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A NOVEL MULTI-OBJECTIVE CHAOTIC CRAZY PSO ALGORITHM FOR OPTIMAL OPERATION MANAGEMENT OF DISTRIBUTION NETWORK WITH REGARD TO FUEL CELL POWER PLANTS

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Abstract. *This paper presents an efficient Multi-objective Crazy Chaotic Particle Swarm Optimization (MCCPSO) evolutionary algorithm to solve the Multi-objective Optimal Operation Management (MOOM) considering Fuel Cell Power Plants (FCPPs) in distribution network. The objective functions of the MOOM problem are to decrease the total electrical energy losses, the total electrical energy cost and the total pollutant emission produced by sources. For the multi-objective optimization problem, the use of weights to form a composite objective function reduces a multiple problem to a single problem. However, it also obviously loses some information in the conversion and this strategy is not expected to provide a robust solution or even help trace the efficient frontier of solutions. Our main thrust is to facilitate a string of solutions of the problem without converting to the original problem to a simpler case. This paper presents a new MCCPSO algorithm for the MOOM problem. The proposed algorithm maintains a finite-sized repository of non-dominated solutions, which gets iteratively updated in the presence of new solutions. Since the objective functions are not the same, a fuzzy clustering technique is used to control the size of the repository within the limits. The proposed algorithm is tested on a distribution test feeder and the results demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto optimal non-dominated solutions of the MOOM problem.*
Keywords: Chaotic crazy particle swarm optimization (CCPSO), Optimal operation management (OOM), Multi-objective optimization, Fuel cell power plant (FCPP)

1. **Introduction.** In recent years, with power system restructuring, public environmental policy, and expanding power demand, distributed generators have an important role in order to satisfy on-site customer energy needs. Major improvements in the economic, operational, and environmental performance of small, modular units have been achieved through decades of intensive research. The fuel cell, one of important distributed generations, has the advantages such as operations on multiple fuels with low emissions, high efficiency and high reliability [1,2].

Because of their low noise and high power quality, fuel cell systems are ideal for use in hospitals or IT centers, or for mobile applications. Its structural modularity allows for simple construction and operation with possible applications for distributed and portable power generation. Its fast response to the changing load condition while maintaining high efficiency makes it perfectly suited to load following applications. Its high efficiency represents less chemical, thermal and carbon dioxide emissions for the same amount of energy conversion and power generation [1,2].

Studies carried out by researching centers show that FCPPs contribution in energy production will become more than 25% in near future. Therefore, it is necessary to study the impact of FCPPs on the power systems, especially on the distribution networks.

Several investigations on optimal operation of the distribution network at the topic of reactive power and voltage control have been reported in the literature. For example, a particle swarm optimization for reactive power and voltage control considering voltage security assessment was proposed in [3]. A simulated annealing approach to fuzzy-based reactive power and voltage control in a distribution system was proposed in [4]. An approach for modeling local controllers and coordinating the local and centralized controllers at the distribution system management was presented in [5]. The reactive power and voltage control problem was solved by means of a quantum computing inspired genetic algorithm in [6]. Optimal use of voltage support distributed generation to support voltage in distribution feeders was presented in [7]. The optimal control of distribution voltage with coordination of distribution installations was proposed in [8]. The methods for the Volt/Var control in radial distribution networks considering Distributed Generations were presented in [9]. Optimal use of voltage support distributed generation to support voltage in distribution feeders was presented in [10]. Voltage and reactive power control in distribution systems and how the presence of synchronous machine-based distributed generation would affect the control were presented in [11]. An approach to daily Volt/Var control in distribution systems with regard to distributed generators was proposed in [12]. A practical algorithm for optimal operation management of distribution network including fuel cell power plants was presented in [13].

At the above-mentioned studies, the MOOM problem is considered as a single-objective one. In this paper, we solve the problem with multi-objective approach.

Based on the above discussion, the optimal operation management (OOM) is a multi-objective optimization problem whose objectives are not the same and commensurable. Therefore, it is difficult to solve the problem by conventional approaches that convert the multiple objectives into a single objective by using a vector of the user-predetermined weights [14,15]. These approaches have several drawbacks. For example, the values of the weights have a major impact on the final solution, and some optimal solutions may not be found if the objective functions are not convex, and they may not work successfully if objective functions have a discontinuous-variable space [14,15].

Due to the simple concept, easy implementation and quick convergence, nowadays, PSO has attracted much attention and wide applications in various kinds of nonlinear optimization problems. However, the performance of traditional PSO greatly depends on its parameters, and it often suffers the problem of being trapped in local optima. In order to overcome local optima problems, we proposed chaotic local search and adjustable parameters of PSO that greatly improve the performance of algorithm. Therefore, in this paper, a novel Multi-objective Chaotic Crazy Particle Swarm Optimization (MCCPSO) algorithm is proposed and implemented to solve the multi-objective optimal operation management problem. In the proposed approach, the objective functions are the total electrical energy losses, the total cost of electrical energy generated by FCPPs and substation bus and the total emission of FCPPs and substation bus. The proposed algorithm maintains a finite-sized repository of non-dominated solutions, which gets iteratively updated in the presence of new solutions. An external memory has been used for the storage of non-dominated solutions found along the search process. Since the objective functions are not similar, a fuzzy clustering algorithm is utilized to manage the size of the external memory.

