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Optimized Power Trading of Reconfigurable Microgrids in Distribution Energy Market

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ABSTRACT Integrating Distributed Energy Resources (DERs) and Micro-Grid (MG) into a system evolved the traditional power system. In spite of their significant advantages, MGs may result in volatility and uncertainty in the power systems. For reliable operation of the grid, energy trading among MGs should be optimized to maintain a fair trading price, maximize participants' profit, and satisfy network constraints. In this paper, the optimal power trading among multiple reconfigurable MGs is formulated as a Mixed-Integer Nonlinear Programming (MINLP) considering all energy resources and their dynamic prices. In spite of the other methods in the literature, the proposed method minimizes the total cost (increase sales and decrease purchases) and transmission loss considering all energy resources in the MGs. In order to flatten the load profile, a time-based load profile is considered for the demand response program. The performance of the proposed model is evaluated on an IEEE 6-bus network as well as a modified IEEE 33-bus test system. The results verify that the proposed method, (i) determines the best configuration among MGs with a switching reduction of about 30%, (ii) optimizes the power generation of energy resources with 12% reduction in energy production, and (iii) optimizes the power trading costs with a 10% reduction in costs compared with the basic model without DR and trade that is introduced as *Scen.*1 in this paper.

INDEX TERMS Microgrid, reconfiguration, power trading, distributed energy resources (DER), demand response, mixed-integer nonlinear programming (MINLP).

NOMENCLATURE

PROBLEM PARAMETERS

G	set of MGs, such as $g, g' \in G$
N	set of buses, such as $n, n' \in N$
E	set of energy resources, such as $e, e' \in E$
D	set of load demands, such as $d \in D$
$St(g, g')$	set of available switches between MGs g and g', $m \in St(g, g')$
T	set of times, such as $t \in T$
i, j	index of time period, such as i-th period or j-th period
Δt	time interval (Hour)
$d_0(i)$ (kWh)	initial demand value in i-th hour
$d(i)$ (kWh)	customer demand in i-th hour
$E(i, i)$	self elasticity
$E(i, j)$	cross elasticity
P_{gne}^{min}	minimum active generation power on MG g, bus n for energy source e
P_{gne}^{max}	maximum active generation power on MG g, bus n for energy source e
Q_{gne}^{min}	minimum reactive generation power on MG g, bus n for energy source e
Q_{gne}^{max}	maximum reactive generation power on MG g, bus n for energy source e
C_{gnet}^{S}	cost of power selling on MG g, bus n, energy source e at time t
P_{gnt}^{d}	active load power on MG g, bus n at time t
$P_{gnt}^{d(i)}$	active DR-based load power on MG g, bus n at time t
Q_{gnt}^{d}	reactive load power on MG g, bus n at time t

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a_{gne}	cost coefficients of energy source e on bus n of MG g
b_{gne}	cost coefficients of energy source e on bus n of MG g
$\|V_{gn}^{min}\|$	minimum voltage magnitude on MG g, bus n
$\|V_{gn}^{max}\|$	maximum voltage magnitude on MG g, bus n
$SL_{gng'n'}^{min}$	minimum power on link between buses n and n' of MGs g and g'
$SL_{gng'n'}^{max}$	maximum power on link between buses n and n' of MGs g and g'
$G_{gng'n'}$	real part of component buses n and n' of MGs g and g' in admittance matrix
$B_{gng'n'}$	imaginary part of component buses n and n' of MGs g and g' in admittance matrix
$\alpha_1, \alpha_2, \alpha_3$	objective function coefficients
R	Branch resistance
X	Branch reactance

PROBLEM VARIABLES

P_{gnet}^{O}	active generation power on MG g, bus n, energy source e at time t
Q_{gnet}^{O}	reactive generation power on MG g, bus n, energy source e at time t
$P_{gtg'n'e'}^{B}$	buying active power by MG g, of MG g', bus n', energy source e' at time t
$Q_{gtg'n'e'}^{B}$	buying reactive power by MG g, of MG g', bus n', energy source e' at time t
$P_{gnetg'}^{S}$	selling active power by MG g, bus n, energy source e to MG g, at time t
$Q_{gnetg'}^{S}$	selling reactive power by MG g, bus n, energy source e to MG g, at time t
$\|V_{gnt}\|$	voltage magnitude of bus n of MG g at time t
$\theta_{gng'n't}$	voltage angle of link between buses n and n' of MGs g and g' at time t
$PL_{gng'n't}$	active power on link between buses n and n' of MGs g and g' at time t
$QL_{gng'n't}$	reactive power on link between buses n and n' of MGs g and g' at time t
$SL_{gng'n't}$	apparent power on link between buses n and n' of MGs g and g' at time t
$St_{mgg't}$	m'th switch status (binary) on link between MGs g and g' at time t
δ_{gnet}	1 if energy source e of bus n of MG g at time t is on (0 for off)

I. INTRODUCTION

Nowadays with the increase of small-scale Distributed Energy Resources (DERs), local energy distribution using small-scale resources is possible like energy distribution in Micro-Grid (MG) [1]. According to the Department of Energy (DoE) [2], MGs can be isolated/connected to other MGs/main-grid. Running on a non-trading mode can increase manageability and reduce transmission loss [3] in MGs. There are two aspects to the negotiations. From one perspective, running in non-trading mode is not possible always and the MGs need to have power trade with other MGs/main grid. From another perspective, Demand Response (DR) programs are an effective way to increase the non-trading of MGs by flattening the load profile and shifting peak loads to low-peak periods. So, a trade-off between these two aspects is needed and power trading with considering DR programs can be good in advance.

Although much research has been done on the power trade between MGs, most of them focus on the amount of exchanged energy/power between MGs, without considering type of energy resources.

Mainly, energy market between MGs has numerous types of energy resources, from conventional to renewable resources. MG's consumers can be prosumers, who can both consume and generate energy [4]. Purchasing and selling power between participants in the energy industry is called power trading, which is developed based on the "Peer to Peer (P2P) economy" concept [5] which is a decentralized model whereby two individuals interact to buy/sell energy with each other. Unlike the decentralized mode, in the centralized method the MGs are not directly related to each other. A central entity is responsible for managing and creating interactions between MGs. In this case, the overall goal of the system is to reduce the cost of all MGs as well as optimizing their switching between MGs along with increasing revenue by selling energy. Selecting the proper energy resources in power trading is still a challenging task. Since MGs have multiple resources at various prices, it is possible to sell power from one or more resources per hour. Based on these cases, two aspects can be considered. The first is the trade between MGs, and the second is the use of DR programs to reduce the need to buy MGs and flatting their load shape.

In the field of trade between MGs, the configuration of MGs will be changed based on trading results. For example, a P2P trade between two MGs needs to connect those MGs directly or indirectly. Therefore, optimal power scheduling inside power trading in a distribution network has to select the best configuration among MGs. Most of the papers consider all available configurations to select the best configuration which is time-consuming [6]. It should be noted that due to the cost of switching, the number of switches per day should not be more than a threshold.

DR programs are the second field which are an opportunity for consumers and prosumers to obtain more benefits by shifting their required load during peak periods in response to time-based or incentive-based rates [7]. The Federal Energy Regulatory Commission (FERC) has defined DR as follows: "Changes in electric usage by demand-side resources from their normal consumption pattern in response to changes in the price of electricity." [8]. This paper uses DR programs inside power trading to decrease the whole cost.

In the field of Power Distribution Network (PDN) scheduling and trading, the Distribution Network (DN) operator has

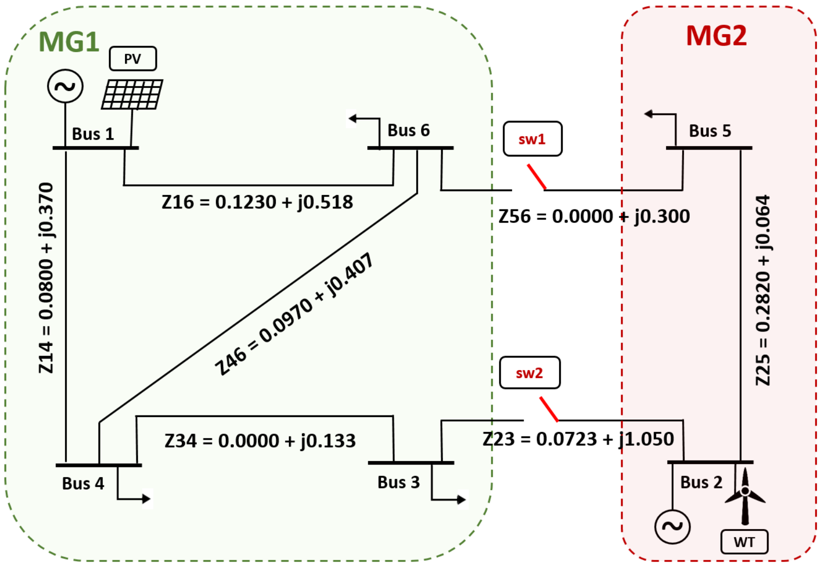


FIGURE 1. An example of a IEEE 6-bus microgrid-based DN.

several goals includes optimal scheduling [9], [10], and optimal power trading [11]. An optimal reconfiguration system for power scheduling in DN is proposed in [6] to enhance the network flexibility. The proposed method considers all network topologies to specifying the best configuration. Reference [12] proposed a model for reconfiguration of a DN for decreasing transmission loss. Different reconfiguration methods with minimizing the transmission loss and network operation's cost are proposed in [13]. Most of these papers [6], [12], [13] consider all available configuration and do not focus on the number of switches per day. The power scheduling in the MGs has to specify the best configuration MGs or the number of required switches per hour.

