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Full Length Article

A novel peer-to-peer energy trading strategy for multi-microgrid loads scheduling based on chance-constrained

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ABSTRACT

Facilitating producer-consumer P2P energy exchange is a viable paradigm in the era of decentralized energy. Energy trading requires the development of a fair pricing mechanism, but when numerous energy systems are involved in the transaction, the problem can get complicated. Through the decentralized coordination of distributed microgrid energy systems and shiftable microgrid appliances, this article introduces a decentralized EMS that facilitates P2P energy trading among prosumers in community. This lowers the energy costs per microgrid compared to operating each microgrid separately. A Chance-Constrained cooperative model connecting manufacturing, commercial, and residential prosumers with guaranteed trade fairness serves as foundation for suggested approach. The model is expanded to take into account several demand-side management strategies and widely utilized energy supply systems. This study offers a more succinct method for figuring out fair prices for multi-energy trading than earlier research. A comparison between chance-constrained optimization outcomes obtained results is implemented utilizing Improved Sparrow Search Algorithm (ISSA), and without optimization techniques. The results show that recommended strategy for microgrid demand control is appropriate and workable. Fair electricity pricing practices are used to minimize energy costs for prosumers in residential, commercial, and industrial sectors. The suggested solution improves overall electricity bills for the home, company, and factory by 80.34%, 61.429%, and 54.069%, respectively.

1. Introduction

Recent developments in digital technology have made it possible for prosumers to transact directly with the UG and other prosumers, opening the door for grid digitization. Energy is sold directly to peers at a higher price than it was sold to UG, and buyers buy energy directly from peers at a cheaper price than they paid when they bought it from UG. The fundamental idea behind P2P energy trading is this. P2P energy trading has attracted increased attention in this area of research in recent years since encouraging P2P trade can be viewed as a way to use spark spread to boost use of renewable energy and lower carbon dioxide emissions.

By establishing energy trading environment where all parties can freely compete and work together, P2P energy trading aims to enhance social welfare in general. According to a number of studies, prosumers may benefit greatly from P2P sharing. But in reality, it's rarely easy to put up a P2P energy trading market. Since extensive sensing and communication infrastructures are needed to provide essential

Abbreviations: P2P, peer-to-peer; ISSA, improved sparrow search algorithm; UG, utility grid's; DERs, distributed energy resources; FIT, feed-in-tariff; DSM, demand-side management; RTP, real-time prices; IoT, Internet of Things; EMS, energy management system; SG, smart grid; FPS, flat price system; MAF, multi-agent framework; RMG, residential microgrids; ADMM, alternating direction method of multipliers; PV, photovoltaic; WT, wind turbine; BSU, battery storage unit.

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Table 1
The most recent research based Optimization techniques in energy management, P2P energy trading frameworks, Demand-side management approaches, Multi-microgrid coordination strategies.

Categories Literature	References	Objective
Optimization techniques in energy management	[2]	Uncertainties and effective demand response strategies were considered in authors' home EMS.
	[3]	Writers presented an IoE-based optimum multi-agent control technique for microgrids utilizing renewable energy sources.
	[4]	Authors provided the ideal position for DG in active distribution networks, a new smart charging electric vehicle, and optimally performing batteries.
	[5]	The authors presented Energy management in microgrid and multi-microgrid
	[6]	The authors discussed how deep reinforcement learning and specialized expertise are used in microgrid energy management.
	[7]	Authors developed an IoT-based optimization technique based on BPSO and BSA for a home DSMS.
	[8]	Writers introduced a fog-based IoE architecture for trans active EMS.
	[9]	Writers obtainable optimization model for EMS.
	[10]	The authors developed IoT-based EMS in smart cities to save energy and lessen peak demand.
	[11]	The writers described an advanced microgrid EMS technique that used a real-time monitoring interface.
	[12]	For household EMS, authors proposed an improved multi-objective cockroach swarm algorithm approach.
	[13]	The authors create a cost-effective dispatch in standalone scheme by utilizing butterfly optimization method.
	[14]	Writers introduced a technique for DSMs in smart homes that combines microgrid management and energy optimization.
	[15]	In accordance with a two-stage optimization model described by authors, several HEMS concurrently optimize their individual energy consumption patterns and compute their flexibility provision, which is transmitted to local distribution companies (LDCs).
	[16]	The authors presented multi-objective optimization procedure for solar and battery energy storage in EMS.
	[17]	The authors explained how household appliances are dynamically coordinated for DSM control in buildings using multiobjective energy optimization.
	[18]	The author reported a chance-constrained optimization in a HEMS.
	[19]	The authors explained how firefly hybridization and particle swarm optimization are used in DSM research.
	[20]	The authors introduced their effective DSM program for smart grid residential load that is based on optimization algorithms.
	[21]	Writers introduced a real-time optimal arrangement controller for a HEMS based on a binary backtracking search method.
	[22]	Based on GOA, writers proposed load-shedding strategy for islanded power system with dispersed energy sources.
	[23]	The writers presented using ITS-BF algorithm to schedule domestic electrical loads.
	[24]	The authors explained how to use hybrid shuffling, frog-leaping, and pattern search algorithms to scale RES with micro grids to reduce costs.
	[25]	Utliize a hybrid gravitational search and pattern search approach, writers introduced EMS and optimal operation of microgrid-based EV.
	[26]	A hybrid crow and pattern search algorithm is a cost-oriented resource scheduling method proposed by the authors for a solar-powered micro grid.
	[27]	writers propose using a Dandelion Optimizer (DO) to accurately ascertain parameters of PEMFC model.
	[28]	The authors suggested an enhanced off-grid wind, photovoltaic, based on the Moth-Flame algorithm.
	[29]	Writers provided an effective DSM-based optimization strategy for intelligent buildings.
P2P energy trading frameworks	[30]	Authors discussed P2P trade and energy management in smart grids.
	[31]	Writers introduced a P2P market mechanism that combines cooperative behaviours and multi-energy coupling.
	[32]	Demand-side management can be easily included into residential and commercial multi-energy systems thanks to the authors' equitable P2P energy trading system.
	[33]	The writers presented Community-based and P2P microgrid systems markets
	[34]	Multi-agent based optimum scheduling and trading method for several micro grids connected to urban transportation networks was given by the authors.
	[35]	A P2P architecture was created by the author to construct islanded microgrids. P2P development is made possible by multi-layered, multi-agent systems and processes that achieve several objectives.
	[36]	The authors introduced blockchain-based decentralized framework for a P2P energy trading market.
	[37]	The authors introduced a distributed P2P energy transaction approach for range of prosumers in microgrid system.
	[38]	P2P energy trading under distribution network constraints while maintaining agents' independence was introduced via writers.
	[39]	Writers used game-theoretic approach to develop a decentralized P2P energy trading strategy in an energy blockchain setting.
	[40]	P2P energy trading in microgrid was obtainable via writers.
	[41–45]	Writers presented a communication system based on blockchain topology
	[46]	The writers presented In smart communities, P2P renewable energy trading and sharing — trading pricing methods
	[47]	The writers presented an energy management and pricing technique for a P2P energy based on the Stackelberg game
	[48]	Advances in digitalization and machine learning for integrated building-transportation were presented by the authors.
	[49]	The writers presented optimizations for P2P trading in net-zero energy communities using battery and hydrogen energy storage

(*continued on next page*)

Table 1 (*continued*)

Categories Literature	References	Objective
Demand-side management approaches	[50]	Writers present a strategy for managing microgrid energy consumption that takes unpredictability into consideration and makes use of practical demand response methods.
	[51]	Writers offered multi-objective scheduling for EMS in IoT-enabled homes, based on arithmetic optimization techniques.
	[52]	A demand response-based multi-agent system was created and put into use for active network management of delivery networks.
	[53]	The authors introduced optimization-based hierarchical EMS.
	[54]	The authors introduced multi-agent approach to optimizing demand response aggregators for homes and businesses
	[55]	The authors presented the smart hybrid microgrid adaptive energy management system.
	[56]	The authors presented a framework for EMS. This gadget establishes a wireless network of several devices on each home via connecting to IP address-based IoT element.
	[57]	For power management, the authors provide a unique fog computing network service. Adoption of fog computing platform makes data safety, accessibility, flexibility, interoperability, and real-time EMS easier.
	[58]	Writers presented an effective smart grid EMS that took DRP and RES into account.
	[59]	Authors offered a comprehensive plan for demand reduction and intelligent EMS for IoE-based loads.
	[60]	Writers demonstrated how to develop and design a modular EMS and integrate it to a battery-powered micro grid that is connected to the grid.
	[61]	The authors provided distributed EMS based on ADMM for microgrid with high penetration of DES.
	[62]	In order to control consumption, the authors proposed time-of-use tariff plan for domestic energy users in Bangladesh.
	[63]	The authors argued that DSMS is an essential component for profitable functioning of residential and rural micro grid systems.
	[64]	A real-time community microgrid scheduling scheme was made available by writers.
	[65]	A novel system-based SCADA methodology was presented by the authors.
	[66]	Writers provided a novel approach to scheduling DER to supply loads within MG in case of a power outage.
	[67]	The authors suggested using a flat price system (FPS) to rationally distribute energy consumption in the SG in order to address the DSM problem.
	[68]	Microgrids for industries was one of improved EMS methods that the authors offered.
	[69]	In smart grid applications with a limited number of devices, the authors presented scenarios for controlling power demand.
	[70]	The authors suggested an algorithm aimed at planning smart device problem for avoiding load change in DSM.
	[71]	The authors suggested a bald eagle search optimization strategy based on IoT to solve day-ahead scheduling issues.

Table 1 (*continued*)

Categories Literature	References	Objective
	[72]	Demand-side scheduling of green energy Authors presented the concept of management in the smart grid.
	[73]	Writers used a RaspberryPi3 to introduce a SCADA-controlled loads.
	[74]	Authors described an EMS based on cloud computing and IoT.
	[75]	Utilizing an ANFIS technique, writers presented an on-grid/off-grid EMS.
	[76]	A work scheduling system for multi-objective DR to RTP was obtainable by writers.
	[77]	For cloud computing platforms, the authors developed a Smart EMS (SEMS) as a service for nano grid devices.
	[78]	A self-learning EMS was obtainable by writers.
	[79]	Writers demonstrated IoE-based real-time electricity scheduling system for HEMS.
	[80]	Integration of a grid-connected photovoltaic-wind hybrid system with adaption converters connected to a shared DC bus was discussed by the authors.
	[81]	In order to identify optimal microgrid topology in existing distribution systems, authors proposed a zonal-based optimal microgrid identification model by zoning network into several clusters.
	[82]	In smart manufacturing, the authors presented ANFIS for robust and effective source chain presentation.
	[83]	The writers concentrated on an integrated UG. Taking an imbalanced grid into consideration, a unique method for controlling the grid side inverter of a DPGS is created.
	[84]	The writers presented a decarbonized microgrid scheme with intelligent electrical markets
	[85]	Writer's obtainable coalition-based game-theoretical building as-service-over-fog energy management system.
Multi-microgrid coordination strategies	[86]	One of the two micro grids that writers studied included the vehicle-to-home concept, offering a case study that demonstrates how appealing this technology is to families.
	[87]	Based on the consensus algorithm, writers obtainable coalitions-game theory for EMS strategies in intelligent micro grids.
	[88]	The authors suggested creating cloud-based MAF for MG in order to promote a smart grid usage culture.
	[89]	A multi-agent system platform was used to integrate ideas of IoT for agent communication and interaction.
	[90]	Writers initially presented consensus algorithm-based decision-making for connected devices in EMS.
	[91]	Writers presented an method to cutting carbon emissions that makes use of AI and RES

information flows between different agents, it is imperative to accurately estimate the possible impact of P2P trading from an individual's perspective beforehand. On-site distributed energy resources have the biggest influence on the P2P trading effect in a well-established microgrid community. Because different prosumers own different kinds of DERs, it is more challenging to assess how DER ownership complexity—which encompasses type, location, configuration, and degree of energy supply-demand matching of each on-site DER system—affects

Table 2
Comparison between the results obtained by without corrective method, ISSA and chance-constrained method based on total electricity bill.

	Total Electricity Bill of Home	% Improvement	Total Electricity Bill of company	% Improvement	Total Electricity Bill of factory	% Improvement
Without any Corrective Action	1248.916	–	10,099.1	–	2769.228	–
Using ISSA Correction Method [93]	856.7951	31.396%	7442.4872	26.305%	2662.772	3.844%
Chance Constrant Method	245.4896	80.34%	3895.2424	61.429%	1271.916	54.069%

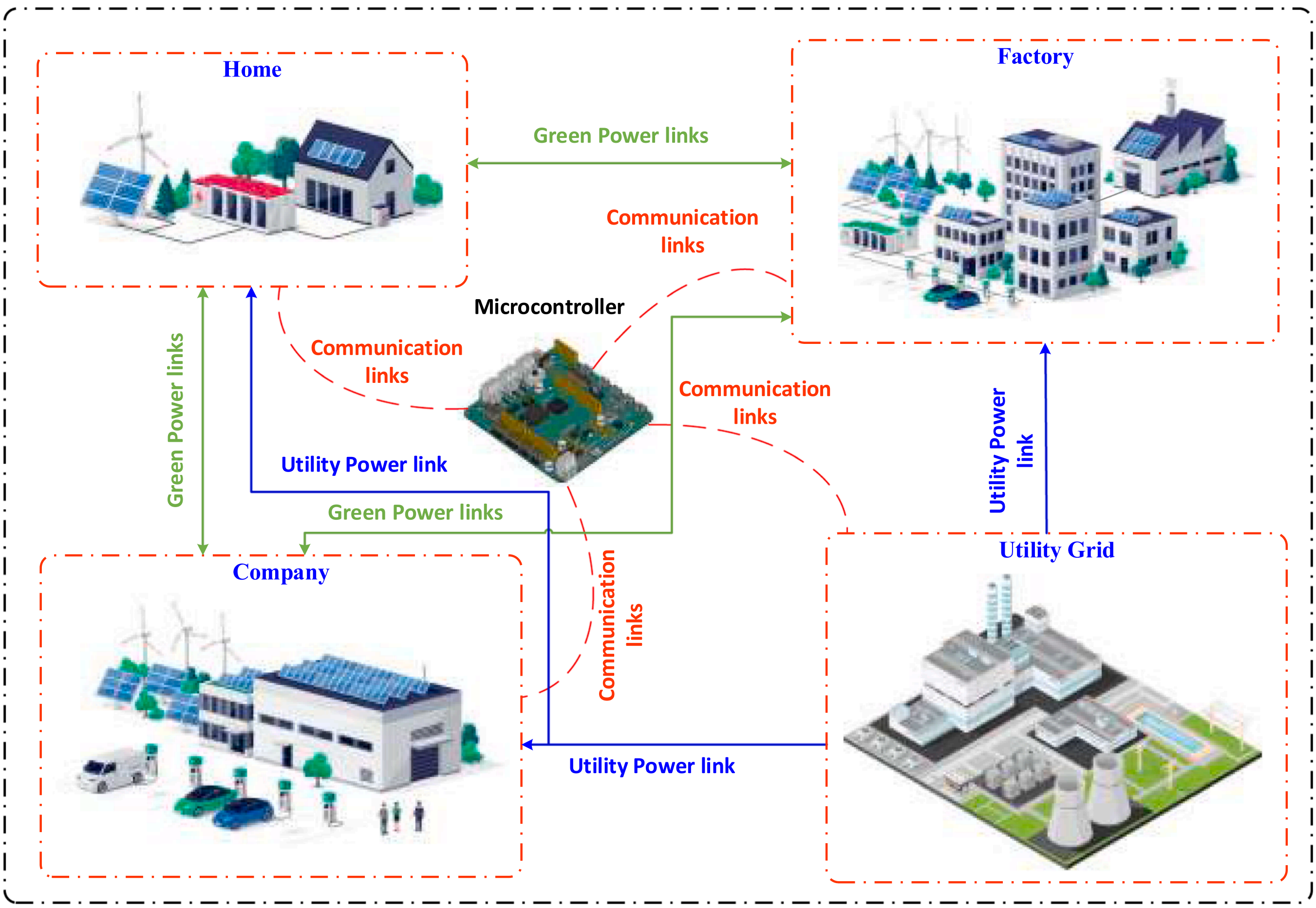


Fig. 1. Proposed P2P system.

P2P trading for people. This study sought to develop a theoretical framework for successful growth of P2P energy trading in microgrid communities by examining advantages and disadvantages of different energy prosumers and consumers in a P2P energy trading market and taking into consideration ownership complexity features of distributed energy resources [1].

