Economical and Environmental Operation of Smart Networked Microgrids under Uncertainties Using NSGA-II

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***Abstract*—The future smart grid is expected to be an interconnected network of small-scale and self-contained microgrids (MGs), in which renewable energy sources (RESs) play significant role in generation level as well as attract special attention to the aim at a friendly environmental society. In this paper, optimal operation of distributed generations (DGs) are analyzed probabilistically due to uncertainties of loads and RESs. In addition, probability distribution function (PDF) is used to describe the fluctuation model of input data. This paper establishes smart networked Microgrids (MGs) based on NSGA-II algorithm, including the lowest operating cost and the least pollutants emission. In order to make a comparison, the problem is converted to a single-objective function and then, solved by two heuristic algorithms, namely particle swarm optimization (PSO) and Imperialist competitive algorithm (ICA). Simulation results support the capability of the proposed algorithm to minimize jointly the operating power and pollution emission as compared to the results obtained by using current heuristics.**

***Index Terms*—Multi-microgrids (MMGs), small-scale energy resources (SSERs), renewable energy sources (RESs), nondominated sorting genetic algorithm II (NSGA-II), uncertainties.**

I. Introduction and Related Work

Global warming, an increase in carbon emissions, and the growing world population and power demand have provoked many counties to build new power infrastructures known as the *smart grid* [1]. The major feature of the smart grid includes more distributed power generations (especially from renewable energy sources), smart charging/discharging of energy storage, two-way communications between the utility company and consumers for a better demand side management, and decentralized operations of power grid in the form of microgrids (MGs) [2]. It is essential to understand the impact of these new features, and how to make optimal economic and technology decisions on the planning and operation of the smart grid [3]. From the perspective of microgrid (MG) owners, obviously, economic operation of the MG is important. Since MGs can participate in power markets and also provide some ancillary services, proper scheduling of the MG is essential from the main grid point of view. Therefore, a suitable strategy should be pursued for the MG operation [4]. A typical MG consists of a wind turbine (WT), a photovoltaic (PV), an energy storage system (ESS), a micro turbine (MT), a fuel cell (FC), combined heat and power (CHP), and thermal/electric loads [5]. The MG has two modes of the operations: *grid-connected mode* and *stand-alone mode*. In grid-connected mode, the MG is able to connect the main grid completely or partially as well as buy/sell from/to the main grid. In this mode, MGs can also provide ancillary services for a network. In stand-alone mode, MG feeds power to the priority loads while there is no any disturbance in the main grid. Economic operation and optimal scheduling are challenging tasks in the case of MG energy management. To address this problem, several researches have done in literature. In paper [6], authors proposed a method to optimize conflicting objectives such as total cost, CO_2 emissions and energy losses for MGs. They used two-layered algorithm to solve the problem such that the outer layer is based on genetic algorithm and inner layer using mixed linear/ quadratic programming model.

The work in [3] proposed the framework to join investment and operation optimization for a MG as a two-period stochastic programming to minimize operating cost in second period based on solving problem in terms of capacities of solar and wind power generations and energy storage. The results are based on realistic meteorological data. Also, they have shown the impact of uncertainty in renewable energy by computing prediction error. In [7], authors considered a multi-objective stochastic algorithm to minimize cost and emission by considering uncertain variables such as the load demands, the market prices, and powers output of PV/WT units. An improved multi-objective teaching-learning-based optimization [8] is applied to solve proposed problems. In order to solve a multi-objective optimization (MOO) with conflicting objectives, like reducing energy cost, power fluctuations of versatile resources, peak loading, emissions and improvement in reliability of service, reference [9] proposed a method such that each objective is quantified valuation functions that can be specified for each MG. Authors in [10] designed a fuzzy optimization theory to change the MOO problem into a nonlinear single objective optimum problem. Method in [11] is adopted to deal with the problem of uncertainty nature of power generations of renewable energy sources (RESs), energy storage and load demand. To cope this issue, stochastic variables computation module is implemented for a MG. It used Monte Carlo simulation hourly to generate various scenarios. In this work, a mixed-integer linear programming is proposed to solve the stochastic scheduling. To minimize each user's electricity payment [12] proposed an optimum real-time load management algorithm by combining real-time pricing (RTP) with inclining block rate (IBR) tariffs to better reflect the fluctuation of the wholesale electricity prices. Moreover, they take into account the load uncertainty unlike most other load management algorithms that assume fix energy demand for residential. The work in [13] addressed the energy consumption scheduling with the uncertainty of PV output power by using the Sample Average Approximation (SAA) technique [13].

