Fuzzified PaCcET for Economic-Emission Scheduling of Microgrids

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***Abstract*—In this paper, a new approach is proposed to solve a multi-objective economic-emission scheduling problem in microgrids (MGs) by simultaneously minimizing the energy and emission costs of the MG with various distributed energy resources (DERs). The proposed approach is an extension of a computationally effective multiobjective optimization technique, Pareto concavity elimination transformation (PaCcET). The proposed approach, referred to as Fuzzified-PaCcET, employs a fuzzy logic controller to dynamically revise crossover and mutation rates in the original PaCcET leading to the faster convergence of the solution. The proposed approach finds the best Pareto front, also referred to as a Non-dominated set (NDS) of solutions, instead of finding a single optimal solution. In order to find the solutions on concave areas of the Pareto front, an iterative objective space transformation is performed in the PaCcET algorithm to allow a linear combination of objective functions (in the transformed objective space). The proposed Fuzzified-PaCcET-based scheduling is implemented on a MG with various dispatchable and non-dispatchable DERs to find the set of optimal solutions according to the total fuel cost of DERs, as well as the most optimum environmental cost. In order to extract the best compromise solution (BCS) among NDS of solutions, a fuzzy-based method is implemented. The comparison of the simulation results of the Fuzzified-PaCcET with that of PaCcET shows that Fuzzified-PaCcET can generate better solution with less computational burden.**

***Index Terms*—Economic-emission scheduling, fuzzy logic controller, multi-objective optimization, PaCcET.**

I. INTRODUCTION

Microgrids (MGs) are small-scale power systems consisting of various distributed energy resources (DERs) such as solar photovoltaics (PVs), small wind turbines, fuel cells, microtubines, energy storage devices, and other controllable loads. MG can also be regarded as a single controllable system providing both power and heat to a certain specific area, and it can be operated in both grid-connected and isolated modes [1]. This enables MGs to meet its continuously varying demands with the help of power imported from the main grid if it is not economical or insufficient to supply only using its own DERs. Therefore, the economic dispatch is needed for a grid connected MG for its optimal operation [2].

Different techniques have been reported in the literature in order to solve the economic emission dispatch (EED) problems in MGs and power systems. In [3], the multi-objective economic load dispatch problem has been solved by reducing it to a single objective problem by treating the emission as a constraint with a permissible limit, which does not consider the tradeoff between generation cost and emissions. A stochastic EED has been formulated in [4], where uncertainties in the system production cost and random nature of the load demand have been considered. A dynamic programming based approach has been presented in [5] to solve EED problem in real-time. In [6], a dynamic non-dominated sorting multi-objective biogeography-based optimization technique has been proposed to solve multi-objective dynamic EED problem considering charging of plug-in electric vehicles (PEVs). An interior search algorithm has been applied in [7] to solve multi-objective EED problem. In [8], an exchange market algorithm, inspired by the method of exchange of shares by stockholders, has been proposed to solve EED and reliability problem in case of thermal power plants. In [9], a normal boundary intersection method has been proposed to solve multiobjective EED problem considering combined heat and power.

The multi-objective optimization problems including EED have been solved using different types of evolutionary algorithms including Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Multi-objective Fireworks Algorithm (MOFWA), Multi-objective Particle Swarm Optimization (MOPSO), and Pareto Concavity Elimination Transformation (PaCcET), to name a few. NSGA-II has been implemented for dynamic EED problem in [10], where a nonlinear constrained multi-objective optimization problem has been formulated. In [11], a θ-dominance based evolutionary algorithm (θ-DEA) has been proposed to solve combined heat and power EED problem. A time-varying acceleration particle swarm optimization (TVAC-PSO) has been presented in [12] for stochastic multi-objective optimization of combined heat and power economic-emission dispatch. In [13], a NSGA-II based approach has been proposed to determine optimal or near-optimal sizes and locations of multi-purpose utility-scale shared energy storage in distribution systems. In [14], a Paired Bacteria Optimization (PBO) algorithm has been been proposed to solve Security Constrained Optimal Power Flow (SCOPF) with distributed load variations and uncertain wind power. In [2], the multi-objective economic emission dispatch problem has been solved using PaCcET.

