



Vaasan yliopisto  
UNIVERSITY OF VAASA

OSUVA Open  
Science

This is a self-archived – parallel published version of this article in the publication archive of the University of Vaasa. It might differ from the original.

## An iterative auction-based method for multi energy trading in a microgrid considering renewable energy uncertainties

**Author(s):** Ebrahimi, Mahan; Ebrahimi, Mahoor; Fallah, Ali; Shafie-Khah, Miadreza; Laaksonen, Hannu

**Title:** An iterative auction-based method for multi energy trading in a microgrid considering renewable energy uncertainties

**Year:** 2024

**Version:** Accepted manuscript

**Copyright** ©2024 Elsevier. This manuscript version is made available under the Creative Commons Attribution–NonCommercial–NoDerivatives 4.0 International (CC BY–NC–ND 4.0) license, <https://creativecommons.org/licenses/by-nc-nd/4.0/>

### Please cite the original version:

Ebrahimi, M., Ebrahimi, M., Fallah, A., Shafie-Khah, M. & Laaksonen, H. (2024). An iterative auction-based method for multi energy trading in a microgrid considering renewable energy uncertainties. *Electric Power Systems Research*, 232, 110381. <https://doi.org/10.1016/j.epsr.2024.110381>

# An Iterative Auction-Based Method for Multi Energy Trading in a Microgrid Considering Renewable Energy Uncertainties

Mahan Ebrahimi<sup>1</sup>, Mahoor Ebrahimi<sup>2</sup>, Ali Fallah<sup>1</sup>, Miadreza Shafie-Khah<sup>2</sup>, Hannu Laaksonen<sup>2</sup>,

<sup>1</sup>Department of Electrical Engineering, Sharif University of Technology, Iran

<sup>2</sup>School of Technology and Innovations, University of Vaasa, Finland

**Abstract**— Due to the significant strides made in renewable energy generating units, they are now an appealing choice for supplying energy with various benefits. Furthermore, the aggregation of different energy generators and resources and the rise of energy conversion facilities, like combined heat and power (CHP), have paved the way for a new category of multi-energy prosumers. This research presents an innovative model for a local energy market structure consisting of an aggregator, prosumers, electricity, gas, and heat utility grids, and consumers. The interplay between these entities is handled as an auction model with proposed bidding strategies in which each player participates to maximize their own objective function. The numerical analysis reveals the impact of the pricing strategy on the prosumers' willingness to provide more energy during peak demand periods. Furthermore, the study highlights the potential for mutually beneficial collaborations between prosumers, which leads to reduced energy costs.

**Index Terms**— Renewable Energy, Microgrid, Iterative Auction, Electricity pricing

## NOMENCLATURE

$\pi_{e,t}$	Elec local market price
$\kappa_{e,t}$	Elec utility market price
$\pi_{h,t}$	Heat local market price
$\kappa_{h,t}$	Heat utility market price
$\kappa_{g,t}$	Gas utility market price
$e_{p,i,t}^{out}$	Sold electricity power of prosumer $i$ at $t$
$e_{p,i,t}^{in}$	Purchased electricity power of prosumer $i$ at $t$
$e_{c,i,t}$	Purchased electricity of Consumer $j$ at $t$
$h_{c,j,t}$	Purchased heat of consumer $j$ at $t$
$h_{i,t}^{CHP}$	Output heat of <i>CHP</i> of prosumer $i$ at $t$
$h_{i,t}^B$	Output heat of boiler of prosumer $i$ at $t$
$h_{i,t}^d$	Heat demand of prosumer $i$ at $t$
$g_{p,i,t}^{in}$	Purchased gas of prosumer $i$ at $t$
$g_{i,t}^{CHP}$	Gas input of <i>CHP</i> of prosumer $i$ at $t$
$g_{i,t}^B$	Gas input of Boiler of prosumer $i$ at $t$
$g_{i,t}^d$	Gas demand of prosumer $i$ at $t$
$\eta_{i,e}^T$	Transformer efficiency of prosumer $i$
$\eta_{i,h}^T$	Heat transformer efficiency of prosumer $i$

$k > 0$	Weibull function shape factor
$c > 0$	Weibull function scale factor
$N$	Number of Prosumers
$h_{p,i,t}^{in}$	Purchased heat of prosumer $i$ at $t$
$e_{i,t}^{S,in}$	Charged electricity in <i>ES</i> of prosumer $i$ at $t$
$e_{i,t}^{S,out}$	Discharged electricity from <i>ES</i> of prosumer $i$ at $t$
$e_{i,t}^{CHP}$	Elec generation of <i>CHP</i> of prosumer $i$ at $t$
$h_{p,i,t}^{out}$	Sold heat of prosumer $i$ at $t$
$e_{i,t}^d$	Elec demand of prosumer $i$ at $t$
$e_{i,t}^{PV}$	<i>PV</i> generation of prosumer $i$ at $t$
$h_{i,t}^{S,in}$	Charged heat in <i>HS</i> of prosumer $i$ at $t$
$h_{i,t}^{S,out}$	Discharged heat from <i>HS</i> of prosumer $i$ at $t$
$e_{i,t}^{Wind}$	Wind turbine generation of prosumer $i$ at $t$
$\eta_{i,e}^{CHP}$	Elec efficiency for <i>CHP</i> of prosumer $i$
$\eta_{i,h}^{CHP}$	Heat efficiency for <i>CHP</i> of prosumer $i$
$\eta_e^S$	Elec Storage efficiency
$\eta_h^S$	Heat storage efficiency
$\eta_{i,h}^B$	Boiler efficiency of prosumer $i$
$k_{\lambda,j}$	Multiplier for logarithmic objective function of consumer $j$
$g_{c,j,t}$	Purchased gas of consumer $j$ at $t$
$\Delta$	Maximum difference of prosumers' bid from their previous iteration's bid
$C_{i,t}^h$	Stored heat in storage of prosumer $i$ at $t$
$C_{i,t}^e$	Stored electricity in storage of prosumer $i$ at $t$
$M$	Number of consumers

## I. INTRODUCTION

### A. Related Works

With the rapid increase in distributed generation and the option to have the energy generation closer to the

consumption points, microgrids are experiencing a development to strengthen their role in the power grid [1]. Distributed energy resources (DERs) include renewable energy sources such as solar panels, wind turbines, and energy storage systems, as well as conventional energy sources like natural gas-fired power plants and combined heat and power systems [2]. These resources can be owned and operated by utilities, independent power producers, or even individual consumers [3]. Moreover, energy storage systems are also used to store the excess energy generated during periods of low demand and to discharge it during periods of high demand. This helps to balance the supply and demand of energy within the microgrid and reduces the need for backup generation from non-renewable sources [4].

