An Advance Retail Electricity Market for Active Distribution Systems and home Microgrid Interoperability Based on Game Theory

Mousa Marzband[a,b,c,d], Masoumeh Javadi[e,f], S. Ali Pourmousavi[g], Gordon Lightbody[a,b]

[a]*Control and Intelligent Systems Group, Department of Electrical and Electronic Engineering, UCC, College Rd., Cork, Ireland*
[b]*SFI Research Centre for Marine and Renewable Energy, MaREI, Ireland*
[c]*Faculty of Engineering and Environment, Department of Maths, Physics and Electrical Engineering, Northumbria University Newcastle, Newcastle upon Tyne NE1 8ST, UK*
[d]*Dept. of Electrical Engineering, Lahijan branch, Islamic Azad University, Lahijan, Iran*
[e]*Dep. of Electrical Power Engineering, Guilan Science and Research Branch, Islamic Azad University, Rasht, Iran*
[f]*Dep. of Electrical Power Engineering, Rasht Branch, Islamic Azad University, Rasht, Iran*
[g]*Research Fellow at the Global Change Institute, The University of Queensland, St Lucia QLD, Australia*

Abstract

The concept of active distribution network has emerged by the application of new generation and storage technologies, demand flexibility, and communication infrastructure. The main goal is to create infrastructure and algorithms to facilitate an increased penetration of distributed energy resources, application of demand response and storage technologies, and encourage local generation and consumption within the distribution network. However, managing thousands of prosumers with different requirements and objectives is a challenging task. To do so, market mechanisms are found to be necessary to fully exploit the potential of customers, known as Prosumers in this new era. This paper offers an advanced retail electricity market based on game theory for the optimal operation of home microgrids (H-MGs) and their interoperability within active distribution networks. The proposed market accommodates any number of retailers and prosumers incorporating different generation sources, storage devices, retailers, and demand response resources. It is formulated considering three different types of players, namely generator, con-

Email address: `mousa.marzband@northumbria.ac.uk Corresponding author` (Mousa Marzband)

sumer, and retailer. The optimal solution is achieved using the Nikaido-Isoda Relaxation Algorithm (NIRA) in a non-cooperative gaming structure. The uncertainty of the generation and demand are also taken into account using appropriate statistical models. A comprehensive simulation study is carried out to reveal the effectiveness of the proposed method in lowering the market clearing price (MCP) for about 4%, increasing H-MG responsive load consumption by a factor of two, and promoting local generation by a factor of three. The numerical results also show the capability of the proposed algorithm to encourage market participation and improve profit for all participants.

Keywords: Active distribution network, retail electricity market, game theory, Nikaido-Isoda relaxation algorithm, home microgrid, microgrid interoperability.

Nomenclature

Acronyms

DR	demand response
DMS	distribution management system
DSO	distribution system operator
DER	distributed energy resource
DGU	dispatchable generation unit
DNO	distribution network operator
EMS	energy management system
ES	energy storage
ES+, ES-	ES during charging/ discharging mode
EV	expected value
HEMS	home energy management system
H-MG	home microgrid
MCEMS	modified conventional energy management system
MCP	market clearing price
MO	market operator
MT	microturbine
NDU	non-dispatchable unit
NIRA	Nikaido-Isoda/relaxation algorithm
NRL	non-responsive load
PBUC	price-based unit commitment
PV	photovoltaic
RLD	responsive load demand
SOC	state-of-charge
TGE	total generated energy
TCE	total consumed energy
TOAT	taguchi's orthogonal array testing
WT	wind turbine

Sets and Indices

θ, β	load demand curve coefficients

a^j, b^j, c^j	coefficients of cost function of DGU in H-MG j
$n/n/n''/n$	number of generators/ consumers/ retailers/ H-MGs
N_s	number of uncertainty scenarios
π^{ES+}	consumer's bids for battery during charging, i.e., ES+ ($/kWh)
Δt	time interval, hour

Constants

ζ^{ES}	efficiency of the battery
$\overline{P}^{(.),j}$, $\underline{P}^{(.),j}$	maximum/minimum output power of (.) in H-MG j (kW)
$\overline{SOC}^{ES,j}$, $\underline{SOC}^{ES,j}$	maximum/minimum state-of-charge (SOC) limits of ES in H-MG j (%)

Parameters

$\pi_t^{i''-}$, $\pi_t^{i''+}$	offer price of retailer i'' at time t for selling/buying to/from H-MGs ($/kWh)
3 $P_{t,s}^{(.),j}$	output power of resource (.) under scenario s in the H-MG j (kW)
$\rho_{t,s}^{(.),j}$	probability of scenario s of resource (.) in the H-MG j

Functions

$\mathbb{C}_t^i$, $\mathbb{R}_t^i$, $\mathbb{J}_t^i$	cost/revenue/profit functions of generator i at time t ($) ($i \in \{1, 2, \cdots, n\}$)
$\mathbb{C}_t^{A,j}$	cost of producing power by (A) in H-MG j ($)
$\mathbb{C}_t^{i''}$, $\mathbb{R}_t^{i''}$, $\mathbb{J}_t^{i''}$	cost/revenue/profit functions of retailer i'' at time t ($) ($i'' \in \{1, 2, \cdots, n''\}$)
$\mathbb{J}_t^{i'}$	cost functions of consumer i' at time t ($) ($i' \in \{1, 2, \cdots, n\}$)
$\pi_t^{H\text{-}MG,j}$	offer price of H-MG j at time t ($/kWh)
$EV_t^{(.),j}$	expected value of energy produced by (.) in H-MG j at time t
$Z(x)$	optimum response function in NIRA
Φ_i	pay-off function of each player i in NIRA
$\Psi(x, y)$	Nikaido-Isoda function

Decision variables

$P_t^{(.),j}$	output power of (.) in H-MG j during the time period t (kW)
X	collective strategy set
4 x	action of each player
$SOC_t^{ES,j}$	SOC of ES in H-MG j at time t (%)

1. Introduction

While the ever-increasing penetration of distributed renewable generation within distribution networks threatens reliable and secure power system operation as a whole, numerous opportunities are emerging which actively engage distribution systems and consumers in the power system operation. To exploit these new opportunities, two concepts have been developed as the major enabling ideas. First, the prosumer concept was born in recent years [1–4] as the ability of electricity consumers to become an active agent in the power system′s operation through local generation, demand flexibility, and storage. The second concept was H-MG [5–11] which is supposed to host a variety of local generation, demand flexibility resources, and storage devices to encourage the possibility of short- or long-term autonomous operation of the system in severe conditions [12, 13]. Combining these two enabling concepts necessitates an advanced retail electricity market with new functionality to enable interactions around energy and ancillary services products. The new market structure is expected to be scalable to accommodate any number and type of participants, and provide the means to encourage local interactions among different prosumers. Additionally, it should offer a comprehensive solution to facilitate the exploitation of available flexibility for the benefit of large power systems and end-users. The proposed market should also be able to handle large number of players, as is likely to happen at the distribution level.

The application of H-MG energy management systems with (e.g., [1, 3–5]) or without energy storage (ES) (e.g., [7–9, 14, 15]), and H-MGs interoperability (e.g., [10, 11, 16]) have been investigated in numerous research papers in the past. Developing general strategies for retail market operation have also been addressed in [17–25]. Colored Petri net technology [21], different game theory approaches using NIRA algorithm [22, 24], Shapely value [24, 26], and Cournot model [25] are among the methods which have been utilized for retail electricity market design. In [26], a retail market based on game theory was proposed for H-MG interoperability. In their proposed structure, all consuming participants were represented by a single player (i.e., aggregator) which does not appreciate different objectives and constraints among participants and the devices. Additionally, this formulation only allows one retailer in the proposed market which does not cope with the reality. Furthermore, using Cournot equilibrium model in [26], decision making is limited to only quantitative variables which is not desirable. In [27], a market structure was proposed as a part of an economic dispatch model for H-MG interoperability. Two types of players, including seller H-MGs as leaders and buyer H-MGs as followers, were introduced which essentially limits operational capability of the method. Moreover, the principles of Transactive Energy was used in [28–31] to develop optimal economic dispatch of H-MGs, charge optimization and optimal participation of electric vehicles. Only two types of players, namely electric vehicles and utility, were considered in [30, 31]. In [30], the cost of electric vehicles' charging and power losses of the distribution network are optimized. Thus, the required functionality is not developed in this method for a large pool of players of different types.

