# Hour Block Based Demand Response for Optimal Energy Trading Profits in Networked Microgrids

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## Abstract

Microgrids are a small-scale power system that integrates Distributed Generation, Energy Storage Systems and controllable loads. The intermittent and variable nature of renewable generation leads to a complex control mechanism required for Microgrids. Microgrids that are geographically close to each other are interconnected to form Networked Microgrids. Networked Microgrids provide enhanced benefits of resource sharing to Microgrids, thus, improving the reliability and operation costs while reducing the environmental impact. The Microgrids, based on their generation and load profiles, can perform energy trading within the Networked Microgrid system for achieving optimized operational costs. In this paper, the impact of a novel hour block-based demand response program in Networked Microgrids is explored. In the proposed model, hour blocks are formed in a Networked Microgrids environment, dependent on generation and load imbalance, the role of Microgrids and the Time-of-Use tariff system. The Particle Swarm Optimization method is used to optimize the individual and overall economic benefits of Microgrids

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in the Networked Microgrid system. The simulations of the proposed method are performed on a Networked Microgrid system having 4 Microgrids. The results show a credible reduction in costs of operation for all Microgrids and the system as a whole.

**Keywords:** Networked microgrid, energy trading, particle swarm optimization, demand response, renewable energy sources, time-of-use-tariff.

## Acronyms

| | |
|---|---|
| *t* | Hour block. |
| *B* | Set of buyer MGs. |
| *S* | Set of seller MGs. |
| *N* | Total number of MGs. |
| *b* | Buyer MG. |
| *s* | Seller MG. |
| *v* | Velocity of Particle. |
| *x* | Particle position. |
| *p* | Particle best position. |
| *g* | Global best position. |
| $MG_i^t$ | Generation in $MG_i$ during t. |
| $Load_i^t$ | Load in $MG_i$ during t. |
| $Load_{i,\ actual}^t$ | Actual total load in $MG_i$ for whole day. |
| $E_i^t$ | Excess energy generated in $MG_i$ during t. |
| $D_i^t$ | Deficit energy in $MG_i$ during t. |
| $T_{grid,s}^t$ | Grid selling tariff during t. |
| $T_{grid,b}^t$ | Grid buying tariff during t. |
| $T_{NMG,s}^t$ | NMG energy selling tariff during t. |
| $T_{NMG,b}^t$ | NMG energy buying tariff during t. |
| $Gen_i^{NE}$ | Energy generated in $MG_i$ during t in NE-zone. |
| $Load_i^{NE}$ | Load demand in $MG_i$ during t in NE-zone. |
| $P_{MG_i,s}^t$ | Energy sold by seller $MG_i$ to NMG during t. |
| $P_{MG_i,b}^t$ | Energy bought by buyer $MG_i$ from NMG during t. |
| $P_{MG_i,b}^{g,NE}$ | Total Energy bought by $MG_i$ from grid during NE zone. |
| $P_{NMG,b}^{g,NE}$ | Total Energy bought by NMG from grid during NE zone. |
| $P_{MG_i,s}^{g,t}$ | Energy sold by seller $MG_i$ to grid during t. |

| | |
|---|---|
| $P^{g,t}_{MG_i,b}$ | Energy bought by buyer $MG_i$ from grid during t. |
| $C^{t}_{MG_i,b}$ | Cost incurred to buyer $MG_i$ during t. |
| $C^{t}_{MG_i,s}$ | Profit earned by seller $MG_i$ during t. |
| $C^{NE}_{MG_i,b}$ | Total cost incurred to $MG_i$ during NE zone. |
| $TC^{NE}_{NMG,b}$ | Total cost incurred to NMG during NE zone. |
| $TC^{t}_{MG_b}$ | Total cost incurred to all buyer $MG_i$'s during t. |
| $TC^{t}_{MG_s}$ | Total profit earned by all seller $MG_i's$ during t. |
| $TC_{MG,i}$ | Total cost for $MG_i$ during whole day. |
| $TC_{NMG}$ | Total cost for NMG during whole day. |

## 1 Introduction

Microgrids (MGs) are considered as building blocks capable of transforming existing power system infrastructure to future Smart Grid (SG) vision [1]. MG is defined as a small Active Distribution Network (ADN) with a fixed electrical boundary, containing and controlling Distributed Energy Resources (DERs) [2, 3]. Distributed Generations (DGs), Energy Storage System (ESS) and controllable load are combined to form DERs. For efficient and stable operation and control of power systems under high penetration of DERs, MGs play a very vital role [4]. MGs can run in either grid-connected or islanded mode. The generation must be greater than the critical peak load for isolated MG operation. The grid-connected mode allows bi-directional power flow of energy between the MG and the utility network. In comparison to conventional and centralized generation systems, MGs provide operators and customers with minimized carbon emissions, enhanced reliability and power quality, reduced power losses and minimized investment costs [5].

The uncertain and intermittent nature of renewable DGs, such as Photo-Voltaic (PV) and Wind, create a demand-supply mismatch in an MG. At one point of time in a day, the generation would be more than load whereas the load may be more than the generation at another time. To overcome this energy imbalance, the inclusion of backup generation, such as diesel generation, use of ESS, application of Demand Side Management (DSM) is considered in individual MGs [6, 7]. The integration of diesel generation is noticed to exacerbate environmental issues, whereas the ESS aggregation in MG is constrained by its limited power, high maintenance costs and losses during charging and discharging.

An alternative mechanism of Multiple Microgrids (MMGs)/Networked Microgrids (NMGs) is considered to minimize the energy imbalances in MGs and their dependence on the main grid. The increased installations of MGs at

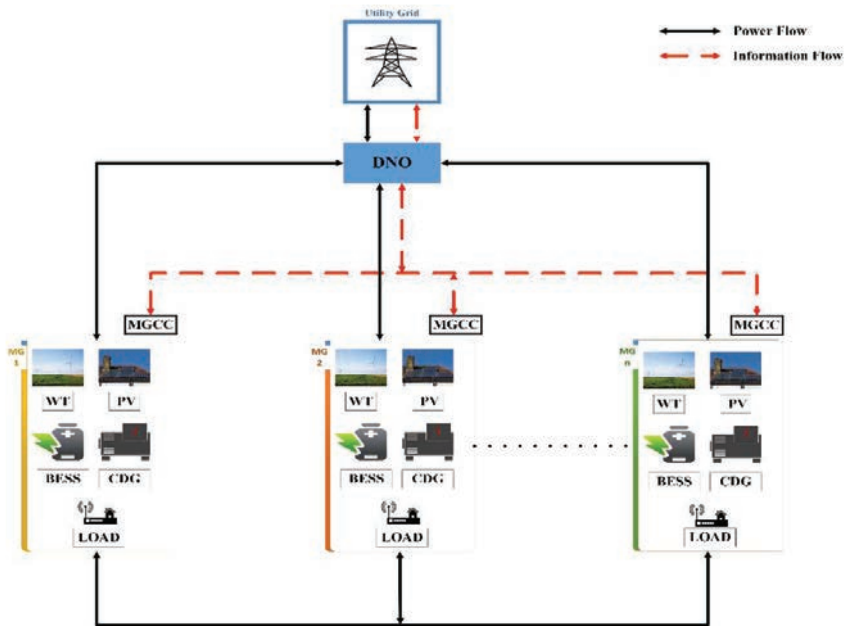


**Figure 1** Architecture of NMG system.

the distribution side allow MGs with different characteristics to operate in clusters. NMGs are known to be installed at the Medium Voltage (MV) level, with several Low Voltage (LV) MGs and DERs connected to the adjacent distribution network [8]. This architecture improves system operation by enhancing plant load factors through better use of Renewable Energy Sources (RES), increasing environmental sustainability, minimizing energy losses, increasing system protection and reliability and allowing MGs to increase profits by trading energy with other MGs [9].

