WT}[t] \geq E_b[t]$, then $\gamma[t] = 0$. Otherwise, if $E_s^{WT}[t] < E_b[t]$, then $\gamma[t] = \big(E_b[t] - E_s^{WT}[t]\big)/E_b[t]$. Consequently, γ is not considered as a decision variable, but rather a conditional variable that is dependent on the production of WT energy. If $E_s^{\mathrm{Tot}}[t] \leq E_b[t]$, the MGO purchases energy from the utility grid at the price λ_b to satisfy the energy needs of buyers.

The MGO's decision variables include the internal prices $p_s^{PV}[t]$, $p_s^{WT}[t]$, and $p_b[t]$, which affect its energy trading activities. Specifically, the MGO sells energy to buyers, including buyer prosumers and CSs, at a price of $p_b[t]$ and purchases energy from sellers among PV and WT prosumers at prices of $p_s^{PV}[t]$ and $p_s^{WT}[t]$, respectively. The MGO's choices regarding these internal prices are crucial in determining its profitability and success in the energy market.

2.2. Stackelberg Game Model

The energy sharing management problem of the microgrid is modeled as a Stackelberg game with a single leader and multiple followers. In this game, the MGO is the leader and possesses decision-making authority over the pricing policy, while PV-WT prosumers and PEV CSs act as followers. The prosumers can adjust their energy consumptions within the bounds of their flexible loads, and they can switch between being a seller or a buyer based on the pricing strategy established by the MGO. PEV CSs can regulate the charging power levels of their PEVs and purchase their entire load demand from the MGO. The game can be mathematically formulated as

$$\begin{aligned} L = \Big\{ & (\mathcal{G} \cup \mathcal{V} \cup \mathrm{MGO}), \{\mathbf{X}_n\}_{n\in\mathcal{G}}, \{\mathbf{D}_{p_n}\}_{n\in\mathcal{G}}, \{\mathbf{L}_i\}_{i\in\mathcal{V}}, \{\mathbf{P}_b\}, \{\mathbf{P}_s^{PV}\}, \\ & \{\mathbf{P}_s^{WT}\}, \{U_n^{PV,ES}(x_n)\}_{n\in\mathcal{G}^{PV}}, \{U_n^{WT,ES}(x_n)\}_{n\in\mathcal{G}^{WT}}, \\ & \{U_i^{CS}(L_i)\}_{i\in\mathcal{V}}, R(p_s^{PV}, p_s^{WT}, p_b) \Big\} \end{aligned} \tag{2.11}$$

which consists of the following components:

- Prosumers in set $\mathcal{G}$ and PEV CSs in set $\mathcal{V}$ are followers. The prosumers and PEV CSs determine their optimum energy consumptions and loads, respectively, based on the pricing policy provided by the MGO.
- $\mathbf{X}_n$ is the set of energy consumption strategies of n^{th} prosumer $(n \in \mathcal{G})$ subject to the constraint $x_n^{\min} \leq x_n \leq x_n^{\max}$.
- $\mathbf{D}_{p_n}$ is the set of ES strategies of n^{th} prosumer $(n \in \mathcal{G})$.
- $\mathbf{L}_i$ is the set of load consumption strategies of i^{th} PEV CS $(i \in \mathcal{V})$ subject to the constraint $l_i^{\min} \leq L_i \leq l_i^{\max}$.

- $\mathbf{P}_b$, $\mathbf{P}_s^{PV}$, and $\mathbf{P}_s^{WT}$ are the sets of strategies, i.e., the vector forms of internal prices p_b, p_s^{PV}, and p_s^{WT}, respectively, determined by the MGO. For each time slot t, internal prices are obtained under the constraints $\lambda_s^{PV} \leq p_s^{PV}[t] < p_b[t] \leq \lambda_b$ and $\lambda_s^{WT} \leq p_s^{WT}[t] < p_b[t] \leq \lambda_b$.
- $U_n^{PV,ES}$ is the utility function of n^{th} PV prosumer with the assistance of an ES system, as given in (2.1), that states the benefit of the prosumer from consuming energy x_n, sharing energy Δ_n with the MGO, producing PV energy E_n^g, and charging/discharging ES with d_{p_n} considering the life loss cost of ES.
- $U_n^{WT,ES}$ is the utility function of n^{th} WT prosumer with the assistance of an ES system, as given in (2.1), that states the benefit of the prosumer from consuming energy x_n, sharing energy Δ_n with the MGO, producing WT energy E_n^g, and charging/discharging ES with d_{p_n} considering the life loss cost of ES.
- U_i^{CS} is the utility function of i^{th} PEV CS, as given in (2.4), that states the benefit of the CS from incoming vehicles and buying energy L_i from the MGO.
- $R(p_s^{PV}, p_s^{WT}, p_b)$ is the profit function of the MGO, as given in (2.9) and (2.10), that states the total profit obtained by conducting energy coordination among the prosumers and PEV CSs, and trading energy with the grid.

With the strategies determined, the main goals of PV-WT prosumers and PEV CSs are to maximize their respective utility functions, as expressed in (2.1) and (2.4), while the MGO's objective is to maximize its profits given in (2.9) and (2.10).

2.3. Methodology

The methodology of this study includes three subsections. First, a day-ahead ES planning model for each prosumer is implemented to improve the net power profile of the prosumers in the forthcoming time periods. To further improve energy sharing, a demand response model based on a Stackelberg game approach is performed to determine the energy consumption for each time slot $t = 1, \ldots, 24$, according to the internal prices set by the MGO. The primary objective of the demand response model is to maximize the operating profit while reducing energy trading with the utility grid. However, in some cases (e.g., planned outages due to the grid not being able to meet the energy need during peak hours or due to maintenance works), aiming to operate in islanded mode by eliminating the energy need over the utility grid may precede the maximization of the operating profit.

For this purpose, changes to the underlying approach are given in the last subsection, to enable the transition from grid-connected mode to islanded mode in some situations where it may be beneficial or necessary for the microgrid to be in islanded mode.

2.3.1. Decision-making process of ES systems

Since SOCs of the ES systems are time-coupled, prosumers often face challenges when deciding how much energy to charge or discharge during energy sharing in real-time. Therefore, it is more reasonable to determine the ES scheduling scheme via day-ahead optimization, despite the risk of forecasting errors and uncertainties, as opposed to real-time optimization [97]. Without the aid of such a day-ahead scheduling model for ES systems, charging and discharging decisions are based only on information from the current time interval, limiting the optimal utilization of stored energy [115]. Thus, in the context of this study, each prosumer adopts a day-ahead ES strategy to determine the exchanging energy of its ES system for the next 24-hour period. As a result, prosumers can effectively decide how to use the surplus energy or how to meet their energy needs with the assistance of such predetermined scheduling before the MGO can set internal prices for the first time slot.

At the beginning of the implementation process, each prosumer n (where $n = 1, \ldots, N$) forecasts its generated energy $\tilde{E}_n^g[t]$ and consumed energy $\tilde{x}_n[t]$, as well as internal prices $\tilde{p}_b[t]$, $\tilde{p}_s^{PV}[t]$, $\tilde{p}_s^{WT}[t]$ for $t = 1, \ldots, 24$. Based on these forecasted values, n^{th} prosumer determines the forecasted exchanging energy of its ES system, $\tilde{d}_{p_n}[t]$, for $t = 1, \ldots, 24$, by using the following model

$$
\begin{aligned}
\min_{\tilde{d}_{pn} \in \mathcal{D}_{\text{pro}}} \sum_{t=t_{\min}}^{t_{\max}} & \Bigg[\frac{\tilde{p}_b[t]}{\tilde{p}_b^{\max}} \max(\tilde{x}_n[t] - \tilde{E}_n^g[t] + \tilde{d}_{p_n}[t], 0) \\
& \quad - \frac{\tilde{p}_s^{\chi,\min}}{\tilde{p}_s^{\chi}[t]} \min(\tilde{x}_n[t] - \tilde{E}_n^g[t] + \tilde{d}_{p_n}[t], 0) \Bigg] \\
\text{s.t.} \quad & \left| \tilde{d}_{p_n}[t] \right| \le d_{p_n}^{\max} \\
& \text{SOC}_{p_n}^{\min} \le \text{SOC}_{p_n}[t] \le \text{SOC}_{p_n}^{\max} \\
& \text{SOC}_{p_n}[t_{\max}] = \text{SOC}_{p_n}^{\min}
\end{aligned}
\tag{2.12}
$$

where $\tilde{p}_s^{\chi}$ (χ denotes either PV or WT) is the forecasted internal selling price vector; $\tilde{p}_b$ is the forecasted internal buying price vector; $\tilde{p}_s^{\chi,\min}$ and $\tilde{p}_b^{\max}$ are, respectively, minimum internal selling price and maximum internal buying price for the considered time period[4]. For the ES system of n^{th} prosumer, $\text{SOC}_{p_n}[t]$ is the state of charge at the end of time slot t; $\text{SOC}_{p_n}^{\min}$ and $\text{SOC}_{p_n}^{\max}$ are, respectively, the lower and upper bounds of SOC; $d_{p_n}^{\max}$ is the upper bound of $\tilde{d}_{p_n}$, and $\mathcal{D}_{\text{pro}}$ is the feasible region of $\tilde{d}_{p_n}$. In addition, the relationship between $\text{SOC}_{p_n}[t]$ and $\tilde{d}_{p_n}[t]$ at the end of time slot t can be given as [116]:

$$\text{SOC}_{p_n}[t] = \begin{cases} \text{SOC}_{p_n}[t-1] + \dfrac{\tilde{d}_{p_n}[t] \times \eta_{p_n}}{E_n^{avl}}, & \tilde{d}_{p_n}[t] \geq 0 \\ \text{SOC}_{p_n}[t-1] + \dfrac{\tilde{d}_{p_n}[t]}{\eta_{p_n} \times E_n^{avl}}, & \tilde{d}_{p_n}[t] < 0 \end{cases} \tag{2.13}$$

where E_n^{avl} and η_{p_n} are, respectively, the available capacity and charging/discharging efficiency of the ES of n^{th} prosumer. It should be noted that $\text{SOC}_{p_n}[t_{\min} - 1] = \text{SOC}_{p_n}^{\min}$.

2.3.2. Procedure for Stackelberg game approach

Once the prosumers have established the day-ahead scheduling strategies for their ES systems, the MGO sets internal prices at the start of each time slot to maximize its profit and encourage prosumers and CSs to participate in energy sharing within the microgrid. The internal pricing procedure for each time slot $t \in \{1, \ldots, 24\}$ is outlined as

- For $i = 1, \ldots, N_V$, each PEV CS i forecasts an initial state vector $\Phi_0^i[t]$ which results an initial load $\tilde{L}_i[t] = P_i(\Phi_0^i[t])^T$ and obtains its preference parameter f_i based on (2.5) as $f_i[t] = p_b[t](\tilde{L}_i[t] + 1)$ where $p_b[t] = \lambda_b$. Then, each CS i submits $\Phi_0^i[t]$, P_i, $f_i[t]$, $l_i^{\min}[t]$, $l_i^{\max}[t]$, and ρ_i to the MGO.
- For $n = 1, \ldots, N$, each prosumer n submits $a_n[t]$, $b_n^{s,\chi}[t]$, $b_n^b[t]$, $b_n^{ss}[t]$, $\tilde{x}_n[t]$, $x_n^{\min}[t]$, $x_n^{\max}[t]$, $\tilde{E}_n^g[t]$, and $\tilde{d}_{p_n}[t]$ to the MGO where χ represents either PV or WT depending on whether the energy produced by n^{th} prosumer comes from solar or wind energy sources.
- Considering (2.2) for given instance $p_s^\chi[t]$ and $p_b[t]$, if $\tilde{\Delta}_n[t] > 0$ ($\tilde{\Delta}_n[t] = \tilde{E}_n^g[t] - x_n[t] - \tilde{d}_{p_n}[t]$ where $x_n[t]$ is obtained from (2.2) for $\Delta_n[t] = \tilde{\Delta}_n[t]$), n^{th} prosumer is considered in the set $\mathcal{S}^\chi$. Otherwise (if $\tilde{\Delta}_n[t] < 0$), n^{th} prosumer is considered in the set $\mathcal{B}$. Therefore, the sets $\mathcal{S}$ and $\mathcal{B}$ are determined dynamically based on prosumers in response to the changes in internal prices. As a result, for a given instance of $p_s^{PV}[t]$, $p_s^{WT}[t]$ and $p_b[t]$, the total energy exchange between the prosumers and CSs becomes

[4] $t_{\min}$ and $t_{\max}$ are, respectively, 1 and 24 for a general day-ahead scheduling problem.

$$\begin{aligned}
\tilde{E}_s^{\chi}\big(p_s^{PV},\, p_s^{WT},\, p_b\big)[t] &= \sum_{n\in\mathcal{S}^{\chi}} \left(\tilde{E}_n^{g}[t] - \tilde{x}_n[t] - \frac{p_s^{\chi}[t]}{\lambda_s^{\chi}} \frac{\frac{\lambda_s^{\chi}\lambda_b}{p_b[t]} b_n^{s,\chi}[t] - p_s^{\chi}[t]}{2a_n[t]} - \tilde{d}_{p_n}[t] \right), \\
\tilde{E}_b\big(p_s^{PV},\, p_s^{WT},\, p_b\big)[t] &= \sum_{n\in\mathcal{B}} \left(\tilde{x}_n[t] + \frac{\lambda_b}{p_b[t]} \frac{\frac{\lambda_s^{\chi}\lambda_b}{p_s^{\chi}[t]} b_n^{b}[t] - p_b[t]}{2a_n[t]} - \tilde{E}_n^{g}[t] + \tilde{d}_{p_n}[t] \right) \\
&\quad + \sum_{i\in\mathcal{V}} \left(\frac{f_i[t]}{p_b[t]} - 1 \right)
\end{aligned} \tag{2.14}$$

where χ denotes either PV or WT.

- Substituting (2.14) in (2.9) and (2.10), the MGO can determine the optimal internal prices $p_s^{PV*}[t], p_s^{WT*}[t]$, and $p_b^{*}[t]$ for the upcoming time slot t by solving the following nonlinear programming problem with linear and nonlinear constraints as

$$\begin{aligned}
\max_{\{p_s^{PV},\, p_s^{WT},\, p_b\}\in\mathcal{P}} \quad & R\big(p_s^{PV}[t], p_s^{WT}[t], p_b[t]\big) \\
\text{s.t.} \quad & \lambda_s^{PV} \le p_s^{PV}[t] < p_b[t] \le \lambda_b \\
& \lambda_s^{WT} \le p_s^{WT}[t] < p_b[t] \le \lambda_b \\
& \frac{f_i[t]}{l_i^{\max}[t]+1} \le p_b[t] \le \frac{f_i[t]}{l_i^{\min}[t]+1}, \; i = 1, \ldots, N_V \\
& c_n(p_s^{\chi}, p_b) \le [0\ 0]^T, \; n = 1, \ldots, N
\end{aligned} \tag{2.15}$$

where, for $n\in\{1,\ldots,N\}$, $x_n^{\min}[t] \le \tilde{x}_n[t] \le x_n^{\max}[t]$ bounds are defined in (2.15) as

$$c_n(p_s^{\chi}, p_b) = \begin{cases}
\begin{bmatrix} 2a_n[t]\lambda_s^{\chi}(x_n^{\min}[t] - \tilde{x}_n[t]) - p_s^{\chi}[t]\left(\lambda_s^{\chi}\dfrac{\lambda_b}{p_b[t]} b_n^{s,\chi}[t] - p_s^{\chi}[t]\right) \\ p_s^{\chi}[t]\left(\lambda_s^{\chi}\dfrac{\lambda_b}{p_b[t]} b_n^{s,\chi}[t] - p_s^{\chi}[t]\right) - 2a_n[t]\lambda_s^{\chi}(x_n^{\max}[t] - \tilde{x}_n[t]) \end{bmatrix}, & \tilde{\Delta}_n[t] > 0 \\[2ex]
\begin{bmatrix} 2a_n[t](x_n^{\min}[t] - \tilde{x}_n[t]) - \dfrac{\lambda_b^2\lambda_s^{\chi} b_n^{b}[t]}{p_s^{\chi}[t] p_b[t]} + \lambda_b \\ \dfrac{\lambda_b^2\lambda_s^{\chi} b_n^{b}[t]}{p_s^{\chi}[t] p_b[t]} - \lambda_b - 2a_n[t](x_n^{\max}[t] - \tilde{x}_n[t]) \end{bmatrix}, & \tilde{\Delta}_n[t] < 0
\end{cases}$$

and χ represents either PV or WT based on the classification of prosumer n. $\mathcal{P}$ is the feasible region of p_s^{PV}, p_s^{WT}, and p_b. Note that the initial internal prices $p_s^{PV}[t]$, $p_s^{WT}[t]$, and $p_b[t]$ of (2.15) are set, respectively, as λ_s^{PV}, λ_s^{WT}, and λ_b.

- The optimal internal prices $p_s^{PV*}[t], p_s^{WT*}[t]$, and $p_b^{*}[t]$ for the upcoming time slot t are declared to PV-WT prosumers and PEV CSs, after which all followers in the game modify their flexible loads for the upcoming time slot t in accordance with the announced internal prices. For $n = 1, \ldots, N$, n^{th} prosumer decides its optimal energy consumption based on (2.2) within its limits. Also, for $i = 1, \ldots, N_V$, i^{th} CS determines its optimum state vector $\Phi^i[t]$ from (2.6) using an initial feasible point

$\Phi_0^i[t]$ for $p_b^*[t]$. This results in the optimal load $L_i[t] = P_i(\Phi^i[t])^T$. Consequently, energy sharing management of the microgrid is completed for the time slot t.

