

# Investigating the Impacts of Pollution and Electric Vehicle Charging Station on Energy Management in Multi-Agent-Microgrids

FARHOOD GHALKHANI<sup>1</sup>, MOHSEN HAYATI<sup>2,\*</sup>, AND HAMDİ ABDİ<sup>3,\*</sup>

<sup>1,2,3</sup>Department of Electrical Engineering, Engineering Faculty, Razi University, Kermanshah, Iran

\* Corresponding author: Email addresses: hayati@razi.ac.ir (Mohsen Hayati), hamdiabdi@gmail.com (Hamdi Abdi)

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Increasing the energy consumption, greenhouse gas emission, the need to improve reliability and sustainable supply of electricity, are some of the most challenging issues in modern power systems. To tackle these challenges, using renewable-energy based sources to reduce dependence on fuel-based energy sources is focused. For this purpose, using the electric vehicles, in the form of distributed generation, as an appropriate solution to replace combustion vehicles is strongly considered. In this paper, the energy management in multi-agent microgrids in an integrated framework including the electric vehicle charging stations and reducing pollution is suggested. In the proposed strategy, to manage the energy optimally, two stages are implemented. First, in each microgrid, local energy management is performed, pollution of diesel generation sources is considered, and the hourly amounts of surplus/shortage powers are determined. At the second stage, the microgrid is connected to the upstream network, and the impacts of electric vehicle charging stations, and also the sale/buy of power are modeled. To improve the power quality and optimize the net power, energy storage systems are used. The results of simulation studies using General Algebraic Modeling System software confirm that by applying the proposed technique the operating costs are optimized. They confirm that the total operation costs of microgrids will be increased by considering the fuel cost and produced pollution by diesel generators. Also, by using the electric vehicles charging stations, the overall costs over 24 hours will be reduced, up to \$792. © 2022 Journal of Energy Management and Technology

**keywords:** Energy management, Multi-agent MGs, Energy storage, Electric vehicles, Pollution

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## NOMENCLATURE

<i>AT</i>	Arrival time	<i>NF</i>	Neuro-fuzzy
<i>DG</i>	Distributed generation	<i>NSGA – II</i>	Non dominated Sorting Genetic Algorithm-II
<i>DICOPT</i>	Discrete and Continuous OPTimizer	<i>PID</i>	Proportional–integral–derivative
<i>ESSs</i>	Energy storage systems	<i>PSO</i>	Particle swarm optimization
<i>EVCSs</i>	Electric vehicle charging stations	<i>SOC</i>	State of charge
<i>EVs</i>	Electric vehicles	$P_{gen}$	Active power generated
<i>GAMS</i>	General Algebraic Modeling System	$p_{gen}^{Max}$	Maximum generation capacity
<i>LP</i>	Linear programming	$U_{gen}$	Binary variable
<i>MARL</i>	Multi-agent reinforcement learning	$r_{gen}$	Ramp up and ramp down limits
<i>MAS</i>	Multi agent system	$a, b, c$	Cost coefficients of diesel generators
<i>MGs</i>	Microgrids	$C_t(P_{gen})$	Fuel cost function of diesel generators
<i>MMG</i>	Multi-energy multi-microgrid	$C_{startup}$	Start-up costs of diesel generators
<i>MOP</i>	Multi-objective optimization problem	$y$	Change of generator status from off to on
		<i>EM</i>	Pollution rate

$P_{bat\_ch}$	Charging rate
$P_{bat\_disch}$	Battery discharge rate
$P_{bat\_cap}$	Maximum battery capacity
$p_{bat\_ch}^{loss}$	Loss rate during charging
$p_{bat\_disch}^{loss}$	Loss rate during discharge
$U_{bat\_ch}$	Binary variables
$U_{bat\_disch}$	Binary variables
$ev_{ev,b}^{soc}$	Stored energy in the car battery
$t$	Time in relationships related to electric vehicles
$at_{ev}$	Electric car arrival time from the parking lot
$dt_{ev}$	Electric car departure time from the parking lot
$P_{shortage}$	Shortage power
$P_{surplus}$	Surplus power
$P_{def}$	Amount of removable load
$p_{def}^{Min}$	Minimum removable load
$p_{def}^{Max}$	Maximum removable load
$C_{def}$	Load handling cost
$P_{curt}$	Amount of interrupted load
$C_{curt}$	Cost of load curtailment
$Pl_{n,m,b}$	Active power flow of lines n, m, and b
$Ql_{n,m,b}$	Reactive power flow through lines n, m, and b
$DV_{n,b}$	The bus voltage magnitude in terms of difference from a per-unit
$DV_{m,b}$	End bus voltage magnitude in terms of difference from a per-unit
$Gl$	Line conductance
$Bl$	Line suspense
$pt_t^{buy\_DN}$	Power purchase price
$pt_t^{sell\_DN}$	Power sale price
$\rho_a, q_i, v_i$	Pollution coefficients
$h_i$	Conversion factor of produced pollution to cost
$\eta_{conv}$	Battery efficiency
$\gamma_{bat}, \beta_{bat}, \alpha_{bat}$	Constant amounts to reconcile various costs
$\delta_{bat}$	Minimum stored energy in the battery
$\zeta$	Constant amount as a definite penalty of the load

## 1. INTRODUCTION

The electricity industry around the world is facing many challenges such as providing the required energy, optimal secure and reliable planning, minimizing environmental pollution, and costly investments [1]. On the other hand, fossil fuels, include coal, gas and oil, are declining sharply. These conditions have led researchers and planners to seek new technologies and strategies. The development of high-efficiency smart grids and the replacement of fossil fuel power plants with renewable energy sources in MGs can be considered as some effective alternatives and new strategies to supply energy [2], [3]. One of the most important issues in this regard is considering economic issues. Providing energy with high reliability, highest quality and minimum cost; can be called the best way to provide energy to consumers. But achieving any of these may result in the loss of another advantage. That is why it is always necessary to strike a balance between these objectives. Introducing the MGs concept into power systems has caused

significant challenges in optimal operation and planning of power systems. These challenges can be addressed by uncertainty in the generation capacity of distributed generation sources, changes in electricity prices in the energy market, load demand changes, and also the widespread use of electric vehicles. Today, the widespread presence of MGs and their entry into traditional power systems raises a new concept called multiple MGs.