A review of different NMG topologies is given in [10–13]. The NMG topology defined in [10] and [11] is based on the connection of NMGs to the feeder. NMG architecture classified in [12] and [13] is based on the type of interconnection with the grid and among the MGs. Each MG has an MG Central Controller (MGCC) to manage DERs and exchange information to other MGs and Distribution Network Operator (DNO) as shown in Figure 1. MG's can directly trade with each other and to the grid through DNO. The energy trading tariff is decided by DNO.

NMG leverage various DSM strategies to close the supply-demand gap. DSM enables consumers to transfer and reduce their peak load in response to generation [14]. Among the DSM methods, Demand Response (DR) programs allow shifting of load in correspondence to generation by consumers and offer price incentives for the same. This enables the reshaping of MG load profiles in an MMG environment. According to a report by the Federal Energy Regulatory Commission (FERC), DR programs are divided into two categories: time-based and incentive-based [15].

In [16], the effect of the DR program in MMG-based ADN is explored. The preceding problem is modeled as a multi-objective optimization problem, solved using a Non-dominated Sorting Genetic Algorithm (NSGA-II) and backward forward load flow. A collaborative multi-objective Energy Management (EM) strategy for the MMG environment is explored in [17]. The multi-objective problem of minimizing MMG's cost while reducing its reliance on the power grid is solved using Compromised Programming (CP). The implemented DR framework is dependent on the price signal. In [18], for Day-Ahead (DA) scheduling of MMGs, a time-based DR solution is proposed. The suggested EMS takes into account load priority, voltage profiles and the number of loads in MGs to mitigate MG operating costs and environmental impacts. The optimal dispatch problem with DR is solved using Particle Swarm Optimization (PSO). A hierarchical bi-level optimization approach with upper side network operator at the high level and MG operator at the lower level for efficient operation of MMGs is proposed [19]. DR program is applied based on Time-of-Use (TOU) price.

In [20], a bi-level Energy Management System (EMS) for isolated NMGs is suggested, with the outer level considering energy and information exchange among interconnected MG. The inner level EMS is responsible for the scheduling of isolated MG, in case of a fault. A novel power exchange pricing scheme is proposed, as well as step-by-step DR program implementation for each MG. The problem is solved by modeling it as a Mixed Integer Linear Programming (MILP) problem. In [21], EMS based on a cooperative market framework is proposed for MMGs operating in both grid-connected and isolated modes. The nodal marginal price is used to clear the market, which maximizes NMG's social welfare. The stochastic problem is solved using MILP. A real-time pricing-based incentive DR program is considered.

In [8], the profits of Distributed Network Operator (DNO) are maximized in the MMG framework, using multi-follower bi-level programming. Energy trading among MGs, as well as the DR program, are implemented. On the top level, the DNO aims to reduce operational costs by taking into account grid power purchasing costs, electricity exchange costs and DER operating costs. At a lower stage, MGs try to optimize the benefits while satisfying DR and energy exchange between DNO and MGs. The problem is described as a MILP problem with Karush-Kuhn-Tucker (KKT) conditions.

A multi-step hierarchical optimization algorithm based on the Multi-Agent System (MAS) is proposed in [22] to minimize the operating costs and increase the reliability of NMGs. In the proposed EMS, adjustable control and DR programs are included. The MILP model is used to model and solve the optimization problem. In [23], an intelligent EMS for local and global markets is proposed. The local market is in charge of energy trade in MGs, while the global market is in charge of energy trading between MGs and the grid. In [24], MAS-based energy trading among smart MGs with DR is proposed. The DR uses a novel incentive strategy focused on energy generation preference at periods of deficit. After the energy contracts are executed, the energy losses are distributed among the DGs and loads using a novel loss distribution method. A priority-driven DR program is used, similar to [23] except that this time the priority is based on the load size and frequency of participation. Agent theory is applied for the simulation of trading and power management. Two-stage energy management based on Mixed-Integer Quadratic Programming (MIQP) and game theory for NMG is proposed in [25]. Here, distribution feeder reconfiguration is applied in the presence of a shiftable load-based DR program. In [26], to optimize the operation cost of interconnected islanded networked microgrids two-level framework is proposed. For, this price-based DR is considered.

This research implements a novel hour block-based DR method using generation and load imbalance, TOU pricing and role of MGs in the NMG environment in comparison to the literature presented in Table 1. The implemented technique has the advantage of reducing the complexity of the DR problem by scaling down from a 24-hour optimization problem to a 6-block optimization. In this article, the NMGs system is assumed to be running in grid-connected mode. Each MG, in this case, is concerned with the coordinated operation of the RES and flexible load under the NMG structure. The objective is to reduce individual MG's running costs, their dependency on the power network and the cost of energy for customers. In MGs, deterministic RES generation and load values are considered. The problem is modeled as an optimization problem to satisfy the interests of both MGs and consumers. PSO, a heuristic method capable of finding an optimal solution, is used to solve the problem.

The remainder of the paper is outlined as follows. The system design and operating strategy for NMGs are defined in Section 2. The optimization technique considered is presented in Section 3. Section 4 describes in

**Table 1** Summary of literature reviewed

| Reference | Objective | NMG Details | Method | Remark |
|---|---|---|---|---|
| [16] | Formation of MG clusters based on different technical indices. The application of the DR program and ESS, with each index and as a multi-objective problem is presented. | IEEE- 69 bus system with PV, wind turbine and ESS | NSGA-II and Backward Forward load flow | The amount of time spent for each GA run is 18hr. The choice of selection of multi-objective problem or DR and ESS with individual index is left to the operator based on technical and economic factors. |
| [17] | Cost Minimization and Green-house gases reduction. | IEEE-6 bus system with 3 MGs. MGs include RES, dispatchable generation, ESS and Fuel cell. | CP | The optimization technique depends upon the distance between the ideal solution and optimal Pareto solution this choice is left to operators. Different values here provide different solutions. |
| [18] | Cost Minimization | System of 3 NMGs. MGs include RES dispatchable generation, ESS and Fuel cell. | PSO | The computational effort required for deriving a solution to each probable scenario is huge. The constraint on power exchange price is not considered. |
| [19] | Optimal operation of NMGs | Modified 18-bus IEEE system with different capacities for 3 MGs. The modified 30 bus IEEE for the upstream network. | Hybrid stochastic/Robust optimization | The MGs are not directly connected but connected through the power market indirectly in the NMG system considered. In the RT market, the optimal number of bids to be submitted by MGs to USN is not given. |
| [20] | Optimal operation of isolated NMGs. | Radial network with 5 NMGs. MGs consist of RES, ESS, dispatchable DG and responsive loads. | MILP | The pricing mechanism proposed for energy trading between NMGs does not consider RES constraints and power line losses. |

(Continued)

