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Energy exchange cooperative model in SDN-based interconnected multi-microgrids

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ABSTRACT

With the expansion of the microgrid systems (MGs) exploitation, the development of multi-microgrid systems (MMGs) is rising. Along with the benefits offered by a microgrid, the combination of several microgrids and their synergies in energy supply augments system stability and reliability and reduces energy costs and losses in transmission lines. With the connection of all microgrids together in an interconnected multi-microgrid (IMMG) and the provision of interoperability and energy sharing in these grids, the perfect platform is created for optimal distribution of energy sharing by the appropriate strategies of an effective energy management system (EMS). The present paper proposes a Software-Defined Networking (SDN) based cooperative model for sharing energy among microgrids via a transactive energy framework (TE) in interconnected multi-microgrids. The proposed model utilizes incentive mechanisms to encourage microgrid collaboration to reduce the final energy supply cost of an IMMG. The current work introduces the energy sharing factor (ESF) that provides an energy exchange mechanism for the IMMG manager. The effectiveness of the proposed model is investigated by a cost reduction analysis that employs the microgrids dataset.

1. Introduction

Microgrids are commonly referred to as distributed power systems with distributed storage devices and controllable loads. The coordination and control of distributed energy sources are key features that distinguish microgrids from simple distribution feeders. The key to achieving productivity benefits is effective energy management in microgrids by optimizing energy production and consumption. However, the technical challenges associated with the design, operation, and control of microgrids are enormous [1,2]. As important as the financial justification for microgrid efficiency is, it is also necessary to consider the electricity market environment and to quantitatively evaluate its benefits to stakeholders [3]. In recent years, IMMGs have become integrated, flexible networks comprised of multiple separate microgrids often geographically close and connected to a distribution bus [4,5]. Since energy is shared among microgrids in multi-microgrid systems, microgrids can meet their demand with their own cheaper, renewable energy sources. All microgrids in an IMMG are interconnected and can share energy among themselves and the macrogrid through power lines [4].

Like a microgrid, multi-microgrid systems can operate either standalone [1,6], or connected to a macrogrid (distribution network) [2,7,8]. Although microgrids cannot benefit from the macrogrid in the standalone or islanded mode, energy sharing through coordination with other microgrids enables them to maintain a supply and demand balance for financial and reliability purposes. Regarding how energy is shared among microgrids, this is achieved via direct distribution lines, designed to prevent energy congestion in the macrogrid [9].

In resource management of multi-microgrid systems, there are three approaches to energy management in these networks. In the first approach, each microgrid has a separate central controller responsible for managing the resources in the microgrid. In what is known as individual energy management, each microgrid manages energy resources to reduce its costs, regardless of production status and demand in other microgrids and the importance of energy balance in neighbor microgrids. Some neighbor microgrids may have surplus energy, and some may have energy deficiencies that are not considered in the management of internal microgrid consumers. In the second approach, all microgrids are managed by a central controller. For all microgrids, this central controller manages how internal resources are consumed and the amount of energy supplied by the macrogrid. In the third approach, which is a combination of the first two approaches, each microgrid has a separate central controller responsible for managing the microgrid resources and, at a higher layer, all

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Nomenclature

Acronyms

CP	Clearing Price
DERs	Distributed Energy Resources
DG	Distributed Generation
DSO	Distribution System Operator
ESF	Energy Sharing Factor
ESS	Energy Storage System
HPC	High Priority Class
IMMG	Interconnected Multi-MicroGrid
MG	MicroGrid
MGCC	MicroGrid Central Controller
MMG	Multi-MicroGrid systems
NC	Normal Class
PCC	Point of Common Coupling
PDA	Periodic Double Auction
REMS	Retail Energy Market Server
TE	Transactive Energy framework
TFS	Transactive Feedback Signal
TI	Time Interval
TIS	Transactive Incentive Signal
TOUP	Time of Use Pricing
WB MG	Winning Buyer MicroGrid
WS MG	Winning Seller MicroGrid

Functions

IsCriticalStatus()	Returns true on IMMG critical status e.g. natural disasters and false otherwise
LowerClass(classi)	Returns the first class that is lower than $class_i$
UpperClass(classi)	Returns the first class that is upper than $class_i$

Parameters/constants

CC_i	Battery rechargeable capacity (kW) of microgrid i's energy storage system
ESF_{min}	Minimum allowed value for energy sharing factor
ESF_{max}	Maximum allowed value for energy sharing factor
N	Total number of microgrids
R_{DI}	Rate of decrease or increase of the energy sharing in each period
T	Last time interval in a period

Variables

C_t^g	Distribution network's energy costs per unit of power in time interval t
C_t^s	Price of energy sales per unit of power in time interval t
C_{Trans}	energy sharing cost
MGCs	Vector of MGs' current classes
MGESFs	Vector of MGs' current energy sharing factors
P_i^{max}	Maximum transferable energy for microgrid i in time interval t
$RE_{n,t}$	The remaining energy of microgrid n in time interval t (kW)
REs	Vector of microgrids' remaining energy (kW)
SE_t	MG's surplus energy in time interval t (kW)
SEs	Vector of microgrids' surplus energy (kW)
$SoC_{i,t}$	Microgrid i's state of charge in time interval t (%)
UMGCs	Vector of MGs' updated classes
UMGESFs	Vector of MGs' updated energy sharing factors

Objective Functions

c_t^{IMMG}	MMG's total costs in time interval t
p_t^{MG}	Microgrid total profits in time interval t

Decision Variables

α_t	The surplus energy fraction which must be injected into macrogrid in time interval t
β_t	The surplus energy fraction, which must be shared with neighbor microgrids
$\lambda_{n,t}$	Microgrid n's remaining energy fraction, which must be supplied from the distribution network
$\mu_{ij,t}$	The energy transferred fraction from microgrid i to microgrid j in time interval t

microgrids are managed by a higher layer controller for the exchange of energy [9]. Comparing the daily energy loss variations in multi-microgrid systems for the first two individual energy management approaches and the third collective approach illustrates the superiority of collective management over individual energy management in each microgrid [9]. In practice, although each microgrid may be inclined to independent management and discrete energy management systems, research studies show that simultaneously implementing energy management for the whole multi-microgrid system is more beneficial and cheaper for each grid than when individually implementing it [9]. The collective energy management method of multi-microgrid systems also averts common problems. It will curb independent behavior solely in accordance with the individual interests of each microgrid and prevent the functioning of microgrids when their depletion of shared resources is detrimental to the whole system.

It is worth noting that the demand-side management process brings together both the mutual benefits of customers and the macrogrid. Customers will benefit from paying the macrogrid for electricity because of the low prices. In turn, the macrogrid can benefit from load balancing and stress reduction for transmission and distribution systems. In dealing with control strategies in multi-microgrid systems, the main issue is the use of private controllers, which must have a certain degree of independence and communicate with each other to carry out specific control measures. A semi-decentralized scheme's need is justified by a significant increase in the size and complexity of the system. Thus, the management of a multi-microgrid system requires a more flexible control and management unit [3].

2. Related works

Energy management methods in multi-microgrid systems are divided into two main categories, centralized and distributed, according to the structure of scheduling optimization [4]. Each type of energy management system has its competencies and features. Creating a deal between them in a single energy management strategy is a challenging task. Hybrid energy management systems have emerged in the literature as a solution for managing IMMGs [10]. In a centralized method, coordination can be satisfied but involves higher communication and computational requirements. As in any other centralized system, there will also be bottlenecks in addition to a lack of privacy. For these reasons, centralized energy management policies are not very popular in IMMGs [4].