1.2. Literature review

Tables 1, 2 shows the most recent research based optimization techniques in energy management, P2P energy trading frameworks, demand-side management approaches, multi-microgrid coordination strategies.

1.2.1. Scientific gaps and limitations

The literature review stated above revealed a number of scientific and knowledge gaps and limitations.

- In many studies, Cost-benefit models for P2P energy sharing do not address fairness, distribution, and allocation, which results in unfairness and a lack of willingness of stakeholders;
- Synergistic collaborations and operations are necessary for mutual economic benefits in terms of convergence towards dynamic pricing equilibrium, whereas some above studies are very limited.
- In many studies, the internal trading pricing approach frequently ignores costs associated with renewable system depreciation, energy transmission losses, and associated infrastructures.
- In many systems, the authors did not use a chance-constrained to minimize the cost.

1.2.2. The contributions of this study

This study's innovation and originality fill the aforementioned scientific gaps.

- Cutting-edge advancements and developments in P2P trading, specifically in the areas of decentralized system modeling, energy sharing mechanisms, and techniques for trade and marginal prices.

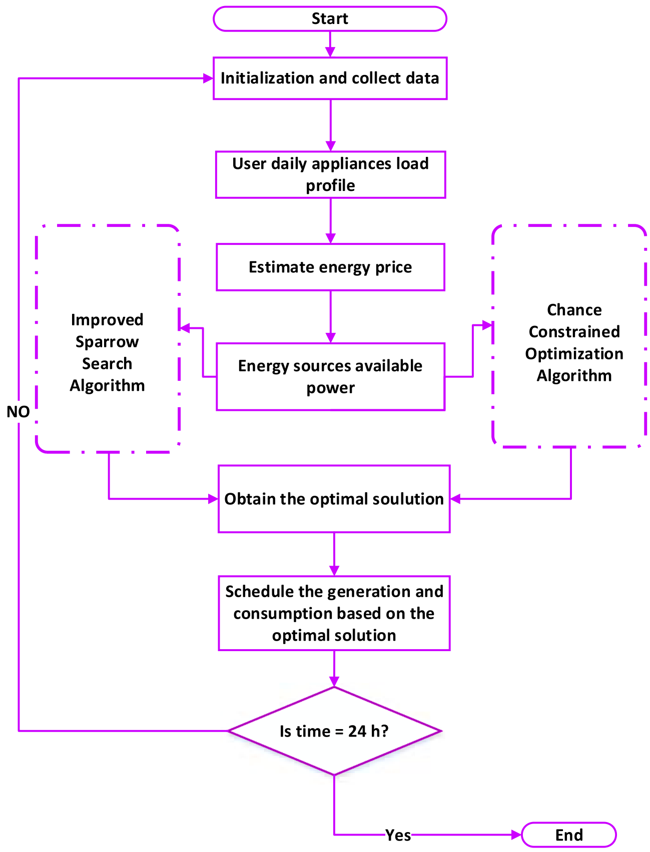


Fig. 2. A comprehensive flowchart for applied optimization methods.

- Dynamic power trading strategies and decision-making approaches are also systematically presented with the goal of finding an equilibrium between the dynamic power trading quantity and internal sell/buy price;
- Synergistic collaborations and operations between multistakeholders were presented to better understand the mutual economic benefits, including prosumer-centric and consumer-centric energy trading, retailer and utility company, agent-based techniques in energy sharing, and economic dispatch;
- To encourage decarbonization, increase system efficiency, provide loss reduction, power support, and congestion management for the power grid, P2P-based approaches to electricity market design are proposed.
- To show the efficacy of the proposed Chance restricted optimization with respect to objectives like energy cost, carbon emission, and PAR, simulation results are compared with Improved Sparrow Search Algorithm (ISSA).

2. Proposed system

P2P network is a DN architecture where participants share some of their own resources with each other, as stated in Ref. [92]. These shared resources, which peers can access directly from one another without the use of middlemen, are essential to the network's services and content, including file sharing. Additionally, removing a single randomly selected entity from a P2P network does not impair the network's communication capabilities.

In order to accomplish particular energy-related objectives, members of P2P energy network share some of their resources (such storage space and renewable energy) and information. Peak load reduction, power cost reduction, network operation, investment cost minimization, and maximizing the usage of renewable energy are a few examples of these objectives. Each peer in the network can communicate directly with the others and take on the roles of either a provider, a receiver, or both without the assistance of an external controller. Moreover, the network can accommodate the addition of a new peer or the removal of an

Algorithm 1
Framework of SSA.

Input
G: maximum iterations
PD: number of producers
SD: number of sparrows who perceive danger
R2: alarm value
n: number of sparrows
Initialize a population of n sparrows and define its relevant parameters
Output: X_{best}, f_g
while $(t < G)$
Rank fitness values and find current best individual and current worst individual
$R2 = rand(1)$
for $i = 1: PD$
update sparrow's location
end for
for $i = (1 + PD): n$
update sparrow's location
end for
for $i = 1: SD$
update sparrow's location
end for
Get current new location
If new location is better than before, update it
$t = t + 1$
end
returen X_{best}, f_g

Algorithm 2
The improved sparrow search algorithm.

Input:
N: *number of sparrows*
T_{max}: *total number of iterations*
PD: *number of producers*
SD: *number of secouters*
ST: *safety value*
Output:
f_{best}: *optimal solution*
X_{best}: *global optimal position*
initialize a population of N sparrows
while $t \le T_{max}$ *do*
Calculating fitness value of individuals
Ranking he fitness values and finding current best and worst individual
for $i = 1 : PD$ *do*
update the producers'position
end for
for $i = (1 + PD) : N$ *do*
update scroungers'position
end for
for $i = 1 : SD$ *do*
update scouters'position
end for
for $i = 1 : N$ *do*
if new position is better than previous position then Using new position to update previous position
end if
if new position is better than optimal position then using new position to update optimal position
end if
end for
$t = t + 1$
end while

existing peer without affecting the system's functionality.

Generally, P2P energy networks consist of two tiers, as shown in Fig. 1: two layers: one for virtual energy trade and the other for physical energy transmission. The virtual energy trading layer functions as a platform where participating peers exchange the necessary data to determine the kind, quantity, and cost of each resource traded with one another, much like a local power market. All peers must have equal access to a virtual layer built on top of a secure information system. Peer generation, demand, and consumption data transmitted from the peer's smart meter over secure communication network are used to build buy and sell orders on the virtual layer. After that, appropriate market mechanism is applied to enable energy trading using created orders. After all of the buy and sell orders from different peers are matched, energy exchange takes place over physical layer. After that, money is paid.

On other hand, the physical energy transfer layer acts as a distribution system to make it easier for peers to physically transmit electricity. This physical network might be a standalone physical micro grid distribution grid that works in tandem with normal grid, or it can be a typical distribution network maintained and managed via Independent System Operator (ISO). It is important to remember that physical distribution of electricity is not directly governed by the financial transactions that take place between peers in the virtual layer. The moment payment is received, in fact, is when the process of integrating a seller's renewable energy to distribution grid actually starts.

2.1. Microgrid-to-microgrid energy trading

The primary objective of P2P energy trading systems in this category is to optimize use of RES to address the imbalance between supply and demand of energy inside microgrids. On one hand, these solutions result in lower electricity costs for the microgrids taking part in the P2P energy exchange. By managing the power flow inside grid, power generation at microgrid may be stabilized even in the face of unpredictable load demand. P2P commerce with the security component included allows distributed energy supply and flexible demands to grow and strengthen the grid in both routine and emergency scenarios.

The buildings that are used for residential, commercial, and industrial reasons account for a significant amount of the energy consumed in cities. Main goal of this research is to give prosumers in the home and workplace the ability to trade electricity and heating energy equitably while accounting for a range of demandside characteristics, using an optimization-based trading aid tool. The suggested integration of commercial, residential, and industrial prosumers is depicted in Fig. 1. The heating network and utility grid connect two prosumers. Energy trading allows for the exchange of surplus heating and power. Due to the two prosumers' large distance from one another and considerable energy loss, there won't be a cooling energy exchange. Fig. 2 shows a comprehensive flowchart for applied optimization methods.

2.2. Sparrow search algorithm (SSA) corrective action

Sparrows come in many different types and are generally gregarious

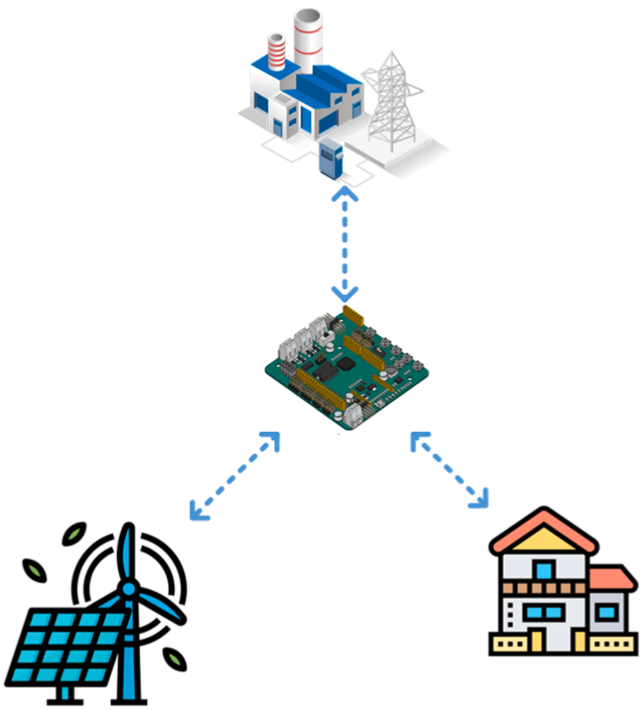


Fig. 3. Complete P2P cooperative.

birds. They are widespread around world and prefer to live in populated areas. They are also omnivorous birds that mostly consume grain seeds or weeds. The fact that sparrows are a frequent bird in the area is well known. The sparrow, in contrast to many other little birds, is very intellectual and has a long memory [93].

In this section created rules based on an imagined version of the sparrows' subsequent behavior in order to keep things simple.

1). Producers generally has enough of energy storage and give the scavengers instructions or feeding sites. Its job is to locate places with an abundance of food. An individual's amount of energy reserves is determined via evaluating their degree of fitness.
2). Sparrows begin to chirp in terror as soon as they spot predator. When alarm value surpasses safety threshold, producers are required to guide every scavenger to secure location.
3). Although all sparrows have the capacity to become producers if they look for more plentiful food sources, proportion of producers to scavengers in population stays constant.The birds that produce would be the most energized. In order to obtain additional energy, some scavengers who are ravenous are more likely to search skies for food.
4). Scavengers follow producer who can provide best food in order to find food. Some scavengers may compete for food while closely monitoring producers in order to boost their own rate of predation.
5). When a threat is spotted, sparrows on group's periphery swiftly go toward the safe zone to take up a better position, while sparrows in group's core fly around aimlessly to stay close to one another.

To find food in simulation experiment, authors must use virtual sparrows. Next matrix shows the positions of the sparrows.:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,d} \end{bmatrix} \tag{1}$$

where d is dimension of variables that require optimization and n is number of sparrows. Consequently, following vector can be used to express sparrows' overall fitness value:

$$F_X = \begin{bmatrix} f\left(\begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,d} \end{bmatrix}\right) \\ f\left(\begin{bmatrix} x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,d} \end{bmatrix}\right) \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ f\left(\begin{bmatrix} x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,d} \end{bmatrix}\right) \end{bmatrix} \tag{2}$$

When n is sparrows number and fitness value of each individual is signified via value in F_X for each row. Those producers who are more fit are prioritized when looking for food in the SSA. Moreover, because it is the producers' responsibility to find food and control population mobility. Consequently, producers are able to forage for food in a greater range of areas than scavengers. Following rules (1) and (2), producer's location is changed as shadows at each iteration:

$$X_{ij}^{t+1} = \begin{cases} X_{ij}^{t} \cdot \exp\left(\dfrac{-i}{\alpha \cdot iter_{\max}}\right) & if\, R_2 < ST \\ X_{ij}^{t} + Q \cdot L & if\, R_2 \geq ST \end{cases} \tag{3}$$

where $j = 1, 2 \ldots d.$ and t denotes current iteration. $X_{i,j}^{t}$ signified value of j^{th} dimension of i^{th} sparrow at iteration t. A constant with most iterations is called itermax. Is a random number with $\alpha \in [0, 1]$. A safety threshold is signified via ST $(ST \in [0.5, 1.0])$ and the alert value is

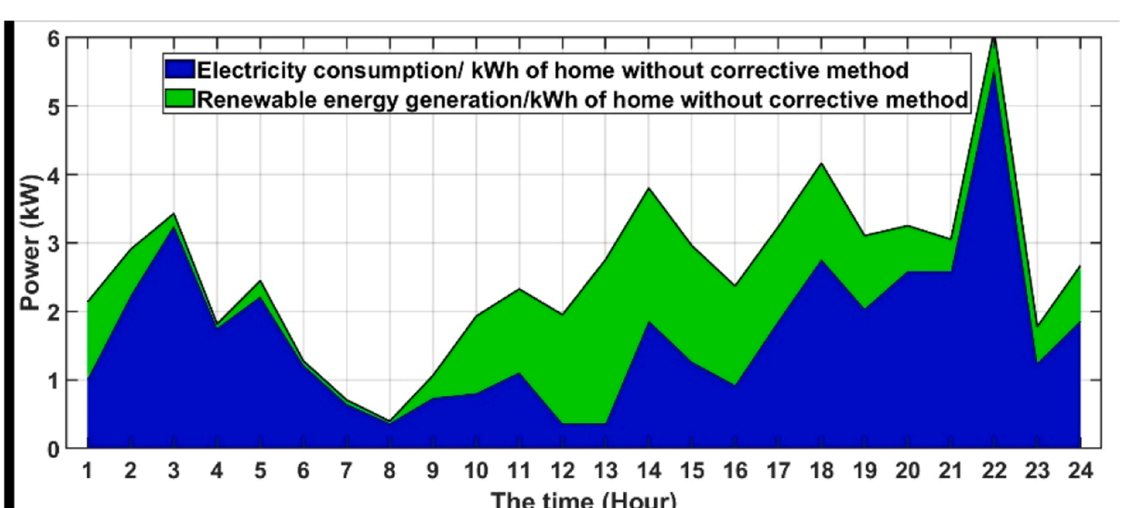


Fig. 4. Renewable energy generation –electricity consumption power mismatch of home without any corrective action.

