

Prosumer-Centric Self-Sustained Smart Grid Systems

Nathan Patrizi, Sara Kathryn LaTouf[✉], *Student Member, IEEE*, Eirini Eleni Tsiropoulou[✉], *Senior Member, IEEE*,
and Symeon Papavassiliou[✉], *Senior Member, IEEE*

Abstract—Modern smart grid systems exploit a two-way interaction paradigm between the utility and the electricity user and promote the role of prosumer, as a new user type, able to generate and sell energy, or consume energy. Within such a setting, the prosumers and their interactions with the microgrid system become of high significance for its efficient operation. In this article, to model the corresponding interactions, we introduce a labor economics-based framework by exploiting the principles of contract theory, that jointly achieves the satisfaction of the various interacting system entities, i.e., the microgrid operator (MGO) and the prosumers. The MGO offers personalized rewards to the sellers and buyers, to incentivize them to sell and purchase energy, respectively. To provide a stable and efficient operation point, while aiming at jointly satisfying the profit and requirements of the involved competing parties, optimal personalized contracts, i.e., rewards and amount of sold/purchased energy, are determined, by formulating and solving contract-theoretic optimization problems between the MGO and the sellers or buyers. The analysis is provided for both cases of complete and incomplete information availability regarding the prosumers' types. Detailed numerical results are presented to demonstrate the operation characteristics of the proposed framework under diverse scenarios.

Index Terms—Contract theory, decision-making, prosumers, smart grid systems, system modeling and optimization.

I. INTRODUCTION

SMART grid (SG) systems have been introduced as an alternative solution to traditional power systems which operate in a centralized manner, generating power in large power stations via the exploitation of fossil fuel resources, and distributing the generated power to consumers [1]. SGs consist of multiple microgrids, which are small-scale power supply networks, accommodating conventional energy units, renewable energy sources, and energy storage systems [2]. One key enabler of SGs is the new type of users, named *prosumers*, who are able to generate, store, sell, and buy energy by mainly exploiting solar photovoltaic panels and storage devices [3], among others. The prosumers are equipped with smart meters to exchange (sell/buy) power with the microgrid operator (MGO), thus, creating a

local energy trading system [4]. In this article, we capture the prosumers' interactions with the MGO in terms of selling and buying energy based on a labor economics framework, while guaranteeing the joint optimization of their profits and enabling the overall microgrid system to converge to a stable point of operation. The main novelty of the article lies in introducing a unified economics-based framework that enables the prosumers (either sellers or buyers) to determine the optimal amount of exchanged energy with the MGO, while jointly the prosumers and the MGO, who are characterized by competing interests, optimize their benefits accounting for their own constraints.

A. Related Work

Several recent research works focus on the operation of microgrid systems aiming to satisfy the consumers' or prosumers' power demand via dealing with the demand response management (DRM) problem [5]. In [6], the interactions among multiple microgrid systems are studied based on the Nash bargaining theory in order to incentivize each microgrid to participate in the proactive energy trading and fair benefit sharing. The authors formulate the corresponding joint optimization problem and solve it by decomposing the problem into two sequential problems, where the first minimizes the social cost and the second one optimizes the trading benefit sharing. The problem of high-levels stochasticity in the energy production of the renewable energy sources is studied in [7]. The authors provide a systematic approach to deal with this problem and provide the enhanced flexibility to the system to satisfy the consumers' power demand via exploiting the fast-ramping units, the energy storage, and the hourly demand response. In [8], the authors introduce a novel transactive energy control mechanism and a pricing rule to capture the interactions among multiple microgrids, aiming at jointly minimizing their operating cost and optimizing the utilization of the renewable energy sources. The authors have provided a detailed comparative evaluation to other centralized and decentralized transactive energy control mechanisms to show the benefits of the proposed approach in terms of the microgrids' effective operation and computational efficiency in microgrids' coordination.

The problem of reducing prosumers' electricity bills, while guaranteeing their minimum power demand constraints is studied in [9] via the introduction of an intelligent residential energy management system. A predictive mechanism of the power demand and supply in a microgrid is introduced in [10] by designing a smart load estimator based on a neural networks' approach. The designed mechanism considers the ambient temperature, the time of day, the hourly price, and the peak demand.

Manuscript received June 11, 2021; revised September 17, 2021 and January 24, 2022; accepted March 1, 2022. This work was supported by the National Science Foundation EPSCoR Program under Grant OIA-1757207. (Corresponding author: Eirini Eleni Tsiropoulou.)

Nathan Patrizi, Sara Kathryn LaTouf, and Eirini Eleni Tsiropoulou are with the Department of Electrical and Computer Engineering, University of New Mexico, Albuquerque, NM 87131 USA (e-mail: npatrizi@unm.edu; sklatouf@gmail.com; eirini@unm.edu).

Symeon Papavassiliou is with the School of Electrical and Computer Engineering, National Technical University of Athens, 15780 Athens, Greece (e-mail: papavass@mail.ntua.gr).

Digital Object Identifier 10.1109/JSYST.2022.3156877

In [11], the authors study the stochastic risk in the demand response by accounting for the uncertainties of islanding duration, and the prediction errors of loads, renewable power generation, and electricity price. The authors formulate a joint energy and reserve scheduling problem aiming at maximizing the operator's profit. Similar stochastic factors in the energy management problem are considered in [12], where the authors introduce a nodal price-based energy management framework in a microgrid to improve the scheduling accuracy. Toward addressing the stochastic energy management, the authors formulate the problem as a mixed integer nonlinear programming and a corresponding heuristic algorithm is introduced in order to determine the energy scheduling. It should be noted here that the above research works follow a system-based approach emphasizing on the operation of the microgrid, without, however, accounting for the unique and personal characteristics of the prosumers.

Focusing on the prosumer-centric microgrid systems, a prospect-theoretic energy trading approach is introduced in [13], in which the prosumers' risk-aware characteristics are considered based on the uncertainty that the selling/buying energy price introduces. The authors formulate a single-leader multiple-follower Stackelberg game, where the microgrid operator (leader) announces the optimal price and the prosumers (followers) determine the amount of energy that they sell or buy, with all the involved entities aiming to optimize their profit. A similar Stackelberg-based approach is followed in [14] that also introduces a reinforcement learning mechanism to enable the consumers to select the utility company that they will purchase energy from, in an autonomous manner. In [15], the prosumers consider the energy as a heterogeneous product depending on the generation technology, its location in the SG, and its owner's reputation. Accordingly, an optimization problem is formulated to minimize the costs of energy losses and battery depreciation, while accounting for the prosumers' preferences regarding the energy.

An incentive-based demand response management framework is introduced in [16] to determine the reliable estimation of demand response quantity and enhance the system reliability. Toward achieving those two goals, the authors have introduced a clustering with demand response levels decision-making algorithm and a reliability constraint-based demand response contingency management scheme, respectively. The consumers' behavioral characteristics for environment responsive demand response potential estimation is studied in [17] based on data analysis models. The authors estimate the consumers' occupancy behavior and renewable energy generation in order to propose a demand response management approach that will guarantee the consumers' comfort constraints.

Placing further emphasis on exploiting the prosumers' unique power generation and demand characteristics, a pricing-based DRM problem is introduced in [18], which jointly considers the prosumers' behavioral characteristics in terms of consuming electricity and the electricity demand of their household devices, which can be of various types. In [19], the authors introduce a distributed system-wide framework aimed at minimizing the prosumers' payments, while guaranteeing their privacy and comfort constraints, via dynamically adapting the system load

profile. In [20] and [21], the authors study the impact of the communication unreliability among the MGO and the prosumers on the DRM performance and the electricity price by formulating a joint maximization problem of the DRM performance with respect to the electricity consumption and price, and solve it by leveraging the dual decomposition method. Labor economics and contract theory have been also introduced in the literature in order to incentivize the prosumers to follow a desired behavior within a microgrid [22]. In particular, in [23], the authors introduce a labor economics framework to capture the interactions of the prosumers and the MGO. A contract-theoretic optimization problem is formulated and solved to determine the optimal amount of purchased electricity and the optimal rewards provided by the MGO to the prosumers for the sake of both parties having optimized profit. It is highlighted that this research work considers the prosumers only as buyers and *not* sellers.

B. Contributions and Outline

Based on the above related work, it is highlighted that the problem of incorporating the dual role of the prosumer, i.e., seller and buyer, within the operation of the microgrid system still remains an open issue. Specifically, it is noted that the research works that have focused on either the system-centric or prosumer-centric operation of microgrids have not jointly considered the optimization of the MGO's and the prosumers' benefits/profits in a unified framework. Additionally, the problem of converging to a stable, smooth, and seamless operation of the microgrid system, while accounting for the unique personal energy generation and demand characteristics of the prosumers to appropriately incentivize them—and not force them—to exchange an optimal amount of energy with the MGO, has not been thoroughly studied in the literature.

In this research work, we strive exactly to tackle these issues by introducing a contract-theoretic framework to capture the interactions of the prosumers, acting either as sellers or buyers, with the MGO [22]. Specifically, the principles of contract theory, which is a labor economics theoretical model mainly introduced for business management, is adopted to jointly achieve the satisfaction of the MGO and the prosumers, which often present competing interests. Accordingly, the relations between the MGO and the prosumers (sellers or buyers) are captured following the labor economics model of employer-employee relationship, while aiming to jointly satisfy the profit and requirements of the involved competing parties. In contrast to the existing research works in the field of transactive energy that mainly exploit the Stackelberg games to implement a two-stage optimization approach, i.e., maximize the profit of the MGO and the prosumers, our proposed framework addresses the problem of maximizing the MGO profit, while guaranteeing that the prosumers will experience the best personalized rewards aligned with their energy generation and demand characteristics. It is also noted that the proposed model and framework is an application-oriented decision-making framework considering the logical interactions among the prosumers and the MGO, and it does not focus on the physical layer of the microgrid system.