For distributed methods, the main techniques investigated in the literature fall into three categories: dual decomposition, game theory, and other distributed strategies [4]. This section will refer to research conducted on each of these categories while taking a closer look at studies coming under this paper's scope. Dual decomposition is a commonly used optimization method, suited to situations where distribution system operators (DSOs) and microgrids belong to different entities [11–14]. The research by [11] presents a hierarchical outage management scheme for dealing with critical events. According to the proposed framework, in the first step, the microgrids plan their available resources via a control-based algorithm. Secondly, the distribution system operator coordinates the energy transmitted among the microgrids and utilizes the unused capacity of their resources to feed the unanswered loads from the first stage. When the macrogrid is out of reach due to critical events, power management can be one of the multi-microgrid systems' most important strengths [11,15–20].

Due to multi-microgrid systems' interconnected structures and the possibility of different ownerships for existing microgrids in the system, changes in energy status have their consequences. When one microgrid attempts to optimize its energy program, the result affects other microgrids. As for the sharing of surplus energy, conflicts may arise between the decisions made by microgrid central controllers. Such challenges provide the perfect platform for applying game theory algorithms to IMMG energy management systems. Researchers often use cooperative and non-cooperative game theory to solve this kind of problem [4]. In cooperative game theories, microgrids coordinate their strategies and share the benefits [21,22].

In the non-cooperative game theory, there is no agreement between microgrids, and every microgrid attempts to maximize its interests [23–25]. Some research has utilized both of these game theory methods. [26] presents a two-level game model, whose upper level is a non-cooperative price game between a multi-microgrid and a macrogrid while the lower level is a cooperative trading loss cost game.

As the number of microgrids in an IMMG rises, the energy optimization problem's volume increases, thus rendering the problem more complicated. The owners of microgrids are also interested in independent management and privacy when sharing extra energy. Therefore, the multi-microgrid energy management system should simultaneously maintain both the independence of each microgrid and the collective management of the microgrids, while fairly allocating power from the macrogrid to each microgrid and evenly exchanging energy between the microgrids.

The present study proposes a cooperative model for energy sharing in IMMGs. This model reduces the total cost of the power supply in microgrids by equitably distributing energy among them while maintaining the conditional independence of each microgrid's central controller. Besides, the main criterion for energy sharing in the literature has been energy cost. Along with considering energy cost for energy sharing management in the IMMG, the current paper defines a new criterion, called the energy sharing factor (ESF).

3. Contributions

3.1. Propose a new incentive policy by defining the energy sharing factor (ESF)

The current work introduces a factor called the energy sharing factor (ESF), whereby microgrids share their surplus energy. In the proposed cooperative model, microgrid's independence is also taken into account in the selling of their surplus energy. Each microgrid can reduce the amount of this factor by sharing its surplus energy at any period and selling its surplus energy by its policies. The energy sharing factor provides conditional independence to the central microgrid controller for managing its surplus resources. The ESF also enables the IMMG manager to have all microgrids participate in the energy sharing plan; however, this depends on the IMMG policy or event occurrence. The proposed factor is an incentive mechanism for microgrids to participate in an energy sharing plan to reduce ESF and take advantage of selling their surplus energy at a higher price. All microgrids agree to participate in the energy sharing plan based on the energy sharing factor.

3.2. Take advantage of SDN in the transactive energy framework

We have taken advantage of the SDN architecture in the transactive energy framework by modeling the SDN-based transactive energy framework, which has not been done before [27]. Given the retail energy market server's role in the transactive energy framework, we consider it as an SDN controller that manages energy in IMMG by exchanging transactive incentive and feedback signals with microgrid central controllers.

3.3. Classify microgrids

The present work employs the concept of class to determine the priority for receiving energy from neighbor microgrids. Microgrids are classified according to their type of operation and the amount of cooperation they have in energy sharing. Some microgrids have consumers that are critical to supplying electricity to, such as hospitals, so these microgrids are given the highest priority. Other microgrids are classified according to their participation in the energy sharing plan. Higher participation means being assigned to a class with a higher priority than a class for non-critical operations.

3.4. Model energy management system of IMMG based on transactive energy framework

The transactive energy framework (TE) defines this energy as a system of control and economic mechanisms that enable dynamic balancing between production and demand across all sectors of the electrical infrastructure by using price as a key operating parameter [28]. Expressing the framework definition across the entire electricity infrastructure indicates that this method applies to the whole electrical system from transmission to mass generation, to the macrogrid, and ultimately to different consumers [29]. Given the broad definition of the transactive energy framework, the current study has adapted this definition to the proposed model and used it to communicate within the IMMG for energy sharing. Articles have been published in recent years about utilizing the transactive energy framework in multi-microgrid systems [30–32]. The model proposed by these articles generally features two layers of microgrids and DSO, energy cost as the decision-making key, and the distribution of energy management. The model introduced by the current study utilizes the transactive energy framework with the new concept of the ESF, along with energy price, in the microgrid and IMMG layers. The proposed model also employs collective energy management in the IMMG.

The rest of the paper is organized as follows. Section 4 presents the system model in four sub-sections: IMMG topology and components, time scheduling, REMS SDN controller modules, and market model. The current work divides the problem into two layers, the microgrid, and IMMG, while Section 5 formulates the problem. Results and discussion are presented in Section 6, which is followed by the conclusions in Section 7.

4. System model

4.1. IMMG topology and components

Similar to microgrids, IMMGs can also operate in either a grid-connected mode or an islanded mode. In the grid-connected mode, microgrids can supply the energy they need by using three of their locally distributed power generation sources, neighbor microgrids, and the macrogrid. Utilizing other microgrids' surplus energy is less costly than that purchased from the macrogrid and results in a reduction in the total cost of the IMMG. In the islanded mode, reliability is crucial in preventing blackouts [33], and this is also true of microgrid systems. The ability to obtain energy from other microgrids increases the reliability of the entire system.

There are three common types of IMMG topologies: radial topology, daisy-chain topology, and mesh topology [4]. In these topologies, the level of interaction and cooperation between microgrids will increase respectively and result in a more complex IMMG energy management system. The current paper employs the mesh topology to develop the proposed energy exchange cooperative model. In the mesh topology, all microgrids are interconnected and can exchange energy with each other. Fig. 1 presents the structure of the proposed SDN-based interconnected multi-microgrid system.

Each microgrid consists of some heterogeneous components, such as distributed power generation (DG), electrical loads, and energy storage systems (ESS). Microgrid power generation may be produced from a range of variable distributed energy resources (DER's), including renewable and fossil-fueled generators. A microgrid can supply its electricity demands with internal resources or receive energy from a macrogrid in a grid-connected mode. The microgrid can also control the power flow at the point of common coupling (PCC) by controlling the charging and discharging of batteries. In each microgrid, the task of energy management is the responsibility of the microgrid central controller (MGCC).

The integration of SDN and microgrids introduces numerous benefits to communication network engineering, including but not limited to strictly defined primary and failover communication paths, end-to-end latency and bandwidth guarantee, real-time monitoring capability, and system-wide visualization [34]. Since in current work the proposed model traffic is not sensitive to the quality of service in communication network at the physical layer, such as latency in real-time traffic, the current work focus is on the upper layers, namely the application layer and the benefits of SDN in this layer and its relationship with the control layer. The SDN application plane comprises SDN applications which are control programs designed to implement the network control logic and strategies. This higher-level plane interacts with the control plane via an open Northbound interface [35]. In current work, the five applications of data collection, energy supply optimization, energy sharing optimization, classification, and ESF calculation are defined at the application plane. In the context of SDN, applications leverage the decoupling of the application logic from the network hardware along with the logical centralization of the network control, to directly express the desired goals and policies in a centralized high-level manner without being tied to the implementation and state distribution details of the underlying networking infrastructure. The Northbound interface implemented by SDN controllers can be regarded as a network abstraction interface to applications, easing network programmability, simplifying control and management tasks, and allowing for innovation [35].