An MG may consist of controllable energy sources as well as renewable energy units that are random in nature. Therefore, the existence of an energy management system for optimal planning of controllable energy generation sources as well as ESS is inevitable. In different sources, various methods such as robust optimization, genetic algorithm, and random optimization have been used for optimal optimization of multiple MGs [4]. In [5], the optimal operation of a complex system includes wind turbine, solar cell, fuel cell, and ESS is proposed. The problem solved by linear programming in GAMS software. Although, this work investigated the impacts of renewable energy sources, it neglected the effects of the electric vehicle charging stations and pollution in microgrid operation costs. The optimization of energy exchange between the MG and the upstream network has been reported in [6]. The shortcoming of the presented work is neglecting the electric vehicle charging stations in the microgrid modeling. The economics of using MGs to provide consumer load in a sample area has been investigated in [7]. Also the centralized energy management system to minimize the operating costs is suggested in [8].

Also, a novel linear programming (LP) two-stage stochastic-based approach for energy management in MGs is suggested in [9], considering dispatch-able resources, uncertain loads, and upstream network electricity price. The authors have modeled the inherently stochastic nature of solar and wind resources and environmental aspects to provide some realistic solutions. This paper applied the linear programming to solve a non-linear mathematical model, in terms of the objective function and problem constraints, which leads to non-realistic optimal solutions. an adaptive multi-agent based online-tuned PID controller applying Neuro-Fuzzy (NF) for dynamic management of DGs in an autonomous MG is suggested in [10], to increase system stability and decrease generation costs. The mentioned work provided a control function allocated to several autonomous units, known as agents, and used the modified Particle Swarm Optimization (PSO) algorithm for tuning of the Neuro-Fuzzy (NF) based PID controller parameters.

In [11] the uncertain day-ahead programming in MGs, is addressed by applying a two-stage stochastic programming to reduce the operation cost and environmental emissions. To handle the multi-objective problem,  $\epsilon$ -constraint method is employed and the simulations were investigated on a MG with one month of real data.

Also, [12] addressed a distributed artificial intelligence technique called multi agent system (MAS) for MG energy management system considering different forecasting agents and a real time correction agent. The distributed energy management and strategy optimization in a regional MG by using a multi-agent reinforcement learning (MARL) framework is introduced in [13] to generate independent real-time market decisions.

an agent-based day-ahead power management framework in multiple-MG to reduce operational costs and improve system resilience is proposed in [14]. it used a multi-objective optimization problem (MOP) covering two goals of maximizing

load coverage and minimizing the operating costs, which solved by applying the Non dominated Sorting Genetic Algorithm- II (NSGA-II).

Also, [15] addressed the optimal energy management in multi-energy multi-microgrid (MMG) networks considering both environmental and economic factors to minimize the operation cost, considering operation constraints and carbon emissions. Furthermore, the multi-agents-based coordination for the optimal management of electrical energy and the proper control at the distributed level considering the renewable energy resources is suggested in [16].

In [17] a decentralized energy management system, in multi-agent systems, was suggested for the efficient charging of EVs, by applying a fuzzy logic controller-based energy management strategy, combined with a charging power controller.

In [18] has proposed a multi-energy generation grid integrated with renewable energy resources, fuel cells, a grid-supporting generator connected with boiler, micro-turbine, and thermal system, energy storage system, and wastes burning power plant to optimal resource management for minimizing the operational costs and emissions.

Also, [19] has investigated the Peer-to-peer (P2P) energy trading and internal energy conversion problems in an interconnected commercial, residential, and industrial multi-agent microgrid by using a multi-agent deep reinforcement learning approach combined with the multi-agent actor-critic algorithm with the twin delayed deep deterministic policy gradient algorithm.

A review of different energy management models in microgrid is presented in [20], based on the structure, control, and technique used.

Among the shortcomings of the previous studies, it can be mentioned that most of the researches do not consider all needed resources and strategies, for example, in [21], only the load response program and wind generation re mentioned, and the other sources of renewable energy resources. and electric vehicles are not molded. Also, in most cases, the MATLAB software was used for simulation.

In this paper, energy management in multiple MGs is investigated by using the GAMS software. In the proposed method, the amount of power shortage/surplus in multiple MGs is determined. To this end, each MG first performs a local planning for its subscribers and energy generation resources, and in this way, their surplus or unsupplied power is determined. Next, the energy exchange with the distribution system is calculated by considering the load flow constraints. To maintain the balance between the power produced by renewable energy sources and the load, ESSs are used in the system and to smooth the load curve and reduce operating costs, the demand response programs are applied. Furthermore, the pollutions caused by diesel generators in MGs is also modeled and their impacts on costs have been investigated. At the next step, assuming connection to the upstream network, the problem is examined in two modes of presence and absence of EVs.

In the simulation case study, both objective functions are defined nonlinearly as the mixed-integer problems. Therefore, DICOPT solver was used to solve the models in GAMS software. The mentioned solver uses a linear solver to solve the linear part and a nonlinear solver to solve the other part. Also, the GUROBI linear and nonlinear CONOPT solvers are considered.

The remainder of the paper is organized as follows. Section 2, presents the problem formulation. The energy management modeling is addressed in section 3. Simulation results and numerical studies are detailed in section 4, and finally the

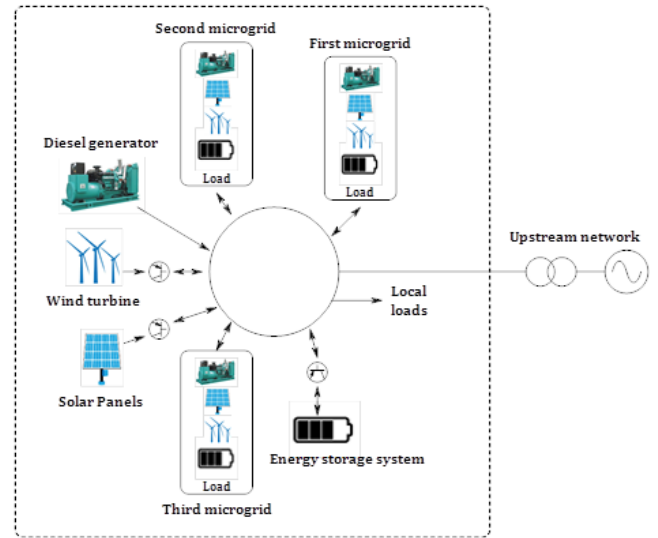


Fig. 1. Multiple MG system structure

conclusions were described.