TABLE I
SUMMARY OF KEY NOTATIONS

Notation	Description [Units]
Set of times slots	$T = \{1, \dots, t, \dots, T \}$
Set of prosumers	$N = \{1, \dots, n, \dots, N \}$
Set of sellers	$S = \{1, \dots, s, \dots, S \}$
Set of buyers	$B = \{1, \dots, \beta, \dots, B \}$
Set of home appliances	$A_n = \{1, \dots, a_n, \dots, A_n \}$
Non-shiftable energy demand	d_n^{Min} [kWh]
Maximum energy demand	d_n^{Max} [kWh]
Energy demand	d_n^t [kWh]
Renewable energy generation	g_n^t [kWh]
Energy generation surplus	b_n^t [kWh]
Seller's (Buyer's) type	$\tau_s^t (\tau_\beta^t)$
Seller's (Buyer's) effort	$e_s^t (e_\beta^t)$
Seller's (Buyer's) utility	$U_s^t(e_s^t) (U_\beta^t(e_\beta^t))$
Seller's (Buyer's) reward	$r_s^t (r_\beta^t)$
Seller's cost	p_s
Seller's evaluation function	$\epsilon(r_s^t(e_s^t))$
MGO's utility (sellers interaction)	$U_{MGO,buy}^t(\mathbf{e})$
MGO's utility (buyers interaction)	$U_{MGO,sell}^t(\mathbf{e}_{buy})$
Buyer's satisfaction function	$f(e_\beta^t)$

The main contributions of this research work that differentiate it from the rest of the existing literature are summarized below.

- 1) A microgrid system is considered consisting of the MGO and the prosumers, who generate energy based on renewable energy sources (e.g., solar photovoltaic panels) and are equipped with energy storage (e.g., Lithium-ion batteries). Each prosumer can dynamically act as seller or buyer based on its unique personal energy generation, demand, and storage characteristics throughout the day.
- 2) A contract-theoretic optimization problem is formulated to capture the interactions among the sellers and the MGO. Following the principles of contract theory, the optimal amount of energy that the sellers sell to the MGO at a specific announced price, and the optimal rewards (e.g., price discount) offered by the MGO, are determined. The ultimate goal of this novel approach is to jointly optimize the profit of the MGO and the sellers via considering their unique personal energy generation, demand, and storage characteristics.
- 3) Toward introducing a unified framework that jointly handles the energy exchange of the buyers with the MGO, a different contract-theoretic optimization problem is formulated to study their interactions. The MGO provides personalized rewards to the buyers, e.g., fixed price, considering their energy demand, while the buyers invest their “effort,” i.e., money, to purchase the amount of energy that covers their demand. The optimal personalized contracts, i.e., optimal personalized reward and purchased energy per buyer, are determined to bring the dynamic interaction of the MGO and the buyers into a stable mode of operation.

- 4) A detailed series of experiments are performed to show the drawbacks and benefits of the proposed prosumer-centric self-sustained smart grid system's operation approach. This is realized under both a benchmarking scenario of complete information and a realistic scenario of incomplete information regarding the prosumers' energy generation, demand, and storage characteristics. A scalability analysis is performed to show the efficiency and robustness of the proposed framework. Also, a detailed study is performed regarding the impact of the prosumers' energy generation and demand characteristics, as well as the MGO's pricing policies, on the interactions of the sellers and buyers with the MGO.

The rest of this article is organized as follows. Section II introduces the human-centric smart grid system model, while Sections III and IV introduce and solve the contract-theoretic optimization problems for the sellers and buyers, respectively. Simulation and comparative results are presented in Section V. Finally, Section VI concludes this article.

II. HUMAN-CENTRIC SMART GRID SYSTEM MODEL

A microgrid system is considered, consisting of the MGO and the prosumers. The prosumers can generate energy via various alternative options, such as solar photovoltaic panels and small wind turbine power generation systems, and can also store the energy in storage systems, such as Lithium-ion batteries [24]. Each prosumer's residential infrastructure is equipped with a smart meter to dynamically measure the energy generation, demand, storage, and exchange (selling or buying) power with the MGO. We examine the interactions of the MGO and the prosumers at each time slot t , with the set of times slots denoted as $T = \{1, \dots, t, \dots, |T|\}$. The sets of prosumers, sellers, and buyers are denoted as $N = \{1, \dots, n, \dots, |N|\}$, $S = \{1, \dots, s, \dots, |S|\}$, and $B = \{1, \dots, \beta, \dots, |B|\}$, respectively, with $S \subseteq N$, $B \subseteq N$, and $|S| + |B| = |N|$. It is highlighted that this research work focuses on the operation and self-sustainability of a single microgrid system, which can potentially be connected with the main grid. However, the exchange of energy with the main grid or with other neighboring microgrid systems is not studied and considered in this article. Nevertheless, the latter issue is of high practical and business importance, that introduces additional economic and operational challenges, and is part of our future research.

Each prosumer has a set of home appliances, $A_n = \{1, \dots, a_n, \dots, |A_n|\}$, which at the duration of one time slot t (e.g., one hour) can be either on, i.e., $\delta_{a_n}^t = 1$, or off, i.e., $\delta_{a_n}^t = 0$. Thus, their total energy demand is $d_n^t = \sum_{a_n \in A_n} \delta_{a_n}^t E_{a_n}$ [kWh] in the duration of a time slot t , where E_{a_n} [kWh] is the energy consumption of the appliance a_n when it is operating during time slot t [25]. It should be noted that a prosumer can shift the operation of some appliances over time, thus, $d_n^{Min} \leq d_n^t \leq d_n^{Max}$. Specifically, d_n^{Min} [kWh] denotes the total energy demand of the appliances of the prosumer n that are nonshiftable over time, e.g., refrigerator or alarm system, while d_n^{Max} [kWh] captures the maximum possible energy demand if all of the prosumer's appliances are active. Thus, the prosumers'

energy demand vector is defined as $\mathbf{D} = [d_1^t, \dots, d_n^t, \dots, d_{|N|}^t]$ per time slot t . Also, the prosumers can generate energy by exploiting their own renewable energy sources. Thus, the prosumers' renewable energy generation vector is defined accordingly as $\mathbf{G} = [g_1^t, \dots, g_n^t, \dots, g_{|N|}^t]$ [kWh] per time slot t . The prosumers can act either as sellers or buyers per time slot t based on their personal energy generation and demand characteristics. In the case that a prosumer acts as a seller, its corresponding total energy demand is covered by its own generated energy. On the opposite case, where the prosumer acts as a buyer, it defines by itself the energy demand at each time slot by deciding to shift (or not) part of the necessary energy for a future time slot based on its own comfort level.

Sellers case: If $g_n^t + b_n^{t-1} \geq d_n^t$, where b_n^{t-1} denotes the prosumer's battery availability from the previous time slot, the prosumer can cover their energy demand without purchasing energy from the MGO, while also dynamically deciding to sell the energy generation surplus to the MGO. The energy generation surplus is calculated as $b_n^{t+1} = b_n^t + (g_n^t - d_n^t)$ [kWh], where a percentage $e_s^t \in [0, 1]$ of it can be sold to the MGO. The energy generation surplus is assumed to be stored in the prosumer's energy storage system, e.g., Lithium-ion batteries. In this case, the prosumer n acts as a seller. It is noted that in our research work we have not explicitly considered the limitation imposed by the maximum energy capacity of the prosumers' batteries and/or the charging/discharging ramp. However, it is highlighted that the probability of exceeding the maximum energy capacity of the prosumers' batteries is very low in our proposed model for the following reasons. Initially, the dynamics of the proposed contract-theoretic model incentivize the sellers to sell part of their energy at each time slot, thus, reducing the amount of energy that they store in their batteries. Second, the prosumers tend to have interchangeable roles of sellers and buyers during the day, thus, the amount that remains stored in the batteries throughout different parts of the day remains relatively low.

Buyers case: If $g_n^t + b_n^{t-1} < d_n^t$, the prosumer's total generated and stored energy is not sufficient to cover their energy demand d_n^t . Thus, the prosumer n acts as a buyer β , and aims to purchase $d_n^t - g_n^t - b_n^{t-1}$ [kWh] amount of energy from the MGO, in consideration of their personal energy needs which are shaped by their respective shiftable and nonshiftable demands.

In the subsequent two sections, we study the overall interactions of the sellers and the buyers with the MGO, in terms of selling and purchasing energy, with consideration of their unique personal energy generation and demand characteristics. Toward achieving this goal, we adopt the principles of contract theory [22]. Contract theory is a labor economics theory that has originally been used for business management purposes and mathematically models the behavior of actors with competing interests, who aim to maximize their profit. In a contract-theoretic model, there exist an "employer" and a set of "employees." The employer offers personalized contracts to the employees, incentivizing them to demonstrate an optimal behavior (in terms of resource usage) via providing rewards. The contract has the form {reward, effort}, where the reward is provided by the employer to the employee for the effort invested

by the latter one. In the specific category of contract-theoretic models adopted here, named *screening models*, the employer is unaware of the exact employees' characteristics and screens them to offer optimal contracts. In the rest of the analysis, the theory of screening models is adopted and appropriately adapted in the microgrid system to capture the interactions of the MGO (employer) with the sellers and buyers (employees). The key notation is summarized in Table I.