By developing an SDN-enabled architecture, we can achieve fast power support among microgrids, transforming isolated local microgrids into integrated IMMGs to achieve the desired resiliency, elasticity, and efficiency [34,36,37]. The current work proposes an SDN-based transactive energy framework that manages energy sharing (the amount and form of inter-MGs energy exchange) through exchanging transactive incentive signal (TIS) and transactive feedback signal (TFS) messages between SDN controllers, which are located retail energy market server (REMS) and microgrid central controllers. In the transactive control system, the local power generation status is transmitted and received using transactive incentive signals and the load adjustment responses by transactive feedback signals, as a way to match the consumer load with the given supply scenario in the macrogrid.

At the application plane, the five applications of data collection, energy supply optimization, energy sharing optimization, classification, and ESF calculation, receive their requirements from the control plane and send back the appropriate responses such as energy sharing plan and microgrids ESF to the control plane. At the control plane, multiple SDN controllers have been proposed in IMMG and microgrids Layers. The SDN controller that is located in the retail energy market server utilizes transactive incentive signal and transactive feedback signal messages to communicate with microgrids' controllers and determines information such as the amount of ESF, energy costs, and how to share energy for all microgrids. Through the OpenFlow protocol, SDN controllers, located in microgrid central controllers, send the necessary information for energy sharing to ESSs, which act as SDN switches.

The proposed model is presented in the application layer. However, the power grid's physical constraints and the power flow, such as voltage limits, are not covered by the present article.

4.2. Time scheduling

The proposed model performs optimization problems in two layers, the microgrid, and IMMG, by dividing the day into specified time intervals. At the beginning of each time interval, all microgrids solve their energy management problem according to their available resources and internal consumers' load demand [38–41] (the current paper does not address the resource optimization problem per microgrid). After that, each microgrid shares the amount of residual energy or energy deficit with a higher layer, i.e., the IMMG, according to its energy sharing factor (ESF).

In the second layer, the retail energy market server solves the IMMG energy management problem based on the microgrids' information and the class of each microgrid. The retail energy market server determines the amount of energy received by a microgrid and the microgrid that supplies the energy. After this stage, microgrids that still have surplus energy or energy deficit participate in a periodic double auction (PDA) market to sell their surplus energy or provide their deficient energy. This process is restarted at the beginning of each interval, and the information is updated. Fig. 2 presents the flowchart of the proposed model.

As shown in Fig. 2, the proposed model is presented in two layers of microgrid and IMMG. In previous works on hybrid energy management systems for multi-microgrids [1,2,6–8], in the second part, energy management is presented in the form

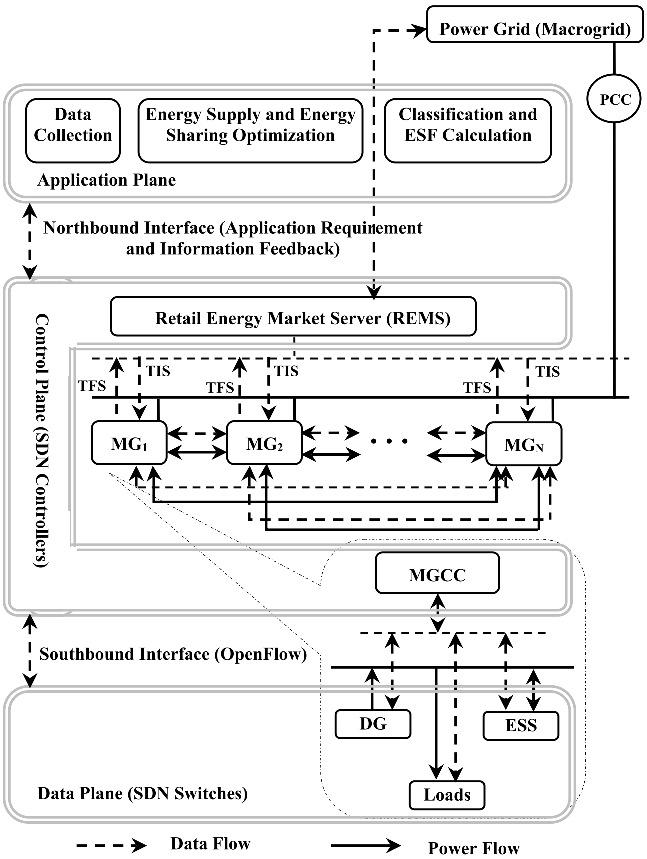

Fig. 1. The proposed SDN-based interconnected multi-microgrid system structure.

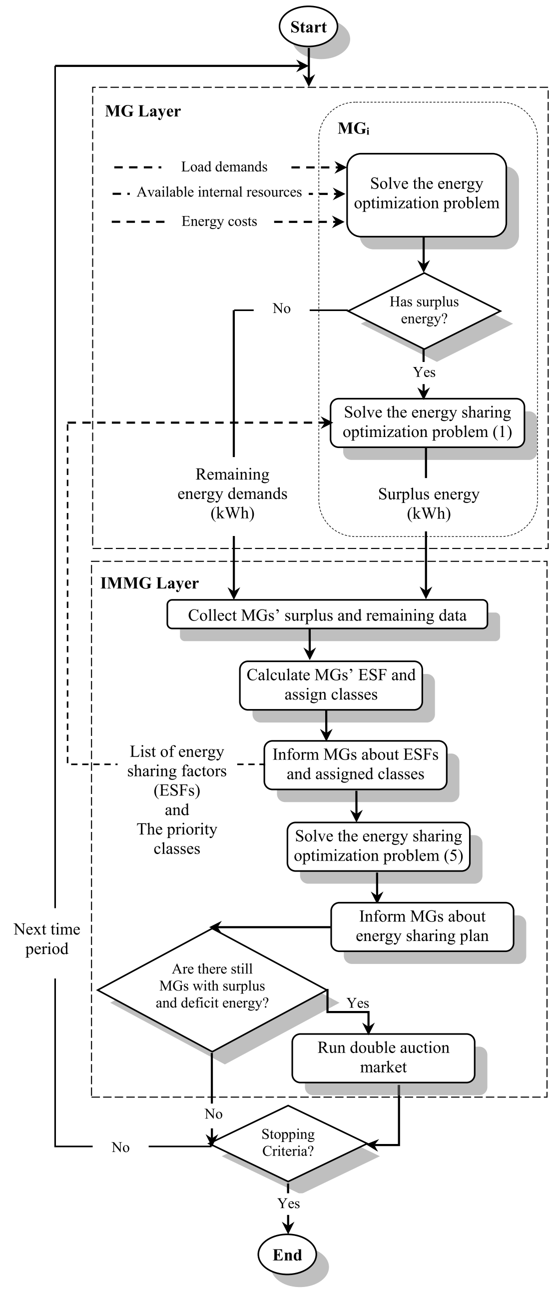

Fig. 2. Flowchart of the proposed cooperative model.

of an optimization problem with a cost minimization objective function. In the proposed model, in order to provide conditional independence for microgrids to increase the revenue from the sale of surplus energy, the problem of optimizing energy management in the second part is presented in two layers of microgrid and IMMG. The microgrids with surplus energy can reduce the amount of energy sharing factor by participating in the energy sharing plan, and by participating in the double auction market, they can make more profit by selling their surplus energy at a higher price in comparison to the IMMG's internal energy price. The proposed model provides a balance between minimizing the cost of IMMG and maximizing the profits of microgrids with surplus energy.