For a given time period t, if $\tilde{E}_s^{\mathrm{Tot}}[t] > \tilde{E}_b[t]$, the MGO takes on the seller role. In this case, the objective function of the nonlinear programming problem expressed in (2.15) can be formulated using the internal prices, along with the relevant parameters and data provided by the prosumers and CSs as follows

$$\begin{aligned}
R\big(p_s^{PV}[t], p_s^{WT}[t], p_b[t]\big) &= \big(p_b[t] - \lambda_s^{PV}\gamma[t] - \lambda_s^{WT}(1-\gamma[t])\big)\tilde{E}_b[t] \\
&\quad + \big(\lambda_s^{PV} - p_s^{PV}[t]\big)\tilde{E}_s^{PV}[t] + \big(\lambda_s^{WT} - p_s^{WT}[t]\big)\tilde{E}_s^{WT}[t] \\
= \big(p_b[t] - \lambda_s^{PV}\gamma[t] - &\lambda_s^{WT}(1-\gamma[t])\big) \\
\times\Bigg(\sum_{n\in\mathcal{B}}\Bigg(&\tilde{x}_n[t] + \frac{\lambda_b}{p_b[t]}\frac{\frac{\lambda_s^{\chi}\lambda_b}{p_s^{\chi}[t]}b_n^b[t] - p_b[t]}{2a_n[t]} - \tilde{E}_n^g[t] + \tilde{d}_{p_n}[t]\Bigg) \\
+ \sum_{i\in\mathcal{V}}\left(\frac{f_i[t]}{p_b[t]} - 1\right)&\Bigg) + \big(\lambda_s^{PV} - p_s^{PV}[t]\big) \\
\times \sum_{n\in\mathcal{S}^{PV}}\Bigg(&\tilde{E}_n^g[t] - \tilde{x}_n[t] - \frac{p_s^{PV}[t]}{\lambda_s^{PV}}\frac{\frac{\lambda_s^{PV}\lambda_b}{p_b[t]}b_n^{s,PV}[t] - p_s^{PV}[t]}{2a_n[t]} - \tilde{d}_{p_n}[t]\Bigg) \\
+ \big(\lambda_s^{WT} - p_s^{WT}[t]\big) \times &\sum_{n\in\mathcal{S}^{WT}}\Bigg(\tilde{E}_n^g[t] - \tilde{x}_n[t] \\
- \frac{p_s^{WT}[t]}{\lambda_s^{WT}}&\frac{\frac{\lambda_s^{WT}\lambda_b}{p_b[t]}b_n^{s,WT}[t] - p_s^{WT}[t]}{2a_n[t]} - \tilde{d}_{p_n}[t]\Bigg)\,.
\end{aligned} \tag{2.16}$$

Otherwise, if $\tilde{E}_s^{\mathrm{Tot}}[t] \le \tilde{E}_b[t]$, the MGO takes on the buyer role. In this case, the objective function can be expressed as

$$\begin{aligned}
R\big(p_s^{PV}[t], p_s^{WT}[t], p_b[t]\big) &= (p_b[t] - \lambda_b)\,\tilde{E}_b[t] + \big(\lambda_b - p_s^{PV}[t]\big)\,\tilde{E}_s^{PV}[t] \\
&\quad + \big(\lambda_b - p_s^{WT}[t]\big)\,\tilde{E}_s^{WT}[t] \\
= (p_b[t] - \lambda_b)\times&\Bigg(\sum_{n\in\mathcal{B}}\Bigg(\tilde{x}_n[t] + \frac{\lambda_b}{p_b[t]}\frac{\frac{\lambda_s^{\chi}\lambda_b}{p_s^{\chi}[t]}b_n^b[t] - p_b[t]}{2a_n[t]} - \tilde{E}_n^g[t] + \tilde{d}_{p_n}[t]\Bigg) \\
+ \sum_{i\in\mathcal{V}}\left(\frac{f_i[t]}{p_b[t]} - 1\right)&\Bigg) + \big(\lambda_b - p_s^{PV}[t]\big) \times \sum_{n\in\mathcal{S}^{PV}}\Bigg(\tilde{E}_n^g[t] - \tilde{x}_n[t] \\
- \frac{p_s^{PV}[t]}{\lambda_s^{PV}}&\frac{\frac{\lambda_s^{PV}\lambda_b}{p_b[t]}b_n^{s,PV}[t] - p_s^{PV}[t]}{2a_n[t]} - \tilde{d}_{p_n}[t]\Bigg) + \big(\lambda_b - p_s^{WT}[t]\big) \\
\times \sum_{n\in\mathcal{S}^{WT}}\Bigg(&\tilde{E}_n^g[t] - \tilde{x}_n[t] - \frac{p_s^{WT}[t]}{\lambda_s^{WT}}\frac{\frac{\lambda_s^{WT}\lambda_b}{p_b[t]}b_n^{s,WT}[t] - p_s^{WT}[t]}{2a_n[t]} - \tilde{d}_{p_n}[t]\Bigg)\,.
\end{aligned} \tag{2.17}$$

Based on (2.16) and (2.17), the sets $\mathcal{B}$ and $\mathcal{S}$ are dynamically determined according to the changes in internal prices that occur during the solution process of (2.15). Also, the feasible regions of p_s^{PV}, p_s^{WT}, and p_b can be divided into two parts: $\mathcal{P}_S$ and $\mathcal{P}_B$. For a time slot t, if $\tilde{E}_s^{\mathrm{Tot}}[t] > \tilde{E}_b[t]$, then $\{p_s^{PV}, p_s^{WT}, p_b\} \in \mathcal{P}_S$, otherwise $\{p_s^{PV}, p_s^{WT}, p_b\} \in \mathcal{P}_B$, where $\mathcal{P}_S \cap \mathcal{P}_B = \emptyset$. All the steps of the real-time pricing are shown in the flowchart in Figure 2.2.

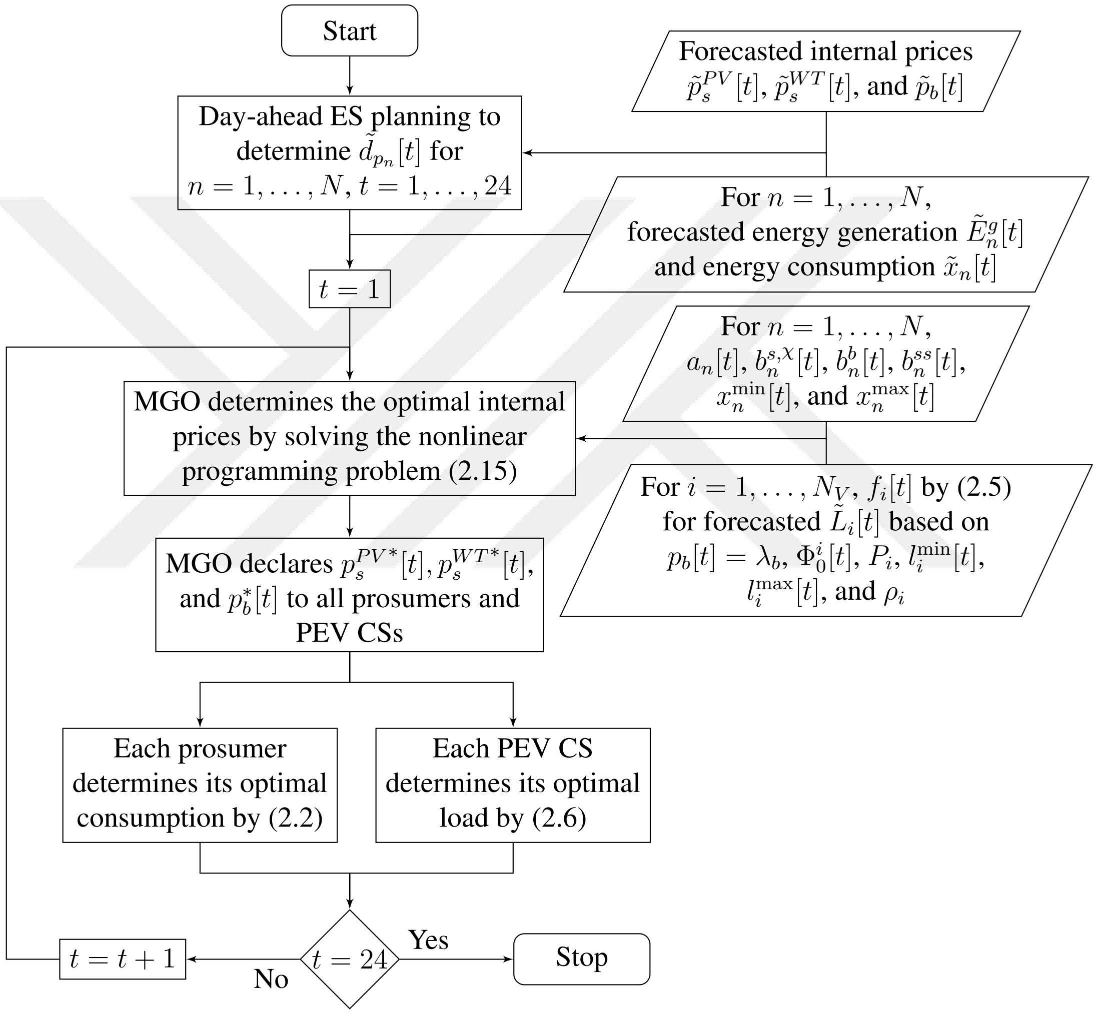

Figure 2.2. *Flowchart of the real-time pricing.*

2.3.3. Islanded mode

For a planned transition from grid-connected mode to islanded mode at the beginning of the time slot t, the MGO sets the optimal internal prices $p_s^{PV*}[t], p_s^{WT*}[t]$, and $p_b^*[t]$ for the upcoming time slot t as a result of solving the following nonlinear programming problem with linear and nonlinear constraints as

$$\begin{aligned} \min_{\{p_s^{PV}, p_s^{WT}, p_b\} \in \mathcal{I}} \quad & |\tilde{E}_b[t] - \tilde{E}_s^{Tot}[t]| \\ \text{s.t.} \quad & \max\left(p_s^{PV}[t], p_s^{WT}[t]\right) < p_b[t] \\ & \frac{f_i[t]}{l_i^{\max}[t]+1} \leq p_b[t] \leq \frac{f_i[t]}{l_i^{\min}[t]+1},\ i = 1, \ldots, N_V \\ & c_n(p_s^{\chi}, p_b) \leq [0\ 0]^T,\ n = 1, \ldots, N \end{aligned} \tag{2.18}$$

where $c_n(p_s^{\chi}, p_b)$ is given after (2.15) and $\mathcal{I}$ is the feasible region of p_s^{PV}, p_s^{WT}, and p_b for the modified cost function and constraints. As it can be seen, since there will be no energy trading between the utility grid and the microgrid, the upper and lower bounds limiting internal prices between the grid prices have been removed for the islanded mode.

3. DESIGN OF A BILLING SCHEME

Most of the proposed energy management strategies for microgrids depend on the forecasted energy values, and therefore, the accuracy of the forecasting directly affects the output of these strategies on real-time applications [85]. Since the game model proposed in this study is performed at the beginning of each time slot based on the forecasted generation, forecasted consumption, and charging/discharging energy obtained from ES scheduling based on these forecasts, the utilities of the prosumers and CSs, and the actual profit of the MGO may not be the same with their scheduling expectations in case of forecasting errors. In addition, the prosumers and CSs may fail to implement the end-game strategies while adjusting their consumptions and loads, respectively, based on the prices determined by the MGO, which can significantly affect the success of the proposed game approach. As a result, the forecasting errors or the mismatches between the determined and actual consumptions/loads may have negative effects on the considered method. To reduce these negative effects, a proper billing procedure guiding the followers is needed. Therefore, in this study, a billing scheme is proposed for the problem addressed to enhance the success of the overall energy management strategy.

At the beginning of the billing scheme design, the hourly deviations of net energy of the prosumers and PEV CSs are modeled. The hourly deviation of net energy of n^{th} prosumer is obtained considering the divergence of actual net energy from scheduled net energy as

$$\delta_n[t] = \begin{cases} (E_n^g[t] - x_n^a[t] - d_{p_n}[t]) - (\tilde{E}_n^g[t] - x_n[t] - \tilde{d}_{p_n}[t]), & \Delta_n[t] > 0 \\ (x_n^a[t] - E_n^g[t] + d_{p_n}[t]) - (x_n[t] - \tilde{E}_n^g[t] + \tilde{d}_{p_n}[t]), & \Delta_n[t] \leq 0 \end{cases} \tag{3.1}$$

where $x_n^a[t]$ is the actual energy consumption of n^{th} prosumer in a time slot t. Similarly, the hourly deviation of load of i^{th} PEV CS is obtained considering the divergence of actual load from scheduled load as

$$\delta_i^{PEV}[t] = L_i^a[t] - L_i[t] \tag{3.2}$$

where $L_i^a[t]$ is the actual load of i^{th} PEV CS in a time slot t. Thus, the total energy deviations of sellers and buyers are expressed as

$$\delta^{s,\mathcal{X}}[t] = \sum_{n \in \mathcal{S}^{\mathcal{X}}} \delta_n[t] \ , \quad \delta^b[t] = \sum_{n \in \mathcal{B}} \delta_n[t] + \sum_{i \in \mathcal{V}} \delta_i^{PEV}[t] \tag{3.3}$$

where χ denotes either PV or WT. By considering the total energy deviations given in (3.3), the actual profit of the MGO can be obtained in two cases as $E_s^{\text{Tot}}[t] + \delta^s[t] > E_b[t] + \delta^b[t]$ and $E_s^{\text{Tot}}[t] + \delta^s[t] \leq E_b[t] + \delta^b[t]$ where $\delta^s[t] = \delta^{s,PV}[t] + \delta^{s,WT}[t]$ in a time slot t.

If $E_s^{\text{Tot}}[t] + \delta^s[t] > E_b[t] + \delta^b[t]$, the MGO takes on the role of seller. The actual profit of the MGO is given as

$$\begin{aligned} R^a[t] =& R^o[t] + \left(p_b[t] - \lambda_s^{PV}\gamma^a[t] - \lambda_s^{WT}\left(1-\gamma^a[t]\right)\right)\delta^b[t] \\ &+ \left(\lambda_s^{PV} - p_s^{PV}[t]\right)\delta^{s,PV}[t] + \left(\lambda_s^{WT} - p_s^{WT}[t]\right)\delta^{s,WT}[t] \end{aligned} \tag{3.4}$$

where $R^o[t]$ is considered as in (2.9) and $\gamma^a[t]$ $(0 \leq \gamma^a[t] \leq 1)$ indicates the actual priority parameter for selling PV and WT energy by the MGO to the utility grid for a time slot t. In this case, if $E_s^{WT}[t] + \delta^{s,WT}[t] \geq E_b[t] + \delta^b[t]$, then $\gamma^a[t] = 0$. Otherwise, if $E_s^{WT}[t] + \delta^{s,WT}[t] < E_b[t] + \delta^b[t]$, then

$$\gamma^a[t] = \frac{\left(E_b[t] + \delta^b[t]\right) - \left(E_s^{WT}[t] + \delta^{s,WT}[t]\right)}{E_b[t] + \delta^b[t]} \ . \tag{3.5}$$

It is assumed that $\delta_n[t]$ and $\delta_i^{PEV}[t]$ values are small deviations, and therefore, they will not change the roles of prosumers and the MGO. Considering (3.4), the effects of prosumers and PEV CSs on the profit of the MGO can be analyzed as shown below:

Case 1: If n^{th} prosumer adopts the role of the seller and $\delta_n[t] > 0$, the prosumer sells more energy than the scheduled energy. Since the MGO is in the seller position, the excessive energy which is sold by the prosumer creates a negative effect on the profit of the MGO. In this case, the extra energy is sold by the prosumer at the price λ_s^p instead of $p_s^\chi[t]$ as a penalty, where

$$\lambda_s^p = \begin{cases} \lambda_s^{WT} & , E_s^{PV}[t] + \delta^{s,PV}[t] = 0, E_s^{WT}[t] + \delta^{s,WT}[t] \neq 0 \\ \lambda_s^{PV} & , E_s^{WT}[t] + \delta^{s,WT}[t] = 0, E_s^{PV}[t] + \delta^{s,PV}[t] \neq 0 \\ \max\left(\lambda_s^{WT}, \lambda_s^{PV}\right) & , E_s^{WT}[t] + \delta^{s,WT}[t] \neq 0, E_s^{PV}[t] + \delta^{s,PV}[t] \neq 0 \end{cases} . \tag{3.6}$$

Therefore, the MGO can balance its revenue with $\lambda_s^p\delta_n[t]$:

$$B_n[t] = p_s^\chi[t]\left(\tilde{E}_n^g[t] - x_n[t] - \tilde{d}_{p_n}[t]\right) + \lambda_s^p\delta_n[t] \ . \tag{3.7}$$

Case 2: If n^{th} prosumer adopts the role of the seller and $\delta_n[t] < 0$, the prosumer sells less energy than the scheduled energy. Since the MGO is in the seller position, selling less energy by the prosumer does not negatively affect the profit of the MGO. Therefore, n^{th}

prosumer still can sell the actual amount of energy at the price $p_s^{\chi}[t]$ without any penalty:

$$B_n[t] = p_s^{\chi}[t] \left(E_n^g[t] - x_n^a[t] - d_{p_n}[t] \right) \ . \tag{3.8}$$

Case 3: If n^{th} prosumer adopts the role of the buyer and $\delta_n[t] > 0$, the prosumer buys more energy than the scheduled energy. Since the MGO is in the seller position, buying more energy by the prosumer does not create a negative effect on the profit of the MGO. Therefore, n^{th} prosumer still can buy the actual amount of energy at the price $p_b[t]$ without any penalty:

$$B_n[t] = p_b[t] \left(x_n^a[t] - E_n^g[t] + d_{p_n}[t] \right) \ . \tag{3.9}$$

Case 4: If n^{th} prosumer adopts the role of the buyer and $\delta_n[t] < 0$, the prosumer buys less energy than the scheduled energy. Since the MGO is in the seller position, the energy that is not purchased by the prosumer creates a negative effect on the profit of the MGO. In this case, the MGO can balance its revenue by considering a penalty function as $p_b[t]\delta_n[t] - \lambda_s^d \delta_n[t]$ where

$$\lambda_s^d = \begin{cases} \lambda_s^{WT} & , E_s^{PV}[t] + \delta^{s,PV}[t] = 0, E_s^{WT}[t] + \delta^{s,WT}[t] \neq 0 \\ \lambda_s^{PV} & , E_s^{WT}[t] + \delta^{s,WT}[t] = 0, E_s^{PV}[t] + \delta^{s,PV}[t] \neq 0 \\ \min\left(\lambda_s^{WT}, \lambda_s^{PV}\right) & , E_s^{WT}[t] + \delta^{s,WT}[t] \neq 0, E_s^{PV}[t] + \delta^{s,PV}[t] \neq 0 \end{cases} . \tag{3.10}$$

Therefore, n^{th} prosumer is penalized for the unpurchased energy:

$$B_n[t] = p_b[t] \left(x_n^a[t] - E_n^g[t] + d_{p_n}[t] \right) - \left(p_b[t] - \lambda_s^d \right) \delta_n[t] \ . \tag{3.11}$$

Case 5: If $\delta_i^{PEV}[t] > 0$, i^{th} PEV CS buys more energy than the scheduled energy. Since the MGO is in the seller position, buying more energy by the CS does not cause a negative effect on the profit of the MGO. Thus, i^{th} CS still can buy the actual amount of energy at the price $p_b[t]$ without penalty:

$$B_i[t] = p_b[t] \left(L_i^a[t] \right) \ . \tag{3.12}$$

Case 6: If $\delta_i^{PEV}[t] < 0$, i^{th} PEV CS buys less energy than the scheduled energy. Since the MGO is in the seller position, the energy that is not bought by the CS creates a negative effect on the profit of the MGO. In this case, the MGO can balance its revenue with a penalty function as $p_b[t]\delta_i^{PEV}[t] - \lambda_s^d \delta_i^{PEV}[t]$ where λ_s^d can be found as in (3.10).