III. SELLERS' AND ELECTRICITY MARKET'S INTERACTIONS

In this section, we capture the interactions of the sellers with the MGO in terms of determining the optimal amount of energy that they sell based on the appropriate incentives, i.e., rewards, provided by the MGO. Each seller $s, \forall s \in S \subseteq N$ is characterized by their type $\tau_s^t = \frac{b_s^{t+1}}{\sum_{\forall s \in S} b_s^{t+1}} \in [0, 1]$, which represents their normalized energy surplus among the sellers, thus, showing their potential to sell energy to the MGO. For notation convenience in the presentation, we consider $\tau_1^t < \dots < \tau_s^t < \dots < \tau_{|S|}^t$.

Based on the principles of contract theory [22], each seller acts as an "employee" investing their personal effort to the "employer," i.e., MGO, while the MGO incentivizes the sellers by providing personalized rewards, e.g., fixed energy price, in order for the MGO and the sellers to jointly optimize their achieved utility. The sellers' and the MGO's utility functions, as defined below in (1) and (2), respectively, represent their actual profit (i.e., satisfaction). The seller's effort is defined as $e_s^t = \frac{b_s^{t+1}}{\max_{\forall s \in S} \{b_s^{t+1}\}} \in [0, 1]$, showing the relative capability of each seller to sell energy to the MGO. Given that $\tau_1^t < \dots < \tau_s^t < \dots < \tau_{|S|}^t$, we have $e_1^t < \dots < e_s^t < \dots < e_{|S|}^t$. The MGO provides personalized rewards $r_s^t = \tau_s^t e_s^t$ to the sellers to incentivize them to sell their available energy surplus. Therefore, a seller with a higher potential to sell energy, who indeed sells a large amount of energy, will receive a high reward. The interaction among the MGO and the sellers, aiming at the joint optimization of their profit by participating in the energy market, concludes to an optimal contract (e_s^{t*}, r_s^{t*}) consisting of the optimal seller's effort e_s^{t*} and the MGO's optimal provided personalized reward r_s^{t*} .

Based on the above discussion, the utility functions of the sellers and the MGO are designed as the actual profit of the participants, while interacting among each other in the microgrid. The seller's utility is captured by the received revenue from selling energy to the MGO [first term of (1)] while also considering their personal cost to locally produce the energy via the exploitation of their personal renewable energy source infrastructure [second term of (1)].

$$U_s^t(e_s^t) = \tau_s^t \epsilon(r_s^t(e_s^t)) - p_S e_s^t \quad (1)$$

The seller's personal cost to produce their energy locally, including the degradation cost of the seller's battery, is denoted as $p_S \in \mathbb{R}^+$ and, in the current analysis, is assumed to be a unitless number. This parameter can be mapped to monetary units, i.e., [\$/kWh], when transferring this model in a real-life implementation and business case. Also, the function $\epsilon(r_s^t(e_s^t))$ represents the evaluation function, i.e., the way a seller interprets the received reward as personal satisfaction based on the

enjoyed revenue. The evaluation function is a strictly increasing, concave, and continuous function with respect to the received reward, as a seller satisfaction increases monotonically with respect to the received reward, while at some point, the seller's satisfaction becomes saturated. For demonstration purposes, and without loss of generality, we consider $\epsilon(e_s^t) = \sqrt{r_s^t(e_s^t)}$. It is highlighted that the sellers are not forced by the MGO to sell their overall available energy surplus at each time slot. To the contrary the sellers are incentivized in a personalized manner to sell an optimal amount of energy that will ultimately optimize their utility, following the principles and dynamics of contract theory.

The MGO's utility from interacting with the sellers is defined as follows [22], [23]:

$$U_{\text{MGO},\text{buy}}(\mathbf{e}) = \sum_{s=1}^{|S|} Pr_s^t \cdot [e_s^t - r_s^t(e_s^t)] \quad (2)$$

where $\mathbf{e} = [e_1^t, \dots, e_s^t, \dots, e_{|S|}^t]$ is the sellers' effort vector. The MGO is unaware of the detailed sellers' energy generation demand and storage characteristics, which in principle could be considered as private information of each prosumer and define the sellers' types. Therefore, it is noted that the MGO is not aware of the prosumers' energy demand vector $\mathbf{D} = [d_1^t, \dots, d_n^t, \dots, d_{|N|}^t]$ and renewable energy generation vector $\mathbf{G} = [g_1^t, \dots, g_n^t, \dots, g_{|N|}^t]$ [kWh] per time slot t , which is private information of each prosumer. Instead, the MGO builds the probability of each prosumer's type (in this case seller's type) by exploiting historical data that are collected via the interaction of the MGO with each prosumer. Thus, the MGO estimates each seller's type τ_s^t with probability Pr_s^t , where $\sum_{s=1}^{|S|} Pr_s^t = 1$. Several types of probability distributions, such as Gaussian, Poisson, and others, can be adopted based on the nature of the examined energy market. The specific distributions of the seller's types, and the corresponding probabilities Pr_s^t , can be determined in a real-life scenario according to the prosumers' energy characteristics that can be collected from their monthly electricity bills, based on a statistical or machine learning analysis. The MGO can generate profit by selling the energy collected from the sellers to the buyers. Thus, (2) represents the MGO's unitless profit from buying energy from the sellers via their invested effort e_s^t [first term of (2)], while considering the MGO's cost to provide rewards r_s^t to the sellers [second term of (2)].

A. Complete Information Scenario

Initially, we consider the benchmarking scenario, where the MGO has *complete information* about the sellers' types. The MGO aims to maximize its own profit from each seller of known type τ_s^t [see (3a)], while providing sufficient rewards to the sellers to maintain their business interactions and energy surplus sales [see (3b)]. Thus, under the complete information scenario regarding the sellers' types, the interactions between the MGO and the sellers can be captured by the following contract-theoretic optimization problem:

$$\max_{\{e_s^t\}_{\forall s \in S}} [e_s^t - r_s^t(e_s^t)] \quad (3a)$$

$$\text{s.t. } \tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq 0 \quad \forall s \in S. \quad (3b)$$

In this case, given that the MGO will provide just the sufficient rewards to incentivize the sellers to sell their energy surplus, (3b) can be considered as an equality.

Theorem 1: The optimal personalized contract between the MGO and each seller under the complete information scenario is $(e_s^{t*}, r_s^{t*}) = (\frac{\tau_s^{t^2}}{2p_s^2}, \frac{\tau_s^{t^2}}{4p_s^2})$.

Proof: By solving (3b) as an equality with respect to the reward, we have $r_s^t = (\frac{p_s e_s^t}{\tau_s^t})^2$. By substituting the latter outcome in (3a), taking the first-order derivative with respect to the effort e_s^t , and setting the outcome equal to zero, we conclude that $e_s^t = \frac{\tau_s^{t^2}}{2p_s^2}$. Thus, the optimal contract is $(e_s^{t*}, r_s^{t*}) = (\frac{\tau_s^{t^2}}{2p_s^2}, \frac{\tau_s^{t^2}}{4p_s^2})$. ■

The above outcome can be used mainly for benchmarking purposes, as sellers will not reveal their private information regarding their types, i.e., energy surplus, to the MGO, in a real-life scenario.

B. Incomplete Information Scenario

In the remaining analysis of this section, we examine the *incomplete information* scenario regarding the sellers' types. In pursuit of capturing the interactions between the sellers and the MGO, five fundamental conditions are examined: individual rationality (IR), incentive compatibility (IC), fairness, monotonicity, and rationality. Those conditions are necessary and sufficient in order to guarantee the feasibility and existence of an optimal contract among the MGO and the sellers. Each condition is analyzed and proved below, while its physical meaning is provided within the context of the MGO's and the sellers' interaction.

Definition 1 [Individual Rationality (IR)]: Each seller should receive a nonnegative utility, i.e., $U_s^t(e_s^t) = \tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq 0 \quad \forall s \in S$, from the optimal contract (e_s^{t*}, r_s^{t*}) .

Definition 2 [Incentive Compatibility (IC)]: Each seller achieves the maximum possible utility when they receive a contract aligned with their personal energy generation, demand, and storage characteristics, i.e., $\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_{s'}^t \epsilon(e_{s'}^t) - p_{s'} e_{s'}^t \quad \forall s, s' \in S$.

The physical meaning of the IR and IC conditions is that each seller should be appropriately incentivized by the MGO by enjoying a positive profit aligned with their personal characteristics in order to sell their energy in the microgrid.

Proposition 1 (Fairness): An optimal contract is fair, i.e., a seller of higher (or equal) type should enjoy a higher (or equal) reward: $r_s^t > r_{s'}^t \Leftrightarrow \tau_s^t > \tau_{s'}^t$ ($r_s^t = r_{s'}^t \Leftrightarrow \tau_s^t = \tau_{s'}^t$).

Proof: We prove the sufficiency and necessity of the fairness condition. Assuming that $\tau_s^t > \tau_{s'}^t$, we can write the following IC constraints for the sellers $s, s' \quad \forall s, s' \in S, s \neq s'$:

$$\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_{s'}^t \epsilon(e_{s'}^t) - p_{s'} e_{s'}^t \quad (4)$$

$$\tau_{s'}^t \epsilon(e_{s'}^t) - p_{s'} e_{s'}^t \geq \tau_s^t \epsilon(e_s^t) - p_s e_s^t. \quad (5)$$

By adding (4) and (5), we have

$$(\tau_s^t - \tau_{s'}^t) \epsilon(e_s^t) \geq (\tau_s^t - \tau_{s'}^t) \epsilon(e_{s'}^t). \quad (6)$$

We know that $\tau_s^t > \tau_{s'}^t$, and $\epsilon(r_s^t(e_s^t))$ is a strictly increasing function with respect to r_s^t , thus, we conclude that $r_s^t > r_{s'}^t$.