4.3. REMS SDN controller modules

The retail energy market server, which acts as the central SDN controller of the IMMG, has five main modules for classifying microgrids and energy management: the energy sharing factor (ESF) calculation, microgrid classification, data collection, and energy supply and sharing optimization.

Considering the growing ratio of Direct Current (DC) loads e.g., computers, lighting systems, and battery chargers in residential and commercial usage, and distributed energy resources e.g., renewable sources, DC microgrids have gained widespread acceptance in modern distribution systems. DC microgrids can offer many benefits over Alternating Current (AC) counterparts such as the elimination of multiple AC/DC conversion stages can lead to a reduction in energy losses and more economical operation [42–45].

Theoretically, more points of failure will reduce reliability. In terms of the need to use AC/DC converters, DC devices, and distributed energy resources require the step of converting direct current to alternating current to connect to the alternating current network. These multiple conversion steps reduce the overall performance and reliability of the systems. Some of these conversion steps can be reduced by connecting these devices directly to a direct current network using a high-performance direct current to a direct current converter. The reliability and efficiency of electrical networks are improved by using direct current distribution in microgrids [45,46].

In a direct current network system, energy sources and loads can be supplied efficiently by selecting an appropriate voltage level and avoiding the use of multistage converter [42,45,47,48]. Therefore, it can be said that by supplying energy through neighbor microgrids in a multi-microgrid, in addition to reduce the cost of energy supply, the reliability and quality of energy received can be improved. The proposed model prioritizes microgrids to assign a higher quality of service in electricity, which means lower cost and higher energy reliability.

To prioritize microgrids that receive energy from neighbor microgrids, the retail energy market server assigns a specific class to each microgrid based on the type of microgrid functionality and its cooperation in energy sharing. Initially, all microgrids are categorized into two classes: high-priority classes (HPC) for critical-function microgrids and normal classes (NC) for other microgrids. Microgrid classification can be viewed as an incentive policy for microgrids to participate in surplus energy sharing, in addition to prioritizing microgrids and their receipt of energy to deal with critical events. Energy sharing is directly related to the ESF and allocates a higher priority class to the microgrid. In the form of a pseudo-code, Algorithm 1 demonstrates how a class is assigned to microgrids and calculates the ESF for each microgrid.

Algorithm 1 Classification and ESF Calculation Module

function ESFModule(*SEs*, *REs*, *MGCs*, *MGESFs*, c_g, c_{trans})

Input: vector of microgrids surplus energy *SEs*, the vector of microgrids remaining energy demands *REs*, the vector of current microgrid classes *MGCs*, the vector of current microgrid ESFs *MGESFs*, vector of macrogrid energy costs c_g, energy sharing cost c_{trans}

Output: vector of updated microgrid classes *UMGCs*, the vector of updated microgrid ESFs *UMGESFs*

```
1  for counter1:=1 to N do
2      tmpVr ← 0
3      for counter2:=tk to T do
4          if cg[counter2] – cTrans > 0 then
5              tmpVr ← tmpVr
6                +(SEs[counter1][ counter2] - REs[counter1][ counter2])
7          end
8      end for
9      if tmpVr > 0 then
10         UMGESFs[counter1] ← MGESFs[counter1] – R_DI
11         if MGCs[counter1] <> HPC then
12             UMGCs[counter1] ← UpperClass(MGCs[counter1])
13         end
14     else
15         UMGESFs[counter1] ← MGESFs[counter1] + R_DI
16         if MGCs[counter1] <> HPC then
17             UMGCs[counter1] ← LowerClass(MGCs[counter1])
18         end
19     end
20     if UMGESFs[counter1] > ESF_max then
21         UMGESFs[counter1] ← ESF_max
22     end
23     if UMGESFs[counter1] < ESF_min then
24         UMGESFs[counter1] ← ESF_min
25     end
26     if IsCriticalStatus() then UMGESFs[counter1] ← ESF_max end
27 end for
```

To calculate the ESF value and class of each microgrid for a time period, Algorithm 1 considers a measure (tmpVr) for an increasing or decreasing ESF value and the assignment of a higher or lower priority class (Algorithm 1, lines 3–8). The measure, tmpVr, is the difference between the remaining energy demand and the surplus energy of a microgrid over time intervals, where the difference between the energy purchase and energy exchange costs is positive. Based on the value obtained for tmpVr, the ESF value, and the assigned class for microgrids (not the HPC class) are updated (Algorithm 1, lines 9–19). If unexpected events occur, such as natural disasters, the REMS manager will adjust the ESF value of all microgrids to the maximum value (ESF_{max}), regardless of a microgrid's participation in the energy sharing plan (Algorithm 1, line 26). After the critical condition ends, the microgrid's ESF value is certainly adjusted to the last value before the event.

The data collection module is responsible for collecting data on all microgrids at defined intervals. These data include information, such as the batteries' state of charge (SoC) in the microgrid storage systems (surplus energy) and the remaining amount of energy to be supplied by the microgrids or, in other words, the energy to be supplied through the macrogrid (energy shortage).

After the required information from the microgrids is gathered, the optimal plan is determined for how to supply or allocate the energy deficit or surplus to the microgrids. The optimization module will determine how and how much power the microgrids need to supply through the macrogrid and other microgrids by obtaining data from the data collection module.

4.4. Market model

The proposed electricity market in this paper is a hybrid market, which consists of three pricing models: (1) The day-ahead time of use electricity pricing, (2) The IMMG internal pricing for energy sharing among microgrids (3) The periodic double auction market pricing. The first pricing model is applied at purchasing energy from the macrogrid, the cost of electricity per kWh is determined by the macrogrid based on time of use. To share energy among neighbor microgrids, the REMS SDN controller determines a specific price for all energy exchanges among microgrids, depending on the production costs. This price will be lower than the cost of purchasing electricity from a microgrid during peak consumption times.

If there are both microgrids with surplus energy and energy deficit, the periodic double auction market will be triggered. A visual abstraction of the market model is shown in Fig. 3. In off-peak hours, due to the low distribution network's energy costs, the aim of minimizing energy supply costs in IMMG by considering the limitation of not creating a challenge for the distribution network will be achieved by purchasing energy from the distribution network. Therefore, the cost of energy sharing among microgrids at off-peak hours is higher than the distribution network's energy cost.

The seller microgrids can participate in this market, depending on the amount of their ESF. Microgrid agents offer to sell bids at a relatively low price, usually far below the generation cost of local units while providing the buying bids at higher prices to ensure that the bids are always admissible [49]. The retail energy market server will compute the market-clearing price and trading allocations after the demand and supply information is collected. An ideal double auction mechanism would satisfy the following four properties of Individual Rationality (IR), Balanced Budget (BB), Truthfulness (TF), and Economic Efficiency (EE). Since the current work's main issue is not the double auction market, the details of its mechanisms are not addressed, and the basic mechanism of the PDA market is utilized.

5. Problem formulation

This section formulates optimization problems in two layers: the microgrid and IMMG. The results of the first-layer optimization problems are given as input to the second-layer optimization problem, i.e., the IMMG layer. The final result will show how to allocate energy to the microgrids' remaining requests while minimizing the system's total energy supply costs.