Distributed generation allows multiple energy generators to participate in the energy trade within the microgrid. This can increase competition and lower the cost of energy [5]. Additionally, by allowing consumers to generate for their own demand, distributed generation can increase the resilience of the microgrid, as it reduces dependence on a centralized energy grid [6]. The local energy market (LEM) is emerging as a promising solution to integrate more DERs into the electricity system. LEMs are platforms that allow for the trading of energy within a specific geographical area, typically at the distribution level [7]. They enable DERs to participate in the energy market by buying and selling energy and related services, such as ancillary services, to balance supply and demand [8]. This allows for a more efficient use of the energy produced by DERs, as well as reducing the need for traditional centralized energy resources.

LEM can provide incentives for the development of renewable energy sources, helping to reduce greenhouse gas emissions and combat climate change [9]. Additionally, LEMs can help to increase energy security by reducing dependence on centralized energy sources, which are often subject to price volatility and supply disruptions [10]. By enabling the integration of energy storage systems, LEMs can help to balance supply and demand, reduce the risk of the use of existing infrastructure, reduce the need for new grid investments, and lower overall energy costs for consumers [11].

As mentioned above, one of the most important goals of designing local energy markets among small-scale prosumers is to bring self-sufficiency which increases the systems' resiliency. In this regard, authors in [12] have investigated three different financial scenarios to increase the self-consumption factor of some PV-equipped apartments through the

peer-to-peer (P2P) market. Similar research is conducted in [13] for trading energy among such PV-equipped apartments. In this paper, the authors have used the Lagrangian relaxation-based method to solve the nonlinear problem. The authors in [14, 15] proposed a blockchain-based double auction mechanism for designing the local energy market among peers. Researchers in [16] used non-cooperative game theory to model the interaction among players inside a local energy market. The authors aimed to devise a fair pricing mechanism for both the electrical and thermal energy sectors.

Authors in [17] have investigated the effects of heat storage on the P2P multi-energy market. Ref. [18] proposes a discrete-timely double-sided auction model for energy trading among peers in near real-time and forward markets. The market design aims to increase the prosumers' benefit using simple bidding rules. Moreover, a home energy management approach is deployed to enhance the distribution system's reliability. In ref. [19], a framework has been introduced to operate a community microgrid. In this architecture, the resulting revenues and costs are shared among the community members. In addition, a market-oriented pricing mechanism for electricity trades is obtained.

The problems in power systems are always combined with uncertainty and different approaches to model them [20]. Authors in [21] modeled the stochastic behavior of renewable energy sources by versatile distribution. They determined the required reserve using a chance-constrained optimization approach. Ref. [22] designed a P2P energy trading model inside a microgrid and utilized a fuzzy multi-objective programming model for investigating renewable generation and demand load uncertainties. In [23], Multilayer neural networks are used for the anticipation of uncertain parameters of the problems regarding the energy management of interconnected microgrids. In [24] also, the employment of a distance-based ambiguity set has been utilized to capture the unknown probability distribution functions. Authors in [25] proposed a model in which the behavior of smart energy hubs and aggregators has been assessed as a bilevel optimization problem. The problem has been transformed to a single level one using the strong duality theorem and Karush-Kahn-Tucker conditions. The enormous number of variables inside the single problem causes the problem to be time-consuming to solve and deploying such a model under a real network with hundreds of prosumers may result in solving complexities.

## B. Contribution

Despite the fact that several studies have investigated the P2P energy trading inside a local energy market, the integration of three energy sectors of electricity, heat and gas inside an auction-based market model with consideration of distributed generations' uncertainty has not been addressed in the existing literature. In this regard, this paper proposes an innovative algorithm for performing the auction among local energy market players to determine the optimal price of electricity and heat energy and persuade prosumers to facilitate energy balance inside a local energy market. As it could be concluded from the previous papers in which the bilevel optimization model was deployed, aggregators at the upper level have a higher level of decision-making authority in comparison with prosumers. In this case, they cannot provide a realistic overview of a fair local energy market. Therefore, in the proposed iterative auction-based model of this paper, the prosumers' and the aggregator's decision-making authorities are equal. Moreover, the higher decision-making authority that our model provides for prosumers, motivates them to be more active in the energy and flexibility provision. This leads to increasing the self-sufficiency of the local energy market, which is highly required in the brand-new distribution system structure. Considering the scalability deficiency of the references discussed in the literature review, in this paper, we separated the optimization problem of each consumer or prosumer into distinctive problems, each of which reports its result to the aggregator to make its own decision. Consequently, we can consider this model a more scalable one in comparison with the similar studies that have been done in this context.

The contribution of this paper is summarized as follows.

- Proposing a novel iterative auction-based model for local energy market which aggregated three energy sectors and provides similar decision-making authority for aggregators, consumers, and prosumers
- Presenting a framework for local energy market that reduces the computational burden of solving complex optimization problems with an enormous number of variables
- Investigating the effect of aggregation of multi-energy prosumers and aggregators on the price balancing of local energy market at consumption peak hours

The rest of this paper is organized as follows. In section II, the problem formulation and explanation are described. Section III demonstrates the auction

algorithm among players, and numerical results are reported in section IV. A conclusion and suggestions for future works are mentioned in section V.

## II. PROBLEM STATEMENT

### A. Review Stage

The energy trading in this paper is divided into two segments: the utility market and the local energy market. The utility market involves players like Generating Companies (Gencos), aggregators, and retailers for three energy sectors of electricity, heat, and gas. The aggregator, acting as a price-taker agent in the utility market, interacts with both the prosumers and the local energy market consumers. A prosumer is defined as a compact energy system equipped with devices like smart meters, combined heat and power (CHP) systems, boilers, actuators, sensors, and electricity and heat storage [20].

The aggregator is in charge of determining energy carrier prices for local energy market, considering the consumers' and prosumers' bids about their input and output energy amounts. This is done based on an iterative method and the local energy market price is cleared when a fixed condition is satisfied. The aggregator purchases/sells the amount of the final bids from/to prosumers and consumers. The aggregator also trades the final difference between supply and demand in the local energy market to the utility market at a fixed price. This explanation is depicted in Figure 1.

However, the aggregator faces a challenge in this setup. If the energy price for the local market is set too high (by the aggregator), the prosumers will be incentivized to generate excess energy and sell it to the aggregator, forcing the aggregator to buy energy at a high price. Conversely, setting a low local market price will cause the prosumers to buy energy, resulting in losses for the aggregator. The energy trading among the aggregator and the prosumers takes place before the final determination of the grid energy price. As a result, any sudden changes in the energy utility price will only affect the aggregator's profit or loss.