On the other hand, assuming that $r_s^t > r_{s'}^t$, we derive that $\epsilon(r_s^t(e_s^t)) > \epsilon(r_{s'}^t(e_{s'}^t))$, thus, we rewrite (6) as: $\tau_s^t[\epsilon(r_s^t(e_s^t)) - \epsilon(r_{s'}^t(e_{s'}^t))] \geq \tau_{s'}^t[\epsilon(r_s^t(e_s^t)) - \epsilon(r_{s'}^t(e_{s'}^t))]$ and we conclude that $\tau_s^t > \tau_{s'}^t$. Similarly, we can prove $r_s^t = r_{s'}^t \Leftrightarrow \tau_s^t = \tau_{s'}^t$.

Proposition 2 (Monotonicity): An optimal contract should have monotonic behavior, i.e., a seller of a higher type will sell more energy and receive a higher reward.

Proof: A seller of higher type receives a higher reward based on Proposition 1, i.e., $r_1^t < \dots < r_s^t < \dots < r_{|S|}^t \Leftrightarrow \tau_1^t < \dots < \tau_s^t < \dots < \tau_{|S|}^t$. Then, based on the monotonic relationship among the reward r_s^t and the effort e_s^t , i.e., $r_s^t = \tau_s^t e_s^t$, we conclude that $e_1^t < \dots < e_s^t < \dots < e_{|S|}^t$. ■

Proposition 3 (Rationality): An optimal contract should be rational, i.e., a seller of higher type should enjoy a higher utility.

Proof: We write the IC condition for two indicative sellers $s \neq s' \quad \forall s, s' \in S$: $\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_{s'}^t \epsilon(e_{s'}^t) - p_s e_{s'}^t \xLeftrightarrow{\tau_s^t > \tau_{s'}^t} \tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_{s'}^t \epsilon(e_{s'}^t) - p_s e_{s'}^t \Leftrightarrow U_s^t(e_s^t) \geq U_{s'}^t(e_{s'}^t)$. We generalize this outcome for any seller $s \quad \forall s \in S$: $\tau_1^t < \dots < \tau_s^t < \dots < \tau_{|S|}^t \Leftrightarrow U_1^t < \dots < U_s^t < \dots < U_{|S|}^t$. ■

The physical meaning of the latter three conditions, i.e., fairness, monotonicity, and rationality, is that an optimal contract (e_s^{t*}, r_s^{t*}) should guarantee all of them in order to incentivize the sellers to sell part or all of their energy surplus during each time slot t , instead of locally storing it for future use. Based on the above analysis, the interactions among the MGO and the sellers can be captured as a contract-theoretic optimization problem aimed at determining the optimal personalized contracts. The optimization problem aims at jointly maximizing the MGO's profit (7a), while guaranteeing the IR (7b), IC (7c), and fairness, monotonicity, and rationality conditions (7d), and is defined as follows:

$$\max_{\{e_s^t, r_s^t\}_{\forall s \in S}} \sum_{s=1}^{|S|} [Pr_s^t(e_s^t - r_s(e_s^t))] \quad (7a)$$

$$\text{s.t. } \tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq 0 \quad \forall s \in S \quad (\text{IR}) \quad (7b)$$

$$\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_{s'}^t \epsilon(e_{s'}^t) - p_s e_{s'}^t \quad \forall s \neq s', s, s' \in S \quad (\text{IC}) \quad (7c)$$

$$0 \leq r_1^t < r_2^t < \dots < r_s^t < \dots < r_{|S|}^t. \quad (7d)$$

The above optimization is clearly nonconvex. Thus, we will reduce its constraints and rewrite it as a convex optimization problem to allow for a tractable and feasible solution. Starting with the IR constraint (7b) and based on the IC and monotonicity conditions, we have: $\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_s^t \epsilon(e_1^t) - p_s e_1^t \quad \forall s \in S$. Also, we know that $\tau_s^t > \tau_1^t \quad \forall s \in S$, thus, $\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_1^t \epsilon(e_1^t) - p_s e_1^t \geq 0$. Also, given that the MGO provides just-sufficient rewards to incentivize the sellers to participate in the microgrid, we can equivalently replace the constraint in (7b) with $\tau_1^t \epsilon(e_1^t) - p_s e_1^t = 0$. Focusing on the reduction of the IC constraints (7c), we introduce the following terminology: 1) $s, s', s' \in \{1, \dots, s-1\}$: downward IC constraints; 2) $s, s-1 \quad \forall s \in S$: local downward IC constraints; 3) $s, s', s' \in \{s+1, \dots, |S|\}$: upward IC constraints; 4) $s, s+1 \quad \forall s \in S$: local upwards IC constraints.

Lemma 1: All the downward IC constraints are captured by the local downward IC constraints. ■

Proof: We write the IC conditions for three sellers, $s-1, s, s+1$, as follows: $\tau_{s+1}^t \epsilon(e_{s+1}^t) - p_s e_{s+1}^t \geq \tau_{s+1}^t \epsilon(e_s^t) - p_s e_s^t$ and $\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_s^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t$. We know that $e_s^t >$

$e_{s-1}^t \xLeftrightarrow{\tau_{s+1}^t > \tau_s^t} \tau_{s+1}^t \epsilon(e_{s+1}^t) - p_s e_{s+1}^t \geq \tau_{s+1}^t [\epsilon(e_s^t) - \epsilon(e_{s-1}^t)] > \tau_s^t [\epsilon(e_s^t) - \epsilon(e_{s-1}^t)] \geq p_s (e_s^t - e_{s-1}^t)$. We apply recursively the latter outcome for all the sellers: $\tau_{s+1}^t \epsilon(e_{s+1}^t) - p_s e_{s+1}^t \geq \tau_{s+1}^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t \geq \dots \geq \tau_{s+1}^t \epsilon(e_1^t) - p_s e_1^t$. Thus, we conclude that $\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_s^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t$, i.e., all the downward IC constraints are captured by the local downward IC constraints.

Lemma 2: All the upward IC constraints are captured by the local downward IC constraint.

Proof: We write again the IC conditions for three indicative sellers, $s-1, s, s+1$, as follows:

$$\tau_{s-1}^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t \geq \tau_{s-1}^t \epsilon(e_s^t) - p_s e_s^t \quad (8)$$

$$\tau_s^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_s^t \epsilon(e_{s+1}^t) - p_s e_{s+1}^t. \quad (9)$$

Based on (9) and the fairness condition, we have the following expression:

$$p_s^t (e_{s+1}^t - e_s^t) \geq \tau_s^t [\epsilon(e_{s+1}^t) - \epsilon(e_s^t)] \geq \tau_s^t \geq \tau_{s-1}^t \tau_{s-1}^t [\epsilon(e_{s+1}^t) - \epsilon(e_s^t)]. \quad (10)$$

Based on (8) and (10), we have: $\tau_{s-1}^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t \geq \tau_{s-1}^t \epsilon(e_s^t) - p_s e_s^t \geq \tau_{s-1}^t \epsilon(e_{s+1}^t) - p_s e_{s+1}^t$. Thus, $\tau_{s-1}^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t \geq \tau_{s-1}^t \epsilon(e_{s+1}^t) - p_s e_{s+1}^t$, showing that all the upward IC constraints hold true, if the IC condition is satisfied for the seller with type τ_{s-1}^t . We apply recursively this outcome: $\tau_{s-1}^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t \geq \tau_{s-1}^t \epsilon(e_{s+1}^t) - p_s e_{s+1}^t \geq \dots \geq \tau_{s-1}^t \epsilon(e_{|S|}^t) - p_s e_{|S|}^t$. Thus, all the upward IC constraints are captured by the local downward IC constraints. ■

Based on the above analysis of the reduction of the IR and IC constraints, we can rewrite the contract-theoretic optimization problem (7a)–(7d) as follows:

$$\max_{\{e_s^t, r_s^t\}_{\forall s \in S}} \sum_{s=1}^{|S|} [Pr_s^t(e_s^t - r_s(e_s^t))] \quad (11a)$$

$$\text{s.t. } \tau_1^t \epsilon(e_1^t) - p_s e_1^t \geq 0 \quad (11b)$$

$$\tau_s^t \epsilon(e_s^t) - p_s e_s^t = \tau_s^t \epsilon(e_{s-1}^t) - p_s e_{s-1}^t \quad (11c)$$

$$0 \leq r_1^t < r_2^t < \dots < r_s^t < \dots < r_{|S|}^t. \quad (11d)$$

The optimization problem (11a)–(11d) is a convex optimization problem and the optimal contract (e_s^{t*}, r_s^{t*}) can be determined based on standard convex optimization methods. Detailed numerical results are presented in Section V.

IV. BUYERS' AND ELECTRICITY MARKET'S INTERACTIONS

In this section, we focus on capturing the interactions of the buyers with the MGO. The goal of each buyer $\beta \quad \forall \beta \in B \subseteq N$ is to purchase the remaining amount of energy $(d_\beta^t - g_\beta^t - b_\beta^{t-1})$ [kWh], that cannot be supported by her local energy generation. The MGO aims to incentivize the buyers to buy the total amount of energy that they need, by providing personalized rewards r_β^t .

In our proposed approach, the interactions between the MGO and the buyers are captured via a contract-theoretic model.