## 2. PROBLEM FORMULATION

In this paper, a multi-MG system considering DGs and ESSs is used to investigate the proposed method. Multiple MG systems consist of independent MGs, controllable (diesel generators) and uncontrollable DGs (solar and wind), and ESS. Fig. 1 shows the general structure of the studied system.

### A. Traditional Distributed Generation Sources

Traditional DGs, such as diesel generators, are a variety of small-scale controllable energy sources. The output power of these resources is calculated as [22]:

$$0 \leq P_{gen}(t) \leq U_{gen}(t) \times P_{gen}^{Max}, U_{gen}(t) \in \{0, 1\} \quad (1)$$

$$|P_{gen}(t) - P_{gen}(t-1)| \leq r_{gen} \times P_{gen}^{Max} \quad (2)$$

In which,  $P_{gen}(t)$  and  $P_{gen}^{Max}$  represent the generated power by the DG at instant  $t$ , and the maximum generation capacity of the source. The variable  $U_{gen}(t)$  is also a binary variable. The fuel cost of diesel generators is modeled by a quadratic function, as [22]:

$$C_t(P_{gen}) = aP_{gen}^2(t) + bP_{gen}(t) + c \quad (3)$$

The coefficients of  $a$ ,  $b$  and  $c$  are the constant values for each generator. The start-up cost is also shown as [23]:

$$C_{startup} = y(t) \times C^{SU} \quad (4)$$

$$y(t) = \max \{(U_{gen}(t) - U_{gen}(t-1)), 0\} \quad (5)$$

$C^{SU}$  is the generator start-up cost and  $y(t)$  indicates a change in generator status from OFF to ON. The pollution caused by

diesel generators, is modeled by [24]:

$$EM = \sum_{i=1}^{Np} v_i + q_i P + \rho_a P_i^2 + \mu_i \exp(\psi_i P_i) \quad (6)$$

$v_i$ ,  $q_i$ ,  $\rho_a$ ,  $\mu_i$  and  $\psi_i$  are the pollution coefficients, and  $h_i$  indicates the conversion factor of the produced pollution to cost.

## B. Renewable DGs

Solar systems and wind turbines are considered as the distributed renewable generation sources. The output power of such units is considered as a function of environmental conditions such as temperature, solar radiation and wind speed. More details can be found in [25].

## C. Energy Storage System

The used storage system is of battery type. The equations (7)-(15) represent the model of this system [23].

$$0 \leq P_{bat\_ch}(t) \leq U_{bat\_ch}(t) \cdot P_{bat\_cap} \cdot (1 - SOC(t-1)) \cdot \frac{1}{1 - P_{bat\_ch}^{loss}} \cdot \frac{1}{\eta_{conv}} \quad (7)$$

$$0 \leq P_{bat\_disch}(t) \leq U_{bat\_disch}(t) \cdot P_{bat\_cap} \cdot SOC(t-1) \cdot (1 - P_{bat\_disch}^{loss}) \cdot \eta_{conv} \quad (8)$$

$$0 \leq P_{bat\_ch}(t) \leq U_{bat\_ch}(t) \cdot \frac{P_{conv\_cap}}{\eta_{conv}} \quad (9)$$

$$0 \leq P_{bat\_disch}(t) \leq U_{bat\_disch}(t) \cdot \frac{P_{conv\_cap}}{\eta_{conv}} \quad (10)$$

$$U_{bat\_ch}(t) + U_{bat\_disch}(t) \leq 1 \quad (11)$$

$$U_{bat\_ch}(t), U_{bat\_disch}(t) \in \{0, 1\}$$

$$SOC(t) = SOC(t-1) - \frac{1}{P_{bat\_cap}} \cdot \left( \frac{1}{1 - P_{bat\_disch}^{loss}} \cdot \frac{1}{\eta_{conv}} \cdot P_{bat\_disch}(t) - (1 - P_{bat\_ch}^{loss}) \cdot \eta_{conv} \cdot P_{bat\_ch}(t) \right) \quad (12)$$

$$0 \leq SOC(t) \leq 1, \quad SOC(t_0) = SOC_{initial}, \quad (13)$$

$$SOC(T) = SOC_{final}$$

In which,  $P_{bat\_ch}(t)$  and  $P_{bat\_disch}(t)$  are the battery charge and discharge rates, respectively,  $P_{bat\_cap}$  indicates maximum battery capacity,  $SOC$  is the state of the charge of battery,  $P_{bat\_ch}^{loss}$  and  $P_{bat\_disch}^{loss}$  indicate the amounts of losses during charging and discharging, and finally  $\eta_{conv}$  and  $P_{conv\_cap}$  define the efficiency and capacity of the power converter device. Eqs. (7)-(10) indicate the charge and discharge rate limits of the battery. As the battery cannot be charged and discharged simultaneously, clause (11) is defined, in which,  $U_{bat\_ch}(t)$  and  $U_{bat\_disch}(t)$  are the binary variables. Eq. (13) also represents the ESS constraints, the initial and final energy at the beginning and end of the energy management period, respectively.