In Figure 1, an example test system with 6 buses in 2 MGs with different loads and generation/energy resources is shown. *Bus*1 and *Bus*2 have conventional generation. *Bus*1 has also a photovoltaic generation and *Bus*2 has also a wind turbine. Buses *Bus*3, *Bus*4, *Bus*5, and *Bus*6 have power load. The two mentioned MGs have two connection switch1 called *sw*1 and *sw*2. The scheduling and trading solution, have to select the best configuration and also the number of switches per hour.

Considering power trading coincide with power scheduling is still a challenging problem and most of the papers focus on one of these problems [6], [14]–[16]. Also in the field of power trading, choosing the involved resource is still a challenge. The trading papers do not focus on the involved energy resource which is sold or bought [4], [14]. In order to address these problems, this paper presents a model of power trading in the reconfigurable MGs by an MINLP model and uses a DR program to flatting the load profile to cause the minimization the cost, switching, and transmission loss. Non-linear problem model selected due to the power scheduling process and its formulation.

The proposed model is able to determine the following: (i) the best configuration between MGs, (ii) power scheduling (the amount of generating power of renewable and non-renewable resources), and (iii) power trading (the amount of power purchased or sold) based on each energy resource per hour. Solving proposed model for each MG allows us to manage each MG in non-trading mode and if the required load was not provided in non-trading mode, dealing with other MGs is possible as trading. The result will lead to a proper configuration between the MGs. The optimization aims of proposed model is minimize the total cost (incomes are modeled as a negative cost) and transmission loss. To demonstrate the effectiveness of the proposed model, it has been implemented on two different MGs (an IEEE 6-bus [17] and an IEEE 33-bus [18] modified distribution network). The proposed DR program has an effect on flatting the load profile and this flat load profile can decrease the trading cost. The main contributions of this paper can be summarized as follows:

- The proposed power trade model can precisely determine the sold/bought resource of energy between MGs per hour and surpasses all scenarios by reducing cost, switching, and also transmission loss.
- Used time-based DR programs have an effect on flatting the load profile which causes minimizing the cost in power trading.
- The proposed model outperforms all scenarios in the context of transmission loss by reducing switches and selecting the best configuration of MGs.
- The scalability of the proposed method confirms the possibility of using it in real environments.

The rest of the paper is organized as follows. Section II reviews related works and MG's concerning research. Section III introduces the used DR program. Section IV describes used methodology and the problem formulation of power trading MINLP model. Section V describes used solution methodology in this paper for running the proposed method. At last, section VI while considering simulation setting, executes the proposed model on an IEEE 6-bus network and an IEEE 33-bus modified test system to reach sensitivity analysis. Section VII concludes the whole paper.

II. RELATED WORK

The focus of this work is power trading in energy market for MGs. As mentioned before, power trading can change MG's configuration. Also DR programs can flat the load profile by shifting load to low-peak hours which leads to ease of scheduling and power trading. Power scheduling has to be performs inside an optimal power trading. In this regard, this paper have considered most of the related researches in the subject of power scheduling, trading, and DR. The related works are categorized and inspected based on configuration, scheduling, trading, and DR which is shown in Table 1.

As demonstrated in Table 1, all reviewed papers have sorted based on their publication date and also have shown whether they have investigated the reconfiguration, scheduling, trading, and DR programs or not, and we have marked them with a check mark and a cross mark respectively. The last row of the table belongs to our proposed model.

An extended responsive load economic model is presented in [19] which is based on price elasticity and customer benefit. The paper focuses on DR programs which is realized by the TOPSIS method. Another paper [20] is focused on incentive-based DR programs including penalties for customers. DR based papers are very useful in reducing network load at peak times, but it is necessary to evaluate its effectiveness in MG's scheduling or trading.

Power trading is another subject which is considered in the proposed method of this paper which can change the configuration of MGs. The paper [21] is focused on reconfiguration with changing the status of switches in a DN without considering DR programs. Also, paper [12] is focused on reconfiguration and scheduling with applying decimal coded quantum particle swarm optimization (DQPSO) to solve feeder reconfiguration of DGs. The optimum reconfiguration instants are achieved based on the switching operations and energy losses costs in [13]. Ref. [22] has been the worthiness of the hourly reconfiguration in the presence of renewable energy resources. Also [23] is proposed an improved indicator to estimate the voltage stability margin of a two-bus system based on both saddle-node and limited induced bifurcations without focusing on trading and DR concepts. A reconfiguration problem is proposed in [24] with minimizing the IMG fuel consumption and the relevant switching operation costs. An architecture model is proposed in [25] for P2P energy trading in a MG with considering the design and interoperability aspects of components.

An incentive and price-based DR program in order to achieve a range of operational and economic advantages are developed in [26]. This paper participated in a two-field

TABLE 1. The categorization of previous researches.

Ref	Year	Objective/s	Reconfiguration	Scheduling	Trading	DR
[19]	2010	price & benefit	×	✓	×	✓
[20]	2010	incentive-based DR	×	✓	×	✓
[21]	2013	switching & transmission loss	✓	✓	×	×
[12]	2015	power-loss	✓	✓	×	×
[13]	2015	power-loss & operation cost	✓	×	✓	✓
[22]	2016	switching operation	✓	✓	×	×
[23]	2016	power loss & loadability	✓	✓	×	×
[24]	2016	operation cost & islanding	✓	✓	×	×
[25]	2016	cost in grid connected MG	×	✓	✓	×
[26]	2017	operational & economical	✓	✓	×	✓
[27]	2017	regional power trading	×	×	×	✓
[28]	2018	gain benefit	✓	✓	✓	×
[29]	2018	operator profit	✓	✓	×	×
[4]	2018	p2p energy trading	×	✓	✓	×
[30]	2019	coalition GT-based individual utility MG	×	×	✓	×
[31]	2019	internal trading	×	✓	✓	×
[32]	2019	game-theoretic energy trading	×	✓	✓	×
[33]	2019	credit rating management	×	✓	✓	×
[34]	2019	digital currency in trading	×	✓	✓	×
[6]	2020	operation cost	✓	✓	×	✓
[35]	2020	actual-price	×	✓	×	✓
[36]	2020	bilateral trading	×	×	✓	✓
[37]	2020	trading prices & cost	×	✓	✓	×
[38]	2020	power losses in grid MG	×	✓	✓	×
[39]	2020	positive demand response	×	✓	×	✓
[40]	2020	power load DR	×	✓	×	✓
Pro.	2020	power cost and loss	✓	✓	✓	✓

contribution, a complete and up-to-date overview of DR enabling technologies and also the benefits and the drivers considered to the adoption of DR programs.

A regional power trading and energy exchange platform is presented in [27] to facilitate in-country and cross-border power and energy trading. An efficient strategy for internal device scheduling and energy trading was developed in [28] by studying multiple interconnected smart MGs. Paper [29] presented a daily risk-based optimal scheduling in the presence of wind turbines in order to MG operator profit maximization. Ref. [4] proposed a hierarchical system architecture model to identify and categorize the key elements involved in P2P energy trading. Another power trading method is proposed in [30] to help MGs in the network trade power locally with neighboring MGs. Another power trading method is proposed in [31] with a three-step internal trading strategy for optimal energy sharing among building MGs, includes; barter trading to exchange energies among building MGs, building MGs sell their remaining surplus energy, and building MGs, which have lower generation cost than the external system. The next power trading based paper is [32] which proposed a simultaneous game-theoretic approach in the P2P energy trading. Ref. [33] is another trading paper with a simultaneous game-theoretic approach in P2P energy trading. The use of a digital currency for the cross-border electricity trading