In particular, the buyers invest an “effort” $e_\beta^t \in [0, 1]$, which represents the percentage of energy that they buy with respect to their total energy need, i.e., $d_\beta^t - g_\beta^t - b_\beta^{t-1}$. Each buyer is characterized by a type $\tau_\beta^t = \frac{d_\beta^t - g_\beta^t - b_\beta^{t-1}}{\max_{\beta \in B} \{d_\beta^t - g_\beta^t - b_\beta^{t-1}\}}$, showing its relative potential compared to the rest of the buyers in terms of buying energy. The MGO offers personalized rewards $r_\beta^t = \tau_\beta^t e_\beta^t$ to each buyer, e.g., fixed energy price, in order to incentivize them to buy energy and not postpone or decrease their energy needs. The buyers’ utility is defined as the gained profit from buying energy from the MGO and is defined as follows:

$$U_\beta^t(e_\beta^t) = \tau_\beta^t f(e_\beta^t) - p_M e_\beta^t. \quad (12)$$

The first term of (12) captures the buyer’s personalized satisfaction from purchasing energy, where $f(e_\beta^t)$ is the buyer’s satisfaction function, e.g., $f(e_\beta^t) = \sqrt{r_\beta^t(e_\beta^t)}$. The latter one captures the buyer’s satisfaction from the consumption of the energy that they buy from the MGO. The buyer’s satisfaction is a strictly increasing, continuous, and concave function with respect to the received reward r_β^t , as the buyer becomes more satisfied by covering more of their appliances’ energy needs while such satisfaction becomes saturated at a specific upper limit of energy need. Also, $p_M \in [0, 1]$ here is considered as a normalized dimensionless parameter representing the energy price, however, in a real-life implementation it can be mapped to realistic values and units [\$/kWh] [26]. The MGO generates profit by selling energy to the buyers at the normalized price $p_M \in [0, 1]$. The MGO’s utility from selling energy to the buyers is obtained as its total profit, and is defined as follows:

$$U_{\text{MGO},\text{sell}}^t(\mathbf{e}_{\text{buy}}) = \sum_{\beta=1}^{|B|} Pr_\beta^t [p_M e_\beta^t - r_\beta^t(e_\beta^t)]. \quad (13)$$

As mentioned before, in the general case, the MGO has partial available information about the potential of each buyer to buy energy, thus, it probabilistically estimates each buyer’s type τ_β^t with probability Pr_β^t , where $\sum_{\beta=1}^{|B|} Pr_\beta^t = 1$. Similarly to the sellers’ case, several types of probability distributions can be adopted based on the nature of the examined energy market to realistically capture the buyers’ characteristics. The goal of the MGO is to maximize its profit, while guaranteeing that the buyers will buy energy from the microgrid market. Considering the benchmarking scenario of complete information of the buyers’ types, the interactions between the MGO and the buyers are formulated as a maximization problem of the MGO’s profit (14a), while considering the optimization of the buyers’ utilities (14b)

$$\max_{\{e_\beta^t\}_{\beta \in B}} [p_M e_\beta^t - r_\beta^t(e_\beta^t)] \quad (14a)$$

$$\text{s.t. } \tau_\beta^t f(e_\beta^t) - p_M e_\beta^t \geq 0 \quad \forall \beta \in B. \quad (14b)$$

Theorem 2: The optimal contract among the MGO and each buyer β under the complete information scenario is $(e_\beta^{t*}, r_\beta^{t*}) = (\frac{\tau_\beta^{t*2}}{2p_M}, \frac{\tau_\beta^{t*2}}{4})$.

Proof: It follows the same philosophy, reasoning and steps of Theorem 1.

Under the realistic scenario of incomplete information regarding the buyers’ types, the conditions of IR (15b), IC (15c), and fairness, monotonicity, and rationality (15d) should hold true. Also, the optimal contract jointly maximizes the MGO’s utility, i.e., profit, as follows:

$$\max_{\{e_\beta^t, r_\beta^t\}_{\beta \in B}} \sum_{\beta=1}^{|B|} Pr_\beta^t [p_M e_\beta^t - r_\beta^t(e_\beta^t)] \quad (15a)$$

$$\text{s.t. } \tau_\beta^t f(e_\beta^t) - p_M e_\beta^t \geq 0 \quad \forall \beta \in B \quad (\text{IR}) \quad (15b)$$

$$\tau_\beta^t f(e_\beta^t) - p_M e_\beta^t \geq \tau_{\beta'}^t f(e_{\beta'}^t) - p_M e_{\beta'}^t \quad \forall \beta \neq \beta' \quad (\text{IC}) \quad (15c)$$

$$0 \leq r_1^t < r_2^t < \dots < r_\beta^t < \dots < r_{|B|}^t. \quad (15d)$$

The optimization problem (15a)–(15d) is nonconvex. Toward solving this problem, we follow similar reasoning as in Section III, and we conclude to the following convex optimization problem, which can be solved with standard convex optimization methods:

$$\max_{\{e_\beta^t, r_\beta^t\}_{\beta \in B}} \sum_{\beta=1}^{|B|} Pr_\beta^t [p_M e_\beta^t - r_\beta^t(e_\beta^t)] \quad (16a)$$

$$\text{s.t. } \tau_1^t f(e_1^t) - p_M e_1^t = 0 \quad (16b)$$

$$\tau_\beta^t f(e_\beta^t) - p_M e_\beta^t \geq \tau_{\beta-1}^t f(e_{\beta-1}^t) - p_M e_{\beta-1}^t \quad (16c)$$

$$0 \leq r_1^t < r_2^t < \dots < r_\beta^t < \dots < r_{|B|}^t. \quad (16d)$$

The solution of the above problem concludes to the optimal contracts $(e_\beta^{t*}, r_\beta^{t*}) \quad \forall \beta \in B$, determining the amount of purchased energy of the buyers and the MGO’s offered personalized rewards to the buyers.

V. NUMERICAL RESULTS

In this section, a detailed evaluation analysis of the proposed contract-theoretic approaches is presented, via modeling and simulation, in order to demonstrate and assess the sellers and buyers interactions with the microgrid operator. Specifically, the pure operation characteristics and performance of the proposed framework for both the sellers and the buyers are presented in Section V-A. The behavior of the prosumers, in terms of acting either as sellers or buyers, is studied in more detail in Section V-B with respect to the energy price, the energy generation cost, and the prosumers’ energy generation characteristics during a day. Finally, the joint behavior of the prosumers and the MGO throughout the day for different energy generation use case scenarios is studied in Section V-C, toward demonstrating and gaining more insights about their tight interconnection and interactions.

In the rest of the simulation results, we consider the following parameters: $d_n^t \in [0.50, 1.50]$ kWh, $g_n^t \in [0, 2]$ kWh, $p_M = 2$, $p_S = 2$. In the rest of the evaluation the key parameters have been set based on actual data for the year of 2020, derived

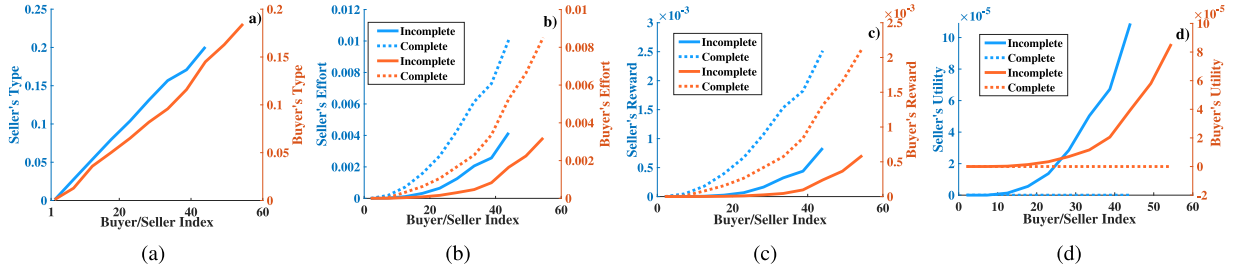


Fig. 1. Pure operation performance under the complete and incomplete information scenarios. (a) Sellers' and buyers' types. (b) Sellers' and buyers' efforts. (c) Sellers' and buyers' rewards. (d) Sellers' and buyers' utilities.

from the U.S. Energy Information Administration [27]. Furthermore, for demonstration purposes and unless otherwise explicitly stated, we examine the system operation for $|T| = 24$ hours and $|N| = 100$ prosumers. The probabilities Pr_s^t and Pr_β^t are obtained assuming that the sellers' and buyers' types follow uniform distributions. For all the presented numerical results, a Monte Carlo analysis has been performed of 10 000 executions to receive more representative outcomes. We have used MATLAB to perform the simulations, and the convex optimization problems (11a)–(11d) and (16a)–(16d) were solved based on the FMINCON optimization tool of MATLAB, where the objective function and the corresponding constraints are provided as inputs. The proposed framework's evaluation was conducted on a desktop computer, 3.8 GHz Intel Core i9, with 32 GB of DDR4 RAM.

A. Pure Operation Performance

Initially, the pure operation performance of the proposed prosumer-centric self-sustained smart grid system model based on the contract-theoretic approach is presented to capture the interactions of both the sellers (Section III) and the buyers (Section IV) with the MGO. One indicative time slot t is considered, where both types of interactions are analyzed.