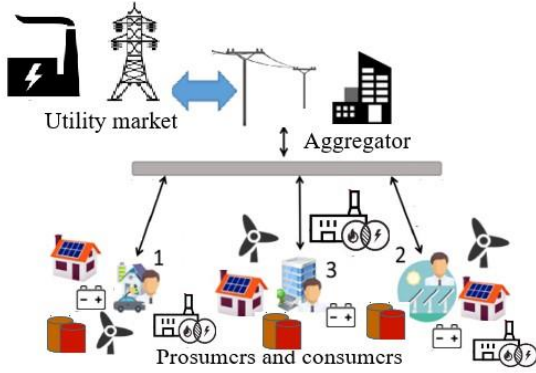


Figure 1: Local energy market structure

### A. Aggregator's decision:

The aim of all three player types in this model is to optimize their financial gains. The aggregator's objective function is divided into two components, as presented in (1). The aggregator has control over the local energy market prices, but the price of gas in the local market is set and equal to the utility market price. As a result, the aggregator does not play any role in determining it. In (1),  $f$  denotes the objective function of the aggregator, and  $x$  is the vector of decision variable for it.

$$\begin{aligned} \text{Max } f(x) = & \sum_t [(\pi_{e,t} - \kappa_{e,t}) (\sum_{i=1}^N e_{p,i,t}^{in} \\ & - e_{p,i,t}^{out} + \sum_{j=1}^M e_{c,j,t}) + (\pi_{h,t} \\ & - \kappa_{h,t}) (\sum_{j=1}^N h_{p,i,t}^{in} - h_{p,i,t}^{out} \\ & + \sum_{j=1}^M h_{c,j,t})] \end{aligned} \quad (1)$$

The aggregator's objective function consists of two parts. Firstly, the amount of electricity purchased by the aggregator from the local market (prosumers) is multiplied by the difference between the local market price and the utility market price. This computation is repeated for the heat in the second part of (1). The price of gas in the local market is set and remains fixed at the same price as the utility market. The aggregator is required to establish the local price within a specific range, which is limited by a minimum and maximum price as specified in equations (2)-(3).

$$\pi_e^{\min} \leq \pi_{e,t} \leq \pi_e^{\max} \quad (2)$$

$$\pi_h^{\min} \leq \pi_{h,t} \leq \pi_h^{\max} \quad (3)$$

### B. Prosumers' decision

The aggregator's price setting affects the energy

input and output for every prosumer. To maximize their profits from selling energy and minimize the cost of purchases, each prosumer considers a three-part objective function that assesses the expenses associated with acquiring and selling each type of energy. In essence, prosumers strive to optimize their revenue while minimizing their expenses.  $S$  and  $y$  denote the objective function and decision variable of prosumers.

$$\text{Max } S_i(y) = \sum_t [\pi_{e,t} (e_{p,i,t}^{out} - e_{p,i,t}^{in}) + \pi_{h,t} \times (h_{p,i,t}^{out} - h_{p,i,t}^{in}) - \pi_{g,t} \times (g_{p,i,t}^{in})] \quad (4)$$

Equations (5) to (7) pertain to the equilibrium of power across three distinct energy carriers in prosumer. Specifically, they are concerned with the balance of power for electricity, heat, and gas.

$$-e_{p,i,t}^{in} \times \eta_{i,e}^T + e_{p,i,t}^{out} / \eta_{i,e}^T + e_{i,t}^{S,in} - e_{i,t}^{S,out} - e_{i,t}^{CHP} - e_{i,t}^{Wind} - e_{i,t}^{PV} + e_{i,t}^d = 0 \quad (5)$$

$$-h_{p,i,t}^{in} \times \eta_{i,h}^T + h_{p,i,t}^{out} / \eta_{i,h}^T + h_{i,t}^{S,in} - h_{i,t}^{S,out} - h_{i,t}^{CHP} - h_{i,t}^B + h_{i,t}^d = 0 \quad (6)$$

$$-g_{p,i,t}^{in} + g_{i,t}^{CHP} + g_{i,t}^B - g_{i,t}^d = 0 \quad (7)$$

Inequalities (8)-(12) represent that the imported or exported energy carriers by the prosumers are restricted and less than their physical capacity.

$$0 \leq e_{p,i,t}^{in} \leq e_{p,i,t}^{in,max} \quad (8)$$

$$0 \leq e_{p,i,t}^{out} \leq e_{p,i,t}^{out,max} \quad (9)$$

$$0 \leq h_{p,i,t}^{in} \leq h_{p,i,t}^{in,max} \quad (10)$$

$$0 \leq h_{p,i,t}^{out} \leq h_{p,i,t}^{out,max} \quad (11)$$

$$0 \leq g_{SEH_{i,t}}^{in} \leq g_{SEH_{i,t}}^{in,max} \quad (12)$$

### C. CHP Constraints

Combined heat and power (CHP) generates electricity and heat power from the input gas based on the mathematical equations described in (13)-(14):

$$e_{i,t}^{CHP} - \eta_{i,e}^{CHP} \times g_{i,t}^{CHP} = 0 \quad (13)$$

$$h_{i,t}^{CHP} - \eta_{i,h}^{CHP} \times g_{i,t}^{CHP} = 0 \quad (14)$$

The constraints related to the capacity limitation of the CHP units for importing gas as well as exporting heat and electricity is presented in inequalities (15)-(17).

$$0 \leq e_{i,t}^{CHP} \leq e_i^{CHP,max} \quad (15)$$

$$0 \leq h_{i,t}^{CHP} \leq h_i^{CHP,max} \quad (16)$$

$$0 \leq g_{i,t}^{CHP} \leq g_i^{CHP,max} \quad (17)$$

### D. Boiler Constraints

Boilers are systems in which the input gas is transformed into heat power. This process is modeled via a linear equation which can be seen in (18). Eqs. (19)-(20) states that boiler's input and output gas and heat could not exceed its physical capacity.

$$h_{i,t}^B - \eta_{i,h}^B \times g_{i,t}^B = 0 \quad (18)$$

$$0 \leq h_{i,t}^B \leq h_{i,t}^{B,max} \quad (19)$$

$$0 \leq g_{i,t}^B \leq g_{i,t}^{B,max} \quad (20)$$

### E. Energy Storages Constraints

In this paper, it is stated that prosumers are equipped with electricity and heat storage. The energy balance between the input, output and stored amount of electricity and heat are determined through Eqs (21) and (22).

$$C_{i,t}^e - C_{i,t-1}^e + e_{i,t}^{S,in} \times \eta_e^S - e_{i,t}^{S,out} / \eta_e^S = 0 \quad (21)$$

$$C_{i,t}^h - C_{i,t-1}^h + h_{i,t}^{S,in} \times \eta_h^S - h_{i,t}^{S,out} / \eta_h^S = 0 \quad (22)$$

In constraints (23)-(28), the storages' input and output power, and the stored energy in energy storage are defined to be smaller than fixed amounts.

$$0 \leq e_{i,t}^{S,in} \leq e_i^{S,in,max} \quad (23)$$

$$0 \leq e_{i,t}^{S,out} \leq e_i^{S,out,max} \quad (24)$$

$$0 \leq C_{i,t}^e \leq C_i^{e,max} \quad (25)$$

$$0 \leq h_{i,t}^{S,in} \leq h_i^{S,in,max} \quad (26)$$

$$0 \leq h_{i,t}^{S,out} \leq h_i^{S,out,max} \quad (27)$$

$$0 \leq C_{i,t}^h \leq C_i^{h,max} \quad (28)$$

As stated in Eqs. (29)-(32), it is assumed that the initial and last hour stored energy in the storage are fixed and equal to half of their maximum capacity.