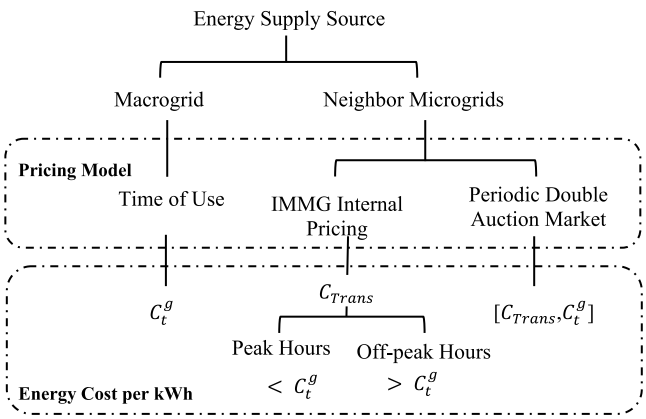

Fig. 3. The Market Model.

5.1. MG layer optimization problem

In the microgrid layer's optimization problem, microgrids with surplus energy are encouraged to cooperate in providing their remaining energy to other microgrids with the help of the energy sharing factor (ESF). In this optimization problem, the objective is to maximize the microgrid's profit from its surplus energy (SE). The microgrid i's optimization problem at the microgrids layer is formulated as follows:

$$Max \sum_{t=t_k}^{T} p_{i,t}^{MG} = Max[[\left(1-ESF_{i,t}\right).\sum_{t=t_k}^{T} \alpha_{i,t}.C_t^s.SE_{i,t}] + [ESF_{i,t}.C_{Trans}.\sum_{t=t_k}^{T} \beta_{i,t}.SE_{i,t}]] \tag{1}$$

$S.t.$

$$\forall t | t \in \{t_k, T\}: SE_{i,t} \le SoC_{i,t}.CC_i \tag{2}$$

$$\forall t | t \in \{t_k, T\}: \alpha_{i,t}.SE_{i,t} + \beta_{i,t}.SE_{i,t} \le P_i^{max} \tag{3}$$

$$\forall t | t \in \{t_k, T\}: \alpha_{i,t} + \beta_{i,t} \le 1 \tag{4}$$

The optimization problem is solved for $(T - t_k)$ time intervals, starting from t_k to time interval T. The decision variables in the microgrids layer optimization problem are α and β, which determine the fractions of surplus energy (SE) that must be injected into a macrogrid at the price of C_t^s or must be shared with neighbor microgrids, respectively. For all microgrids, the cost of energy sharing among them (C_{Trans}) is assumed to be constant over time. Inequalities (2) and (3) determine the maximum surplus energy based on the state and capacity of the energy storage system and the maximum transferable energy for microgrid i in time interval t, respectively.

The energy sharing factor (ESF) will be constant each time the optimization problem is solved, from the beginning time interval (t_k) to the last time interval (T) and its changes will be applied to the next optimization problem-solving period.

5.2. IMMG layer optimization problem

The proposed cooperative model's objective function in the IMMG layer is to minimize the cost of the energy supply (c_t^{IMMG}) for the remaining microgrid requests through other microgrids and the macrogrid. The optimization problem is solved for $(T - t_k)$ time intervals, starting from t_k to time interval T. The cost function (c_t^{IMMG}) is divided into two parts: the cost of purchasing energy from the macrogrid (C_t^g) and the cost of exchanging energy among neighbor microgrids (C_{Trans}).

The decision variables in the proposed optimization problem are λ and μ, which determine the fractions of the remaining microgrids' electricity demands (RE) that must be supplied from the macrogrid or neighbor microgrids, respectively.

The expression, $\mu_{ij,t}$ denotes the fraction of energy transferred from microgrid i to microgrid j during time interval t. Inequality (6) limits the amount of energy supplied from the neighbor microgrids' sources. With the total remaining energy, expression (7) guarantees the balance of energy exchanged between the microgrids and the energy supplied by the macrogrid. The optimization problem at the IMMG layer is formulated as follows:

$$Min \sum_{t=t_k}^{T} c_t^{IMMG} = Min \sum_{t=t_k}^{T} [C_t^g . \sum_{n=1}^{N} \lambda_{n,t}.RE_{n,t} + C_{Trans}. \sum_{i=1}^{N}\sum_{j=1}^{N} \mu_{ji,t}.RE_{i,t}] \tag{5}$$

$S.t.$

$$\forall i, t | i \in \{1, N\}, t \in \{t_k, T\}: \sum_{j=1}^{N} \mu_{ij,t}.RE_{j,t} \le \beta_{i,t}.SE_{i,t} \tag{6}$$

$$\forall j, t | j \in \{1, N\}, t \in \{t_k, T\}: \lambda_{j,t}.RE_{j,t} + \sum_{i=1}^{N} \mu_{ij,t}.RE_{j,t} = RE_{j,t} \tag{7}$$

$$\forall i, t | i \in \{1, N\}, t \in \{t_k, T\}: \sum_{j=1}^{N} \mu_{ij,t}.RE_{j,t} \le SoC_{i,t}.CC_i \tag{8}$$

$$\forall n, t | n \in \{1, N\}, t \in \{t_k, T\}: \lambda_{n,t}.RE_{n,t} + \sum_{i=1}^{N} \mu_{in,t}.RE_{n,t} \le P_n^{max} \tag{9}$$

$$\forall i, t | i \in \{1, N\}, t \in \{t_k, T\}: \sum_{j=1}^{N} \mu_{ij,t}.RE_{j,t} \le P_i^{max} \tag{10}$$

$$\forall n, t | n \in \{1, N\}, t \in \{t_k, T\}: 0 \le \lambda_{n,t} \le 1 \tag{11}$$

$$\forall i, j, t | i, j \in \{1, N\}, t \in \{t_k, T\}: 0 \le \mu_{ij,t} \le 1 \tag{12}$$

Inequalities (8) to (10) determine the energy sharing constraints based on the state of the energy storage systems and the maximum transferable energy between receivers and transmitters, respectively.

6. Results and discussion

The numerical test of the proposed model is performed in an IMMG system with six microgrids. All microgrids are connected to a bus, and the schedule period for the next day starts at 00:00 A.M. $t_k = 0$ and ends at 11:00 P.M. $(t_k = T = 23)$. Table 1 provides the microgrids' surplus energy and remaining energy demand profile for one time period (24 time-intervals). The surplus energy of each microgrid in time interval t is determined by the capacity of its ESS (CC_i) and the state of charge ($SoC_{i,t}$). Positive numbers mean surplus energy, and negative numbers represent the remaining energy demands of each microgrid during that time interval. According to the number of microgrids in this experiment, six NC classes (NC1 to NC6) are considered. In addition, it is assumed that MG6 has critical applications and is placed

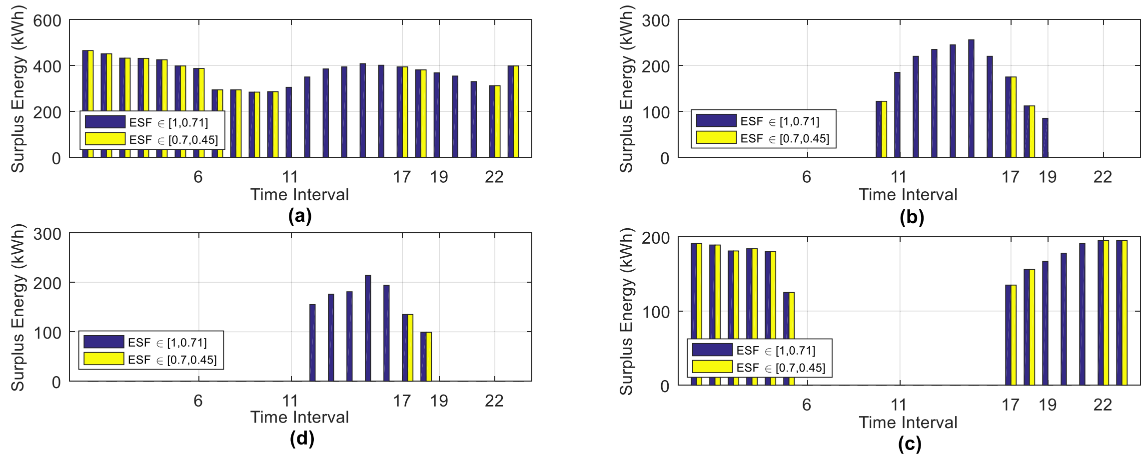

Fig. 4. Shared energy of microgrids with surplus energy (i.e. (a) MG1, (b) MG2, (c) MG4, and (d) MG6), based on the ESF value.