**Table 1** Continued

| Reference | Objective | NMG Details | Method | Remark |
|---|---|---|---|---|
| [21] | Optimal operation of NMGs. | 3 NMG system is considered. Each MG consists of RES, dispatchable DG, ESS and loads. | MILP | |
| [8] | Maximize the profits of DNO | 3 NMG system is considered. Each MG consists of RES, dispatchable DG, ESS and loads. | Multi-follower bilevel programming | Each level of problem is considered as a single bus system without considering the constraints of the network. The uncertainties of RES, the role of BES are not considered. |
| [22] | Cost minimization and increase reliability | 3 NMG system is considered. Each MG consists of RES, dispatchable DG, ESS and loads. | MAS | The amount of time taken to reach an optimal solution is high because of the centralized solver which considers all system constraints, network constraints, demand flexibility and generation availability. |
| [23] | Application of DR in NMG. | 2 NMG system is considered. | MAS | The RES is not considered in the NMG system.<br>The energy transmission lines are considered to be ideal without any transmission losses. |
| [24] | Cost minimization for consumers. | IEEE 37 node distribution with 2 MGs. Each MG consists of RES. | MAS | The priority-based DR method may lead to starvation of loads with low priority. |
| [25] | Optimal operation and cost minimization | Modified 69-bus distribution network. | MIQP and game theory | The costs obtained of some individual MGs and disco are more compared to the centralized approach. |
| [26] | Cost minimization | 3 NMG system is considered. Each MG consists of RES, dispatchable DG, ESS and loads. | MILP | The costs of individual MGs are not provided. |

detail the problem structure of the mentioned problem and the illustrative application of the suggested process. Section 5 contains detailed findings of improvement in MGs benefits and whole NMG operational costs. Finally, this study is concluded in Section 6.

## 2 System Architecture

A benchmark framework for NMGs, based on different topologies for NMGs already discussed in the previous section, is proposed in [27]. The benchmark system is modified to facilitate energy trading amongst the MGs, as shown in Figure 2. The NMG system considered has four individual MGs of different sizes with individual MG interconnected to each other and connected to the distribution network, as well. The total NMG system consists of 40 Buses and 44 transmission lines. Each MG is considered to consist of PV and wind generation along with controllable loads. The details of each MG are presented in Table 2. The first bus of each MG i.e., bus numbers 101, 201, 301, 401 are considered as a slack bus. The MGs are interconnected to each other through the Point of Common Coupling (PCC). The MGs within the

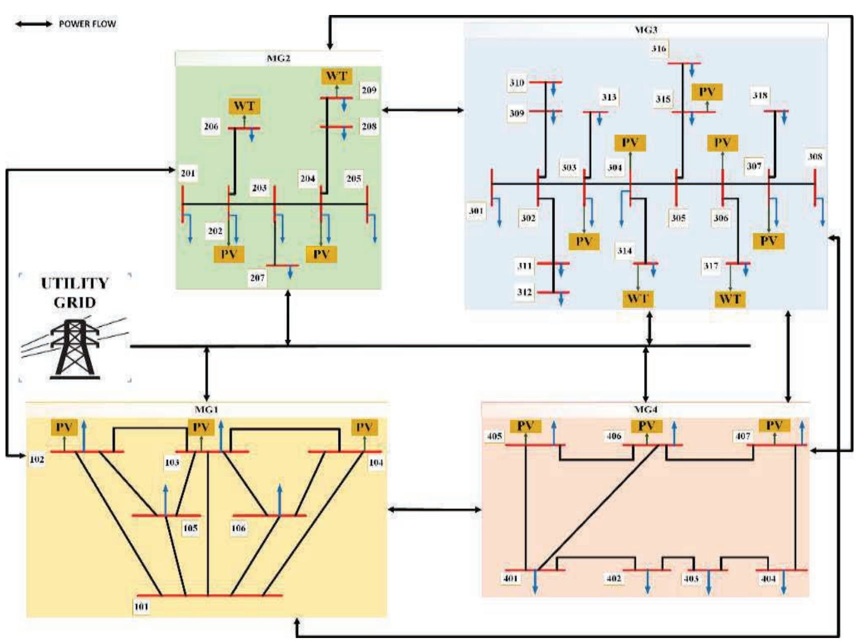


**Figure 2** Single Line Diagram of NMG system [27].

**Table 2** Details of MGs of the NMG system [4]

| Components | $MG_1$ | $MG_2$ | $MG_3$ | $MG_4$ | Total |
|---|---|---|---|---|---|
| **Buses** | 6 | 9 | 18 | 7 | 40 |
| **Lines** | 11 | 8 | 17 | 8 | 44 |
| **PV systems** | 3 | 3 | 6 | 3 | 15 |
| **WT systems** | 0 | 2 | 2 | 0 | 4 |

NMG environment can exchange energy with each other and the grid through dedicated lines.

Each MG in the NMG framework will generate power ($Gen_i^t$) and has a load ($Load_i^t$) that needs to be supplied during each hour block. Due to the variability in the generation, when $Gen_i^t > Load_i^t$ in an MG, then the respective MG acts as a seller for the corresponding hour block. After meeting their corresponding load, each seller MG has excess energy as given in Equation (1). This surplus energy is exchanged with other MGs or the utility network. These sellers allude to a set S represented through Equation (2).

$$E_i^t = Gen_i^t - Load_i^t \; \forall i \in N \tag{1}$$

$$S = \{\forall i \in N | Gen_i^t \geq Load_i^t\} \tag{2}$$

In contrast, if $Load_i^t > Gen_i^t$ for an MG, then the respective MG functions as a buyer for the corresponding hour block. Each buyer MG has deficit energy defined by Equation (3). The buyer MGs purchase power from other MGs or the grid to meet their corresponding demand during the hour block. The group of buyers is represented as a set B defined through Equation (4).

$$D_i^t = Load_i^t - Gen_i^t \; \forall i \in N \tag{3}$$

$$B = \{\forall i \in N | Gen_i^t < Load_i^t\} \tag{4}$$

In hour block t, the utility network sells energy at $T_{grid,s}^t$ and purchases electricity at $T_{grid,b}^t$. To activate energy trading within the NMG, the MGs should trade energy within the NMG environment at a tariff rate between $T_{grid,s}^t$ and $T_{grid,b}^t$. This tariff setting constraint for $T_{NMG,s}^t$ and $T_{NMG,b}^t$ is specified in Equation (5). In case, this constraint is not satisfied, the MGs shall trade energy with the grid rather than other MGs and the objective of forming NMG for energy trading shall cease to exist.

$$T_{grid,b}^t \leq T_{NMG,s}^t = T_{NMG,b}^t \leq T_{grid,s}^t \tag{5}$$

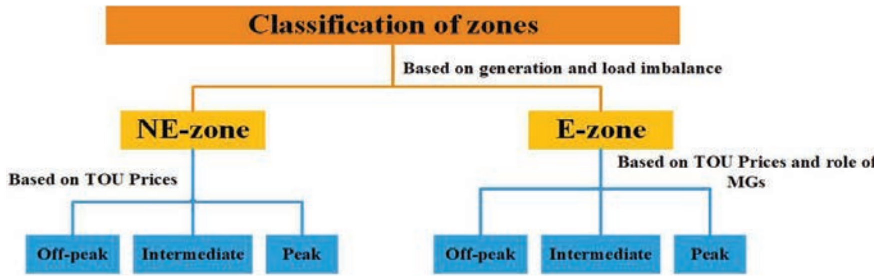


**Figure 3** Classification of hour blocks.

## 2.1 Formation of Hour Blocks

Initially, based on the collective generation and load profiles of MGs, two zones are defined as Excessive zone (E-zone) and Non-Excessive zone (NE-zone). The E-zone is formed when the energy generated by any of the MGs is greater than the load to be supplied by corresponding MGs in the NMG environment. Conversely, when the energy generated by all MGs in the NMG system is less than the load of that individual MG, it is defined as NE-zone.