$$C_{i,0}^e = C_i^{e,max} / 2 \quad (29)$$

$$C_{i,24}^e = C_i^{e,max} / 2 \quad (30)$$

$$C_{i,0}^h = C_i^{h,max} / 2 \quad (31)$$

$$C_{i,24}^h = C_i^{h,max} / 2 \quad (32)$$

### F. Consumers' Decision-making Problem

Consumers decide their own energy usage based on the aggregator's pricing strategy. A unique convenience function is assigned to each consumer to quantify their level of satisfaction with their energy consumption, represented in equation (33) [21]. This function is obtained by subtracting the total energy cost from the utility gained by consuming energy. As the purchased energy amount increases, the logarithmic part of (33) and the total paid by the consumer rise. Larger values of the constants  $k_{1,j}$  and  $k_{2,j}$  indicate a greater willingness of the consumer to purchase energy, and these values are not influenced by the aggregator.  $h$  and  $l$  denote the objective function and decision variable of consumers.

$$\begin{aligned} Max h_j(l) = & \sum_{t=1}^T -e_{c,j,t} \times \pi_{e,t} \\ & + k_{1,j} Ln(k_{2,j}(e_{c,j,t} \\ & + 1)) - h_{c,j,t} \times \pi_{h,t} \\ & + k_{1,j} Ln(k_{2,j}(h_{c,j,t} \\ & + 1)) - g_{c,j,t} \times \pi_{g,t} \\ & + k_{1,j} Ln(k_{2,j}(g_{c,j,t} \\ & + 1)) \end{aligned} \quad (33)$$

Consumers could not import energy beyond a fixed limit. Constraints (34)-(36) present this fact.

$$0 \leq e_{c,j,t} \leq e_{c,j}^{max} \quad (34)$$

$$0 \leq h_{c,j,t} \leq h_{c,j}^{max} \quad (35)$$

$$0 \leq g_{c,j,t} \leq g_{c,j}^{max} \quad (36)$$

## III. PROBLEM STATEMENT

### A. Auction-based trading process

The auction starts with an initial price determination by the aggregator based on the historical data of previous days. Every prosumer and consumer tries to determine its optimum energy input and output in different hours considering the initial price. At the next iterations, the aggregator solves its optimization problem to maintain the energy prices based on the prosumers and consumers' announced values for their input and output. However, to prevent any possible arbitrage from other players, there is a limitation on their import and export levels in two consecutive iterations. In other words, their announced amounts for the selling and purchasing energy should not considerably differ from their previous bid. As a result, eqs. (8)-(12) are replaced with (37)-(41) in prosumers' problem.

$$e_{p,i,t,z-1}^{in} - \Delta \leq e_{p,i,t,z}^{in} \leq e_{p,i,t,z-1}^{in} + \Delta \quad (37)$$

$$e_{p,i,t,z-1}^{out} - \Delta \leq e_{p,i,t,z}^{out} \leq e_{p,i,t,z-1}^{out} + \Delta \quad (38)$$

$$h_{p,i,t,z-1}^{in} - \Delta \leq h_{p,i,t,z}^{in} \leq h_{p,i,t,z-1}^{in} + \Delta \quad (39)$$

$$h_{p,i,t,z-1}^{out} - \Delta \leq h_{p,i,t,z}^{out} \leq h_{p,i,t,z-1}^{out} + \Delta \quad (40)$$

$$g_{p,i,t,z-1}^{in} - \Delta \leq g_{p,i,t,z}^{in} \leq g_{p,i,t,z-1}^{in} + \Delta \quad (41)$$

$z$  and  $\Delta$  represent iteration number and the maximum allowed change in players decision between two consecutive iterations. Similarly, consumers utilize (42)-(44) instead of (34)-(36) when solving their optimization problem from 2<sup>nd</sup> iteration to the last iteration.

$$e_{c,j,t,z-1} - \Delta \leq e_{c,j,t,z} \leq e_{c,j,t,z-1} + \Delta \quad (42)$$

$$h_{c,j,t,z-1} - \Delta \leq h_{c,j,t,z} \leq h_{c,j,t,z-1} + \Delta \quad (43)$$

$$g_{c,j,t,z-1} - \Delta \leq g_{c,j,t,z} \leq g_{c,j,t,z-1} + \Delta \quad (44)$$

The last iteration is distinguished when two consecutive iterations result in the same bids for prosumers and consumers. The iterative auction model process has been explained in Figure 2 and the following algorithm table.

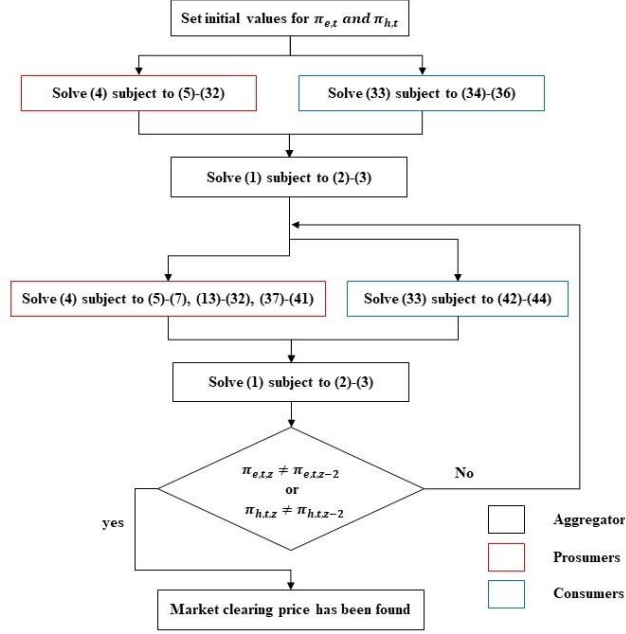


Figure 2: iterative auction model flowchart

### Begin

- **Initialize:** Setting initial values for  $\pi_{e,t,0}$  and

$\pi_{h,t,0}$ .

- **prosumers:** Solve (4) subject to (5)-(32)

considering  $\pi_{e,t,0}, \pi_{h,t,0}$  for determining

$e_{p,i,t,0}^{out}, e_{p,i,t,0}^{in}, h_{p,i,t,0}^{out}, h_{p,i,t,0}^{in}, g_{p,i,t,0}^{in}$

- **consumers:** Solve (33) subject to (34)-(36)

considering  $\pi_{e,t,0}, \pi_{h,t,0}$  for determining

$e_{c,j,t,0}, h_{c,j,t,0}, g_{c,j,t,0}$ .