Eq. (14) models the operating cost of the battery storage system. In this model, three types of costs regarding the battery damages during operation are considered: the cost of fast charging, the cost of successive changes of charge and discharge, and the cost of rapid discharge of the battery [26].

$$C_{bat} = \alpha_{bat} \cdot \sum_t [P_{bat\_ch}^2(t) + P_{bat\_disch}^2(t)] + \beta_{bat} \cdot \sum_t [P_{bat\_ch}(t) \cdot P_{bat\_disch}(t+1) + P_{bat\_disch}(t) \cdot P_{bat\_ch}(t)] + \gamma_{bat} \cdot \sum_t [\min(SOC(t) - \delta_{bat}, 0)]^2 \quad (14)$$

## D. Electric vehicles

The equations governing the charging and discharging modes of EVs are defined as [23]:

$$ev_{ev,t}^{soc} = ev_{ev,t-1}^{soc} + ev_{ev,t}^{ch} \cdot \eta_{ev}^{ch} - \frac{ev_{ev,t}^{disch}}{\eta_{ev}^{disch}}, \quad \text{if } (t > at_{ev}) \quad (15)$$

$$ev_{ev,t}^{soc} = ev_{ev,t-1}^{soc,in} + ev_{ev,t}^{ch} \cdot \eta_{ev}^{ch} - \frac{ev_{ev,t}^{disch}}{\eta_{ev}^{disch}}, \quad \text{if } (t > at_{ev}) \quad (16)$$

$$ev_{ev,t}^{soc} \leq ev_{ev}^{soc,max}, \quad ev_{ev,t}^{soc} \geq ev_{ev}^{soc,min} \quad (17)$$

$$ev_{ev,t}^{ch} \leq ev_{ev}^{ch,max} \cdot u_{ev,t}^{ch}, \quad ev_{ev,t}^{ch} \geq ev_{ev}^{ch,min} \cdot u_{ev,t}^{ch} \quad (18)$$

$$ev_{ev,t}^{disch} \leq ev_{ev}^{disch,max} \cdot u_{ev,t}^{disch}, \quad ev_{ev,t}^{disch} \geq ev_{ev}^{disch,min} \cdot u_{ev,t}^{disch} \quad (19)$$

Eqs. (15) and (16) indicate the constraints for updating the battery capacity of electric vehicles and  $ev_{ev,t}^{soc}$  shows the stored energy and  $ev_{ev,t-1}^{soc}$  the stored energy in the previous hour, and  $\eta$  defines the battery efficiency. Eqs. (17) to (19) also indicate the constraints governing the charging and discharging of EVs.

$$ev_{ev,t}^{ch} + ev_{ev,t}^{disch} \leq 1 \quad (20)$$

Eq. (20) indicates that charging and discharging are not possible, simultaneously.

$$u_{ev,t}^{ch} + u_{ev,t}^{disch} = 0, \quad \text{if } (t < at_{ev} \text{ or } t > dt_{ev}) \quad (21)$$

Eq. (21) indicates that before the arrival of the car and also after the departure of the car, the binary variables belonging to the charge and discharge are zero and as a result, they cannot be applied.

$$ev_{ev,t}^{soc} = ev_{ev}^{soc,max} \times 0.3 \quad (22)$$

Eq. (22) indicates that the car should have at least 30% of the maximum battery capacity, when leaving the EVCS. The mentioned charge capacity enables the EVs to reach home or the next EVCS, and it is obvious that this number can be different based on the distribution system topology and the location of the parking lots. Also,  $t$  represents the time, arrival time (AT) and departure time (DT) represent the arrival and departure times of EVs from the parking lot, respectively.

### E. Modeling the shortage and surplus power

When operating MGs, the concepts of shortage power ( $P_{shortage}$ ) and surplus power ( $P_{surplus}$ ) are introduced, due to the random nature of renewable energy sources or energy prices in the upstream network, and operating costs of local controllable resources. Depending on the energy price, the operator of each MG can sell its surplus power to the upstream network. On the other hand, if there is no power supply and there is a lack of energy inside the MG and the inability of local resources to provide power to subscribers, the operator buys power from the upstream network, according to the electricity price.

### F. Loads

Here, two types of loads are considered. The first one are the loads that can be removed when they are interruptible and the second one are the fixed types. For time-varying loads, it is necessary to provide a certain amount of required energy during different time periods. Also, in the case of curtailed loads, they can be curtailed by paying the money. Therefore, the first category loads have the ability to participate in demand response programs. On the other hand, fixed loads are sensitive and uninterruptible loads that must be supplied at the same time. Eqs. (23) to (26) indicate the minimum and maximum and the amount of energy of removable loads, displacement cost and curtailed cost, respectively.

$$P_{def}^{Min} \leq P_{def}(t) \leq P_{def}^{Max} \quad (23)$$

$$E_{def}^{Min} \leq \sum_{t=1}^{24} P_{def}(t) \leq E_{def}^{Max} \quad (24)$$

$$C_{def} = \psi \cdot \left[ E_{def}^{Max} - \sum_{t=1}^{24} P_{def}(t) \right] \quad (25)$$

$$C_{curt} = \zeta \cdot \left[ \sum_{t=1}^{24} P_{curt}(t) \right] \quad (26)$$

In which,  $P_{def}(t)$  is the amount of removable load, and  $P_{def}^{Min}$  and  $P_{def}^{Max}$  indicate the minimum and maximum values of removable loads.  $E_{def}^{Min}$  and  $E_{def}^{Max}$  determine the limitations of portable load.  $C_{def}$  is the cost of removing the load and  $\psi$  is a constant value.  $P_{curt}(t)$ ,  $C_{curt}$  and  $\zeta$  represent the amount of interrupted load, the definite cost of the load and a fixed amount as the final penalty of the load, respectively.

### G. Network Modeling

The distribution system under study is a radial network. Bus 1 is a reference that is connected to the upstream network and has a variable power and voltage magnitude of 1 per unit.

$R_{ij}$  and reactance  $X_{ij}$ , are the resistance and reactance of the line between buses  $i$  and  $j$ . The voltage magnitude of bus  $i$  and current passing through the line are shown by  $V_i$  and  $I_{ij}$ , Respectively. The output power of each bus is calculated based on the following equations:

$$S_i(t) = S_i^{battery}(t) + S_i^{load}(t) - S_i^{gen}(t) \quad (27)$$

$$S_i(t) = P_i(t) + jQ_i(t) \quad (28)$$

In which,  $S_i$ ,  $S_i^{battery}$ ,  $S_i^{load}$  and  $S_i^{gen}$  represent the pure net injected power, battery power, load power and generator power in the  $i^{th}$  bus, respectively.  $P_i(t)$  and  $Q_i(t)$  are the active, and reactive powers of the  $i^{th}$  bus.