A. Goal of this paper

Despite the intermittent loads behaviors and generated powers by wind turbines (WTs) and PVs, there exists several deterministic methods to deal with MG operation problems. Hence, in this paper, stochastic method takes into account to solve MG operation problems. Moreover, all the input data such as loads and generated powers by WTs and PVs are described as PDF. We connected MG to each others and Main Grid to build multi-microgrids (MMGs) in order to supply/absorb energy either by MGs or Main Grid. Since, the traditional techniques such as MILP do not cope well with large scale problems, we exploit NSGA-II algorithm to address this problem. In addition, NSGA-II implements to yield the best expected Pareto optimal front. In details, we present a further step with respect to these proposals by considering optimal power dispatch problem as a multi-objective function and solved by NSGA-II algorithm. In addition, due to presence of RESs such as WTs and PV systems as well as intermittency in load demand side, the proposed problem is analyzed from stochastic and probabilistic viewpoints. As another important contribution of the paper, MMG is introduced as future generation of typical microgrid. In MMG environment, transaction of power among any microgrid plays a crucial role in both creating balance between load generation and providing economical-environmental profits to not only consumers but also power producers. Finally, the NSGA-II algorithm can properly handle the proposed complicated problem in comparison with single-objective functions, which are solved by PSO and ICA algorithms.

The rest of this paper is organized as follows. In Section II, the problem is described briefly with relevant MG probabilistic power resources modeling and presented the proposed NSGA-inspired algorithm. In Section III, we evaluate and compare the performance of proposed algorithm through simulations. Finally, Section IV concludes the paper.

II. Proposed Model and Algorithm

In this section, after a brief overview of the NSGA-II method, we describe the exploited models for the RESs over MGs, cost modeling of MG components and proposed method.

A. Preliminarily of NSGA-II

The Fast Elitist Nondominated Sorting Genetic Algorithm for MOO, NSGA-II [14], is the modified version of NSGA [15] which has a better sorting algorithm. As an usual in evolutionary optimization, the algorithm starts with the population initialization (parent population). Then, the populations are sorted based on non-domination[1] into each front and Crowding distance[2]. Now, we have parent P_0 with size N and use binary tournament selection, recombination and mutation operators to create offspring population Q_0 of size N. From the first generation onward, the procedure is different. P_0 and Q_0 are combined to make individuals of the next generation ($R_t = Q_t \cup P_0$) of size $2N$. Then, to generate new parent population for the next generation P_{t+1}, R_t is sorting according to non-domination and add solutions to P_{t+1} from the first front till the size exceeds N. If by adding all the solutions in the last accepted front the population size exceeds N, then the last one are sorted in descending order based on their crowding distance until to fill the size of N. Recombine P_{t+1} by Binary Tournament Selection, Recombination and Mutation to produce new offspring Q_{t+1}. Hence, the process repeats until the termination condition is met.

B. System architecture

Fig.1 summarizes the system architecture. We considered three MGs. They can be more according to smart distribution grid sizes with the following components: energy resources such as PV, WT, MT, FC and CHP. Each MG is connected to other MGs and Main Grid in order to sell/buy from/to other MGs or Main Grid. Each MG can share its data including the amount of generated energy by resources, load demand with other MGs via the main management unit. We define the generation power through the SSERs and load as a PDF in order to model the fluctuation.

C. Probabilistic modeling of load/WT/PV

Certainly, the load as the most obvious uncertain variable plays a crucial role in power system operation. The variation of the load in distribution feeder contains deterministic and stochastic components. The daily and weekly variations in the demand mainly depend on the behavioral patterns of different energy consumers. The normal distribution is widely used for

[1] An individual is said to dominate, if its objective functions of it is no worse than the other and at least in one of its objective functions it is better than the other.

[2] Crowding distance is compared only if the rank for both individuals are the same.