- **aggregator:** Solve (1) subject to (2)-(3)

considering

$e_{p,i,t,0}^{out}, e_{p,i,t,0}^{in}, h_{p,i,t,0}^{out}, h_{p,i,t,0}^{in}, g_{p,i,t,0}^{in}, e_{c,j,t,0},$

$h_{c,j,t,0}, g_{c,j,t,0}$

for determining  $\pi_{e,t,1}, \pi_{h,t,1}$ .

### While

$\pi_{e,t,z} \neq \pi_{e,t,z-2}$  OR  $\pi_{h,t,z} \neq \pi_{h,t,z-2}$

- **prosumers:** Solve (4) subject to (5)-(7),

(13)-(32), (37)-(41) considering  $\pi_{e,t,z-1},$

$\pi_{h,t,z-1}$  for determining

$e_{p,i,t,z}^{out}, e_{p,i,t,z}^{in}, h_{p,i,t,z}^{out}, h_{p,i,t,z}^{in}, g_{p,i,t,z}^{in}$

- **consumers:** Solve (33) subject to (42)-(44)

considering  $\pi_{e,t,z}, \pi_{h,t,z}$  for determining

$e_{c,j,t,z}, h_{c,j,t,z}, g_{c,j,t,z}$ .

- **aggregator:** Solve (1) subject to (2)-(3) considering

$e_{p,i,t,z}^{out}, e_{p,i,t,z}^{in}, h_{p,i,t,z}^{out}, h_{p,i,t,z}^{in}, g_{p,i,t,z}^{in},$

$e_{c,j,t,z}, h_{c,j,t,z}, g_{c,j,t,z}$  for determining

$\pi_{e,t,z+1}, \pi_{h,t,z+1}$ .

### End

### B. Renewable energy stochastic model

To account for the uncertain nature of wind speed, scenarios are generated based on historical meteorological data. In order to achieve this, the data for a given hour of the day is used to determine the probability distribution functions (PDFs) for that particular hour. The Weibull distribution is a commonly used tool for characterizing the wind speed distribution function, as it allows for flexible modeling of the probability distribution.

A modeling approach is used to incorporate the unpredictable variability of wind speed, which is achieved by defining multiple scenarios according to the historical meteorological data. In order to accomplish this, the historical data for each hour of the day is utilized to derive the probability distribution functions (PDFs). The Weibull distribution is a widely used approach to characterize the wind speed distribution function, given its ability to provide a flexible representation of the probability distribution.

$$f_v(v) = \frac{k}{c} \left( \frac{v}{c} \right)^{k-1} \exp \left[ - \left( \frac{v}{c} \right)^k \right] \quad (45)$$

The shape factor (k) is assumed to be 2 at all hours. The scale factor (c) is also obtained from solving the eq. (46) [22].

$$c = \frac{\bar{v}}{\Gamma \left( 1 + \frac{1}{k} \right)} \quad (46)$$

The probability distribution function (PDF) for the wind speed of all hours is partitioned into three parts, and each section is assigned a distinct scenario. The probability of each scenario is computed using equation (47). The wind speed value of each scenario, denoted as  $\omega$ , is considered as weighted average of the interval. This approach results in a total of 324 scenarios for wind speed.

In addition to modeling wind speed, the stochastic nature of solar irradiation is also taken into account by the Beta distribution function and historical meteorological data. Similar to the wind speed modeling, the solar irradiation PDF of all hours are partitioned into three sections, each of which are assigned with a unique scenario. The scenarios' probability is calculated using equation (49).

$$Pr_{\omega_{v,i}} = \int_{\omega_{v,i}}^{\omega_{v,i+1}} f_v(v)dv \quad (47)$$

$$f_r(r) = \begin{cases} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} r^{\alpha-1}(1-r)^{\beta-1} & : 0 \leq r \leq 1; \alpha, \beta \\ 0 & : o.w \end{cases} \quad (48)$$

$$P_{\omega_{r,i}} = \int_{\omega_{r,i}}^{\omega_{r,i+1}} f_r(r)dr \quad (49)$$

$\alpha$  and  $\beta$  are determined considering the historical meteorological data, using (50) and (51) [23].

$$\alpha = \bar{r} \left( \frac{\bar{r}(1-\bar{r})}{\sigma^2} - 1 \right) \quad (50)$$

$$\beta = (1-\bar{r}) \left( \frac{\bar{r}(1-\bar{r})}{\sigma^2} - 1 \right) \quad (51)$$

To generate the needed scenarios for PV and wind generation and their respective probabilities their corresponding probability distribution functions have been utilized. However, conducting the optimization considering all scenarios is a highly time-consuming task. To address this, we employed a scenario reduction technique outlined in [24] to identify 20 equivalent scenarios. The equivalent scenarios for both PV and wind generation are then simulated, and the outcomes are analyzed and reported.

#### IV. SIMULATION RESULTS

The evaluation of the proposed model was conducted on a test system comprising four prosumers, four consumers, and an aggregator. Details regarding the prosumers are provided in Table 2, while the factors of convenience function of the consumers can be found in Table 1.

In this paper, in order to solve the mixed-integer linear optimization problem, the optimization toolbox available in Matlab 2021a has been utilized.

Table 1: Information of consumers

	Consumer 1	Consumer 2	Consumer 3	Consumer 4
$K_1$	180	139	157.5	180
$K_2$	1000	20	10	100

Table 2: Information of prosumers

	Pro 1	Pro 2	Pro 3	Pro 4
$\eta_e$	0.51	0.40	0.55	0.49
$\eta_h$	0.50	0.50	0.27	0.33
$g_{in,CHP}^{max}$	70	70	70	70
$N_{Batt}$	15	15	15	15
$N_{PV}$	20	40	60	30
$N_{Wind}$	40	40	30	30
$\eta_B$	0.95	0.85	0.90	0.90
$g_{in,B}^{max}$	50	50	50	50
$g_{in,I}^{max}$	90	90	90	90

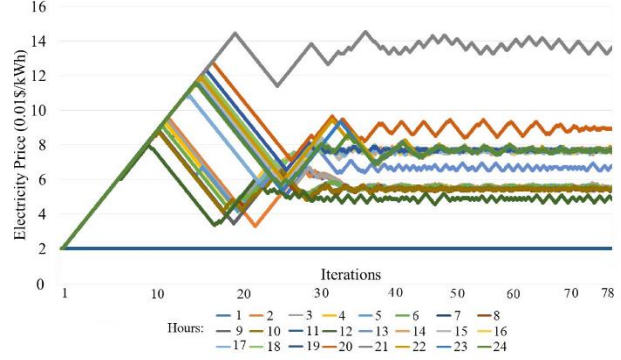


Figure 3: Electricity clearing price in each iteration

Figure 3 shows how the clearing price is determined with the increase in the number of iterations. It is clear that after 78 iterations, the players' interactions lead to a repetitive outcome, which is the reason for the bidding process termination. It is worth mentioning that the high number of iterations to reach convergence is due to the small value of  $\Delta$ , which is 0.0005 \$/kWh in the simulation. Convergence could be achieved with fewer iterations when  $\Delta$  is set to a larger value.

