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Probabilistic Energy Manement of micro-grids with respect to Economic and Environmental Criteria

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Abstract. Recently, the use of renewable energy such as wind and solar energy has rapidly increased in micro-grids. Due to the fluctuation of wind speed and solar radiation, the scheduling of wind turbines (WTs) and photovoltaic (PV) plants are difficult in micro-grids. In this paper, a probabilistic energy management system (PEMS) is used to optimize the operation of a grid-connected micro-grid via Economic and Environmental Criteria. For optimal operation of WTs and PVs with other DERs, the fluctuations of WT and PV power generation has been considered and a multiobjective probabilistic economic/environmental load dispatch is presented. For optimal operation of the micro-grid, a complete mathematical model for energy storage system (ESS) is introduced. Finally, an efficient improved bacterial foraging-based fuzzy satisfactory optimization algorithm is proposed to solve the multi-objective problem. The results show that the PEMS can optimize total operation cost and net emissions of the micro-grid, simultaneously.

Keywords: Micro-grid, probabilistic energy management system (PEMS), distributed energy resources (DERs), bacterial foraging optimization (BFO)

1. INTRODUCTION

In recent years, due to economical and environmental issues, the application of distributed energy resources (DERs) such as wind turbine (WT), photovoltaic (PV), biomass, micro-turbine (MT), etc; have been widespreadly increased [1]. A micro-grid comprises a low-voltage distribution network with DERs, storage devices and controllable loads which can operate either interconnected or isolated from the main distribution grid as a controlled entity [2,3]. Recently, many researchers have focused on control and operational planning of the micro-grids. Generally, their researches can be classified in three parts: modeling of micro-grid and obtaining proper objective functions, proposing different strategies for energy management in micro-grids, and introducing different optimization algorithms to optimize their objective functions. For modeling the operation of the micro-grids, DERs and energy storage system (ESS) are the important parts which can play a vital role in energy management of the micro-grids. The ESS can reduce the fluctuations of unpredictable resources such as WTs and PVs and can improve the performance of the micro-grids. Some references have focused on modeling of renewable energy sources to optimize their operations [4,5]. Some other references have proposed different models for scheduling of storages in micro-grids [6,7]. But for optimal operation of the micro-grid, only economic objectives are considered. However, because of the pollutants emission of the DERs, only the economic objectives may not satisfy all the requirements for optimal operation of the micro-grids. So, to obtain the optimal solutions, the environmental and economic objectives must be considered, simultaneously. To obtain the optimal set points of DERs in micro-grids, some literatures have considered both cost and emission objective functions [8]. Some literatures have used the emission as a constraint and some other have used the linear combination of different objectives as a weighted sum and solve the problem with

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single objective function [9,11]. But due to conflicting meaning of emission and cost, some other literatures have used multi-objective optimization techniques [12-14]. To solve multi-objective problems some literatures have considered Fuzzy algorithms [15-19]. K.M. Passino, proposed Bacterial Foraging Optimization (BFO) algorithm which is based on the foraging behavior of E.coli bacteria [20]. Many researchers have used BFO algorithm for small-scale optimization. But this algorithm has poor convergence properties in the large and complex search space and the populations may stick around optima [8]. In this regard, some researchers have proposed modified BFO to achieve the best answers [9]. In this paper, a smart energy management system (PEMS) is presented for optimizing the operational planning of an interconnected micro grid over a 24-hour time interval. The PEMS tries to schedule different DERs and smart ESS in such a way that the total operation cost and the net emission are minimized. For optimal operation of the micro-grid, a comprehensive formulation for the PEMS is presented. In this regard, the mathematical models for renewable energy sources (WT & PV) are presented. Also, a smart model for ESS which consists of practical constraints is developed. An efficient modified Bacterial Foraging Optimization (MBFO) algorithm is proposed to optimize both operating cost and net emission, while all constraints are satisfied. An interactive fuzzy satisfying method is also introduced to derive a satisfying solution for the decision maker (DM). To evaluate the feasibility and accuracy of the proposed algorithm, the mentioned method is applied to a test system and the results are compared with other optimization algorithms.