In particular, Fig. 1(a)–(d) presents the sellers' and buyers' types (τ_s^t, τ_β^t), efforts (e_s^t, e_β^t), rewards (r_s^t, r_β^t), and utilities (U_s^t, U_β^t), respectively, under the scenarios of complete and incomplete information of the prosumers' types from the MGO's perspective. For demonstration purposes, the sellers' and buyers' IDs have been sorted with respect to their increasing types. The results show that the higher the seller's type is [see Fig. 1(a)], the more energy surplus it has, thus, it is incentivized more by the MGO to sell its available energy by being offered a higher reward [Fig. 1(c)—left vertical axis]. Consequently, it appears that indeed it sells more energy by investing a greater effort [Fig. 1(b)—left vertical axis]. Thus, the seller of greater energy surplus ultimately achieves a higher utility [Fig. 1(d)—left vertical axis]. With reference to the sellers, and by comparing the complete (i.e., benchmarking) and the incomplete (i.e., realistic) information scenarios, we observe that under the former, the MGO can fully exploit the sellers' energy surplus. This in turn means that the MGO provides to the sellers higher rewards to incentivize them to sell the vast majority of their available energy [Fig. 1(c)—left vertical axis], which indeed translates to having the sellers actually selling a higher amount of energy

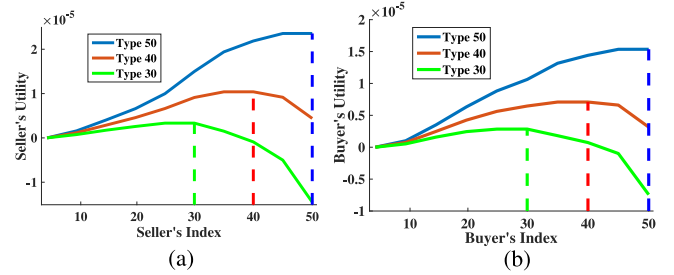


Fig. 2. Incentive compatibility condition (a) Seller's utility. (b) Buyer's utility.

[Fig. 1(b)—left vertical axis], as compared to the incomplete information scenario.

Focusing our analysis on the buyers perspective and interactions with the MGO, we observe that a buyer with higher need to purchase energy, i.e., of higher type [see Fig. 1(a)], is incentivized more by the MGO to do so [Fig. 1(c)—right vertical axis]. Thus, a buyer of higher type by ultimately purchasing more energy [Fig. 1(b)—right vertical axis], it covers the majority of its energy needs and accordingly achieves a higher utility [Fig. 1(d)—right vertical axis]. Comparing the complete and incomplete information scenarios with reference to the buyers, the results confirm our theoretical analysis and observation, by clearly demonstrating that higher rewards are provided to the buyers [Fig. 1(c)—right vertical axis] in the complete information scenario, who purchase more energy [Fig. 1(b)—right vertical axis] compared to the incomplete information scenario. It should be highlighted that under the complete information scenario, both the sellers and the buyers achieve zero utility [Fig. 1(d)—right vertical axis], as the MGO provides just the sufficient rewards to marginally incentivize them to contribute to the microgrid's smooth and seamless operation. Also, the results confirm that the individual rationality, incentive compatibility, fairness, monotonicity, and rationality conditions hold true for both the sellers and the buyers under all the scenarios.

Specifically, Fig. 2(a) and (b) presents the sellers' and buyers' utility for the corresponding optimal contracts derived for each type for three indicative sellers and buyers with IDs $s = \{30, 40, 50\}$, and $\beta = \{30, 40, 50\}$, respectively. The results reveal that both the sellers and the buyers achieve the highest possible utility, when receiving the optimal personalized contract that is designed accounting for their unique energy generation, demand, and storage characteristics. This observation confirms the validity of the incentive compatibility condition. Also, the

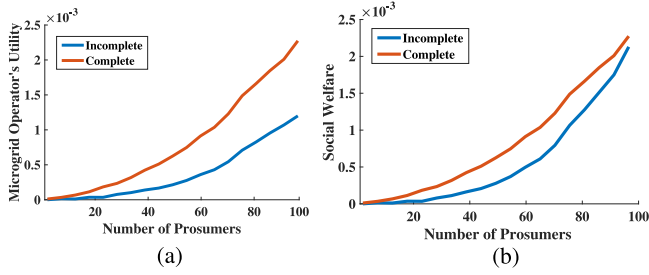


Fig. 3. MGO's utility and social welfare under the complete and incomplete information scenarios. (a) Microgrid operator's utility. (b) Social welfare.

results show that a seller or buyer of a higher type achieves a higher utility, confirming the validity of the rationality condition.

Moreover, Fig. 3(a) and (b) illustrates the MGO's utility and overall microgrid system's social welfare as a function of the number of prosumers residing in the microgrid system under the complete and incomplete information scenarios. The results show that better MGO's utility and social welfare is achieved under the complete information scenario, as the MGO can provide more targeted rewards by knowing the sellers' and buyers' exact types. However, it is highlighted that the incomplete information scenario, which is a realistic implementation of the microgrid system, achieves acceptable social welfare, especially, for increasing number of prosumers, with only 7% worse social welfare compared to the complete information scenario, for the case of 100 prosumers.

B. Prosumer's Behavior Throughout the Day

In this section, we study the impact of various system and prosumer characteristics, such as energy price p_M , energy generation cost p_S , and prosumer's energy generation $g_n^t \forall n \in N, \forall t \in T$, on the behavior of the prosumers in terms of acting as sellers or buyers, throughout the operation of a day.

In particular, Fig. 4(a) and (b) presents the percentage of prosumers that act as sellers in order to maximize the average prosumers' utility, the MGO's utility, and the social welfare, respectively, as a function of the number of prosumers in the microgrid. Three different scenarios of energy price p_M and energy generation costs p_S are considered: 1) even cost with $p_M = p_S = 2$; 2) high buyer cost with $p_M = 6, p_S = 2$; 3) high seller cost with $p_M = 2, p_S = 6$. The results reveal that when the energy generation cost is high (high seller cost scenario), a smaller percentage of sellers is incentivized to sell energy, as their energy production cost is high, and the sellers prefer to keep their generated energy for future use. In contrast, when the energy price is high (high buyer cost scenario), the sellers can achieve a higher profit by selling their generated energy to the MGO, thus, a higher percentage of prosumers acts as sellers. The even cost scenario presents an intermediate behavior between the high seller and the high buyer cost scenarios. Also, comparing the prosumer-centric approach [see Fig. 4(a)] against an MGO-centric approach [see Fig. 4(b)] that aims at maximizing the MGO utility, we observe in the latter case a higher offset of the percentages of the prosumers acting as sellers for the high seller and even cost scenarios, as the MGO aggressively provides

rewards to the prosumers to sell their energy. The opposite holds true for the high buyer scenario, as the MGO prefers to sell its available energy to the buyers at a higher price, as compared to buying energy from the sellers. An intermediate behavior of the percentages of the prosumers acting as sellers is observed when the goal is to solely maximize their social welfare [see Fig. 4(c)], as the selfish behavior of the MGO and the prosumers is balanced.

Fig. 5(a) and (b) presents the prosumers' average energy generation and the percentage of them that act as sellers during the day, respectively, for two comparative scenarios: 1) high generation scenario; and 2) low generation scenario, where the prosumers have high and low energy generation capacity, respectively. The prosumers' energy generation is solely based on solar photovoltaic panels. The results reveal that during the sunny periods of the day, the prosumers generate more energy [see Fig. 5(a)], thus, a greater percentage of them is incentivized to act as sellers [see Fig. 5(b)] in both examined scenarios. In the high generation scenario, it is observed that the prosumers generate sufficient amount of energy to cover their personal energy needs, thus, they act as sellers for the majority of the day's duration. It is noted that the energy price and generation costs are assumed to remain fixed throughout the day.

The above analysis is extended in Figs. 5 and 6, where both the prosumers and MGO average utilities are presented for two different scenarios: high buyer cost with $p_M = 6, p_S = 2$ (Fig. 5); and high seller cost with $p_M = 2, p_S = 6$ (see Fig. 6), respectively. The energy generation characteristics for both scenarios follow the behavior presented in Fig. 5(a). The results reveal that when the energy price p_M is high and the energy generation cost p_S is low, more prosumers act as sellers, thus, their average utility is higher [see Fig. 6(a)], compared to the alternative scenario [see Fig. 7(a)]. This trend is expected as the prosumers generate energy with low cost. The offset of the high and low Generation scenarios in Figs. 8(a) and 9(a) stems from the corresponding percentage of prosumers that act as sellers. Also, the benefit of the prosumers corresponds to the loss of the MGO, thus, the exact flipped trend is observed in Figs. 6(b) and 7(b) regarding the achieved MGO's utility.

C. Impact of Energy Generation and Demand on the Prosumers' and MGO's Interactions

In the following, we focus our study on the impact of the prosumers' energy generation and demand characteristics on their interactions with the microgrid system during a day. We consider an evolving behavior where the prosumers' demand is low for $t \in [0, 8]$, then it increases for $t \in [8, 16]$, and then drops again for $t \in [16, 24]$, representing the realistic prosumers' energy demand during the day. The aforementioned case, is evaluated and studied under three different scenarios regarding the prosumers' energy generation capacity, i.e., high, medium, and low. Following a similar methodology with our evaluation in the previous figures in this section (i.e., considering high buyer cost and high seller cost alternatives), two sets of results are produced and presented, differentiated exactly with respect to the considered energy price p_M , and the energy generation cost

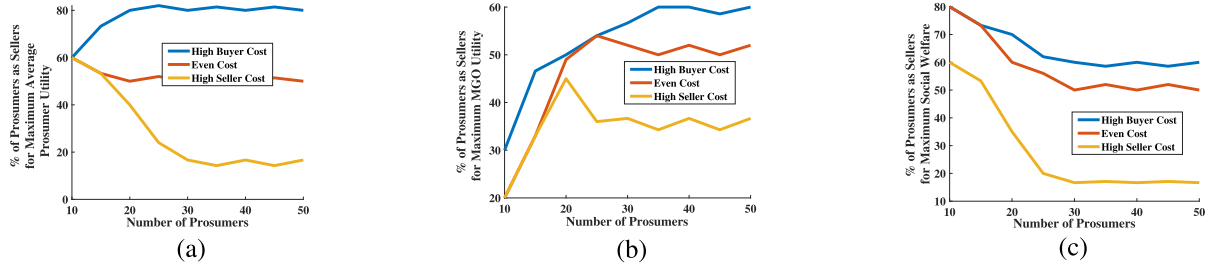


Fig. 4. Percentage of prosumers acting as sellers to achieve maximum (a) prosumers' average utility (i.e., prosumer-centric), (b) MGO utility (i.e., MGO-centric), and (c) social welfare, versus increasing number of prosumers, under three scenarios.