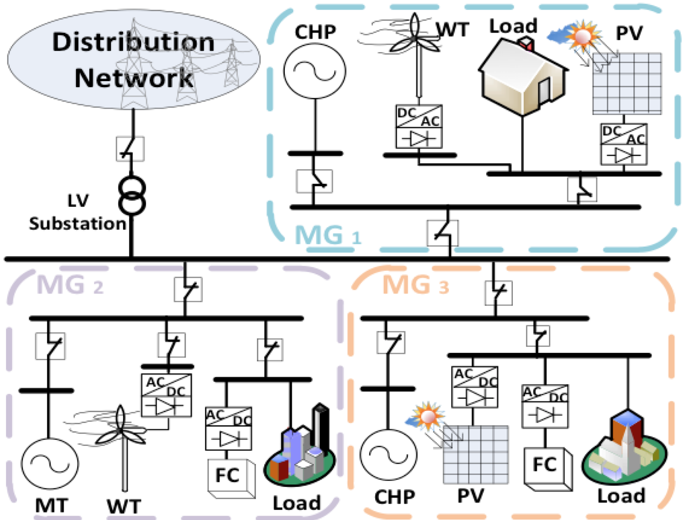


Fig. 1: Network structure with three MGs.

load distribution [16]. The PDF for the normal distribution of load power has been following:

$$f(P_{l,MG}) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{(P_i-\mu)^2}{2\sigma^2}\right), \quad (1)$$

The power outputs of RERs depend on the availability of the primary resources such as wind speed, solar irradiation and etc. The generated power by the wind turbine depends on the wind speed. Wind speed varies every minute, hour, day and season of the year, which highlights the importance of a probability model. The Weibull distribution is used to represent the distribution for the wind speed v for long term planning purposes. In weather forecasting to describe wind speed distributions, as the natural distribution often matches the Weibull shape[3]. Thus, The PDF of Weibull is defined as following:

$$f_v(v) = \begin{cases} \frac{\beta}{\alpha} \times (\frac{v}{\alpha})^{\beta-1} \times \exp(\frac{v}{\alpha})^{\beta} & v \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Since the simulated wind speed was generated using (2), the real power generation $P_{G,WT}(v)$ by WT can be obtained as follow:

$$P_{G,WT}(v) = \begin{cases} 0 & 0 \leq v \leq v_{ci} \text{ or } v \geq v_{\infty} \\ P_{r,WT} \frac{v^2 - v_{ci}^2}{v_r^2 - v_{ci}^2} & v_{ci} \leq v \leq v_r \\ P_{r,WT} & v_r \leq v \leq v_{co} \end{cases} \quad (3)$$

Maximum value of generated power by each WT is considered 200 kW. The generated power by a PV module varies according to the solar radiation on the earths surface, which mainly depends on the installation site and the weather conditions. In this paper, irradiation is modeled by Beta distribution function. The PV modules are tested at standard test condition (STC). The output power of the module can be calculated as follow:

$$P_{PV}(R) = \begin{cases} P_{r,PV}\left(\frac{R^2}{R_{STD}R_c}\right) & 0 \leq R \leq R_c \\ P_{r,PV}\left(\frac{R}{R_{STD}}\right) & R_c \leq R \leq R_{STD} \\ P_{r,PV} & R_{STD} \leq R \end{cases} \quad (4)$$

[3] http://www.reuk.co.uk/Wind-Speed-Distribution-Weibull.htm

In this paper, the rated power of each PV is considered 150 kW.

D. Cost modeling

In this paper, the cost includes of the cost of power generation, power transaction, operation and maintenance and pollutant emission costs. The proposed objective function is based on mentioned costs. The cost of power generation is increased with increasing primary energy. The cost of consumed energy by WTs and PVs is zero. In other SSERs such as fuel cells (FCs), micro turbines (MTs) and CHPs, there is linear relation between energy consumption and fuel cost. Therefore, the relation between the generation cost and the generated power are described for units (i.e., FC, MT and CHP) as bellow:

$$C_{g,unit} = \alpha_{\alpha} \times P_{g,unit}, \quad (5)$$

In above formula, the value of C_g for WTs and PVs is zero. The total power generation in each MG is sum of the generated powers by available units in same MG. Although, the $C_g - P_g$ relation is linear for dispatchable units, but the zero values for WTs and PVs makes eq.(5) nonlinear for a MG. Indeed, with this condition the cost function is nonlinear. Another cost of units which is related to their generated power, operation and maintenance (O&M) cost. This cost with a coefficient ($K_{O\&M}$) for each unit can be described as bellow:

$$C_{O\&M,unit} = K_{O\&M,unit} \times P_{g,unit}, \quad (6)$$

The transaction cost are considered in MGs. In presented structure for MG, all MGs are connected to main grid and exchange power with each-other. Whilst, one of the important ideas of the paper is the exchange of power between MGs. In other words, in addition to sharing power with main grid, each MG can supply its power shortage from other MGs through available power lines. So, each MG makes contact with main grid and other MGs to supply its local load. These relations between MGs and external grid contain transaction costs for MGs. The SSERs of MGs after covering its local load, it has surplus power that should be consumed. Based on existing conditions, MG can sell this surplus power to other MGs or external grid, otherwise, it should buy power, if it is unable to provide sufficient power to its loads. In this paper, the priority in selling/purchasing power is firstly by MGs, then with the main grid. Indeed, we want to decrease the effect of main grid or even remove main grid in some case studies. Hence, in some conditions, all MGs operate in island mode and they are unlinked from external grid. In order to explain mathematically the transaction cost, related formulation to purchase and sold costs of each MG is represented in:

$$C_{buy,MG} = c_{MG} \times P_{buy,MG}, \quad (7)$$

$$C_{sell,MG} = d_{MG} \times P_{sell,MG}, \quad (8)$$

where c_{MG} and d_{MG} are the cost of purchased an sold power coefficients, respectively. The cost of power transaction of each MG in the network is described as follow:

$$C_{trans,MG} = C_{buy,MG} - C_{sell,MG}, \quad (9)$$

Since, for a MG it is not reasonable to purchase and sell energy on the market at the same time or sample, we have the following constraints to purchased and sold powers:

$$\begin{cases} \text{if } P_{g,MG} - P_{l,MG} > 0 \Rightarrow P_{buy,MG} = 0, P_{sell,MG} > 0, \\ \text{if } P_{g,MG} - P_{l,MG} < 0 \Rightarrow P_{buy,MG} > 0, P_{sell,MG} = 0, \end{cases} \tag{10}$$

Each MG emits some pollutants into air. This pollution is achieved from generated power by units of MGs that consists NO_x, SO_2 and CO_2. The pollution emission cost $C_{E,unit}$ for each unit can be described as follows. Pollution coefficient for each pollutant γ have been described in [16].

$$C_{E,unit} = \sum_{j=1}^{3} \gamma_j \times (\rho_{unit,j} \times P_{g,unit}), \tag{11}$$

E. Multi-objective function

The first objective is related to minimize the operation cost of whole MGs $F_{PG}(s)$, which consists of power generation, interchangeable power and O&M costs.

$$F_{PG}(s) = \sum_{unit=1}^{9} [C_{g,unit}(s) + C_{O\&M,unit}(s)] + \sum_{MG=1}^{3} C_{trans,MG}(s), \tag{12}$$

The second objective is minimizing the total amount of pollution. Electricity suppliers have to generate high amount of power to ensure supply-demand balance in any MGs so that contribute highly to CO_2, NO_x and SO_2 emissions and production of air pollutants. Therefore, the second objective is to minimize the emission amount. It is presented in:

$$F_{PE}(s) = \sum_{unit=1}^{9} M_{E,unit}(s), \tag{13}$$

F. Objective constraints

In order to best control on the optimal power dispatch problem, there are some important conditions in cost function. The main equal constraint of the proposed problem is supply-demand balance. In this condition, generated power in each MG must provide sufficient power electricity to its local loads considering network losses and transaction power. This condition is applied to all MGs as bellow:

$$P_{g,MG}(s) = P_{l,MG}(s) + P_{trans,MG}(s) + P_{loss,MG}(s), \tag{14}$$

where $P_{loss,MG}(s)$ is calculated using power flows coefficients [17] and $P_{trans,MG} \triangleq P_{buy,MG} - P_{sell,MG}$. The generated power of each unit $P_{g,unit}(s)$ must be within its lower and upper operating limits. It may mathematically formulated by eq.(15):

$$P_{g,Min}(s) < P_{g,unit}(s) < P_{g,Max}(s), \forall\, unit = 1, \dots, 9, \tag{15}$$

Also, each MG can buy/sell power from/to other MGs and main grid to an extent. The unequal constraints for purchased and sold powers are as follow:

$$P_{buy,Min}(s) < P_{buy,MG}(s) < P_{buy,Max}(s), \forall\, MG = 1, 2, 3, \tag{16}$$

$$P_{sell,Min}(s) < P_{sell,MG}(s) < P_{sell,Max}(s), \forall\, MG = 1, 2, 3, \tag{17}$$

In inequality conditions, minimum and maximum values of each constraint can change based on available conditions. Note that, these values are adjusted by users.