2. Optimal Operation Management of Distribution Networks with Regard to FCPPs.

2.1. Objective functions.

The purpose of MOOM problem is to minimize the following objective functions.

i) Total electrical energy losses

$$\begin{aligned}
&\min f_1\left(\overline{X}\right) = \sum_{t=1}^{N_d} P_{Loss}^t = \sum_{t=1}^{N_d}\sum_{i=1}^{N_b} R_i \times \left|I_i^t\right|^2 \\
&\overline{X} = \left[\overline{P_G}, \overline{Tap}, \overline{Q_C}\right]_{1\times n} \\
&\overline{P_G} = \left[\overline{P_{g1}}, \overline{P_{g2}}, ..., \overline{P_{gN_g}}\right] \\
&\overline{P_{g_i}} = \left[P_{g_i}^1, P_{g_i}^2, ..., P_{g_i}^{N_d}\right]; \quad i = 1, 2, 3, ..., N_g \\
&\overline{Tap} = \left[\overline{Tap_1}, \overline{Tap_2}, ..., \overline{Tap_{N_t}}\right] \\
&\overline{Tap_i} = \left[Tap_i^1, Tap_i^2, ..., Tap_i^{N_d}\right]; \quad i = 1, 2, 3, ..., N_t \\
&\overline{Q_C} = \left[\overline{Q_{c1}}, \overline{Q_{c2}}, ..., \overline{Q_{cN_c}}\right] \\
&\overline{Q_{c_i}} = [Q_{c_i}^1, Q_{c_i}^2, ..., Q_{c_i}^{N_d}]; \quad i = 1, 2, 3, ..., N_c \\
&n = N_d \times (N_g + N_t + N_c)
\end{aligned} \tag{1}$$

where, $\overline{X}$ is state variables vector including active power of FCPPs, N_g is number of FCPPs, N_t is number of transformers, N_c is number of capacitors, N_d is number of load variation steps, N_b is number of branches, R_i is resistance of i^{th} branch, I_i is current of i^{th} branch, $\overline{P_G}$ is active power of all FCPPs during the day, $\overline{P_{g_i}}$ is active power of the i^{th} FCPP during the day and $\overline{Tap}$ is tap vector representing tap position of all transformers in the next day, $\overline{Tap_i}$ is tap vector including tap position of the i^{th} transformer in the next day, Tap_i^t is tap position of the i^{th} transformer for the t^{th} load level step and n is number of state variables. $\overline{Q_C}$ is capacitors reactive power vector including reactive power of all capacitors in the next day, $\overline{Q_{c_i}}$ is capacitors reactive power vector including reactive power of the i^{th} capacitor in the next day, $Q_{c_i}^t$ is reactive power of the i^{th} capacitor for the t^{th} load level step.

ii) Total cost of electrical energy

$$\begin{aligned}
&\min f_2\left(\overline{X}\right) = \sum_{t=1}^{N_d} \text{Cost}^t = \sum_{t=1}^{N_d} (C_{\text{FC}}^t + C_{\text{substation}}^t) \\
&C_{FC}^t = 0.04^{\$/KWh} \times \sum_{j=1}^{N_g} \frac{P_{g_j}^t}{\eta_j} \\
&PLR_j^t = \frac{P_{g_j}^t}{P_{\max_j}} \\
&\text{For } PLR_j < 0.05 \Rightarrow \eta_j = 0.2716 \\
&\text{For } PLR_j \geq 0.05 \Rightarrow \eta_j = 0.9033PLR_j^5 - 2.9996PLR_j^4 + 3.6503PLR_j^3 \\
&\qquad\qquad\qquad\qquad\quad -2.0704PLR_j^2 + 0.3747 \\
&C_{\text{substation}}^t = \text{price}^t \times P_{\text{sub}}^t
\end{aligned} \tag{2}$$

where, η_j is electrical efficiency of j^{th} FC, PLR_j^t is part load ratio of j^{th} FC, P_{sub} is power generated at substation bus of distribution feeders, C_{FC} is cost of electrical energy generated by FCPPs, $C_{\text{substation}}$ is cost of power generated at substation bus and price^t is energy price for the t^{th} load level step.