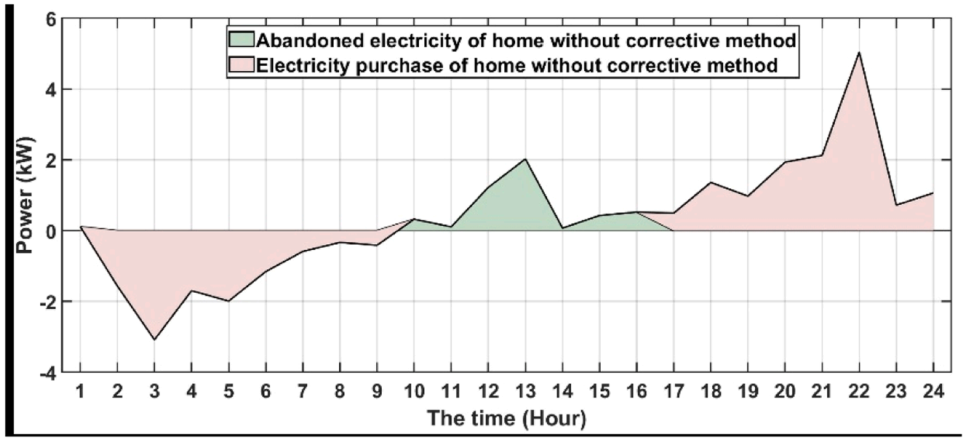
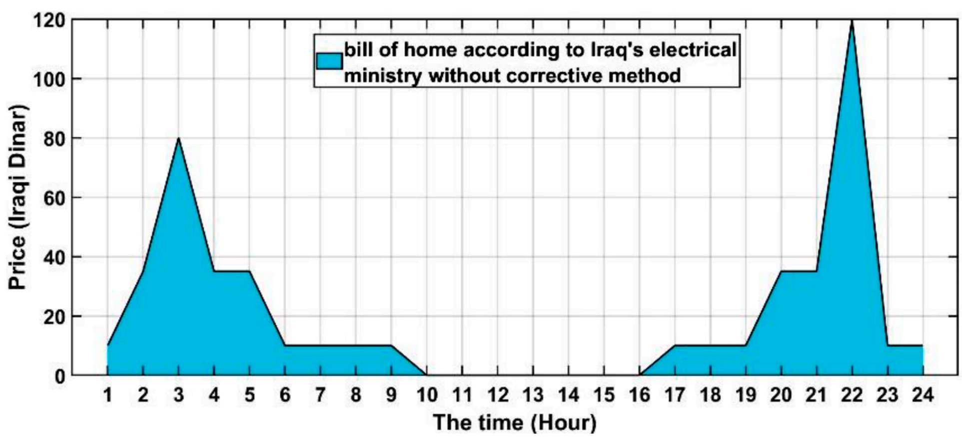
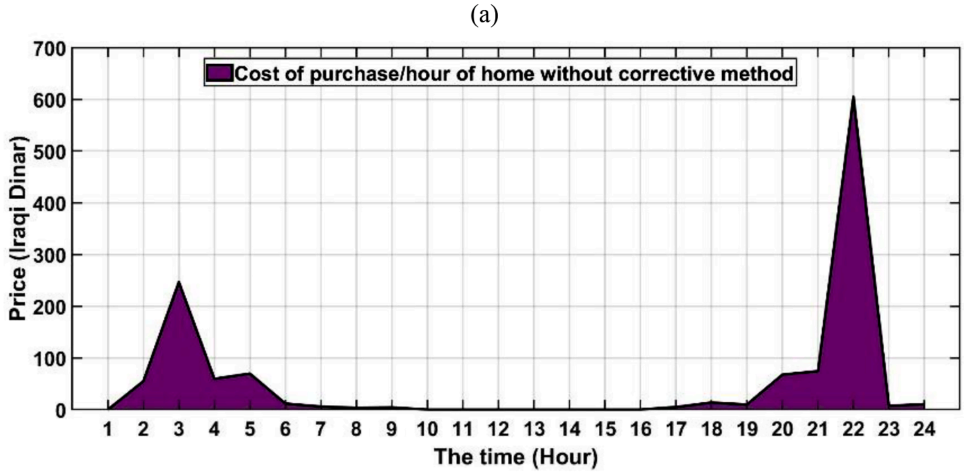


Fig. 5. Abandoned electricity of home-electricity purchase of the home without any corrective action.



(a)



(b)

Fig. 6. A) bill of home according to Iraq's electrical ministry without corrective method, b) Cost of purchase of home without corrective method.

signified via R_2 ($R_2 \in [0,\ 1]$). A random number with a normal distribution is called Q. L displays a $1 \times d$ matrix with 1 for each element. Producer switches to wide search mode when $R_2 < ST$, which indicates that there are no predators in area. $R_2 \geq ST$ shows that some sparrows have detected predator; if this is case, all sparrows need to fly right away to safer areas.

The scavengers have to put Eqs. (3) and (4) into practice. As was previously said, certain scavengers pay more attention to the producers. They immediately resign from their current positions to fight for the wonderful meal as soon as they learn that the producer have discovered it. If they are successful, they can immediately collect the food from the producer; if not, they must proceed according to Eq. (4). The scrounger's position update formula is explained here:

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{x_{worst}^{t} - x_{i,j}^{t}}{i2}\right) & if\ i > n/2 \\ X_{p}^{t+1} + \left|X_{ij}^{t} - X_{ip}^{t+1}\right| \cdot A^{+} \cdot L & otherwise \end{cases} \tag{4}$$

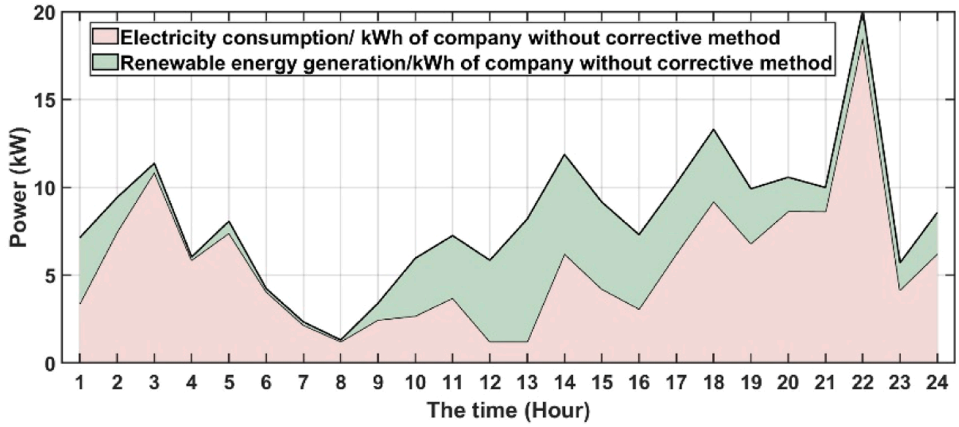


Fig. 7. Renewable energy generation –electricity consumption power mismatch of the company without any corrective action.

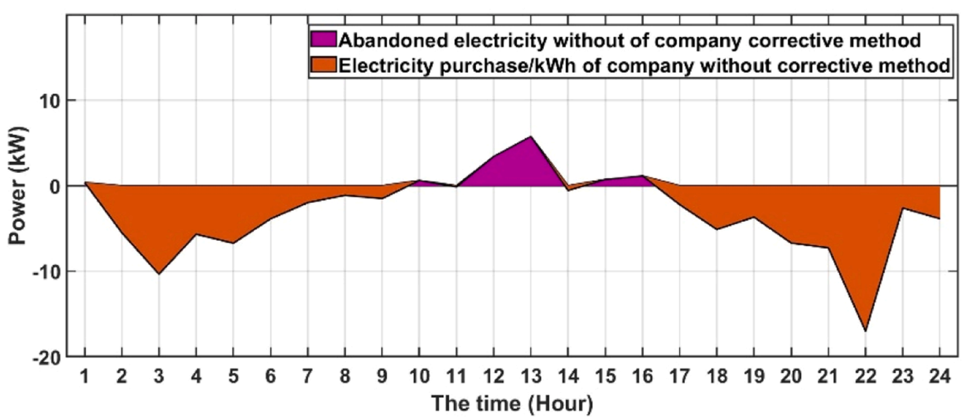


Fig. 8. Abandoned electricity of home-electricity purchase of the company without any corrective action.

where the producer's optimum location is denoted by X_P. X_{worst} shows the poorest place in world right now. A shows a $1 \times d$ matrix in which a random value of either 1 *or* -1 is assigned to every element. For $A^+ = A^T\left(AA^T\right)^{-1}$. The ith scrounger with lowest fitness grade is most likely famished when $i > n/2$. We assume that in hypothetical experiment, these threat-aware sparrows comprise between 10% and 20% of the whole population. The beginning locations of these birds are selected at random from the population. Eq. (5) can be used to illustrate the mathematical model as follows.:

$$X_{ij}^{t+1} = \begin{cases} X_{best}^t + \beta \cdot \left|X_{ij}^t - X_{best}^t\right| & if\, f_i > f_g \\ X_{ij}^t + K \cdot \left(\dfrac{\left|X_{ij}^t - X_{worst}^t\right|}{(f_i - f_w) + \varepsilon}\right) & if\, f_i = f_g \end{cases} \tag{5}$$

Where X_{best} is current global ideal location. As step size control parameter, β denotes normal distribution of random numbers with a variance of 1 and 0. $K \in [-1, 1]$ is the random number we have. where f_i is sparrow's fitness value at that moment. Currently, f_g and f_w signify global best and worst fitness values, respectively. Least constant, ε, prevents zero-division mistake.

To keep things simple, when sparrow is at group's boundary when $f_i > f_g$. The center of the population is represented by X_{best}, which is also safe in its vicinity. Since they are aware of the threat, the middle-class sparrows ought to approach the other birds, as demonstrated by $f_i = f_g$. K is step size control coefficient, and it also designates direction in which sparrow travels. Pseudo code demonstrated in Algorithm 1 can be used to outline fundamental steps of SSA.

2.2.1. Model of the ISSA

2.2.1.1. Elite opposition-based learning strategy with Chebyshev chaotic map. A quality of initial population have a direct impact on algorithm's convergence performance in swarm intelligence optimization. The accuracy and rate of convergence will be slowed down by the uneven distribution and unstable quality that result from initial population in SSA being formed at random. Chaotic mapping has three properties: regularity, ergodicity, and randomness. It has recently been used to enhance the initial population quality of swarm intelligence algorithms. Among the often utilized chaotic maps are the Tent chaotic map, the Kent chaotic map, and the Logistic chaotic map. In this study, the population is initialized using Chebyshev chaotic map. Compared to chaotic mapping that was previously discussed, the Chebyshev chaotic map is more straightforward, independent of the beginning value, and generates more uniformly distributed mapping outputs. The equation for the Chebyshev chaotic map is [94]:

$$x^{t+1} = \cos\left(t\cos^{-1}\left(x^t\right)\right) \tag{6}$$

where a random number $x^t \epsilon\, [0,\ 1]$ is present. The following equation creates the starting population after acquiring the Chebyshev chaotic sequence:

$$X_{i,j}{}^{t+1} = lb_j + \left(ub_j - lb_j\right) \times x^t \tag{7}$$

where lb_j and ub_j are lower and upper bounds, respectively, of search space's j^{th} dimension. Using the elite opposition-based learning technique (EOLS), the initial population's quality is raised. There are some exceptional sparrows in the population. Elite individuals are better than

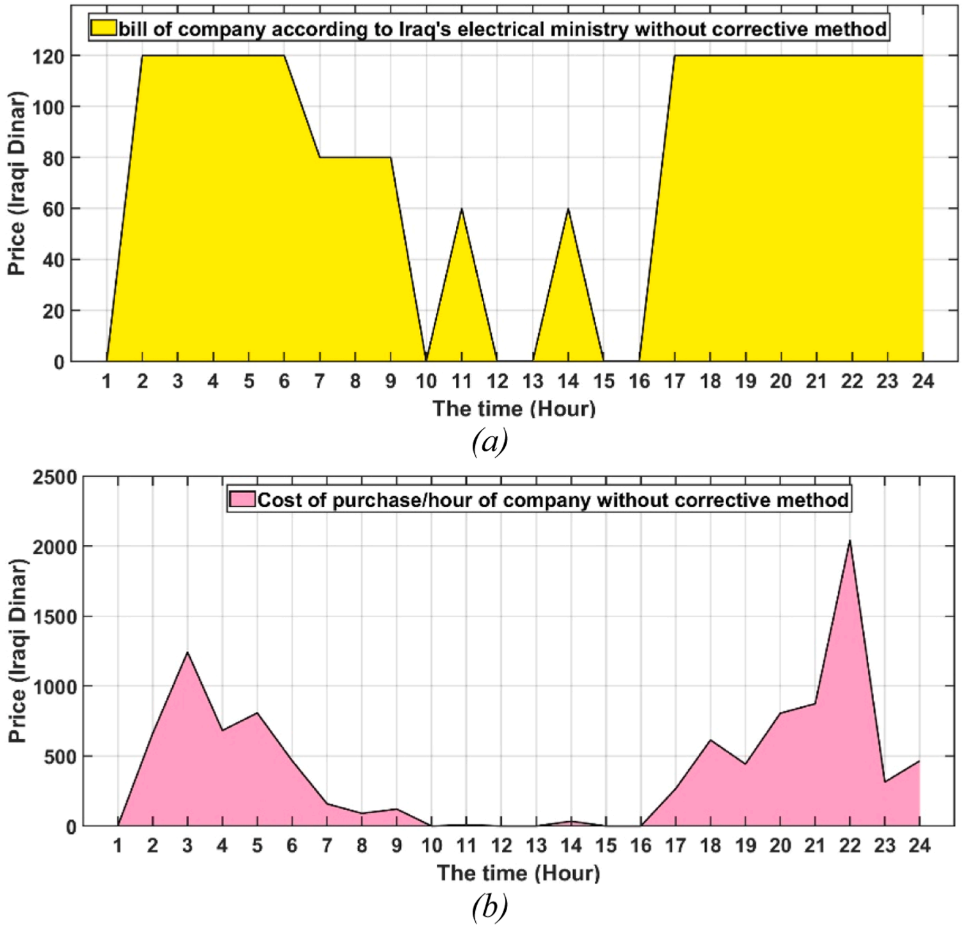


Fig. 9. A) Bill of the company according to Iraq's electrical ministry without any corrective action, b) Cost of purchase of the company without any corrective action.

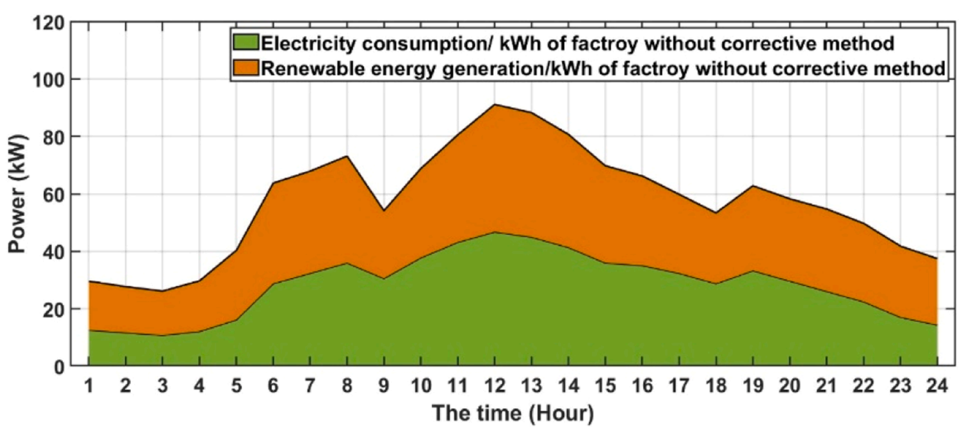


Fig. 10. Electricity consumption and renewable energy generation of factory without any corrective action.

others in every way, including spotting and thwarting the adversary. The objective behind the EOLS is to employ elite individuals' information to generate the starting population as much as possible. By doing this, the population will be more diverse, higher quality, and the algorithm will be kept from settling on the local optimal answer. Those with limited fitness value in the overall population are typically considered elite. After the initial population acquisition, the individuals are ranked based on their fitness levels, and the elite group is selected from a subset of the lowest-scoring individuals. The elite opposition of each elite member of the elite group can be computed using following formula:

$$\widetilde{X_{i,j}} = \mu\left(\widetilde{lb_j} + \widetilde{ub_j}\right) - X_{i,j} \tag{8}$$

where $\widetilde{lb_j}$ and $\widetilde{ub_j}$ denote, respectively, lower and upper bounds of individual in starting population in j^{th} dimension of current search space, and $\mu\ \epsilon[0,\ 1]$ is a random number. After calculating each person's fitness values, n people with low fitness values are chosen to make up the beginning population.

2.2.1.2. Levy flight strategy and dynamic weight factor. The producers in the sparrow population are in charge of finding regions where there is an

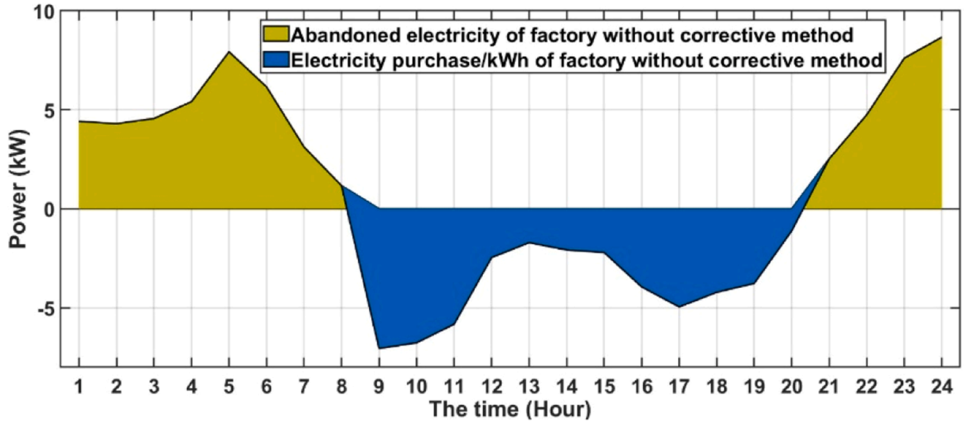


Fig. 11. Abandoned electricity and electricity purchase of factory without any corrective action.