III. Performance Evaluation

We have evaluated the performance of the proposed by using MATLAB platform under Microsoft Windows 8 x64 on Intel Core i5 by comparing it with methods such as ICA [16], and PSO [17]. We evaluate the dispatch of power problem among loads of MGs considering pollutant effects over the structured network in Fig.1.

A. Test setup

In order to feed the optimization solution, 500 samples is used for every input data in given interval. Moreover, the characteristic of the generation units and emission factors of pollution emissions (i.e., PV, CHP, MT, FC, WT) are listed in Tables I and II, respectively.

B. Results

1) Pareto in NSGA-II: In order to evaluate the optimization solution using NSGA-II, we need to demonstrate the state of the two objectives Pareto related to each-other. Indeed, Fig.2 shows the Pareto front of NSGA-II for total emission amount (TEA) in (kg/h) and total operation cost (TOC) in $(\$/h)$.

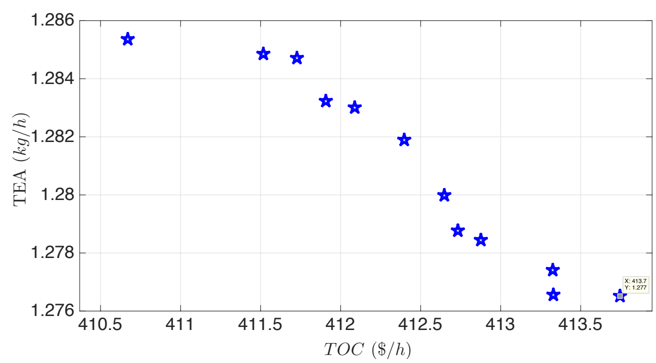


Fig. 2: Pareto front of NSGA-II for the optimization problem eqs.(12) and (13): TOC: total operation cost; TEA: total emission amount.

2) TOC and TEA on MGs: In this scenario, the total operation cost and emission amount of three considered MGs are shown in Figs.3a-3c and Figs.3d-3f based on normal PDF, respectively. We conclude that the PDFs of TOC and TEA are normal distributions. This is the thing that we expected from the shape of load power in eq.(1).

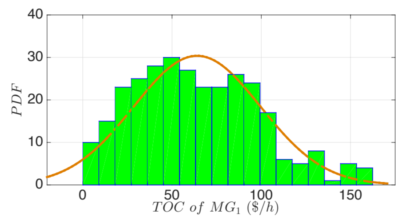
3) Performance of the NSGA-II-based method: As we know, each MG emits pollutant into air. The pollution substances can be NO_x, SO_2 and CO_2. In this test scenario, the cumulative distribution function (CDF) of total emission and cost mass of pollutions related to the MG_3 is demonstrated in Figs.4a and 4b. Moreover, in Fig.4c, we aim at testing the performance of the proposed method by focusing on the generated powers of the engaged MGs of Fig.1.

TABLE I: Default values of the charactristics of generation units.

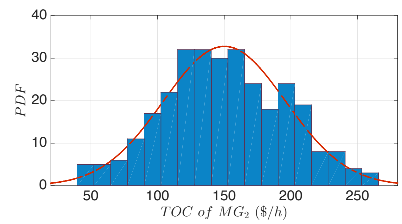
MG number	MG_1			MG_2			MG_3		
Unit type	**PV**	**CHP**	**WT**	**WT**	**MT**	**FC**	**PV**	**CHP**	**FC**
$Minimum$ (kW)	0	50	0	0	50	30	0	50	30
$Maximum$ (kW)	150	450	200	200	450	200	150	450	200
$O\&M$ $(\$/kWh)$	0.1095	0.00587	0.1095	0.1095	0.00587	0.00419	0.1095	0.00587	0.00419
$Installation$ $(\$/kW)$	3176.9	1772.3	1906.2	1906.2	1588.5	4447.7	3176.9	1772.3	4447.7

TABLE II: Default values of the emission factors of pollution emissions.