A day will have multiple E-zones and NE-zones. The creation of these zones is based on TOU prices and load imbalance in the MGs. The role of MGs as a buyer or seller further splits the E-zones as shown in Figure 3. These zones may be present during off-peak, intermediate and peak tariff periods. The hour blocks once created cannot be merged or further split in the remaining part of the process. In the NE-zone, there are only buyer MGs whereas, in E-zone, the MGs in the NMG environment maybe act as sellers or buyers. The consumers in the MGs can benefit by shifting their loads between these demarcated zones, according to the DR program. PSO is utilized to obtain the optimal load scheduling in the NMG framework. The load that can be shifted from one zone to another is restricted to 20% [30] as shown through Equation (6). The total daily load of an MG should not vary even after responding to the DR program. In other words, the total daily load should remain constant for an individual MG of the NMG environment as given by Equation (7).

$$0.8 * Load_i^t \leq Load_i^t \leq 1.2 * Load_i^t \tag{6}$$

$$\sum_t Load_i^t = Load_{i,actual} \tag{7}$$

## 3 Particle Swarm Optimization (PSO)

PSO is a population-based evolutionary technique for solving non-linear equations in real-valued search space, inspired by bird flocking, fish schooling and swarm theory [29]. PSO considers initial solutions to be random variables known as particles. Each particle navigates the search space by interacting with other particles and moving at a velocity through iterations [30]. The velocity ($v_i$) is dynamically modified according to Equation (8). The velocity is based on the personal flying experience and companion particle's findings. Each particle position in PSO is represented by a set $x_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\}$ where n denotes the number of dimensions. The best position achieved by a particle is stored as $p_i = \{p_{i1}, p_{i2}, \ldots, p_{in}\}$. The best position among all the particles is considered as the global best and is represented by ($g$). As in Equation (9), the velocity of a particle changes its location from one point to the next in between iterations.

$$v_n^{i+1} = \omega * v_n^i + c_1 * Rand * (p_n^i - x_n^i) + c_2 * rand * (p_{gn}^i - x_n^i) \quad (8)$$

$$x_n^{i+1} = x_n^i + v_n^{i+1} \quad (9)$$

By maintaining its value constant or adjusting dynamically, the inertia constant ($\omega$) balances the global and local search of particles. A higher inertia value implies global search, while a lower value implies local search. In [31], the authors suggested the $\omega$ value to be greater than 1.0 for early exploration and reduced this to a value less than 1.0 to focus on the best area found in the exploration. A constant inertia value is considered in this study. The speed of flying particles towards the optimum position is represented by the acceleration constants ($c_1$ and $c_2$). $c_1$ is an experimentally dependent factor that represents the exploration coefficient. $c_2$ is nominated as the exploitation coefficient and is instrumental in finding the global optimal solution [32]. $c_1$ and $c_2$ are considered to be 2.05. Rand and rand are random functions generating a random value between 0 to 1. In Equations (8) and (9), 'i' represents the iteration number of PSO.

## 4 Problem Formulation

Each MG in the NMG system under study is equipped with PV and wind generation, which intend to supply power to the respective loads during each time t. However, due to the intermittent nature of PV and wind power generation power imbalance is observed in MG. The power produced is either insufficient or excessive in comparison to the load and this requires the MGs to purchase/sell electricity from/to the grid or other MGs. To reduce dependency on the utility network, based on the power generation and load, the two zones NE-zone and E-zone are established here as previously mentioned. Equations (5), (6) and (7) represent the constraints for the energy trading problem in the NMG environment.

The electricity produced in the NE-zone is inadequate to meet the total load of MGs, the entire deficit of energy is purchased from the grid as in Equation (10). The total cost incurred for buying this energy is given in Equation (11). Equations (12) and (13) give the respective power purchased and cost incurred by individual MGs during the NE zones.

$$P^{g,NE}_{NMG,b} = \left\{ \sum_{i=1}^{N} Load_i^{NE} - \sum_{i=1}^{N} Gen_i^{NE} \right\} \tag{10}$$

$$TC^{NE}_{NMG,b} = P^{grid,t}_{NMG,b} * T^{t}_{grid,s} \tag{11}$$

$$P^{g,NE}_{MG_i,b} = \{Load_i^{NE} - Gen_i^{NE}\} \tag{12}$$

$$C^{NE}_{MG_i,b} = \{P^{g,NE}_{MG_i,b} * T^{t}_{grid,s}\} \tag{13}$$

In E-zone, the amount of energy generated is higher than the amount of load to be supplied in certain MGs. For a given E-zone there might arise any of the following two conditions, based on the total generation and total load demand of the NMG:

1. Excess Generation
2. Excess Demand.

## 4.1 Excess Generation

In this case, the excess energy generated by seller MGs is greater than or equal to the amount of energy required by buyer MGs in the NMG framework. The seller MGs trade energy with buyer MGs at a price that satisfies the constraint given in Equation (5). The fraction of energy sold by seller MGs to buyer MGs is following the proportional trading strategy outlined in Equation (14).

$$P^{t}_{MG_i,s} = \frac{E_i^t}{\sum_{j=1}^{S} E_j^t} * \sum_{k=1}^{B} D_k^t \tag{14}$$

If any excess energy remains with the seller's MGs, it is traded with utility as in Equation (15). Equations (16) and (17) give the cost incurred by each buyer MG and all buyer MGs together respectively.

$$P^{g,t}_{MG_i,s} = E^t_i - P^t_{MG_i,s} \tag{15}$$

$$C^t_{MG_i,b} = D^t_i * T^t_{NMG,s} \tag{16}$$

$$TC^t_{MG_b} = \sum_{i=1}^{B} C^t_{MG_i,b} \tag{17}$$

The profit gained by each seller MG and all seller MGs together from trading excess energy is provided in Equations (18) and (19) respectively.

$$C^t_{MG_i,s} = P^t_{MG_i,s} * T^t_{NMG,s} + P^{g,t}_{MG_i,s} * T^t_{grid,b} \tag{18}$$

$$TC^t_{MG_s} = \sum_{i=1}^{S} C^t_{MG_i,s} \tag{19}$$

## 4.2 Excess Demand

In this condition, the energy generated by seller MGs is insufficient to meet the buyer MG's total load in NMG. The buyer MGs obtain a fraction of their required demand from seller MGs and the remaining energy is obtained from the grid. The energy bought by a buyer MG from the NMG framework is shown in Equation (20) and the remaining deficit energy purchased from the grid is given in Equation (21). The cost of energy for individual buyer MG and that for all buyer MGs together are given in Equations (22) and (23).

$$P^t_{MG_i,s} = \frac{E^t_i}{\sum_{j=1}^{S} E^t_j} * \sum_{k=1}^{B} D^t_k \tag{20}$$

$$P^{g,t}_{MG_i,b} = D^t_i - P^t_{MG_i,b} \tag{21}$$

$$C^t_{MG_i,b} = P^t_{MG_i,b} * T^t_{NMG,s} + P^{g,t}_{MG_i,b} * T^t_{grid,s} \tag{22}$$

$$TC^t_{MG_b} = \sum_{i=1}^{B} C^t_{MG_i,b} \tag{23}$$

The amount of price earned by individual seller MG and all seller MGs together for this case is given by Equations (24) and (25).

$$C^t_{MG_i,s} = E^t_i * T^t_{NMG,s} \tag{24}$$

$$TC^t_{MG_s} = \sum_{i=1}^{S} C^t_{MG_i,s} \tag{25}$$

The total cost incurred to individual MGs and the NMG system for a whole day is given by Equations (26) and (27).

$$TC_{MG,i} = C^{NE}_{MG_i,b} + \sum C^t_{MG_i,b} + \sum C^t_{MG_i,s} \quad \forall t \in \{NE, E\} \tag{26}$$

$$TC_{NMG} = TC^{NE}_{NMG,b} + \sum TC^t_{MG_b} + \sum TC^t_{MG_s} \quad \forall t \in \{NE, E\} \tag{27}$$

## 4.3 Flowchart

The proposed methodology is depicted through a flowchart in Figure 3. Initially, the PV and Wind generation along with its load profile are obtained for each MG. The input data should also have the TOU prices, specified by the utility/grid. The zones are established using the power imbalances in NMG, the TOU prices and also the role of MGs, according to Figure 4. The DR program is implemented using PSO while satisfying the constraints on load transfer between zones, given by Equations (6) and (7). The price range for trading in each zone is kept within a given range as represented by Equation (5).