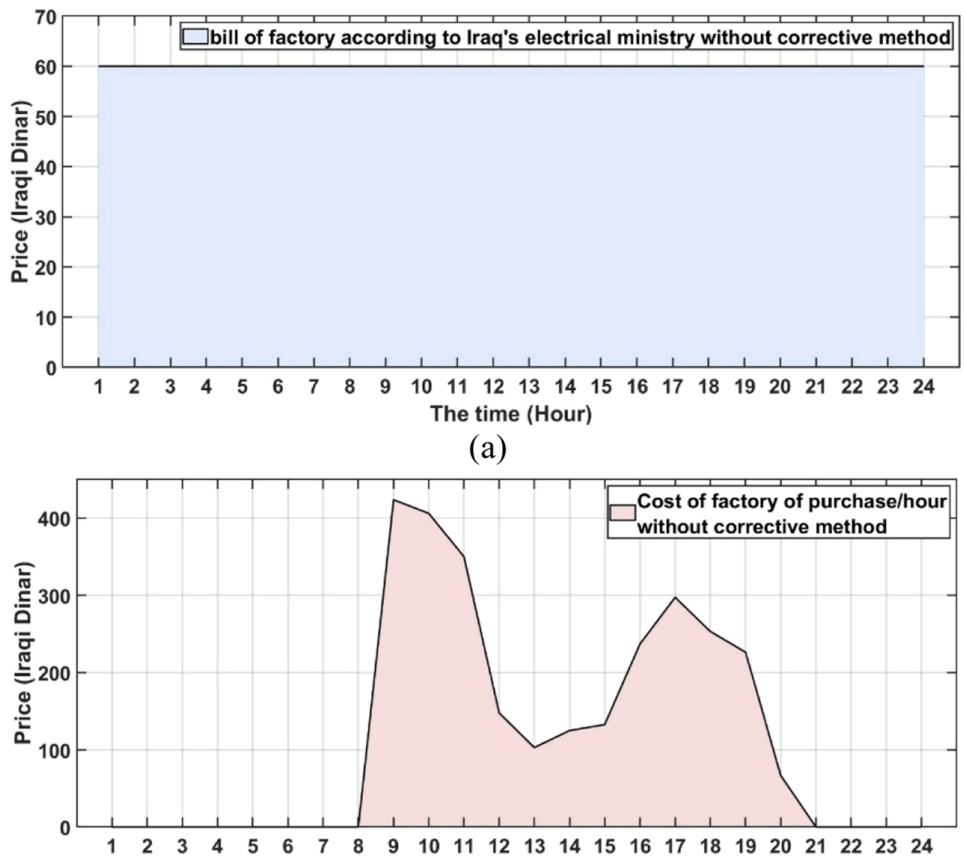


Fig. 12. A) Bill of factory according to Iraq's electrical ministry, b) The cost of purchase of factory without any corrective action.

abundance of food and utilizing their search area to the fullest. Therefore, in order to balance local extraction and global exploration, producers need to employ flexible strategies. To solve this issue, this study presents the dynamic weight factor, which has the following definition:

$$X_{ij}^{t+1} = \begin{cases} \omega \cdot {X_{ij}}^{t} \cdot \exp\left(\dfrac{-i}{\alpha \cdot T_{max}}\right), & R_2 < \mathrm{ST} \\ \omega \cdot {X_{ij}}^{t} + Q \cdot L, & R_2 \geq \mathrm{ST} \end{cases} \tag{9}$$

$$\omega = \left(\frac{T_{max} - t + 1}{T_{max}}\right)^{t} + \delta \tag{10}$$

In order to prevent dynamic weight factor ω from becoming too tiny in later stages of the loop, $\delta \in [0, 0.1]$ is a random variable. Dynamic weight factor ω balances the capacities of both by ensuring that the producers can undertake local exploitation at the conclusion of the iteration with a lower step size and global exploration at the beginning with a bigger step size.

Exploitation can only take place in later stages of iteration very close to local optimal solution if producers have already settled into local optimal solution in early stages of the iteration. This work uses the Levy flight technique to avoid such a situation by providing the producers with the option to abandon local optimal solution at a later iterational

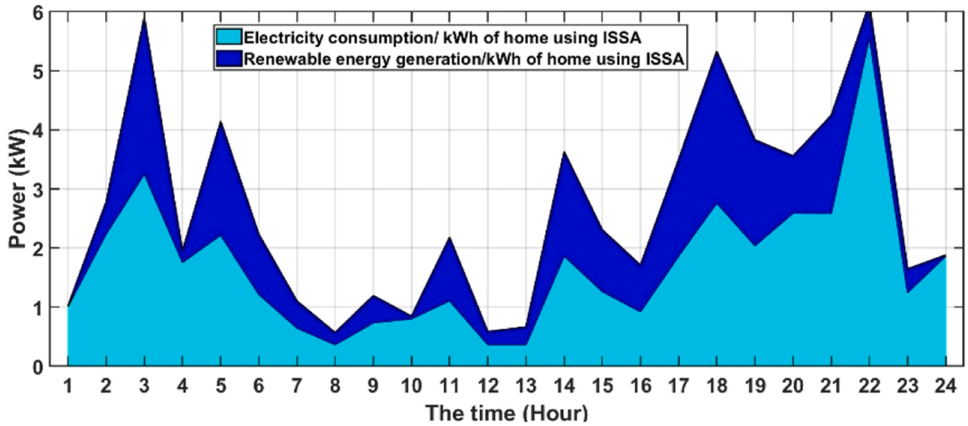


Fig. 13. Renewable energy generation –electricity consumption power mismatch of home using ISSA corrective action.

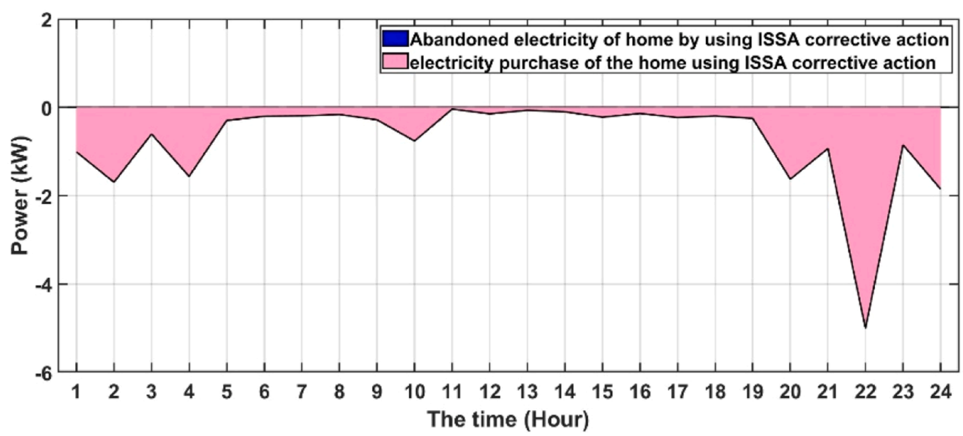


Fig. 14. Abandoned electricity of home-electricity purchase of the home using ISSA corrective action.

stage. The Levy distribution controls the step size of the Levy flight, a non-Gaussian random process. Given how challenging it is to calculate the Levy flight step size, simulations frequently employ the Mantegna algorithm, whose formula is as:

$$s = \frac{u}{|v|^{1/\beta}} \tag{11}$$

where $u \sim N(0, \ \sigma_u{}^2), \ v \sim N(0, \ \sigma_v{}^2), \ \sigma_u$ and σ_v is defined as:

$$\sigma_u = \left[\frac{\Gamma(1+\beta)\sin\ (\pi\beta/2)}{\Gamma((1+\beta)/2)2^{(\beta-1)/2}}\right]^{1/\beta} \tag{12}$$
$$\sigma_v = 1$$

where conventional gamma function, Γ, is used. The number $\beta \ \epsilon \ (0, 2)$ is arbitrary. A following equation is used to update producers' positions after Levy flight steps are obtained:

$$\widetilde{X_i^t} = X_i^t + 0.01s\left(X_i^t - X_b^t\right) \tag{13}$$

where the producers' location, as determined by (9), is represented by X_i^t. Current global optimum location is X_b^t. The characteristics of Levy distribution suggest that Levy flight includes a number of little actions that can strengthen the producers' ability to exploit the market locally. Large steps are occasionally taken to assist producers in leaving the local optimal solution and improving their capacity for global exploration. The Levy flight technique and the dynamic weight factor work together to successfully boost producer efficiency, reduce the likelihood that producers would choose the locally optimal option, and better balance potential for both local exploitation and global exploration.

2.2.1.3. Mutation strategy. A colony of sparrows' scavengers will monitor the producers' activities. When they find food, the producers fight to increase their stores of energy. Some scavengers will fly away from group to look for isolated areas to forage when their energy levels are low. Scavengers in SSA follow a flight path that is determined by:

$$p(x, y, z) = \frac{j\rho c}{\lambda}\sum\nolimits_{n=1}^{N} u_n \frac{F_n \Delta w \Delta h}{R_n} e^{-(\alpha+jk)R_{SR}} \mathrm{sinc}\frac{k\widetilde{x}_n \Delta w}{2R} \mathrm{sinc}\frac{k\widetilde{y}_n \Delta h}{2R} \tag{14}$$

where the imaginary unit is represented by $j = \sqrt{-1}$. The medium's density is denoted by ρ. The sound wave's wavelength is represented by λ. The sound wave velocity in $X_{worst}{}^t$ and $X_{i,j}{}^t$ $(i > n/2 \ in \ (2))$ is represented by c.,The scavengers may not always locate regions with plenty of food, even with this updating approach. This paper uses the following mutation method to direct the scavengers' flight path and increase population diversity.

$$X_{i,j}{}^{t+1} = X_{i,j}{}^t + \eta\left(X_P{}^{t+1} - X_{i,j}{}^t\right) \tag{15}$$

where the random integer is $\eta \ \epsilon \ [0, \ 1]$. The aforementioned algorithm will increase the scavengers' chances of discovering high-quality food by directing them to optimal position $X_P{}^{t+1}$. Algorithm 2 illustrates the ISSA implementation phases in experiment for $i > n/2$.

2.3. Chance constrained corrective action

A competing method for resolving optimization issues in the face of

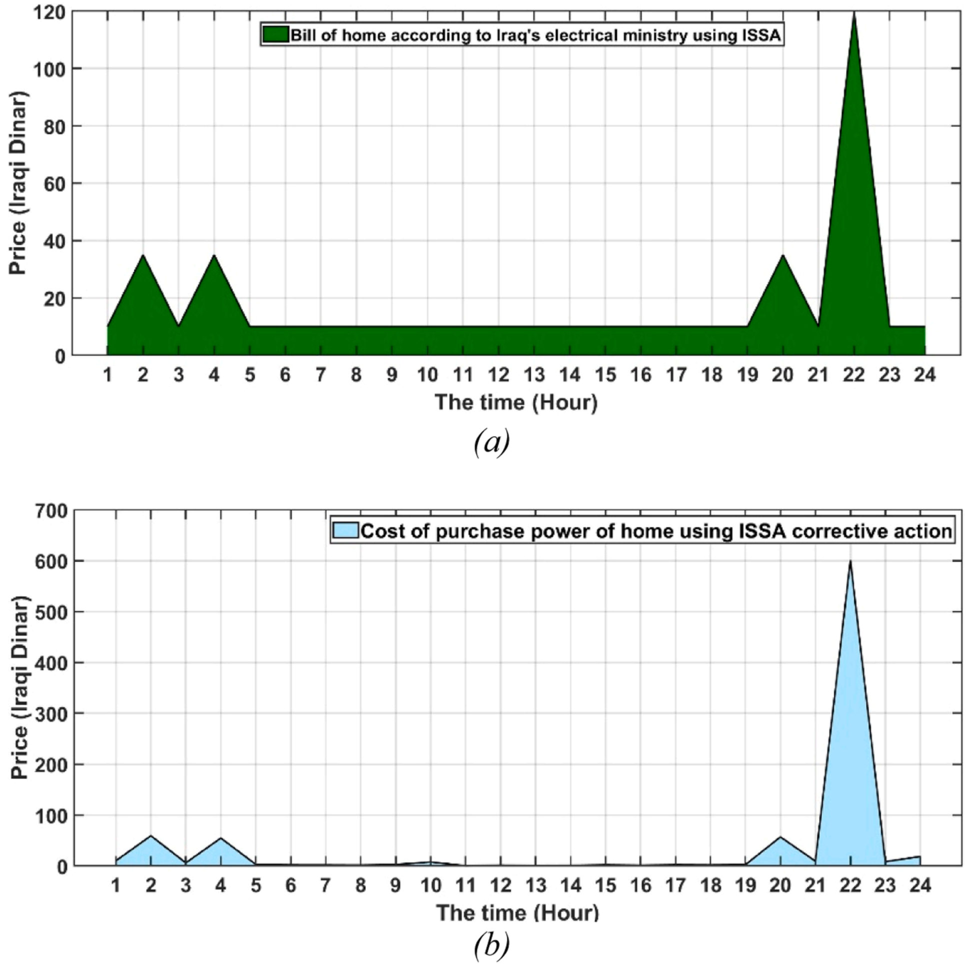


Fig. 15. A) Bill of home according to Iraq’s electrical ministry, b) The electricity bill of home using ISSA corrective action.

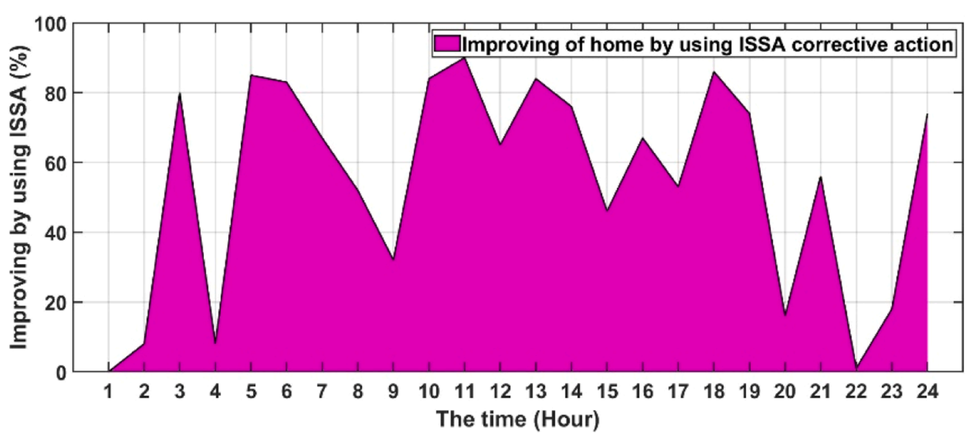


Fig. 16. Improving of home using ISSA corrective action.

uncertainty is chance constrained programming. Miller and Wagner (1965) and Charnes and Cooper (1959) were the first to present this approach. Its primary characteristic is that the final decision guarantees the likelihood of adhering to limits, or the degree of certainty that it is feasible. Therefore, it is possible to quantify the relationship between profitability and reliability using chance-constrained programming. Stated differently, the problem’s solution offers thorough details on the cost-effectiveness as a function of the intended degree of confidence in meeting the process restrictions [95].

Uncertainties can be broadly divided to two groups: internal uncertainties, which reflect a lack of process knowledge, like as model parameters, and external uncertainties, which include feed rate and/or composition, recycle flows, temperature and pressure of coupled operating units, raw material and utility supply, customer demand, prices, and market conditions. A small number of experimental data points are frequently used to regress model parameters. Previous research has focused more on internal uncertainty than external uncertainty. In most cases, statistical regression from previously available data,

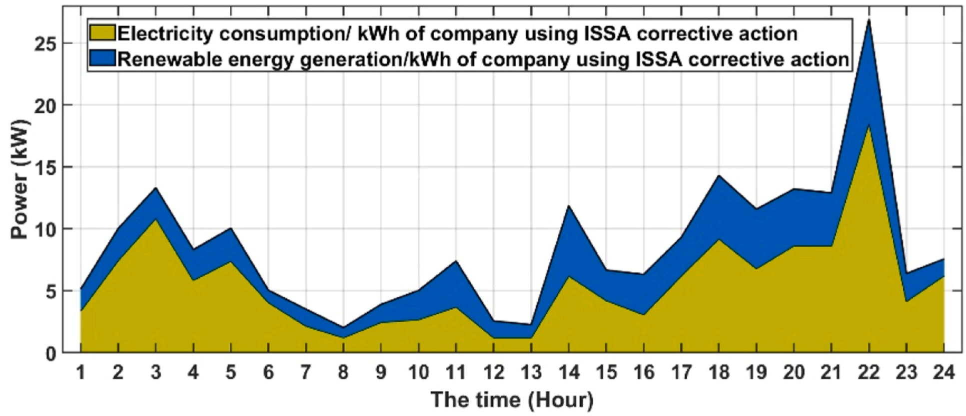


Fig. 17. Generation-demand power mismatch of company using ISSA corrective action.