Thus, i^{th} CS is penalized for the unpurchased energy:

$$B_i[t] = p_b[t]\left(L_i^a[t]\right) - \left(p_b[t] - \lambda_s^d\right)\delta_i^{PEV}[t] \; . \tag{3.13}$$

As a result, for $E_s^{\text{Tot}}[t] + \delta^s[t] > E_b[t] + \delta^b[t]$, the profit of the MGO is updated as

$$\begin{aligned} R_{upd}^a[t] =& \sum_{n\in\mathcal{B}} B_n[t] + \sum_{i\in\mathcal{V}} B_i[t] - \sum_{n\in\mathcal{S}^\chi} B_n[t] \\ &+ \lambda_s^{PV}\left(E_s^{PV}[t] + \delta^{s,PV}[t] - \gamma^a[t]\left(E_b[t] + \delta^b[t]\right)\right) \\ &+ \lambda_s^{WT}\left(E_s^{WT}[t] + \delta^{s,WT}[t] - \left(1 - \gamma^a[t]\right)\left(E_b[t] + \delta^b[t]\right)\right) \; . \end{aligned} \tag{3.14}$$

If $E_s^{\text{Tot}}[t] + \delta^s[t] \leq E_b[t] + \delta^b[t]$, the MGO takes on the role of buyer. The actual profit of the MGO is given as

$$\begin{aligned} R^a[t] =& R^o[t] + \left(p_b[t] - \lambda_b\right)\delta^b[t] + \left(\lambda_b - p_s^{PV}[t]\right)\delta^{s,PV}[t] \\ &+ \left(\lambda_b - p_s^{WT}[t]\right)\delta^{s,WT}[t] \end{aligned} \tag{3.15}$$

where $R^o[t]$ is defined as in (2.10). As in the previous case, it is assumed that $\delta_n[t]$ and $\delta_i^{PEV}[t]$ values are small deviations, and therefore, they will not change the roles of prosumers and the MGO. Considering (3.15), the effects of prosumers and PEV CSs on the profit of the MGO can be analyzed as shown below:

Case 7: If n^{th} prosumer adopts the role of the seller and $\delta_n[t] > 0$, the prosumer sells more energy than the scheduled energy. Since the MGO is in the buyer position, selling more energy by the prosumer does not negatively affect the profit of the MGO. Thus, n^{th} prosumer still can sell the actual amount of energy at the price $p_s^\chi[t]$ without any penalty:

$$B_n[t] = p_s^\chi[t]\left(E_n^g[t] - x_n^a[t] - d_{p_n}[t]\right) \; . \tag{3.16}$$

Case 8: If n^{th} prosumer adopts the role of the seller and $\delta_n[t] < 0$, the prosumer sells less energy than the scheduled energy. Since the MGO is in the buyer position, the energy that is not sold by the prosumer creates a negative effect on the profit of the MGO. At this point, the MGO can balance its revenue by considering a penalty function as $\lambda_b\delta_n[t] - p_s^\chi[t]\delta_n[t]$:

$$B_n[t] = p_s^\chi[t]\left(E_n^g[t] - x_n^a[t] - d_{p_n}[t]\right) + \left(\lambda_b - p_s^\chi[t]\right)\delta_n[t] \; . \tag{3.17}$$

Case 9: If n^{th} prosumer adopts the role of the buyer and $\delta_n[t] > 0$, the prosumer purchases more energy than the scheduled energy. Since the MGO is in the buyer position, the extra energy which is bought by the prosumer creates a negative effect on the profit of the MGO. In this case, the extra energy is purchased by the prosumer at the price λ_b instead of $p_b[t]$ as a penalty. Therefore, the MGO can balance its revenue with $\lambda_b \delta_n[t]$:

$$B_n[t] = p_b[t]\big(x_n[t] - \tilde{E}_n^g[t] + \tilde{d}_{p_n}[t]\big) + \lambda_b \delta_n[t] \; . \tag{3.18}$$

Case 10: If n^{th} prosumer adopts the role of the buyer and $\delta_n[t] < 0$, the prosumer buys less energy than the scheduled energy. Since the MGO is in the buyer position, buying less energy by the prosumer does not negatively affect the profit of the MGO. Thus, n^{th} prosumer still can buy the actual amount of energy at the price $p_b[t]$ without any penalty:

$$B_n[t] = p_b[t]\left(x_n^a[t] - E_n^g[t] + d_{p_n}[t]\right) \; . \tag{3.19}$$

Case 11: If $\delta_i^{PEV}[t] > 0$, i^{th} PEV CS buys more energy than the scheduled energy. Since the MGO is in the buyer position, the additional energy purchased by the CS negatively affects the profit of the MGO. In this case, the extra energy is bought by the CS at the price λ_b instead of $p_b[t]$ as a penalty. Therefore, the MGO can balance its revenue with $\lambda_b \delta_i^{PEV}[t]$:

$$B_i[t] = p_b[t]\left(L_i[t]\right) + \lambda_b \delta_i^{PEV}[t] \; . \tag{3.20}$$

Case 12: If $\delta_i^{PEV}[t] < 0$, i^{th} PEV CS buys less energy than the scheduled energy. Since the MGO is in the buyer position, buying less energy by the CS does not cause a negative effect on the profit of the MGO. Thus, i^{th} CS still can buy the actual amount of energy at the price $p_b[t]$ without any penalty:

$$B_i[t] = p_b[t]\left(L_i^a[t]\right) \; . \tag{3.21}$$

As a result, for $E_s^{\text{Tot}}[t] + \delta^s[t] \leq E_b[t] + \delta^b[t]$, the actual profit of the MGO is updated as

$$\begin{aligned} R_{upd}^a[t] = & \sum_{n \in \mathcal{B}} B_n[t] + \sum_{i \in \mathcal{V}} B_i[t] - \sum_{n \in \mathcal{S}^X} B_n[t] - \lambda_b \Big(E_b[t] + \delta^b[t] - \big(E_s^{PV}[t] \\ & + \delta^{s,PV}[t] + E_s^{WT}[t] + \delta^{s,WT} \big) \Big) . \end{aligned} \tag{3.22}$$

4. ENERGY SHARING MANAGEMENT BETWEEN MICROGRIDS

In this chapter, the problem of energy sharing management between microgrids is presented, along with the game approach to address this problem.

4.1. Problem Statement

Let $\mathcal{M} = \{1, \ldots, N_M\}$ be the set that contains all of the microgrids, where $N_M = |\mathcal{M}|$ denotes the number of different microgrids. First, the network topology (usually partially connected mesh topology) needs to be modeled by describing the interactions between the microgrids with a weighted directed graph that has N_M nodes. The edges between these nodes represent the energy trading between the microgrids. The directions of the edges show us the direction of the energy transfer (for example, one node can receive energy from another or one node can send energy to another). Mutual energy transfer between two nodes can be represented with two edges oriented to each other. Considering l^{th} (where $l \in \mathcal{M}$) microgrid, the incoming edges are coming from the microgrids which can transfer energy to l^{th} microgrid, and the outgoing edges are connected to the microgrids which can receive energy from l^{th} microgrid. An example for a directed graph of l^{th} microgrid can be given as in Figure 4.1.

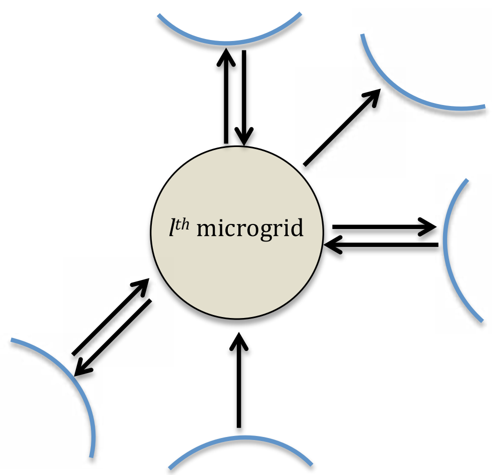

Figure 4.1. *The part of the directed graph around l^{th} microgrid.*

In a topology at a time, some of these edges are not present in the graph depending on whether the microgrid is a buyer or a seller. Weights assigned to the edges are determined between 0 and 1 according to the characteristics of the energy transfer between the nodes (microgrids) that the edge is connected to and express the relative efficiency of an energy transfer on the assigned edge compared to the other edges. In the topology, each microgrid is considered to be connected to the utility grid, and the weight between them is chosen as 1. Accordingly, the relevant weights are determined according to the efficiency at the other edges compared to the energy transfer with the utility grid. To indicate the weighted graph, an adjacency matrix can be defined such that the element in row i and column j represents the weight of the edge from i^{th} node to j^{th} node. Let us denote the weight of the edge (i, j) by $\beta_{i,j}$ and define the adjacency matrix as

$$\begin{bmatrix} 0 & \beta_{1,2} & \dots & \beta_{1,N_M} \\ \beta_{2,1} & 0 & \dots & \beta_{2,N_M} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{N_M,1} & \beta_{N_M,2} & \dots & 0 \end{bmatrix}.$$

Then, if i^{th} and j^{th} microgrids mutually exchange energy, $\beta_{i,j}$ and $\beta_{j,i}$ can be chosen accordingly or one of them can be chosen as zero according to the direction of the energy exchange. Although the relevant weights may change over time or depending on operating conditions, it is assumed that they do not change within the considered time interval.

Similar to the approach proposed for energy sharing management of a single microgrid, a central energy sharing provider (ESP) is considered to coordinate the energy management between microgrids and the utility grid by determining internal selling (p_s^m) and internal buying (p_b^m) prices under constraint $\lambda_s^m \leq p_s^m < p_b^m \leq \lambda_b^m$. In order to simplify the previously proposed approach, the export price λ_s^m considered in this chapter does not distinguish between PV or WT. Accordingly, considering the current tariffs determined for Turkey, λ_s^m and λ_b^m are taken as 0.017 USD/kWh and 0.182 USD/kWh, respectively. In this context, the ESP aims to maximize its own profit, while microgrids determine their energy consumptions through their assigned utilities where they can get benefits from the energy sharing compared to trade with the utility grid directly.

Let $\mathcal{M}_B$ be the set that contains the microgrids in buyer position, and let $\mathcal{M}_S$ be the set that contains the microgrids in seller position. In a time slot t, each microgrid $l \in \mathcal{M}$ can produce energy $E_l^m[t]$ and consume energy $x_l^m[t]$. Thus, the microgrid l can trade its energy $E_l^m[t] - x_l^m[t]$ with the ESP. If $E_l^m[t] - x_l^m[t] > 0$, l^{th} microgrid is considered in the set $\mathcal{M}_S$ by selling its surplus energy to the ESP. Otherwise, if $E_l^m[t] - x_l^m[t] < 0$, l^{th} microgrid is considered in the set $\mathcal{M}_B$ by purchasing its energy demand from the ESP.

Then, the utility function of l^{th} microgrid can be given as

$$U_l\big(x_l^m[t]\big) = \begin{cases} k_l[t]\ln\big(1 + x_l^m[t]\big) + \alpha_l^s[t]p_s^m[t]\big(E_l^m[t] - x_l^m[t]\big), & E_l^m[t] > x_l^m[t] \\ k_l[t]\ln\big(1 + x_l^m[t]\big) + \alpha_l^b[t]p_b^m[t]\big(E_l^m[t] - x_l^m[t]\big), & E_l^m[t] \le x_l^m[t] \end{cases} \quad (4.1)$$

where k_l is the preference parameter which changes with behavioral characteristics of the microgrid, and accordingly, $k_l[t]\ln\big(1+x_l^m[t]\big)$ is the utility that l^{th} microgrid achieves from consuming $x_l^m[t]$. As can be seen from (4.1), a microgrid with higher preference parameter would be more interested in consuming more energy to attain its maximum utility level compared to a microgrid with lower preference parameter. In (4.1), $\alpha_l^s[t]$ and $\alpha_l^b[t]$ are, respectively, seller and buyer weighted average factors to be determined by weights of the directed graph which are assigned according to the characteristics (e.g., length of transmission line, capacity, availability rate, maintenance/life-loss rate) of energy exchange between microgrids, such that

$$\alpha_l^s[t] = \frac{\sum_{j\in\mathcal{M}_B} \beta_{l,j}\big(x_j^m[t] - E_j^m[t]\big)}{\sum_{j\in\mathcal{M}_B}\big(x_j^m[t] - E_j^m[t]\big)} \text{ and } \alpha_l^b[t] = \frac{\sum_{j\in\mathcal{M}_S}\big(E_j^m[t] - x_j^m[t]\big)}{\sum_{j\in\mathcal{M}_S} \beta_{j,l}\big(E_j^m[t] - x_j^m[t]\big)}. \quad (4.2)$$

Therefore, for a time slot t, $\alpha_l^s[t]p_s^m[t]\big(E_l^m[t] - x_l^m[t]\big)$ is the weighted revenue that the microgrid receives from selling its surplus energy to the ESP with $\alpha_l^s[t]p_s^m[t]$ selling price, whereas $\alpha_l^b[t]p_b^m[t]\big(E_l^m[t] - x_l^m[t]\big)$ is the weighted negative revenue when the microgrid buys energy from the ESP with $\alpha_l^b[t]p_b^m[t]$ buying price. From (4.1), with the condition $E_l^m[t] - x_l^m[t] \neq 0$, the extremum value of $x_l^m[t]$ can be calculated with given prices p_s^m and p_b^m as

$$x_l^m[t] = \begin{cases} \dfrac{k_l[t]}{\alpha_l^s[t]p_s^m[t]} - 1, & E_l^m[t] > x_l^m[t] \\ \dfrac{k_l[t]}{\alpha_l^b[t]p_b^m[t]} - 1, & E_l^m[t] \le x_l^m[t] \end{cases}. \quad (4.3)$$

As a coordinator, the ESP sets the internal prices and conducts energy sharing between microgrids. For each time slot t, the total energy trading among sellers and buyers can be obtained as

$$E_s^m[t] = \sum_{l\in\mathcal{M}_S}\big(E_l^m[t] - x_l^m[t]\big), \quad E_b^m[t] = \sum_{l\in\mathcal{M}_B}\big(x_l^m[t] - E_l^m[t]\big) \quad (4.4)$$

where E_s^m is the total energy that the ESP buys from seller microgrids in the set $\mathcal{M}_S$, and E_b^m is the total energy that the ESP sells to buyer microgrids in the set $\mathcal{M}_B$. Thus, the profit function of the ESP with $p_s^m[t]$ and $p_b^m[t]$ decision variables can be formulated as

$$R_{ESP}(p_s^m, p_b^m)[t] = \begin{cases} \begin{array}{c} \alpha_l^b[t] p_b^m[t] E_b^m[t] - \alpha_l^s[t] p_s^m[t] E_s^m[t] \\ +\lambda_s^m\big(E_s^m[t] - E_b^m[t]\big) \end{array} & , \; E_s^m[t] > E_b^m[t] \\ \begin{array}{c} \alpha_l^b[t] p_b^m[t] E_b^m[t] - \alpha_l^s[t] p_s^m[t] E_s^m[t] \\ +\lambda_b^m\big(E_s^m[t] - E_b^m[t]\big) \end{array} & , \; E_s^m[t] \leq E_b^m[t] \end{cases} . \quad (4.5)$$

4.2. Definition and Implementation of Game Approach

The proposed single-leader multi-follower game approach given in Section 2.2 is extended to solve the problem of energy sharing management between microgrids. In the game, the ESP takes the leader role and determines the pricing policy to coordinate energy sharing, where the microgrids are followers. The game is defined as

$$L^m = \Big\{(\mathcal{M} \cup \text{ESP}), \{\mathbf{X}_l^m\}_{l \in \mathcal{M}}, \{\mathbf{P}_b^m\}, \{\mathbf{P}_s^m\}, \big\{U_l\big(x_l^m\big)\big\}_{l \in \mathcal{M}}, R_{ESP}\big(p_s^m, p_b^m\big)\Big\} \quad (4.6)$$

which includes the followings:

- The microgrids given in set $\mathcal{M}$ are the followers and decide their optimal energy consumptions according to the internal prices determined by the ESP.
- $\mathbf{X}_l^m$ is the set of consumption strategies of l^{th} microgrid subject to the constraint $x_{l_{\min}}^m \leq x_l^m \leq x_{l_{\max}}^m$.
- $\mathbf{P}_b^m$ and $\mathbf{P}_s^m$ are the sets of strategies of the ESP, which are the vector forms of internal prices p_b^m and p_s^m, respectively. For each time slot t, these strategies are determined by the ESP subject to the constraint $\lambda_s^m \leq p_s^m[t] < p_b^m[t] \leq \lambda_b^m$.
- U_l is the utility function of l^{th} microgrid, as given in (4.1), that states the microgrid's benefit from consuming energy x_l^m and trading energy $E_l^m - x_l^m$ with the ESP.
- $R_{ESP}\big(p_s^m, p_b^m\big)$ is the profit function of the ESP, as given in (4.5), that states the total profit obtained by conducting energy sharing between microgrids and trading energy with the utility grid.

With the strategies determined, the objectives of each microgrid and the ESP are to maximize the utility in (4.1) and the profit in (4.5), respectively.

For each time slot t, l^{th} microgrid forecasts its produced energy $\tilde{E}_l^m[t]$ and consumed energy $\tilde{x}_l^m[t]$. Based on these forecasts, the microgrid l adopts the seller or buyer role. Then, l^{th} microgrid calculates its preference parameter $k_l[t]$ by using the following equation (which is obtained from (4.3) for $x_l^m[t] = \tilde{x}_l^m[t]$, $E_l^m[t] = \tilde{E}_l^m[t]$)

$$k_l[t] = \begin{cases} \big(\tilde{x}_l^m[t]+1\big)\alpha_l^s[t]p_s^m[t], & \tilde{E}_l^m[t] > \tilde{x}_l^m[t] \\ \big(\tilde{x}_l^m[t]+1\big)\alpha_l^b[t]p_b^m[t], & \tilde{E}_l^m[t] \leq \tilde{x}_l^m[t] \end{cases} \tag{4.7}$$

where the reference internal prices $p_s^m[t]$ and $p_b^m[t]$ are set, respectively, as λ_s^m and λ_b^m. Then, l^{th} microgrid submits $k_l[t]$, $\tilde{E}_l^m[t]$, and its role (seller or buyer) to the ESP. Thus, for a time slot t, total energy trading between sellers and buyers can be obtained as

$$\tilde{E}_s^m[t] = \sum_{l \in \mathcal{M}_S} \left(\tilde{E}_l^m[t] - \frac{k_l[t]}{\alpha_l^s[t]p_s^m[t]} + 1 \right), \tag{4.8}$$

$$\tilde{E}_b^m[t] = \sum_{l \in \mathcal{M}_B} \left(\frac{k_l[t]}{\alpha_l^b[t]p_b^m[t]} - 1 - \tilde{E}_l^m[t] \right). \tag{4.9}$$

By substituting (4.8) and (4.9) into (4.5), a piece-wise profit function is obtained with respect to p_b^m and p_s^m. Then, the objective function of the ESP is

$$\begin{aligned} \max \quad & R_{ESP}(p_s^m[t], p_b^m[t]) \\ \text{s.t.} \quad & \lambda_s^m \leq p_s^m[t] < p_b^m[t] \leq \lambda_b^m \\ & \frac{k_l[t]}{\alpha_l^s[t]\big(x_{l_{\max}}^m[t]+1\big)} \leq p_s^m[t] \leq \frac{k_l[t]}{\alpha_l^s[t]\big(x_{l_{\min}}^m[t]+1\big)}, \ \forall l \in \mathcal{M}_S \\ & \frac{k_l[t]}{\alpha_l^b[t]\big(x_{l_{\max}}^m[t]+1\big)} \leq p_b^m[t] \leq \frac{k_l[t]}{\alpha_b^s[t]\big(x_{l_{\min}}^m[t]+1\big)}, \ \forall l \in \mathcal{M}_B \end{aligned} \tag{4.10}$$

where the constraint on the power consumption of l^{th} microgrid is denoted as $x_{l_{\min}}^m[t] \leq x_l^m[t] \leq x_{l_{\max}}^m[t]$. By solving (4.10), the ESP can determine the optimal internal prices $p_b^{m*}[t]$ and $p_s^{m*}[t]$ for the upcoming time slot t. Considering the established internal prices of the ESP and the preference parameter determined from (4.7), each microgrid l obtains its optimal energy consumption by (4.3) for the time slot t. The ESP cannot increase its profit by adjusting internal prices from $(p_b^{m*}[t], p_s^{m*}[t])$, and no microgrid can improve its utility by choosing strategies other than end-game consumption.