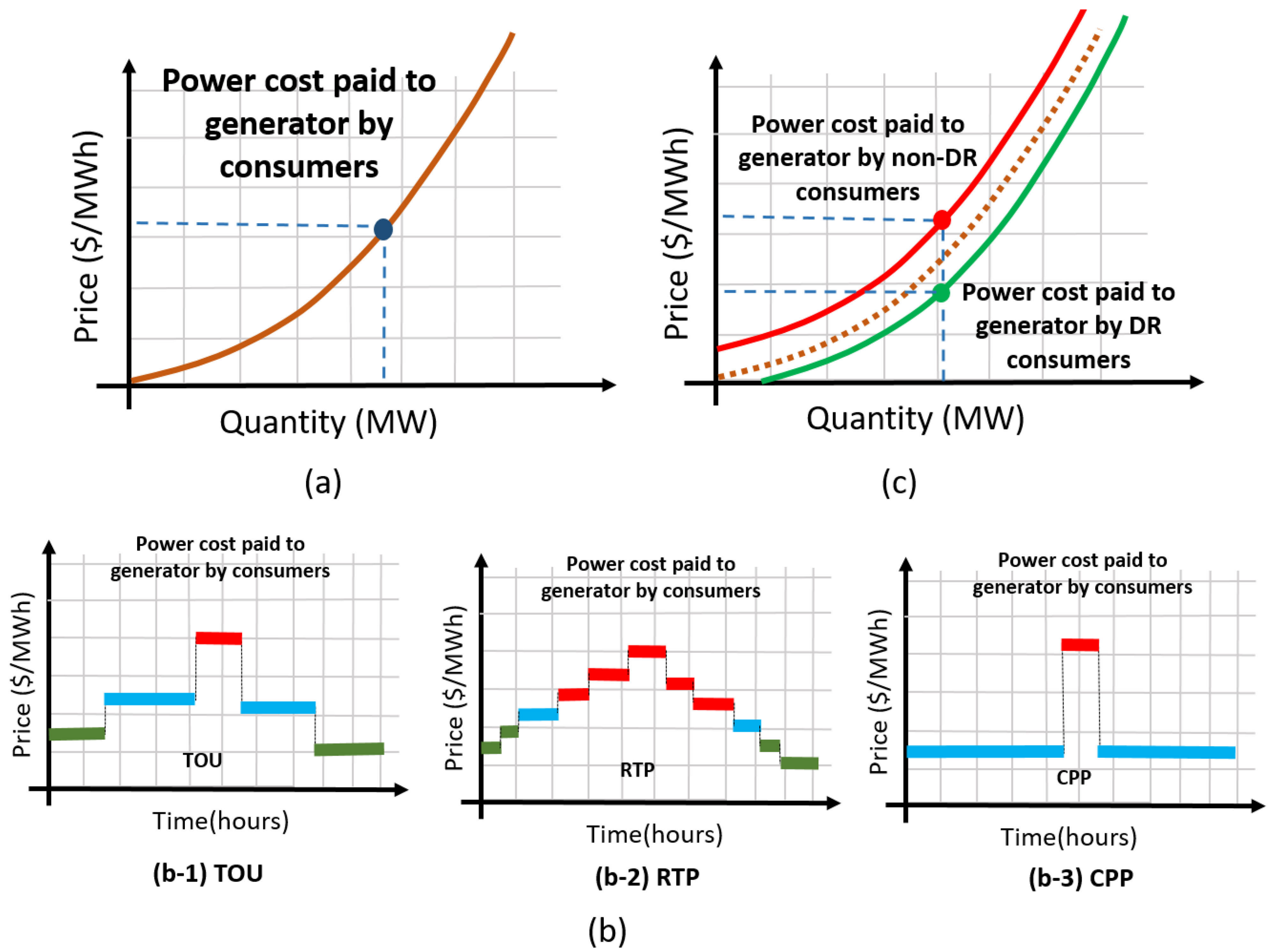


FIGURE 2. DR programs price. (a) Conventional cost function. (b) Time-based DR and (c) incentive-based DR programs price.

settlement based on the special drawing rights of the International Monetary Fund is presented in [34].

A DR-based optimization model of MG-based DN is proposed in [6] to enhance the network scheduling flexibility. A new measure capturing the impact of DR on consumers is presented in [35] which introduced real or actual price. The Alternating Direction Method of Multipliers (ADMM) is used to decompose the problem to enable distributed optimization in [36]. P2P trading prices were calculated based on the market participation conditions in [37].

Another P2P trading is provided in [38] which utilized an IEEE 8500-node distribution test feeder to capture the large-scale performance of trading. The Ref. [39] presented the concept of positive demand response (PDR) to prevailing hourly prices. Reference [40] is another DR power scheduling method with the aim design a questionnaire to assess electricity load shifting technical.

The previous researches demonstrated in Table 1, are focused on PDN configuration, power scheduling, trading, and DR programs. The related works in the field of power scheduling and trading, focus on the amount of DER generation and the amount of sold or bought power between MGs, without considering the amount of sold or bought energy based on each energy resource. Also, in the field of configuration, most of the papers check all available configuration to chose the best one for each MG. These problems are addressed in this paper.

In fact, the proposed MINP model can choose involved energy resources in trading per hour, which is not considered before. Selecting the best configuration between MGs based on trading results and also using the DR program to flattening the required load and minimizing the cost is another focus of proposed model.

III. DEMAND RESPONSE PROGRAM CONCEPT

DR programs are an opportunity for consumers and prosumers to participate in the operation of power scheduling by shifting their required load during peak periods in response to time-based or incentive-based rates [7]. In fact, this change in demand occurs when the electricity price increase or decrease in the amount of one unit of power. The real cost function in PDN without the DR program is a quadratic function with three cost function coefficients like $ax^2 + bx + c$ which is shown in Figure 2(a). DR programs include two types of strategies: (i) time-based and (ii) incentive-based. The time-based DR programs change the power cost based on time with different functions. The cost function in peak times is higher than off-peak times which is shown in Figure 2(b). The time-based DR programs divide into three different groups based on used function in determining the power cost include the time of use (TOU), real-time pricing (RTP), and critical peak pricing (CPP). For example, RTP is demonstrated in Figure 2(b-2) which power cost changes based on time and it has the highest amount in peak time and cost reductions in descending order from peak to off-peak times. The incentive-based DR programs are based on incentives and penalties. Users with DR elasticity pay less than real price because of incentive programs and users without DR elasticity pay more than real price because of penalty programs which are shown in Figure 2(c). Elasticity defined the amount of power change based on power cost change. Elasticity parameter is shown in Equation (1).

$$E = \frac{\rho_0}{d_0} \cdot \frac{\partial d}{\partial \rho} \tag{1}$$

In Equation (1), ρ_0 and d_0 are respectively initial price and initial load. d and ρ are respectively load and electricity price [8], [41]. Elasticity has two parts: self-elasticity and cross-elasticity. Self-elasticity ($E(i, i)$) is defined as changing the amount of load in ith period because of the electricity price changing in ith period which is always negative and cross-elasticity ($E(i, j)$) is defined as changing the amount of load in ith period because of the electricity price changing in jth period which is always positive. These defines are shown in Equation (2) and (3) [41].

$$E(i, i) = \frac{\rho_0(i)}{d_0(i)} \cdot \frac{\partial d(i)}{\partial \rho(i)} \tag{2}$$

$$E(i, j) = \frac{\rho_0(j)}{d_0(i)} \cdot \frac{\partial d(i)}{\partial \rho(j)}, \quad i \neq j \tag{3}$$

The consumers and prosumers have two different types of load models. Single load model which cannot move to another period of time and the loads' sensitivity is the same as self-elasticity that is demonstrated in Equation (4). Multi load model can move to different periods of time and the loads' sensitivity is the same as cross-elasticity that is demonstrated in Equation (5) [41].

$$d_{SingleLoad}(i) = d_0(i)\{1 + \frac{E(i, i)\langle \rho(i) - \rho_0(i) \rangle}{\rho_0(i)}\} \tag{4}$$

$$d_{MultiLoad}(i) = d_0(i) + \sum_{j=1, j\neq i}^{24} E(i, j)\frac{d_0(i)}{\rho_0(j)}\langle \rho(j) - \rho_0(j) \rangle \tag{5}$$

The final responsive load model is calculated by combining equations (4) and (5) which is demonstrated in Equation (6) [41].

$$d(i) = d_0(i)\Big\{1 + \frac{E(i, i)\langle \rho(i) - \rho_0(i) \rangle}{\rho_0(i)} + \sum_{j=1, j\neq i}^{24} E(i, j)\frac{\rho(j) - \rho_0(j)}{\rho_0(j)}\Big\} \tag{6}$$

In this paper, it is assumed that the system operator only uses time-based DR programs. In fact, the most significant problem in this paper is power trading in configurable MGs considering DR programs. So, in order to consider the effect of DR on power load and the trading results, a simple DR program is selected to flatting the power load model.

IV. PROPOSED MODEL

In this section mathematical modeling and concept of network reconfiguration is presented.

A. PROPOSED POWER TRADING METHODOLOGY

This section aims at introducing the proposed design and system model used as a reference throughout the paper. As shown in Figure 1, the proposed model assumes that the used system has several buses located in a number of MGs. Each bus can be a generator, consumer, or prosumer. In fact, each bus can have multiple types of energy resources including a number of renewable and non-renewable resources. In this paper for facilitating the formulation, all energy resources, and also the required load of each bus are referenced with their bus number.

Also, this section introduces DR programs and also the MINLP model for power trading in a central mode between MGs. MG power trading needs an architecture like an energy trade architecture includes items like the power grid, ICT, control, and business layers. This paper uses the proposed architecture in [4] for power trading in MG which is in a central mode. This architecture has a central virtual distribution system operators (DSOs). The central DSO receives both energy sellers list items and energy buyers' orders. After the orders are placed by peers, they are either accepted or rejected by DSOs, and energy suppliers. The only difference in our paper is that the proposed optimization model tries to plan the distribution network with mentioned aims without receiving buyers' orders. Instead of receiving buyers' orders, it sends the incentive programs to consumers and also prosumers to encourage them to participate in load shifting programs and the results are demonstrated in the simulation results section.

As mentioned before, this paper solves power trading with a non-linear optimization model considering DR and the most contributions are: (i) selecting the best configuration between MGs aiming to reduce power loss and also the number of the required switching, (ii) power scheduling or determining the amount of generating power of all renewable and non-renewable resources on each hour, and (iii) power trading or determining the amount of power purchased or sold based on each energy resource considering time and cost.

B. PROBLEM FORMULATION

This section introduces an MINLP formulation for the problem of power trading in the MG-based distributed network, regarding DR programs subject to technical constraints, and cost constraints.

Such a formulation considers mainly five input sets: the set of MGs G, the set of buses N which each bus belong to a MG with a subscript like gn (means bus n of MG g), the set of energy resources E which each energy resource can be renewable or non-renewable and each energy resource belong to a bus of a MG and we introduced it with subscript gne (means energy resource e on bus n of MG g). The set of demands D which each demand belongs to a bus, the set of available switched between MGs g and g', $St(g, g')$, and the set of times T. In this paper, we used a 24-hour scheduling time $|T| = 24$.

1) OBJECTIVE FUNCTION

The objective function includes four terms: (i) the cost of bought and sold power, (ii) the cost of generated power, (iii) power loss, and (iv) switching. The proposed model from the central operator point of view which tries to manage power trading. So, in the first section of the objective function, each MG needs to calculate its own benefit which is calculated by Equation (7). This equation computes the difference between total bought power cost and total sold power cost for each MG per hour. In fact, all microgrids need to sell their extra energy if the microgrid is not used inside, and vice versa, if they need more energy than their production capacity, they buy it.

$$Cost_{trade} = \sum_{g\in G}\sum_{t\in T}\left(\sum_{g'\in G,\neq g}\sum_{n'\in N}\sum_{e'\in E} P^{B}_{gtg'n'e'}C^{S}_{g'n'e't} - \sum_{n\in N}\sum_{e\in E}\sum_{g'\in G,\neq g} P^{S}_{gnetg'}C^{S}_{gnet}\right)\Delta t \tag{7}$$

In Equation (7), $P^{B}_{gtg'n'e'}$ shows the bought power by MG g at time t from energy source e' on bus n' of MG g'. The $C^{S}_{g'n'e't}$ shows the cost of power which is sold by MG g' and bought by MG g at time t. Respectively, $P^{S}_{gnetg'}$ and C^{S}_{gnet} show the amount of sold power and its cost of MG g, bus n, energy source e at time t.