2. OPTIMIZATION PROBLEM

The aim of the proposed PEMS is to find the optimal set points of DERs, storage system and also the amount of exchanging power with the utility grid with respect to economical and environmental criteria. The objective functions which must be optimized are formulated as follow:

2.1. Operating cost minimization

The total operation cost which includes the costs of selling power of DERs, maintenance and shut-down and startup costs, and the cost of exchanging power with the utility grid, can be written as follow:

$$(1)\; J_1 = Min\sum_{t=1}^{T}\left\{\sum_{i=1}^{N_g}\left[u_i(t)P_{gi}(t)(B_{gi}(t)+K_{OM_i})+S_{gi}\left|u_i(t)-u_i(t-1)\right|\right]+\sum_{j=1}^{N_{Es}}\left[u_j(t)P_{Sj}(t)B_{Sj}(t)\right]\right\}$$

In above equation, N_g is the number of distributed energy resources, N_{Es} is the number of energy storage devices, $B_{gi}(t)$ is the bid of i^{th} distributed energy resources, $P_{gi}(t)$ is output power of i^{th} distributed energy resources, $P_{Sj}(t)$ is the power of j^{th}ESS, $B_{Sj}(t)$ is the bids of j^{th} ESS, $u_i(t)$ indicates off/on states of equipments, S_{gi} is the shut-down /start-up cost of i^{th} distributed energy resources, $P_{Grid}(t)$ is exchanging power between micro-grid and utility grid, $B_{Grid}(t)$ is price of energy in upstream grid, and K_{OM_i} maintenance coefficient of i^{th} distributed energy resources.

2.2. Pollutants emission minimization

To minimize the total emission pollutants we consider NO_X, SO_2, and CO_2. This objective function can be formulated as follow:

$$J_2 = Min\sum_{t=1}^{T}\left\{\left(\sum_{i=1}^{T_E}\sum_{j=1}^{N} EF_{ij}P_{gi}(t)\right) + P_{Grid}(t)EF_{grid}\right\} \tag{2}$$

In above equation, EF_{ij} is the emission coefficient for the i^{th} distributed energy resources with j^{th} type. T_E is the type of emission such as NO_X, SO_2 , and CO_2, N is the number of distributed energy resources which generate emission pollutants, and EF_{grid} is the emission coefficient of the upstream grid.

2.3. Constraints

- **Electrical balance:**

$$\sum_{i=1}^{N_g} P_{gi}(t) + \sum_{j=1}^{N_{Es}} P_{Sj}(t) + P_{Grid}(t) = P_{L\_elec}(t) \tag{3}$$

Where $P_{L\_elec}(t)$ is the electrical load of the costumers.

- **Electrical limitation:**

$$\begin{cases} P_{gi,\min}(t) \le P_{gi}(t) \le P_{gi,\max}(t) \\ |P_{Grid}| \le P_{exch}^{\max} \end{cases} \tag{4}$$

- **ESS limits:**

$$\begin{cases} P_S(t)/\eta_D \le P_{dech}^{\max} & \text{For discharging } (P_S(t) > 0\ ) \\ -\eta_C P_S(t) \le P_{ch}^{\max} & \text{For charging } (P_S(t) < 0\ ) \end{cases} \tag{5}$$

$$E_S^{\min} - E_S(0) \le \sum_{k=1}^{t} P_S(k) \le E_S^{\max} - E_S(0) \qquad \forall t = 1,2,...,T \tag{6}$$

$$\frac{1}{\eta_D}\sum_{P(t)>0,t=1}^{T} P_S(t) + \eta_C \sum_{P(t)<0,t=1}^{T} P_S(t) = 0 \tag{7}$$