5. SIMULATIONS AND RESULTS

In this chapter, case studies are presented to demonstrate the effectiveness of the proposed strategies on real-like microgrids. The simulation results for energy sharing management problems including a single microgrid and multiple microgrids are discussed, respectively, in Section 5.1 and Section 5.2.

5.1. Energy Sharing Management of a Single Microgrid

Energy sharing management of a microgrid including five prosumers (three of them PV prosumers and two of them WT prosumers) and three PEV CSs for $t = 7, \ldots, 19$ is considered as a case study. For the prosumers, a_n (where $n = 1, \ldots, N$) are determined as 0.001, 0.004, 0.002, 0.009, and 0.007, respectively. $b_n^{s,\chi}$, b_n^b, and b_n^{ss}, $n = 1, \ldots, N$, are all determined as 1. For $n = 1, \ldots, N$, $x_n^{\min}[t] = 0.7\,\tilde{x}_n[t]$ and $x_n^{\max}[t] = 1.3\,\tilde{x}_n[t]$ for $t = 7, \ldots, 19$. ζ^{PV} and ζ^{WT} are determined as $0.067\,\mathrm{USD/kWh}$ and $0.037\,\mathrm{USD/kWh}$, respectively. It is assumed that each prosumer n (where $n = 1, \ldots, N$) included in the case study has an ES system with the specifications as $\mathrm{SOC}_{p_n}^{\min} = 20\%$, $\mathrm{SOC}_{p_n}^{\max} = 90\%$, $E_n^{avl} = 50\,\mathrm{kWh}$, and $d_{p_n}^{\max} = 20\,\mathrm{kW}$. In addition, the life loss cost of the ES systems, $c_{d_{p_n}}$, is chosen as 0.0007. For PEV CSs, the charging levels of i^{th} (where $i = 1, \ldots, N_V$) CS are defined, respectively, as $\begin{bmatrix} P_1^1 & \cdots & P_1^5 \end{bmatrix} = \begin{bmatrix} 3.3 & 3.6 & 6.6 & 7 & 7.2 \end{bmatrix}$, $\begin{bmatrix} P_2^1 & \cdots & P_2^6 \end{bmatrix} = \begin{bmatrix} 7.2 & 9.6 & 11.5 & 17 & 19.2 & 22 \end{bmatrix}$, and $\begin{bmatrix} P_3^1 & \cdots & P_3^5 \end{bmatrix} = \begin{bmatrix} 19.2 & 22 & 43 & 50 & 100 \end{bmatrix}$. For $i = 1, \ldots, N_V$, $l_i^{\min}[t] = 0.5\,\tilde{L}_i[t]$ and $l_i^{\max}[t] = 1.5\,\tilde{L}_i[t]$ for $t = 7, \ldots, 19$.

Forecasted values of energy generation and consumption of all prosumers are shown in Figure 5.1. The initial net energy of n^{th} prosumer (where $n \in \mathcal{G}$) can be found based on these forecasts as $\tilde{E}_n^g[t] - \tilde{x}_n[t]$, which indicates the adopted role of the considered prosumer prior to ES scheduling. Specifically, if the net energy value is positive, the prosumer acts as a seller, while a negative net energy value shows that the prosumer acts as a buyer at the beginning of the day-ahead ES planning. If the net energy value is zero, the prosumer is self-sufficient for the corresponding time period.

5.1.1. Day-ahead ES scheduling

As the first step of the implementation process, all the prosumers obtain their ES strategies based on the defined specifications, forecasted values of generated and consumed energy, and forecasted internal prices shown in Figure 5.2. Thus, the exchanging energy $\tilde{d}_{p_n}[t]$ (where $n = 1, \ldots, N$) of the ES systems are determined from (2.12) and

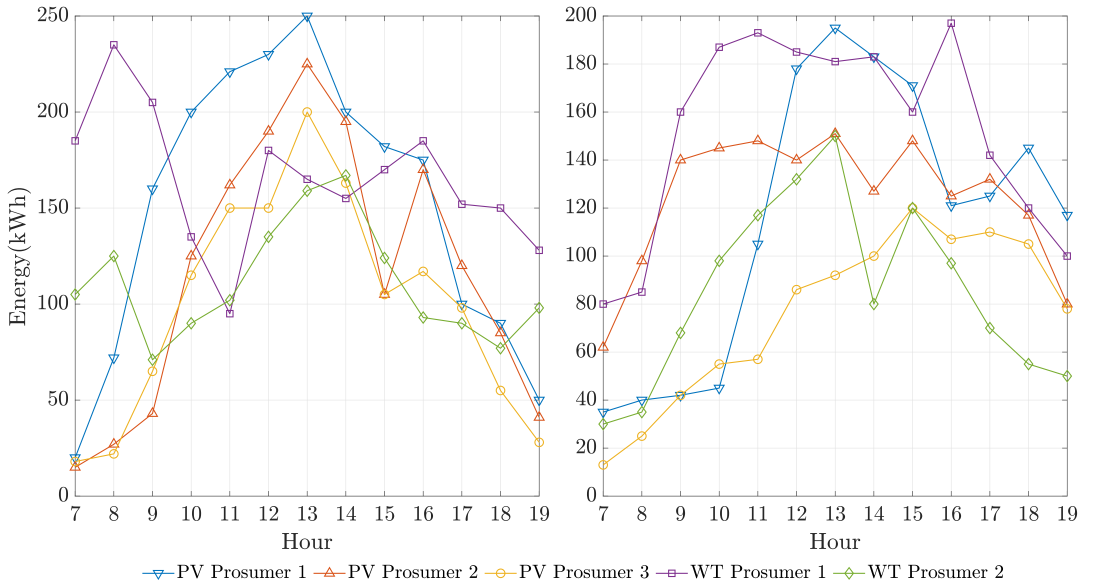

Figure 5.1. *Forecasted values of energy generation (left) and energy consumption (right) of PV-WT prosumers.*

shown in Figure 5.3. Accordingly, $\mathrm{SOC}_{p_n}[t]$ (where $n = 1, \ldots, N$) of the ES systems are derived from (2.13) (see Figure 5.4). It can be seen in Figure 5.4 that the ES systems all end with the SOC value of 20%, which is the same as their initial SOC values. It can also be analyzed that the SOCs remain between the upper and lower bounds during scheduling. After the ES scheduling is completed, the net energy of n^{th} prosumer (where $n \in \mathcal{G}$) is updated considering $\tilde{d}_{p_n}[t]$ as $\tilde{E}^g_n[t] - \tilde{x}_n[t] - \tilde{d}_{p_n}[t]$, which shows the initial role of the prosumer at the start of the game procedure.

The ES strategy for buyer prosumers aims to discharge their batteries during times of high internal buying prices to reduce their energy purchases. On the other hand, for

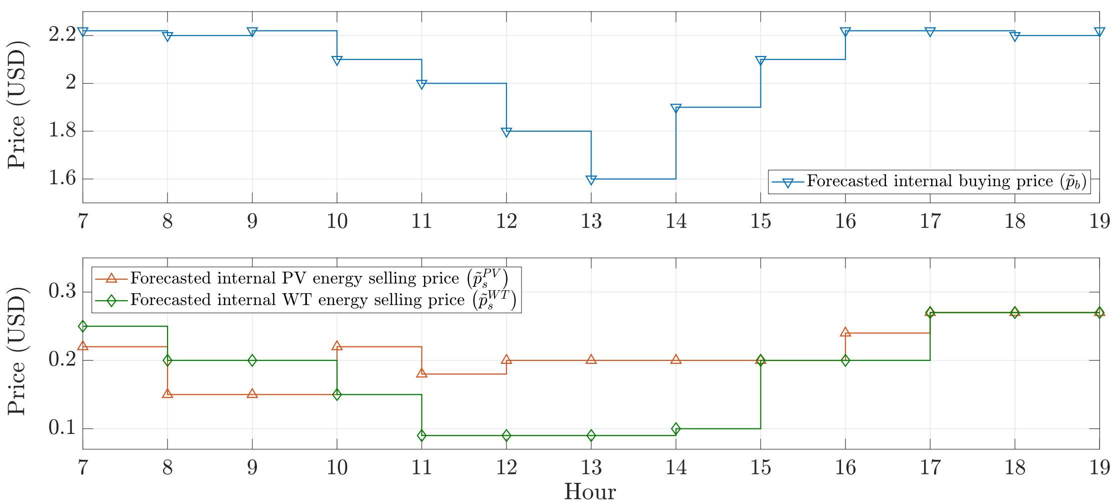

Figure 5.2. *Forecasted internal prices.*

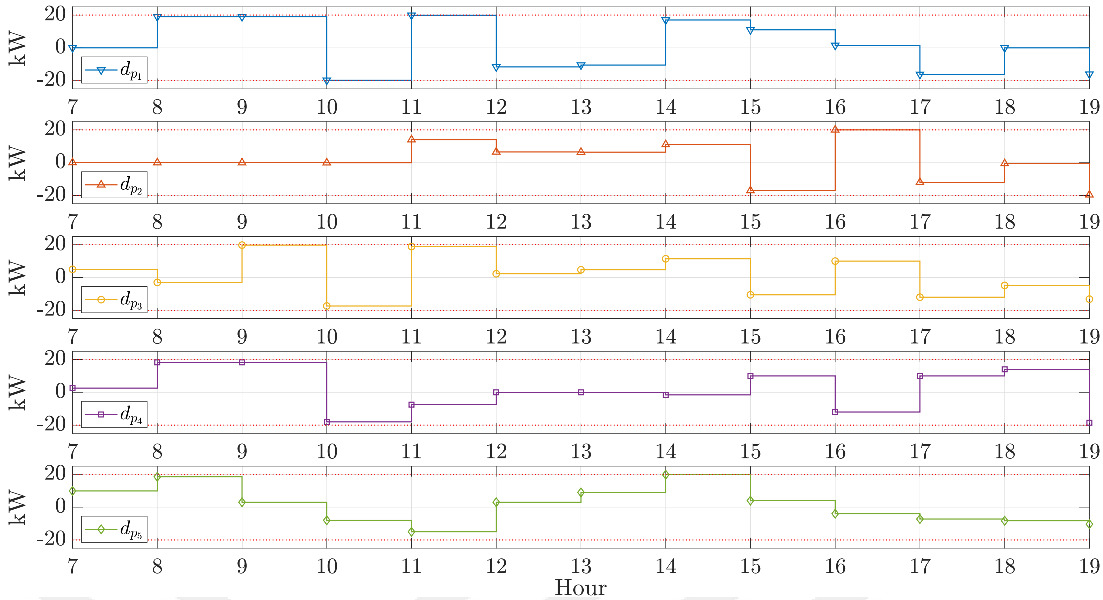

Figure 5.3. $\tilde{d}_{p_n}[t]$ *(where $n = 1, \ldots, N$) of the ES systems.*

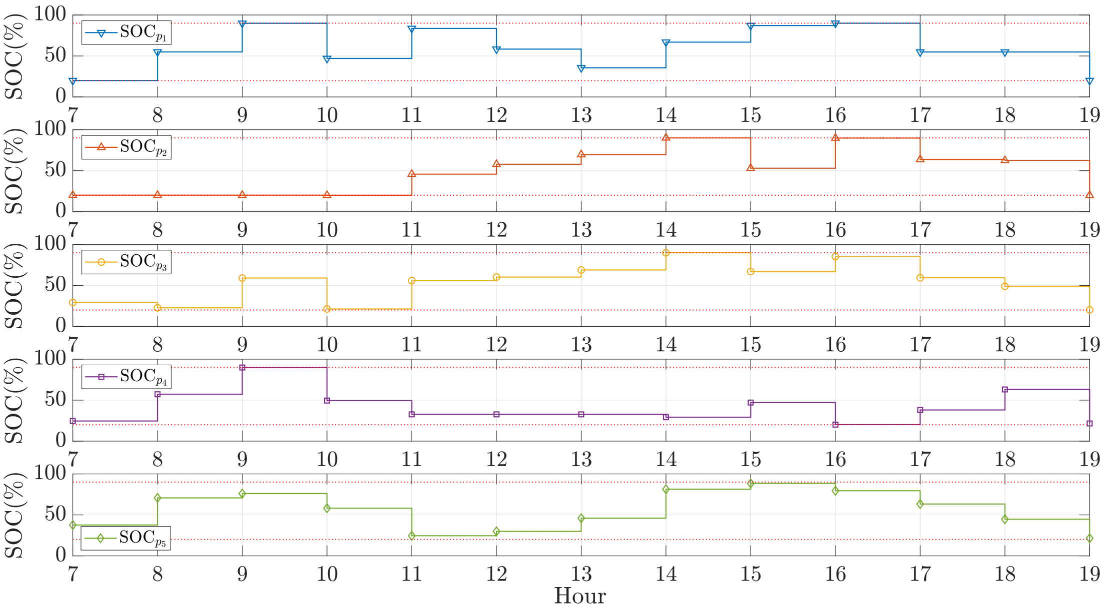

Figure 5.4. $\mathrm{SOC}_{p_n}[t]$ *(where $n = 1, \ldots, N$) of the ES systems.*

seller prosumers, the ES strategy aims to charge their batteries during times of low internal selling prices, intending to utilize the stored energy when additional energy is required beyond production capacity. It can be seen from Figure 5.2 that, in time slot 16, $\tilde{p}_b$ is at its highest value. According to Figure 5.3, both WT prosumers, which behave as buyers based on the forecasted generation and consumption values, discharge their batteries to meet required energy demands due to the high internal buying price in the considered time slot. On the other hand, Figure 5.3 shows that PV prosumer 1, acting as a seller, utilizes its surplus energy to charge its battery during time slots 8 and 9 in response to the quite low $\tilde{p}_s^{PV}$ value (see Figure 5.2). However, it is important to note that the ES strategy is not limited to just storing excess energy for sellers and releasing energy for buyers to fulfill their energy requirements. Seller prosumers can benefit from decreasing penalties for discharges as the internal selling price increases, allowing them to sell stored energy at profitable rates during these time intervals. Similarly, buyer prosumers can take advantage of lower internal buying prices to purchase energy for charging their batteries. For example, Figure 5.2 presents a quite high $\tilde{p}_s^{PV}$ in time slot 10, and Figure 5.3 shows that despite having excess energy, PV prosumer 1 and PV prosumer 3 discharge their batteries in this time slot.

Besides the aforementioned statements, it is not sufficient to evaluate the ES system strategy based only on the forecasted prices of a specific time slot. To assess the unexpected outcomes of the ES strategy for any given time slot, one must also consider its impact on other time slots. Hence, when monitoring the charging or discharging behavior in a particular time slot, the pricing policy of the entire day should be taken into account within the given ES scheduling algorithm. Consequently, various scenarios may arise for the ES scheduling of prosumers, which would consider the forecasted pricing scheme in combination with the algorithm's defined constraints. For instance, even though $\tilde{p}_s^{WT}$ is quite high in time slot 17 (as given in Figure 5.2), Figure 5.3 shows that WT prosumer 1, acting as a seller, charges its battery with the excess energy. This decision is taken because the internal buying price is observed to be at its peak value around these time intervals.

5.1.2. Real-time pricing and results of game approach

Considering the specified parameters, day-ahead ES planning, forecasted energy generations and consumptions of the prosumers, and forecasted loads of CSs, the proposed game model is carried out using MATLAB to optimize energy sharing in the microgrid for the considered time period. Thus, the end-game internal prices $p_b[t]$, $p_s^{PV}[t]$, and $p_s^{WT}[t]$ are obtained from the game procedure and shown in Figure 5.5. It is evident that these prices bear a notable resemblance to the forecasted internal prices considered during day-ahead ES scheduling (see Figure 5.2).

Each prosumer n obtains its optimal energy consumption based on the end-game internal prices. Thus, the end-game net energy of n^{th} prosumer can be represented as

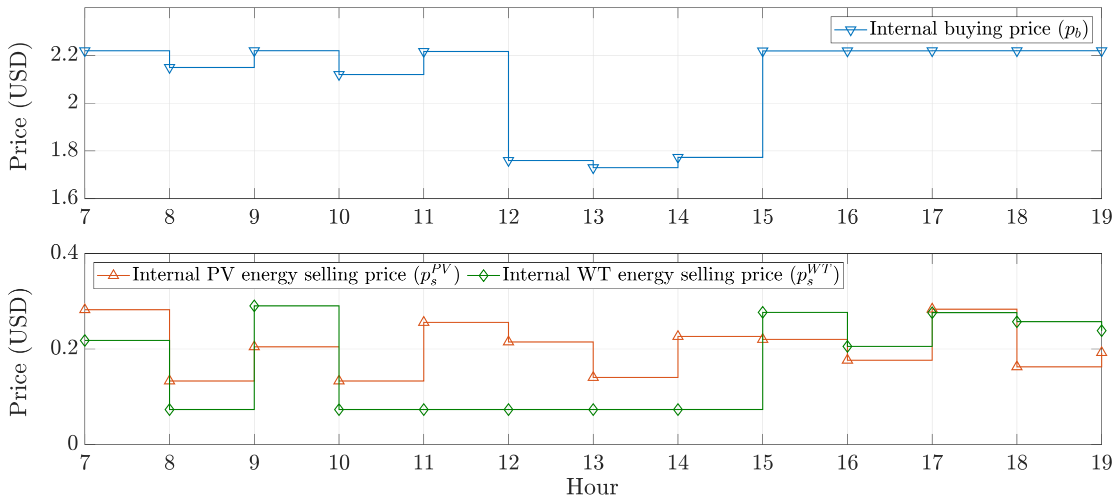

Figure 5.5. *End-game internal prices.*

$\tilde{E}_n^g[t] - x_n[t] - \tilde{d}_{p_n}[t]$. Figure 5.6 shows the comparison of the net energies of the prosumers, including the end-game net energy (bottom) and the initial net energies[5] with ES systems (upper right) and without ES systems (upper left).