In the second section of the objective function, the total cost of power generation is calculated based on cost function which is shown in Equation (8).

$$Cost_{generation} = \sum_{g\in G}\sum_{n\in N}\sum_{e\in E}\sum_{t\in T}(a_{gne}P^{O}_{gnet} + b_{gne}) \tag{8}$$

In Equation (8), P^{O}_{gnet} shows the active power generation on MG g, bus n and energy source e at time t.

In the third section of the objective function which is shown in Equation (9) [6], the power loss is calculated.

$$power_{loss} = \sum_{g,g'\in G}\ \sum_{\substack{n,n'\in N,\\ n\neq n'}}\ \sum_{t\in T}\left(Real\left(\frac{|V_{gnt} - V_{g'n't}|^2}{R_{gng'n'} - jX_{gng'n'}}\right)\right) \tag{9}$$

In Equation (9), a complex number is calculated based on available links between pair buses. This equation is a general for calculating the power loss in a centralized managed distributed system.

In the fourth section of the objective function which is shown in Equation (10), the number of changes in the switches are calculated with the aim of minimizing. In fact, this equation tries to minimize the switching between MGs with the aim of reducing the effort for changing the switches status. An open switch tries to be open again in the next time interval, if it was open on the previous time and vice versa.

$$N_{switch} = \sum_{g\in G}\sum_{t\in T}\sum_{\substack{g'\in G,\\ g'\neq g}}\left(\sum_{m\in St(g,g')} St_{mgg't} + |St_{mgg't} - St_{mgg'(t-1)}|\right) \tag{10}$$

In equation (10), $St(g, g')$ is the set of available switches between MGs g and g' that should be minimized. The $St_{mgg't}$ and $St_{mgg'(t-1)}$ are a binary variable and show the status of switch between MG g and g' respectively at time t and $(t-1)$.

The main objective function with the four mentioned subsection is shown in Equation (P1a). As shown the main objective function combines these subsections with adding four different coefficient for showing their importance. The coefficients are a number which are same as each other when the importance of all parts of the objective function are the same.

Now we need to add the constraints. Since the proposed model considers DR programs, the formulation has to define in two shapes; without DR program (section IV-B2), and with DR program (section IV-B3). The cost computation process is different in these two modes which is discussed with detail in the DR concept section.

2) FORMULATION WITHOUT DR

The power trading without DR programs can be formulated as Problem IV-B2 with a minimization objective function with four coefficients and some constraints. (P1a)–(P1y), as shown at the bottom of the next page.

Constraints (P1b) and (P1c) show the power equality equations. They enforce that, for each MG at each time, the summation of generated and bought power be equal to the summation of demanded and sold power. As demonstrated, in order to have a soft constraint it is changed with less than or equal. These constraints try to meet a tradeoff between power trading based on dynamic cost and loss. Constraints (P1d) and (P1e) define the power flow equations [6]. Constraints (P1f) and (P1g) enforce the total generated power minus the load demand per bus (owned by one MG) at any time be equal to the sum of power on all links connected to the mentioned bus. This constraint performs the power scheduling inside power trading. Constraint (P1h) enforces that the apparent power on links is related to the active and reactive power of the links. Constraints (P1i) and (P1j) enforce the status of m'th switch between MGs g and g' be greater than traded power between mentioned MGs. These constraints will change the switch status to one if there was at least one trade among MGs.

They use constraints (P1k) and (P1l) to complete this task. Constraints (P1m) and (P1n) limit the active and reactive power between the minimum and maximum values of active and reactive powers. In fact, each resource has a generation interval which cannot be changed and has to be satisfied in model results. Constraint (P1o) limits the voltage magnitude between the minimum and maximum available values. Constraint (P1p) limits the apparent power between the minimum and maximum apparent power. Constraint (P1q) ensures that the traded power between MGs should be equal. Constraint (P1r) ensures that the sum of sold power on a MG be less than or equal to generated power on it. Constraint (P1s),

$$\min(\alpha_1 Cost_{trade} + \alpha_2 Cost_{generation} + \alpha_3 Power_{loss} + \alpha_4 N_{switch}), \tag{P1a}$$

subject to:

$$\sum_{n\in N} P^d_{gnt} + \sum_{g'\in G}\sum_{n'\in N}\sum_{e'\in E} P^B_{gtg'n'e'} \le \sum_{n\in N}\sum_{e\in E}\sum_{g'\in G} P^S_{gnetg'} + \sum_{n\in N}\sum_{e\in E} P^O_{gnet}, \quad \forall g\in G\ \forall t\in T, \tag{P1b}$$

$$\sum_{n\in N} Q^d_{gnt} + \sum_{g'\in G}\sum_{n'\in N}\sum_{e'\in E} Q^B_{gtg'n'e'} \le \sum_{n\in N}\sum_{e\in E}\sum_{g'\in G} Q^S_{gnetg'} + \sum_{n\in N}\sum_{e\in E} Q^O_{gnet}, \quad \forall g\in G\ \forall t\in T, \tag{P1c}$$

$$PL_{gng'n't} = |V_{gnt}|^2 G_{gng'n'} - |V_{gnt}||V_{g'n't}|(G_{gng'n'} cos\theta_{gng'n't} + B_{gng'n'} sin\theta_{gn'g'n't}),$$
$$\forall g, g'\in G\ \forall n, n'\in N\ \forall t\in T, \tag{P1d}$$

$$QL_{gng'n't} = -|V_{gnt}|^2 B_{gng'n'} - |V_{gnt}||V_{g'n't}|(G_{gng'n'} sin\theta_{gng'n't} - B_{gng'n'} cos\theta_{gn'g'n't}),$$
$$\forall g, g'\in G\ \forall n, n'\in N\ \forall t\in T, \tag{P1e}$$

$$\sum_{e\in E} P^O_{gnet} - P^d_{gnt} = \sum_{g'\in G,\Omega g}\ \sum_{n'\in N,\Omega n} PL_{gng'n't}, \quad \forall g\in G\ \forall n\in N\ \forall t\in T, \tag{P1f}$$

$$\sum_{e\in E} Q^O_{gnet} - Q^d_{gnt} = \sum_{g'\in G,\Omega g}\ \sum_{n'\in N,\Omega n} QL_{gng'n't}, \quad \forall g\in G\ \forall n\in N\ \forall t\in T, \tag{P1g}$$

$$SL_{gng'n't} \simeq PL_{gng'n't} + QL_{gng'n't}, \quad \forall g, g'\in G\ \forall n, n'\in N\ \forall t\in T, \tag{P1h}$$

$$P^B_{gtg'n'e'}/(P^B_{gtg'n'e'} + \epsilon) \le St_{mgg't}, \quad \forall m\in St(g,g')\ \forall g, g'\in G \tag{11}$$
$$\forall n'\in N\ \forall e'\in E\ \forall t\in T, \tag{P1i}$$

$$P^S_{gnetg'}/(P^S_{gnetg'} + \epsilon) \le St_{mgg't}, \quad \forall m\in St(g,g')\ \forall g, g'\in G\ \forall n\in N \tag{12}$$
$$\forall e\in E\ \forall t\in T, \tag{P1j}$$

$$P^B_{gtg''n'e'}/(P^B_{gtg''n'e'} + \epsilon) \le St_{mgg't}, \quad \forall m\in St(g,g')\ \forall g, g', g''\in G \tag{13}$$
$$\forall n'\in N\ \forall e'\in E\ \forall t\in T, \tag{P1k}$$

$$P^S_{gnetg''}/(P^S_{gnetg''} + \epsilon) \le St_{mgg't}, \quad \forall m\in St(g,g')\ \forall g, g', g''\in G\ \forall n\in N \tag{14}$$
$$\forall e\in E\ \forall t\in T, \tag{P1l}$$

$$P^{min}_{gne}\delta_{gnet} \le P^O_{gnet} \le P^{max}_{gne}\delta_{gnet}, \quad \forall g\in G\ \forall n\in N\ \forall e\in E\ \forall t\in T, \tag{P1m}$$

$$Q^{min}_{gne}\delta_{gnet} \le Q^O_{gnet} \le Q^{max}_{gne}\delta_{gnet}, \quad \forall g\in G\ \forall n\in N\ \forall e\in E\ \forall t\in T, \tag{P1n}$$

$$V^{min}_{gn} \le V_{gnt} \le V^{max}_{gn}, \quad \forall g\in G\ \forall n\in N\ \forall t\in T, \tag{P1o}$$

$$SL^{min}_{gng'n'} \le SL_{gng'n't} \le SL^{max}_{gng'n'}, \quad \forall g, g'\in G\ \forall n, n'\in N\ \forall t\in T, \tag{P1p}$$

$$P^B_{gtg'n'e'} = P^S_{g'n'e'tg}, \quad \forall g, g'\in G\ \forall n'\in N\ \forall e'\in E\ \forall t\in T, \tag{P1q}$$

$$\sum_{g'\in G,\neq g} P^S_{gnetg'} \le P^O_{gnet}, \quad \forall g\in G\ \forall n\in N\ \forall e\in E\ \forall t\in T, \tag{P1r}$$

$$\delta_{gnet}\in\{0,1\}, \quad \forall g\in G\ \forall n\in N\ \forall e\in E\ \forall t\in T, \tag{P1s}$$

$$St_{mgg't}\in\{0,1\}, \quad = \forall m\in St(g,g')\ \forall g, g'\in G\ \forall t\in T, \tag{P1t}$$

$$\epsilon > 0, \tag{P1u}$$

$$P^O_{gnet}, Q^O_{gnet} \ge 0, \quad \forall g\in G\ \forall n\in N\ \forall e\in E\ \forall t\in T, \tag{P1v}$$

$$P^B_{gtg'n'e'}, Q^B_{gtg'n'e'} \ge 0, \quad \forall g, g'\in G\ \forall n'\in N\ \forall e'\in E\ \forall t\in T, \tag{P1w}$$

$$P^{S\prime}_{gnetg}, Q^{S\prime}_{gnetg} \ge 0, \quad \forall g, g'\in G\ \forall n\in N\ \forall e\in E\ \forall t\in T, \tag{P1x}$$

$$\theta_{gng'n't}, PL_{gng'n't}, QL_{gng'n't}, SL_{gng'n't} \ge 0, \quad \forall g, g'\in G\ \forall n, n'\in N\ \forall t\in T, \tag{P1y}$$

and (P1t) show the δ_{gnet} and $St_{mgg't}$ are binary and have to be zero or one as demonstrated in Table Nomenclature. Constraint (P1u), (P1v), (P1w), (P1x), and (P1y) demonstrate the controlling equations and show the non-negative parameters and variables.