Equations (29), and (30) respectively represent the active and reactive power flows of each line in a radial network, based on power flow equations.

$$Pl_{n,m,t} = (DV_{n,t} - DV_{m,t})Gl_1 + (\theta_{n,t} - \theta_{m,t}) \cdot Bl_1 \quad (29)$$

$$Ql_{n,m,t} = (DV_{n,t} - DV_{m,t})Bl_1 - (\theta_{n,t} - \theta_{m,t}) \cdot Gl_1 \quad (30)$$

$$Pl_{n,m,t} \leq Pl_{l,t}^{max}, \quad Ql_{n,m,t} \leq Ql_{l,t}^{max} \quad (31)$$

Eq. (31) expresses the maximum active, and reactive power capacities of power lines.

In the above equations,  $Pl_{n,m,t}$ ,  $Ql_{n,m,t}$ ,  $DV_{n,t}$ ,  $DV_{m,t}$ ,  $\theta_{n,t}$ ,  $\theta_{m,t}$ ,  $Gl_1$  and  $Bl_1$  represent the active, and reactive powers passing through each line, the bus magnitude voltage at the sending and receiving ends based on the difference with one per-unit, the angles of the sending and receiving ends in terms of radians, conductance and susceptance in terms of  $1/\Omega$ .

## 3. ENERGY MANAGEMENT MODELING

This section, details the energy management method in multiple MG systems in the studied energy management method, surplus and shortage powers are considered at different hours. Initially, each MG operator performs a local energy management to determine the output of each unit and the loads participating in the demand response programs.

### A. Local Energy Management of Each MG

Each MG operator tries to minimize its operating costs by solving the energy management problem. The following equation represents the objective function of MG optimization, including the cost of generators, batteries, the cost of purchasing power from the upstream network, the cost of selling power to the upstream network, and the costs associated with demand response programs.

$$\begin{aligned} & \min \sum_t \sum_i \left[ C_t(P_{gen}^i) + C_{startup,t}^i \right] + C_{bat} \\ & + \sum_t \left[ pr_t^{buy,DN} \cdot P_t^{shortage} - pr_t^{sell,DN} \cdot P_t^{surplus} \right] \\ & + \sum_t C_{def,i} + \sum_i C_{curt,i} \end{aligned} \quad (32)$$

In Eq. (32),  $pr_t^{buy,DN}$  and  $pr_t^{sell,DN}$  are the electricity purchase and sale prices from the distribution network. it minimizes the cost of MGs without considering pollution, which varies in terms of pollution costs, as shown in Eq. (33).

$$\begin{aligned} & \min \sum_t \sum_i \left[ C_t(P_{gen}^i) + C_{startup,t}^i + h_i \times EM(i,t) \right] + C_{bat} \\ & + \sum_t \left[ pr_t^{buy,DN} \cdot P_t^{shortage} - pr_t^{sell,DN} \cdot P_t^{surplus} \right] \\ & + \sum_t C_{def,i} + \sum_i C_{curt,i} \end{aligned} \quad (33)$$

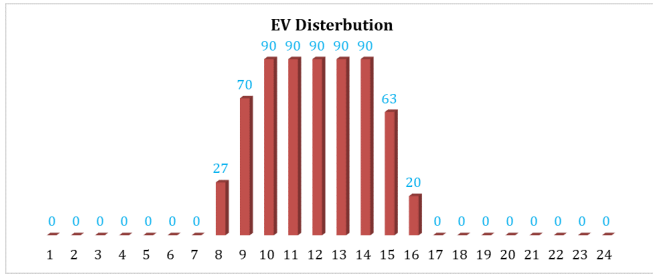


Fig. 2. 24-hour distribution chart of cars

### B. Distribution Network Energy Management

Once the output of the MG units is determined, the distribution network starts the energy management process. The objective function at this stage is based on Equation (34) in which the costs associated with the operation of the distribution network in the presence of MGs and distributed generation resources are minimized.

$$\begin{aligned}
 J = & \sum_{dg} \sum_t Gen \cos t_{dg,t} \\
 & + \sum_s \sum_t P_{s,t}^{buy} . P_{Buy_t} - P_{s,t}^{sell} . P_{Sell_t} \\
 & + \sum_n C_n^{def} + C_n^{curt} + \sum_{ess} C_{ess}^{bat} + \sum_i \sum_t MG_{i,t}^{sell} . P_{Buy_t}
 \end{aligned} \tag{34}$$

$P_{Buy_t}$  and  $P_{Sell_t}$  are the electricity purchase and sale prices from the distribution network.  $MG_{i,t}^{sell}$  is the amount of purchase of the distribution network from the surplus of the  $i$ -th-MG. Each MG begins to reschedule its units once its status is determined.

### C. Distribution Network Energy Management in the presence of EVCSs

In this paper, EVs with two parking lots at the distribution network level have been added to the second stage, i.e. the energy management at the distribution level. It is assumed that 100 cars are evenly divided between two parking lots, allocated in buses 11 and 23. The initial distribution of EVs is determined according to the daily working hours. The possibility of the presence of EVs is presented by the normal distribution, to distribute the entire EVs in the first and last two hours, i.e. the arrival and departure times of EVs from the EVCSs, which is random. The final numbers are also modified using a mobility coefficient of 0.1. The 24-hour distribution diagram of EVs with one run is shown in Fig. 2.

## 4. SIMULATION RESULTS AND NUMERICAL STUDIES

Fig. 3. shows the different steps of proposed strategy for energy management.