Furthermore, the modeling of renewables' probabilistic behavior using the Weibull and Beta distribution functions enables the incorporation of the unpredictable variability of wind speed and solar irradiation into the optimization framework, leading to a more accurate representation of the system. The scenario reduction technique proves to be effective in reducing the computational complexity of the optimization problem while maintaining a reasonable level of accuracy.

Table 3 presents the three energy carriers' utility price and clearing price of electricity and heat in local energy market, and also shows how much energy is traded with utility market. As it could be seen, the amount of traded energy with utility market is small amount in all hours. This shows how the model is successful in generating a self-sufficient local network and make it independent from utility market. In other words, the model successfully manages the overgeneration of electricity during low-demand hours by incentivizing prosumers to use their CHP units. By managing overgeneration and incentivizing flexibility in energy use, the proposed model could help to reduce curtailment of renewable energy sources and support their integration into the energy system.

##### A. Load Energy Market Price Balancing

The proposed model utilizes a unique approach where the equilibrium price is determined solely based on local production and consumption rather than being

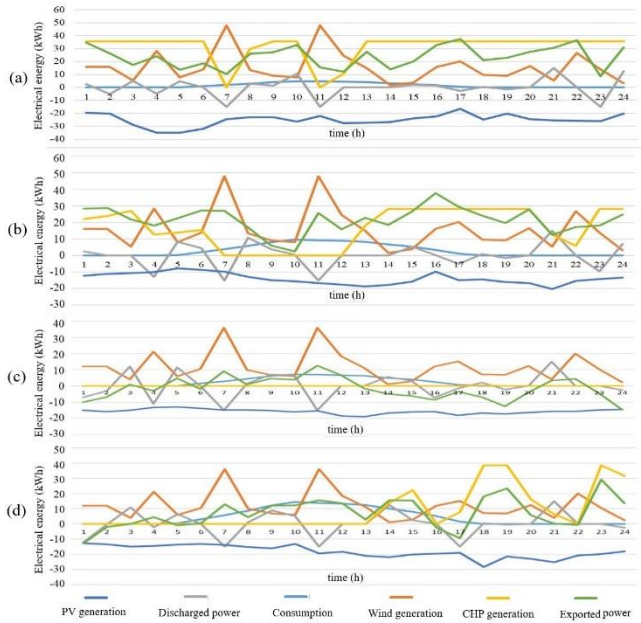


Figure 5: Energy generation and consumption for four prosumers:  
 (a): prosumer 1, (b): prosumer 2,  
 (c): prosumer 3, (d): prosumer 4

influenced by external energy market prices. This approach could potentially disrupt the traditional energy market design, which relies on centralized generation and transmission of electricity. The role of aggregators in such a system would also change, as they would become more responsible for managing local energy production and consumption. A visual representation of the comparison between the electricity and heat prices of local and utility market is presented in Figure 5. According to the Table 3, the electricity and heat local market prices are observed to be lesser than the utility market prices during hours 15 and 17, respectively.

Figure 4 depicts the energy generation and consumption of each of 4 prosumers in different hours. It could present which prosumers are more willing to use their CHP and boiler, considering their demand and renewables generation at that hour. The utilization of renewable energy sources, such as PVs and wind turbines, can lead to an overabundance of electricity during low-demand hours, as shown in Figure 5 and Figure 4. In such cases, the marginal cost of electricity is zero, and there would be overgeneration for electricity. Thus, the aggregator doesn't have to increase energy prices to incentivize prosumers to use their CHP units as demonstrated in Figure 4, where no prosumer utilizes its CHP unit at hours 7 and 11.

To balance energy generation and consumption, the proposed model employs a dynamic pricing strategy. During high-demand hours, the aggregator raises energy prices to encourage prosumers to generate

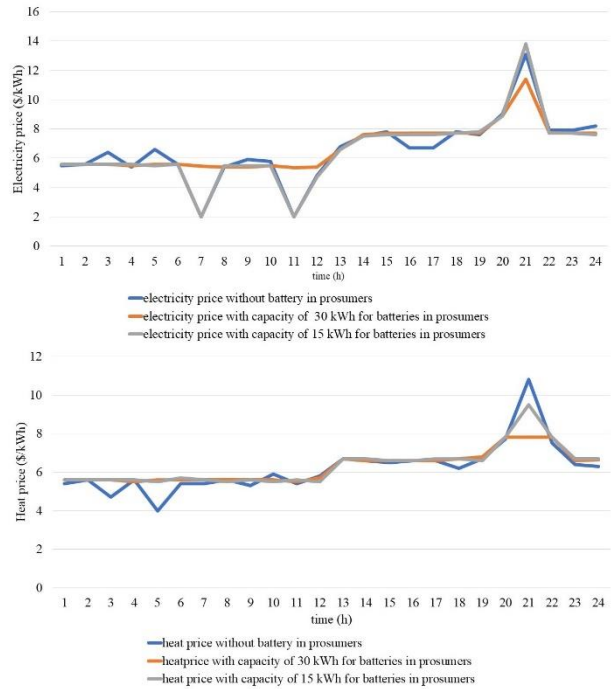


Figure 4: Electricity and heat prices with different scenarios of battery existence in prosumers

more energy and motivate consumers to use less energy. For example, at hour 21, the increase in gas prices results in a rise in local heat prices, making it expensive to use CHP and boilers, as depicted in Figure 6.

#### Prosumers and Their Competition for Making Profit

Prosumer 1 stands out among other prosumers as it operates the most efficient CHP with the lowest marginal cost (Table 2). As it is shown in Figure 6 prosumer1 consistently receives gas at maximum capacity to generate high-priced electricity and heat. However, prosumer2 has the least efficient boiler among the prosumers, making it unable to compete in selling heat. Consequently, it refrains from using its boiler to generate heat.

The proposed model introduces potential cooperation between prosumers that generate different types of energy, creating a competitive market and increasing their financial profits. For example, Table 2 illustrates that prosumer2 operates an efficient CHP unit, while prosumer4's boiler is 5% more efficient than prosumer2's. Therefore, prosumer2's electricity generation results in a drop in local market electricity prices. This drop would cause a profit for all the prosumers that are electricity purchasers.