3) FORMULATION WITH TIME-BASED DR

The power trading with DR programs can be formulated as Problem P2 with the same minimization objective function and some constraints. (P2a) and (P2d), as shown at the bottom of the next page.

Constraint (P2b) is almost equal to Constraint (P1b), the only difference is in power load which is changed from p^{d}_{gnt} to $p^{d(i)}_{gnt}$. Because $d(i)$ is the DR-based load power and in this section, it has to calculate by Equation (6). Constraint (P2c) is almost equal to Constraint (P1f) again the only difference is in power load which must be calculated with DR-based power load Equation (6).

V. SOLUTION METHODOLOGY

This section contributes to understanding the methodology of proposed model. The whole schema is shown in Figure 3. As demonstrated in Figure 3, the proposed model after receiving input data or parameters, selects the trading type (without DR or with DR). In power trading without DR, the $P1a$ problem is selected and in the power trading with DR, the $P2a$ problem is selected. Then the selected problem is solved for all MGs ($g = 1 \ldots |G|$) on all available times (T = 24h or 1day) and for all pair MGs.

The solution in this paper is Interior Point OPTimizer (IPopt) which is a software library for large scale nonlinear optimization of continuous systems [42]. IPopt can exploit parallelization of the linear solvers by implementing a branch and bound and branch and cut technique and you have the guarantee that the optimal solution is a good approximation of the global one given the MIP-gap you set. The MIP-gap, is a bound obtained by taking the minimum of the optimal objective values of all of the current leaf nodes. Finally, the difference between the current upper and lower bounds is known as the gap [43].

The solving results will show the scheduling, trading and configuration results. In fact, scheduling results show the amount of each generation in each MG. The trading results show the amount of sold or bought energy based on each energy resource on each time and configuration results show the number of switching based on time. As shown in Figure 3, section $Cost_{generation}$ of objective function considers the amount of power generation as scheduling results. This section of objective function can used in preparing a basic model without DR and power trading that will be described with detail in Section VI-B1. The other sections of objective function consider amount of power trading between MGs and their configuration.

VI. SIMULATION RESULTS

To demonstrate the effectiveness of our optimization MINLP model, we evaluated it on two different test system; an IEEE 6-bus test systems (presented in Section VI-B), and a modified IEEE 33-bus test system (presented in Section VI-C). In the second test system, the meaning of a modified system is a 33-bus system with added energy source to form an energy market with various resources. This modification was needed to verify how our approach can be actually exploited in a real system. Both of the test systems were evaluated in four various scenarios to comparing the results. Also, in each test system, the effect of proposed power trading model, DR-based model and also switching method was studied. At last, a scalability test was performed which its results presented in Section VI-D which indicates the performance of the proposed method in the real environment.

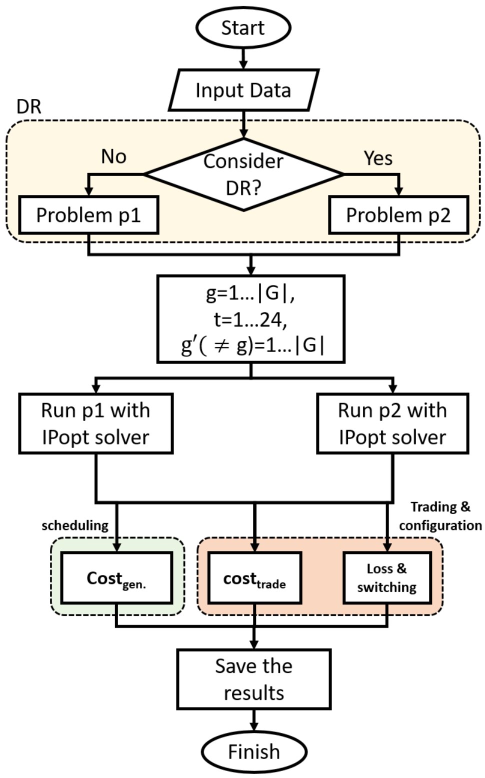


FIGURE 3. The solution methodology of proposed model.

A. SIMULATION SETTING

As representatives of the distribution network, an IEEE 6-bus [17] and an IEEE 33-bus [18] test system with some modification and some random resources have been selected. In all of the simulations, the used inputs are summarized below.

- $|G|$: which shows the number of MGs. The MGs are selected randomly without any focus on the MG extraction subject as our assumption.
- $|N|$: shows the total number of buses which can belong to the MGs.
- $max_{n \in N}\{|E_n|\}$: shows the maximum number of possible energy resource per bus on the distribution network.

E is the set of all available energy resources and E_n is the set of energy resource for bus n.

- α_1 *to*α_4: are the coefficients of different sections of the objective function which set to 1 in the standard state and can be different value based on the importance of objective functions.
- DR programs: a time-based DR program is considered in this paper as shown in Figure 2(b).
- $|T|$: shows the total optimization time and as in other literature proposals [6] it set to 24-hour or a day with 1-hour hops.
- $|St(g, g')|$: shows the set of available switches between each pair of MGs g and g'.

The proposed methodology, the generator of the random DN, and the loads and MGs of the test systems have been implemented in a Python library. Pyomo 5.6 was used as modelling language [44], [45] on python 3.7 and ipopt (Interior Point OPTimizer, pronounced eye-pea-opt) solver from the COIN-OR [46] initiative was utilized to obtain optimal results. Also, the hardware system was a workstation with a 2.1GHz Intel(R) Core i7-8550 Processor, and 12 GB of RAM under the operating system as Ubuntu 16.04.01 LTS.

In fact, since Linux, Mac OS/X and other Unix variants typically have Python pre-installed, the IPopt solver can be install and run the proposed model with a minimum 2 GHz processor and 8 GB RAM under any Linux/windows operation system.

The price-elasticity of loads (cross-elasticity and self-elasticity) are considered between 0.01 and -0.2 respectively which is shown in Table 2 and the participating factor in this research is supposed to be 10%.

TABLE 2. Self and cross elasticities.

	peak	mid-peak	off-peak
peak	-0.1	0.016	0.012
mid-peak	0.016	-0.1	0.01
off-peak	0.012	0.01	-0.1

The time-based DR programs are includes; TOU, RTP, and CPP as shown in Figure 2(b). In this paper, a TOU program is used. In these programs, the peak (on-peak), off-peak, and mid-peak time periods shown in Table 3. All of the simulations of this paper done in a DN with residential loads. In the TOU program, the cost of electricity is change based on peak and off-peak times. We set peak consumption times between

TABLE 3. Different time periods electricity prices of time-based DR.

Program	Electricity Price (R/KWh)	Time
TOU	40 at off-peak, 160 at mid-peak and 400 at peak	off-peak period: 23:00 to 7:00 mid-peak period: 7:00 to 12:00 and 18:00 to 20:00 peak period: 12:00 to 18:00 and 20:00 to 23:00
RTP	160 160 160 20 40 500 40 20 500 200 160 200 20 20 40 40 40 160 160 200 200 500 500 200	-
CPP	40 at off-peak and 400 at peak	off-peak period: O.W peak period: 12:00 to 18:00 and 20:00 to 23:00

12 to 18 and 20 to 23, mid-peak consumption times between 7 to 12 and 18 to 20, and off-peak consumption times between 23 to 7. In the RTP program, the electricity price changes between 20 to 50 per hour. In the CPP program, the electricity price has two different levels of peak and off-peak. The peak consumption times are set between 12 to 18 and 20 to 23, and the other times are set to off-peak consumption. DER have a great impact on DR program parameters and as WT and PV are used in this paper, their operation cost coefficients are assumed be $c = 0.001$ in this paper.