In the simulation performed, both objective functions are defined nonlinearly and are nonlinear mixed-integer problems. Therefore, DICOPT solver was used to solve the models using GAMS software. The DICOPT solver has high speed and accuracy and is dedicated to solving nonlinear problems considering different constraints. In other words, the DICOPT solver uses a linear solver to solve the linear part and a nonlinear solver to solve the nonlinear part. In this simulation, linear

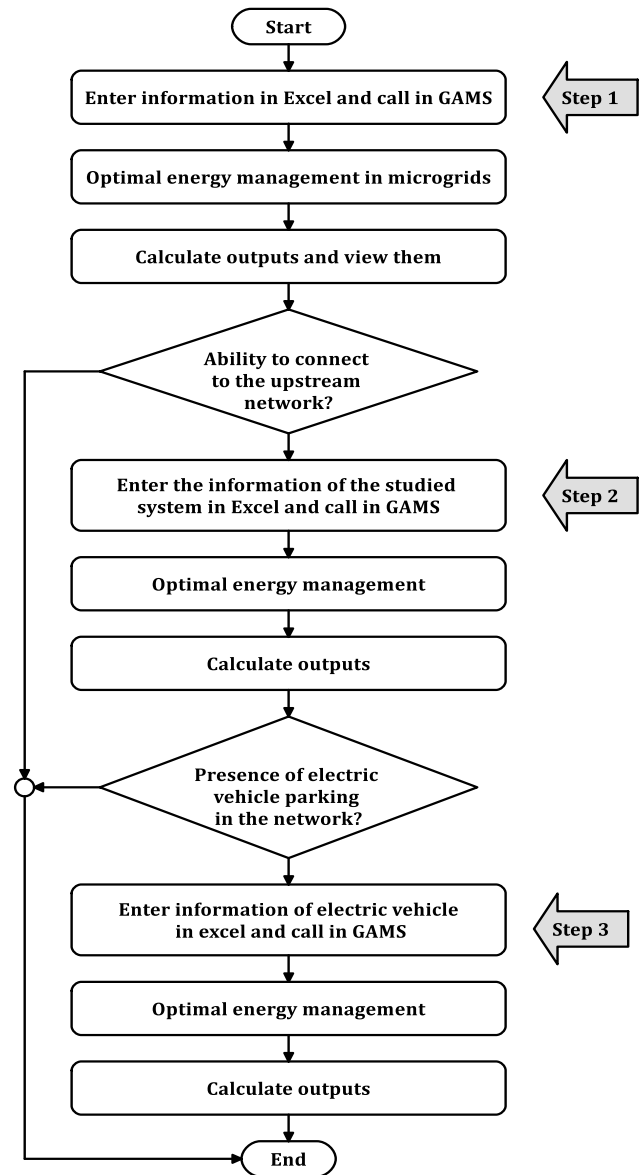


Fig. 3. The proposed flowchart for energy management

solver is GUROBI and non-linear solver is CONOPT. The system under study is the 33-bus IEEE distribution network, which is shown in Fig. 4.

This network including three separate MGs. MGs 1 and 2 include, a solar unit, a wind unit, an ESS and a diesel generator, but MG 3 does not include a diesel generator. The generators data and energy storage data are presented in Tables 1 and 2, respectively. Fig. 5 shows the daily load curve of MGs and distribution network. Also, the hourly price of buying and selling energy is based on the price of energy exchange stated in [23].

### A. Energy Management Neglecting Pollution

In this section the problem of minimizing the operation MG cost, neglecting the pollution is solved. The power generated by the solar and wind units of MGs during 24 hours are shown in Figs 6, and 7.

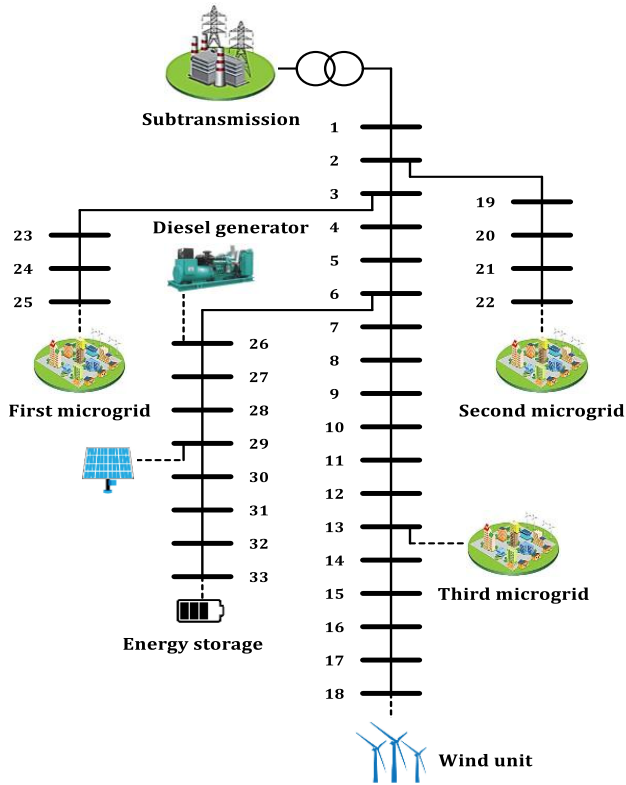


Fig. 4. The configuration of the multiple MG system

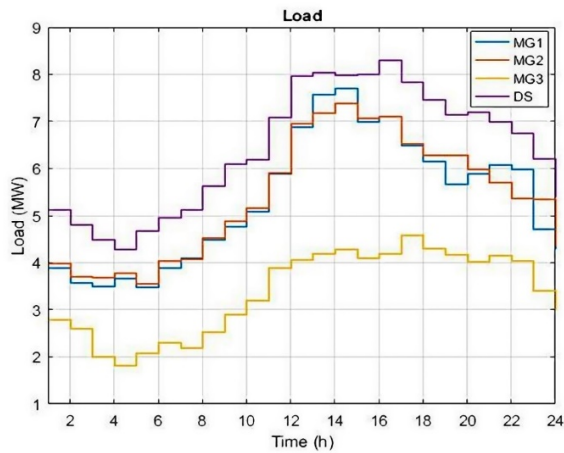


Fig. 5. The daily load curve of distribution network and MGs

Also, the generation quantities of renewable energy resources installed in the distribution network (wind and solar) are shown in Fig. 8.

The purchase and sale prices of energy, based on the price of energy exchange in South Korea, are shown in Fig. 9 [23].