Table 1
MGs surplus energy and remaining energy demands.

Time interval	*Surplus/Remaining energy* (kWh)					
	MG1	MG2	MG3	MG4	MG5	MG6
0	+465	0	−366	+191	−266	0
1	+451	0	−244	+189	−86	0
2	+432	0	−236	+181	−46	0
3	+431	0	−222	+184	−78	0
4	+425	0	−231	+180	−65	0
5	+398	0	−289	+125	−74	0
6	+387	0	−261	0	−70	0
7	+294	0	−347	0	−38	0
8	+294	0	−387	0	−95	0
9	+284	0	−547	0	−112	0
10	+286	+122	−702	0	−90	0
11	+305	+185	−654	0	−78	0
12	+350	+220	−644	0	−75	+155
13	+385	+235	−636	0	−94	+176
14	+394	+245	−636	0	−222	+181
15	+408	+256	−631	0	−216	+214
16	+401	+220	−644	0	−366	+194
17	+394	+175	−636	+135	−563	+135
18	+381	+112	−702	+156	−655	+99
19	+368	+85	−689	+167	−890	0
20	+354	0	−667	+178	−865	0
21	+330	0	−644	+191	−842	0
22	+312	0	−547	+195	−623	0
23	+398	0	−467	+195	−589	0

in the HPC class, while other microgrids are placed in the NC6 class at the start of the system. For the first period, the energy sharing factor for all microgrids is set to 1 ($ESF_{max} = 1$). Here, the current research assumes that a macrogrid provides energy according to the time of use pricing (TOUP) model. For peak hours in this model, the price is 2.5 times the average electricity price; for off-peak hours, the price is one-third of the average electricity price. In the proposed model, the peak hours of use are set from 12 to 18 h and 20 to 23 h, while the off-peak hours are from 23 to 7 h. Also, the electricity sales price during peak hours is twice the average electricity price. The energy sales price to the macrogrid will be lower than the energy purchase price for all time intervals. In [50], a fog-based architecture is presented for transactive energy management systems, in which the energy exchange price function is determined based on the amount of available sales energy and the macrogrid's energy price.

In the presented architecture, the retail energy market server determines the inter microgrid energy price and broadcasts the transactive incentive signal to all microgrids having a shortage of energy. In the current research, the cost of energy sharing among microgrids is assumed to be constant throughout the day. This cost is lower than the macrogrid's energy purchase price during peak hours and higher than the energy purchase price during off-peak hours. To make prices independent from a specific currency, prices are divided by the average electricity price per kilowatt.

6.1. MG layer optimization results

In the microgrid layer, all microgrids with surplus energy (in this experiment, microgrids 1, 2, 4, and 6) solve the optimization problem (1) concerning the electricity sales price (C_t^s), energy sharing price (C_{Trans}), and their energy sharing factor (ESF). At the start of the system, the ESF is set to a maximum value (ESF_{max}) for all microgrids and is updated in each period, according to Algorithm 1.

Fig. 4 presents the graphs of four microgrids' shared energy, 1, 2, 4, and 6, based on their surplus energy in Table 1. Depending on the amount of the ESF assigned to the microgrid, the amount of energy shared at each time interval varies. Fig. 4 shows the energy sharing rate in the [1, 0.71] and [0.7, 0.45] intervals for the ESF. Concerning the electricity sales price to the macrogrid and the price of energy sharing among microgrids, the energy sharing rate drops to zero for ESF values below 0.45. According to test conditions, maintaining the minimum participation of microgrids in the energy sharing plan requires setting the minimum value for ESF (ESF_{min}) to 0.45. As shown in Fig. 4, in the [1, 071] interval for the ESF, the maximum amount of energy sharing by microgrids occurs even at peak hours when the energy sales price reaches its maximum.

As can be seen in the optimization problem (1), the three parameters C_t^s, C_{Trans} and $ESF_{i,t}$ are involved in determining the amount of energy shared by microgrids with surplus energy. The amount of difference between the selling price of energy and the price of energy sharing among neighbor microgrids affects the effectiveness of the energy sharing factor. According to the parameters, four states are debatable. In the state when the value of $\left(1 - ESF_{i,t}\right).C_t^s$ is lower than $ESF_{i,t}.C_{Trans}$ and C_t^s is also lower than C_{Trans}, microgrids with surplus energy tend to sell their surplus energy to the neighbor microgrids, which the aims of minimizing energy supply costs in IMMG and maximizing the revenue of microgrids with surplus energy will achieve. If C_{Trans} is lower than C_t^s, the goal of maximizing the revenue of microgrids with surplus energy will not be achieved, which due to the microgrid participation in the multi-microgrid energy sharing plan, the amount of ESF will decrease in the next time intervals.

Conversely, if the value of $\left(1 - ESF_{i,t}\right).C_t^s$ is greater than $ESF_{i,t}.C_{Trans}$ and C_t^s is also greater than C_{Trans}, the microgrid will

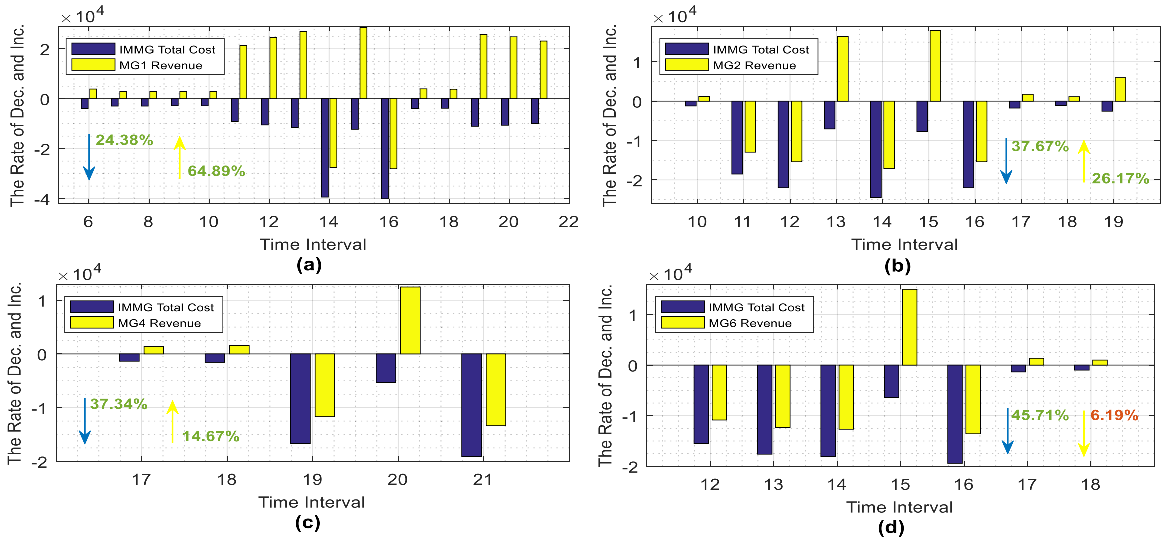

Fig. 5. The rate of change in the IMMG total cost and the microgrids' revenue.