In all of the tests, the generation amounts have been measured in four different scenarios as follow:

1) Scenario1 ($notDR - notTrading$): this scenario does not take into account any of the DR and power trade in power scheduling. This scenario only uses the $Cost_{generation}$ function (Equation (8)) in objective function with Problem (IV-B2) constraints without buying and selling variables $P^B_{gtg'n'e'}$, $Q^B_{gtg'n'e'}$, $P^S_{gnetg'}$, and $Q^S_{gnetg'}$. In fact, this scenario is the simplest state of the proposed model.
2) Scenario2 ($notDR - Trading$): this scenario does not take into account the DR program but uses power trade scheduling which is same as Problem (IV-B2). This scenario corresponds exactly to the references [4] and [14] which have same conditions as the model suggested in this article.
3) Scenario3 ($DR - notTrading$): this scenario does not take into account the power trade program but uses DR-program in scheduling. This scenario only uses the $Cost_{generation}$ function (Equation (8)) in objective function with Problem (P2) constraints without buying and selling variables $P^B_{gtg'n'e'}$, $Q^B_{gtg'n'e'}$, $P^S_{gnetg'}$, and $Q^S_{gnetg'}$.

$$\min(\alpha_1 Cost_{trade} + \alpha_2 Cost_{generation} + \alpha_3 Power_{loss} + \alpha_4 N_{switch}), \tag{P2a}$$

$$\text{subject to: } \sum_{n\in N} p^{d(i)}_{gnt} + \sum_{g'\in G}\sum_{n'\in N}\sum_{e'\in E} P^B_{gtg'n'e'} \le \sum_{n\in N}\sum_{e\in E}\sum_{g'\in G} P^S_{gnetg'} + \sum_{n\in N}\sum_{e\in E} P^O_{gnet}, \quad \forall g\in G\ \forall t\in T, \tag{P2b}$$

$$\sum_{e\in E} P^O_{gnet} - P^{d(i)}_{gnt} = \sum_{g'\in G,\Omega g}\ \sum_{n'\in N,\Omega n} PL_{gng'n't}, \quad \forall g\in G\ \forall n\in N\ \forall t\in T, \tag{P2c}$$

$$(\text{P1c}) - (\text{P1e}),\ (\text{P1g}) - (\text{P1y}) \tag{P2d}$$

This scenario corresponds exactly to the reference [6] with the same condition.

4) Scenario4 ($DR - Trading$): This scenario considers both the DR program and the power trade in power scheduling which is same as Problem (P2).

B. SIMULATIONS ON IEEE 6-BUS TEST SYSTEM

To analyze the model presented in the preceding section, a primary test distribution network (Figure 1) is considered. It presents a test distribution network that consists of two MGs and 6 bus nodes. In this network, each MG's basic data such as the number of loads, the number of generation resources, energy resource types, and connection data is presented in Table 4. The structure of this distribution test system and also its line data are shown in Figure 1. A sample bus data of 6-bus test system is shown in Table 5.

TABLE 4. MGs basic data in distribution Network shown in Figure 1.

MG	#Bus	#Load Point	#Generation unit	Generation type	Related switch
MG1	4	3	2	PV, Tradition	sw1,sw2
MG2	3	1	2	WT, Tradition	sw1,sw2

TABLE 5. A sample input data of IEEE 6-bus test system in two selected time of a day (one peak and one non-peak time).

Bus No	Load (kW) peak	Load (kW) non-peak	Max power supply (kW)
1 (Traditional)	0	0	20
1 (PV)	0	0	6
2 (Traditional)	0	0	12
2 (WT)	0	0	14
3	5	5	0
4	3	2	0
5	12	9	0
6	2	2	0
sum	22	18	52

1) INVESTIGATING THE IMPACT OF POWER TRADING AND DR PROGRAMS

The power scheduling and power trading results are shown in this subsection for the 6-bus test system (Figure 1).

The results of generation amounts in the 6-bus test system are shown in Table 6 based on four scenarios. As shown, the simulations are performed at two different peak and non-peak times. In this paper non-peak is used to refer to both of mid-peak and off-peak times. In the first scenario, the MINLP is solved with an objective function and without considering power trading and DR programs, the generation of four available energy resources shows that each MG tries to supply its own loads in both peak and non-peak times. In the second scenario, the MINLP is solved without considering the DR program and the results demonstrate that MGs work together to meet their needs with low-cost resources. In this Simulation, the cost of energy resources is set in the way that, the cost of traditional electrical resources is lower than renewable resources to see the trading power between MGs. It happens in both of the simulations in peak and non-peak times. In the third scenario, MINLP is solved with a DR program and the results show that in the peak times, production is decreased and vice versa in the off-peak times, the production is increased in order to balance the load and to show the shifted load. At last in the fourth scenario, the MINLP is solved with trading and DR program and the results show that again, two mentioned MGs have trade with each other, in order to use the low-cost resources. In scenarios 2 and 4, because of the trade between two MGs, both of the available switches between them are open.

The results of these simulations support the claim that the cost of trading in the energy market is reduced. The reason for the cost reduction is to model the proposed method based on the choice of energy source involved in the trade. When MGs know which energy source they are trading at and at what cost, they are therefore less likely to incur costs.

In another test, the amount of generation for one energy resource on the 6-bus disributed network is measured again on four mentioned scenarios. In this test, the traditional energy resource, on bus 1 in MG $MG1$ is selected which was displayed with variable $P_{gnet} = P_{(1,1,\text{``}Tradition'',t)}$ in the proposed model. This variable shows the power of tradition energy resource, on bus 1 of MG 1, at time t that can be between 1 to 24. The results are shown in Figure 4. In this test, an energy resource with less cost than other energy resources is selected, because we wanted to see the power trading. Because of the cost, the selected energy resource sold power to the other MG. In the Figure 4, the red fold line shows the first scenario (without DR and without power trading), as shown in this scenario, the generation of the energy resource completely depends on the load and it has a high amount in the peak time (12 to 18 and 20 to 23), and also it has a low amount in the non-peak times. In the second scenario, which is the yellow line, the model has power trading only. So, in the second scenario, the amount of generation is increased, in order to supply the other MG loads by selling. In the third scenario (the blue dotted line) which has DR program only, the amount of generation is changed in peak and non-peak times, due to load shifting. At last, in the last scenario which is shown by the green line, although the amount of generation is shifted from peak times to off-peak and mid-peak times, it is increased due to power trading. The monitored energy resource in this test had less cost than others, so it can supply other loads by power selling.

The results of this test imply that the proposed model can surpass other models presented in the three first scenarios in the context of power generation by about 12%. As mentioned the other models cannot decrease power generation in the selected bus. Although Figure 4 demonstrates one of the buses' results, the same results happened for other buses.

2) INVESTIGATING THE IMPACT OF DR PROGRAMS

The effect of DR programs on load shape is shown in Figure 5. As mentioned this test is performed on two different

TABLE 6. The amount of generation based on energy resources in two peak and non-peak time in four different scenarios (kW) on IEEE 6-bus test system.

Generation units			Scenario 1		Scenario 2		Scenario 3		Scenario 4	
microgrid	bus	energy resource	peak	non-peak	peak	non-peak	peak	non-peak	peak	non-peak
1	1	Traditional	7	6	10	8	7.6	8	9.5	11
1	1	PV	3	3	3	3	3	3	3	3
2	2	Traditional	4	5	6	6	4	6	4	3.5
2	2	WT	8	4	3	1	5.2	2.8	3.3	2.3

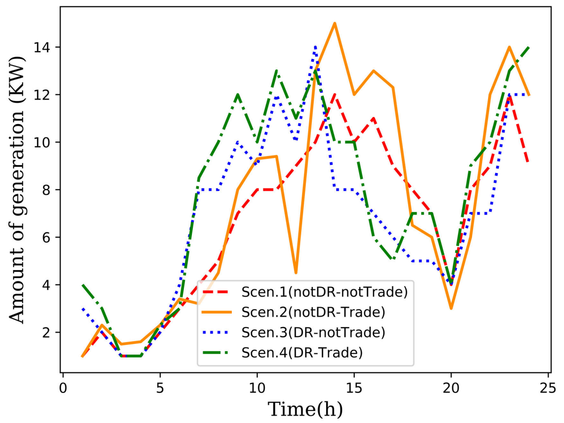


FIGURE 4. Amount of generation in traditional energy resource of *bus* 1 test Table 6 in four different scenarios.

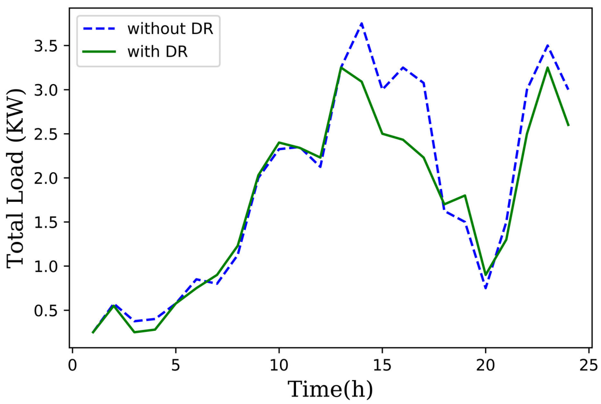


FIGURE 5. The effect of DR programs on load shape in 6-bus test system.

scenarios; without DR and with DR. In the first scenario, the total load of one network bus is measured without DR program, and as shown the load is high in peak loads (between 12 to 18 and 18 to 20) and is low in non-peak times. In the second scenario, in the presence of DR program, the total load of one network bus is decreased in peak times and is increased in the non-peak times.

3) INVESTIGATING THE IMPACT OF POWER TRADING

In order to consider the power trading in a distribution network, the total cost of MGs with and without power trading is measured and the results are shown in Table 7. The $MG1$ always works in isolating mode, but $MG2$ Buys power in the presence of power trading. So the cost of $MG2$ becomes

TABLE 7. Total cost of MGs with and without power trading in IEEE 6-bus distribution network.

	total cost	
#MG	without Trade	with Trade
1	23.803	25.605
2	27.65	24.70
sum	51.453	50.305

reduce. The sum of the cost is reduced which demonstrates the ability of the proposed model in solving the problem by adding power trade programs. In this test, the total cost is computed by Equation (11).

$$total_{cost} = Cost_{trade} + Cost_{generation} \tag{11}$$

4) INVESTIGATING THE IMPACT OF SWITCHING

This section measures the number of switching. As mentioned in the third section of the objective function (Equation (9)), the proposed model decreases the number of switching. So, we measure the number of switching in the mentioned distribution network in two scenarios without DR program and with DR which is shown in Figure 6. In the scenario of using DR programs, the number of changes in the switch ($sw1$) of Figure 1 is equal to four. In fact, in this network, most of the time there is power trading between two MGs and they are in non-trading mode only in five hours (3 to 6 and 14) of a day as shown in the Figure 6. It shows the ability of the proposed model in decreasing the number of switching. However, when we do not use the DR program in the evaluation test, the number of switching reaches more than five cases, and the MGs are often in the non-trading mode.