iii) Total emission produced by sources

$$\begin{aligned} &\min f_3\left(\overline{X}\right) = \sum_{t=1}^{N_d} Emission^t = \sum_{t=1}^{N_d} \left(E_{FC}^t + E_{Grid}^t\right) \\ &E_{FC}^t = NOx_{FC}^t + SO2_{FC}^t = (0.03 + 0.006)^{lb/MWh} \times \sum_{j=1}^{N_g} P_{g_j}^t \\ &E_{Grid}^t = NOx_{Grid}^t + SO2_{Grid}^t = (5.06 + 7.9)^{lb/MWh} \times P_{\text{sub}}^t \end{aligned} \tag{3}$$

where, E_{FC}^t is emission of FCPP, E_{Grid}^t is emission of large scale sources (substation bus that connects to grid), NOx_{FC}^t is nitrogen oxide pollutants of FCPP, $SO2_{FC}^t$ is sulphur oxide pollutants of FCPP, NOx_{Grid}^t is nitrogen oxide pollutants of grid and $SO2_{Grid}^t$ is sulphur oxide pollutants of grid for the t^{th} load level step.

iv) Voltage deviation index

Voltage deviation also is considered as the objective function. It determines the difference between the voltages in nodes with respect to the nominal voltage. The voltage deviation is calculated as follows.

$$\min f_4\left(\overline{X}\right) = \frac{\sum_{t=1}^{N_d} \sum_{i=1}^{N_{bus}} \left| \frac{V_i^t - V_i^*}{V_i^*} \right|}{N_d} \tag{4}$$

where, V_i^* is the desired voltage of network at the bus i, V_i^t is the voltage magnitude of the i^{th} bus during time t and N_{bus} is the number of buses.

2.2. Constraints.

- Active power constraints of FCPPs:

$$P_{\min,FC}^t \le P_{gi}^t \le P_{\max,FC}^t \tag{5}$$

$P_{\min,FC}$ is minimum active power of the i^{th} FCPP and $P_{\max,FC}$ is maximum active power of the i^{th} FCPP.

- Distribution line limits:

$$\left|P_{ij}^{Line}\right|^t < P_{ij,\max}^{Line} \tag{6}$$

$\left|P_{ij}^{Line}\right|^t$ and $P_{ij,\max}^{Line}$ are the absolute power flowing over distribution lines and maximum transmission power between the nodes i and j, respectively.

- Tap of transformers:

$$Tap_i^{\min} < Tap_i^t < Tap_i^{\max} \tag{7}$$

$Tap_i^{\max}$ and Tap_i^t are the minimum and maximum tap positions of the i^{th} transformer, respectively.

- Unbalanced three-phase power flow equations.
- Substation power factor

$$Pf_{\min} \le Pf^t \le Pf_{\max} \tag{8}$$

$Pf_{\min}$, $Pf_{\max}$ and Pf^t are the minimum, maximum and current power factor at the substation bus during time t.

- Bus voltage magnitude

$$V_{\min} \leq V_i^t \leq V_{\max} \tag{9}$$

V_i^t, $V_{\max}$ and $V_{\min}$ are the voltage magnitudes of the i^{th} bus during time t and the maximum and minimum values of voltage magnitudes, respectively.

3. **Multi-objective Optimization Framework.** A general multi-objective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows [14,15].

$$\begin{array}{l} \text{Minimize } F = [f_1(X), f_2(X), ..., f_n(X)]^T \\ \text{Subject to: } \begin{cases} g_i(X) < 0 & i = 1, 2, ..., N_{ueq} \\ h_i(X) = 0 & i = 1, 2, ..., N_{eq} \end{cases} \end{array} \tag{10}$$

where, $f_i(X)$ is the i^{th} objective function, $g_i(X)$ and $h_i(X)$ are the equality and inequality constraints, respectively. X is the vector of the optimization variables. n is the number of objective functions.

For a multi-objective optimization problem, any two solutions X_1 and X_2 can have one of two possibilities: one dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution X_1 dominates X_2 if the following two conditions are satisfied:

$$\begin{array}{l} \forall j \in \{1, 2, ..., n\}, \ f_j(X_1) \leq f_j(X_2) \\ \exists k \in \{1, 2, ..., n\}, \ f_k(X_1) < f_k(X_2) \end{array} \tag{11}$$

If any of the above condition is violated, the solution X_1 does not dominate the solution X_2. If X_1 dominates the solution X_2, X_1 is called the non-dominated solution. The solutions that are non-dominated within the entire search space are denoted as *Pareto-optimal* and constitute the *Pareto-optimal set* or *Pareto-optimal front*.

Since the objective functions are imprecise, a fuzzy-based clustering procedure has been utilized to control the size of repository. In the procedure, a fuzzy membership function is used to recognize the best compromise solution. In other words, decision making is done when the repository gets filled. For any individual in the repository, the membership function of each objective function is defined as follows:

$$\mu_{fi}(X) = \begin{cases} 1, & f_i(X) \leq f_i^{\min} \\ 0, & f_i(X) \geq f_i^{\max} \\ \dfrac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}}, & f_i^{\min} \leq f_i(X) \leq f_i^{\max} \end{cases} \tag{12}$$

where, $f_i^{\min}$ and $f_i^{\max}$ are the lower and upper limits of each objective function, respectively.