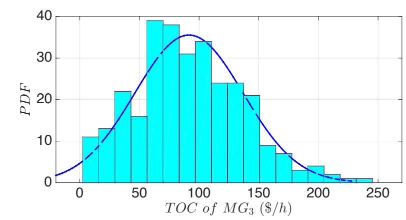
Pollutant	$(\$/kg)$	ρ_{CHP}, (kg/kWh)	ρ_{MT}, (kg/kWh)	ρ_{FC}, (kg/kWh)	ρ_{PV}, (kg/kWh)	ρ_{WT}, (kg/kWh)
NO_x	10.0714	0.00010	0.00003	0.00044	0	0
SO_2	2.2747	0.000007	0.000006	0.000008	0	0
CO_2	0.0336	0.001370	0.001078	0.001596	0	0



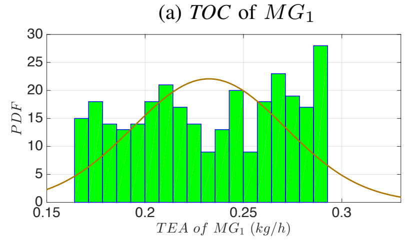
(a) *TOC* of MG_1



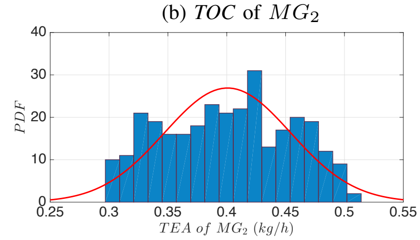
(b) *TOC* of MG_2



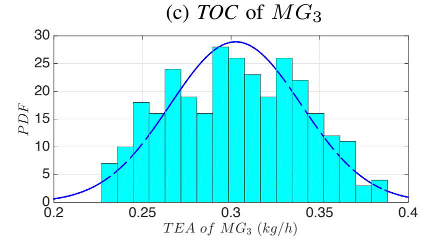
(c) *TOC* of MG_3



(d) *TEA* of MG_1

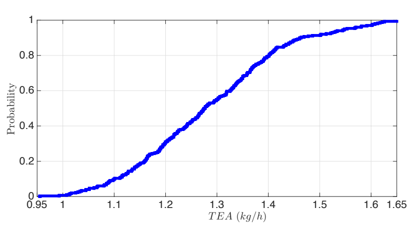


(e) *TEA* of MG_2

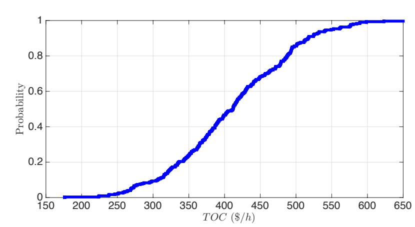


(f) *TEA* of MG_3

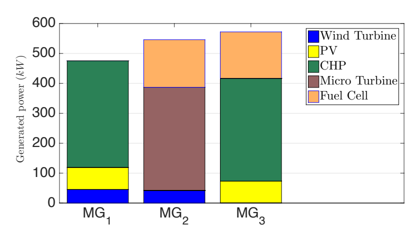
Fig. 3: Figs. 3a-3c: TOC in $(\$/h)$; Figs. 3d-3f: TEA in (kg/h), for the MGs; TOC: total operation cost, TEA: total emission amount.



(a) CDF of TEA in (kg/h).



(b) CDF of TOC in $(\$/h)$.



(c) Generated powers of MGs.

Fig. 4: Figs.4a-4b: CDF of TEA and TOC of MG_3 and Fig.4c: generated powers of MGs under the scenario III-A; TOC: total operation cost, TEA: total emission amount.

4) Performance Comparisons: In the second test set of scenarios, we test the NSGA-II-based method performances under various settings and compare the attained results against of ICA [16] and PSO [17] methods. Indeed, we focused on the performance of the NSGA-II-based method in terms of power and cost types. The results of the average (*mean*) and the standard deviation (SD) of MGs' power/cost types (generation, purchased and selling components of the optimization problem in eq. (12)) are presented in Tables III and IV, respectively. We may draw a conclusion from these tables that the average generation cost/power of NSGA-II in all MGs are lower than ICA and PSO due to using Pareto front characteristic in order to find optimum power and cost altogether.