3. INTERACTIVE FUZZY SATISFACTORY METHOD

In this work, an interactive fuzzy satisfactory method is used to achieve the best solution for multi-conflicting objectives. In this method, because of the imprecise nature of the judgment of DM, the objective functions are converted to linear membership functions. in this regard, the maximum and minimum of each objective function should be obtained to calculate those membership functions. After that, the membership function of i^{th} objective function is calculated as[21,22]:

$$\mu_i(\theta) = \begin{cases} 1 & J_i(\theta) \le J_i^{\min} \\ \dfrac{J_i^{\max} - J_i(\theta)}{J_i^{\max} - J_i^{\min}} & J_i^{\min} < J_i(\theta) < J_i^{\max} \\ 0 & J_i^{\max} \le J_i(\theta) \end{cases} \tag{8}$$

Where $J_i(\theta)$ is the i^{th} objective function, and $J_i^{\min}(J_i^{\max})$ is the minimum (maximum) of i^{th} objective function. In this algorithm, the value of $J_i^{\min}$ and $J_i^{\max}$ are calculated using the results obtained separately by optimizing each objective function. The value of 1 for the membership function indicates that the DM is fully satisfied while the zero value shows that it is not satisfied at all. After calculating $\mu_i(\theta)$, the reference membership values should be chosen by DM. . The reference membership values for all objective function should be chosen as a real number between [0, 1]. These reference membership values indicate the importance for each objective function. Then, to obtain the optimal solution, the following min-max problem must be solved [23]:

$$\underset{\theta \in Z}{Min}\left\{Max\ \left[\mu_{ri} - \mu_i(\theta)\right]\right\} \quad i = 1, 2, ..., N_{obj} \tag{9}$$

In above min-max problem, the reference membership value of i^{th} objective function is defined as μ_{ri}, N_{obj} is the number of all objective functions, and Z represents the non-inferior solutions. After defining reference membership values, they should be updated to achieve the solutions which satisfy the DM. In each step, the DM verifies the obtaining solutions and finally, chose the most satisfying solutions.

4. UNCERTAINTY CHARACTERIZATION BASED ON THE 2M PEM

To explain the inherent uncertainties involved in the power systems, probabilistic techniques have been utilized [24]. These methods implement the approximate description to obtain statistical moments from m input random variables. Among different well-known techniques in this area, the First Order Second Moment Method [25] andPEMare the predominant ones. The most important disadvantage of this method is the dependency of the technique to the derivatives of nonlinear functions under study. Firstly, the original PEMwas proposed by Rosenbluth [26].However, its performancewas greatly depended on the numerous simulations required to implement the proposed technique. Therefore, extensiveefforts were established to overcome such deficiency. Su was the first to use 2mPEM method in the probabilistic load flow [27]. One of these schemes is 2m PEM[28]. Due to the variable nature of the wind speed as well as the uncontrollable factors related to the load demands, it is necessary to model these variables in a probabilistic environment. In the context of EED, the SO must be able to characterize the distribution functions of output random variables (i.e. total electrical energy cost and total fuel combustion emission) through the distributionfunctions of input random uncertainties (i.e. load demand and wind speed). Basically, the Deterministic Wind-thermal Economic Dispatch or Deterministic Wind-thermal Emission Dispatch can be mathematically defined as a function of the input set of variables named z as shown in Eq. (10). Note that T is a nonlinear function as described in Section 2. Mathematically, the deterministic EOM of the MGs can beexpressed as:

$$S = f\ (v) \tag{10}$$

where v is the set of input variables, S is the output of EOM problem and f is the set of the energy and operation cost equations. In order to solve the deterministic EOM problem, all IRVs are considered equal to their forecasted values. However, the real values for some variables may differ from their forecasted values [29] such as the errors in the forecasted available output powers of the WT and PV units. The function f transfers the uncertainty from the IRVs to the output variable. Considering m IRVs, (10) can be written as:

$$S = f\ (c, z_1, z_2, ..., z_m) \tag{11}$$

where c is the set of certain variables, $z_i (i = 1, ..., m)$ are input variables under uncertainty with the probability function Df_{z_1} The idea behind the PEM is to calculate the statistical information of the output variables using the solution set of the deterministic EOM problem for only few estimated values of IRVs. In order to find the statistical moments of the output random variable, 2m PEM needs only first few central moments of the IRVs, i.e. the mean μ_{pl} ,variance σ_{pl} and skewness coefficients. This attribute is a remarkable advantage of the point estimate methods where implementing the features of IRVs is a difficult task to reach [21]. The 2m PEM produces two probability concentrations for each IRV, $\left(z_{l,1}, w_{l,1}\right)$ and $\left(z_{l,2}, w_{l,2}\right)$. The $z_{l,po}$ ($po = 1,2$) is called the poth location of z_l and $w_{l,po}$ ($po = 1,2$) is aweighting factor which specifies the importance of the corresponding location in evaluating the statisticalmoments of the output randomvariable. The deterministic EOMis simulated 2m times in the proposed probabilistic method. In each simulation, one of the IRV is fixed to one of its locations, and the other IRVs are equal to their mean value as follows:

$$S_{(l,po)} = f\,(c, \mu_{z_1}, \mu_{z_2}, \ldots, z_{l,po}, \ldots, \mu_{z_m}) \qquad po = 1,2 \qquad (12)$$
$$l = 1,2,\ldots,m$$

Where $z_{l,1}$ and $z_{l,2}$ are the specified locations of the IRV z_1, and μ_{Z_1} is the mean value of the left over IRVs. Once the solutions of 2m deterministic EOM, $S_{(l,po)}$, are explored, the mean and the standard deviation of the output random variable can be estimated.

5. THE PROPOSED MBFO ALGORITHM

The classical BFO has been successfully used for low-dimensioned optimization problems. But this algorithm indicates poor convergence properties for large scale search space and the populations may stick around optima. Therefore, to obtain the best answers in such a complex problem, the algorithm must be modified. In this paper, two modifications for BFO algorithm are considered. These modifications are presented as follow: 1) In classical BFO, Elimination and Dispersal prevent bacteria from being trapped in local optima [9]. But this process is not efficient for finding global optima in a large constrained problem. For solving this problem, a mutation strategy is proposed. In this regard, after each chemotactic step, the mutation strategy to update the positions of the bacteria is used. By using this strategy, the bacterium can have a better movement and the accuracy of the optimization algorithm for finding the local and global solutions is significantly improved. This mutation strategy can be presented as follow:

assume that θ^{k_1}, θ^{k_2} and θ^{k_3} are the position of 3 random bacterium and k_1, k_2 and k_3 are random and integer numbers in [0,S] where $k_1 \neq k_2 \neq k_3$. Then, by considering the mutation strategy, the position of the mutation bacterium can be calculated as follow:

$$\theta_{mut}(j,k,l) = \theta^{k_1}(j,k,l) + F \times \left(\theta^{k_2}(j,k,l) - \theta^{k_3}(j,k,l)\right) \qquad (13)$$

where F is the mutation factor and is considered between [0.1, 1]. After that, let $\vec{\theta}^{i}_{NEW} = \left[\theta^i_{new1}, \theta^i_{new2}, \theta^i_{new3}\right]$ the position vector which elements are the new positions of the bacteria. These new positions can be obtained as follow:

$$\theta^i_{new1} = \begin{cases} \theta^i & Cr_1 > rand \\ \theta_{mut} & else \end{cases}, \qquad \theta^i_{new2} = \begin{cases} \theta^i & Cr_2 > rand \\ \theta_{best} & else \end{cases}, \qquad \theta^i_{new3} = \begin{cases} \theta_{best} & Cr_3 > rand \\ \theta_{mut} & else \end{cases} \qquad (14)$$

Where Cr_1, Cr_2 and Cr_3 are chosen in [0, 1] and θ_{best} is the position of bacteria which has the least value of the objective function. After calculating $\theta^i_{new1}, \theta^i_{new2}$ and θ^i_{new3}, their related objective function values should be obtained and if those values are less than the value of $J(\theta^i)$, then their positions must be replaced with θ^i.