In the proposed algorithm, the values of $f_i^{\min}$ and $f_i^{\max}$ are evaluated using the results achieved by optimizing each objective separately (single objective optimization).

For each individual in the repository, the normalized membership value is evaluated as follows:

$$N\mu(j) = \frac{\sum_{k=1}^{n} \omega_k \times \mu_{fk}(X_j)}{\sum_{j=1}^{m} \sum_{k=1}^{n} \omega_k \times \mu_{fk}(X_j)} \tag{13}$$

where, m is the number of non-dominated solutions. ω_k is the weight for the k^{th} objective function. This membership function shows a type of decision making criteria that is adaptive and changes with the available decision options. In the fuzzy-based clustering, the normalized membership values are sorted and the best individuals are selected and stored in the repository.

4. **The Proposed Approach.** The standard PSO algorithm is not suited to resolve multi-objective optimization problems. Thus, to render the PSO algorithm capable of dealing with multi-objective problems, some modifications become necessary. Some of the methods are shown in literature [16-18]. In this paper, the standard PSO algorithm is modified and improved in order to facilitate a multi-objective optimization approach, i.e., multi-objective chaotic crazy particle swarm optimization (MCCPSO), in which Pareto-dominance [19] is employed to handle the problem. Through incorporating certain global attraction mechanisms, the repository of previously found non-dominated solutions would make the convergence toward globally non-dominated solutions possible.

4.1. **Crazy PSO.** The modified velocity and position of each particle for fitness evaluation in the next iteration are calculated using the following equations:

$$\begin{aligned} V_i^{(t+1)} &= \omega \times V_i^{(t)} + c_1 \times rand_1(\cdot) \times \left(P_{best_i} - X_i^{(t)}\right) \\ &\quad + c_2 \times rand_2(\cdot) \times \left(G_{best} - X_i^{(t)}\right) \qquad (14) \\ X_i^{(t+1)} &= X_i^{(t)} + V_i^{(t+1)} \qquad (15) \end{aligned}$$

where, t is the current iteration number, ω is the inertia weight, c_1 and c_2 are weighting factors of the stochastic acceleration terms, which pull each particle towards the P_{best_i} and G_{best} positions (Usually, these parameters are selected in the range [0-4]), $rand_1(\cdot)$ and $rand_2(\cdot)$ are two random functions in the range of [0, 1], P_{best_i} is the best previous experience of i^{th} particle that is recorded and G_{best} is the best particle among the entire population. A large inertia weight factor is used during initial exploration and its value is gradually reduced as the search proceeds. The concept of time-varying inertial weight is given by:

$$\begin{aligned} &\omega = (\omega_{\max} - \omega_{\min}) \times \frac{iter_{\max} - iter}{iter_{\max}} + \omega_{\min} \\ &\omega_{\max} = 0.9; \quad \omega_{\min} = 0.4 \end{aligned} \qquad (16)$$

where $iter_{\max}$ is the maximum number of iterations. To improve the convergence of PSO algorithm, a constriction factor is introduced.

$$\begin{aligned} V_i^{(t+1)} = C \times \Big[&\omega \times V_i^{(t)} + c_1 \times rand_1(\cdot) \times \left(P_{best_i} - X_i^{(t)}\right) \\ &+ c_2 \times rand_2(\cdot) \times \left(G_{best} - X_i^{(t)}\right)\Big] \end{aligned} \qquad (17)$$

where,

$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \qquad 4.1 \le \varphi \le 4.2 \qquad (18)$$

As φ increases, the factor C decreases and convergence becomes slower because population diversity is reduced. To handle the problem of premature convergence in PSO, the concept of craziness was introduced. The idea was to randomize the velocities of some of the particles, referred to as "crazy particles", selected by applying a certain probability. The probability of craziness ρ_{cr} is defined as a function of inertia weight,

$$\rho_{cr} = \omega_{\min} - \exp\left(-\frac{\omega^{(t)}}{\omega_{\max}}\right) \qquad (19)$$

Then velocities of particles are randomized as per the following logic:

$$V_i^{(t)} = \begin{cases} rand(0, V_{\max}) & \text{if } \rho_{cr} \geq rand(0,1) \\ V_i^{(t)} & \text{otherwise} \end{cases} \tag{20}$$

If the PSO algorithm tends to saturate in the beginning a high value of ρ_{cr} is used to create crazy particles, and a relatively lower value is used at later stages of search.

4.2. **Chaotic local search.** A chaotic search can traverse every state in a certain space, and every state is visited only once, which is helpful to avoid being trapped in local optima. Therefore, to improve the search behavior, we propose a chaotic PSO method that combines PSO with chaotic local search (CLS) [20].