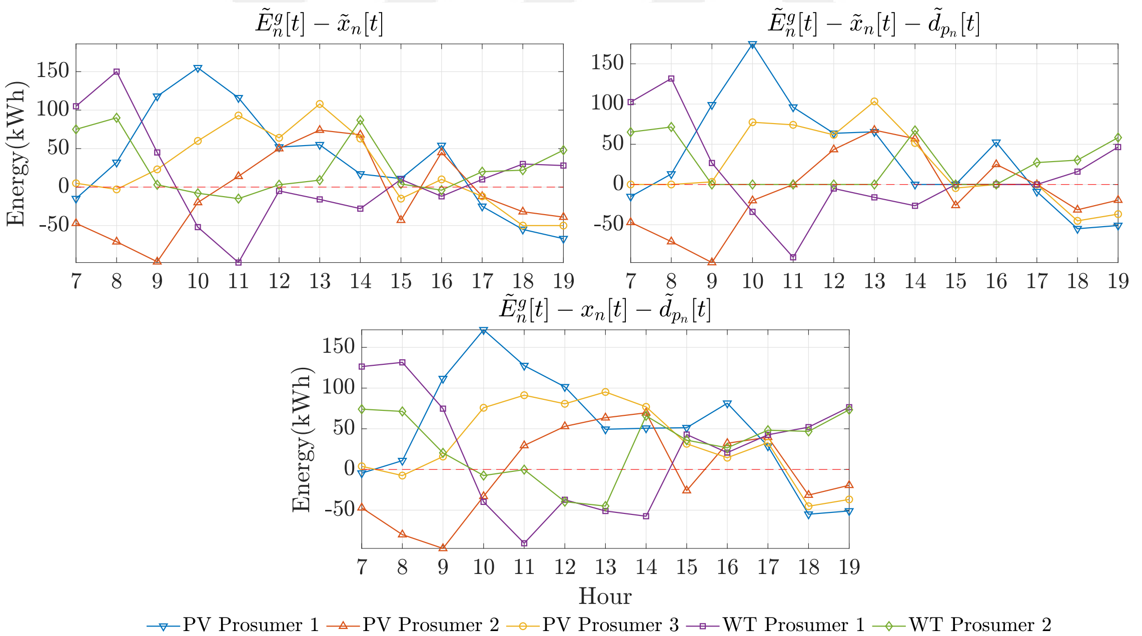

Figure 5.6. *Comparison of the net energies of the prosumers, including the end-game net energy (bottom) and the initial net energies with ES systems (upper right) and without ES systems (upper left).*

As can be seen in Figure 5.6, the initial roles of prosumers at the beginning of the game, determined based on the forecasted consumption values, change at specific time intervals according to the end-game internal prices. For example, PV prosumer 3 switches

[5]Initial net energies of n^{th} prosumer (where $n \in \mathcal{G}$) with and without ES systems can be represented, respectively, as $\tilde{E}_n^g[t] - \tilde{x}_n[t] - \tilde{d}_{p_n}[t]$ and $\tilde{E}_n^g[t] - \tilde{x}_n[t]$.

from being a buyer to a seller in time slot 15 to reduce energy needs in the microgrid. Likewise, in time slot 17, PV prosumer 1 decreases its consumption in response to the rise in internal selling PV price and becomes a seller based on its end-game consumption.[6] Furthermore, regarding the comparison of the initial net energies with and without ES systems shown in Figure 5.6, a point worth noting is the behavior of prosumers in response to the day-ahead ES scheduling. Since the primary goal of ES scheduling is self-sufficiency on the prosumer basis, it can be observed that prosumers generally tend towards self-sufficiency after the ES scheduling (particular attention to WT prosumer 2).

The differences between the end-game consumption and the forecasted consumption $\left(\text{i.e., } x_n[t] - \tilde{x}_n[t]\right)$ of each prosumer are shown in Figure 5.7. Positive values indicate an increase in consumption after the application of end-game internal prices, while negative values indicate a decrease in consumption.

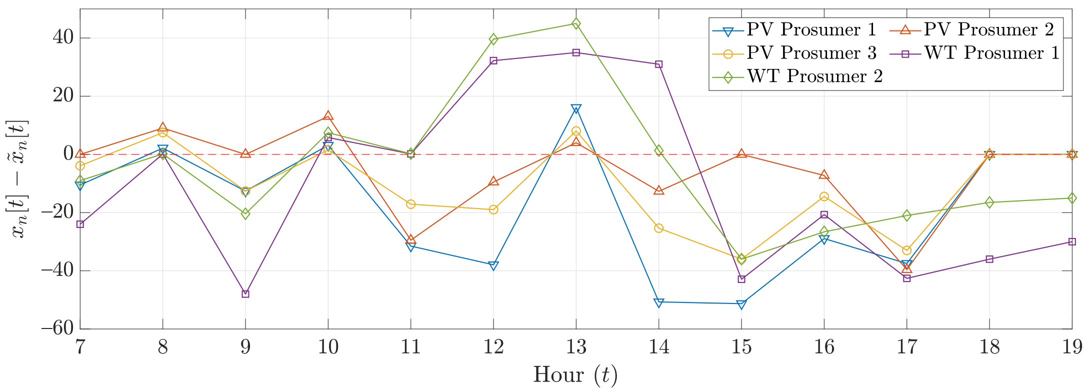

Figure 5.7. *Differences between the end-game consumption and the forecasted consumption of each prosumer.*

Forecasted and end-game numbers of vehicles at each level of charging power available in the considered PEV CSs are shown in Figure 5.8, Figure 5.9, and Figure 5.10. Accordingly, the comparison of the forecasted loads (based on the utility grid prices) and the end-game loads (based on the internal prices) of PEV CSs is shown in Figure 5.11. Since PEV CSs only behave as buyers in the problem, they are not affected by changes in internal selling prices. If $p_b[t]$ is kept at λ_b, the end-game loads of CSs do not differ from the forecasted loads, as forecasted loads are obtained based on the grid prices. Furthermore, PEV CSs tend to increase their loads in line with the decrease in $p_b[t]$.

Total buying, total selling, and net energies of the microgrid (i.e., PV-WT prosumers and PEV CSs) based on the end-game internal prices are shown in Figure 5.12. Further-

[6] Note that the role changes observed in this study are not allowed in previously examined studies.

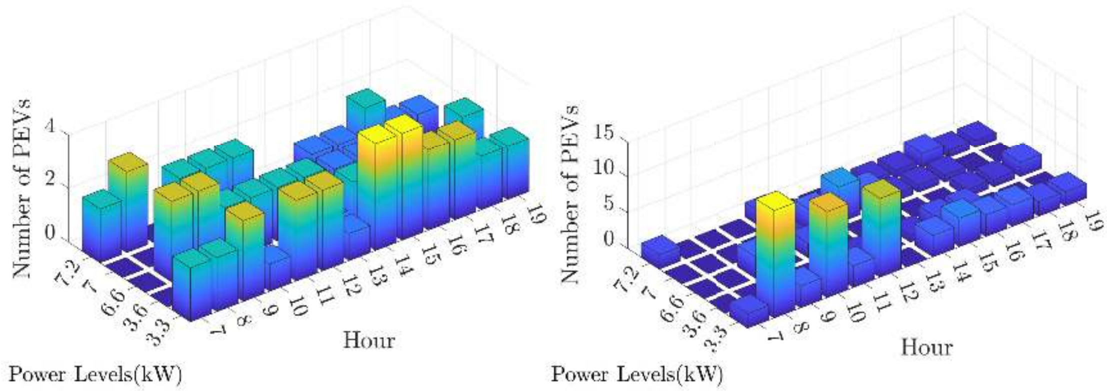

Figure 5.8. *Forecasted (left) and end-game (right) numbers of vehicles at each level of charging power available in Level 1 PEV CS (i.e., forecasted and end-game states of Level 1 PEV CS).*

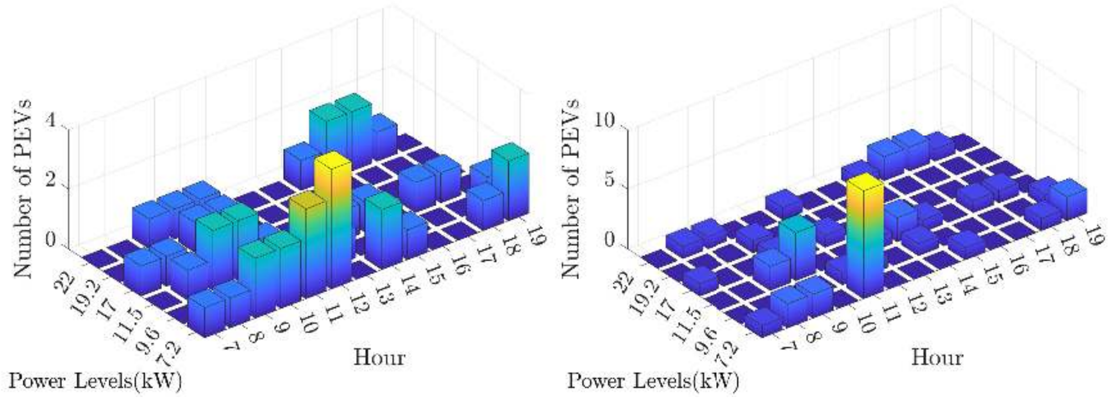

Figure 5.9. *Forecasted (left) and end-game (right) numbers of vehicles at each level of charging power available in Level 2 PEV CS (i.e., forecasted and end-game states of Level 2 PEV CS).*

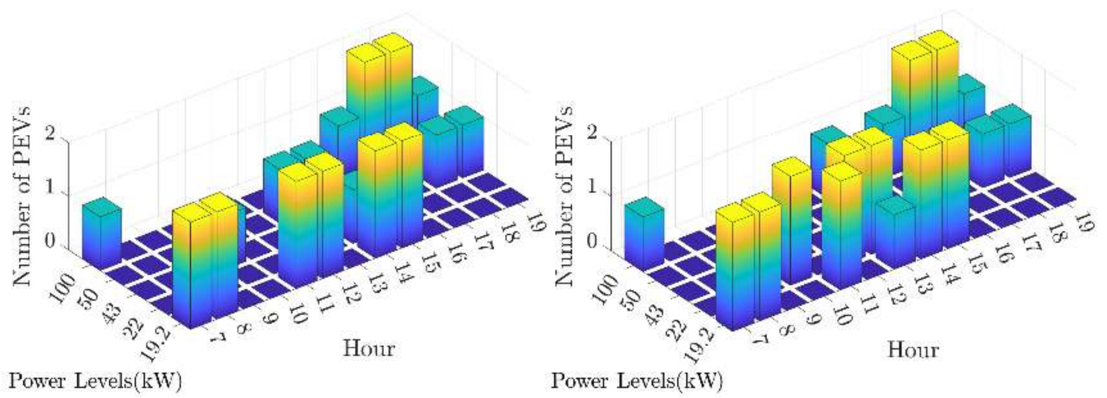

Figure 5.10. *Forecasted (left) and end-game (right) numbers of vehicles at each level of charging power available in Level 3 PEV CS (i.e., forecasted and end-game states of Level 3 PEV CS).*

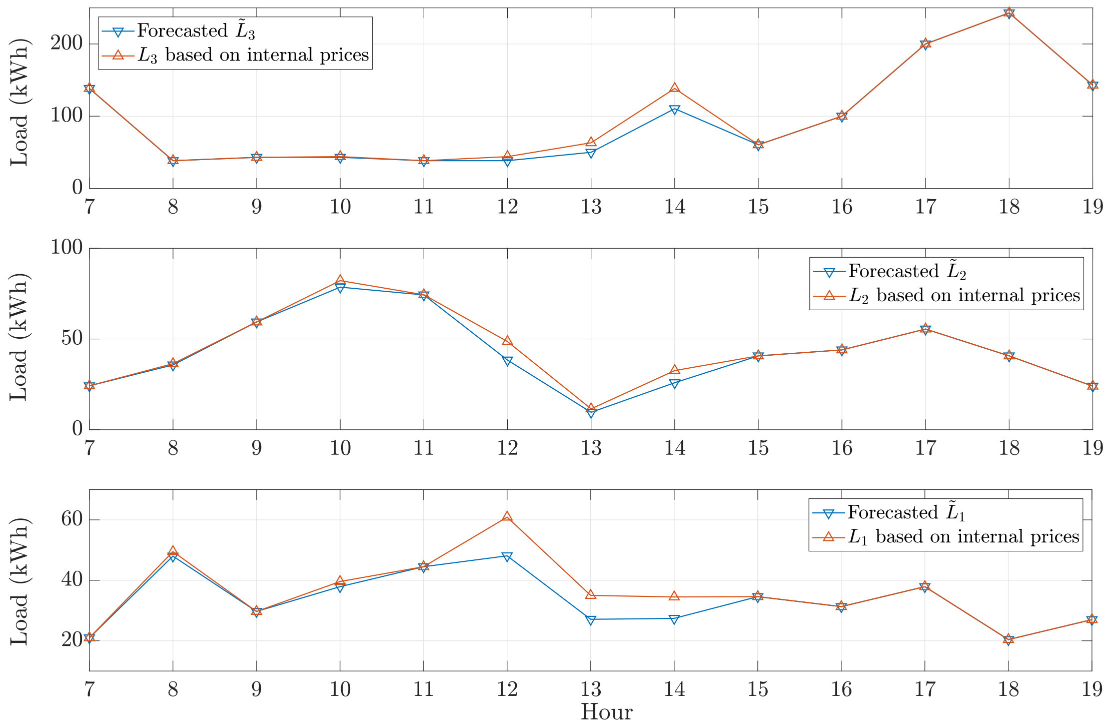

Figure 5.11. *Comparison of the forecasted loads (based on the utility grid prices) and the end-game loads (based on the internal prices) of PEV CSs.*

more, Figure 5.13 shows the comparison of the net energies of the microgrid, including the end-game net energy (based on the final consumptions and loads) and the initial net energies with and without ES systems (based on the forecasted consumptions and loads). As can be seen in Figure 5.13 that the game model implemented by the MGO leads to a reduction in energy trading with the utility grid. Therefore, within the limitations of the MGO, the proposed energy management algorithm appears to decrease the microgrid's reliance on the grid while aiming to maximize the operational profit.

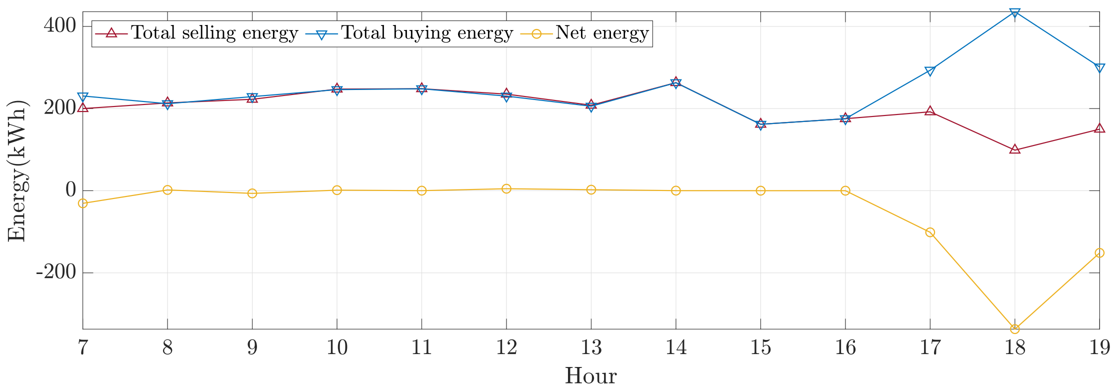

Figure 5.12. *Total buying, total selling, and net energies of the microgrid (i.e., PV-WT prosumers and PEV CSs) based on the end-game internal prices.*

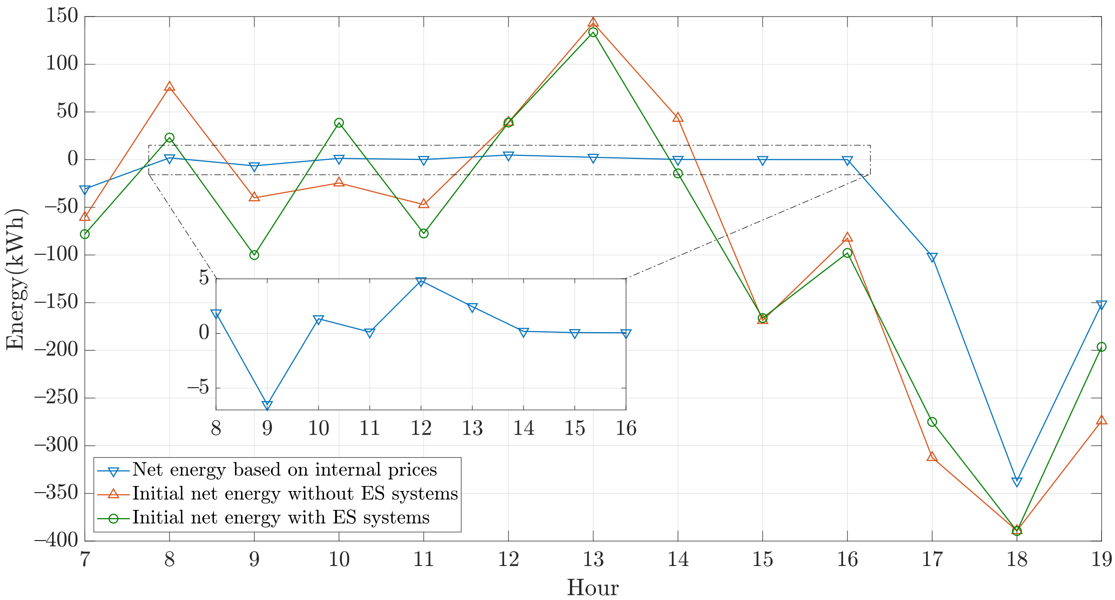

Figure 5.13. *Comparison of the net energies of the microgrid, including the end-game net energy (based on the final consumptions and loads) and the initial net energies with and without ES systems (based on the forecasted consumptions and loads).*

The comparison between the MGO's initial profit based on the utility grid prices (without ES systems) and end-game profit based on the internal prices is shown in Figure 5.14. It is obvious that the end-game prices increase the profit of the MGO while reducing the grid dependency.

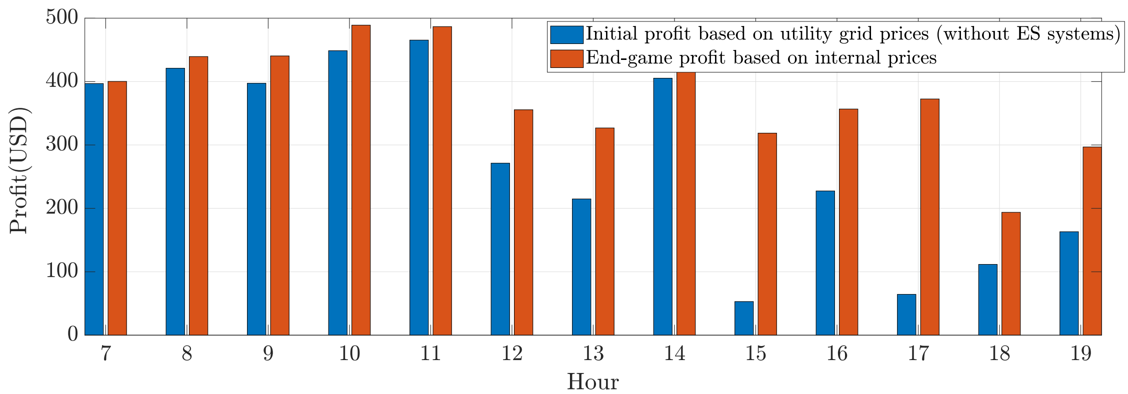

Figure 5.14. *Comparison between the MGO's initial profit based on the utility grid prices (without ES systems) and end-game profit based on the internal prices.*

5.1.3. Billing scheme

The effect of the proposed billing scheme on the overall energy management strategy is analyzed in this subsection. To evaluate the performance of this scheme, various case studies are presented at specific time slots, including 9, 12, and 11.