2) The length unit step of the bacteria plays an important role in accuracy and speed of convergence in BFO algorithm. If the step size is very high, then the precision of global optima decreases, and if it is very small, the convergence speed becomes low. The authors in [9], have proposed a non-linear decreasing dynamic step size which can improve the capability and accuracy of optima searching. In this research, dynamic function instead of constant step size is used. This dynamic step size is shown as follow:

$$C(i, j+1) = \left(\frac{C(i,j) - C(N_C)}{N_C + C(N_C)}\right)(N_C - j) \tag{15}$$

6. RESULTS AND DISCUSSION

In this part, the proposed PEMS is applied to optimize the operation of a typical grid-connected micro-grid, for 24-hour time interval.The micro-grid consists of WT, PV, MT, FC, and smart ESS. The micro-grid can exchange limited power with upstream grid for supplying the customer's load demand with respect to economical and environmental criteria All information from the micro-grid is sent to PEMS and finally, the PEMS obtains the optimal set points of DERs and storage devices, in such a way that the total operation cost and the net emission are simultaneously minimized. All DERs generate electrical power according to their limits. The power limitation of the DERs and their related shut-down /Start-up costs and the emission factors are represented in table 1(a) and 1(b), respectively. The electrical load demands in kW is tabulated in table 2. The DERs bid, storage bid and the hourly electricity prices of utility grid in Euro/kW are taken in table 3 [13]. The normalized forcasted WT &PV power generation is shown in figure 1. It also be mentioned that for the energy storage system, $E_S^{\max} = 150kW and E_S(0) = 5kW$.

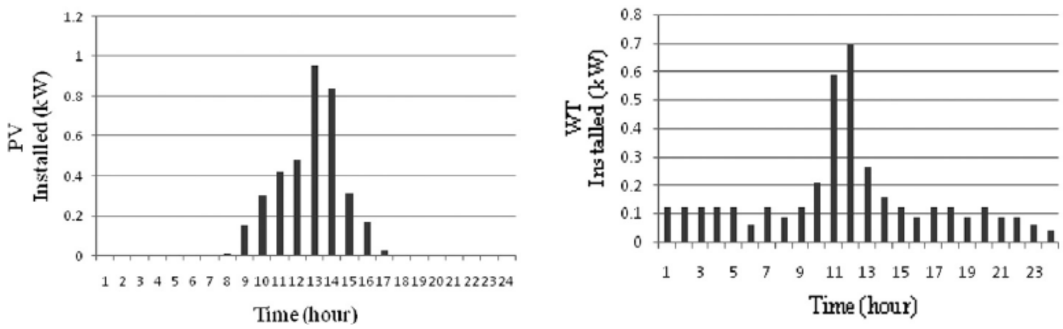

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Figure 1. Normalized forcasted WT &PV power generation

Table 1. (a)Installed DG sources (b)Emission factors

ID	type	Min power (kW)	Max Power (kW)	Start up/shut down cost (Euro/kW)
1	MT	6	30	0.107
2	FC	3	30	0.138
3	PV	0	25	0
4	WT	0	20	0
5	ESS	-30	30	0

(a)

Emission type	Emission factors (kg/MWh)			
	MT	FC	Boiler	Grid
NOX	0.2	0.0136	1.812	2.295
CO2	724	489	845	922
SO2	0.0036	0.0027	2.545	3.583

(b)

Table 2. Micro-grid electrical load demands in kW.