This paper proposes the Fuzzified-PaCcET, an extension to PaCcET, to solve a multi-objective Economic Emission scheduling problem that minimizes the emission apart from

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minimizing generation cost of various distributed energy resources (DERs). The Fuzzified-PaCcET employs a fuzzy logic controller to dynamically revise crossover and mutation rates in the original PaCcET leading to the faster convergence of the solution. The Fuzzified-PaCcET is implemented on a MG with various DERs to obtain the most economic operating condition not only by minimizing the total fuel cost but also by finding the most environmentally friendly solutions. To extract the best compromise solution (BCS) from NDS of solutions, an approach based on fuzzy set theory is implemented. The results show that the Fuzzified-PaCcET can generate better solution than PaCcET with less computational time.

The rest of the paper is organized as follows. The method of formulation of economic-emission scheduling problem with the description of objective functions and constraints are presented in Section II. Section III describes the proposed multi-objective optimization technique, which is the combination of the original PaCcET and a fuzzy logic controller. Also, the proposed solution methodology is explained in Section III. Section IV presents the simulation results and discussions, along with the comparison of the proposed Fuzzified-PaCcET technique with PaCcET in terms of convergence and the dominated hypervolume. Section V provides concluding remarks.

II. Economic-Emission Scheduling Problem Formulation for MGs

Since the objective of this paper is to minimize both economic and emission costs, a multi-objective economic-emission scheduling problem is to be formulated. The two objectives for the economic-emission scheduling problem under consideration are as follows [2].

1) Economic cost minimization

$$\min\{F_g = \sum_{t=1}^{T} \left[q_t P_{grid}^t + \sum_{i=1}^{N_g} (a_i {P_{DER}^{i,t}}^2 + b_i P_{DER}^{i,t} + c_i)\right]\}, \quad (1)$$

2) Fuel emission minimization

$$\min\{E_g = \sum_{t=1}^{T} \left[\sum_{i=1}^{N_g} (k_e^i P_{DER}^{i,t})\right]\}, \quad (2)$$

where q_t and P_{grid}^t are electricity rate and the amount of power exchanged between the main grid and the MG at time t, respectively. The total scheduling time T is divided into subintervals t. P_{grid}^t is positive if power is being bought from the main grid and negative if power is being sold to the main grid. The generation cost comprising of power generation and operation and maintenance costs of a DER is a quadratic function of $P_{DER}^{i,t}$, the active power of DER i at time t. In (1), a_i, b_i, and c_i represent the cost coefficients of each DER and N_g represents the total number of dispatchable DERs. Non-dispatchable resources such as solar photovoltaics (PVs) and wind-turbines are considered as negative loads. Equation (2) is the other objective function that represents the cost related to emission as an index for environmental conservation, where k_e^i is the emission cost coefficient of ith DER.

The constraints of the optimization problem are as follows.

$$\sum_{i=1}^{N_g} P_{DER}^{i,t} + \sum_{j=1}^{N_{nd}} P_{nd}^{j,t} + P_{grid}^t - P_{load}^t = 0, \quad (3)$$

$$P_{min}^i < P_{DER}^{i,t} < P_{max}^i, \quad (4)$$

where (3) represents active power balance equation, $P_{nd}^{j,t}$ is the active power generated by jth non-dispatchable resource at time t, P_{load}^t is the total load of MG at time t, and N_{nd} is the total number of non-dispatchable resources. Equation (4) represents the active power limit constraint of dispatchable DER, P_{min}^i and P_{max}^i respectively being minimum and maximum limit of ith DER.

III. Proposed Multi-objective Optimization Technique

A. Background

The proposed Fuzzified-PaCcET technique draws from many distinct concepts from within multi-objective research, some of which are briefly described as follows [15].

Dominance: A solution dominates another solution if it scores lower on all criteria. A solution is said to weakly dominate another solution if it scores equal on some objectives, but less on other ones.

Pareto front: The outcome of a multi-objective optimization problem is a set of solutions referred to as Pareto front. Each point (or solution) in the Pareto front cannot be dominated by other points in feasible solutions.