In Table 3, the financial profit or loss of the aggregator is depicted. The aggregator earns 148.10\$ in 24 hours. Most of this value is obtained in hours 7 and 11 where the energy balance could not be achieved due to the

Table 3: Simulation Results

Hour	Utility gas price	Utility electricity price	Local market electricity clearing price	Utility heat price	Local market heat clearing price	Total Electricity trading with utility market	Total Heat trading with utility market	Aggregators' financial profit
1	5.0	6.0	5.6	5.0	5.6	1.72	2.36	-0.688
2	5.0	5.0	5.6	8.0	5.6	-1.35	-0.21	-0.81
3	5.0	5.0	5.6	6.0	5.6	2.80	1.12	1.68
4	5.0	5.0	5.6	6.5	5.6	0.22	1.98	0.132
5	5.0	5.0	5.5	7.0	5.5	-0.20	-6.08	-0.1
6	5.0	7.0	5.6	8.0	5.7	2.83	3.62	-3.962
7	5.0	6.0	2.0	9.0	5.6	-9.66	-6.58	38.64
8	5.0	5.0	5.5	10.0	5.5	0.44	2.95	0.22
9	5.0	6.0	5.5	5.0	5.6	-0.37	8.53	0.185
10	5.0	6.0	5.5	6.0	5.5	-0.53	-0.34	0.265
11	5.0	6.5	2.0	7.0	5.6	-23.02	4.93	103.59
12	5.0	7.0	4.7	8.0	5.5	-0.24	-1.34	0.552
13	6.0	7.25	6.6	9.0	6.7	-0.26	-3.00	0.169
14	6.0	7.5	7.5	8.0	6.7	-0.00	3.08	0
15	6.0	7.75	7.6	7.0	6.6	3.79	-1.91	-0.5685
16	6.0	8.0	7.6	6.0	6.6	-1.40	-1.42	0.56
17	6.0	8.0	7.6	5.0	6.7	-1.16	-1.92	0.464
18	6.0	7.5	7.7	4.0	6.7	-0.38	3.86	-0.076
19	6.0	7.0	7.8	5.0	6.6	0.31	-0.40	0.248
20	7.0	8.0	8.9	6.0	7.8	-0.76	0.30	-0.684
21	10.0	9.0	13.8	7.0	9.5	1.45	0.72	6.96
22	7.0	10.0	7.7	8.0	7.8	-0.39	-0.22	0.897
23	6.0	11.0	7.7	9.0	6.7	0.05	-2.04	-0.165
24	6.0	8.0	7.6	10.0	6.7	-1.49	1.09	0.596

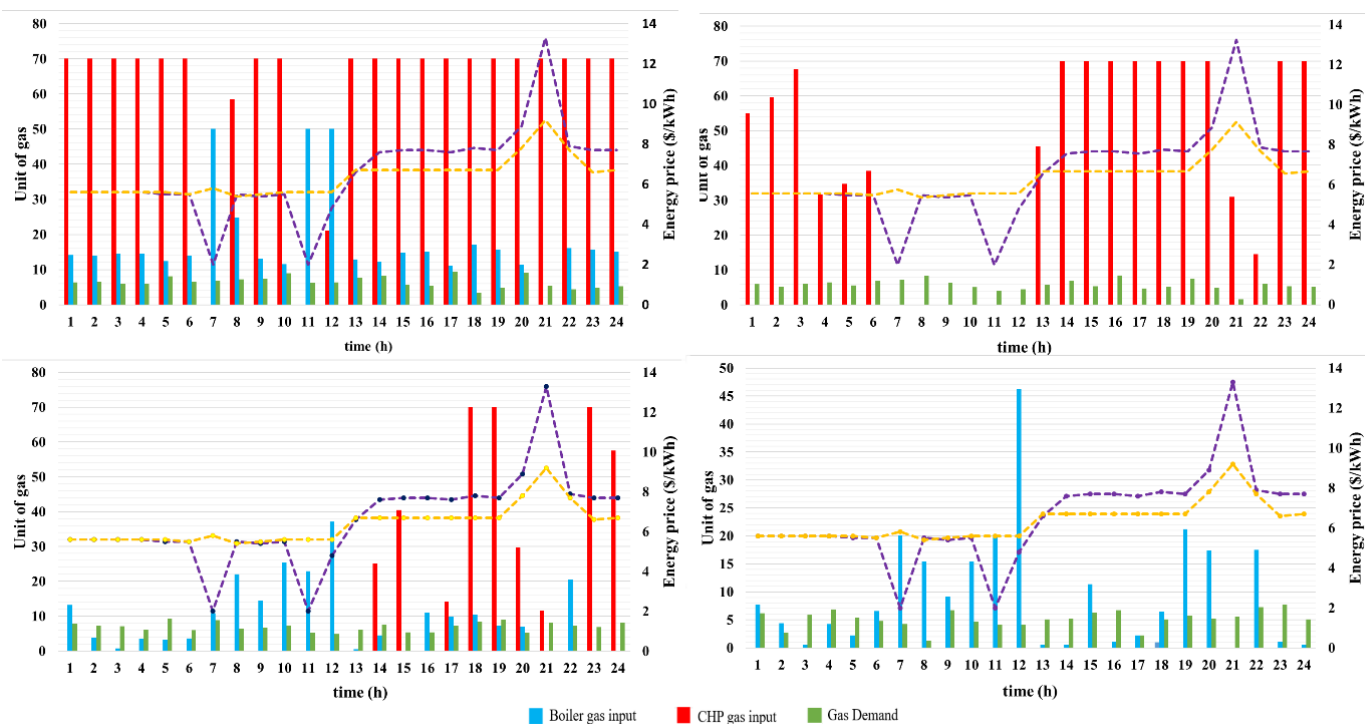


Figure 6: Gas allocation in prosumers

excess energy generation of renewables. The gain of 6.17\$/hour in such network shows that the dynamic pricing model utilized in this paper also prevents the single aggregator to create a monopoly.

As described earlier, the prosumers are motivated to supply more energy to the grid when energy prices increase. They do this by using two methods: first, by operating their CHP and boiler at maximum capacity, and second, by storing energy during low-demand hours and

selling it during peak hours. For instance, as depicted in Figure 5, there is a price hike in electrical and heat energy at hour 21. To take advantage of this peak price, the prosumers store energy during previous hours and discharge it at hour 21, as shown in Figure 4. Notably, a significant amount of the injected electrical energy during peak hours comes from stored energy reserves. It can also be seen in Figure 5 that the higher capacity of the prosumers' batteries could result in a smoother hourly local energy market price. In other words, when the simulation has been performed with prosumers without the capability of energy storing, the number of peaks in hourly price increases. On the other hand, by doubling the capacity of prosumers' batteries (in comparison with the main simulation data), the peaks have been shaved, and consumers' ability to buy energy in peak hours experienced a significant rise.

The proposed model aims to balance energy consumption and generation in the local energy market, which leads to reduced profits for the aggregator. Nonetheless, it increases the consumers' access to energy by lowering prices during most hours of the day and motivates the prosumers to produce energy at high-demanded hours. This, in turn, reduces the microgrid's dependency on the utility market and improves its self-sufficiency. In addition, despite the fact that the mathematical formulation inside the present work and [25] are almost similar, and the clearing price trends in both articles are same as each other, the number of decision variables and the time needed to solve the problems in the present work is significantly lower and this is what makes our model a scalable one. Also, the most preference of the present work in comparison with the articles inside the literature review is the different modeling of the prosumers and the consumer. For the consumers, the model focuses on the role of demand response on the consumers' behavior, whereas for the prosumers it is really important to show the effects of aggregation of multi energy sectors on the prosumers' decision.