Hour 1	Hour 2	Hour 3	Hour 4	Hour 5	Hour 6	Hour 7	Hour 8	Hour 9	Hour 10	Hour 11	Hour 12
52	50	50	51	56	63	70	75	76	80	78	74
Hour 13	Hour 14	Hour 15	Hour 16	Hour 17	Hour 18	Hour 19	Hour 20	Hour 21	Hour 22	Hour 23	Hour 24
72	72	76	80	85	88	90	87	78	71	65	56

Table 3. DERs and storage bids.

Hour	MT (Euro /kWh)	FC (Euro /kWh)	PV (Euro/kWh)	WT (Euro/kWh)	Battery (Euro/kWh)	utility Price (Euro/kWh)
1	0.0823	0.1277	0	0.021	0.1192	0.033
2	0.0823	0.1277	0	0.017	0.1192	0.027
3	0.0831	0.1285	0	0.0125	0.1269	0.02
4	0.0831	0.129	0	0.011	0.1346	0.017
5	0.0838	0.1285	0	0.001	0.1423	0.017
6	0.0838	0.1292	0	0.015	0.15	0.029
7	0.0846	0.1292	0	0.021	0.1577	0.033
8	0.0854	0.13	0.0646	0.033	0.1608	0.054
9	0.0862	0.1308	0.0654	0.062	0.1662	0.215
10	0.0862	0.1315	0.0662	0.125	0.1677	0.572
11	0.0892	0.1323	0.0669	0.15	0.1731	0.572
12	0.09	0.1315	0.0677	0.155	0.1769	0.572
13	0.0885	0.1308	0.0662	0.125	0.1692	0.215
14	0.0885	0.1308	0.0654	0.135	0.16	0.572
15	0.0885	0.1308	0.0646	0.115	0.1538	0.286
16	0.09	0.1315	0.0638	0.085	0.15	0.279
17	0.0908	0.1331	0.6538	0.035	0.1523	0.086
18	0.0915	0.1331	0.0662	0.025	0.15	0.059
19	0.0908	0.1338	0	0.02	0.1462	0.05
20	0.0885	0.1331	0	0.23	0.1462	0.061
21	0.0862	0.1315	0	0.033	0.1431	0.181
22	0.0846	0.1308	0	0.015	0.1385	0.077
23	0.0838	0.13	0	0.021	0.1346	0.043
24	0.0831	0.1285	0	0.017	0.1269	0.037

In the first step, the PEMS is applied to grid-connected micro-grid and then, we minimize the operation cost and the net emission, separately. To prove the effectiveness and accuracy of the proposed algorithm, the results are compared with some other optimization algorithms such as genetic algorithm and (particle swarm optimization). In this regard, the statistical indices of average and standard deviation for these algorithms are evaluated. These results are shown in tables 4. By comparing the results we come to the conclusion that the proposed MBFO algorithm is efficient for solving such a high-dimensioned problem and has better indices of average and standard deviation. According to the results, the total operating cost is = 48.73073 Euro for a day ahead interval. In the last step, the proposed Multi-objective MBFO algorithm is used to minimize both objective functions (total operation cost and net emission), simultaneously. The results of are shown in table 12. In the optimization process, three different reference memberships are considered as the interactive input values. Then, the values of membership function and objective function are calculated for each reference membership values. As shown in table 12, in the first interaction all of reference membership values are set to one. After inputting reference membership values, the proposed algorithm solves the min-max problem (equation 9). The results indicate that the optimum nonferior solutions can not satisfy the DM. In interaction two, μ_{r1} and μ_{r2} are updated ($\mu_{r1} = 0.6 and \mu_{r2} = 0.65$). The results represent that with new μ_{r1} and μ_{r2}, the operating cost and the emission is improved. In third interaction, to obtain the better solution, a smaller values are given to μ_{r1} and μ_{r2} ($\mu_{r1} = 0.5 and \mu_{r2} = 0.55$). In this interaction, the outputs are improved in both operation cost and emission which can satisfy the DM. In this interaction, the outputs are improved in both operation cost and emission which can satisfy the DM.

Table 4. The minimum total operating cost of the micro-grid.