To summarize, the following shortcomings can be identified in the existing literature related to the retail electricity market at the distribution level:

- Lack of a general framework for analyzing and modeling players' behavior in a deregulated competitive electricity market at the residential distribution level in [10, 15, 16, 32–35].
- No investigation into the impact of prosumers on the economic operations of future residential distribution systems through probabilistic methodologies [18, 20, 21, 25].
- No supply bidding mechanism for the players in the electricity market [15, 16, 22, 24–26].
- No MCP calculation based on the Nash equilibrium point, market bids, and double-sided auction in [15–17, 22, 24–26].
- No implementation of demand response (DR) and ES in an efficient manner to exploit full capabilities of these resources [22, 24, 26].
- No solution is proposed to guarantee the benefit of all players with competing objectives in a multiple ownership environment in [15–17, 21, 30, 31] while the proposed solutions in [18, 19, 25, 28, 29] do not guarantee the optimality of the final solution.

- In [15, 16, 22, 24, 26], retailers are not considered as players in the market for all players.
- Interoperability of H-MGs with each other as well as retailers are not considered in [27, 36].

In this paper, a comprehensive retail market is developed within the realm of prosumers' and active distribution networks' era. Game theory is adopted to establish a scalable solution where any number of players can participate in trading energy. In order to provide a comprehensive solution, H-MG concept is implemented which accommodates local non-dispatchable/dispatchable generation units (NDU/DGU), ES, and responsive load demand (RLD). The proposed market structure encourages local generation consumption. Moreover, the proposed market facilitates interoperability of H-MGs, where excess energy of one H-MG can be stored or momentarily consumed in another H-MG. The optimal operation of the system with multiple H-MGs leads to the simultaneous optimization of H-MGs and distribution network pay-off functions. In this study, the Nikaido-Isoda/Relaxation Algorithm (NIRA) is used to solve the optimization problem based on a non-cooperative game. Also, the stochastic nature of load demand and renewable generation is considered in the proposed market.

The major contributions of this paper can be summarized as follows:

- Proposing an advanced electricity market for active distribution networks based on game-theory;
- Handling multiple retailers which increases competition and decreases electricity prices for the end-users;
- Modeling interaction among non-cooperative players with competing objectives through game-theory which guarantees fairness of the market schedules by achieving Nash equilibrium;
- Accommodating both DR resources and storage devices in the market operation to achieve a comprehensive solution exploiting all flexibilities.

This paper is organized as follows: The concept of H-MG is developed and explained in Section 2 while conceptual design of the proposed market is outlined in Section 3. Section 4 presents structure of price-based unit commitment (PBUC) unit for retailers participation in the proposed market. The problem formulation for the NIRA algorithm is given in Section 5 while the MCP calculation based on a double-sided auction is developed in Section 6. Simulation results and discussions are presented in Section 7. Finally, the paper is concluded in Section 8.

2. H-MG Concept

H-MG, in this paper, refers to a green building that could have generation resources, storage devices, and flexible demand, as shown in Fig. 1. Similar to conventional microgrids, green buildings are able to independently supply their required power to some extent [37–40]. Additionally, green buildings can represent flexibility in terms of generation, storage, and demand response, in the same way as a microgrid does. Also, green buildings are capable of operating in an environment where they can physically trade energy with other green building. As one may realize, a green building can be defined perfectly as a microgrid with similar functionality [41, 42]. Since the focus of this paper is on residential buildings, the H-MG term is adopted. The concept of H-MG has already been used in literature on a DC-AC microgrid at residential level [43–47].

Each H-MG can have generation resources (controllable distributed energy resources (DER) and NDU), load (non-responsive load (NRL) and RLD), and ES devices. Every generation unit, DR during load reduction, and storage in discharging mode are classified as an individual generator, while each load entity (i.e. ES in charging mode, NRL, and RLD) is tagged as an independent consumer. In this framework, each player is trying to satisfy its own objective(s), i.e., generators try to maximize their profit while consumers look after minimizing their operation cost.

In a similar manner to microgrid interoperability, several H-MGs, connected to the same network through a market operator or similar platform, can sell their excess energy to adjacent H-MGs or supply their power shortage through neighbours instead of purchasing energy from retailers. For a microgrid to be able to do this, it is necessary to have an energy management system (EMS) to make decisions in day-ahead and real-time operation. In this paper, every H-MG is assumed to have a home energy management system (HEMS) which is able to send/receive signals to/from a market operator, as explained later in detail. HEMS could functionally be able to predict local load demand, renewable generation, and demand flexibility, and to generate scenarios for the stochastic parameters. The HEMS is physically connected to generation, storage, and DR resources in the H-MG to operate them accordingly, and to the market operator to participate in energy trading. Therefore, HEMS is an integral part of the H-MG concept and the proposed market mechanism in this paper. Another feature of H-MGs in this study is that a single H-MG can have both generator and consumer as players in the market. This feature is preferred in this study to generalize market operation and formulation for every ownership situation, such as when tenants of the H-MG are not the owner of the building, generation and storage devices. In this framework, contradictory and competing objectives of the players can be conveniently sought.

3. The proposed retail market structure

A schematic diagram of the proposed market structure is shown in Figure 2. The market operator (MO) is the entity who manages the retail market and its participants. The MO could be either a separate entity overseen by the distribution network operator (DNO) or the distribution management system (DMS) or a part of existing distribution system operator (DSO)/DMS which alternatively becomes a flexible DSO. In any case, the functionalities of the proposed market structure will remain the same. The optimum price is calculated by the MO using information received from buyers and sellers.

As shown in Figure 2, multiple retailers can engage in the market by submitting separate sets of supply and demand bids in order to trade energy. H-MGs also can participate in the retail market to trade energy, and possibly ancillary service products. It should be noted that while HEMS only considers the benefit of a sin-

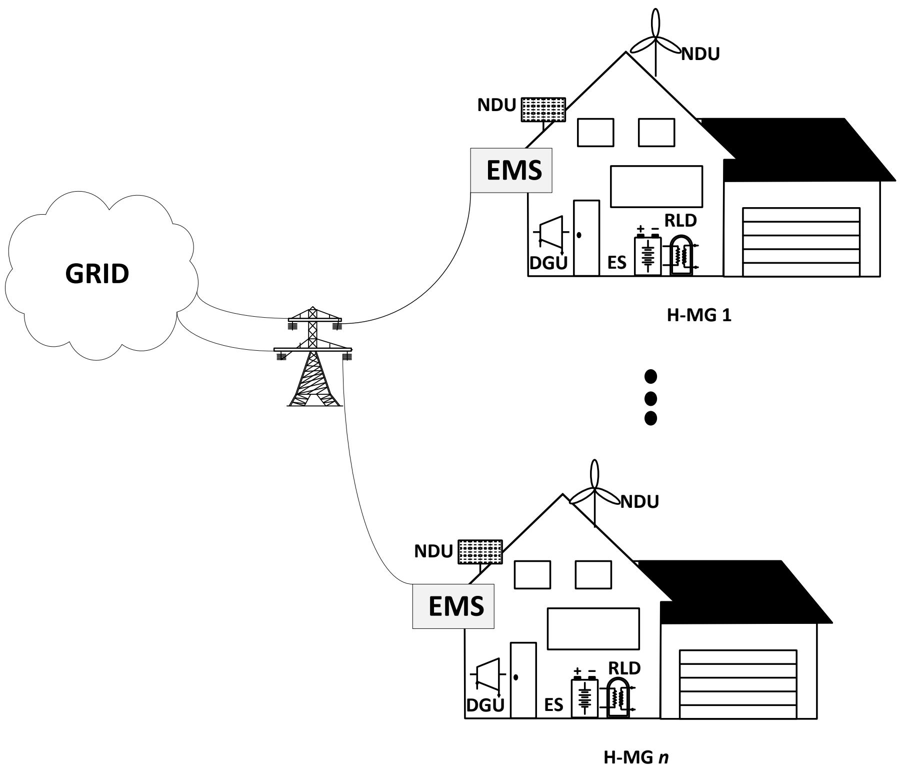

Figure 1: Typical green building, re-defined as H-MG for the purpose of this study