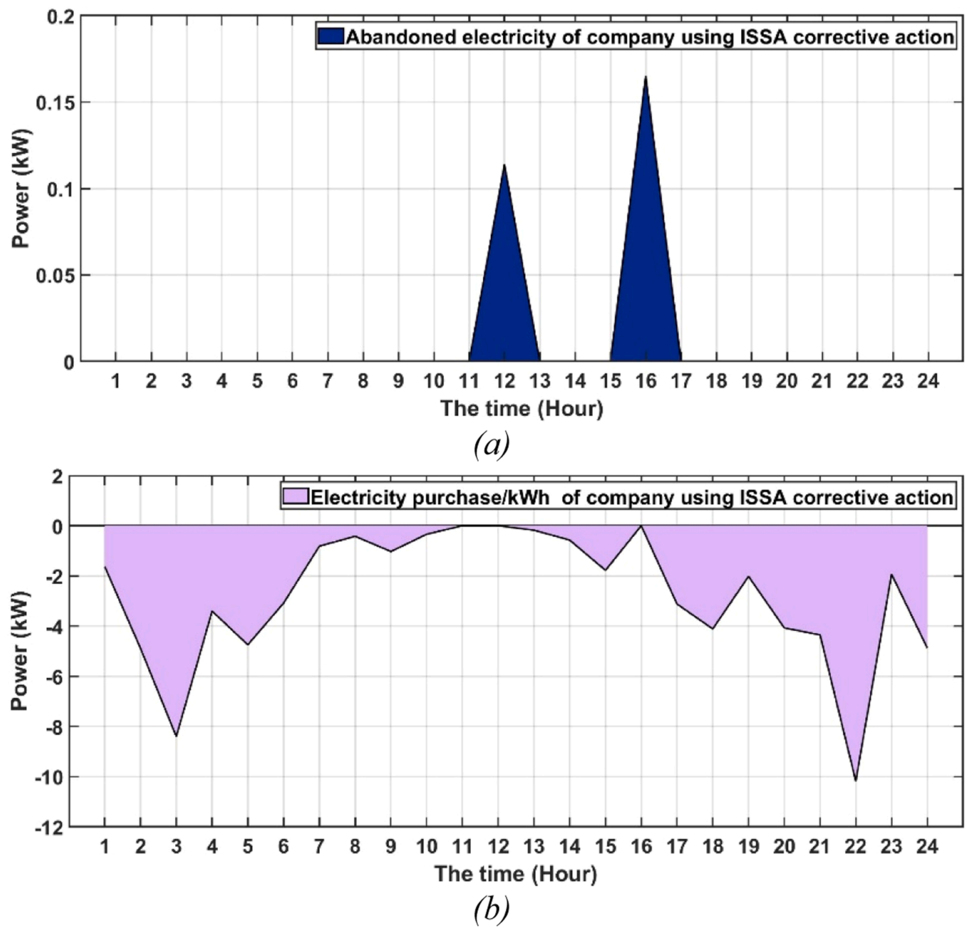


Fig. 18. a) Abandoned electricity and, b) electricity purchase of company using ISSA corrective action.

interpolation, or extrapolation can be used to determine distribution of uncertain variable. Gathering process data for dispersion analysis has become comparatively simple due to growing popularity of computer-based process monitoring schemes. Stochastic distribution of uncertain variables can take many different forms, and they can be coupled or uncorrelated. In engineering practice, the normal (Gaussian) distribution is frequently regarded as a sufficient assumption for a large number of uncertain variables. Usually, the variance and mean statistics are available. Nevertheless, the output variables will likewise be uncertain as a result of these uncertain variables spreading throughout the process. It is extremely challenging to analytically characterize the output distribution for a nonlinear process.

2.3.1. Formulation of the problem

Examined a market that contains a collection of agents classified as either consumers or producers of energy or reserves. Reserve customers require the reserve to offset their uncertainty, much like energy consumers do in order to meet their demands. Since excess generation can always be reduced, we assume that the only source of uncertainty is from renewable agents and only the deficiency situation is taken into account. As stated in [96], all agents are expected to be truthful and logical, meaning they constantly choose their course of action to optimize their

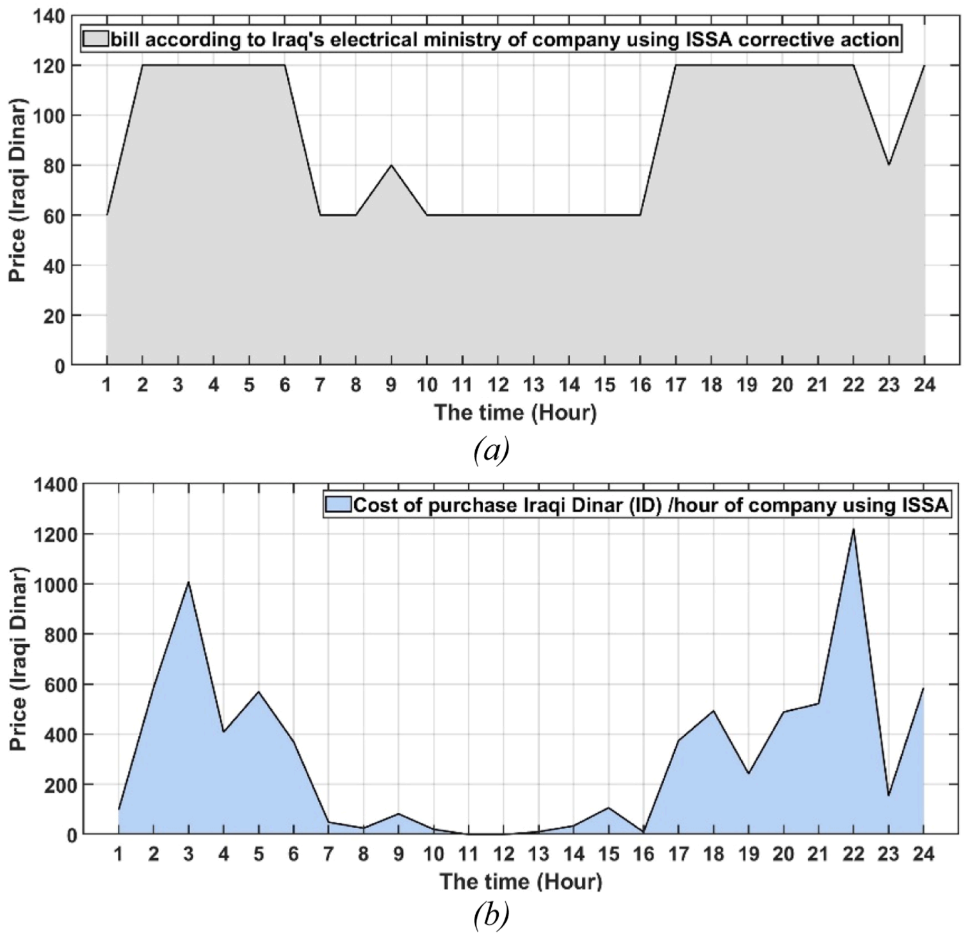


Fig. 19. A) Bill according to Iraq's electrical ministry of company, b) The electricity bill of company using ISSA corrective action.

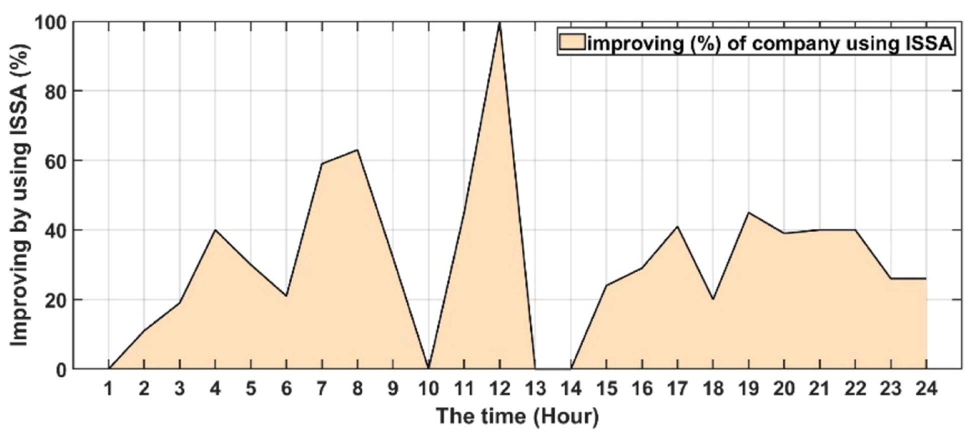


Fig. 20. Improving using ISSA corrective action.

own gains. The following suggests a market mechanism for a single slot market that operates one day in advance.

2.3.1.1. P2P trading. Compared to current centralized markets, P2P method for power markets is far more decentralized. All agents must give the SO all of their information, including cost or utility function, power constraints, and uncertainty, in order for SO to centrally decide how to dispatch energy and reserves in centralized market. All agents, however, are allowed to freely negotiate the amounts and prices of multi-bilateral exchanges with one another in a P2P market. Players are directly involved in the P2P process, which protects their anonymity and is impervious to player failure or quit.

To simulate trading procedure, net power injection E_n of separately agent $n \in \Omega$ is split to the sum of bilaterally traded quantities with a set of adjacent agents $m \in \omega_n$.

$$E_n = \sum\nolimits_{m \in \omega_n} E_{nm,} \forall n \in \Omega \tag{16}$$

A sale or production is represented by a positive value of E_{nm}, whereas a buy or consumption is represented via negative number. The set of choice variables is $\{E_{nm} | n \in \Omega, m \in \omega_n\}$. $\mathrm{E}_n = \{E_{n1} \dots E_{nm}\}$ is used to

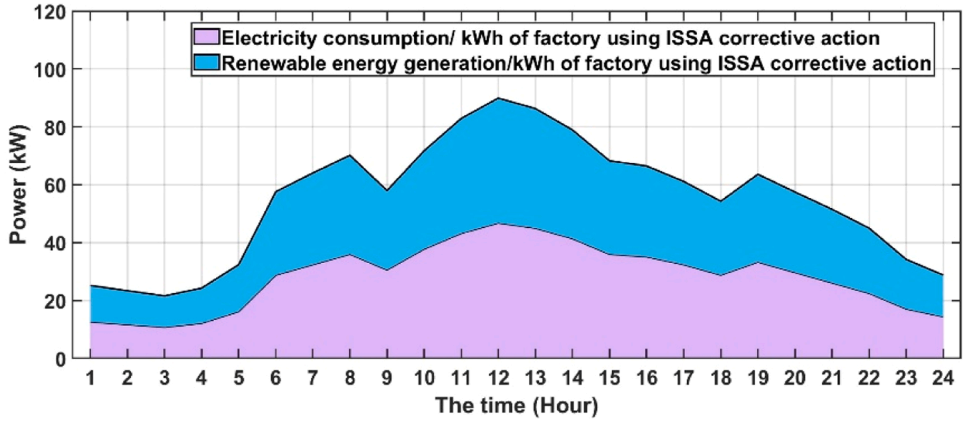


Fig. 21. Generation-demand power mismatch of factory using ISSA corrective action.

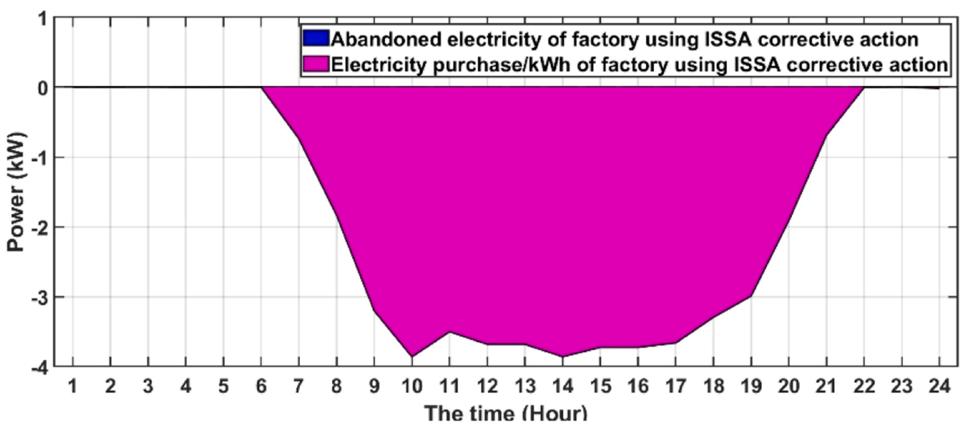


Fig. 22. Abandoned electricity and electricity purchase of Factory using ISSA corrective action.

symbolize entire collection of agent n's transactions in order to simplify notations. The limits $\underline{E_n}$ and $\overline{E_n}$ limit the power set-points of agent *n*.

$$\underline{E_n} \le E_n \le \overline{E_n},\ \forall n \in \Omega \tag{17}$$

$(\underline{E_n}\overline{E_n} \ge 0)$ restricts each agent to either producer or consumer. Therefore, if it is a producer, the decision variables must be positive (E_nm≥0), and if it is consumer, it must be negative ($E_{nm} \le 0$).

$$\begin{cases} E_{nm} \ge 0, & \forall(n,m) \in (\Omega_g \cup \Omega_r, \omega_n) \\ E_{nm} \le 0, & \forall(n,m) \in (\Omega_u, \omega_n) \end{cases} \tag{18}$$

where sets of conventional generators, renewable generators, and consumers are denoted by Ω_g, Ω_r and Ω_u, respectively. Assumed to be strictly convex functions are producer generation cost or consumer utility $C_n^e(E_n)$, which is positive for generators and negative for customers.

Likewise, each agent's reserve injection R_n is divided as

$$R_n = \sum\nolimits_{m\in\omega_n} R_{nm}, \forall n \in \Omega \tag{19}$$

A set of reserve decision variables is $\{R_{nm} | n \in \Omega, m \in \omega\}$, while entire set of reserve transactions is represented by $\mathbf{R}_n = \{R_{n1} \ldots R_{nm}\}$. An agent n's reserve level is limited via boundaries $\underline{R_n}$ and $\overline{R_n}$.

$$\underline{R_n} \le R_n \le \overline{R_n},\ \forall n \in \Omega \tag{20}$$

Every agent is limited to either the consumer or the reserve supplier $(\underline{R_n}\overline{R_n} \ge 0)$. Therefore, if the agent is a reserve supplier, its decision variables must be positive ($R_{nm} \ge 0$); if it is a reserve consumer, they must be negative ($R_{nm} \le 0$).

$$\begin{cases} R_{nm} \ge 0, & \forall(n,m) \in (\Omega_g \cup \Omega_u, \omega_n) \\ R_{nm} \le 0, & \forall(n,m) \in (\Omega_r, \omega_n) \end{cases} \tag{21}$$

Additionally, assumed that the consumer utility function or reserve production cost $C_n^r(R_n)$ is strictly convex, with a positive value for non-renewable generators and a negative value for renewable ones. In this case, we think the idea of "reserve utility" is useful and significant. By penalizing the shortage or creating an incentive system, SO can incentivize renewable agents to enhance quality of generation. Renewable agents can be considered the "reserve utility" and can avoid penalties or get subsidies if they can accurately provide power to ensure safety of power systems.