be reluctant to participate in the multi-microgrid energy sharing plan, and the only goal of maximizing the revenue of the microgrids with surplus energy will be achieved, which due to the non-participation of the microgrid in the energy sharing plan, the amount of ESF will increase in the next time intervals, and then with the participation of the microgrid in the energy sharing plan, the goal of minimizing IMMG costs will be achieved. Finally, if C_t^s is lower than C_{Trans}, by increasing the amount of ESF in the next intervals, the two goals of minimizing energy supply costs in IMMG and maximizing the revenue of microgrids will be achieved.

The rate of change in the cost of energy supply in the multi-microgrid and the microgrid revenue, as a result of the microgrid's decision on the amount of sharing surplus energy, is shown in Fig. 5 at time intervals other than off-peak hours. In this experiment, the value of R_{DI} is set to 0.1 and the minimum ESF (ESF_{min}) is set to 0.45. MG1 has a higher percentage of revenue accretion due to its participation in the energy sharing plan at more time intervals.

6.2. IMMG layer optimization results

By the usage of data generated from the microgrid layer optimization problem, the IMMG layer optimization problem is solved. In this experiment, it is solved for the data obtained for two intervals, ESF ∈ [1, 0.71] and ESF ∈ [0.7, 0.45]. Table 2 presents the results for the ESF in [1, 0.71].

The Lambda (λ) column provides the fraction of residual energy supplied by the macrogrid for the two microgrids with an energy deficiency (i.e., microgrids 3 and 5). The Mu (μ) column reports the fraction of energy supplied from microgrids with surplus energy (i.e., microgrids 1, 2, 4, and 6). As seen in Table 2, the macrogrid supplies the energy required for microgrids 3 and 5 during off-peak hours, and, at other time intervals, the priority is to supply energy from neighbor microgrids.

Fig. 6 shows the total cost of the IMMG for one time period (24 time-intervals), both at the time of applying a cooperative model and not applying a cooperative model for the two intervals, [1, 0.71] and [0.7, 0.45], for the ESF. As shown in Fig. 6(a), utilizing the surplus energy of neighbor microgrids, especially at peak hours, exerts a significant impact on reducing total IMMG costs.

In the present experiment, at the time of maximum energy sharing by microgrids (the ESF in [1, 0.71]), a 35.3% reduction in IMMG energy supply costs is achieved (Fig. 6(a)). As shown

Table 2
IMMG layer optimization results for ESF ∈ [1, 0.71].

Time Int.	Lambda (λ)		Mu (μ)							
			MG1		MG2		MG4		MG6	
	MG3	MG5	MG3	MG5	MG3	MG5	MG3	MG5	MG3	MG5
0	1	1	0	0	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0	0
4	1	1	0	0	0	0	0	0	0	0
5	1	1	0	0	0	0	0	0	0	0
6	0	0	1	1	0	0	0	0	0	0
7	0.153	1	0.847	0	0	0	0	0	0	0
8	0.24	1	0.76	0	0	0	0	0	0	0
9	0.481	1	0.519	0	0	0	0	0	0	0
10	0.547	0	0.279	1	0.147	0	0	0	0	0
11	0.37	0	0.347	1	0.283	0	0	0	0	0
12	0	0	0.418	1	0.342	0	0	0	0.241	0
13	0	0	0.354	1	0.369	0	0	0	0.277	0
14	0.06	0	0.27	1	0.385	0	0	0	0.285	0.151
15	0	0	0.255	1	0.406	0	0	0	0.339	0
16	0.303	0	0.054	1	0.342	0	0	0	0.301	0
17	0.513	0.06	0	0.7	0.275	0	0	0.24	0.212	0
18	0.235	0.678	0.543	0	0	0.171	0.222	0	0	0
19	0.877	0.399	0	0.413	0.123	0	0	0.188	0	0
20	1	0.385	0	0.409	0	0	0	0.206	0	0
21	0.703	0.608	0	0.392	0	0	0.297	0	0	0
22	1	1	0	0	0	0	0	0	0	0
23	1	1	0	0	0	0	0	0	0	0

in Fig. 6(b), the amount of IMMG energy supply cost reduction is 2.8% at the minimum energy sharing (the ESF in [0.7, 0.45])). In the proposed model, the maximum power supply through the macrogrid occurs during the off-peak hours, and the maximum power exchanged through neighbor microgrids occurs during peak hours. In addition to significantly reducing the energy supply cost for the IMMG, this will improve the macrogrid's stability during peak hours.

Table 3 shows the IMMG cost reduction due to applying the proposed cooperative model and energy supply from neighbor microgrids and the macrogrid.

The cost of energy sharing among microgrids (C_{Trans}) is assumed to be constant at all time intervals. If the energy sharing price among the microgrids follows the macrogrid price pattern,

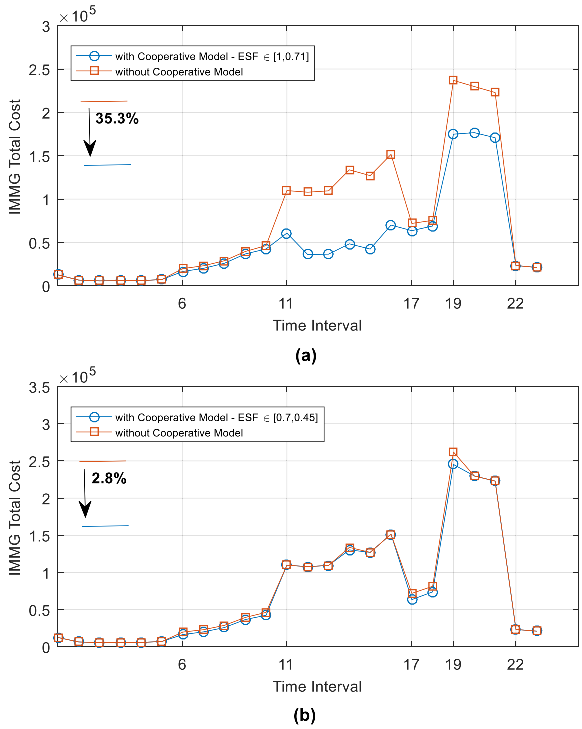

Fig. 6. The total cost of an IMMG when applying the cooperative model and when not applying the cooperative model for two intervals [1, 0.71] and [0.7, 0.45] for the ESF.

i.e., 2.5 times C_{Trans} during peak hours, the total energy supply costs in the IMMG increase. In this experiment, the IMMG energy supply cost, for the ESF value in the range [1, 0.71], increases by 28.04%, compared to the constant energy sharing price. This comparison is shown in Fig. 7.

6.3. PDA market results

Since the ESF gives conditional independence to the microgrids participating in the IMMG energy sharing plan, they can sell their surplus energy in the PDA market and achieve more profit.