In time slot 9, the MGO takes on the role of buyer (see Figure 5.13), and PV Prosumer 1, PV Prosumer 3 and both WT prosumers behave as sellers (see Figure 5.6). To see the effect of Case 8, let $\delta_1[9], \delta_3[9], \delta_4[9], \delta_5[9] < 0$, which means that the amount of selling energy is less than the scheduled selling energy. For this, it is assumed that the actual exchanging energy of the ES systems of these prosumers, $d_{p_1}[9], d_{p_3}[9], d_{p_4}[9]$, and $d_{p_5}[9]$, are increased from, respectively, $\tilde{d}_{p_1}[9], \tilde{d}_{p_3}[9], \tilde{d}_{p_4}[9]$, and $\tilde{d}_{p_5}[9]$ by 0% to 50% (measured by mean absolute percentage error (MAPE)) of the corresponding forecasted $\tilde{d}_{p_n}[9]$ (for $n = 1, 3, 4, 5$) of the ES systems. The actual consumptions and productions of these prosumers are chosen as their end-game consumptions and forecasted productions. Since the MGO is in the buyer position in this time slot, Case 8 is validated. Figure 5.15 shows the comparison of the profits of the MGO before and after regulation under different errors. As can be seen, based on (3.15), the profit of the MGO decreases with increasing error rates before regulation. However, based on (3.22), the profit of the MGO remains constant for each error rate with the application of the billing procedure in the considered time slot.

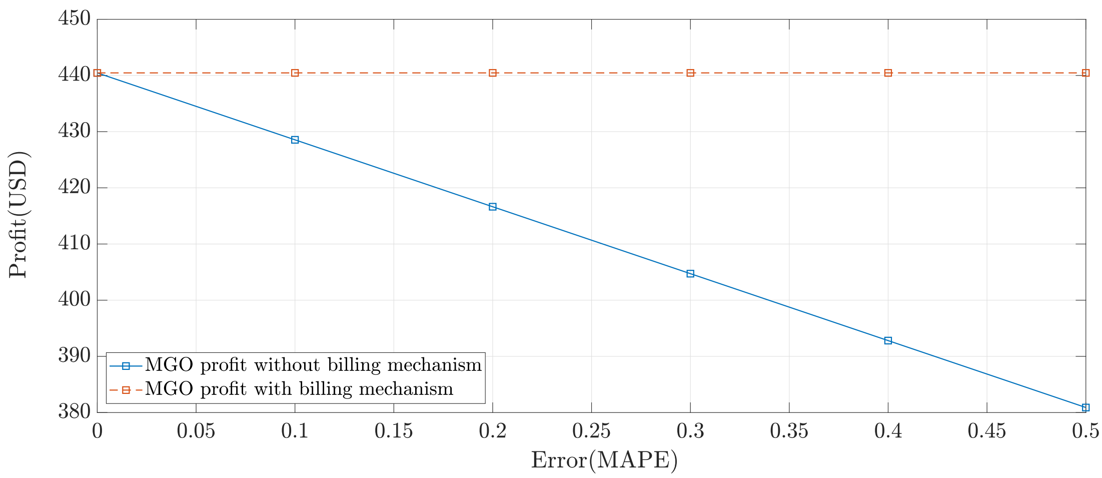

Figure 5.15. *Comparison of the profits of the MGO before and after regulation under different errors in time slot 9.*

Figure 5.16 shows the comparison of the revenues of PV prosumer 1, PV prosumer 3, WT prosumer 1, and WT prosumer 2, which act as sellers in time slot 9, under different errors. Before the application of the billing procedure, the revenues of these prosumers decrease with the error rates from 0% to 50% because of selling less energy. Since the required energy is purchased from the utility grid with λ_b, the MGO can balance its revenue by penalizing these prosumers with $(\lambda_b - p_s^{\chi}[9])\delta_n[9]$ for $n = 1, 3, 4, 5$ after the application of the billing procedure. Thus, the regulation decreases the revenues of the considered prosumers compared to the pre-regulation case in this time slot.

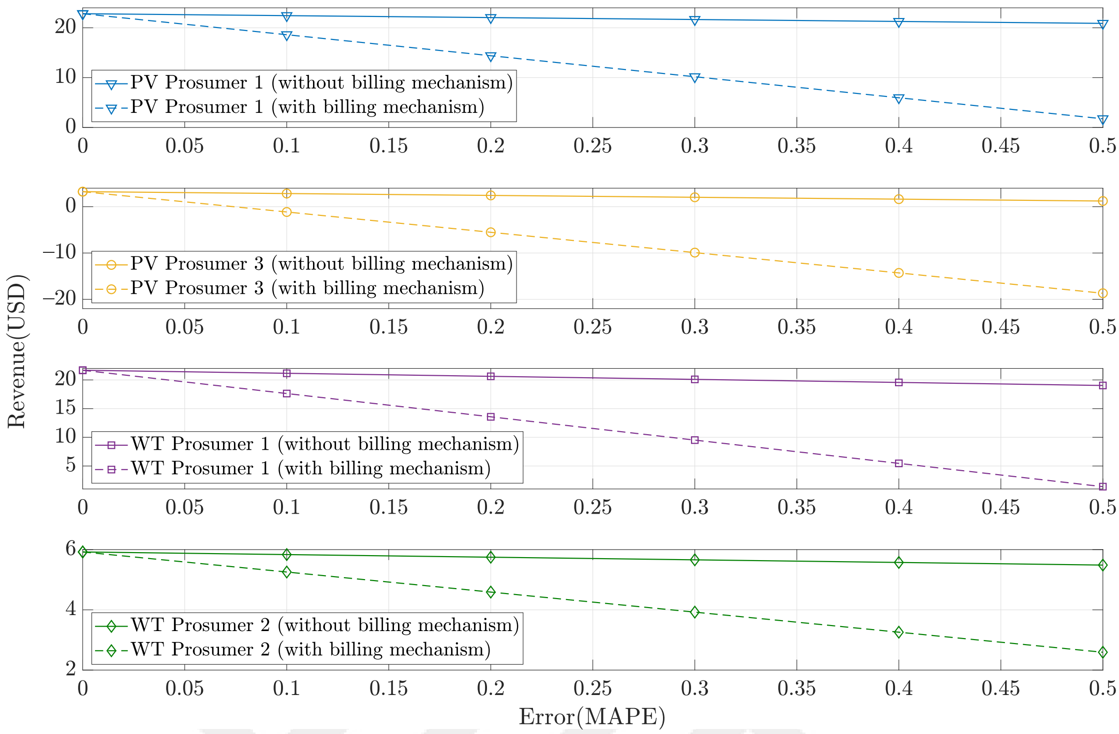

Figure 5.16. *Comparison of the revenues before and after regulation under different errors in time slot 9.*

In time slot 12, the MGO takes on the role of seller (see Figure 5.13), and both WT prosumers and all PEV CSs behave as buyers (see Figure 5.6). To see the effect of Case 4 and Case 6, let $\delta_4[12], \delta_5[12], \delta_1^{PEV}[12], \delta_2^{PEV}[12], \delta_3^{PEV}[12] < 0$, which means that the amount of buying energy is less than the scheduled buying energy. For this, it is assumed that the actual consumptions of WT prosumers and actual loads of PEV CSs, $x_4^a[12], x_5^a[12], L_1^a[12], L_2^a[12]$, and $L_3^a[12]$, are decreased from, respectively, $x_4[12], x_5[12]$, $L_1[12], L_2[12]$, and $L_3[12]$ by 0% to 50% (measured by MAPE) of the corresponding $x_n[12]$ (for $n = 4, 5$) of the considered prosumers and $L_i[12]$ (for $i = 1, 2, 3$) of PEV CSs. The actual productions of these prosumers and exchanging energies of their ES systems are chosen as their forecasted productions and exchanging energies. Since the MGO is in the seller position in this time slot, Case 4 and Case 6 are validated. Figure 5.17 shows the comparison of the profits of the MGO before and after regulation under different errors. As can be seen, based on (3.4), the profit of the MGO decreases with increasing error rates before regulation. However, based on (3.14), the profit of the MGO remains constant for each error rate with the application of the billing procedure.

Figure 5.18 shows the comparison of the revenues of all WT prosumers and PEV CSs, which act as buyers in time slot 12, under different errors. Before the application

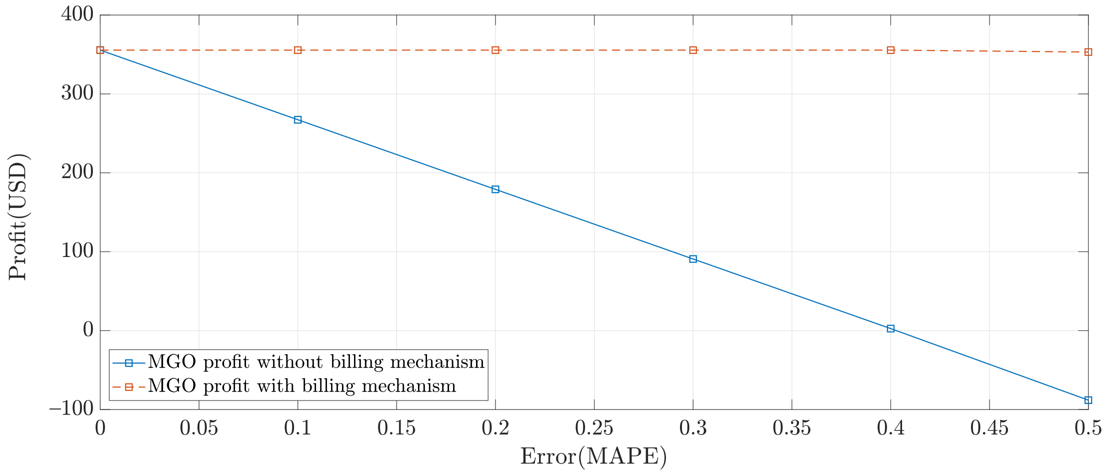

Figure 5.17. *Comparison of the profits of the MGO before and after regulation under different errors in time slot 12.*

of the billing procedure, the revenues of these prosumers and CSs increase with the error rates from 0% to 50% because of buying less energy. Since the unpurchased excess energy is sold to the grid with λ_s^d, the MGO can balance its revenue by penalizing WT prosumers and CSs with $(p_b[12] - \lambda_s^d)\delta_n[12]$ for $n = 4, 5$ and $(p_b[12] - \lambda_s^d)\delta_i^{PEV}[12]$ for $i = 1, 2, 3$, respectively, after the application of the billing procedure. Thus, the regulation decreases the revenues of the considered prosumers and CSs compared to the pre-regulation case in this time slot.

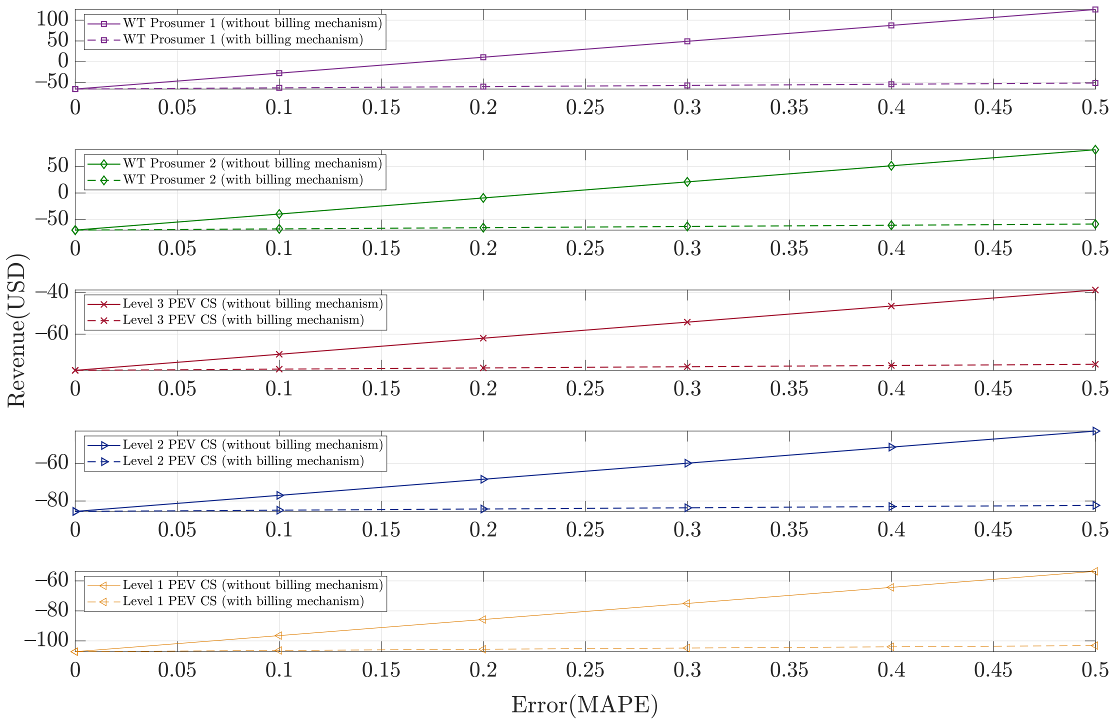

Figure 5.18. *Comparison of the revenues before and after regulation under different errors in time slot 12.*

In time slot 11, the MGO takes on the role of seller (see Figure 5.13), and all PV prosumers behave as sellers (see Figure 5.6). To see the effect of Case 1, let $\delta_1[11], \delta_2[11], \delta_3[11] > 0$, which means that the amount of selling energy is more than the scheduled selling energy. For this, it is assumed that the actual productions of these prosumers, $E_1^g[11], E_2^g[11]$, and $E_3^g[11]$, are increased from, respectively, $\tilde{E}_1^g[11], \tilde{E}_2^g[11]$, and $\tilde{E}_3^g[11]$ by 0% to 50% (measured by MAPE) of the corresponding forecasted $\tilde{E}_n^g[11]$ (for $n = 1, 2, 3$) of the considered prosumers. The actual consumptions of PV prosumers and exchanging energies of their ES systems are chosen as their end-game consumptions and forecasted exchanging energies. Since the MGO is in the seller position in this time slot, Case 1 is validated. Figure 5.19 shows the comparison of the profits of the MGO before and after regulation under different errors. As can be seen, based on (3.4), the profit of the MGO decreases with increasing error rates before regulation. However, based on (3.14), the profit of the MGO remains constant for each error rate with the application of the billing procedure.

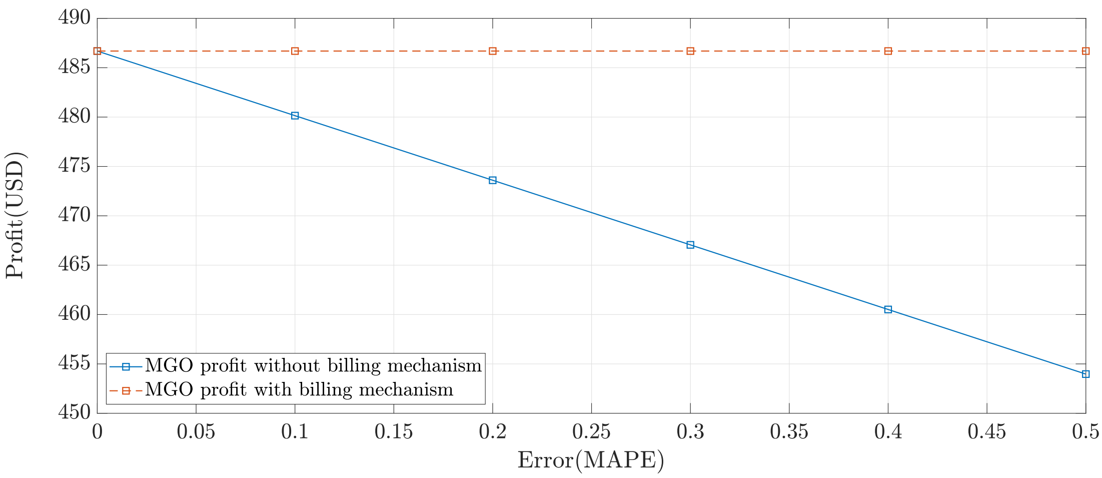

Figure 5.19. *Comparison of the profits of the MGO before and after regulation under different errors in time slot 11.*

Figure 5.20 shows the comparison of the revenues of PV prosumers, which act as sellers in time slot 11, under different errors. Before the application of the billing procedure, the revenues of these prosumers increase with the error rates from 0% to 50% because of selling more energy. Since the extra energy purchased from PV prosumers is sold to the grid with λ_s^p, the MGO can balance its revenue by buying this excess energy from the prosumers with λ_s^p instead of $p_s^{PV}[11]$ after the application of the billing procedure. Thus, the regulation decreases the revenues of PV prosumers compared to the pre-regulation case in this time slot.

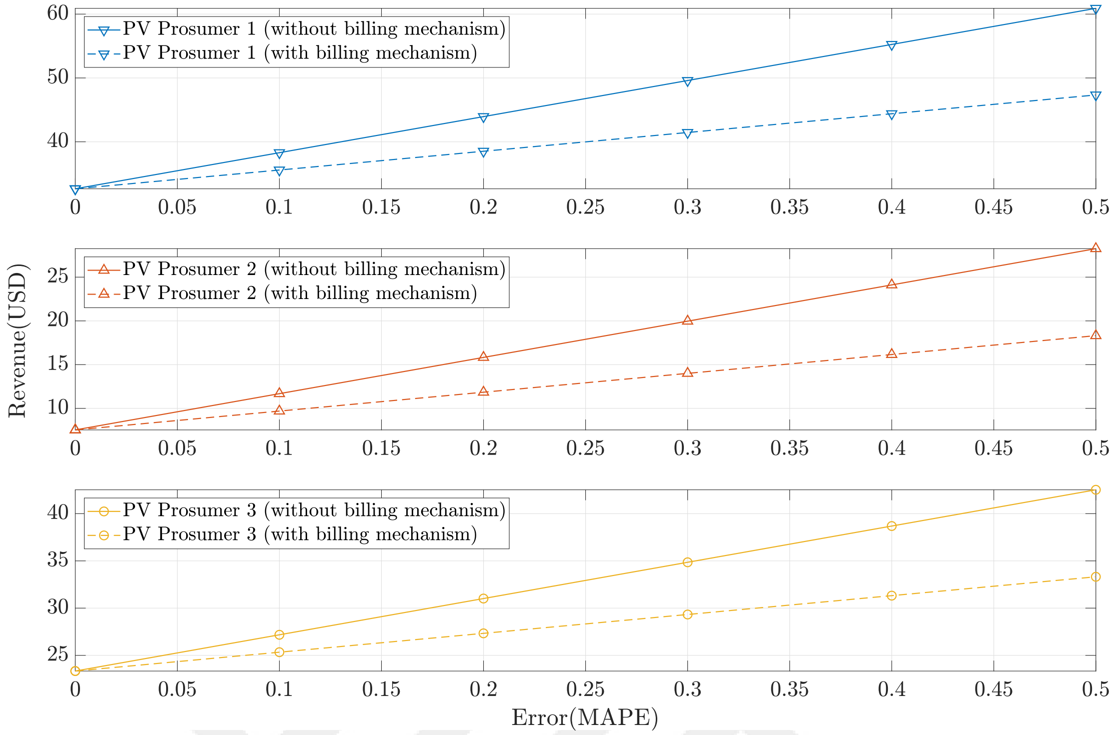

Figure 5.20. *Comparison of the revenues before and after regulation under different errors in time slot 11.*

5.1.4. Islanded mode

The previously obtained end-game results indicate that the microgrid is in the buyer position during evening hours to meet its significant energy demand (see Figure 5.13). Thus, in this case study, the islanded mode is aimed for $t = 17, \ldots, 19$. To achieve this objective, some decision parameters need to be optimized for the considered time slots. For $n = 1, \ldots, N$, $b_n^{s,\chi}[17] = 0.8$, $b_n^{s,\chi}[18] = b_n^{s,\chi}[19] = 0.5$, $b_n^b[17] = 0.9$, and all other relative benefit coefficients are chosen as 1. For $n = 1, \ldots, N$, $x_n^{\min}[17] = 0.5\,\tilde{x}_n[t]$, $x_n^{\max}[17] = 1.5\,\tilde{x}_n[t]$, $x_n^{\min}[18] = x_n^{\min}[19] = 0.3\,\tilde{x}_n[t]$, and $x_n^{\max}[18] = x_n^{\max}[19] = 1.7\,\tilde{x}_n[t]$. For $i = 1, \ldots, N_V$, $l_i^{\min}[t] = 0.5\,\tilde{L}_i[t]$ and $l_i^{\max}[t] = 1.5\,\tilde{L}_i[t]$ for $t = 17, \ldots, 19$.