In worst situation, a sufficient amount of reserve is required, i.e.,

$$\underline{E_n} \le E_n + R_n \le \overline{E_n},\ \forall n \in \Omega \tag{22}$$

Lastly, balance constraints describe market equilibrium between energy/reserve production and consumption; in P2P market, they can be substituted via set of reciprocity constraints, which are specified as:

$$\begin{cases} E_{nm} + E_{mn} = 0, & \forall(n,m) \in (\Omega, \omega_n) \\ R_{nm} + R_{mn} = 0, & \forall(n,m) \in (\Omega, \omega_n) \end{cases} \tag{23}$$

2.3.1.2. Chance-restricted social cost reduction issue. Under the limitations, P2P joint market's goal is to minimize social cost of each agent. Issue is stated as:

$$\min \sum_{n\in\Omega} \left(C_n^e(E_n) + \tilde{C}_n^e(\mathbf{E}_n) + C_n^r(R_n) + \tilde{C}_n^r(\mathbf{R}_n) \right) \tag{24}$$

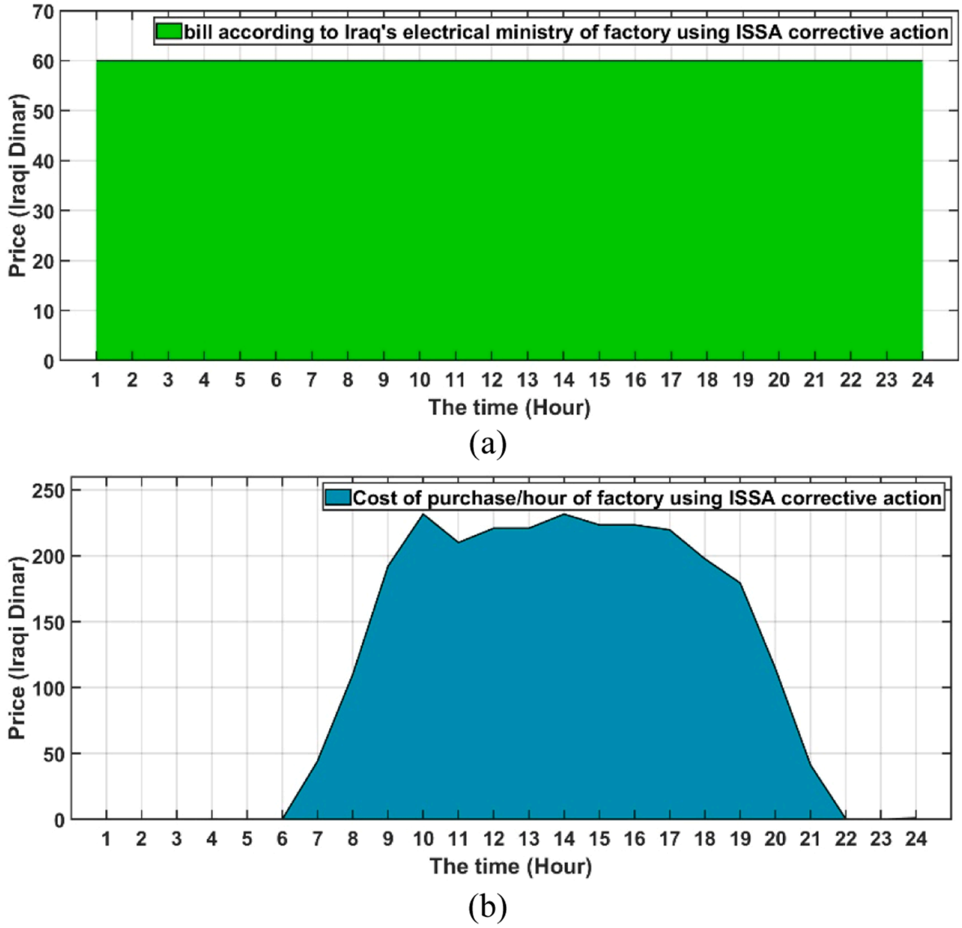


Fig. 23. A) Bill according to Iraq's electrical ministry of Factory, b) Cost of purchase/hour using ISSA corrective action.

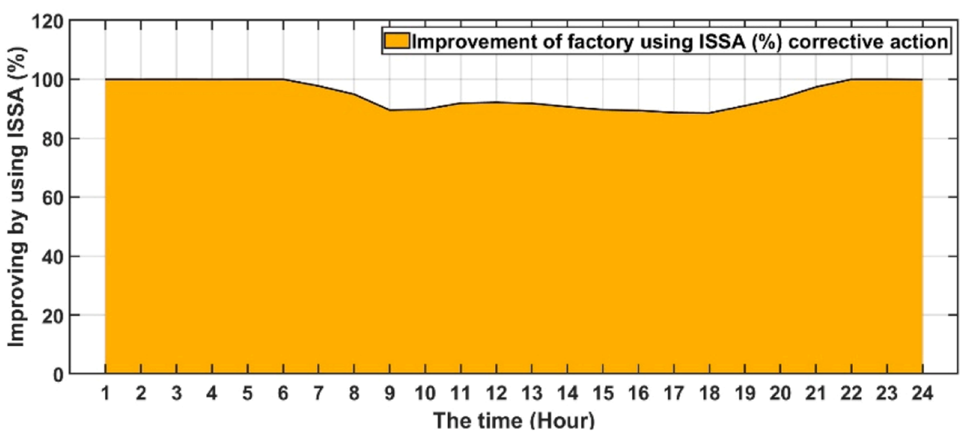


Fig. 24. Improving of Factory using the ISSA *corrective action*.

$$\mathbb{P}\{\widetilde{R}_n \geq R_n\} \geq 1 - \epsilon_n,\ \forall n \in \Omega \tag{25}$$

The generating power of renewable agents is fixed at the predicted value. A related forecast uncertainty distribution is obtained once the projected power is provided, and the chance-constrained method is used to calculate the necessary reserve for each renewable agent. According to Eq. (25) the real uncertainty $\widetilde{R}_n$ within scheduled reserve R_n has a probability of at least one via acceptable probability.

As a convex optimization problem, the social cost reduction problem have unique optimum that can be found using variety of centralized techniques. Though, it cannot protect privacy because it necessitates the disclosure of all agent information. A P2P technique is therefore preferred. The construction of fully decentralized P2P joint market that can solve above social cost reduction problem with optimal dispatches will come next (24).

2.4. *Complete P2P joint*

Each renewable agent can independently calculate required reserve without disclosing private uncertainty information, and each agent can

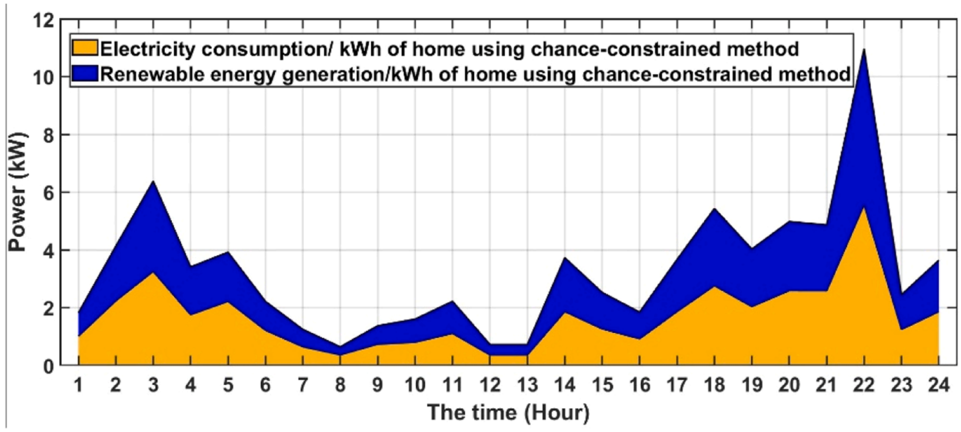


Fig. 25. Renewable energy generation –electricity consumption power mismatch of home using chance-constrained corrective action.

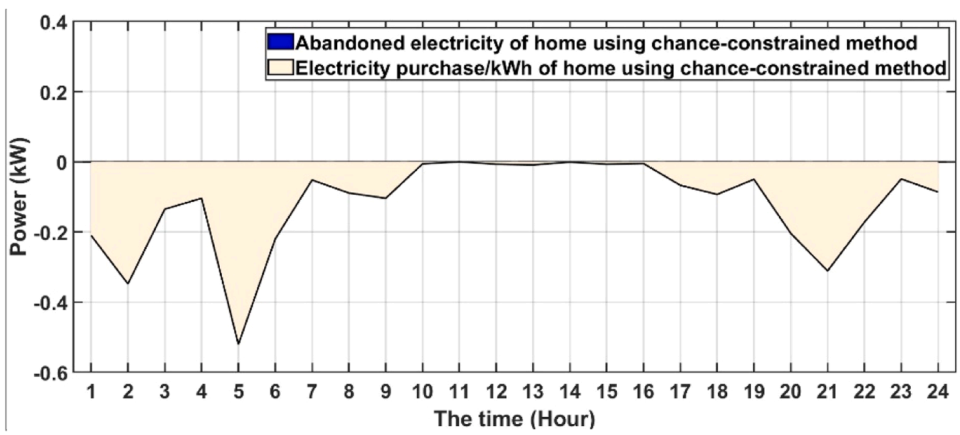


Fig. 26. Abandoned electricity of home-electricity purchase of the home using chance-constrained corrective action.

bargain with neighbors to exchange energy and reserves in the entire P2P joint market. To do this, we must transform the chance constraint (25) from its probability form into a deterministic version that is consistent with (24). In addition, a SO assists in completing the computation of power flows and voltage angles by acting as a single actor in the market. The consensus ADMM is then used to construct a decentralized bargaining mechanism. Fig. 3 displays market structure of complete P2P joint market.

2.5. Modeling system-generation resources

2.5.1. Photovoltaic solar

Eq. (1) is the formula that describes I-V behavior of PV cell circuit model with one diode and two resistors [97,98].

$$I = I_{PV} - I_O\left\{\exp\left(\frac{V+IR_s}{\alpha V_T}\right) - 1\right\} - \frac{V+IR_s}{R_{sh}} \tag{26}$$

where the photocurrent is denoted by I_{PV}, series resistor by R_s, diode reverse saturation current by I_O, ideality factor by α, the shunt resistor by R_{sh}, which accounts for current leakage through highly conductive shunts across p-n junction, and thermal voltage of diode, V_T, which is affected via electron charge (q), number of series-connected cells (n), Boltzmann constant (k), and diode's temperature (T).

$$V_T = n\frac{kT}{q} \tag{27}$$

2.5.2. Wind turbine modeling

Output power of a wind turbine is primarily determined via its radius and wind speed in area under consideration. Remaining variables, like air density, are either constants or can be made so via setting them to value strongminded via control algorithm [99]:

$$P_m = \frac{1}{2}\rho A_t C_p(\lambda.\ \beta)V_w^3 \tag{28}$$

One definition of the performance factor (C_p) is;

$$C_p(\lambda.\beta) = 0.5176\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{-\left(\frac{21}{\lambda_i}\right)} + 0.0068\lambda \tag{29}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3+1} \tag{30}$$

2.5.3. Energy storage

One of the most crucial components of microgrid is energy storage, and power systems will encounter a number of difficulties when a sizable amount of renewable energy becomes available in future. Energy storage technology, which reduces intermittent character of variable renewable energy, is one of most crucial technologies for reaching high penetration [100,101].

$$E_B(t) = E_B(t-1) + \left[P_B^{dis}(t)\,/\,\eta_{dis} - P_B^{ch}(t)\ \times \eta_{ch}\right]\ \forall t, B \tag{31}$$

$$E_B^{\min} \le E_B(t) \le E_B^{\max}\ \forall t, B \tag{32}$$

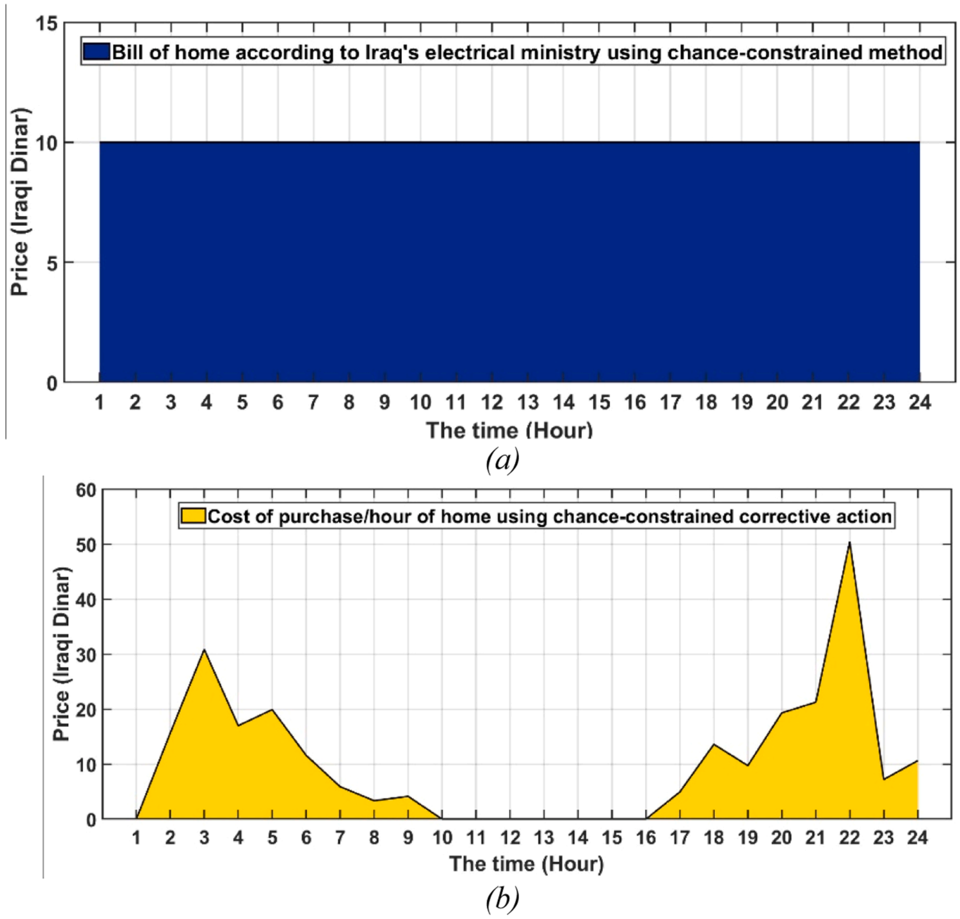


Fig. 27. A) Bill of home according to Iraq's electrical ministry, b) Cost of home of purchase/hour using chance-constrained corrective action.

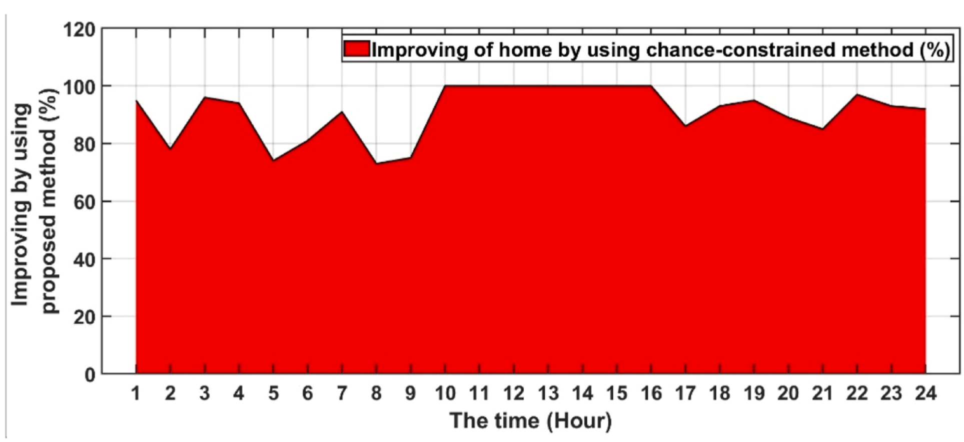


Fig. 28. Improving of home using chance-constrained corrective action.

$$P_B^{dis}(t)/\eta_{dis} \leq P_B^{\max} \times \mu_B(t)\ \forall t, B \quad (33)$$

$$P_B^{ch}(t)\ \times \eta_{ch} \leq P_B^{\max} \times (1 - \mu_B(t))\ \forall t, B \quad (34)$$

Eq. (31) describes the energy of the battery during charging and discharging, whereas Eq. (32) establishes battery's maximum energy capacity. Discharge and charge power at any given time are represented by Eqs. (33) and (34) respectively.

3. System modelling and simulation results

This section shows how to test and validate the suggested approach using the MATLAB/Simulink environment. Photovoltaic (PV), wind turbine (WT), and battery storage unit (BSU) for backup power make up the suggested microgrid system. Uncertainty is increased by RERs, system load demand, and fluctuating market pricing. The primary issues in smart microgrid energy scheduling are managing these unpredictable characteristics and figuring out the optimal system parameter scheduling. To establish the best schedule for the unknown smart microgrid parameters, a stochastic technique is used, accounting for several

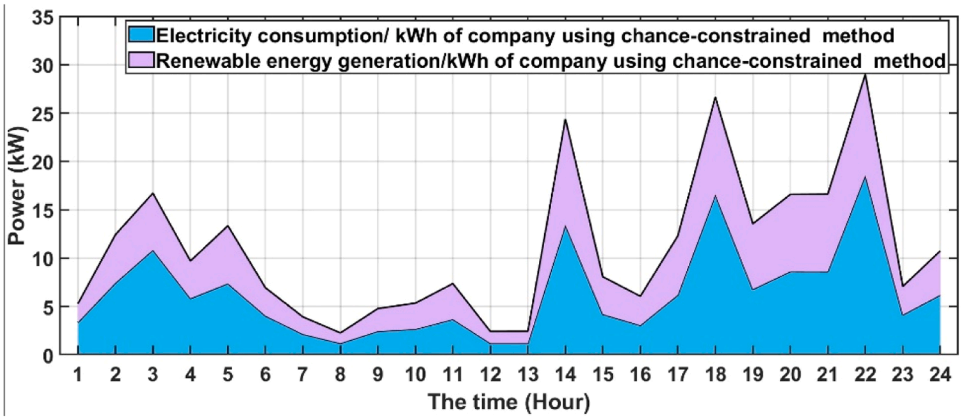


Fig. 29. Generation-demand power mismatch of company using chance-constrained corrective action.