There are two CLS procedures can be shown as follows:

The CLS which is based on the logistic method can be defined by the following equation:

$$\begin{aligned} &Cx_i = \left[cx_i^1, cx_i^2, ..., cx_i^{N_g}\right]_{1\times N_g}, i = 0, 1, 2, ..., N_{choas} \\ &cx_{i+1}^j = 4 \times cx_i^j \times \left(1 - cx_i^j\right), j = 1, 2, ..., N_g \\ &cx_i^j \in [0, 1], cx_0^j \notin \{0.25, 0.5, 0.75\} \\ &cx_0^j = rand(\cdot) \end{aligned} \tag{21}$$

where, cx_i^j indicates the j^{th} chaotic variable, N_{choas} is the number of individuals for CLS, N_g is number of FCPPs and $rand(\cdot)$ is a random number between [0, 1].

At first, a particle randomly selected from the repository (X_g) is considered as an initial population for CLS (X_{cls}^0). X_{cls}^0 is scaled into [0, 1] according the following equation:

$$\begin{aligned} &X_{cls}^0 = \left[x_{cls,0}^1, x_{cls,0}^2, ..., x_{cls,0}^{N_g}\right]_{1\times N_g} \\ &Cx_0 = [cx_0^1, cx_0^2, ..., cx_0^{N_g}] \\ &cx_0^j = \frac{x_{cls,0}^j - P_{\min,FC}^j}{P_{\max,FC}^j - P_{\min,FC}^j}, j = 1, 2, ..., N_g \end{aligned} \tag{22}$$

Then, the chaos population for CLS is generated as follows:

$$\begin{aligned} &X_{cls}^i = \left[x_{cls,i}^1, x_{cls,i}^2, ..., x_{cls,i}^{N_g}\right]_{1\times N_g}, i = 1, 2, ..., N_{choas} \\ &x_{cls,i}^j = cx_{i-1}^j \times \left(P_{\max,FC}^j - P_{\min,FC}^j\right) + P_{\min,FC}^j, j = 1, 2, ..., N_g \end{aligned} \tag{23}$$

The objective functions are evaluated for all individuals of CLS. Non-dominated solutions should be finding and storing into a separate memory subsequently.

5. **Application of the MCCPSO Algorithm on the MOOM Problem.** To apply the MCCPSO algorithm in the MOOM problem, the following steps should be taken and repeated:

Step 1: Define the input data.
Step 2: Transfer the constraint MOOM problem to an unconstraint one.

The multi-objective MOOM problem should be transformed into an unconstrained one by constructing an augmented objective function incorporating penalty factors for any value violating the constraints as follows.

$$F(\overline{X}) = \begin{bmatrix} F_1(\overline{X}) \\ F_2(\overline{X}) \\ F_3(\overline{X}) \end{bmatrix}_{3\times 1} = \begin{bmatrix} f_1(\overline{X}) + k_1\left(\sum_{j=1}^{N_{eq}} \left(h_j(\overline{X})\right)^2\right) + k_2\left(\sum_{j=1}^{N_{ueq}} \left(Max[0, -g_j(\overline{X})]\right)^2\right) \\ f_2(\overline{X}) + k_1\left(\sum_{j=1}^{N_{eq}} \left(h_j(\overline{X})\right)^2\right) + k_2\left(\sum_{j=1}^{N_{ueq}} \left(Max[0, -g_j(\overline{X})]\right)^2\right) \\ f_3(\overline{X}) + k_1\left(\sum_{j=1}^{N_{eq}} (h_j(\overline{X}))^2\right) + k_2\left(\sum_{j=1}^{N_{ueq}} \left(Max[0, -g_j(\overline{X})]\right)^2\right) \end{bmatrix}_{3\times 1} \tag{24}$$

where, $F(\overline{X})$ is the objective function values of the multi-objective OOM problem. $F_1(\overline{X})$, $F_2(\overline{X})$ and $F_3(\overline{X})$ are the values of the augmented $f_1(\overline{X})$, $f_2(\overline{X})$ and $f_3(\overline{X})$, respectively. N_{eq} and N_{ueq} are the number of equality and inequality constraints, respectively. $h_j(\overline{X})$ and $g_j(\overline{X})$ are the equality and inequality constraints, respectively. k_1 and k_2 are the penalty factors. Since the constraints should be met, the values of the parameters should be high. In this paper, the values have been considered 10,000,000.

Step 3: Generate the initial population and initial velocity.