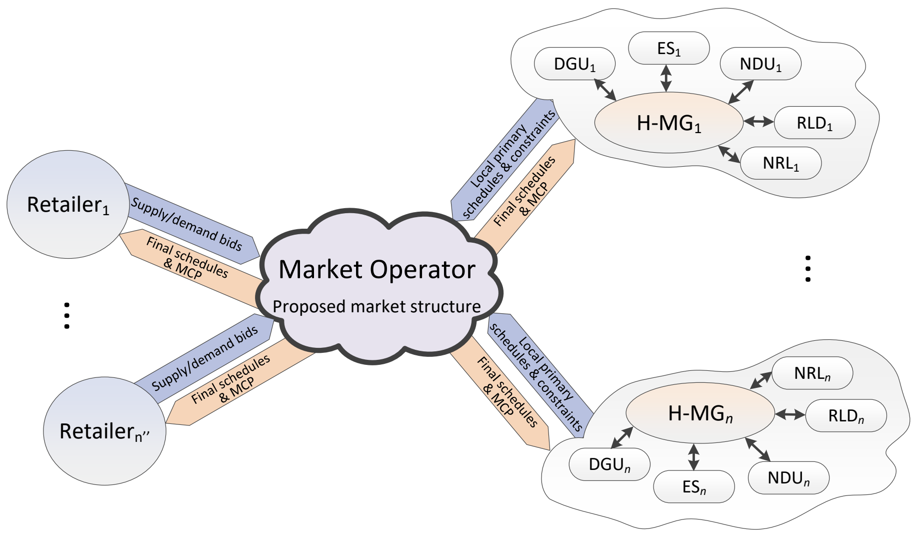

Figure 2: Interaction of DNO, MO and multiple H-MG within the proposed market structure

gle H-MG, the proposed market structure seeks a global solution where all players benefit from participation in the market. To do so, non-cooperative game theory is adopted in this study, which is solved repeatedly by using game theory specific method, i.e., NIRA. In this kind of game, players with opposing goals are seeking to achieve their own interests. The proposed market structure will be explained in the next section in detail. Each player may have to some extent (or completely) a contradictory pay-off function compared with others. All of them try to maximize their welfare by regulating their strategies. The decision of each player has effect on the overall MCP.

The proposed market enables interactions among H-MGs and with retailers to exchange power and utilize generation resources optimally.

For the proposed structure to work, two types of information must be communicated from the H-MGs to the MO: 1- Specifications of each H-MG including the rated capacity of the existing devices, operational constraints, and cost functions which do not change on a daily basis. Therefore, they will be broadcast to the MO once they join the market, and be updated quarterly or annually or by a notice from H-MG owner. 2- Dynamic information such as the day-ahead forecast of renewable generation and load demand, and the availability of generators and consumers which have to be communicated on a daily basis. As one can appreciate, the proposed structure looks similar to the wholesale electricity market at the transmission level in terms of data exchange. Therefore, the required communication is relatively minimal in real-time. Retailers are also required to submit supply and demand bids for the entire day to the MO. In return, every H-MG and retailer receives optimal schedules from the MO for the day-ahead operation. It is worth mentioning that the proposed market structure could also be deployed in real-time operation with the same principles without any changes. Moreover, if HEMS has enough computational power and memory, it can locally run the proposed operation in steps 1 and 2, as shown in Figure 3. Otherwise, they can act as a communication channel between H-MG and MO, and to operate internal devices upon receiving schedules from MO. Interoperability of the H-MGs is yet another feature of the proposed market. When a H-MG comes across excess generation, after satisfying its local demand, it tends to sell excess power to other H-MGs or retailers in the market based on the MCP. Alternatively, a H-MG with power shortage can purchase the cheapest available energy from other H-MGs or retailers. To encourage H-MGs to participate in the market with more local generation, their excess power, which has not been sold to other H-MGs, will be purchased by retailers at the MCP [48]. This will, in turn, decrease electricity prices for consumers, which will be shown in the simulation studies. It also reduces power losses by boosting local generation and consumption. To further enhance the robustness of the proposed market structure against load and generation uncertainties, a stochastic framework for market operation is created, the details of which will be explained later in this section. Without loss of generality, day-ahead market operation is considered for the rest of the paper.

The proposed market runs through the following steps, as shown in Figure 3:

Step 1: The first step is to estimate the generation capacity of photovoltaic (PV) and wind turbine (WT) as NDUs and also NRL for the day-ahead using HEMS. In order to consider the inherent variability of renewable generation and load demand, a stochastic framework is employed based on scenario generation and the appropriate distribution function of the random parameter. Load and solar irradiation uncertainty are modelled using a normal distribution [49] with known mean and standard deviation. In addition, wind speed variability is estimated using a Weibull distribution for 24-hours ahead [49]. Numerous scenarios are generated for each uncertainty parameters. However, running this optimization for all scenarios is time consuming and computationally expensive. As a result, Taguchi's orthogonal array testing (TOAT) method is used to reduce the number of scenarios [49],[50]. The TOAT method selects the minimum number of scenarios while preserving the main statistical information of the entire dataset. More details on the stochastic framework of this study can be found in [49].

Step 2: In this step, the unit commitment problem is solved for each scenario achieved by TOAT method in Step 1 for every H-MG. A complicated modified conventional energy management system (MCEMS) is developed by the authors to manage DERs, DR resources, and ES+/ES- for the entire day. Basically, a power management problem is solved for every time step of the day ahead. The outcome is the primary schedule of each generator and consumer in each scenario including the charge/discharge operation schedule of the ES devices, load increase/reduction of DR, and the amount of power shortage or excess for each time step for the next day. Step 2 is designed to satisfy the local load demand using onsite generation to the maximum possible extent; this will result in a higher system efficiency and a larger penetration of DERs at the distribution level. The MCEMS algorithm is fairly complicated; interested readers are encouraged to consult [46] for further details. Step 1 and 2 can be carried out either at the H-MG level using local HEMS or by the MO centrally. The former structure reduces communication intensity and respects H-MG privacy to some level. The latter, however, decreases the upfront cost of required devices to participate in the market for each H-MG, which encourages more participation. In either case the proposed market mechanism will remain intact.

Step 3: From Step 2, the shortage and excess power of each H-MG is known for every scenario without considering the retailers and interoperability among H-MGs. In

Step 3, however, a scheduling problem is solved (in the PBUC unit) in the presence of participating retailers and power shortage/surplus of each H-MG. As it is shown in Figure 3, each retailer participates in the market by submitting two separate sets of bids: bid-in demand for purchasing excess power from H-MGs, and bid-in supply for selling power to support H-MGs with power shortage. Bids are submitted in the form of blocks of price and energy quantity. Step 3 also determines the upper limit for sold/purchased power to/from each retailer while maximizing exploitation of the H-MG generation. Further details are given in Section 4.