Utopian and nadir points: The best possible solution obtained by optimizing each objective function individually is referred to as utopian point. This point is an infeasible and unattainable solution due to the conflict between the objectives. Nadir point is the upper bound of the Pareto front. It is the solution resulting from the worst value for each objective function in the Pareto front. It is to be noted that the nadir point is a concept that is different from the worst feasible point in the complete set of solutions.

Dominated hypervolume: The dominated hypervolume refers to the feasible space of multi-objective optimization problem that is enclosed by nadir and Pareto points. This concept is widely used as a criterion to compare the accuracy and performance of different types of multi-objective optimization techniques.

B. Fuzzified-PacCET

Fuzzified-PaCcET, an extension to PaCcET, is a new iterative multi-objective transformation. It transforms the objective space in such a manner as to make the Pareto Front convex, and a single user-defined parameter is sufficient for it [15]. Fuzzified-PaCcET is composed to two main components, viz, the original PaCcET and a fuzzy logic controller.

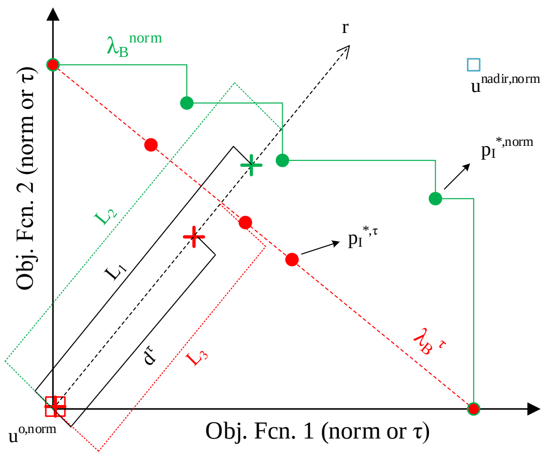

Fig. 1. Visualization of PaCcET. It transforms the green cross (a normalized point) to red cross (a transformed point) and green dots on the normalized border (λ_B^{norm}) to red ones on the transformed border (λ_B) [15].

1) PaCcET: PaCcET searches the points in the Pareto front in multi-objective optimization problem based on the linear combination of multiple objective functions in the transformed space using optimizers with single objective function. The PaCcET starts by calculating the utopian u^o and nadir u^{nadir} points by minimizing each objective function individually. In the first step, all other points are normalized and mapped from multi-objective space (λ) to a normalized space (λ^{norm}) using (5).

$$v^{norm}(i) = \frac{v(i) - u^o(i)}{u^{nadir}(i) - u^o(i)}, \tag{5}$$

where $v^{norm}(i)$ is the ith element of normalized point v.

In the second step, the normalized space λ^{norm} is mapped to a transformed space (λ^τ) using (6)-(11) .

$$r = \frac{v^{norm}}{|v^{norm}|}, \tag{6}$$

$$L_1 : \|v^{norm}\|_1 = \sum_i v_i^{norm}, \tag{7}$$

$$L_2 : \|v\|_B = \min(\gamma) \ni \gamma r \geq p_I^*, \tag{8}$$

$$L_3 = \|v\|_{hp} = \beta \ni \sum_i \beta r_i = (m-1), \tag{9}$$

$$d^\tau = L_3 \frac{L_1}{L_2} = \|v\|_{hp} \frac{\|v_1^{norm}\|}{\|v\|_B}, \tag{10}$$

$$v_\tau = d^\tau r, \tag{11}$$

where L_1 is linear combination or Manhattan distance from $u^{o,norm}$ to v^{norm}, L_2 is distance from $u^{o,norm}$ to the normalized dominated border λ_B^{norm} along r, L_3 is distance from $u^{o,norm}$ to the normalized utopian hyperplane λ_B^{norm} along r, m is the number of objective functions, and p_I^* is the Pareto front at Ith iteration. Figure 1 shows all the variables employed in the PaCcET.