The seller microgrids offer sell bids at a relatively low price while the buyer microgrids providing the buying bids at higher prices to ensure that the bids are always admissible [49]. Given that it is possible to buy energy through macrogrid at the price of C_t^g, the sell bids of the seller microgrids must be lower than this amount. Also, since the goal of seller microgrids from participating in the double auction market is to increase revenue, buyers should provide the buying bids with values higher than C_{Trans}, otherwise, the market will not be cleared. The buyer microgrids' bids and seller microgrids' asks are uniformly distributed over $[C_{Trans}, C_t^g]$ at any time interval t.

In the present experiment, while the ESF value is in the range [0.7, 0.45], it is feasible to participate in the PDA market for surplus energy microgrids and, of course, energy-deficient microgrids. If the IMMG layer optimization problem for buyer microgrids (energy-deficient microgrids) suggests purchasing energy from the macrogrid, these microgrids can participate in the PDA market to reduce energy supply costs. The essential point here is the risk of participating in the PDA market, leading to a loss of energy supply. According to the flowchart shown in Fig. 2, at the end of each time interval, the possibility of running a PDA market is measured. In the present experiment, at the minimum energy sharing (the ESF in [0.7, 0.45]), it is possible to run a PDA market

Table 3
IMMG cost reduction due to applying the cooperative model.

ESF	MGs' Remaining Power $(kWh)_{\text{SuppliedFrom}}$		Cost of $Power_{\text{SuppliedFrom}}$		
	Macrogrid	Neighbor microgrids	Macrogrid	Neighbor microgrids	
				With the Cooperative Model	Without Cooperative Model
[1, 0.71]	≈9877.4	≈9248.8	≈718 910	≈460 390	≈1 103 973
[0.7, 0.45]	≈15837.3	≈3289.2	≈1 632 933	≈1 801 941	≈1 853 819

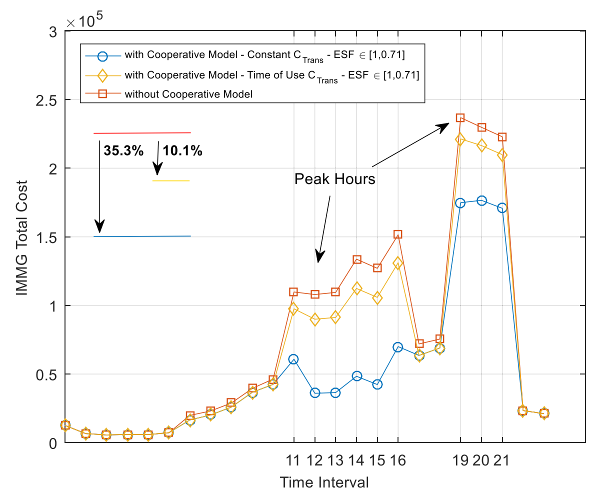

Fig. 7. The comparison of IMMG total cost between constant and time of use energy sharing pricing models.

in the 10 time-intervals of 10–16 and 19–21. Fig. 8 presents an instance of running the PDA market in these time intervals and the energy supply cost reduction rate for the buyer microgrids. The WS MG, WB MG, and CP phrases in Fig. 8 stand for the winning seller microgrids, the winning buyer microgrids, and the clearing price, respectively. Compared to Fig. 6(b), which shows the amount of cost reduction at the minimum ESF, assuming a supply of energy deficits from the macrogrid, the proposed model reduces the cost on average by 8.9% through using the PDA market among the microgrids of an IMMG.

The seller microgrids can trade their surplus energy in the PDA market at a higher price than the energy sharing cost among neighbor microgrids through the proposed model's conditional independence. The extent to which the seller microgrids' profits increased via the PDA market is shown in Fig. 9. The Winning TI in Fig. 9, presents the percentage of time intervals when the microgrid has been winning in the market. By trading in the PDA market, each seller microgrid can increase its revenue from its surplus energy sales by 23 percent.

7. Conclusion

Interconnected multi-microgrid systems (IMMG) are increasingly being developed because of their many advantages. Along with these benefits, there are also challenges posed by their energy management systems. The present work introduces a cooperative model for energy sharing among microgrids based on the SDN-based transactive energy framework. In the proposed model, a concept is defined as the energy sharing factor (ESF), which determines the amount of surplus energy sharing per microgrid. Over time, the ESF is updated based on each microgrid's

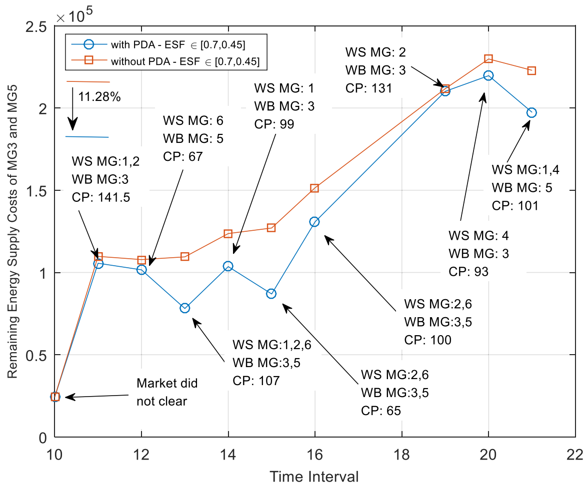

Fig. 8. Buyer microgrids energy supply cost through the PDA market. WS MG, WB MG, and CP stand for the winning seller microgrids, the winning buyer microgrids, and the clearing price, respectively.

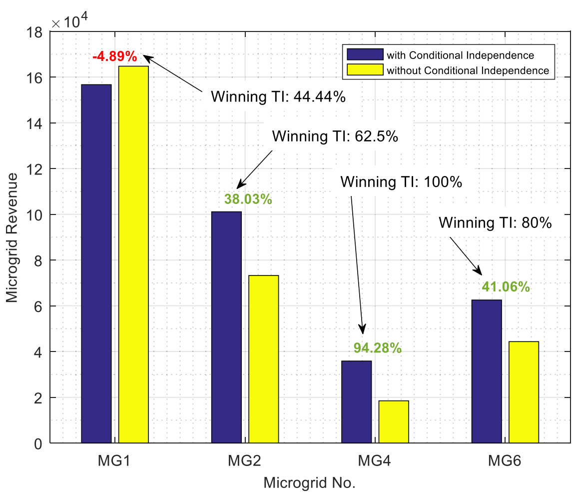

Fig. 9. Seller Microgrids revenue through the conditional independence mechanism. The Winning TI presents the percentage of time intervals when the microgrid has been winning in the market.

participation in the energy sharing plan. Additionally, when unforeseen events occur, the ESF allows the REMS manager to utilize all of the microgrids in the energy sharing plan. For maximizing profits, the ESF gives conditional independence to the microgrids participating in the IMMG energy sharing plan.

By assigning a class to microgrids, the current study determines the priority of allocating additional energy to microgrids that face energy shortages, where a higher priority class means lower cost and higher energy reliability. The proposed cooperative model's optimization problems are solved in two layers, the microgrid, and IMMG, and the result determines the ESF amount, the class assigned to each microgrid, and the energy sharing plan for the time period. The numerical results demonstrate that the proposed model reduces the cost of the IMMG energy supply and maintains the microgrid's conditional independence for achieving maximum profit through the PDA market. Future works intend to improve ESF updates by adding additional criteria to the ESF calculation module. Moreover, for achieving results closer to those of real conditions, the current authors will utilize real-time pricing for modeling the macrogrid's energy purchase and sales prices.

CRediT authorship contribution statement

Reihaneh Haji Mahdizadeh Zargar: Conceptualization, Methodology, Software, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Mohammad Hossein Yaghmaee:** Validation, Formal analysis, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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