Step 4: Primary schedules from Steps 1, 2, and 3 are calculated based on local MCEMS operation. They do not therefore consider interoperation among the H-MGs, nor the global benefit of the players. Using the consumers' and generators' schedules (i.e., $\mathrm{Inp}_{2\to3,4}$) as well as the retailers upper limits for purchasing and selling energy in each scenario as the start point (i.e., $\mathrm{Inp}_{3\to4}$), the NIRA algorithm is used to determine the global optimal schedules of the players. This is achieved as a Nash equilibrium considering both local and global constraints. In this step, stochastic optimization is formulated by solving the NIRA algorithm. To start the game, the expected values of the schedules from previous steps are calculated and utilized. The formulation for Step 4 is given in section 5.

Step 5: The MCP is calculated in Step 5 based on the Nash equilibrium and the bids submitted by the players using a double-sided auction. From there, the financial benefit for every player in the market is obtained based on the MCP and optimal schedules obtained in Step 4. This step is explained in Section 6 in more detail.

4. PBUC unit

As explained earlier, the retailers participate in the proposed market structure with two sets of bids: supply and demand. In Steps 1 and 2, the shortage/excess energy of each H-MG is calculated without considering the retailers' participation in order to promote local energy generation and utilization. In PBUC unit, the upper trading limit for retailers in both supplier and consumer modes is determined based

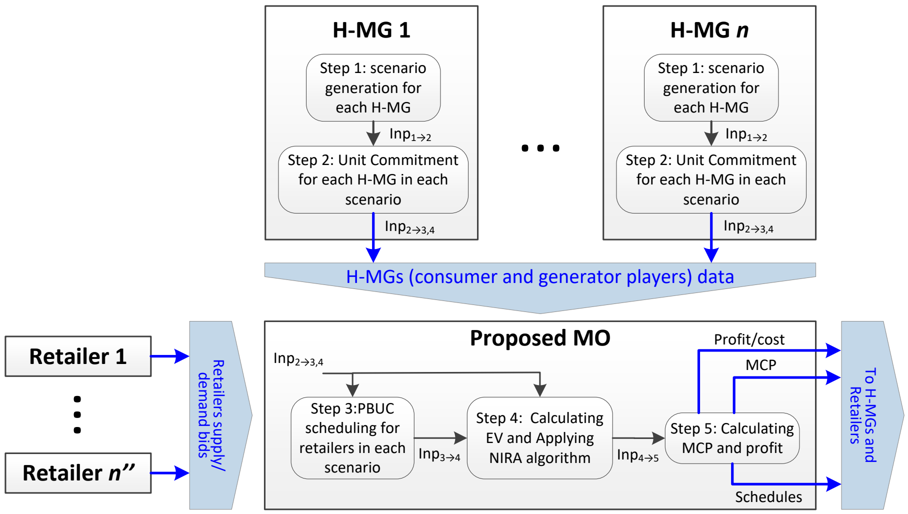

Figure 3: Step-by-step process of implementing the proposed market structure

on excess/shortage energy of each H-MG; this is essential for our calculations in Step 4. First, total energy shortage of all H-MGs is calculated. Then, the PBUC unit sorts the H-MGs with excess energy and retailers' supply bids according to their offer prices in ascending order. In this way, either H-MGs (with excess generation) or retailers with lower prices will be awarded first. Energy awarded to each retailer in this Step will be used as the upper limit in Step 4.

Since it is desired to purchase any extra energy from H-MGs in order to promote local generation, the PBUC algorithm checks through all the H-MGs with unsold excess energy for the entire day. The total amount of excess energy will then be calculated and the retailers with the highest demand bids will be sorted in ascending order. Consequently, the retailers with highest demand price will be awarded to purchase power from the H-MGs with unsold excess energy. This will set a maximum upper bound for the retailers' energy demand. The two sets of upper limits for retailers (in supply and demand modes) will be communicated to Step 4 (i.e., $\mathrm{Inp}_{3\to4}$) where a NIRA algorithm is implemented to solve an optimization problem.

5. Problem formulation of Step 4

In this step, the NIRA algorithm is adopted to co-optimize the pay-off function of each player using a central decision-making process. This is done by calculating the players' Nash equilibrium using a special type of game theory known as NIRA [49],[51]. The final outcome of this step is the optimal dispatch of each player in the market by calculating the Nash equilibrium through an iterative loop. In the rest of this section the NIRA algorithm formulation is presented. Variables in the NIRA algorithm, i.e., x_i, are the generation/consumption dispatch of each player. The initial guess, i.e., x^0, for all players is selected based on the information obtained from Steps 2 and 3. In this regard, it is assumed that the nature of the electricity market is proportional to the game theory with n participants in a non-cooperative game. H-MG information (such as cost functions, characteristics of generation and consumption devices, and physical constraints), primary dispatches calculated in Step 2, upper limits obtained in Step 3, and retailers' supply and demand bids are among the input parameters to this unit.

This unit has two important tasks to accomplish which are formulated as two sub-problems: 1- maximizing Eq. (1) [49], and 2- applying the relaxation algorithm and updating Eq. (2) [49].

$$\Psi(x,y) = \sum_{i=1}^{n} [\Theta_i(y_i|x) - \Theta_i(x)] \tag{1}$$

$$Z(x) = \arg\max_{y \in X} \psi(x,y) \qquad x, Z(x) \in X \tag{2}$$

Both tasks are followed interactively by the NIRA unit until the difference of $Z(x)$ between two consecutive iterations becomes smaller than a predefined threshold. The first sub-problem solution is not optimal but satisfies a Nash equilibrium. Sub-problem 2, on the other hand, uses the relaxation technique through a number of iterations to push the results to an optimal point. After the initial value definition, x^0, it is possible to create $\Phi_i(x)$, i.e., the first sub-problem. Then, solutions of the first sub-problem gradually converge to a new stable state in the second sub-problem which are considered as the desired results. If values of $\Psi(x,y)$ becomes zero, no player can unilaterally improve its pay-off $\Phi_i(x)$. Therefore, a balanced (approximate) response is achieved for the electricity market clearing by following the global (Eq. 13) and local constraints (Eq. 14-22).

In the following sub-sections, a mathematical formulation is presented using the key components in the proposed retail electricity market, namely retailers and H-MGs' players consisting of generators and consumers.

5.1. Generator

Generation resources include DGU, NDU and ES in discharging mode. The profit of generator i at time t, $\mathbb{J}_t^i$, can be expressed and maximized as follows:

$$\textbf{max} \;\; \mathbb{J}_t^i = \mathbb{R}_t^i - \mathbb{C}_t^i, \;\; t \in \{1, 2, \cdots, 24\}, \;\; i \in \{1, 2, \cdots, n\} \tag{3}$$

where the revenue of generator i is defined as:

$$\mathbb{R}_t^i = \pi_t^{\text{H-MG},j} \times [P_t^{\text{DGU},j} + P_t^{\text{NDU},j} + P_t^{\text{ES-},j} - P_t^{\text{NRL},j}] \tag{4}$$

$$\pi_t^{\text{H-MG},j} = -\theta \times (P_t^{\text{NRL},j} + P_t^{\text{RLD},j}) + \beta, \;\; \theta > 0 \tag{5}$$

$$P_t^{\text{NRL},j} = \sum_{s=1}^{N_s} \rho_{t,s}^{\text{NRL},j} \times P_{t,s}^{\text{NRL},j}, \;\; j \in \{1, 2, \cdots, n\} \tag{6}$$

In Eq. (4), the load offer price (i.e., inverse load demand curve), $\pi_t^{\text{H-MG},j}$, is calculated using Eq. (5) which, for the sake of simplicity is assumed to be the same at any given time t; $P_t^{\text{NRL},j}$ is the expected value at hour t in kW which is calculated by multiplying the probability of each uncertainty scenario, i.e., $\rho_{t,s}^{\text{NRL},j}$, by the kW value of that scenario, i.e., $P_{t,s}^{\text{NRL},j}$, according to the Eq. (6).