Considering the specified parameters, the Stackelberg game is performed based on the modified nonlinear programming problem given in (2.18) for $t = 17, \ldots, 19$. It should be noted that since the microgrid is independent of the utility grid in time slots 17-19 to satisfy islanded mode, the utility grid price constraints in determining the internal prices have been removed in the modified problem, and the end-game prices are determined under the constraint $\max\left(p_s^{PV}[t], p_s^{WT}[t]\right) < p_b[t]$ for these time slots. The obtained end-game prices in islanded mode are shown in Figure 5.21. As can be seen in Figure 5.21, the internal buying price $p_b[t]$ is higher than λ_b where $t = 17, \ldots, 19$, which is expected according to the modified price constraints. Based on the end-game prices in islanded mode, the net energy curves of PV-WT prosumers and loads of CSs are shown in Figure 5.22.

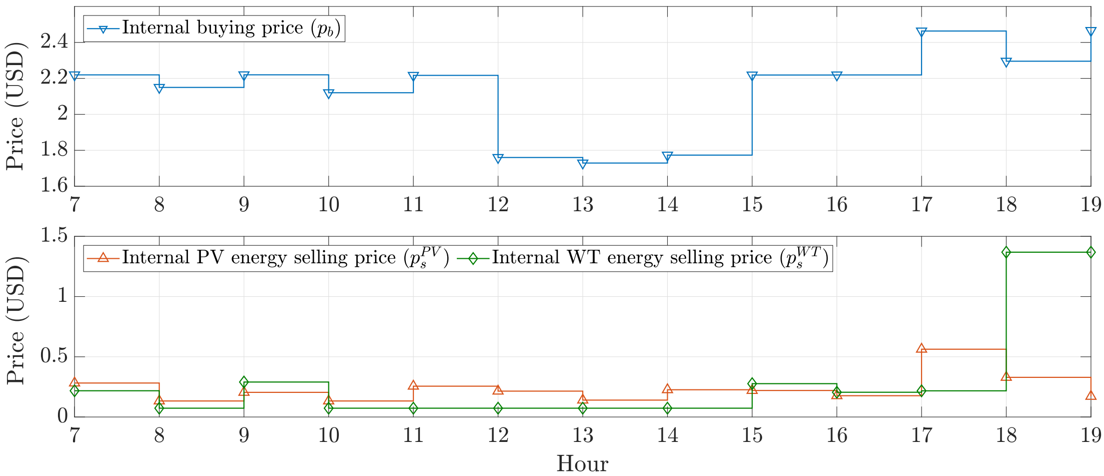

Figure 5.21. *End-game prices in islanded mode for $t = 17, \ldots, 19$.*

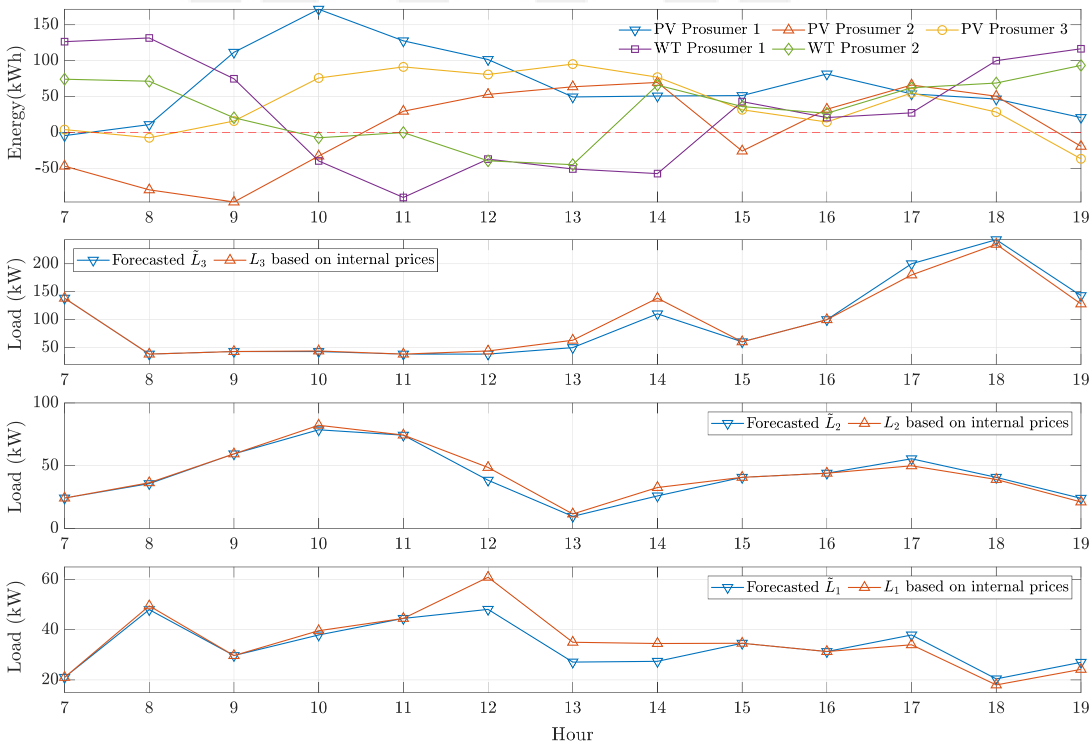

Figure 5.22. *End-game net energy curves of PV-WT prosumers and end-game loads of PEV CSs in islanded mode for $t = 17, \ldots, 19$.*

According to the comparison of Figure 5.11 and Figure 5.22, for $t = 17, \ldots, 19$, it is observed that the increase in $p_b[t]$ in the modified approach (see $p_b[t] > \lambda_b$ from Figure 5.21) motivates all CSs to decrease their load demands. Before the changes to the underlying approach regarding islanded mode, as shown in Figure 5.11, the forecasted loads and end-game loads of CSs are the same in the considered time slots (see $p_b[t] = \lambda_b$ from Figure 5.5). However, as a result of performing the modified approach, it can be seen in Figure 5.22 that the end-game loads of CSs become less than their forecasted loads.

Based on Figure 5.6 (bottom) and Figure 5.22, for $t = 17, \ldots, 19$, as can be seen that seller prosumers sell more energy to the MGO when there is an increase in internal selling prices in the modified approach compared to the prices given in Figure 5.5. For example, in time slots 18 and 19, both WT prosumers increase their selling energy with the rise in $p_s^{WT}[t]$. Likewise, in time slot 17, all PV prosumers sell more energy to the MGO in response to the increase in $p_s^{PV}[t]$. It should be noted that some prosumers are motivated to switch their roles in the modified approach according to the internal price changes. For example, as shown in Figure 5.6 (bottom), all PV prosumers behave as buyers in time slots 18 and 19. However, it can be seen in Figure 5.22 that PV Prosumer 1 switches its role from a buyer to a seller in these time slots. PV Prosumer 2 and PV Prosumer 3 also give the same reaction to the price changes in time slot 18.

Considering the results of the modified approach, total buying, total selling, and net energies of the microgrid are shown in Figure 5.23. As can be seen from Figure 5.23, the microgrid can successfully operate in islanded mode for $t = 17, \ldots, 19$.

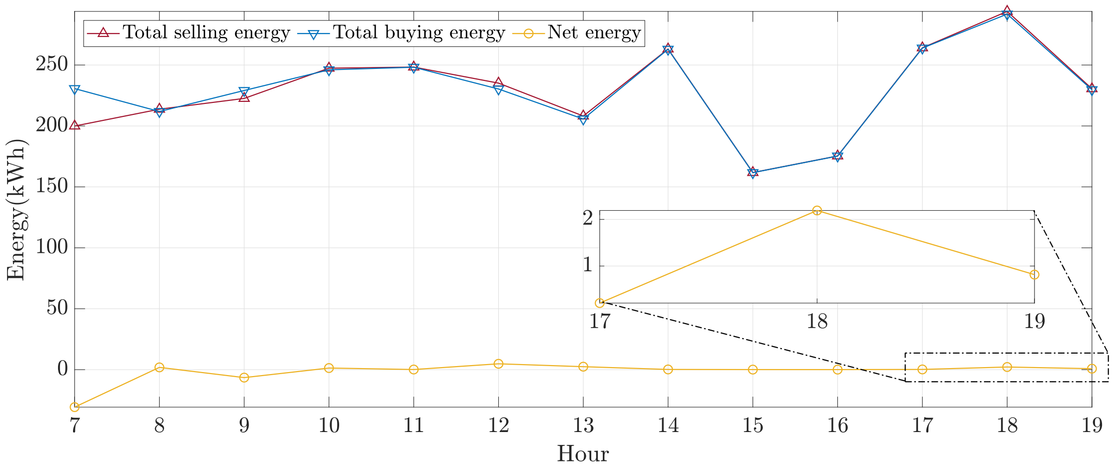

Figure 5.23. *Total buying, total selling, and net energies of the microgrid in islanded mode for $t = 17, \ldots, 19$.*

5.2. Energy Sharing Management Between Multiple Microgrids

In this section, the management of energy sharing between three microgrids for $t = 7, \ldots, 19$ is considered as a case study. The weights of the edges are defined as $\beta_{1,2} = \beta_{2,1} = 1$, $\beta_{1,3} = \beta_{3,1} = 0.4$, $\beta_{2,3} = \beta_{3,2} = 0.4$. Forecasted values of energy generation and consumption of all microgrids are shown in Figure 5.24 and Figure 5.25, respectively. The difference between the forecasted energy generation and consumption of l^{th} microgrid $\left(\text{i.e., } \tilde{E}_l^m[t] - \tilde{x}_l^m[t]\right)$ determines whether the microgrid behaves as a seller or a buyer in the relevant time slot. If $\tilde{E}_l^m[t] - \tilde{x}_l^m[t] > 0$, the microgrid adopts the seller role due to its surplus energy. Otherwise, if $\tilde{E}_l^m[t] - \tilde{x}_l^m[t] < 0$, the microgrid takes on the role of buyer since it needs energy.

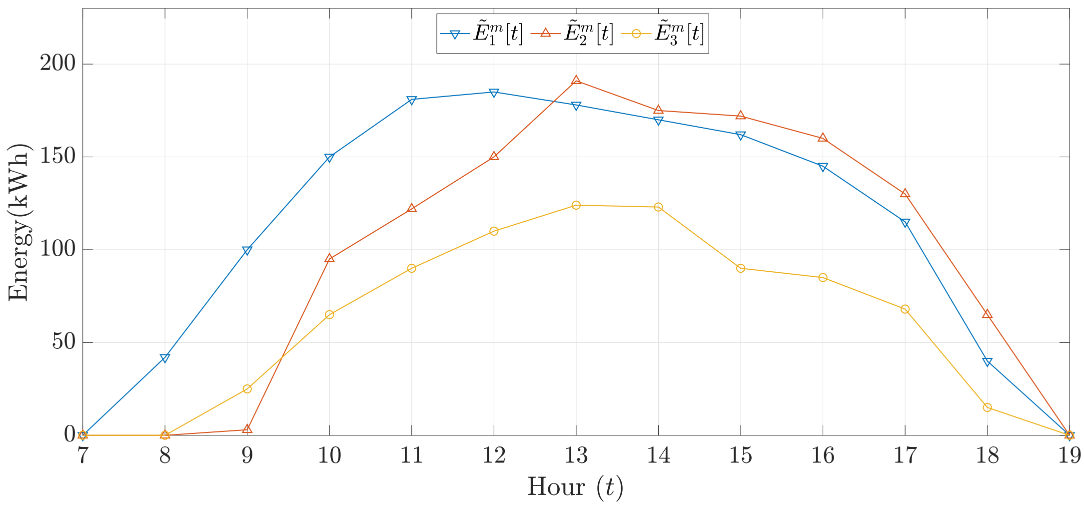

Figure 5.24. *Forecasted values of energy generation of all microgrids.*

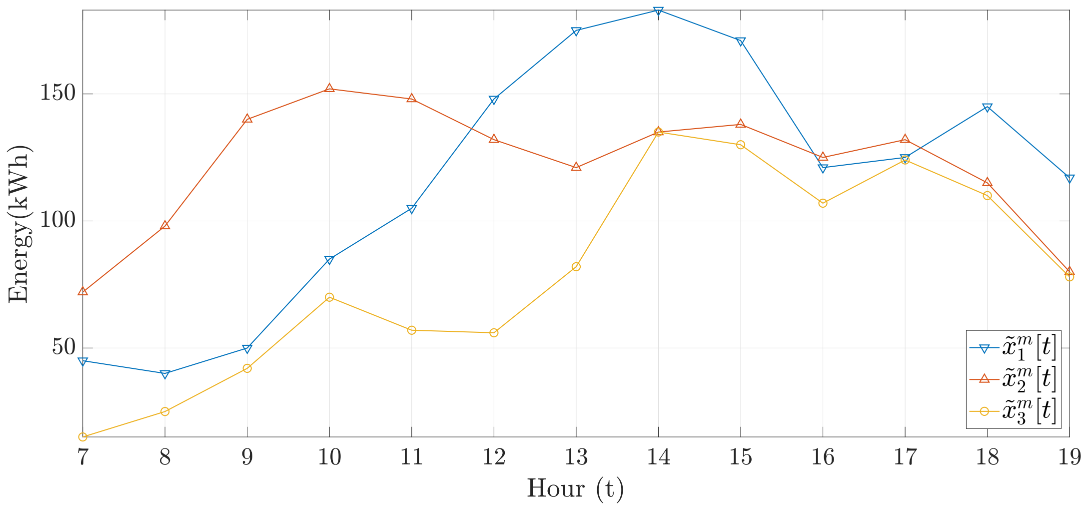

Figure 5.25. *Forecasted values of energy consumption of all microgrids.*

Considering the specified parameters, and forecasted energy generations and consumptions of the microgrids, the Stackelberg game model is carried out based on the problem given in (4.10) to optimize energy sharing between the microgrids for the considered time period. The-end game internal selling price p_s^m and internal buying price p_b^m are shown in Figure 5.26.

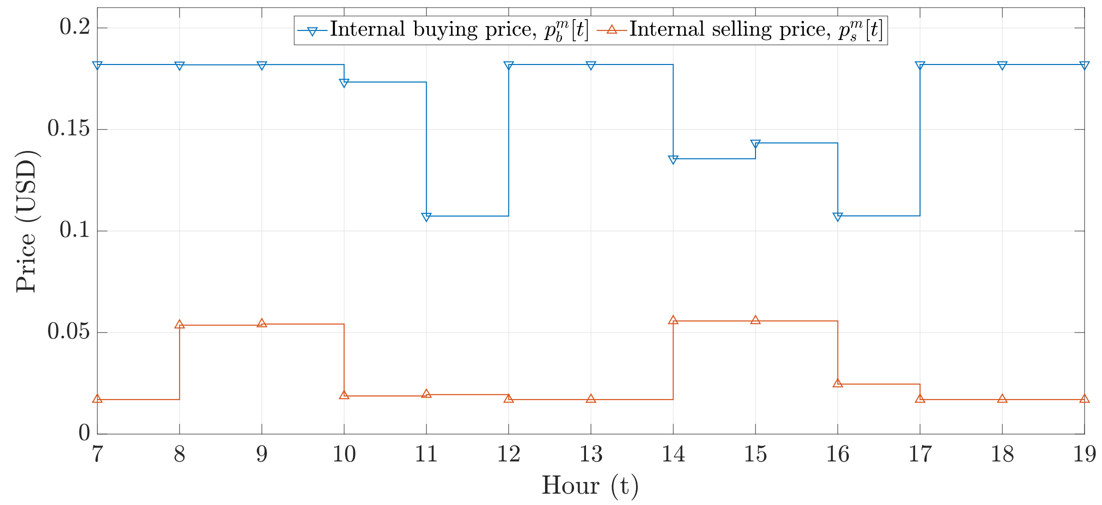

Figure 5.26. *End-game internal prices.*

Each microgrid l obtains its optimal energy consumption based on the determined internal prices. The differences between the end-game consumption and the forecasted consumption of each microgrid $\left(x_l^m[t] - \tilde{x}_l^m[t] \text{ for } l = 1, 2, 3\right)$ are shown in Figure 5.27.