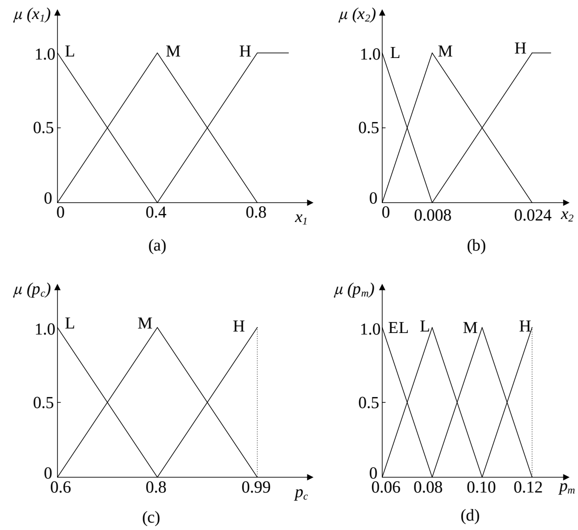

Fig. 2. The membership function of inputs and outputs of fuzzy logic controller.

In the last step a function, referred to as PaCcET Linear Combination (PLC), is determined which is a linear combination of the elements of v^τ.

$$PLC = \sum_i v_i^\tau. \tag{12}$$

PaCcET finds the points with PLC less than 1 in each iteration using single-objective optimizers. In this paper, genetic algorithm (GA) is used as single objective optimizer.

2) Fuzzy logic controller: Since GA is used as single objective optimizer, normally crossover and mutation rates are constants. Contrary to this, the proposed Fuzzified-PaCcET technique utilizes a fuzzy logic controller to dynamically update crossover and mutation rates. The crossover and mutation rates are updated in such a manner so as to enhance diversity of the population in the early stage of evolution, improve global search ability in the medium stage of evolution, and strengthen the convergence of the algorithm in the late stage of evolution [16]. The inputs of the fuzzy logic controller are x_1 and x_2 and its outputs are crossover rate p_c and mutation rate p_m.

The fuzzy logic controller consists of three parts: fuzzification, fuzzy reasoning, and defuzzification. In fuzzification process, the crisp quantities are converted into fuzzy quantities. The crisp quantities $x_1(n)$ and $x_2(n)$ for nth generation, given respectively by (13) and (14), are converted into fuzzy quantities using membership functions shown in Figure 2(a) and 2(b).

$$x_1(n) = \frac{|F^{max}(n) - F^{avg}(n)|}{|F^{max}(n)|}, \tag{13}$$

$$x_2(n) = \frac{|F^{avg}(n) - F^{avg}(n-1)|}{|F^{max}(n)|}, \tag{14}$$

where $x_1(n)$ denotes the normalized Euclidean distance between maximum objective vector F^{max} and average objective vector F^{avg} both at nth generation, $x_2(n)$ denotes the normalized euclidean distance between average objective vector at nth generation and that at $(n-1)$th generation.

The membership functions for inputs and outputs of fuzzy logic controller are shown in Figure 2. Each membership function μ, lying on the interval [0,1], expresses the degree of membership that the specific combination of parameters has in a particular fuzzy set. The inputs x_1 and x_2 have three fuzzy sets, viz, L (low value), M (medium value), and H (high value). Crossover rate p_c has three fuzzy sets, viz, L, M, and H as shown in Figure 2(c), and mutation rate p_m has four fuzzy sets, viz, EL (extra low value), L, M, and H as shown in Figure 2(d).

In the fuzzy reasoning part, also referred to as fuzzy inference system, the fuzzy values of the outputs are obtained on the basis of fuzzy rules. For the rule-based fuzzy reasoning, linguistic variables are used as antecedents and consequents. The antecedents are used to express an inference, which when satisfied result in certain consequents [17]. Table I shows the IF-THEN fuzzy rules in the early, medium, and late stages of evolution [16]. The fuzzy rule-based system adopts IF-THEN fuzzy rules, given by, IF antecedent and THEN consequent. For example, in the early stage of evolution, if x_1 is M and x_2 is L, then membership function M is used as fuzzy set for crossover rate p_c and membership function H is used as fuzzy set for mutation rate p_m.

The degree of membership for crossover and mutation rates are determined as follows.

$$\mu(p_c) = \mu(p_m) = \min\{\mu(x_1), \mu(x_2)\}. \tag{15}$$

In the defuzzification part of the fuzzy logic controller, the fuzzy quantities $\mu(p_c)$ and $\mu(p_m)$ are converted to crisp quantities p_c and p_m, respectively. The crisp value of an output is determined using the centroid method. The centroid method, also referred to as center of area or center of gravity, is the most prevalent and is regarded as physically appealing of all the defuzzification methods [18] and is given by the following algebraic expression.

$$z^* = \frac{\int \mu(z).zdz}{\int \mu(z)dz}, \tag{16}$$

where z any quantity to be defuzzified, i.e., z is p_c or p_m.