Eq. (7) is total cost of generator *i* which consists of DGU and ES costs. The DGU generation cost in H-MG j has been formulated as a quadratic function in Eq. (8), where a_j, b_j and c_j are the coefficients of the cost function for DGU i of H-MG j. Cost of ES energy is expressed by Eq. (9). For simplicity, the offer price for all the players in a H-MG is assumed to be the same at each time interval. Therefore, the following relation can be presented.

$$\mathbb{C}_t^i = \mathbb{C}_t^{\text{DGU},j} + \mathbb{C}_t^{\text{ES+},j} \tag{7}$$

$$\mathbb{C}_t^{\text{DGU},j} = a^j \cdot (P_t^{\text{DGU},j})^2 + b^j \cdot P_t^{\text{DGU},j} + c^j, \;\; a^j > 0 \tag{8}$$

$$\mathbb{C}_t^{\text{ES+},j} = \pi^{\text{ES+}} \times P_t^{\text{ES+},j} \tag{9}$$

5.2. Consumer

This group of players consists of RLD loads in each H-MG. The objective is to minimize their operation cost (exploitation cost) by managing their own dispatchable loads while maintaining a certain comfort level, as follows:

$$\textbf{min}\ \ \mathbb{J}_t^{i'} = \pi_t^{\text{H-MG},j} \times P_t^{\text{RLD},j},\ i' \in \{1, 2, \cdots, n\} \tag{10}$$

where offered price by H-MG j is obtained from Eq. (5).

5.3. Retailer

This type of player represents retailers in purchasing the excess power from the H-MGs as well as selling power to the H-MGs with power shortage. $\mathbb{J}_t^{i''}$ is defined as the retailers' profit from exchanging energy in the market at time *t* which has to be maximized:

$$\textbf{max}\ \ \mathbb{J}_t^{i''} = \mathbb{R}_t^{i''} - \mathbb{C}_t^{i''},\ i'' \in \{1, 2, \cdots, n''\} \tag{11}$$

where revenue and cost functions are:

$$\mathbb{R}_t^{i''} = \pi_t^{i''-} \times P_t^{i''-},\ \ \mathbb{C}_t^{i''} = \pi_t^{i''+} \times P_t^{i''+} \tag{12}$$

In Eq. (12), $\pi_t^{i''-}$ and $\pi_t^{i''+}$ are offered prices by retailer i''.

5.4. General Constraints

A set of constraints are defined to respect the physical limits of the devices and distribution system, as follows:

$$\begin{aligned} &\sum_{j=1}^{n} (P_t^{\text{DGU},j} + P_t^{\text{NDU},j} + P_t^{\text{ES-},j}) + \sum_{i''=1}^{n} P_t^{i''-}) \\ &= \sum_{j=1}^{n} (P_t^{\text{NRL},j} + P_t^{\text{ES+},j} + P_t^{\text{RLD},j}) + \sum_{i''=1}^{n} P_t^{i''+}) \end{aligned} \tag{13}$$

$$\underline{P}^{\text{DGU},j} \leqslant P_t^{\text{DGU},j} \leqslant \overline{P}^{\text{DGU},j} \tag{14}$$

$$0 \leqslant P_t^{\text{NDU},j} \leqslant EV_t^{\text{NDU},j}, EV_t^{\text{NDU},j} = \sum_{s=1}^{N_s} \rho_{t,s}^{\text{NDU},j} \times P_{t,s}^{\text{NDU},j} \tag{15}$$

$$0 \leqslant P_t^{\text{ES-},j}(P_t^{\text{ES+},j}) \leqslant \overline{P}^{\text{ES-},j}(\overline{P}^{\text{ES+},j}),\ \forall t \tag{16}$$

$$\underline{SOC}^{\text{ES},j} \leqslant SOC_t^{\text{ES},j} \leqslant \overline{SOC}^{\text{ES},j} \tag{17}$$

$$\mathrm{SOC}_{t+1}^{\mathrm{ES},j} - \mathrm{SOC}_{t}^{\mathrm{ES},j} = \frac{(P_t^{\mathrm{ES}+,j} - P_t^{\mathrm{ES}-,j}) \times \Delta t}{\zeta^{\mathrm{ES}} \mathrm{ES}_{\mathrm{Tot}}^{\mathrm{ES},j}} \tag{18}$$

$$0 \leqslant P_t^{\mathrm{RLD},j} \leqslant \zeta \times P_t^{\mathrm{NRL},j} \tag{19}$$

$$0 \leqslant P_t^{i''-}(P_t^{i''+}) \leqslant EV_t^{i''-}(EV_t^{i''+}) \tag{20}$$

The supply and demand balance is guaranteed using Eq. (13) at all times; Eqs. (14) and (15) represent operational constraints of DGU and NDU units, respectively. Renewable generation limitation is enforced by Eq. (15) by using the expected value as the upper level. The maximum charge/discharge power of the battery is also modelled by Eq. (16). Eqs. (17) and (18) represent the SOC limits of the battery considering its round-trip efficiency, ζ^{ES}. Eq. (19) defines the amount of available responsive load based on the total NRLs. $EV_t^{i''+}$ and $EV_t^{i''-}$ (kW) are expected power purchased (sold) by retailer i'' at time t from (to) H-MGs which are calculated by:

$$EV_t^{i''-} = \sum_{s=1}^{N_s} \rho_{t,s}^{i''-} \times P_{t,s}^{i''-} \tag{21}$$

$$EV_t^{i''+} = \sum_{s=1}^{N_s} \rho_{t,s}^{i''+} \times P_{t,s}^{i''+} \tag{22}$$

where $\rho_{t,s}^{i''-}$ and $\rho_{t,s}^{i''+}$ are the probability of each scenario s at time t during selling and purchasing power.

6. MCP Unit

In this unit, MCP is calculated based on the schedules obtained from the Nash equilibrium calculation (i.e. optimum capacity of each player in the market) and supply and demand bids submitted by the participants using a forward market with a double-sided auction [52]. The forward market aggregates the supply and demand in the merit order in terms of price-quantity pairs. The quantities are optimal schedules obtained from Step 4, and the prices are supply and demand bids submitted by the players. As expected, the aggregated supply and demand quantity-price values are monotonically increasing and decreasing step-wise curves, respectively.

MCP will be the intersection of the aggregated supply and demand curves. Finally, the pay-off function will be computed for each player based on the MCP.

7. Simulation results and discussions

A comprehensive simulation study is carried out to evaluate the benefit of the proposed market for all stakeholders. Three case studies are defined as follows:

- CASE I: Three H-MGs connected to a single retailer are simulated where no market mechanism exists, and every H-MG, equipped with MCEMS, is attempting to only minimize its operation cost. It is used as the base-case scheme for comparison purposes.
- CASE II: Three H-MGs are singly connected to a single retailer under the proposed market structure.
- CASE III: Three H-MGs connected to two retailers under the proposed market structure.

It is assumed that every H-MG has two players including a consumer and a generator, where both players have similar ownership. In other words, the tenants of each H-MG are also the owners of the devices in the H-MG. A comparison between CASE II and CASE III shows the effectiveness of the proposed market mechanism in handling multiple players and helps to quantify the benefit of having higher competition in the market. Additionally, the goal of having three H-MGs and two retailers in CASE III is to provide diversity of players while keeping the size of the simulation studies tractable for analysis and discussions. Please note that there is no limitation on the number of players, including generator, consumer, and retailer.