The initial population and initial velocity for each particle are randomly generated as follows:

$$\begin{aligned} & population = \begin{bmatrix} \overline{X}_1 \\ \overline{X}_2 \\ \ldots \\ \overline{X}_{N_swarm} \end{bmatrix} \\ & X_0 = [x_0^1, x_0^2, \ldots, x_0^{N_g}] \\ & x_0^j = rand(\cdot) \times (x_i^{\max} - x_i^{\min}) + x_i^{\min}, \quad j = 1, 2, \ldots, N_g \\ & \overline{X}_i = [x_i^j]_{1\times n}, \quad i = 1, 2, 3, \ldots, N_{swarm} \\ & x_i^j = 4 \times x_{i-1}^j\left(1 - x_{i-1}^j\right) \\ & n = N_d \times (N_g + N_t + N_c) \end{aligned} \tag{25}$$

$$\begin{aligned} & velocity = \begin{bmatrix} V_1 \\ V_2 \\ \ldots \\ V_{N\,swarm} \end{bmatrix} \\ & V_i = [v_i]_{1\times n}, \quad i = 1, 2, 3, \ldots, N_{swarm} \\ & v_i = rand(\cdot) \times (v_i^{\max} - v_i^{\min}) + v_i^{\min} \\ & n = N_d \times (N_g + N_t + N_c) \end{aligned} \tag{26}$$

where, v_i and x_i are the velocity and position of the i^{th} state variable, respectively and N_g is number of FCPPs, N_d is number of load variation steps. $rand(\cdot)$ is a random function generator between 0 and 1. n is the number of state variables.

Step 4: $i = 1$.

Step 5: Select the i^{th} individual.

Step 6: If the individual is a non-dominated solution, it is stored into the repository and the fuzzy clustering is used to control the size of repository.

Step 7: Select local best solution.

Step 8: If all individuals are selected, go to Step 9, otherwise $i = i + 1$ and return to Step 5.

Step 9: Select global best as follows:

To maintain the proposed algorithm diversity along the population fronts and allows to develop a reasonable representation of the Pareto-optimal front, a form of sharing should be carried out. This form of sharing put forward when there is no preference between several candidates.

The sharing procedure is performed as follows for the i^{th} candidate:

Step 9-0: $i = 1$

Step 9-1: Compute a normalized Euclidean distance measure with another individual j in non-dominated solutions in the repository, as follows:

$$Ed_{ij} = \sqrt{\sum_{k=1}^{2} \left(\frac{M_k^i - M_k^j}{M_k^u - M_k^l} \right)^2} \tag{27}$$

where, k is the counter of problem objectives. The parameters M_k^u and M_k^l are the upper and lower values of the k^{th} objective function M_k.

Step 9-2: This distance Ed_{ij} is compared with a pre-specified niche radius r_{niche} and the following sharing function value is computed as:

$$sf(Ed_{ij}) = \begin{cases} 1 - \left(\dfrac{Ed_{ij}}{r_{niche}} \right)^2 & \text{if } Ed_{ij} \leq r_{niche} \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

Step 9-3: Set $j = j + 1$, go to Step 9-1; else calculate niche count for the candidate i^{th} as follows:

$$Nc_i = \sum_{j=1}^{N_R} sf(Ed_{ij}) \tag{29}$$

Step 9-4: Set $i = i + 1$, If $i \leq N_R$, go to Step 9-1; else arrange all the solutions in descending order according to their niche count values.

Step 9-5: Choose the first solution resulting from Step 9-4 to global best solution.

Step 10: Update the velocity and position of the i^{th} state variable.

Step 11: Check the termination criteria:

The values of the objective functions for each individual are evaluated by using the results of the distribution load flow. If the individual is non-dominated, store it into the repository and use the fuzzy clustering to control its size, else the termination criteria is checked. If the termination criteria is satisfied, finish the algorithm, otherwise the initial population is replaced with the new population of swarms and then goes back to Step 4.

6. **Simulation Results.** The proposed MCCPSO algorithm is tested on a distribution test system. The tested system is a 11-kV radial distribution system as shown in Figure 1. The related information of this network is shown in [21].

It is assumed that 58 FCPPs are located in this network. There are one FCPP at buses 24, 35, 56, 61, 66, 69, 89, 117 and two FCPPs at buses 10, 29, 37, 112, 114 and three FCPPs at buses 77, 116 and four FCPPs at buses 19, 33, 44, 52, 73, 100 and five FCPPs at buses 83, 106 that each of these sources can generate 250 kW active power. Also 58 capacitors are placed in the network that one capacitor exists at buses 36, 60, 78, 90, 118 and two capacitors at buses 34, 38, 41, 45, 54, 67, 72, 85, 105 and three capacitors at