The results of local energy management of MGs neglecting pollution are shown in Figs 10-12. In addition, Table 3 shows the surplus and shortage power of each MG. The results show, that when the energy price is high, the diesel generator is producing its maximum power. Also, the energy storage system starts to be discharged when the energy price is high, and in contrast, it charged when the price is low. Looking at the values in Table 3, it is clear that when the energy is cheap, MGs have shortage

Table 1. Generators data

Parameter	Distribution network	MG 1	MG 2
$a$	12	15	20
$b$	75	85	80
$c$	0	0	0
$C^{SU}$	15	15	13
$r_{gen}$	0.2	0.3	0.2
$P_{gen}^{Max}$	2	4.5	1.5
$\rho$	0	6.49	5.638
$q$	0	-5.55	-6.047
$v$	0	4.091	2.543
$\mu$		2	5
$\psi$		0.02857	0.03333

Table 2. Energy storage data

Parameter	Distribution network	MG 1	MG 2	MG 3
Capacity	3	1	1	1
Primary energy	1.2	0.2	0.2	0.2
final energy	1.5	0.5	0.5	0.5
Converter capacity	750	500	500	500
Converter efficiency	99	98	98	98

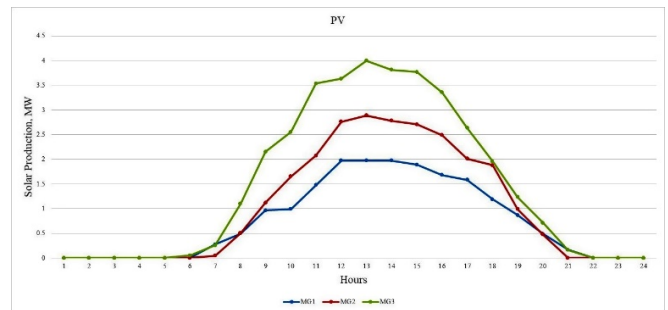


Fig. 6. Generated power by solar units in 24 hours (MW)

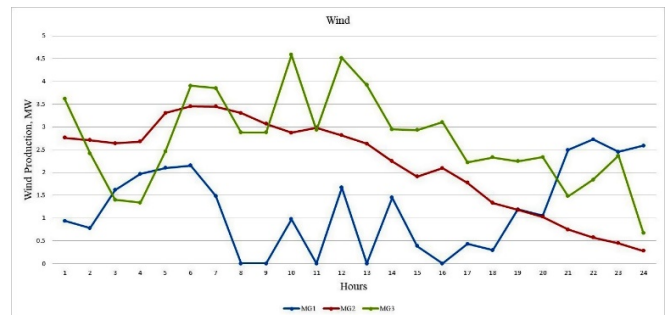
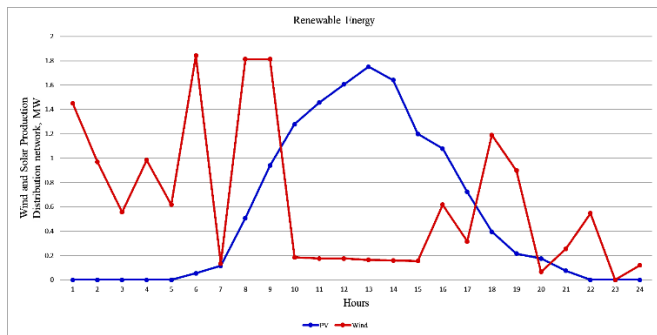


Fig. 7. Generated power by wind units in 24 hours (MW)

power and when the energy price is high, they produce surplus power.

**Table 3.** Shortage and surplus powers of MGs

Time	Shortage power (MW) MG 1	Shortage power (MW) MG 2	Shortage power (MW) MG 3	Surplus power (MW) MG 1	Surplus power (MW) MG 2	Surplus power (MW) MG 3
1	3.156	2.415	0	0	0	0
2	2.99	2.848	1.745	0	0	0
3	1.521	2.073	1.643	0	0	0
4	1.882	2.323	2.003	0	0	0
5	2.116	1.976	1.678	0	0	0
6	0.841	0.74	0	0	0	0
7	0	0	0	0	0	0.347
8	0	0	0	0	0	2.365
9	0	0	0	0	2.257	3.113
10	0	0	0	1.183	2.338	4.987
11	0	0	0	0.302	2.392	3.738
12	0	0	0	1.865	1.595	5
13	0	0	0	0.193	1.842	5
14	0	0	0	1.394	0.614	4.251
15	0	0	0	0.452	0.532	4.474
16	0	0	0	0	0.444	3.725
17	0	0	0	0.261	0.232	1.185
18	0	0	0	0	0	0.905
19	0	0	0	0.706	0	0.218
20	0	0	0	0	0	0
21	0	0.875	0	0	0	0
22	1.179	3.369	1.278	0	0	0
23	1.967	5	0.774	0	0	0
24	2.85	5	5	0	0	0



**Fig. 8.** Wind and solar generated powers installed in distribution network in 24 hours (MW)

**B. Energy Management Considering Pollution**

In this section minimizing the operation MG cost, considering the pollution is addressed. It should be mentioned that only the pollution of traditional generation sources (diesel generators) is modeled.

Table 4 shows the total operation cost of MGs before and after considering the cost of pollution. As it is depicted in this Table, modeling the pollution in objective function, leads to increasing the total operation cost of MGs including diesel generators.

Modeling the pollution of diesel generators reduces their output power. This leads to decrease the total generated power of microgrid, and consequently it has less surplus power, or more shortage power. This ultimately increases the total operation costs of MGs. Figs 13, and 14., show the output power by diesel generator in the first MG in two modes, with and without pollution modeling.



**Fig. 9.** Energy purchase and sale prices (\$/MWh) [23]

**C. Energy Management Considering EVCSs**

In this section, the impacts of EVCSs on MG operation costs are investigated. The EVCSs are allocated in in buses 11, and 23. The results obtained are presented in Table 5. It should be mentioned that the maintaining cost of the EVCSs is assumed \$ 20 per hour.

As can be seen, considering the EVCs will led to decrease the total operation cost of MGs.