The particles are randomly generated to represent the load during different zones for each MG and the NMG energy prices during the E-zones. The Equations (14)–(25) calculate the amount of energy traded between the seller and buyer MGs, cost incurred to each buyer and seller MG and overall NMG system costs. These evaluations help obtain the objective function value for a particular particle. The individual and global best particles are demarcated. Velocity is calculated for each particle and the positions are changed accordingly. The process continues till the stopping criteria are met. The limits for different parameters have to be kept within range at all times during the optimization process.

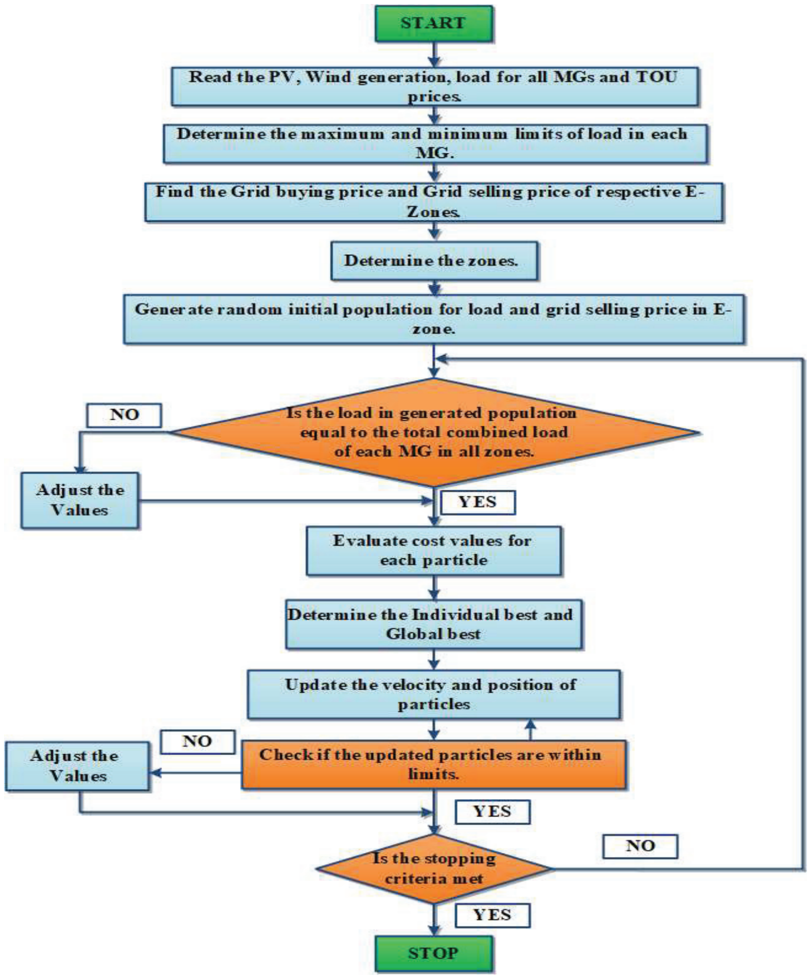


**Figure 4** Flowchart of proposed methodology.

## 5 Results

The proposed experiment is implemented and analyzed in MATLAB software. The NMG system consists of 4 MGs, where $MG_1$ is a 6-bus system, $MG_2$ is a 9-bus system, $MG_3$ is an 18-bus system and $MG_4$ is a 7-bus system respectively. In the proposed structure of NMG, each MG can trade energy with all other MGs and the utility grid. Each MG is installed with PV, wind energy and schedulable loads. The combined PV and wind energy

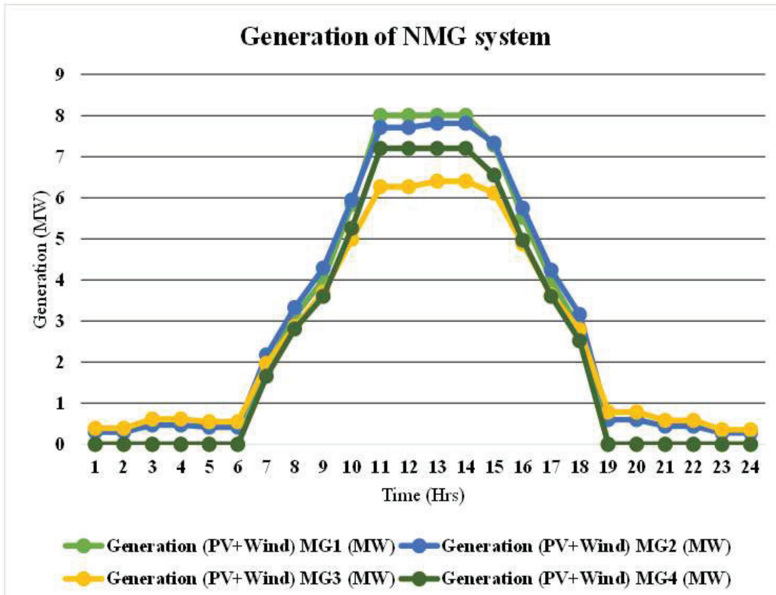


**Figure 5** PV and wind generation in NMGs.

generation for a certain day is shown in Figure 5. The PV, wind and load data is considered through a deterministic approach and the calculations are performed for the 12th of February. The load for the corresponding day is as shown in Figure 6.

The TOU prices for the day are taken from [28]. The utility buying price, i.e., the price at which the grid buys energy from the NMG, is considered to be a third of the grid selling price given by $\frac{1}{3} * T^t_{grid,s}$. The TOU prices for all hours of the day are shown in Figure 7. These prices are classified as off-peak, intermediate and peak periods as summarized in Table 3. The periods: 1 – 7, 11 – 12 and 22 – 24 hours are considered as off-peak with $T^t_{grid,s}$ as 93.6 (USD/MWh). For intermediate, the periods are 8 – 10, 13 – 18 and 21 hours with $T^t_{grid,s}$ as 124.8 (USD/MWh) and 19 – 20 is peak period with the $T^t_{grid,s}$ as 156 (USD/MWh). The parameters considered for PSO are given in Table 4.