C. SIMULATIONS ON IEEE-RTS 33-BUS MODIFIED SYSTEM

This section evaluates the 33-bus distribution network. The modified distribution network with 33 buses is shown in Figure 7 has four MGs and 33 buses. Each bus can have up to two energy resources. In most network buses, there is a load. Network details are shown in Table 8. All of the bus and line data of the IEEE 33-bus test system were used from [18]. Although selecting the MGs and also adding the renewable ESs were done by assumption.

As shown in Table 8, we modified the IEEE 33-bus test system by adding new energy resources and loads. Each bus in this system can have a maximum of two energy resources.

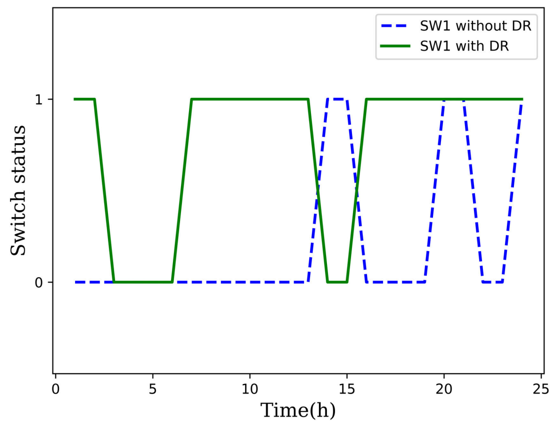


FIGURE 6. The status of the switches connected to the MGs in 6-bus test system.

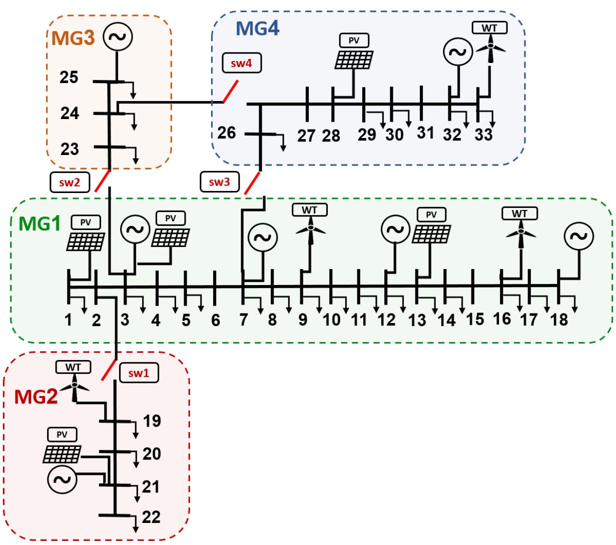


FIGURE 7. IEEE-RTS 33-bus modified test system.

TABLE 8. MGs basic data in IEEE 33-bus modified test case system.

MG	#Bus	#Load Point	#Generation unit	Generation type	Related switch
MG1	18	15	9	PV, WT, Tradition	sw1,sw2,sw3
MG2	4	4	3	PV, WT	sw1
MG3	3	3	1	Tradition	sw2
MG4	8	5	3	PV, WT, Tradition	sw3,sw4

The first MG ($MG1$) has 18 buses, 15 loads, and 9 energy resources which five of them are renewable energy resources and the others are non-renewable. This MG is connected to other MGs by three switches. The other three MGs $MG2$, $MG3$, and $MG4$ have 4, 3, and 8 buses respectively, Also they have 4, 3, and 5 load points, and 3, 1, and 3 generation units respectively. MGs $MG3$ and $MG4$ are connected to each other by $sw4$ which can be seen in Figure 7. We repeated the four evaluations we did on the sample test system in the previous section on this section's 33 bus system also. The results are given as follows.

1) INVESTIGATING THE IMPACT OF POWER TRADING AND DR PROGRAMS

The power scheduling and power trading results are shown in this subsection for the IEEE RTS modified 33-bus test system (Figure 7). The generation amounts per energy resource are measured in four different scenarios as mentioned in Subsection VI-B1.

The results of this assessment, which show the production values of all energy resources during the twenty-four hours of the day, are shown in Table 9. As shown in the first scenario (without DR and power Trading), all MGs are isolated, and therefore MG $MG3$, with only one energy resource is unable to meet all of its needs. For this reason, the phrase (NS) in the table means Not Sufficient. Of course, the same thing happened in the third scenario. Other MGs are able to meet their needs in non-trading mode.

In the first scenario, all the needs of MGs are met by their internal energy resources. In the second scenario, due to the possibility of trade between MGs, the needs of $MG3$ are met by purchasing power, and therefore the production of energy resources is increased. In the third scenario, due to the lack of trade, the $MG3$ loads are not met. Also, due to the availability of DR and load shift programs, the amount of production decreases during peak hours and increases during low consumption hours. In the fourth scenario, due to trade and DR programs, the production of other energy resources to meet the needs of $MG3$ is increased. To better understand the issues raised in this assessment, the sum of the products and loads as well as the amount of power purchased or sold by each MG are shown in Table 10. From this table, it can be seen that in scenarios $scen.1$ and $scen.3$, all the needs of $MG3$ are not met. Because MGs cannot trade with each other. But in $scen.2$ and $scen.4$, due to the possibility of trade between MGs, all the requirements are met. The total sales in MGs are shown in this table. Based on Table 9, the total power generation decreased by about 12% because of used DR programs in the power trading model.

In another test, the amount of generation for one energy resource on the modified 33-bus distribution network is measured on four mentioned scenarios. In this test, a PV energy resource, on bus 1 in MG $MG1$ is selected which is displayed with variable $P_{gnet} = P_{(1,1,``PV",t)}$ in the proposed model. This variable shows the power of PV, on bus 1 of MG 1, at time t that can be between 1 to 24. The results are shown in Figure 8. In the Figure 8, the red fold line shows the first scenario (without DR and without power trading), as shown in this scenario, the generation of the energy resource completely depends on the load and it has a high amount in the peak time (12 to 18 and 20 to 23), and also it has a low amount in the non-peak times. In the second scenario, which is the yellow line, the model has power trading only. So, in the second scenario, the amount of generation is increased, in order to supply the other MG loads by selling. In the

TABLE 9. The amount of generation based on energy resources in two peak and non-peak time in four different scenarios (kW) on IEEE RTS modified 33-bus system, (NS means not sufficient).

Generation units			Scenario 1		Scenario 2		Scenario 3		Scenario 4	
microgrid	bus	energy resource	peak	non-peak	peak	non-peak	peak	non-peak	peak	non-peak
1	1	PV	16.3	14	18.01	13	10.1	17.4	12	17.4
1	3	Traditional	5	5	7.5	6	5	5.2	7.3	7.2
1	3	PV	8.5	8	8	8.4	7	9	7.8	11.6
1	7	Traditional	30	20.2	33	18	25.6	26	27.02	24
1	9	WT	11	9.1	8.2	11	11.4	12.2	8.5	13.2
1	12	Traditional	12.2	7.8	13	7.1	10	9	14.7	8
1	13	PV	0	0	0	0	0	3.5	0	4
1	16	WT	0	0	0	0	0	0	0	0
1	18	Traditional	8.1	0	9.4	0	5	0	4.5	0
2	19	WT	4	2.9	7.3	3.8	4.08	2	5	4.8
2	21	PV	0	0	0	2	0	0	0	0
2	21	Traditional	0	0	0	1.02	0	0	0	0
3	25	Traditional	4 (NS)	4 (NS)	4	4	4	4	4 (NS)	4 (NS)
4	28	PV	6	5	9	7.7	4	.5	4	9.1
4	32	Traditional	7.1	7.8	10	9.2	6	8	8.2	10.1
4	33	WT	6.2	4	0	0	4.9	5.8	2	2.1

TABLE 10. Results of power trading in the modified IEEE-RTS 33-bus of Figure 7, (NS means not sufficient).

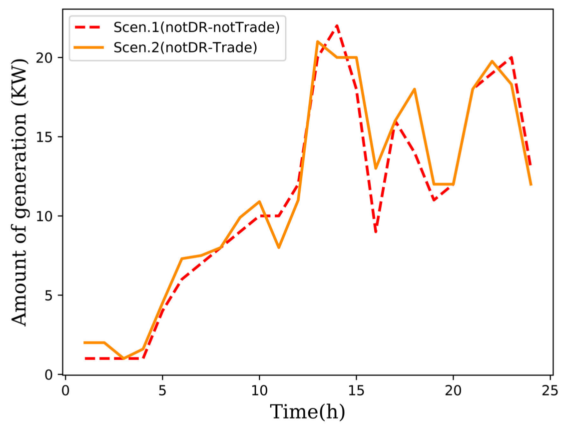
		Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	MG	peak	non-peak	peak	non-peak	peak	non-peak	peak	non-peak
Generation	1	90	63	96	63	73	81	79	84
	2	4	2	7	6	4	2	5	4
	3	4 (NS)	4 (NS)	4	4	4 (NS)	4 (NS)	4	4
	4	19	16	19	16	14	20	14	21
	sum	117	85	126	89	95	107	102	113
load	1	90	63	90	63	73	81	73	81
	2	4	2	4	2	4	2	4	2
	3	13	8	13	8	11	10	11	10
	4	19	16	19	16	14	20	14	20
	sum	126	89	126	89	102	113	102	113
Selling	1	-	-	6	0	-	-	6	3
	2	-	-	3	4	-	-	1	2
	3	-	-	0	0	-	-	0	0
	4	-	-	0	0	-	-	0	1
	sum	-	-	9	4	-	-	7	6
Buying	1	-	-	0	0	-	-	0	0
	2	-	-	0	0	-	-	0	0
	3	-	-	9	4	-	-	7	6
	4	-	-	0	0	-	-	0	0
	sum	-	-	9	4	-	-	7	6

third scenario (the blue dotted line) which has DR program only, the amount of generation changes in peak and non-peak times, due to load shifting. At last, in the last scenario which is shown by the green line, although the amount of generation shifted from peak times to non-peak times, it increased due to power trading. The monitored energy resource in this test has less cost than others, so it can supply other loads by power selling.