Each H-MG consists of a set of generation resources including WT and PV as NDUs, microturbine (MT) as DGU, ES, and consumers with NRL and RLD loads. In Figure 4(a)-(c), PV, WT, and NRL prediction, respectively, are given for the three H-MGs for the day ahead. It can be seen from Figure 4(c) that all three H-MGs are less flexible (i.e., have higher NRL) during second peak hours in the evening. PV, WT, and NRL prediction profiles for each H-MG and the specifications of the DERs have been obtained from [46], and are given in the Appendix (Section 9). Retailers'

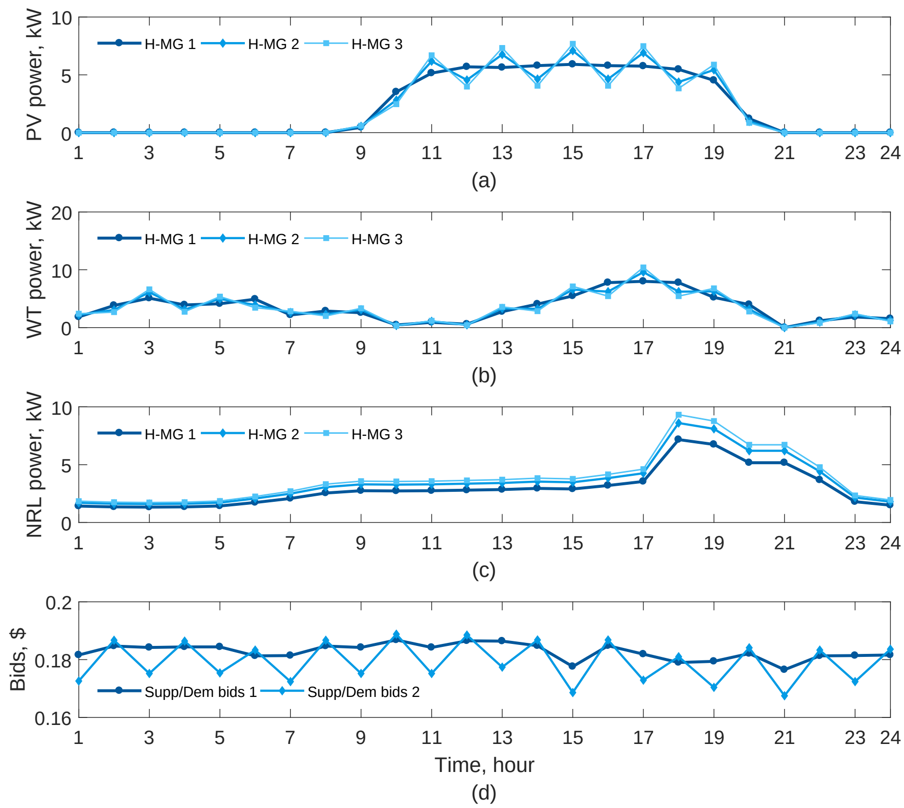

Figure 4: Predicted WT, PV, NRL, and supply/demand bids of retailers profiles for the entire day-ahead for each H-MG

supply/demand bids are also shown in Figure 4(d). In CASE II, only retailer 1 exists while both retailers participate in the market operation in CASE III. Without loss of generality, it is assumed that supply and demand bids are the same for each retailer. A simulation study is then carried out for all three CASES according to the definition with the given data and parameters. In the rest of this section, the simulation results are presented and explained.

Figure 5(a) shows the total generated energy (i.e., TGE) produced locally by the three H-MGs in a day of operation for three cases. It can be seen that TGE is increased for all three H-MGs from CASE I to CASE II, and from CASE II to CASE III. Increasing TGE from CASE II to CASE III proves that having more players in the

Table 1: Comparison among the different cases in terms of TGE improvement

	CASE I	CASE II	CASE III
CASE I	—-	-166.3%	-238.3%
CASE II	62.4%	—-	-27.0%
CASE III	70.4%	21.3%	—-

market improves competition, resulting in larger local production. It also proves the effectiveness of the proposed market approach to facilitate a higher amount of local generation. TGE for H-MG2 in CASE III is slightly less improved compared to CASE II which is because of the competition in the market. The Nash equilibrium, obtained in CASE II and CASE III, fulfills the objectives of all players while respecting their constraints. Therefore, no player can increase its pay-off by unilateral changes of its strategy space. It means that no player has preference relative to any other players at the Nash equilibrium point. In Figure 5(b), TGE of each H-MG in CASE II and CASE III is compared with the base-case, i.e., CASE I, to quantify improvement caused by the proposed market structure. On average, TGE is increased 266% and 338% in CASE II and CASE III, respectively, compared to CASE I.

To further compare TGE in different cases, Table1 is created using the following equation:

$$\eta_{i,j} = \frac{\mathrm{TGE}_{\mathrm{CASE}_i} - \mathrm{TGE}_{\mathrm{CASEj}}}{\mathrm{TGE}_{\mathrm{CASE}_i}} \qquad i, j \subset \{\text{‘CASE I’ , ‘CASE II’, ‘CASE III’}\} \tag{23}$$

where positive values show an increase in TGE, and negative values implies a decrease in TGE. It can be seen from Table 1 that the average TGE is improved from CASE I to CASE III. Adding only one more retailer in CASE III led to about 21% improvement in TGE, which is significant. This is about a 27% improvement when it is normalized based on CASE II.

Total consumed energy (TCE) in the three cases and each H-MG is shown in Figure 6(a). It can be seen from the figure that TCE for all H-MGs is increased from CASE I to CASE II, and from CASE II to CASE III. This proves that the larger the number of players, the higher the amount of served load in the context of RLD. The

Table 2: Comparison among the different cases based on TCE improvement

	CASE I	CASE II	CASE III
CASE I	—-	-87.5%	-132.7%
CASE II	46.7%	—-	-24.1%
CASE III	57.0%	19.4%	—-

reason is that higher competition reduces the overall cost of operation for all players which encourages more consumption through RLD. While the trend is almost the same for H-MG 1 and 3, H-MG 2 shows less improvement in served RLD in CASE III compared to CASE II. The reason is linked to the lower TGE improvement for H-MG 2 in CASE III, as shown in Figure 5(a), where competition is boosted in the market by having two retailers. In Figure 6(b) TCE for CASE II and CASE III compared to CASE I for the three H-MGs. On average, it is increased by 189% and 235% in CASE II and CASE III, respectively. H-MG 1 has the highest improvement among existing H-MGs.

Overall improvement of TCE from CASE I to CASE II and CASE III is reported in Table 2. Similar to TGE, the improvement is more obvious from CASE I to CASE II and CASE III compared to the improvement from CASE II to CASE III. Nevertheless, CASE III shows about 19% more TCE compared to CASE II, which is quite significant. If CASE II is compared with CASE III, the improvement is about 24%.

Total served RLD throughout the day of simulation is given in Table 3 for each H-MG in the different cases. It is clear that lower MCP and higher availability of local generation significantly increased the total served RLD from CASE I to CASE II and CASE III. This means that consumers will pay less per kWh while consuming more electricity, which is facilitated by the proposed market structure.

Average battery SOC of each H-MG in the three cases is plotted in Figure. 7(a). It can be seen that the battery SOC is maintained at 79% level on average, which has significant positive impact on battery lifetime and reliability of the system operation. The daily SOC profile for each H-MG is also shown in Figure 7(b)-(d) for all H-MGs. Also, it can be seen that the SOC in all cases for all H-MGs reaches to 80%

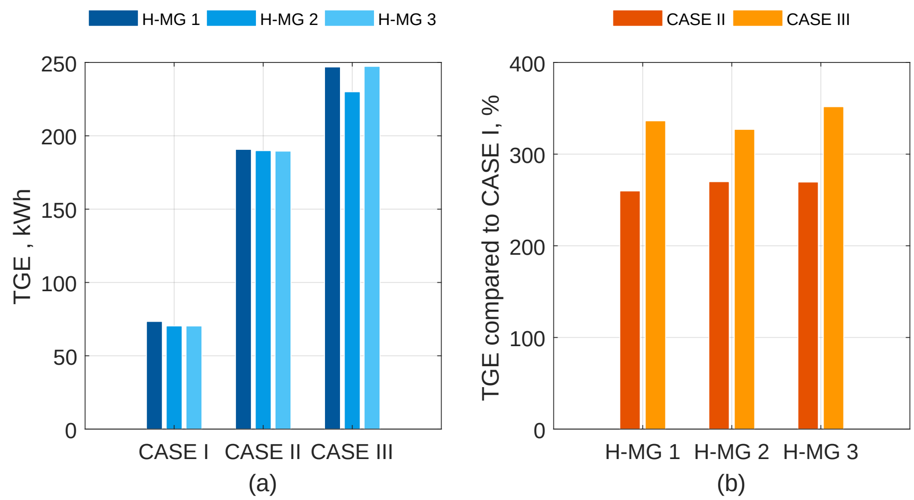

Figure 5: (a) TGE of three H-MGs during the 24-hour simulation in all cases, (b) CASE II and CASE III in comparison with CASE I