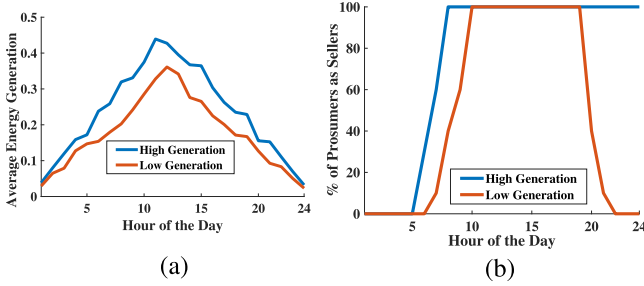


Fig. 5. (a) Average energy generation. (b) Percentage of prosumers acting as sellers under high and low energy generation.

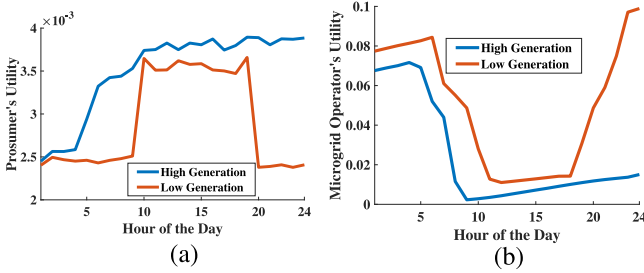


Fig. 6. (a) Average prosumers' utility. (b) MGO's utility for $p_M = 6, p_S = 2$, under high and low energy generation.

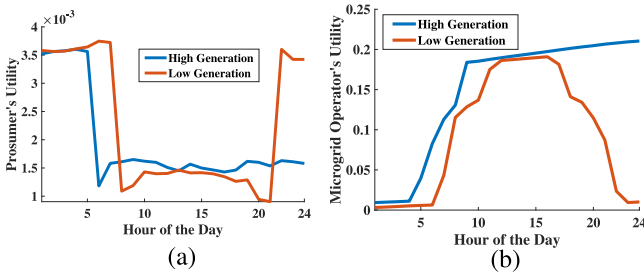


Fig. 7. (a) Average prosumers' utility. (b) MGO's utility for $p_M = 2, p_S = 6$ under high and low energy generation scenarios.

p_S , i.e., $p_M = 6, p_S = 2$ for Fig. 8(a)–(d) and $p_M = 2, p_S = 6$ for Fig. 9(a)–(d).

Specifically, Fig. 8(a)–(c) presents the percentage of prosumers acting as sellers, their average utility, and the MGO's utility during the day, respectively, for the three aforementioned energy generation scenarios. The results reveal that in the high energy generation scenario, all the prosumers act as sellers, as they have sufficient energy surplus to support their personal

energy need, while the exact opposite holds true in the Low energy generation scenario [see Fig. 8(a)]. In order to gain insight about the behavior of the curves for the medium energy generation scenario, we should turn our attention to Fig. 8(d).

Particularly, with reference to the medium energy generation scenario, Fig. 8(d) presents the behavior of the prosumers' average utility and the MGO's utility for different percentages of prosumers acting as sellers. We observe that the maximum prosumers' average utility is achieved, when approximately 60% of the prosumers act as sellers. Correlating this value with the results in Fig. 8(a), we observe that approximately 60% of the prosumers act as sellers, except for the time interval 11 A.M.–3 P.M., when the prosumers' energy demand becomes high, and accordingly fewer prosumers are acting as sellers. Also, given that the energy generation cost is low, i.e., $p_S = 2$, as compared to the energy price, which is high, i.e., $p_M = 6$, the prosumers that generate a lot of energy achieve higher utility compared to the scenario of generating small amount of energy [see Fig. 8(b)]. The exact opposite is observed from the MGO's perspective [see Fig. 8(c)]. Focusing on the medium energy generation scenario, we observe that during the morning hours $t \in [0, 11]$, the prosumers generate more energy, thus, accumulating energy surplus, and 60% of them act as sellers [see Fig. 8(a)], achieving the maximum possible utility [see Fig. 8(d)], thus, their average achieved utility increases [see Fig. 8(b)]. In the slot $t \in [10, 11]$, their energy demands increase and the percentage of prosumers acting as sellers drops to 20% [see Fig. 8(a)], achieving the lowest possible utility [see Fig. 8(d)], driving their average utility to drop [see Fig. 8(b)]. Similar analysis can be derived and followed for the rest of the day. Still focusing on the medium energy generation scenario but from the MGO's perspective, we jointly study Fig. 8(c) and (d). We observe that for the time periods $t \in [0, 10] \cup [15, 24]$, where the percentage of the prosumers acting as sellers is approximately 60% [see Fig. 8(a)], the MGO achieves a relatively high utility [see Fig. 8(d)], and slowly increases its profit during those time periods. On the other hand, for the time interval $t \in [10, 15]$, where only 20% of the prosumers act as sellers [see Fig. 8(a)] due to their personal high energy demand, the MGO achieves the highest possible utility [see Fig. 8(d)], as the MGO has set its price at a high value, i.e., $p_M = 6$. Thus, during this period, the MGO accumulates a higher profit.

Last, a symmetric scenario is presented in Fig. 9, where a low energy price ($p_M = 2$) and high energy generation cost ($p_S = 6$) is considered instead. The point that should be highlight here

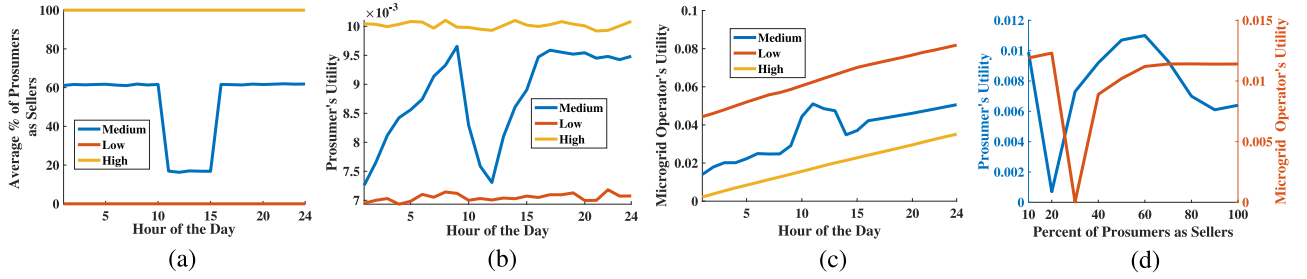


Fig. 8. (a) Percentage of prosumers acting as sellers, (b) prosumers' average utility, and (c) MGO's utility during the day for the three energy generation scenarios ($p_M = 6, p_S = 2$). (d) achieved utility in the system of for different percentages of prosumers functioning as sellers.

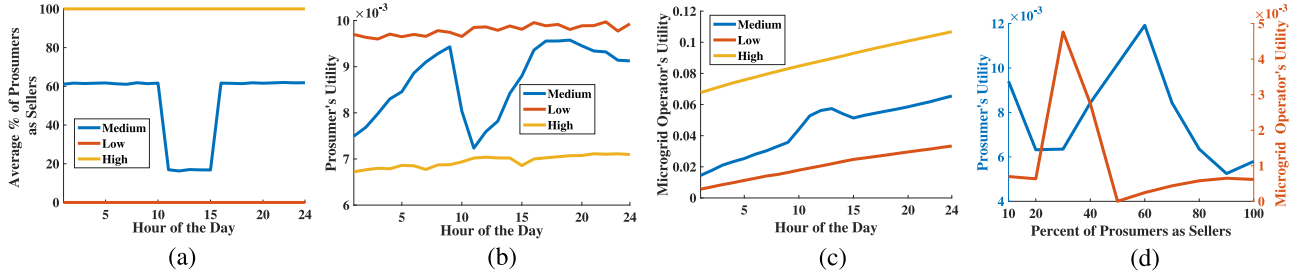


Fig. 9. (a) Percentage of prosumers acting as sellers, (b) prosumers' average utility, and (c) MGO's utility during the day for the three energy generation scenarios ($p_M = 2, p_S = 6$). (d) achieved utility in the system for different percentages of prosumers functioning as sellers.

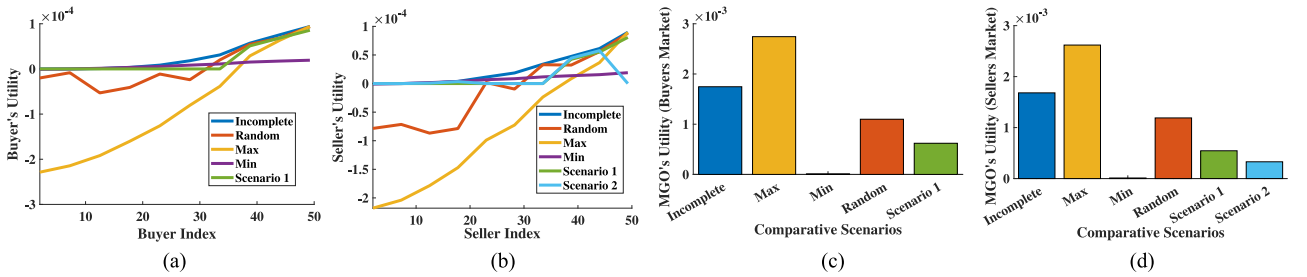


Fig. 10. Comparative evaluation—buyers and sellers utility and MGO's utility for the buyers and sellers market, respectively.