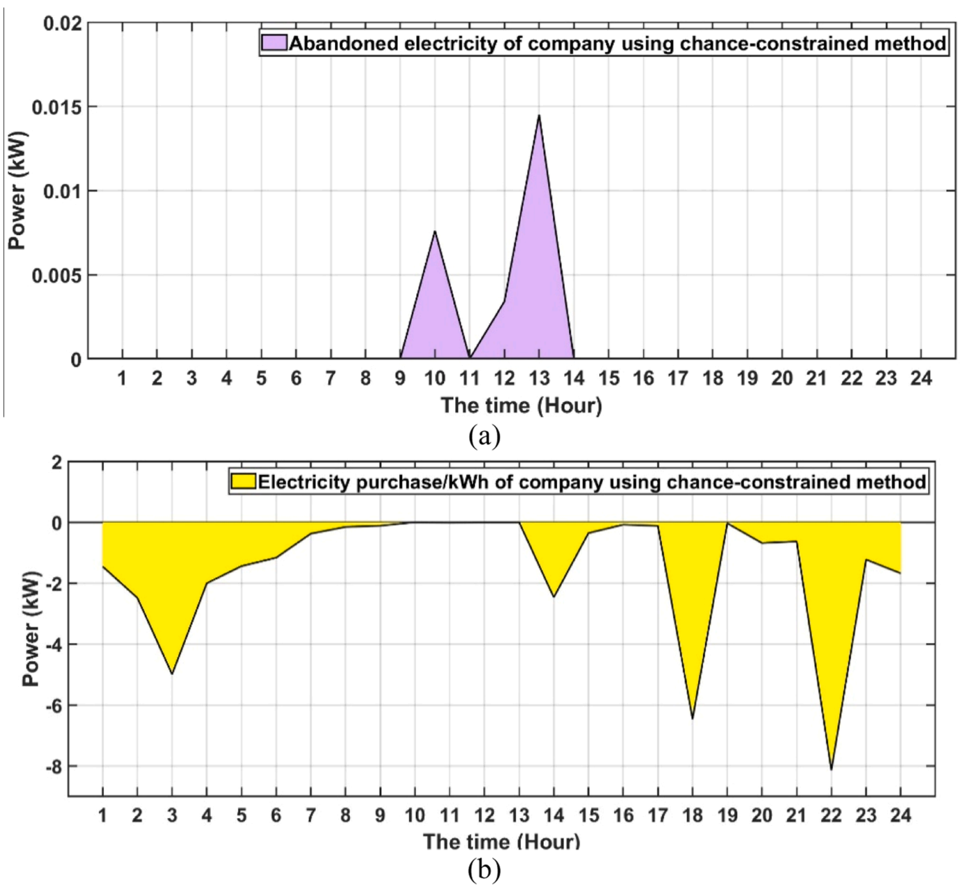


Fig. 30. a) Abandoned electricity and b) electricity purchase of company using chance-constrained corrective action.

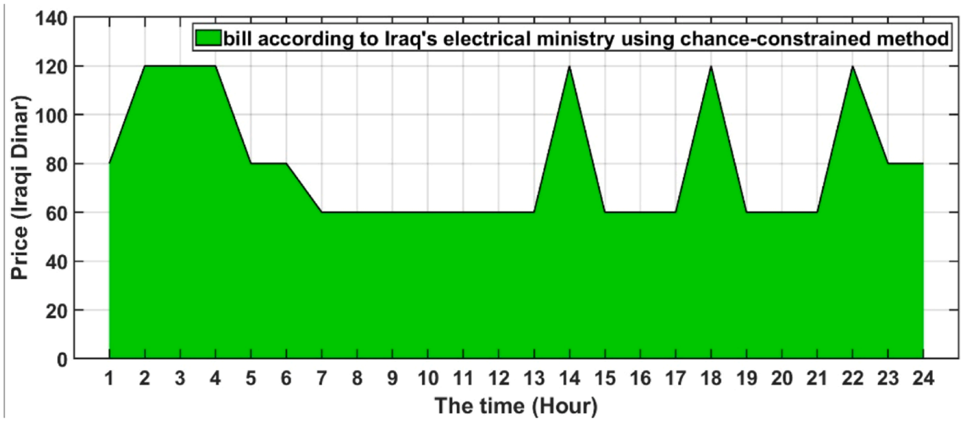
scenarios and their associated probabilities. Many scenarios have been designed to assess uncertainty of RERs, load demand, and energy price violation based on historical data from smart microgrid. Next, we apply the modified Elephant herding optimization to these scenarios to identify the best ones. Consequently, an optimization method is used to determine the smart microgrid's ideal energy schedule. Three microgrids make up each of the four linked loads in the suggested system. The following three scenarios are implemented in order to validate the suggested demand management plan for smart microgrids:

1. Scenario#1 Results without corrective methods
2. Scenario#2 Results with the Improved Sparrow Search Algorithm (ISSA) only
3. Scenario#3 Results with the chance-constrained optimization

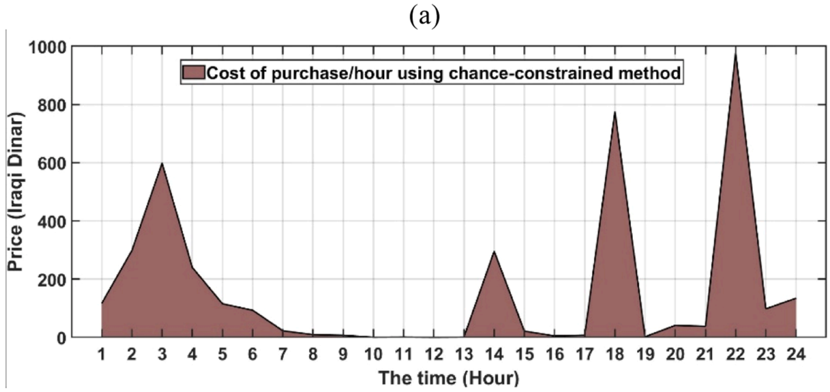
3.1. Scenario#1 results without corrective methods

In this scenario, proposed model system is applied based on without corrective method between residential, commercial, and factory prosumers. The results obtained by using this scenario are illustrated in below figures.

Fig. 4 shows Renewable energy generation –electricity consumption



(a)



(b)

Fig. 31. A) Bill according to Iraq's electrical ministry of company, b) Cost of company purchase/hour using chance-constrained corrective action.

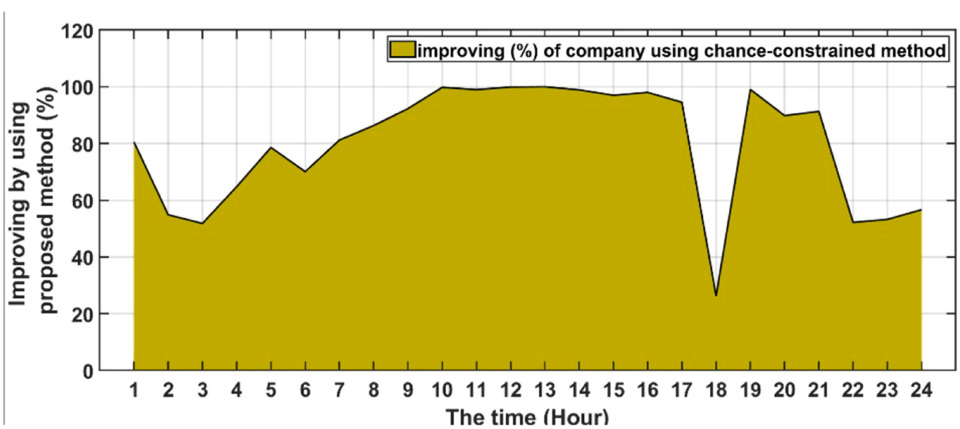


Fig. 32. Improving (%) of company using chance-constrained method.

power mismatch without any corrective action. Fig. 5 shows abandoned electricity of home-electricity purchase of the home without any corrective action. Fig. 6 shows A) bill of home according to Iraq's electrical ministry without any corrective action, and b) Cost of purchase of home without any corrective action. Fig. 7 shows renewable energy generation –electricity consumption power mismatch of the company without any corrective action. Fig. 8 shows abandoned electricity of home-electricity purchase of the company without any corrective action. Fig. 9 shows bill of the company according to Iraq's electrical ministry without any corrective action, b) Cost of purchase of the company without any corrective action. Fig. 10 shows Electricity consumption and renewable energy generation of factory without any corrective action. Fig. 11 shows abandoned electricity and electricity purchase of factory without any corrective action. Fig. 12 shows A) bill of factory according to Iraq's electrical ministry, b) The cost of purchase of factory without any corrective action

3.2. Scenario#2 results with Improved Sparrow Search Algorithm (ISSA) only

In this scenario, proposed model system is applied based on a *Improved Sparrow Search Algorithm (ISSA)* for residential, commercial, and factory prosumers. Results obtained by using this scenario are illustrated in below figures.

Fig. 13 shows renewable energy generation –electricity consumption power mismatch of home using ISSA corrective action. Fig. 14 shows abandoned electricity of home-electricity purchase of the home using ISSA corrective action. Fig. 15 shows A) bill of home according to Iraq's

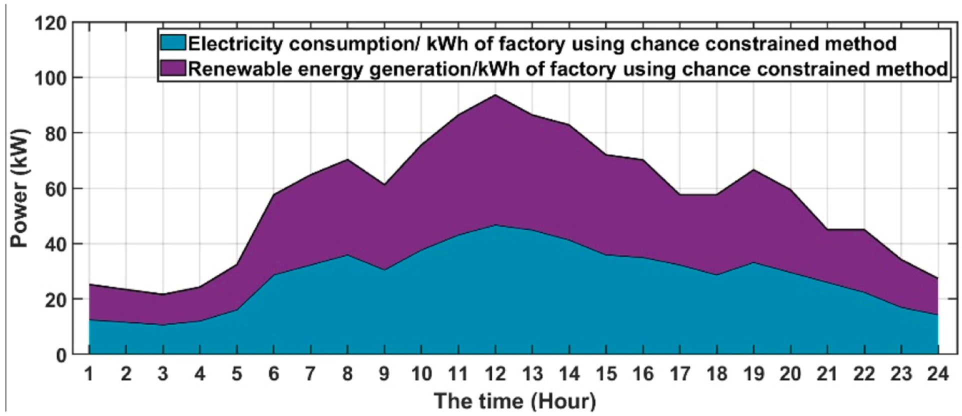


Fig. 33. Generation-demand power mismatch of Factory using chance-constrained corrective action.

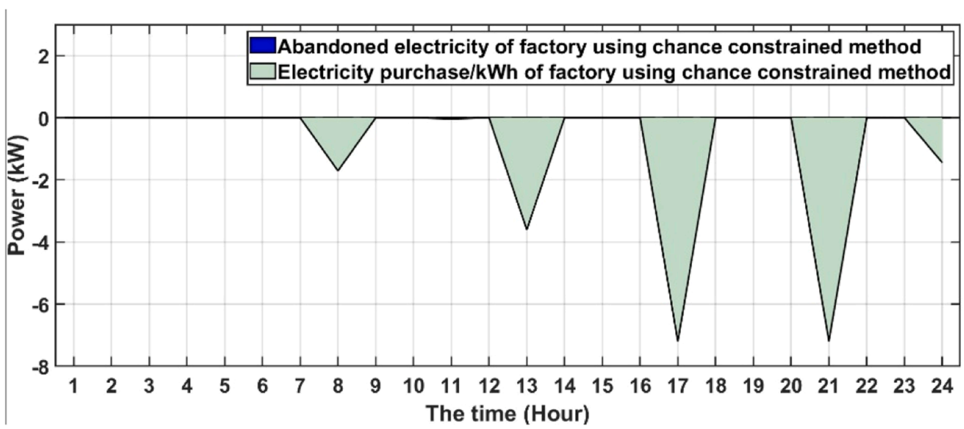


Fig. 34. Abandoned electricity and electricity purchase of Factory using chance-constrained corrective action.

electrical ministry, b) The electricity bill of home using ISSA corrective action. Fig. 16 shows Improving of home using ISSA corrective action. Fig. 17 displays Generation-demand power mismatch of company utilizing ISSA corrective action. Fig. 18 displays abandoned electricity and electricity purchase of company using ISSA corrective action. Fig. 19 shows A) bill according to Iraq's electrical ministry of company, b) The electricity bill of company using ISSA corrective action. Fig. 20 shows improving using ISSA corrective action. Fig. 21 shows Generation-demand power mismatch of factory using ISSA corrective action. Fig. 22 shows abandoned electricity and electricity purchase of Factory using ISSA corrective action. Fig. 23 shows A) bill according to Iraq's electrical ministry of Factory, b) Cost of purchase/hour using ISSA corrective action. Fig. 24 shows improving of Factory using the ISSA corrective action.

The enhanced Sparrow Search Algorithm (ISSA) approach enhanced generation and demand balance, according to the results of Scenario 2. However, this is not the best option because loss still influences mismatching between generation and demand.

3.3. Scenario#3 results with the chance-constrained

In this scenario, the proposed model system is applied based on a Chance-Constrained cooperative model between residential, commercial, and factory prosumers. The results obtained by using this scenario are illustrated in below figures.

Fig. 25 shows Renewable energy generation –electricity consumption power mismatch of home using chance-constrained corrective action. Fig. 26 shows abandoned electricity of home-electricity purchase of the home using chance-constrained corrective action. Fig. 27 shows A) bill of home according to Iraq's electrical ministry, b) Cost of home of purchase/hour using chance-constrained corrective action. Fig. 28 shows Improving of home using chance-constrained corrective action. Fig. 29 shows Generation-demand power mismatch of company using chance-constrained corrective action. Fig. 30 shows abandoned electricity and electricity purchase of company using chance-constrained corrective action. Fig. 31 shows A) bill according to Iraq's electrical ministry of company, b) Cost of company purchase/hour using chance-constrained corrective action. Fig. 32 shows improving (%) of company using chance-constrained method. Fig. 33 shows Generation-demand power mismatch of Factory using chance-constrained corrective action. Fig. 34 shows abandoned electricity and electricity purchase of Factory using chance-constrained corrective action. Fig. 35 shows A) bill according to Iraq's electrical ministry of Factory, b) Cost of purchase/hour using chance-constrained corrective action. Fig. 36 shows improving of factory using the chance-constrained corrective action

3.4. Discussions and analysis

P2P energy trading allows consumers and prosumers to directly exchange surplus energy, offering benefits such as reduced costs, increased renewable energy adoption, and enhanced grid stability. Also, by facilitating local energy exchange, P2P trading can reduce reliance on centralized power grids, potentially decreasing transmission losses and improving overall grid stability.

A comparison between results obtained without corrective method, using ISSA correction method, and the chance-constrained method based on the total electricity bill is shown in Table 2.