Optimization algorithm	Best solution		Worst solution (Euro)		Average (Euro)		Standard deviation (Euro)	
	operating cost (Euro)	net emission (kg)	operating cost (Euro)	net emission (kg)	operating cost (Euro)	net emission (kg)	operating cost (Euro)	net emission (kg)
GA	55.573	715.162	59.364	721.258	57.825	718.21	0.3845	1.321
PSO	52.356	711.489	57.245	716.254	54.853	713.281	0.2841	1.232
MBFO	48.73073	703.234	48.986	704.673	48.815	703.682	0.0951	0.1255

Table 5. Results of the Multi-objective MBFO algorithm.

Interaction	Reference membership function value	Membership function value	Total cost function and emission
1	$\mu_{r1} = 1$ $\mu_{r2} = 1$	$\mu_1 = 0.6712$ $\mu_2 = 0.5482$	$J_1 = 112.5642\text{Euro}$ $J_2 = 876.258 Kg$
2	$\mu_{r1} = 0.6$ $\mu_{r2} = 0.65$	$\mu_1 = 0.4925$ $\mu_2 = 0.6135$	$J_1 = 107.1857\text{Euro}$ $J_2 = 846.834 kg$
3	$\mu_{r1} = 0.5$ $\mu_{r2} = 0.55$	$\mu_1 = 0.4999$ $\mu_2 = 0.5001$	$J_1 = 103.6767\text{Euro}$ $J_2 = 847.7009 kg$

7. CONCLUSION

In this paper, a new multi-objective PEMS is proposed to optimize the operation of a micro-grid in such a way that the total operating cost and the net emission are simultaneously minimized. To reduce the net emission of the micro-grid, renewable energy sources such as WT and PV are used and their comprehensive mathematical models are extracted. A smart ESS model with practical constraints is also introduced to decrease the both emission and operating cost and improves the micro-grid performances. The PEMS optimization module uses an improved bacterial foraging-based fuzzy satisfactory optimization algorithm to optimize the multi-objective problem. Comparing the results with other optimization algorithms shows that the PEMS works very well and can determine the optimal set points of DERs, battery storage, and also the amount of exchanging power between utility and micro-grid, with respect to economical and environmental issues.

REFERENCES

[1] Molderink A, Bakker V, Bosman M.G.C, Hurink J.L, Smit G.J.M. A three-step methodology to improve domestic energy efficiency. Innovative Smart Grid Technologies (ISGT) 2010; p:1-8

[2] Tsikalakis A. G, Dimeas A, Hatziargyriou N. D, Lopes J, Kariniotakis G. Management of microgrids in market environment. International Journal of Distributed Energy Resources 2006; 2(3):177–193.

[3] Lasseter R. H. Microgrids. IEEE Power Engineering Society Winter Meeting 2002; 1: 305 –308.

[4] Asanol H, Bandol S. Economic Analysis of Microgrids. Power Conversion Conf 2007; pp:654-658

[5] Hernandez-Aramburo C.A, Green T.C, Mugniot N. Fuel consumption minimization of a microgrid. IEEE Trans. Ind. Application 2005; 41(3): 673-681.

[6] Tsikalakis A.G, Hatziargyriou N.D. Centralized control for optimizing microgrids operation. IEEE Trans Energy Conversion 2008; 23(1): 241–248.

[7] Dinghuan Zhu, Rui Yang, Hug G. Managing Microgrids with Intermittent Resources: A Two- Layer Multi-Step Optimal Control Approach. North American Power Symposium (NAPS) 2010; pp:1-8.

[8] Passino K. M. Biomimicry of bacterial foraging for distributed optimization and control. IEEE Control Systems Magazine 2002 ; 22(3):52–67.

[9] Farhat I.A, El-Hawary M.E. Dynamic adaptive bacterial foraging algorithm for optimum economic dispatch with valve-point effects and wind power. IET Transmission & Distribution Generation 2010;4(9):989-999.