In the next simulation, we demonstrate the emission amount and cost for ICA, PSO, and NSGA-II as is reported in Table V. We conclude that the NSGA-II-based method could decrease amount of emission as well as cost for MG_3 compared with ICA and PSO.

In the last simulation, we obtain the optimal solution of different techniques and evaluate the resulting total operation cost (TOC), total emission amount (TEA) and implementation execution time takes to run the methods under the setting of

TABLE III: Statistics of MGs' power in (kW) with three different methods in three MGs; Pwrs: Powers type, Gnr: Generation, Pur.:Purchased.

Pwrs	MGs	ICA [16]		PSO [17]		NSGA-II	
		Mean	SD	Mean	SD	Mean	SD
Gnr.	MG_1	473.24	63.76	476.75	67.98	475.52	66.9
	MG_2	547.85	66.09	555.31	67.20	545.97	66.9
	MG_3	586.17	63.51	573.83	62.98	572.01	60.7
Pur.	MG_1	120.97	142.06	116.50	140.38	118.29	145.0
	MG_2	183.49	189.67	176.41	191.42	183.62	195.9
	MG_3	140.15	173.54	148.27	179.58	146.69	181.2
Sold	MG_1	57.79	99.28	56.84	101.89	57.39	100.5
	MG_2	47.30	101.60	47.67	97.40	45.55	97.2
	MG_3	64.72	113.67	60.50	110.16	57.11	105.7

TABLE IV: Statistics of MGs' cost with three different methods in three MGs; Gnr: Generation, Purch.:Purchased.

Costs	MGs	ICA [16]		PSO [17]		NSGA-II	
		Mean	SD	Mean	SD	Mean	SD
Gnr.	MG_1	34.22	7.10	34.95	7.14	34.85	7.38
	MG_2	116.52	12.89	117.81	13.04	115.94	12.71
	MG_3	63.96	9.45	62.40	9.10	62.18	9.01
Purch.	MG_1	23.46	27.72	22.53	27.22	22.94	28.23
	MG_2	34.81	36.33	33.70	36.77	35.10	37.74
	MG_3	27.25	33.83	28.83	35.04	28.48	35.24
Sold	MG_1	10.21	17.72	10.19	18.46	10.17	17.73
	MG_2	8.52	18.41	8.60	17.68	8.16	17.51
	MG_3	11.54	21.03	11.03	20.27	10.48	19.59

TABLE V: Statistics of MGs' emission with three different methods.

Emission type	MGs	ICA [16]		PSO [17]		NSGA-II	
		Mean	SD	Mean	SD	Mean	SD
Amount (kg)	MG_1	0.23	0.04	0.23	0.04	0.23	0.04
	MG_2	0.40	0.05	0.41	0.06	0.40	0.05
	MG_3	0.31	0.04	0.30	0.04	0.30	0.04
Cost ($\$/h$)	MG_1	0.50	0.08	0.50	0.08	0.50	0.08
	MG_2	0.67	0.10	0.69	0.11	0.67	0.11
	MG_3	0.52	0.08	0.51	0.08	0.51	0.08

scenario III-A. The obtained results are reported in Table VI. We drive two conclusions from this table. First, The average of TOC and TEA of the NSGA-II method outperforms others solutions due to minimizing jointly TOC and TEA using Pareto front. Second, the standard deviation of the proposed method is lower than ICA and PSO which is indicated that the proposed method would be good alternative than current methods.

TABLE VI: Optimal solution between ICA, PSO and The proposed method; TOC: total operation cost, TEA: total emission amount.

Solutions	TOC ($\$/h$)		TEA (kg/h)		CPU Time (s)
	Mean	SD	Mean	SD	
ICA [16]	411.50	86.15	1.31	0.16	85
PSO [17]	410.84	84.32	1.30	0.15	93
NSGA-II	410.67	84.16	1.28	0.14	106

IV. Conclusions

In this paper, we exploit the NSGA-II algorithm in order to jointly minimize power cost which consists of generated power, purchased power, sold power, O&M cost, and emission for the smart distribution grids with interconnected cooperation of MGs. Based on the probabilistic behavior of the inputs include load and renewable energy that are defined in PDF. Efficiency of the proposed model is investigated by comparing the results of NSGA-II algorithm with the other heuristic algorithms: ICA and PSO. Numerical results illustrated that NSGA-II could find better solution between objectives, power and emission cost when it is compared with the ICA and the PSO methods.

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