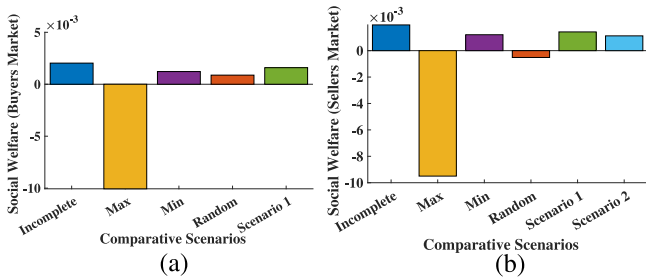


Fig. 11. (a) Buyers and (b) sellers social welfare.

is that the average utility of the prosumers with high energy generation is lower compared to the ones with low energy generation as the energy generation cost is higher. The exact opposite behavior is presented by the MGO's utility, as more prosumers tend to buy energy from it.

D. Comparative Evaluation

In the following, we provide a detailed comparative evaluation analysis of the proposed framework, against alternative

strategies, with respect to both the sellers' and the buyers' interactions with the MGO. Specifically, we consider the following scenarios: 1) incomplete: the proposed realistic incomplete information scenario of the prosumers' types from the MGO's perspective; 2)–4) max, min, and random: the prosumers sell/buy their maximum, minimum, and random amount of energy, respectively; 5) Scenario 1: the prosumers sell/buy in total the same amount of energy as in the proposed incomplete information scenario (for fairness in the comparison) allowing first the prosumers of higher type to sell/buy their total amount of energy; 6) Scenario 2: the sellers sell in total the same amount of energy as in the proposed incomplete information scenario, however, the sellers that will sell their total amount of energy are selected randomly. Fig. 10 (a)–(d) presents the buyers' and sellers' utility as a function of their type (the sellers' and buyers' IDs have been sorted with respect to their increasing types), as well as the MGO utility. The results reveal that the proposed incomplete information contract-theoretic framework overall outperforms all other scenarios, achieving better results for the prosumers, while simultaneously leading to realistic benefits for the MGO. It is noted that though the max scenario leads to higher values for the MGO utility, this happens at the cost of

significantly penalizing the prosumers (both sellers and buyers), leading to very low utility values for the overwhelming majority of them. The combined effect of each framework, accounting for both the prosumers and MGO utilities, is demonstrated by the corresponding social welfare as shown in Fig. 11(a) and (b), referring to the behavior of the overall examined system, where we clearly see that the proposed framework achieves higher values than all other examined strategies.

VI. CONCLUSION

In this article, the paradigm of prosumer-centric self-sustained smart grid systems is introduced, by capturing and properly modeling the interactions of the prosumers with the microgrid operator via a labor economics-based approach. The prosumers throughout the system operation may serve as sellers or buyers, based on their personal energy generation, demand, and storage characteristics. The MGO offers personalized rewards to the sellers and buyers to incentivize them to sell and purchase energy, respectively. The contract-theoretic optimization problems between the MGO and the sellers and the MGO and the buyers respectively, are formulated and solved to determine the optimal personalized contracts, i.e., rewards and amount of sold/purchased energy. Detailed numerical and comparative evaluation results—obtained via modeling and simulation—are presented to demonstrate the operation of the proposed framework and highlight its main characteristics, under various diverse scenarios.

Part of our current and future work refers to the incorporation of the prosumers reactions to the energy price fluctuation, which introduces risk in their decision to act as sellers or buyers. In our efforts to study and address this problem, the principles of prospect theory are adopted. Furthermore, along the same lines, we plan to consider a system where multiple MGOs may coexist and therefore the prosumers may dynamically get associated with different MGOs at different times, thus, introducing several uncertainties within a more competitive market overall.

REFERENCES

- [1] G. Hafeez *et al.*, “An innovative optimization strategy for efficient energy management with day-ahead demand response signal and energy consumption forecasting in smart grid using artificial neural network,” *IEEE Access*, vol. 8, pp. 84415–84433, 2020.
- [2] A. Al Hadi, C. A. S. Silva, E. Hossain, and R. Chaloo, “Algorithm for demand response to maximize the penetration of renewable energy,” *IEEE Access*, vol. 8, pp. 55279–55288, 2020.
- [3] R. Zhou, Z. Li, and C. Wu, “An online procurement auction for power demand response in storage-assisted smart grids,” in *INFOCOM*, 2015, pp. 2641–2649.
- [4] A. Kumari, R. Gupta, S. Tanwar, S. Tyagi, and N. Kumar, “When blockchain meets smart grid: Secure energy trading in demand response management,” *IEEE Netw.*, vol. 34, no. 5, pp. 299–305, Sep./Oct. 2020.
- [5] D. Li, W.-Y. Chiu, H. Sun, and H. V. Poor, “Multiobjective optimization for demand side management program in smart grid,” *IEEE Trans. Ind. Inform.*, vol. 14, no. 4, pp. 1482–1490, Apr. 2017.
- [6] H. Wang and J. Huang, “Incentivizing energy trading for interconnected microgrids,” *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 2647–2657, Jul. 2018.
- [7] A. Nikoobakht, J. Aghaei, M. Shafie-Khah, and J. P. S. Catalão, “Assessing increased flexibility of energy storage and demand response to accommodate a high penetration of renewable energy sources,” *IEEE Trans. Sustain. Energy*, vol. 10, no. 2, pp. 659–669, Apr. 2019.
- [8] T. Morstyn and M. D. McCulloch, “Multiclass energy management for peer-to-peer energy trading driven by prosumer preferences,” *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4005–4014, Sep. 2019.
- [9] S. L. Arun and M. P. Selvan, “Intelligent residential energy management system for dynamic demand response in smart buildings,” *IEEE Syst. J.*, vol. 12, no. 2, pp. 1329–1340, Jun. 2018.
- [10] E. S. Kang, S. J. Pee, J. G. Song, and J. W. Jang, “A blockchain-based energy trading platform for smart homes in a microgrid,” in *Proc. 3rd Int. Conf. Comput. Commun. Syst.*, 2018, pp. 472–476.
- [11] M. Vahedipour-Dahraie, H. Rashidizadeh-Kermani, and A. Anvari-Moghaddam, “Risk-based stochastic scheduling of resilient microgrids considering demand response programs,” *IEEE Syst. J.*, vol. 15, no. 1, pp. 971–980, Mar. 2021.
- [12] D. Prudhviraj, P. B. S. Kiran, and N. M. Pindoriya, “Stochastic energy management of microgrid with nodal pricing,” *J. Modern Power Syst. Clean Energy*, vol. 8, no. 1, pp. 102–110, 2020.
- [13] W. Liu, J. Zhan, and C. Y. Chung, “A novel transactive energy control mechanism for collaborative networked microgrids,” *IEEE Trans. Power Syst.*, vol. 34, no. 3, pp. 2048–2060, May 2019.
- [14] P. A. Apostolopoulos, E. E. Tsiropoulou, and S. Papavassiliou, “Demand response management in smart grid networks: A two-stage game-theoretic learning-based approach,” *Mob. Net. Appl.*, pp. 1–14, 2018.
- [15] H.-H. Chang, W.-Y. Chiu, H. Sun, and C.-M. Chen, “User-centric multiobjective approach to privacy preservation and energy cost minimization in smart home,” *IEEE Syst. J.*, vol. 13, no. 1, pp. 1030–1041, Mar. 2019.
- [16] Z. Zhang, Y. Huang, H. Chen, Q. Huang, and W.-J. Lee, “A novel hierarchical demand response strategy for residential microgrid,” *IEEE Trans. Ind. Appl.*, vol. 57, no. 4, pp. 3262–3271, Jul./Aug. 2021.
- [17] K. Baek, E. Lee, and J. Kim, “Resident behavior detection model for environment responsive demand response,” *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 3980–3989, Sep. 2021.
- [18] Y. Liu, L. Xiao, G. Yao, and S. Bu, “Pricing-based demand response for a smart home with various types of household appliances considering customer satisfaction,” *IEEE Access*, vol. 7, pp. 86463–86472, 2019.
- [19] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, “Optimal residential load management in smart grids: A decentralized framework,” *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 1836–1845, Aug. 2016.
- [20] C. Yang and W. Lou, “On optimizing demand response management performance for microgrids under communication unreliability constraint,” in *Proc. GLOBECOM*, 2015, pp. 1–6.
- [21] C. Yang, J. Yao, W. Lou, and S. Xie, “On demand response management performance optimization for microgrids under imperfect communication constraints,” *IEEE Internet Things J.*, vol. 4, no. 4, pp. 881–893, Aug. 2017.
- [22] P. Bolton *et al.*, *Contract Theory*. Cambridge, MA, USA: MIT Press, 2005.
- [23] N. Irtija, F. Sangoleye, and E. E. Tsiropoulou, “Contract-theoretic demand response management in smart grid systems,” *IEEE Access*, vol. 8, pp. 184976–184987, 2020.
- [24] S. Wang, S. Bi, and Y.-J. A. Zhang, “The impacts of energy customers demand response on real-time electricity market participants,” in *Proc. Int. Conf. Commun.*, 2018, pp. 1–7.
- [25] S. Wang, S. Bi, and Y.-J. A. Zhang, “Demand response management for profit maximizing energy loads in real-time electricity market,” *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6387–6396, Nov. 2018.
- [26] L. Jia and L. Tong, “Dynamic pricing and distributed energy management for demand response,” *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1128–1136, Mar. 2016.
- [27] USA EIA, “U.S. Energy information administration,” 2021. [Online]. Available: <https://www.eia.gov/>