TABLE I
FUZZY RULES IN THE EARLY/MEDIUM/LATE STAGE OF EVOLUTION

Fuzzy value of crossover rate p_c				
$\mu(p_c)$		x_1		
		L	M	H
x_2	L	L/M/L	M/M/L	H/H/L
	M	L/M/L	M/M/L	M/H/L
	H	L/M/M	M/H/M	M/M/M
Fuzzy value of mutation rate p_c				
$\mu(p_c)$		x_1		
		L	M	H
x_2	L	H/H/L	H/M/L	M/M/EL
	M	H/L/L	H/L/EL	M/L/EL
	H	M/L/EL	M/L/EL	M/L/EL

In this way, the fuzzy logic controller is used to dynamically update crossover and mutation rates over generations. Figure 3 shows the flowchart of Fuzzified-PaCcET technique to find Pareto front of the multi-objective optimization problem.

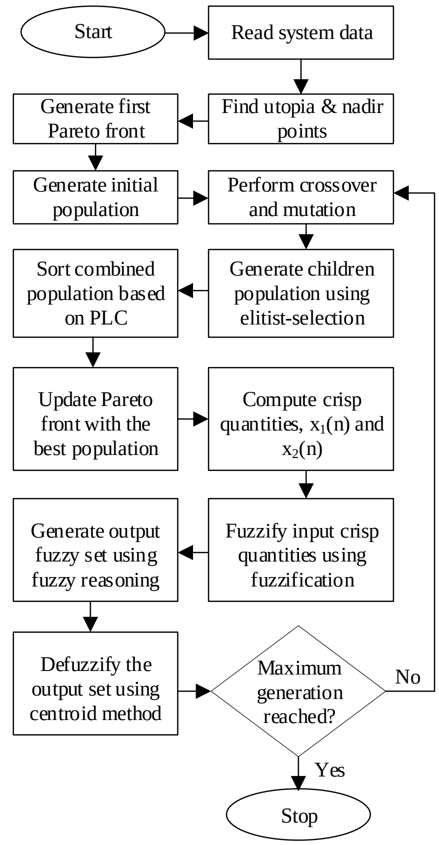

Fig. 3. Flowchart of the proposed economic-emission optimization technique

IV. CASE STUDIES AND DISCUSSIONS

A. Case Study Parameters

In this paper, the proposed Fuzzified-PaCcET is applied to economic-emission multi-objective scheduling of microgrid (MG) in either grid-connected or islanded mode. The MG consists of three dispatchable DERs, one non-dispatchable PV generation, and time-varying loads. In this paper, the economic-emission scheduling of dispatchable DERs is performed according to the most-probable PV generations and loads during each scheduling period. The cost coefficients of the dispatchable DERs are shown in Table II and load, PV generation, and the electricity price for different scheduling hours are presented in Table III. The day-ahead electricity price schedule for distribution network retail customers is adopted from the ComEd utility [19].

TABLE II
COST COEFFICIENTS DATA OF DISPATCHABLE DERS

Titles	P_{max} (kW)	P_{min} (kW)	c (¢)	b (¢/kWh)	a (¢/kWh^2)	k_e (¢/kWh)
DER1	200	40	954	63.6	0.0018	5
DER2	240	48	813	61.1	0.0011	6
DER3	400	80	1054	45.4	0.0005	8

B. Comparison

The superiority of PaCcET for solving multi-objective optimization problems in power systems, including economic-

TABLE III
HOURLY LOAD, PV GENERATION AND ELECTRICITY PRICE DATA

Hour	P_{load} (kW)	P_{pv} (kW)	q_t (¢/kWh)	Hour	P_{load} (kW)	P_{pv} (kW)	q_t (¢/kWh)
1	308	0	56	**13**	693	114	79
2	341	0	55	**14**	770	132	70
3	308	0	51	**15**	825	111	77
4	319	0	51	**16**	781	97.5	77
5	341	0	50	**17**	814	82.5	83
6	407	3	51	**18**	792	61.5	83
7	517	13.5	54	**19**	759	40.5	77
8	649	27	56	**20**	693	18	76
9	704	51	66	**21**	649	4.5	76
10	814	72	78	**22**	594	0	74
11	737	102	85	**23**	561	0	72
12	748	108	83	**24**	429	0	68