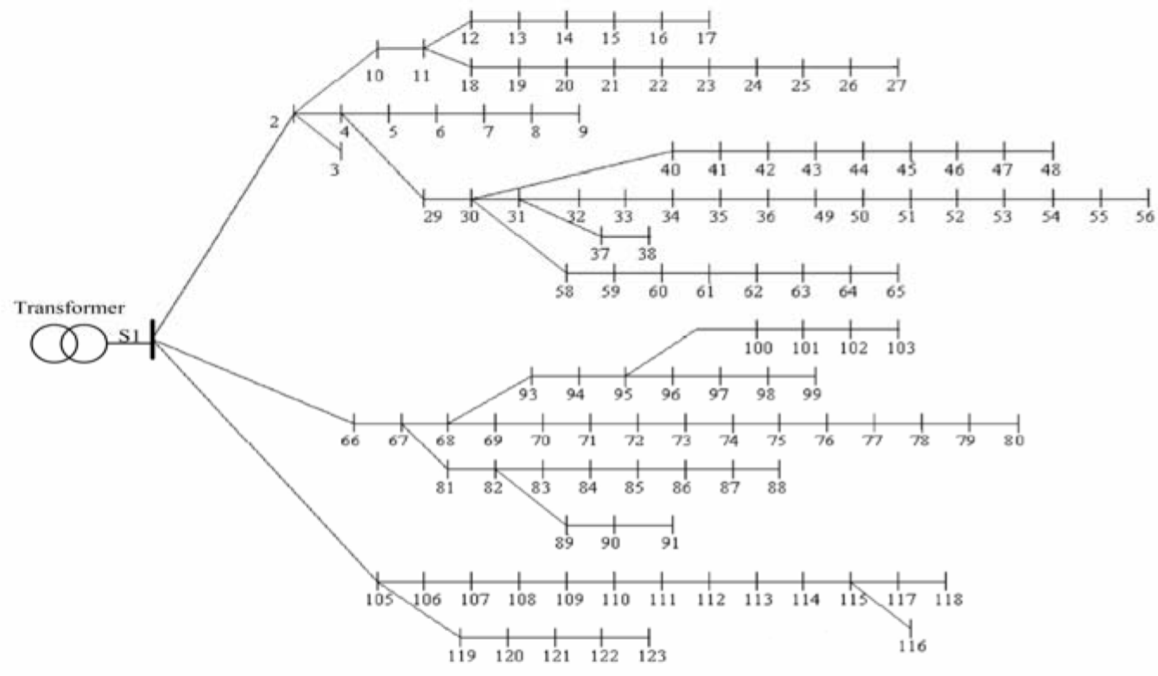

FIGURE 1. Single line diagram of 119-bus test system

buses 11, 51, 81, 107, 116 and four capacitors at buses 21, 30, 75, 102, 111 that reactive power of each capacitor is 200 kVar. Also, it is assumed that there is a transformer in substation bus. It has 21 tap positions ($[-10, -9, \ldots, 0, 1, 2, \ldots, 10]$) and its MADOT in a day is 30. It can change voltage from –10% to +10%.

In the daily MOOM problem, it is assumed that daily load variations and daily energy price variations are changed as shown in Figure 2.