## 5.1 Hour Blocks

The hour blocks are created through the imbalance between load and generation and the variation in prices. If $Gen^t_i$ is less than $Load^t_i$ for a particular MG,

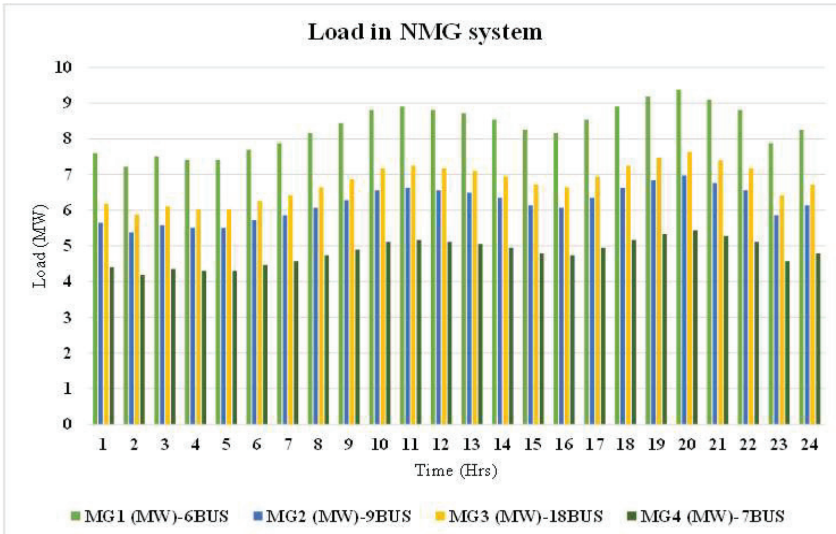


**Figure 6** Load in NMGs.

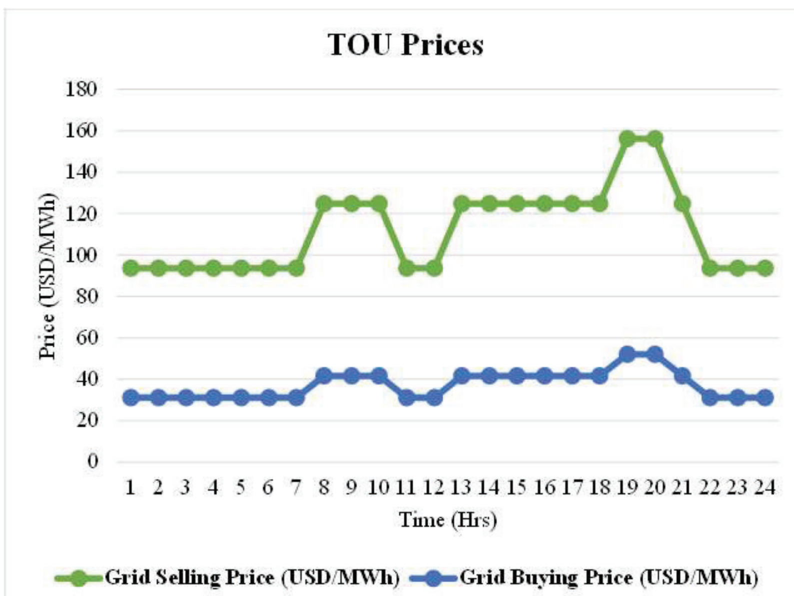


**Figure 7** TOU Prices for NMGs.

**Table 3** TOU prices for the day and its classification

| Period | Time (Hrs) | Grid Selling Price (USD/MWh) | Grid Buying Price (USD/MWh) |
|---|---|---|---|
| **Off-peak** | 1 – 7, 11 – 12, 22 -24 | 93.6 | 31.2 |
| **Intermediate** | 8 – 10, 13 – 18 and21 | 124.8 | 41.6 |
| **Peak** | 19 – 20 | 156 | 52 |

**Table 4** PSO parameters

| Topology | Values |
|---|---|
| **Particles** | 100 |
| **Iterations** | 500 |
| $\boldsymbol{\omega}$ | 0.729 |
| $\boldsymbol{C}_1$ | 2.05 |
| $\boldsymbol{C}_2$ | 2.05 |
| **rand, Rand** | between 0 and 1 |

it has to purchase energy from the utility or other MGs. On the other hand, if $Gen_i^t$ is greater than $Load_i^t$, MG has excess energy which can be sold. An E-zone can be formed for a particular hour block/duration if any MG within the NMG environment has excess energy and the TOU prices remain constant during this period. The hour blocks when none of the MGs within the NMG environment have the energy to sell, are considered as NE-zone. The E-zone may further be split if one or more of the MGs changes its role from buyer to seller and vice versa. Once the zones are created at the beginning of the optimization technique then they cannot be merged or increased even if the MG role changes in the optimal solution.

The whole day is divided into 6 blocks based on their classification as E-zone or NE-zone. Figures 8 and 9 give the zone-wise distribution of generation and load respectively. Out of these 6 zones, 3 zones are NE-zones and 3 zones are E-zones. During (1–7), (8–9), (17–18), (19–20), 21 and (22–24) hrs, all MGs face deficit energy and these hour blocks are considered as NE-zones. At 10 and 16 hrs, $MG_4$ has excess energy, whereas, at (11–12) and (13–15), $MG_2$ and $MG_4$ generate excess energy and these hour blocks are considered as E-zones.

## 5.2 Case Studies

The different modes of NMG operation considered in this paper are discussed in this sub-section.