[10] Marnay C, Venkataramanan G, Stadler G, Siddiqui A, Firestone R, Chandran R. Optimal Technology Selection and Operation of Microgrids in Commercial Buildings. IEEE Trans Power Syst 2008; 23(3):975-982

[11] Chakraborty S, Weiss M.D, Simoes M.G. Distributed intelligent energy management system for a single-phase high frequencyAC microgrid. IEEE Trans. Ind. Electron 2007; 54(1):97–109.

[12] Dukpa A, Dugga I, Venkatesh B, Chang L. Optimal participation and risk mitigation of wind generators in an electricity market. IET Renew. Power Gener 2010; 4(2):165–175.

[13] Chen C. Duan S.. CAI T Liu B. Hu G. Smart energy management system for optimal microgrid economic operation. IET Renew. Power Gener 2011; 5(3):258–267.

[14] G.P. Granelli, M. Montagna, G.L. Pasini, P. Marannino, Emission constrained dynamic dispatch, Electric Power Syst 1992; 24: 56-64.

[15] C.S. Chang, K.P. Wong, B. Fan, Security-constrained multiobjective generation dispatch using bicriterion global optimization, IEE Proc. Gener. Transm. Distrib1995; 142 (4):406-414.

[16] Sun J, Fang W, Wang D, Xua W. Solving the economic dispatch problem with a modified quantum-behaved particle swarm optimization method. Energy Conversion Management 2009; 50(12):2967-2975

[17] Bhuvaneswari R, Edrington C. S, Cartes D.A. Online Economic Environmental Optimization of a Microgrid Using an Improved Evolutionary Programming Technique. North American Power Symposium 2009; pp: 1 – 6.
[18] Conti S, Rizzo S.A. Optimal Control to Minimize Operating Costs and Emissions of MV Autonomous Micro-Grids with Renewable Energy Sources. International Conference on Clean Electrical Power 2009; p: 634 – 639.
[19] Lin WM, Cheng FS, Tsay MT. Nonconvex economic dispatch by integrated artificial intelligence. IEEE Trans Power Syst 2001; 16(2):307-311.
[20] Wang L, Singh Ch. Environmental/economic power dispatch using fuzzified multi-objective particle swarm optimization algorithm. Electr Power Syst Res 2007; 77:1654-1664.
[21] Huanga H.Z, Gub Y.K, Duc X. An interactive fuzzy multi-objective optimization method for engineering design. Engineering Applications of Artifcial Intelligence 2006; pp: 451–460.
[22] Abido M.A. Environmental/Economic Power Dispatch using Multiobjective Evolutionary Algorithms. IEEE Transaction on Power System, 2003; 18(4): 1529-1537.
[23] Sakawa M., Yano H. An interactive fuzzy satisfying method using augmented minimax problems and its application to environmental systems. IEEE Trans. SMC 1985; 17(6): 720–729.
[24] Anvari-Moghaddam A, Seifi A, Niknam T, M. Multi-objective operation management of a renewable MG with back-up micro-turbine/fuel cell/battery hybrid power source. Energy 2011;36(11):6490-6507.
[25] Soroudi A, Aien M, Ehsan M. A probabilistic modeling of photo voltaic modules and wind power generation impact on distribution networks. IEEE Syst J 2011;99:1e10.
[26] Harr E. Probabilistic estimates for multivariate analysis. Appl Math Model 1989;13(5):313e8.
[27] Hong HP. An efficient point estimate method for probabilistic analysis. Reliab Eng Syst Saf 1998;59:261e7.
[28] Schellenberg A, Rosehart W, Aguado J. Cumulant-based probabilistic optimal power flow (P-OPF) with Gaussian and gamma distributions. IEEE Trans Power Syst 2005;20(2):773e81
[29] Morales JM, Perez-Ruiz J. Point estimate schemes to solve the probabilistic power flow. IEEE Trans Power Syst 2007;22:1594e601.