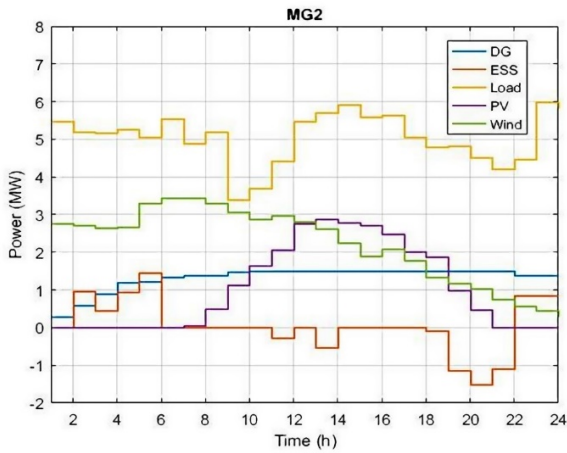


**Table 4.** Comparing the total operation cost of MGs with and without pollution (\$)

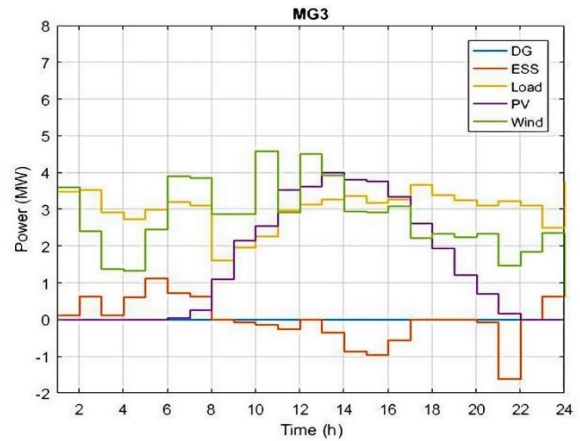
The total operation cost of MGs considering the pollution	The total operation cost of MGs neglecting the pollution
11,908	9,828

**Table 5.** Comparing the total operation cost of MGs with and without pollution (\$)

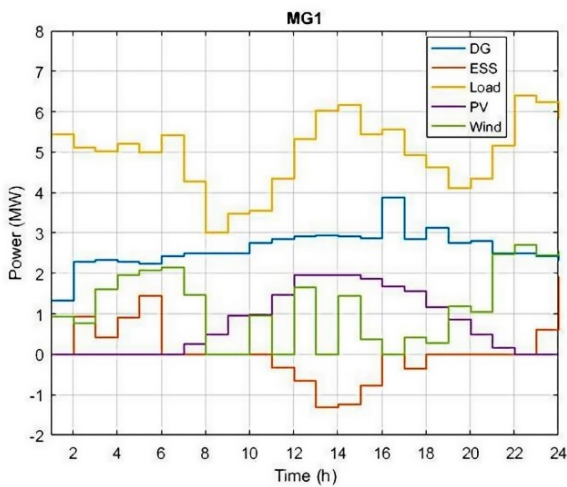
Considering the EVCSs, and maintenance costs	Considering the EVCSs	Neglecting the EVCSs
15,877 \$	15,397 \$	16,189 \$



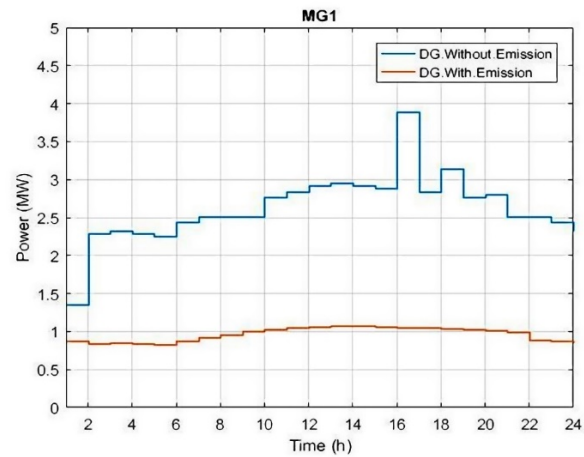
**Fig. 10.** Local scheduling of the first MG in 24 hours



**Fig. 12.** Local scheduling of the third MG in 24 hours



**Fig. 11.** Local scheduling of the second MG in 24 hours

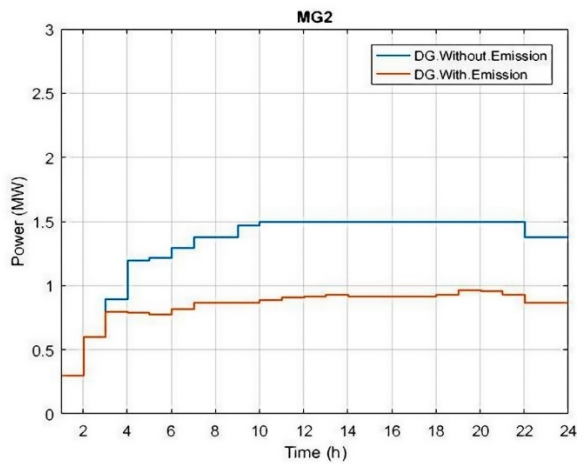


**Fig. 13.** Generated power by the first MG diesel generator in two modes with and without pollution

**5. CONCLUSION**

In this paper, the energy management in multi-agent MGs, consists of several MGs, local DGs, and ESS during 24 hours is discussed. Initially, each MG manages its own local energy. In local energy management, the pollution of diesel generators was also molded and its effect on total operation cost of MGs investigated. Then the amount of surplus and shortage power is determined. In the next stage, the distribution system is also considered in the problem formulation. In this stage, the effect of EVs was considered in the distribution network in the form

of two EVCSs. It was also observed that by considering the cost and pollution of diesel generators, the generated power of diesel generators will change, and ultimately the total operation cost is increased. Also, by performing energy management, MGs have no power supply during the hours when energy is cheap and MGs have surplus power during the hours when the price is high. These reduce the total operation costs of MGs. Also, the results show that considering the EVCSs generally has a positive effect on final operation costs and decreases the overall costs. In general, by using the proposed method the operating costs in 24 hours will be increased to 792 \$ per day. Some of



**Fig. 14.** Generated power by the second MG diesel generator in two modes with and without pollution

the most important challenging issues of the proposed strategy that can be pointed out are the need to optimal allocation of electric vehicles charging stations, replacing the traditional transportation system with the electric one, and need to modern power systems. Also, providing the required infrastructure and the optimal placement of wind and solar generation units is the other important subjects which should be clearly addressed.

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