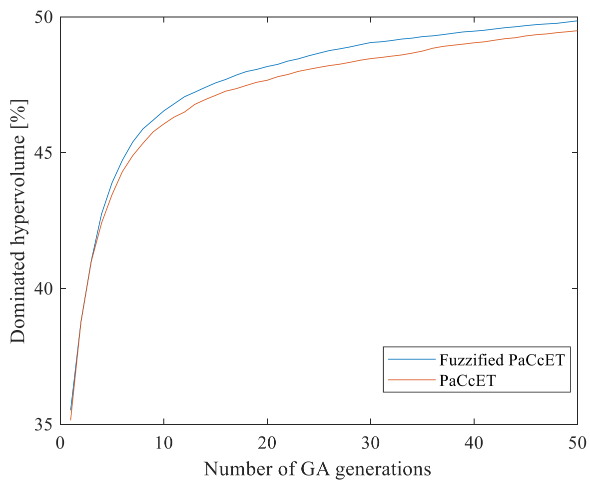

Fig. 4. Comparison of dominated hypervolume for Fuzzified-PaCcET and PaCcET with respect to number of GA iterations

reliability scheduling or Volt-Var control in distribution networks, is previously established in [20], [21]. For comparison of Fuzzified-PaCcET with the original PaCcET, different criteria can be used. According to our prior results, the convergence and diversity of the best Pareto points are the most important ones. Various metrics such as distance, diversity, and hypervolume metrics can be used to compare the results of different multi-objective optimization techniques. Dominated hypervolume is a metric that measures the area enclosed by the Pareto front and the nadir point. It identifies the closeness between the Pareto front to the feasible area boundary. Figure 4 shows the percentage of dominated hypervolume as a function of number of GA genrations for PaCcET and Fuzzified-PaCcET. It can be seen from the figure that Fuzzified-PaCcET proceeds faster than PaCcET towards the Pareto front.

Figure 5 and Figure 6 show the comparison of Pareto fronts obtained using Fuzzified-PaCcET and PaCcET after 25 and 50 GA generations, respectively. In each of the scenarios, the population size is 40. From these two figures, we can see that Fuzzified-PaCcET converges to final solution faster than PaCcET. But after large number of iterations, both the methods may converge to same solutions.

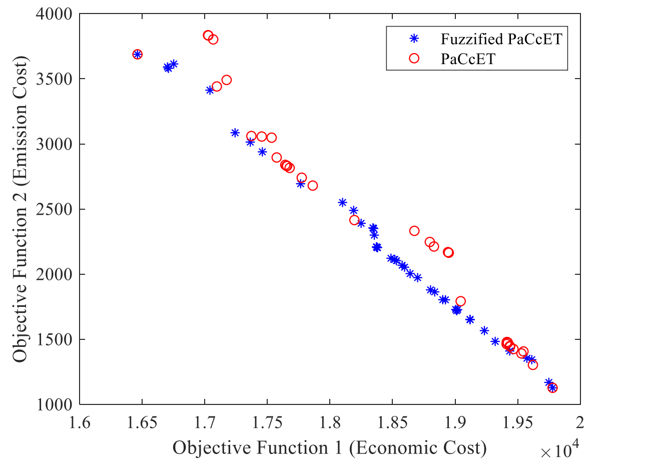

Fig. 5. Pareto fronts obtained using Fuzzified-PaCcET and PaCcET after 25 GA generations