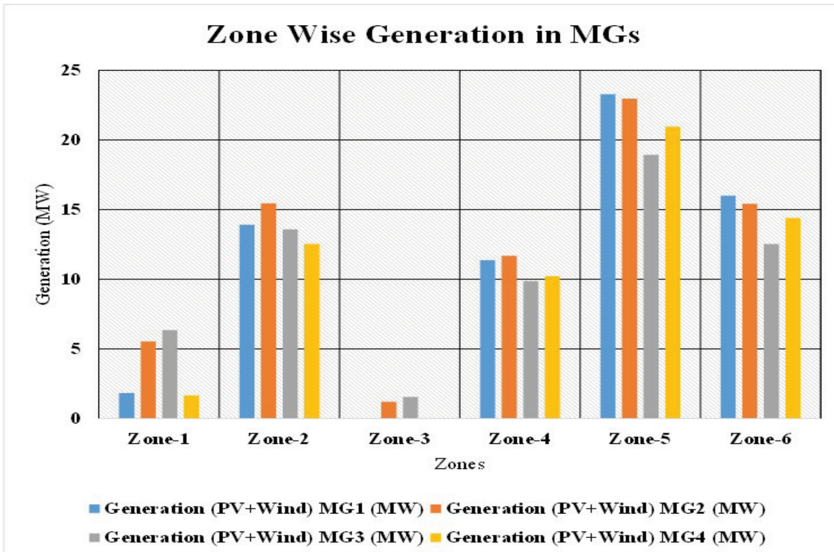


**Figure 8** Zone wise generation in NMG.

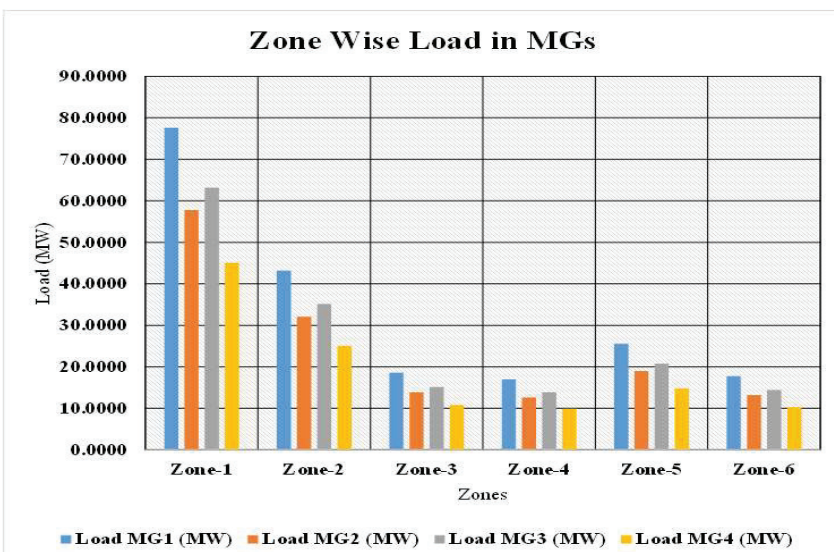


**Figure 9** Zone Wise Load in NMG.

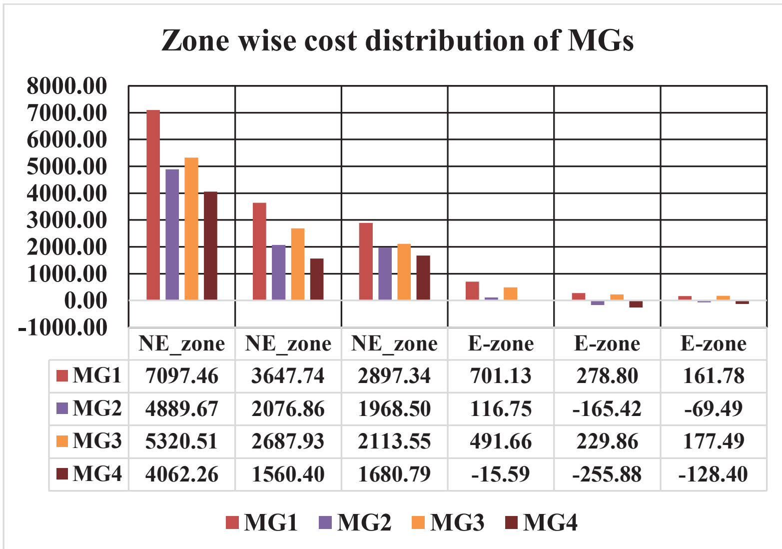


**Figure 10** Costs of individual mg based on base case.

Case I (Without hour blocks): In the first case, the generation and load are considered to be the same as shown in Figures 5 and 6 and TOU prices as shown in Figure 7. The operating cost of each MG for each zone is shown in Figure 10. The proposed objective function verifies the cost in each MG and NMG based on TOU prices in each zone without applying DR programs or hour blocks.

The total combined cost of each MG for the whole day is $MG_1$: 14784.26 (USD/MWh), $MG_2$: 8816.86 (USD/MWh), $MG_3$: 11021 (USD/MWh) and $MG_4$: 6903.59 (USD/MWh) respectively. The total operating cost of the whole NMG system is 41525.71(USD/MWh).

Case II (Cost Minimization considering DR and hour blocks): In this case, the DR program and hour blocks are applied for the minimization of costs for each MG as well as the overall NMG system. PSO is applied for the implementation of the DR program in the NMG framework. The results are compiled after executing PSO 40 times. The comparison of zone-wise actual load and the load distribution according to PSO is shown in Figure 11. The role of each MG as a buyer or seller is dependent on the optimal load schedule obtained through PSO which is displayed in Table 5.

The mean of energy trading price of MGs ($T^t_{MG,s}$) in NMG framework for 3 E-zones after multiple executions of PSO are obtained as 74.88

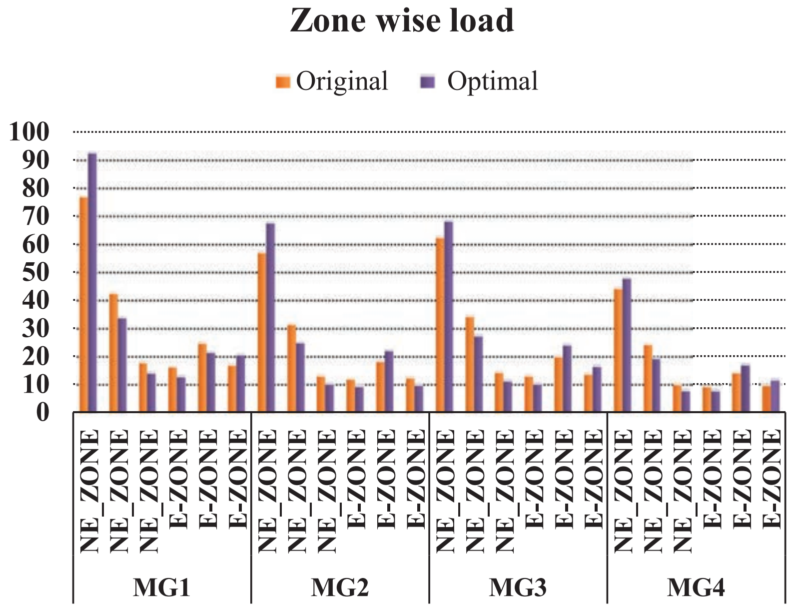


**Figure 11** Comparison of original and optimal case.

**Table 5** Role of each MG

| $MG_1$ | $MG_2$ | $MG_3$ | $MG_4$ | Zone |
|---|---|---|---|---|
| Buyer | Buyer | Buyer | Buyer | NE-zone |
| Buyer | Buyer | Buyer | Buyer | NE-zone |
| Buyer | Buyer | Buyer | Buyer | NE-zone |
| Buyer | Seller | Buyer | Seller | E-zone |
| Seller | Seller | Buyer | Seller | E-zone |
| Buyer | Seller | Buyer | Seller | E-zone |

(USD/MWh), 83.2 (USD/MWh) and 56.41 (USD/MWh) respectively. The optimal costs for energy trading in E zones are obtained as 41.6 (USD/MWh), 41.6 (USD/MWh) and 31.2 (USD/MWh) respectively.

The standard deviation for load in each zone and the trading prices for the E-zones are shown in Table 6.

In Table 7, the results obtained through PSO show an improvement in costs compared to the base case. There is a 6.21% and 7.03% reduction in total operating costs of NMG for mean and optimal PSO results respectively as compared to the case I. The implementation of the DR program also adds to the minimization of operation costs in individual MGs.

**Table 6** Zone wise standard deviation of load and price

| Zone | $MG_1$ | $MG_2$ | $MG_3$ | $MG_4$ | Price |
|---|---|---|---|---|---|
| **NE-zone** | 5.81 | 5.42 | 4.36 | 3.95 | – |
| **NE-zone** | 0.00 | 3.33 | 0.00 | 3.04 | – |
| **NE-zone** | 1.98 | 0.87 | 0.00 | 1.31 | – |
| **E-zone** | 2.75 | 2.27 | 2.32 | 1.80 | 41.28 |
| **E-zone** | 3.82 | 3.19 | 3.08 | 2.37 | 42.13 |
| **E-zone** | 2.23 | 2.08 | 2.27 | 1.69 | 30.79 |

**Table 7** Optimal results of energy trading for Case 1 and 2

| MGs | Case 1 | Case 2 (Mean) | Savings (%) | Optimal Solution | Savings (%) |
|---|---|---|---|---|---|
| $\boldsymbol{MG_1}$ | 14784.26 | 14040.89 | 5.03 | 13753.61 | 6.97 |
| $\boldsymbol{MG_2}$ | 8816.86 | 8194.54 | 7.06 | 8464.89 | 3.99 |
| $\boldsymbol{MG_3}$ | 11021.00 | 10416.23 | 5.49 | 9980.88 | 9.44 |
| $\boldsymbol{MG_4}$ | 6903.59 | 6294.95 | 8.82 | 6405.17 | 7.22 |
| **NMG** | 41525.71 | 38946.61 | 6.21 | 38604.55 | 7.03 |

## 6 Conclusion

In this paper, a novel hour block-based DR approach is proposed for energy trading in NMG. The proposed model aims to minimize the operation cost of individual MGs and the NMG system. In the proposed methodology, based on generation and load imbalance the zones are formed, which are further classified based on TOU prices and roles of MGs. The suggested approach reduces the complexity since instead of 24 hours, only 6 blocks are to be optimized. A comparison is presented between different trading scenarios. The results indicate a significant reduction in operating costs of individual MGs and the NMG network with the application of the proposed DR program. The PSO method is applied for obtaining the optimal solution. The hour block method of applying DR helps reduce the complexity of the problem and reduces the time required for obtaining optimal results.