## V. CONCLUSION

In this study, the interaction of multi-energy prosumers, consumers, and aggregator has been investigated inside a novel approach for designing the local energy market. The renewables' generation uncertainty has been modeled by Weibull and Beta distribution. The proposed bilevel model has been solved by an iterative double auction-based method. The results show how this model could lead to increase consumers' ability to buy energy in peak-demanded hours. Also, the balance between energy generation and consumption in all hours has been resulted from the pricing policy of the aggregator to maximize its financial profit. This caused the proposed model to be suitable for the microgrids which are aimed to be self-sufficient. In addition, the potential cooperation among prosumers could be seen,

which leads to the higher welfare for all of them. The study also showed that energy prices were influenced primarily by local production and consumption, rather than external factors.

## REFERENCES

- [1] B. Singh and P. K. Dubey, "Distributed power generation planning for distribution networks using electric vehicles: Systematic attention to challenges and opportunities," *Journal of Energy Storage*, vol. 48, p. 104030, 2022.
- [2] S. Hadayeghparast, A. S. Farsangi, and H. Shayanfar, "Day-ahead stochastic multi-objective economic/emission operational scheduling of a large scale virtual power plant," *Energy*, vol. 172, pp. 630-646, 2019.
- [3] I. Dokk Smith, J. K. Kirkegaard, and K. Szulecki, "A functional approach to decentralization in the electricity sector: learning from community choice aggregation in California," *Journal of Environmental Planning and Management*, pp. 1-31, 2022.
- [4] F. D. Wijaya, "A Strategy to Balance Supply and Demand Fluctuation for RES-Based Microgrids in Isolated Area," *International Energy Journal*, vol. 22, no. 4, 2022.
- [5] L. A. Soriano, M. Avila, P. Ponce, J. de Jesús Rubio, and A. Molina, "Peer-to-peer energy trades based on multi-objective optimization," *International Journal of Electrical Power & Energy Systems*, vol. 131, p. 107017, 2021.
- [6] Y. Wang, A. O. Rousis, and G. Strbac, "On microgrids and resilience: A comprehensive review on modeling and operational strategies," *Renewable and Sustainable Energy Reviews*, vol. 134, p. 110313, 2020.
- [7] V. Dudjak *et al.*, "Impact of local energy markets integration in power systems layer: A comprehensive review," *Applied Energy*, vol. 301, p. 117434, 2021.
- [8] E. Ghiani, M. Galici, M. Mureddu, and F. Pilo, "Impact on electricity consumption and market pricing of energy and ancillary services during pandemic of COVID-19 in Italy," *Energies*, vol. 13, no. 13, p. 3357, 2020.
- [9] O. Sabishchenko, R. Rebilas, N. Szczygiol, and M. Urbański, "Ukraine energy sector management using hybrid renewable energy systems," *Energies*, vol. 13, no. 7, p. 1776, 2020.
- [10] S. L. Cox, L. Beshilas, and E. L. Hotchkiss, "Renewable energy to support energy security," National Renewable Energy Lab.(NREL), Golden, CO (United States), 2019.
- [11] M. Meliani, A. E. Barkany, I. E. Abbassi, A. M. Darcherif, and M. Mahmoudi, "Energy management in the smart grid: State-of-the-art and future trends," *International Journal of Engineering Business Management*, vol. 13, p. 18479790211032920, 2021.
- [12] M. B. Roberts, A. Bruce, and I. MacGill, "A comparison of arrangements for increasing self-consumption and maximising the value of distributed photovoltaics on apartment buildings," *Solar Energy*, vol. 193, pp. 372-386, 2019.
- [13] Z. Xu, G. Hu, and C. J. Spanos, "Coordinated optimization of multiple buildings with a fair price mechanism for energy exchange," *Energy and Buildings*, vol. 151, pp. 132-145, 2017.
- [14] E. Mengelkamp, B. Notheisen, C. Beer, D. Dauer, and C. Weinhardt, "A blockchain-based smart grid: towards sustainable local energy markets," *Computer Science-Research and Development*, vol. 33, pp. 207-214, 2018.
- [15] B. P. Hayes, S. Thakur, and J. G. Breslin, "Co-simulation of electricity distribution networks and peer to peer energy trading platforms," *International Journal of Electrical Power & Energy Systems*, vol. 115, p. 105419, 2020.
- [16] R. Jing, M. N. Xie, F. X. Wang, and L. X. Chen, "Fair P2P energy trading between residential and commercial multi-

- energy systems enabling integrated demand-side management," *Applied Energy*, vol. 262, p. 114551, 2020.
- [17] P. Huang *et al.*, "Transforming a residential building cluster into electricity prosumers in Sweden: Optimal design of a coupled PV-heat pump-thermal storage-electric vehicle system," *Applied Energy*, vol. 255, p. 113864, 2019.
- [18] W. El-Baz, P. Tzscheutschler, and U. Wagner, "Integration of energy markets in microgrids: A double-sided auction with device-oriented bidding strategies," *Applied energy*, vol. 241, pp. 625-639, 2019.
- [19] B. Cornélusse, I. Savelli, S. Paoletti, A. Giannitrapani, and A. Vicino, "A community microgrid architecture with an internal local market," *Applied Energy*, vol. 242, pp. 547-560, 2019.
- [20] L. A. Roald, D. Pozo, A. Papavasiliou, D. K. Molzahn, J. Kazempour, and A. Conejo, "Power systems optimization under uncertainty: A review of methods and applications," *Electric Power Systems Research*, vol. 214, p. 108725, 2023.
- [21] Z. Guo, P. Pinson, S. Chen, Q. Yang, and Z. Yang, "Chance-constrained peer-to-peer joint energy and reserve market considering renewable generation uncertainty," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 798-809, 2020.
- [22] F. Y. Vincent, T. H. A. Le, and J. N. Gupta, "Sustainable microgrid design with multiple demand areas and peer-to-peer energy trading involving seasonal factors and uncertainties," *Renewable and Sustainable Energy Reviews*, vol. 161, p. 112342, 2022.
- [23] S. A. Mehraban and R. Eslami, "Multi-microgrids energy management in power transmission mode considering different uncertainties," *Electric Power Systems Research*, vol. 216, p. 109071, 2023.
- [24] Z. Shi, T. Zhang, Y. Liu, Y. Feng, R. Wang, and S. Huang, "Optimal design and operation of islanded multi-microgrid system with distributionally robust optimization," *Electric Power Systems Research*, vol. 221, p. 109437, 2023.
- [25] M. Ebrahimi and A. Sheikhi, "A local integrated electricity-heat market design among multi Smart Energy Hubs with renewable energy generation uncertainty," *Electric Power Systems Research*, vol. 218, p. 109217, 2023.