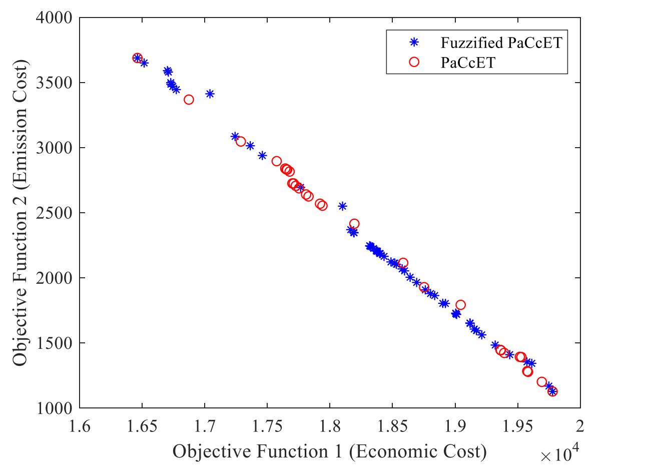

Fig. 6. Pareto fronts obtained using Fuzzified-PaCcET and PaCcET after 50 GA generations

C. Best Compromise Solution

Once the final Pareto front including non-dominated solutions is obtained by Fuzzified-PaCcET technique, the best compromise solution (BCS) is chosen from non-dominated solutions using a fuzzy membership approach. The following function is used to calculate the membership value of each point on the final Pareto front [20].

$$\mu_i(k) = \begin{cases} 1 & \text{if } f_i(k) < f_i^m \\ \frac{f_i^M - f_i(k)}{f_i^M - f_i^m} & \text{if } f_i^m < f_i(k) < f_i^M \\ 0 & \text{if } f_i^M < f_i(k) \end{cases} \tag{17}$$

where $\mu_i(k)$ is the membership value of the ith objective function of kth Pareto point. For each Pareto point, the normalized membership value, $\mu^{norm}(k)$, is computed as follows.

$$\mu^{norm}(k) = \frac{\sum_{i=1}^{N_o} \mu_i(k)}{\sum_{j=1}^{N_P} \sum_{i=1}^{N_o} \mu_i(j)}, \tag{18}$$

where N_o and N_P are the number of objective functions and Pareto points, respectively. The BCS is the solution with the maximum value of μ^{norm}.

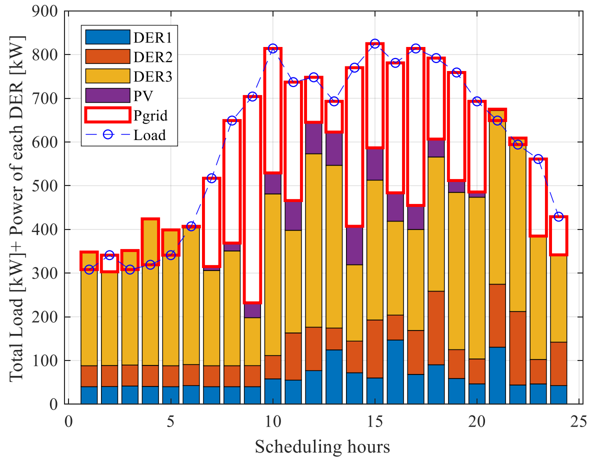

Fig. 7. Hourly loads, scheduled power generation of DERs, and power exchange between main grid and MG based on Fuzzified-PaCcET optimization

Using the BCS obtained using (17) and (18), the values of $P_{DER}^{i,t}$ and P_{grid}^{t} over the entire scheduling horizon can be computed. Figure 7 shows the hourly loads, scheduled power generation of DERs, and the power exchange between the main grid and the microgrid when the Fuzzified-PaCcET algorithm is run for 100 generations with the population size of 40. In the figure, transparent bars with red border represent the power transfer P_{grid}^{t}. When the transparent bar is above the load line, the power is sold to the main grid and when it is below the load line, the power is bought from the main grid.

V. Conclusion

In this paper, a Fuzzified-PaCcET technique has been proposed for economic-emission scheduling of microgrids with dispatchable DERs. The proposed Fuzzified-PaCcET is composed of a fuzzy logic controller in addition to the original PaCcET. The PaCcET has been used to iteratively transform multi-objective space to allow a linear combination of objective functions to find the solutions on concave areas of the Pareto front. The fuzzy logic controller has been employed to dynamically update crossover and mutation rates at different stages of evolution of the Pareto solution. The comparison of the dominated hypervolume of the Pareto solutions between PaCcET and Fuzzified-PaCcET has shown that Fuzzified-PaCcET can generate superior solution with less number of iteration and computational time. This feature makes it more attractive for practical applications with resource-constrained computational devices.

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