## References

[1] Yeliz Yoldas, Ahmet Önen, SM Muyeen, Athanasios V Vasilakos, and İrfan Alan. Enhancing smart grid with microgrids: Challenges and opportunities. *Renewable and Sustainable Energy Reviews*, 72:205–214, 2017.

[2] Dan T Ton and Merrill A Smith. The us department of energy's microgrid initiative. *The Electricity Journal*, 25(8):84–94, 2012.

[3] Sina Parhizi, Hossein Lotfi, Amin Khodaei, and Shay Bahramirad. State of the art in research on microgrids: A review. *Ieee Access*, 3:890–925, 2015.

[4] Nikos Hatziargyriou, Hiroshi Asano, Reza Iravani, and Chris Marnay. Microgrids. *IEEE power and energy magazine*, 5(4):78–94, 2007.

[5] IRE Series. Microgrids and active distribution networks. *The institution of Engineering and Technology*, 2009.

[6] HSVS Kumar Nunna and Suryanarayana Doolla. Energy management in microgrids using demand response and distributed storage—a multi-agent approach. *IEEE Transactions on Power Delivery*, 28(2):939–947, 2013.

[7] Ashok M Jadhav, Nita R Patne, and Josep M Guerrero. A novel approach to neighborhood fair energy trading in a distribution network of multiple microgrid clusters. *IEEE Transactions on Industrial Electronics*, 66(2):1520–1531, 2018.

[8] Mehdi Jalali, Kazem Zare, and Heresh Seyedi. Strategic decision-making of distribution network operator with multi-microgrids considering demand response program. *Energy*, 141:1059–1071, 2017.

[9] Liang Che, Xiaping Zhang, Mohammad Shahidehpour, Ahmed Alabdulwahab, and Abdullah Abusorrah. Optimal interconnection planning of community microgrids with renewable energy sources. *IEEE Transactions on Smart Grid*, 8(3):1054–1063, 2015.

[10] Guodong Liu, Michael R Starke, Ben Ollis, and Yaosuo Xue. Networked microgrids scoping study. *ORNL, TN.[Online]*. Available: https://info.ornl.gov/sites/publications/files/Pub68339.pdf, 2016.

[11] Mahamad Nabab Alam, Saikat Chakrabarti, and Arindam Ghosh. Networked microgrids: State-of-the-art and future perspectives. *IEEE Transactions on Industrial Informatics*, 15(3):1238–1250, 2018.

[12] Eduard Bullich-Massagué, Francisco Díaz-González, Mònica Aragüés-Peñalba, Francesc Girbau-Llistuella, Pol Olivella-Rosell, and Andreas Sumper. Microgrid clustering architectures. *Applied energy*, 212: 340–361, 2018.

[13] Hualei Zou, Shiwen Mao, Yu Wang, Fanghua Zhang, Xin Chen, and Long Cheng. A survey of energy management in interconnected multi-microgrids. *IEEE Access* 7:72158–72169, 2019.

[14] John S Vardakas, Nizar Zorba, and Christos V Verikoukis. A survey on demand response programs in smart grids: Pricing methods and

optimization algorithms. *IEEE Communications Surveys & Tutorials*, 17(1):152–178, 2014.

[15] Michael Lee, Omar Aslam, Ben Foster, David Kathan, Jordan Kwok, Lisa Medearis, Ray Palmer, Pamela Sporborg, and Michael Tita. Assessment of demand response and advanced metering. *Federal Energy Regulatory Commission, Tech. Rep*, 2013.

[16] Hossein Haddadian and Reza Noroozian. Multi-microgrid-based operation of active distribution networks considering demand response programs. *IEEE Transactions on Sustainable Energy*, 10(4):1804–1812, 2018.

[17] Hamid Karimi and Shahram Jadid. Optimal energy management for multi-microgrid considering demand response programs: A stochastic multi-objective framework. *Energy*, 195:116992, 2020.

[18] Nima Nikmehr, Sajad Najafi-Ravadanegh, and Amin Khodaei. Probabilistic optimal scheduling of networked microgrids considering time-based demand response programs under uncertainty. *Applied energy*, 198:267–279, 2017.

[19] Mohammad Saeed Misaghian, Mohammadali Saffari, Mohsen Kia, Mehrdad Setayesh Nazar, Alireza Heidari, Miadreza Shafie-khah, and João PS Catalão. Hierarchical framework for optimal operation of multiple microgrids considering demand response programs. *Electric power systems research*, 165:199–213, 2018.

[20] Seyed Ehsan Ahmadi and Navid Rezaei. A new isolated renewable based multi microgrid optimal energy management system considering uncertainty and demand response. *International Journal of Electrical Power & Energy Systems*, 118:105760, 2020.

[21] Ramin Bahmani, Hamid Karimi, and Shahram Jadid. Stochastic electricity market model in networked microgrids considering demand response programs and renewable energy sources. *International Journal of Electrical Power & Energy Systems*, 117:105606, 2020.

[22] Van-Hai Bui, Akhtar Hussain, and Hak-Man Kim. A multiagent-based hierarchical energy management strategy for multi-microgrids considering adjustable power and demand response. *IEEE Transactions on Smart Grid*, 9(2):1323–1333, 2016.

[23] HSVS Kumar Nunna and Suryanarayana Doolla. Demand response in smart distribution system with multiple microgrids. *IEEE transactions on smart grid*, 3(4):1641–1649, 2012.

[24] HSVS Kumar Nunna, Amit Mohan Saklani, Anudeep Sesetti, Swathi Battula, Suryanarayana Doolla, and Dipti Srinivasan. Multi-agent based

demand response management system for combined operation of smart microgrids. *Sustainable Energy, Grids and Networks*, 6:25–34, 2016.

[25] Behzad Javanmard, Mohammad Tabrizian, Meghdad Ansarian, and Amir Ahmarinejad. Energy management of multi-microgrids based on game theory approach in the presence of demand response programs, energy storage systems and renewable energy resources. *Journal of Energy Storage*, 42:102971, 2021.

[26] Ali Jani, Hamid Karimi, and Shahram Jadid. Hybrid energy management for islanded networked microgrids considering battery energy storage and wasted energy. *Journal of Energy Storage*, 40:102700, 2021.

[27] Mahamad Nabab Alam, Saikat Chakrabarti, and Xiaodong Liang. A benchmark test system for networked microgrids. *IEEE Transactions on Industrial Informatics*, 16(10):6217–6230, 2020.

[28] Hongbin Wu, Xin Liu, Bin Ye, and Bin Xu. Optimal dispatch and bidding strategy of a virtual power plant based on a stackelberg game. *IET Generation, Transmission & Distribution*, 14(4):552–563, 2019.

[29] James Kennedy and Russell Eberhart. Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks*, volume 4, pages 1942–1948. IEEE, 1995.

[30] Yuhui Shi and Russell C Eberhart. Empirical study of particle swarm optimization. In *Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406)*, volume 3, pages 1945–1950. IEEE, 1999.

[31] Daniel Bratton and James Kennedy. Defining a standard for particle swarm optimization. In *2007 IEEE swarm intelligence symposium*, pages 120–127. IEEE, 2007.

[32] H Abdi, M Ranjbaran, P Nazari, and H Akbari. A review on pso models in power system operation. *International Journal of Emerging Technology and Advanced Engineering* 3(7), 2013.

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