The total electricity bill of home without correction methods is

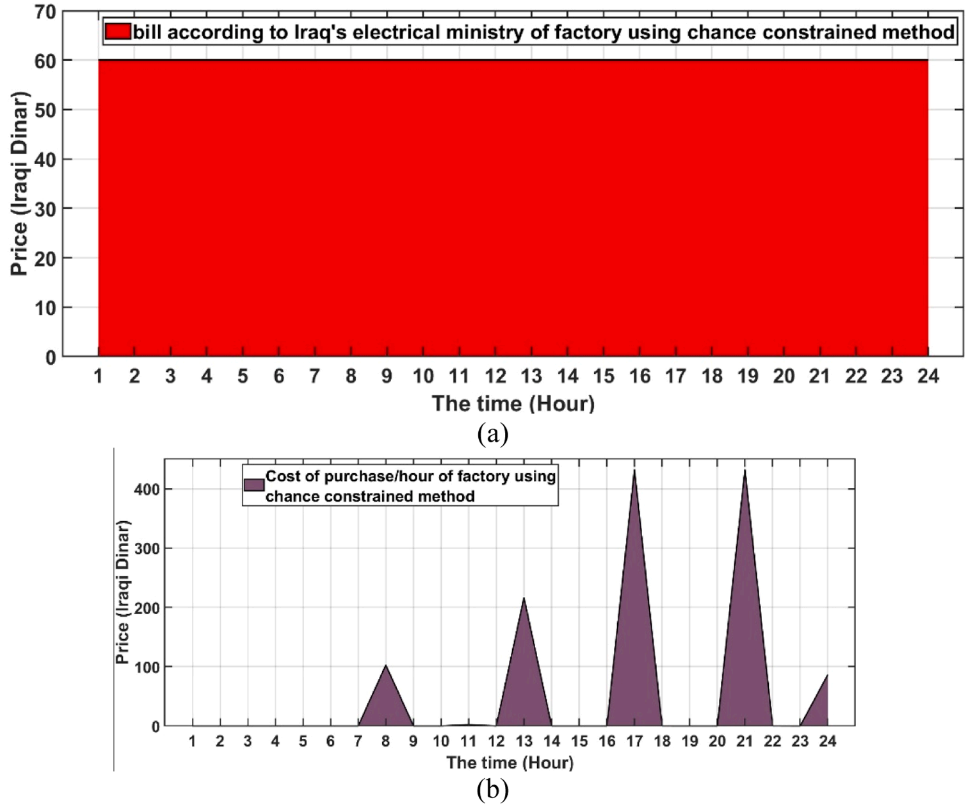


Fig. 35. A) Bill according to Iraq's electrical ministry of Factory, b) Cost of purchase/hour using chance-constrained corrective action.

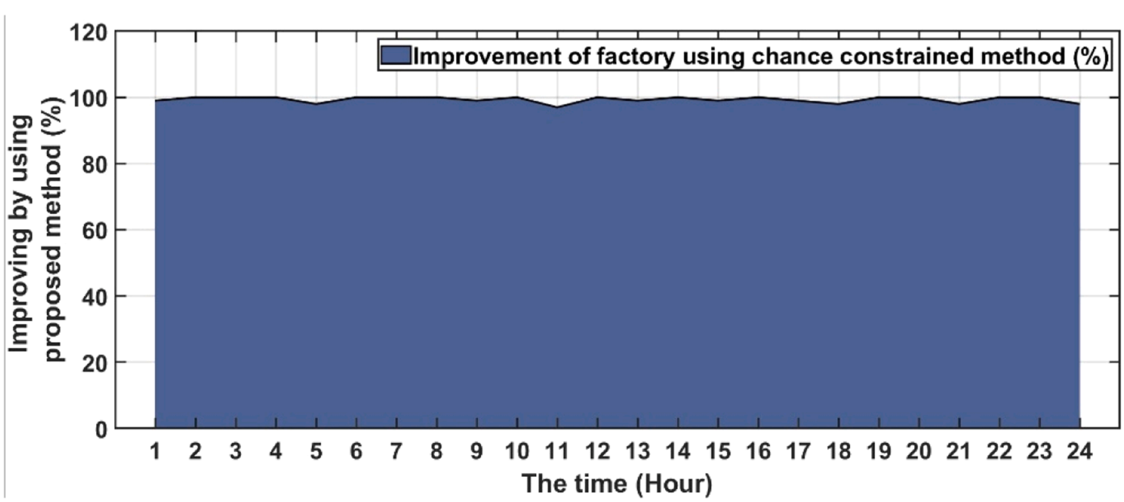


Fig. 36. Improving of Factory using the chance-constrained corrective action.

1248.91566 (ID). But after applying ISSA correction method, cost is found 856.7951(ID), and after applying chance-constrained correction method, cost is found 245.48964(ID). By comparing ISSA correction method and chance-constrained correction method with without correction methods, the ISSA algorithm saved 31.396% per day, and chance-constrained correction method saved 80.34% per day.

The total electricity bill of company without correction methods is 10,099.1 (ID). But after applying the ISSA correction method, cost is found 7442.4872 (ID), and after applying chance-constrained correction method, cost is found 3895.2424 (ID). By comparing ISSA correction method and chance-constrained correction method with without correction methods, the ISSA algorithm saved 26.305% per day, and the chance-constrained correction method saved 61.429% per day.

The total electricity bill of factory without correction methods is 2769.228 (ID). But after applying the ISSA correction method, cost is found 2662.772 (ID), and after applying chance-constrained correction method, cost is found 1271.916 (ID). By comparing ISSA correction method and chance-constrained correction method with without correction methods, the ISSA algorithm saved 3.844% per day, and the chance-constrained correction method saved 54.069% per day.

The comparison of the three scenarios—a) for a residence, (b) for a business, and (c) for a factory—based on the total power bill is displayed in Fig. 25. The comparison of the three situations based on improvement (%) is displayed in Fig. 26. Table 2 compares the outcomes of ISSA, suggested approach based on total electricity cost, and ISSA without the corrective procedure. A comparison of the three scenarios—a) for a

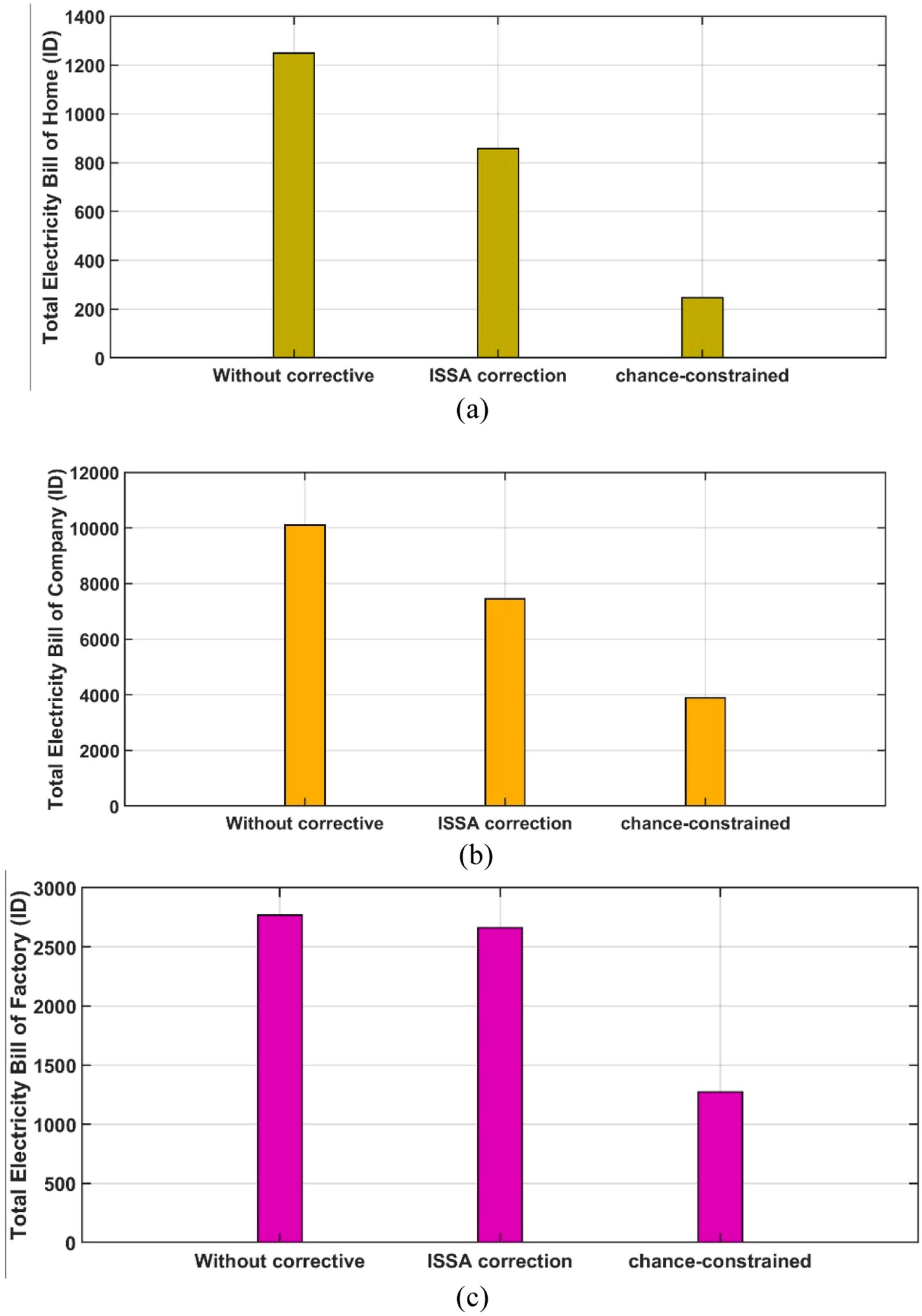


Fig. 37. Comparison between three scenarios based on total electricity bill, a) for home, (b) for company, (c) for factory.

residence, (b) for a business, and (c) for a factory—based on the total electricity bill is shown in Fig. 37. A comparison of the three situations based on improvement (%) is shown in Fig. 38.

An application's execution time requirement is computed for the chance-constrained scenario in order to verify and examine its complexity. Fig. 39 provides a visual depiction of the execution time. These numbers show that the program's execution time and memory use both rise with the number of loads taking part in the coalition. The execution time for residences, businesses, and factories is displayed in Fig. 39.

3.5. Correlate the existing energy trading mechanism with proposed energy trading mechanism

The current energy trading mechanisms, primarily dominated by centralized grid and traditional utilities, are evolving towards more decentralized and participatory models like P2P energy trading. The proposed mechanisms leverage P2P technologies to facilitate direct energy exchange between consumers and producers, thereby enhancing transparency, efficiency, and lowering costs. Here's a breakdown of the correlation:

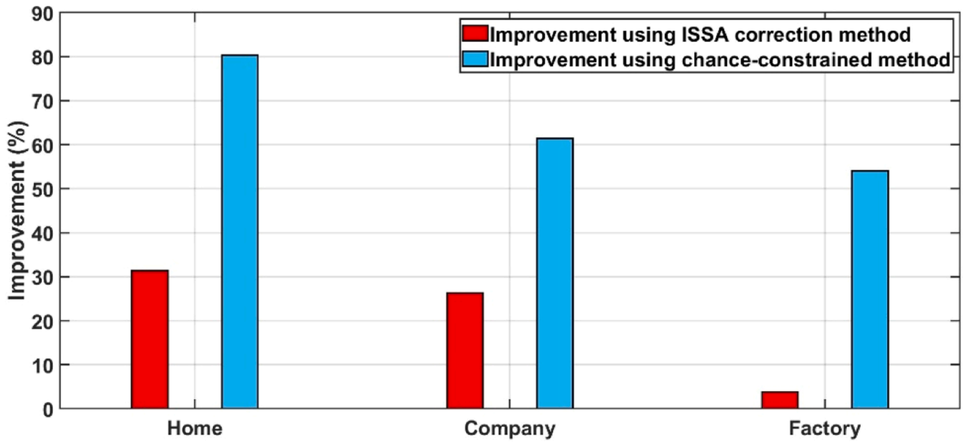


Fig. 38. Comparison between three scenarios based on improvement (%).

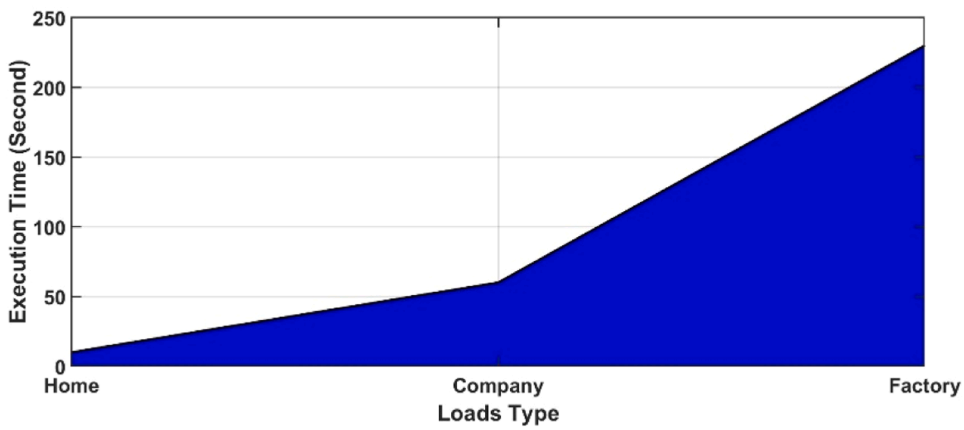


Fig. 39. Application running execution time.

1. Bridging the gap: The proposed mechanisms aim to integrate with the existing centralized infrastructure by allowing prosumers to connect to grid and also participate in decentralized P2P trading.
2. Incentivizing distributions' energy resources: The proposed Decentralized P2P trading can incentivize adoption of distributions' energy resources, like as photovoltaics and wind turbines
3. Evolutionary approach: Existing centralized energy trading transition to a proposed decentralized P2P energy system may involve a phased approach, gradually incorporating P2P trading alongside existing centralized structures.

4. Conclusion

The decentralized EMS presented in this paper allows prosumers in community to trade energy with one another while taking into account the energy and financial flow between homes, businesses, and factories. It also guarantees that each microgrid will experience a further decrease in energy costs when operating as a part of a community system as opposed to operating separately. By distributing the optimization tasks among the various Controller platforms placed in each microgrid, hierarchical energy management system lowers overall processing and computation time.

In order to assess P2P multi-energy trading amongst factory, residential, and commercial prosumers while taking integrated DSM into account, this study develops an optimization model. The suggested model may be a useful and effective trading-aiding instrument to establish fair trading prices and offer suggestions for the best designs of energy infrastructure. A case study demonstrates how successful the suggested strategy.

A comparison between results obtained without corrective method, using ISSA correction method only, and the chance-constrained method based on total electricity bill is shown in this paper. Where the total electricity bill of home without correction methods is 1248.91566 (ID). But after applying the ISSA correction method, cost is found 856.7951 (ID), and after applying chance-constrained correction method, cost is found 245.48964(ID). By comparing ISSA correction method and chance-constrained correction method with without correction methods, the ISSA algorithm saved 31.396% per day, and chance-constrained correction method saved 80.34% per day. Whereas The total electricity bill of company without correction methods is 10,099.1 (ID). But after applying the ISSA correction method, cost is found 7442.4872 (ID), and after applying chance-constrained correction method, cost is found 3895.2424 (ID). By comparing ISSA correction method and chance-constrained correction method with without correction methods, the ISSA algorithm saved 26.305% per day, and the chance-constrained correction method saved 61.429% per day. Finaly The total electricity bill of factory without correction methods is 2769.228 (ID). But after applying ISSA correction method, cost is found 2662.772 (ID), and after applying chance-constrained correction method, cost is found 1271.916 (ID). By comparing ISSA correction method and chance-constrained correction method with without correction methods, the ISSA algorithm saved 3.844% per day, and chance-constrained correction method saved 54.069% per day.

According to simulation results, utilizing the chance-constrained smart bidding technique for P2P trade has decreased the grid dependency and electricity prices of consumers and prosumers.

Future studies can examine the transformer's electrical and thermal limitations by leveraging the prosumer's versatility, potentially improving its performance within the distribution network. Furthermore, this work does not consider the thermal models of the commercial, industrial, and residential sectors, such as thermal energy storage and heat pumps. These models can be added later to add demand-side flexibilities and broaden the proposed framework.

Research ethics

We further confirm that any aspect of the work covered in this manuscript that has involved human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript. IRB approval was obtained (required for studies and series of 3 or more cases). Written consent to publish potentially identifying information, such as details or the case and photographs, was obtained from the patient(s) or their legal guardian(s).

Intellectual property

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

CRediT authorship contribution statement

Bilal Naji Alhasnawi: Formal analysis, Data curation, Conceptualization. **Basil H. Jasim:** Validation, Resources, Conceptualization. **Raad Z. Homod:** Software, Investigation, Conceptualization. **Bahamin Bazooyar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Marek Zanker:** Validation, Supervision, Software. **Vladimír Bureš:** Software, Resources, Methodology, Data curation.

Declaration of competing interest

No conflict of interest exists. We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.nexus.2025.100536.

Data availability

The data used for this research and preparation of this article can be accessed from Brunel University of London repository at: https://doi.org/10.17633/rd.brunel.25713888.v1.

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