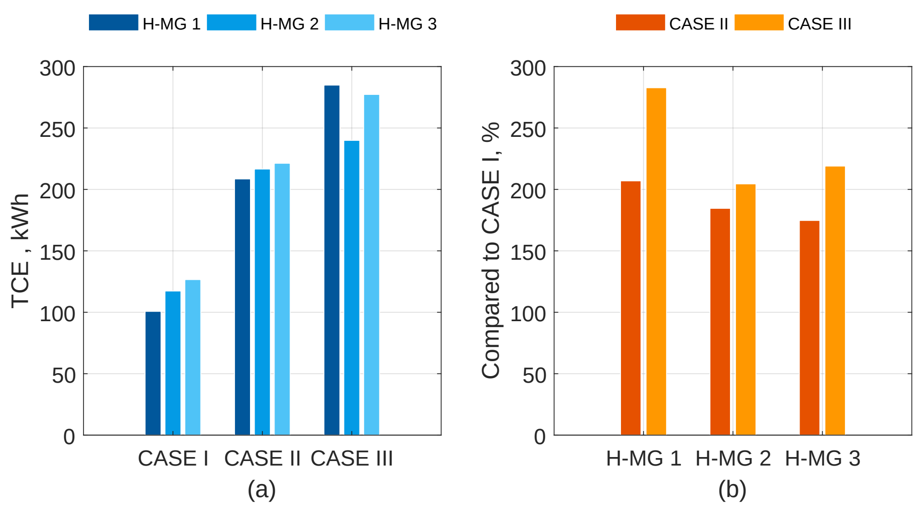

Figure 6: (a) TCE in three H-MGs during the 24-hour simulation in all cases, (b) CASE II and CASE III compared to CASE I

Table 3: Total RLD (kWh) for the H-MGs during the 24-hour simulation in all cases

	H-MG 1	H-MG 2	H-MG 3
CASE I	15.5	12.2	10.4
CASE II	126.2	108.5	98.9
CASE III	203.0	132.8	159.2

in the early hours where battery initial SOC was set to 50%. In other words, the battery in all cases is charged at mid-night when the price of electricity is cheap and WT is generating power. Having batteries at full-charge increases the system's overall reliability and resilience with respect to sudden power shortage and unwanted incidents.

The consumer's pay-off is a function of operation cost and the purchased electricity from other players; the result of which is shown in Figure 8(a) based on simulation studies. Daily pay-off values (aggregated for the whole day) after market settlement is given in the figure. The results consistently show an increased operational cost of the consumers because of higher served RLD, as shown in Figure 6(a), in CASE II and CASE III by the proposed market structure. It agrees with all of the analyses so far as well as the willingness of consumers to increase consumption when MCP are satisfactorily low.

In Figure 8(b), the daily aggregated pay-off (i.e., profit) for generators are shown for three cases and H-MGs. It can be seen that the profit of generators increased from CASE I to CASE III for all H-MGs. The negative values of the generators in CASE I means that they cannot meet their NRL at all times. Therefore, they have to purchase energy from retailers to meet the energy shortage. Please note that the cost of serving NRL is formulated in generator' utility function in Eq. 3. It in turn increases the profit of the single retailer in CASE I, as shown in Figure 8(c).

The overall benefit of multiple retailers is depicted in Figure 8(c). Not surprisingly, the overall profit for the retailers is the highest in CASE I because energy shortage of the H-MGs in that case is only compensated by the retailer. When the proposed market is utilized, overall retailer pay-off is reduced by 14.4% and 11.4%

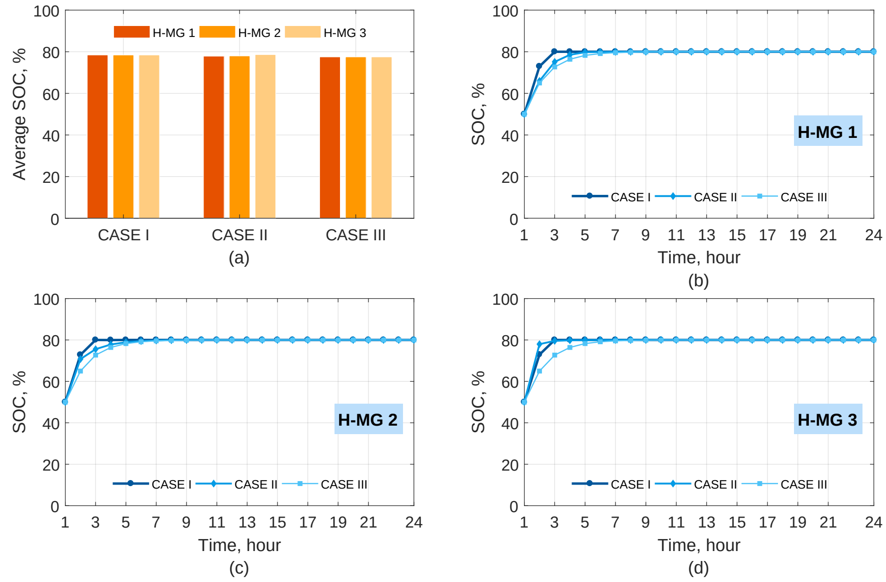

Figure 7: Battery operation for all cases and H-MGs: (a) daily average SOC, (b)-(d) SOC of the battery in 24-hour simulation for all three cases.

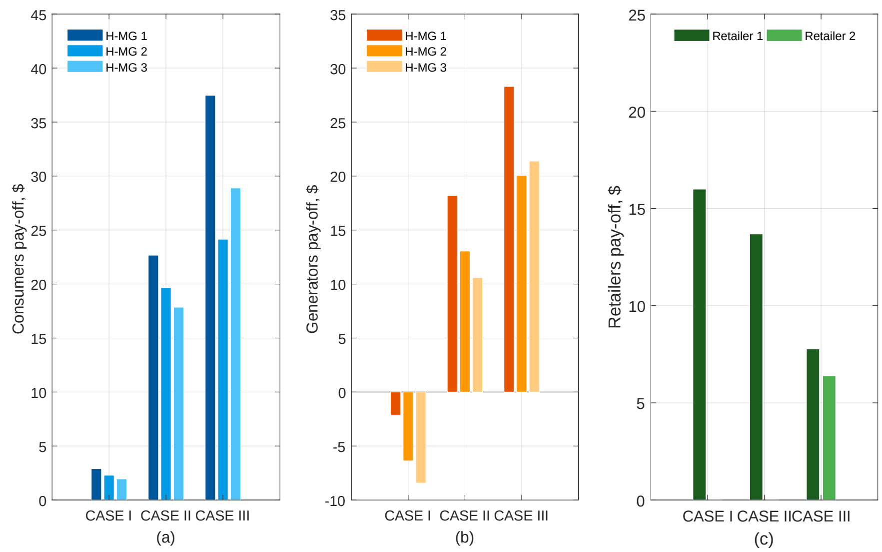

Figure 8: Accumulated pay-off of (a) consumers, (b) generators, and (c) retailers for each case and H-MG in 24-hour simulation study.

in CASE II and CASE III, respectively, compared to the base-case, i.e., CASE I. The retailers however received 3.5% more profit in CASE III in comparison with CASE II. This is the benefit of having more players in the proposed market structure where CASE III with eight players represents the greater competition and provides more benefits for every participants.