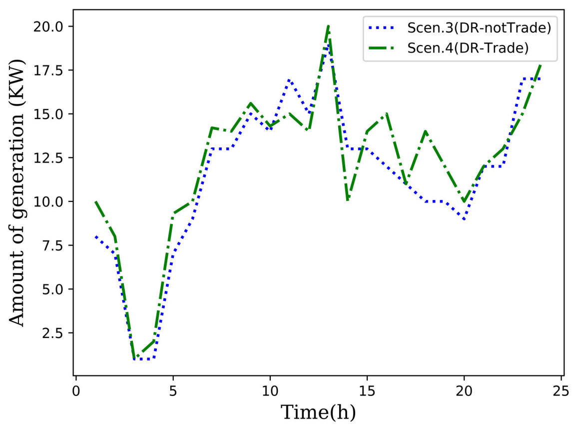
The results of this test imply that the proposed model can surpass other models presented in the three first scenarios in the context of cost reduction. In fact, the reduction of cost completely depends on the power trading model and also adding a DR program. As shown the other models cannot decrease power generation in the selected bus. Although Figure 8 demonstrates one of the buses' results, the same results happened for other buses.

2) INVESTIGATING THE IMPACT OF DR PROGRAMS

The result of the effect of DR programs on load shape is in the Figure 9. As shown, in the first scenario, the total load of one network bus measured without DR program, and as shown the load is high in peak loads (between 12 to 18 and 18 to 20) and lower at non-peak times. In the second scenario, in the presence of DR program, the total load of one network bus decreased in peak times and increased in off-peak and mid-peak times which implies the strength of the proposed model in presence of DR programs on load shape.



(a) without DR program



(b) with DR program

FIGURE 8. Amount of generation in a PV energy resource on *bus*1 of modified IEEE 33-bus in Table 9 in four different scenarios.

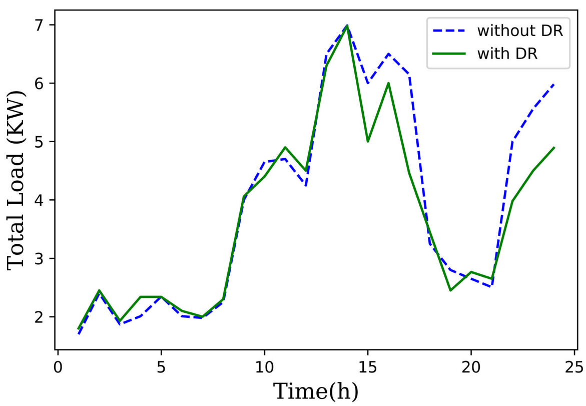


FIGURE 9. The effect of DR programs on loads shape in IEEE RTS 33-bus test system.

3) INVESTIGATING THE IMPACT OF POWER TRADING

In order to consider the power trading in a distribution network, the total cost of MGs with and without power trading is measured and the results are shown in Table 11. In this test, we compute the total cost by Equation (11). As demonstrated in Table 11, the cost of $MG1$ and $MG2$ are increased due to generating more power and selling it. The cost of the forth MG is not changed due to the lack of trade with other MGs. The cost of $MG3$ has increased due to the purchasing of the required power, which it is not able to produce on its own. Note that in the first case (without trade) because the total needs of the $MG3$ are not met, the final cost is less than the total cost in the second case (with Trade). This indicates the strength of the proposed model in stating the reason for not meeting all the needs of MGs. In this test the sum of the cost in proposed model is reduced about 10% which demonstrates the ability of the proposed model in solving the problem by adding power trade programs.

TABLE 11. Total cost of MGs with and without power trading in modified IEEE 33-bus distribution network.

	total cost	
#MG	without Trade	with Trade
1	32.47	34.15
2	8.79	9.35
3	4.98	6.33
4	9.42	9.42
sum	55.66	59.25

4) INVESTIGATING THE IMPACT OF SWITCHING

This section measures the number of switching. We measure the number of switching in the mentioned distribution network in two scenarios without DR program and with DR which is shown in Figure 10. The selected switch is $sw2$ which connects two MGs $MG1$ and $MG3$. Before implementing DR program, switch $sw2$ required eight changes, most of which occurred due to the power trading between the two MGs $MG1$ and $MG3$. Also, most of the trade took place during peak hours $(17-21, 7-10$, and $12-14)$. After implementing DR program, switch $sw2$ requires only four changes. The decrease in the number of changes is due to the addition of the third part to the objective function, which prevents any changes in the switch status. But the power trade still exists between the two MGs. Most business hours are also peak consumption times. This test demonstrates a reduction in required switching in two different scenarios, without DR, and with DR. The required reduction in this test computed about 30% which is an average between different tests such Figure 10.

D. SCALABILITY ANALYSIS

This section presents the scalability results to demonstrate how the model scales with an increasing number of buses and MGs. In such type of analysis, all the required scenarios are generated simultaneously and the solution for all time slots is computed. In this campaign, we systematically explore scenarios with the number of buses between 1 to 150 while the number of MGs is set to $1/10$ times the number of buses and the maximum number of energy resources per bus is set

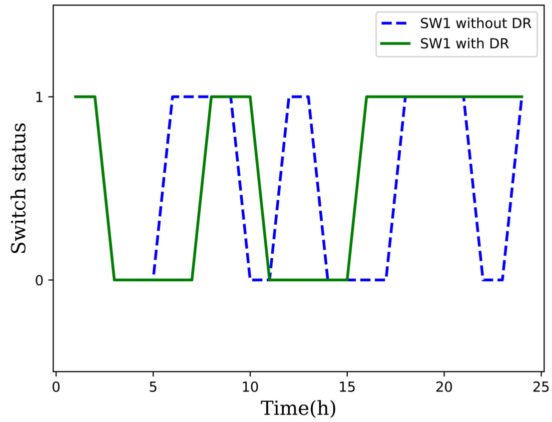


FIGURE 10. The status of the switches connected to the MGs in IEEE 33-bus.

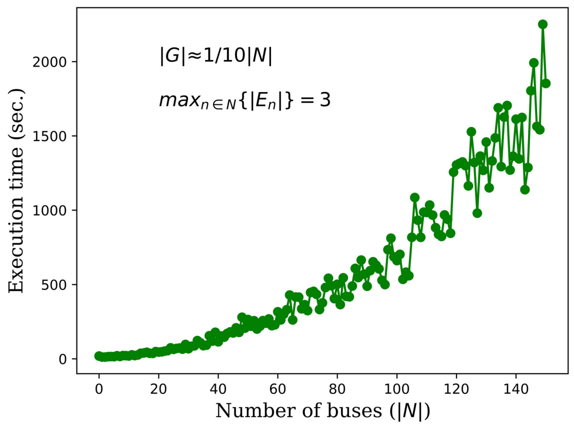


FIGURE 11. Scalability test on DN with increasing the number of buses.

to 3. The obtained results are summarized in Figure 11; even if the proposed model requires more time than models that focus on only power scheduling or power trading to find a solution, it still scales and it takes in the worst considered scenario (150 nodes and 15 MGs) about 30 minutes to find the optimal solution, making the proposed method feasible also for large systems. The required simulation time depends on the number of variables and constraints which is shown in Table 12. As shown in Table 12, the first column with 6-bus is the network in Figure 1. This distribution network had 2 MGs and the maximum number of energy resources per bus was 1. Based on Table 12, it had about 1400 variables and about 2000 constraints, and the obtained execution time was 20.82 seconds. The second column shows the next test system with 33-bus which obtained about 30 minutes for execution time. These results show the scalability of the proposed model.

The computational complexity of the proposed model depends on used solution method. Since IPopt optimization method is used in this paper, so its complexity is important in running process. IPopt solves the Karush-Kuhn-Tucker (KKT) conditions of sequence of barrier problem. Solving

TABLE 12. Scalability results.

	6-bus	33-bus
$\|G\|$	2	4
$max\{\|E_n\|\}$	1	3
Number of parameters	180	2206
Number of Variables	1400	13000
Number of constraints	2000	17000
Simulation time (sec.)	20.82	122.82

the KKT system is the most computationally intensive step in the solution of the Nonlinear Problem (NLP). A crucial advantage that IPopt offer over active-set solvers is that the structure of the KKT matrix does not change between iterations. So, the computational complexity of this strategy is in general favorable, scaling nearly linearly [42].

VII. CONCLUSION

In this paper, we have proposed an MINLP formulation for power trading in reconfigurable MGs with selecting involved energy resources. Time-based DR programs were used in the proposed model which have flattened the profile load and have reduced the cost of MGs. The effectiveness of the proposed model has been assessed by performing simulations and experiments in a test prototype environment and an IEEE 33-bus test system. The results have shown how our solution allows for obtaining savings in power costs with respect to basic methods without trading and DR programs. The reduction in costs in the experimental section was calculated at about 10%. The cost reduction in the proposed model is due to the modeling done and the involvement of energy resources in trade between MGs. Also, the reduction in the power generation and required switching, was calculated at about 12% and 30% respectively. Using the DR program can flat the power load in order to isolate the MGs and minimizing the cost of trading. The solution is effective even for large-size problem instances that can be optimally solved within 30 minutes for 150 buses. A future work is on MG clustering by applying graph-based algorithms.

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