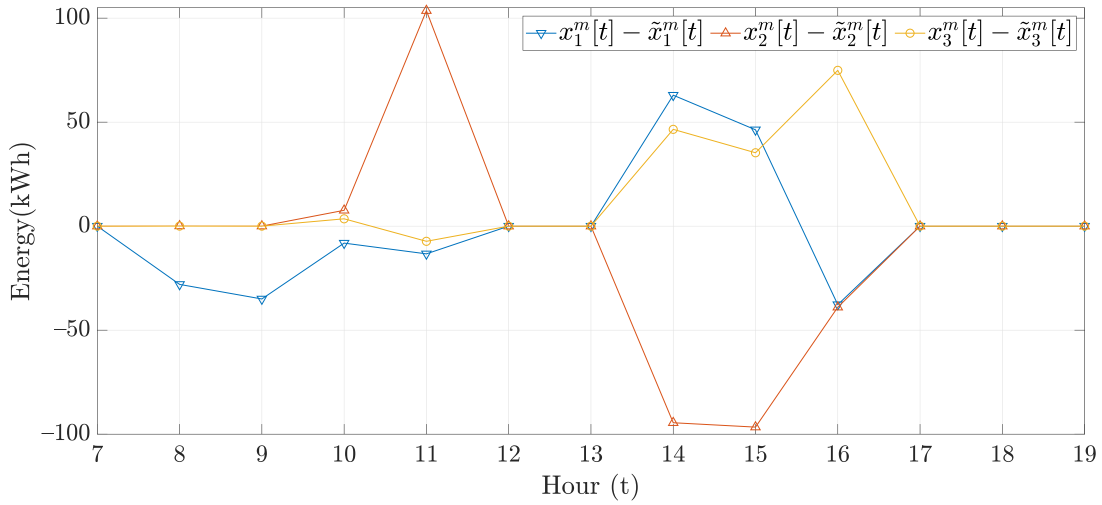

Figure 5.27. *Differences between the end-game consumption and the forecasted consumption of each microgrid.*

The comparison of the initial net energy $\left(\tilde{E}_l^m[t] - \tilde{x}_l^m[t]\right)$ and the end-game net energy $\left(\tilde{E}_l^m[t] - x_l^m[t]\right)$ of each microgrid l is shown in Figure 5.28. The relationship between the changes in consumption values of the microgrids and end-game prices can be analyzed similarly to that in the previous section. Note that the increase in p_s^m motivates sellers to sell more energy and the decrease in p_b^m motivates buyers to buy more energy. To validate these statements, time slots 15 and 14 can be considered, respectively. As can be seen in Figure 5.28, in time slot 15, the seller Microgrid 2 increases the amount of its selling energy by decreasing its consumption with the rise in p_s^m. Also, in time slot 14, the buyer microgrids (i.e., Microgrid 1 and Microgrid 3) increase their energy purchases by consuming more energy with the fall in p_b^m.

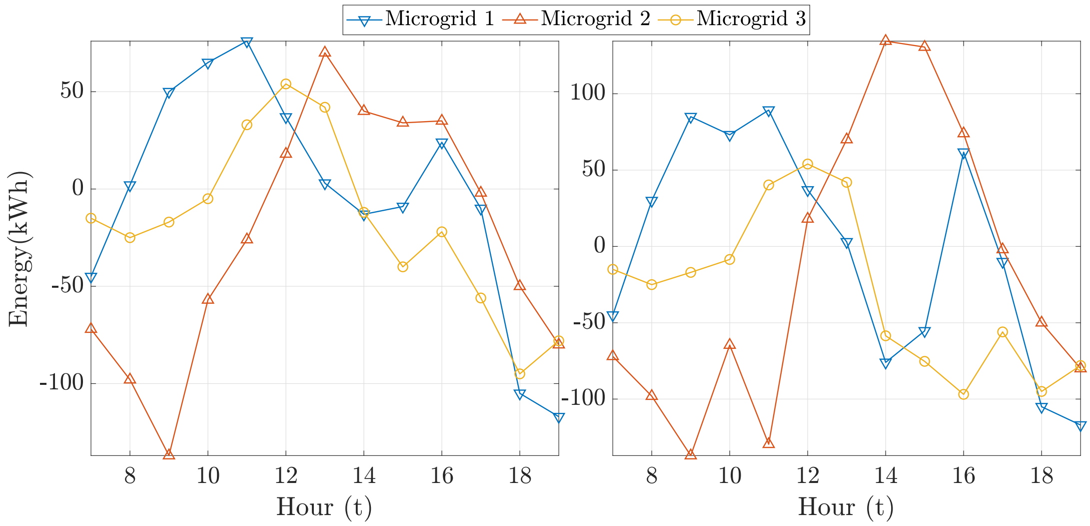

Figure 5.28. *Comparison of the initial (left) and end-game (right) net energies of the microgrids.*

The differences between the utilities of each microgrid based on the utility grid prices and end-game prices are shown in Figure 5.29. As can be seen, the utilities of seller and buyer microgrids increase in line with the rise in internal selling price and the fall in internal buying price, respectively. For instance, Microgrid 3 is a buyer in time slot 16, and the utility of this microgrid significantly increases in response to the sharp fall in p_b^m. A similar situation can be observed for Microgrid 2 in time slot 11. As another example, Microgrid 2 is a seller in time slot 14, and the utility of this microgrid increases with the rise in p_s^m.

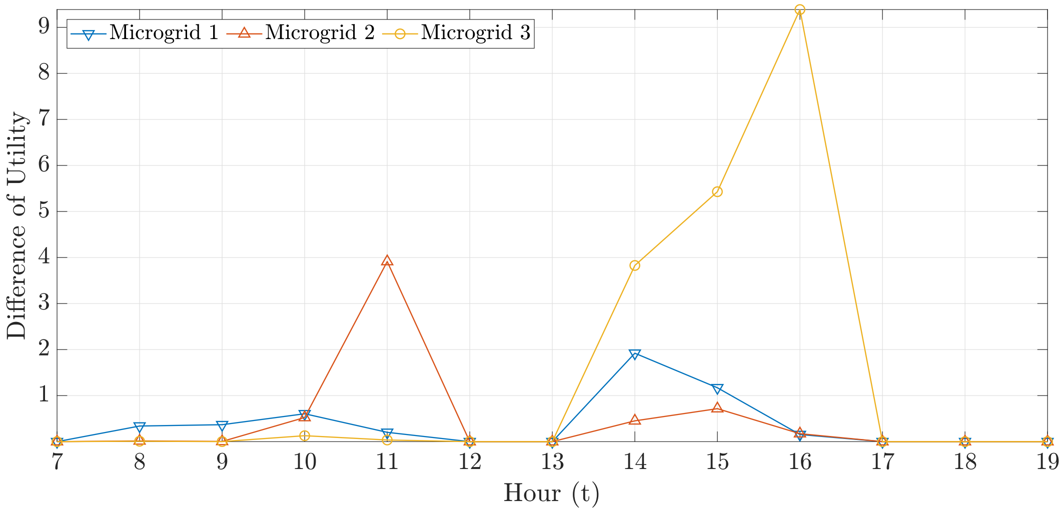

Figure 5.29. *Differences between the utilities of each microgrid based on the utility grid prices and end-game prices.*

The comparison of the ESP's profit based on the utility grid prices and end-game prices is shown in Figure 5.30. In time slots 7, 12, 13, and 17-19, since all microgrids are either sellers or buyers, the ESP cannot trade energy between them. Consequently, p_b^m and p_s^m take the same values as λ_b^m and λ_s^m, respectively (see Figure 5.26). This leads to zero profit for the ESP in these time slots. However, in the remaining time slots, the ESP's profit is positively affected by the end-game prices. Thus, it can be concluded from Figure 5.29 and Figure 5.30 that the internal prices can increase the ESP's profit, meanwhile improving the utilities of the microgrids.

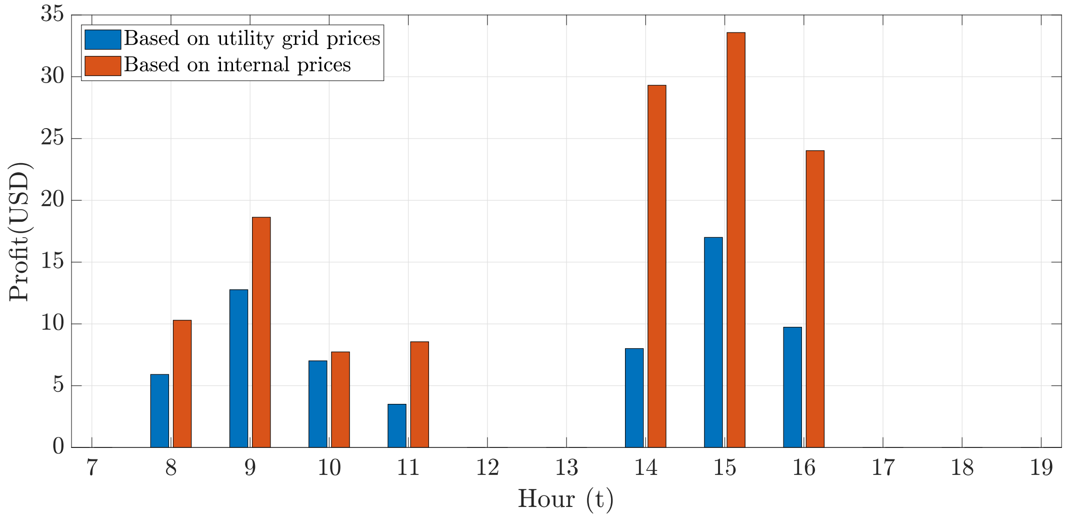

Figure 5.30. *Comparison of the ESP's profit based on the utility grid prices and end-game prices.*

6. CONCLUSION AND FUTURE RESEARCH

In Section 6.1, the concluding remarks of this thesis are given. Then, in Section 6.2, regarding the present contributions of this thesis, the possible research objectives for the future are discussed.

6.1. Conclusion

In this dissertation, Stackelberg game-based strategies for energy sharing management of microgrids are developed. In this regard, a single-leader multi-follower Stackelberg game approach is proposed to optimize energy sharing in a microgrid including PV-WT prosumers equipped with ES systems and PEV CSs. The MGO serves as the leader that conducts energy sharing by setting prices for internal buying and selling transactions. In addition, all prosumers and PEV CSs are the followers that adjust their consumptions and loads, respectively, based on the pricing policy of the MGO. The role of each prosumer within the microgrid can be that of either a seller or a buyer, which is determined by its production and consumption, as well as its charging or discharging behavior. Unlike the prosumers, PEV CSs are limited to acting only as buyers in the given problem. Through the proposed game approach, the MGO aims to maximize its profit while ensuring that both prosumers and CSs act in their interests. After the energy sharing management of a microgrid is established, the problem is extended to address the management of energy sharing between microgrids. Similar to the game approach proposed for a single microgrid, the ESP takes the leader role in the problem-solving and determines internal selling and buying prices to coordinate the energy sharing between microgrids, which act as followers. With the game-based strategies developed in this dissertation, several significant contributions to the literature are presented.

In the existing studies, buyer and seller roles owned by prosumers are determined according to their forecasted production and consumption values at the start of each time interval, and even if altering their assigned roles based on updated prices could lead to increased benefits, their designated roles remain fixed throughout the given time period. In addition, the chosen utility functions of prosumers do not have prosumer-based parameters, which they can determine in line with their preferences. These points significantly limit prosumers in terms of flexibility. Unlike the previous studies, in the proposed Stackelberg game approach, prosumers are not constrained to stay in their initial roles and they can switch roles from buyer to seller or seller to buyer based on the final prices. Moreover, prosumers can exhibit a more active behavior in the microgrid by designing their energy consumption strategies based on their specified decision parameters reflecting the behavioral characteristics.

During the design of the energy management algorithm for the microgrid, the problem of planning the energy demands of PEV CSs is handled differently from similar studies. Rather than considering them as regular consumers that supply their energy needs from the microgrid as total loads, independent from vehicle numbers and charging levels, the energy demands of each station are determined as variable demands according to its operational characteristics. Thus, the energy planning of CSs is based on determining the number of PEVs that each station can accept within a specified time interval, taking into account the vehicle charging levels. To achieve this, the problem of planning the energy demands of PEV CSs has been transformed into an integer programming problem, as opposed to a non-linear programming problem.

The modifications made to the proposed approach enable the microgrid to operate independently from the utility grid and satisfy the requirements of islanded mode during time slots when energy is exchanged with the grid based on the end-game results. This is important because there may be some situations where the microgrid needs to reduce reliance on the grid by moving away from the goal of profit maximization, which is the focus of typical game-theoretic approaches. The identified modifications provide greater flexibility and adaptability in the operation of the microgrid, allowing it to disconnect from the utility grid when required.

To address the uncertainties arising from renewable energy generation, energy consumption, and energy exchange in ES systems, a billing procedure is proposed for the comprehensive problem discussed in this thesis. Since the exact implementation of the leader's strategy is required, the accuracy of forecasting directly affects the overall success of the end-game strategies on real-time applications. A well-designed billing scheme, such as the one proposed here, can enhance the robustness of the game approach by minimizing the negative impacts of forecasting errors or possible mismatches between determined and actual energy values.

Lastly, as mentioned above, the game approach proposed for managing energy sharing within a single microgrid has been extended to address the issue of energy sharing between multiple microgrids. The resulting solution effectively balances the energy needs of each microgrid based on the preferences and constraints of individual microgrid owners, while optimizing energy distribution among microgrids.

6.2. Future Research

As future research objectives, the problems of managing energy sharing within a microgrid and between microgrids, which have been discussed in this dissertation, can be integrated into each other to form a two-stage problem. This problem should be designed comprehensively to develop energy management strategies that bring the mentioned independent problems together at the optimum point.

To obtain energy management algorithms for the two-stage problem, it is essential to consider the goals of active end users in the microgrid, all the parametric definitions and constraints they determine, as well as the internal dynamics of these end users. Additionally, the operational characteristics of energy transmission lines between microgrids, such as capacity, availability rate, and maintenance/life-loss rate, must be involved in the problem. Thus, once the solution proposals are obtained, they can be adapted to the real-time system structure in the best way possible. As a result, the development of a unique holistic perspective by considering the energy sharing management problems of both microgrids and their active end users, who are the building blocks of these microgrids, would undoubtedly make a significant contribution to the literature.

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Research Projects

- "Optimum Energy Management of Microgrids Including Prosumers with Energy Storage Units and Photovoltaic/Wind Energy Systems, and Plug-in Electric Vehicle Charging Stations" supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under grant number 121E351, 01.10.2021 - 01.10.2022 (Scholar)
- "Total Consideration of Optimum Energy Management between Microgrids with Smart Home Energy Management and Testing Appropriate Energy Management Strategies Using Real Data" supported by the Scientific and Technological Research

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- "Meeting the Energy Need of a Home with Renewable Power Systems by Ensuring Energy Supervision at Anadolu University İki Eylül Campus and Development of Google Map Based PV Panel Installation/Cost Analysis Simulation System" supported by the Scientific Research Projects Commission of Anadolu University under grant number 1505F512, 21.07.2015 - 01.12.2017 (Researcher)
- "Solar Energy Analysis of a Home by Considering Outdoor Parameters" supported by the Scientific Research Projects Commission of Anadolu University under grant number 1604F170, 13.05.2016 - 28.04.2017 (Researcher)
- "Analysis of the Relationship Between Production Values Obtained from Wind Turbine and Instant Wind Speed at İki Eylül Campus" supported by the Scientific Research Projects Commission of Eskişehir Technical University under grant number 1705F291, 06.06.2017 - 01.10.2019 (Researcher)
- "Analysis of Production Values of Solar Panels Using New Methods and Home Energy Management" supported by the Scientific Research Projects Commission of Eskişehir Technical University under grant number 19ADP005, 02.07.2019 - 30.09.2021 (Researcher)
- "Optimum Energy Management of Microgrids" supported by the Scientific Research Projects Commission of Eskişehir Technical University under grant number 20DRP003, 31.01.2020 - ongoing (Researcher)
- "Energy Management for Smart Homes Using Mathematical and Heuristic Methods" supported by the Scientific Research Projects Commission of Eskişehir Technical University under grant number 20ADP091, 03.12.2020 - ongoing (Researcher)
- "Development of Renewable Energy Potential of Eskişehir Technical University 2 Eylül Campus: Case Study Improvement in Energy Management Model" supported by the Scientific Research Projects Commission of Eskişehir Technical University under grant number 22GAP265, 20.06.2022 - ongoing (Researcher)
- "Optimum Energy Management Using Indoor and Outdoor Parameters in Household Microgrid" supported by the Scientific Research Projects Commission of Eskişehir Technical University under grant number 22ADP141, 31.01.2022 - ongoing (Researcher)

Journal Papers

- Ö. Erol and Ü. Başaran Filik, "A Stackelberg game approach for energy sharing management of a microgrid providing flexibility to entities," Applied Energy, vol. 316, p. 118944, 2022.
- Ö. Erol and Ü. Başaran Filik, "Improvement and evaluation of daily global solar radiation decomposition models using meteorological parameters: A case study for Turkey," International Journal of Green Energy, vol. 19, no. 15, pp. 1633 - 1648, 2022.
- Ö. Ayvazoğluyüksel and Ü. Başaran Filik, "Estimation methods of global solar radiation, cell temperature and solar power forecasting: A review and case study in

Eskişehir," Renewable and Sustainable Energy Reviews, vol. 91, pp. 639 - 653, 2018.

- Ö. Ayvazoğluyüksel and Ü. Başaran Filik, "Estimation of monthly average hourly global solar radiation from the daily value in Çanakkale, Turkey," Journal of Clean Energy Technologies, vol. 5, no. 5, pp. 389 - 393, 2017.

Conference Papers

- Ö. Erol and Ü. Başaran Filik, "A Stackelberg Game Approach for Energy Sharing Management of a Microgrid Including Photovoltaic and Wind Turbine Prosumers," in 11th International Conference on Power Science and Engineering (ICPSE), Eskişehir, Turkey, 2022. *(The best presentation award)*
- Ö. Ayvazoğluyüksel and Ü. Başaran Filik, "A New Model to Estimate Global Solar Radiation on Horizontal Surface in Eskişehir," in 16th International Conference on Clean Energy (ICCE), Famagusta, N. Cyprus, 2018.
- Ö. Ayvazoğluyüksel and Ü. Başaran Filik, "Power Output Forecasting of a Solar House by Considering Different Cell Temperature Methods," in 10th International Conference on Electrical and Electronics Engineering (ELECO), Bursa, Turkey, 2017.
- Ö. Ayvazoğluyüksel and Ü. Başaran Filik, "Hourly Global Solar Radiation Estimation from the Daily Value in İki Eylül Campus in Eskişehir," in International Energy & Engineering Conference (UEMK), Gaziantep, Turkey, 2016.
- Ö. Ayvazoğluyüksel, Ü. Başaran Filik, and T. Filik, "Remotely Monitoring and Modelling of Renewable Energy of a Controlled Home Placed in A.U. Iki Eylül Campus," in 8th International Ege Energy Syposium (IEESE), Afyonkarahisar, Turkey, 2016.
- Ü. Başaran Filik, Ö. Ayvazoğluyüksel, and T. Filik, "A.Ü. İki Eylül Kampüsünde Google Harita Tabanlı Fotovoltaik Panel Kurulum/Maliyet Analizi Benzetim Sistemi Geliştirilmesi," in 1st International Workshop on Construction and Electricity Applications on Vocational Education (IWCEA), Eskişehir, Turkey, 2015.
- Ü. Başaran Filik, Ö. Ayvazoğluyüksel, and T. Filik, "A.Ü. İki Eylül Kampüsünde Güneş/Rüzgâr Verilerini İzleme ve Hibrit Enerji Üretim Sisteminin Kurulması," in 1st International Workshop on Construction and Electricity Applications on Vocational Education (IWCEA), Eskişehir, Turkey, 2015.
- Ö. Ayvazoğluyüksel and Ü. Başaran Filik, "Akıllı Şebeke Sisteminin Anadolu Üniversitesi Mühendislik Fakültesi için Matlab/Simulink Ortamında Modellenmesi," in 3rd International İstanbul Smart Grid Congress and Fair (ICSG), İstanbul, Turkey, 2015.

Funding/Scholarship

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- TÜBİTAK 2250 Graduate Scholarship Performance Program, 2022-1
- TÜBİTAK 2211-A National Graduate Scholarship Program, 2017-1
- TÜBİTAK 2209-B University Students Industry-Oriented Research Projects Support Program, 2013-1