The MCPs are shown in Figure 9 for every hour in all CASES. It can be seen that the highest MCP occurred in CASE I where there is not a market mechanism. Average MCP in CASE I, CASE II, and CASE III is 0.188, 0.1805, and 0.183, respectively, for the whole day which shows a 3.82% and 2.5% reduction in CASE II and CASE III compared to CASE I. It can be seen from Fig. 9 that the MCP is noticeably lower for the second peak hours from 18:00 to 21:30 in all cases because of the price-consumption model adopted in Eq.(5). During evening peak hours, total RLD and NRL are relatively large. Therefore, their demand offers in the market are reasonably low which resulted in low MCPs during these hours. Low MCPs around 2:30 AM to 3:30 AM occur because of offer prices and Nash Equilibrium points for the given profile in those hours.

Although absolute value of MCP is the lowest in CASE II, the TCE was the highest in CASE III. It means that the MCP per kWh of satisfied RLD is lower in CASE III, which is depicted in Fig.10. An exception is in hour 20, where the MCP per unit of served RLD is always lower than the MCP in CASE II and significantly lower compared to CASE I. It consequently proves that increasing the number of players resulted in lower MCP per unit of served RLD. It is worth mentioning that the amount of served RLD depends on decreasing the MCP. In fact, because of improving competition between sellers according to increasing the number of suppliers in the market, the consumers prefer to increase their RLD based on proper MCP, as shown in Table 3. Please note that in hours 1, 7, 8, 21 to 24 of CASE I, no RLD is met. Therefore, they are represented by "inf" in Fig. 10.

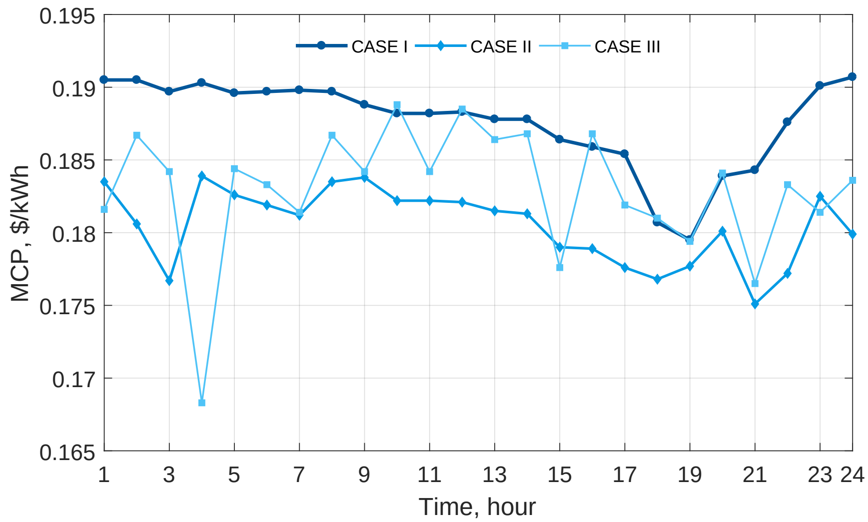

Figure 9: Hourly MCPs in 24-hour simulation in all cases.

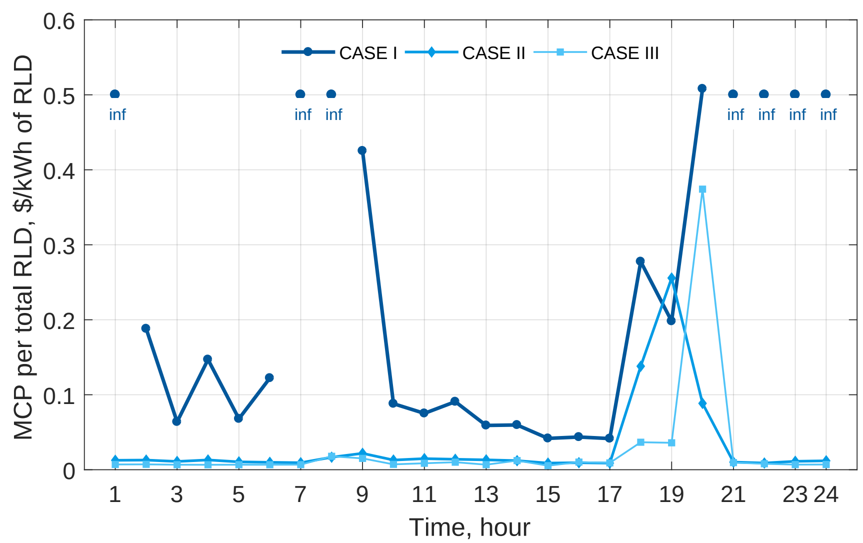

Figure 10: MCP per unit of total served RLD in all cases.

8. Conclusion

In this study, a centralized market structure suitable for distribution networks has been proposed considering the concept of H-MG. Game theory is adopted and the different players are formulated with competing objectives. It is shown that the proposed market structure provides a global optimal scheduling for exchanging power among H-MGs, while fulfilling the contradictory objectives of the various players. In the proposed non-cooperative structure, players are encouraged to trade in the local market to facilitate exploitation of the existing resources (either generation, storage, or demand response) for the benefit of the power system operation. In addition, the proposed market structure is formulated to be scalable, comprehensive, and less computationally-intensive.

The numerical simulation results reveal that the proposed market empowers H-MG interoperability so that maximum possible load will be served locally by onsite generation resources. Also, it results in minimum operational cost and consequently maximum profit for generators. Furthermore, increasing the number of players in the market resulted in increased competition which eventually resulted in lower relative MCPs for consumers (considering significant increase in the amount of served RLD) and a larger profit for generators.

In future work, the authors are planning to improve market operation by integrating the possibility of coalition formation among different players. Additionally, physical constraints of the network, such as voltage at different locations and power flow through lines, will be formulated as an optimal power flow (OPF) problem. Furthermore, various bidding strategies by the three players will be investigated to quantify market efficiency and performance.

9. Appendix

The specifications of the simulation studies are given in Table 4. Also, Table 5 presents the specifications of the devices in each H-MGs and the coefficients of the load demand prices.

Table 4: The input data of the proposed game structure

Input data	Value in CASE III (CASE II)
number of H-MGs	3 (1)
number of retailers	2 (1)
number of players	8 (3)
Type of game	static (static)
Players' dimensions vector	[4,1,4,1,4,1,2,2] ([4,1,2])
Upper bound level of players	∞ (∞)
Lower bound level of players	0 (0)
Termination tolerance	$1e^{-5}$ ($1e^{-5}$)
Maximum number of iterations allowed by the relaxation algorithm	150 (100)

Table 5: Rated profile of DERs

Parameter	Value	Symbol
ES system		
Maximum ES power during dis/charging modes (kW)	$\overline{P}^{ES+}/\overline{P}^{ES-}$	0.816/3.816
Initial SOC at T (%)	SOC_I	50
Maximum/minimum SOC (%)	$\overline{SOC}/\underline{SOC}$	80/20
Initial stored energy in ES (kWh)	E^{ES}_{I}	1
Total capacity of ES (kWh)	E^{ES}_{Tot}	2
Consumer bid by ES+ ($/kWh)	π^{ES+}_{t}	0.145
PV system		
Maximum/minimum instantaneous power for PV (kW)	$\overline{P}^{PV}/\underline{P}^{PV}$	6/ 0
WT system		
Maximum/minimum instantaneous power for WT (kW)	$\overline{P}^{WT}/\underline{P}^{WT}$	8/ 0.45
MT system		
Maximum/minimum instantaneous power for MT (kW)	$\overline{P}^{MT}/\underline{P}^{MT}$	12/ 3.6
Coefficients of cost function of DGU	a($/kW^{2}h)	[$6e^{-6}$,$7e^{-6}$,$8e^{-6}$]
	b($/kWh)	[0.01,0.015,0.013]
	c($/h)	0
Load coefficients		
Load demand curve coefficients	θ($/kwh)	0.001
	β($/h)	0.18
Maximum coefficient of RLD related to NRL	ζ	5

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