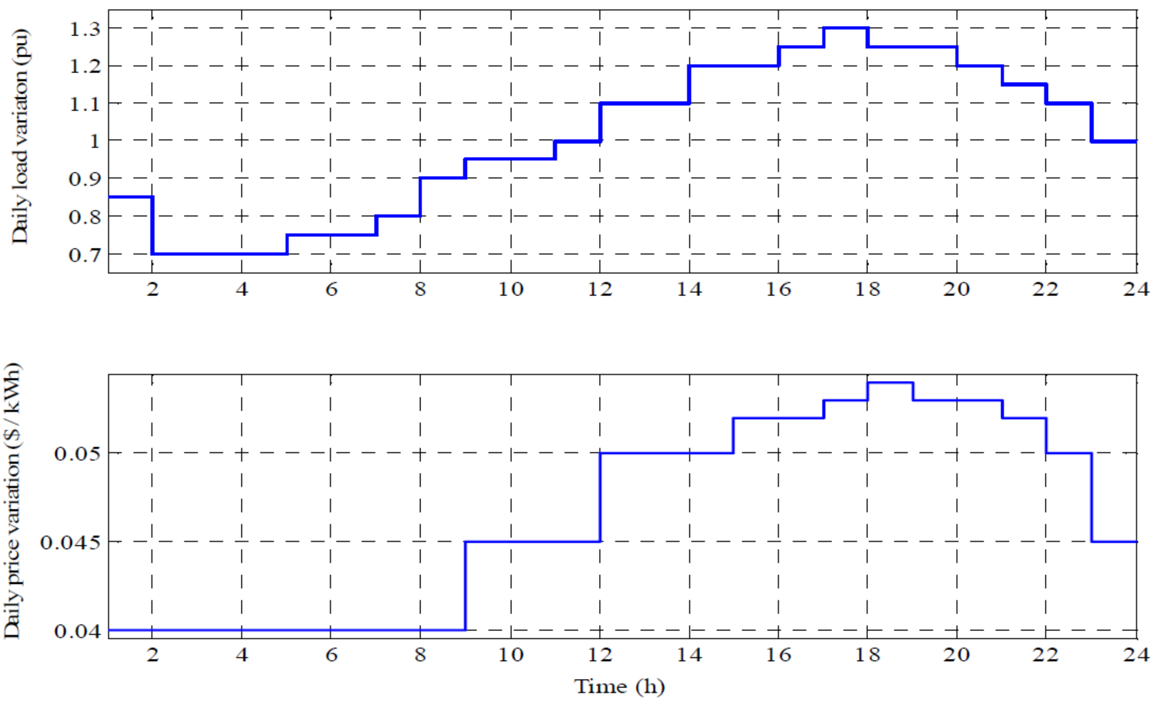

FIGURE 2. Daily energy price and load variations

At first, the total cost of electrical energy, the total emission, the total electrical energy losses and voltage deviation objectives are separately optimized to find the extreme points of the trade-off front. The best results obtained by optimizing the objectives separately are shown in Tables 1-4 respectively. These tables present a comparison among the results of GA (Genetic Algorithm) [13], ACO (Ant Colony Optimization) [12], PSO, Crazy PSO, Chaotic PSO, CCPSO (Chaotic Crazy PSO) algorithms for 20 random tails for three objective functions.

Table 1. Comparison of average and standard deviation for 20 trails (cost objective function)

Method	Average ($)	Standard deviation ($)	Worst solution ($)	Best solution ($)	CPU Time (Sec)
CCPSO	26084.15551	0.00000	26084.15551	26084.15551	123.43
Crazy PSO	30322.82309	1415.54446	31294.23819	28084.15327	132.89
Chaotic PSO	34129.95156	2150.81425	37285.70021	30227.74607	143.04
PSO	41469.84746	3571.17238	44730.92712	32440.91378	153.51
ACO [12]	37322.86271	3214.05514	40257.83441	29196.82240	138.16
GA [13]	43543.33983	3749.73100	46967.47348	34062.95947	161.19

Table 2. Comparison of average and standard deviation for 20 trails (emission objective function)

Method	Average (lb)	Standard deviation (lb)	Worst solution (lb)	Best solution (lb)	CPU Time (Sec)
CCPSO	2.105777644 3814E+09	0	2.105777644 3814E+09	2.105777644 3814E+09	134.22
Crazy PSO	2.1357805E +09	2.3597200E +07	2.20584906E +09	2.105863421 2345E+09	142.23
Chaotic PSO	2.146006593 9782E+09	6.055609996 8924E+07	2.275822430 0235E+09	2.105978064 1932E+09	160.14
PSO	3.974351259 2634E+09	3.697791372 4514E+08	4.394345062 1029E+09	3.056683262 7996E+09	194.83
ACO [12]	3.576916133 3371E+09	3.328012235 2063E+08	3.954910555 8926E+09	2.751014936 5196E+09	175.35
GA [13]	4.173068822 2266E+09	3.882680941 0740E+08	4.614062315 2081E+09	3.209517425 9396E+09	204.57

As shown in the tables, the algorithm is capable of finding the global solutions for each objective function. Some of the works which introduced in literature are a little difference with our research and in other words, we have in new idea that does not exist in previous work to compare with them. Nonetheless, we do a comparison between our work and some more similar literature [12,13] in Tables 1-4. It can be seen that best value of the objective functions which found with the proposed method (CCPSO) is much better than the solutions of the methods used in literature.

The proposed approach has been implemented to optimize the objectives simultaneously. The three-dimensional Pareto front for the objectives with CCPSO algorithm is shown in Figures 3-6. In this problem with four objective functions, four three-dimensional Pareto front would be obtained with the objectives *Emission*, *Cost*, P_{Loss} and *Voltage deviation*. It is worth mentioning that the Pareto optimal set has 200 non-dominated solutions generated by a single run.

TABLE 3. Comparison of average and standard deviation for 20 trails (P_{Loss} objective function)

Method	Average (kWh)	Standard deviation (kWh)	Worst solution (kWh)	Best solution (kWh)	CPU Time (Sec)
CCPSO	2268.81230	0.00000	2268.81230	2268.81230	120.76
Crazy PSO	2863.89416	763.18618	4983.19449	2437.54331	129.74
Chaotic PSO	3067.50490	972.21210	5540.63453	2577.34524	137.18
PSO	10936.85164	2149.20080	13601.22311	5288.95650	281.51
ACO [12]	9843.16648	1934.28072	12241.10080	4760.06085	253.36
GA [13]	11483.69422	2256.66084	14281.28427	5553.40433	295.59

TABLE 4. Comparison of average and standard deviation for 20 trails (voltage deviation objective function)

Method	Average (p.u)	Standard deviation (p.u)	Worst solution (p.u)	Best solution (p.u)	CPU Time (Sec)
CCPSO	0.76901	0.00000	0.76901	0.76901	125.46
Crazy PSO	1.24291	0.29610	1.88796	0.98554	160.79
Chaotic PSO	1.51366	0.31298	2.09729	1.14127	186.19
PSO	2.11038	0.32758	2.50445	1.33544	217.87
ACO [12]	1.89934	0.29482	2.25401	1.20190	196.08
GA [13]	2.21590	0.34396	2.62967	1.40221	228.76

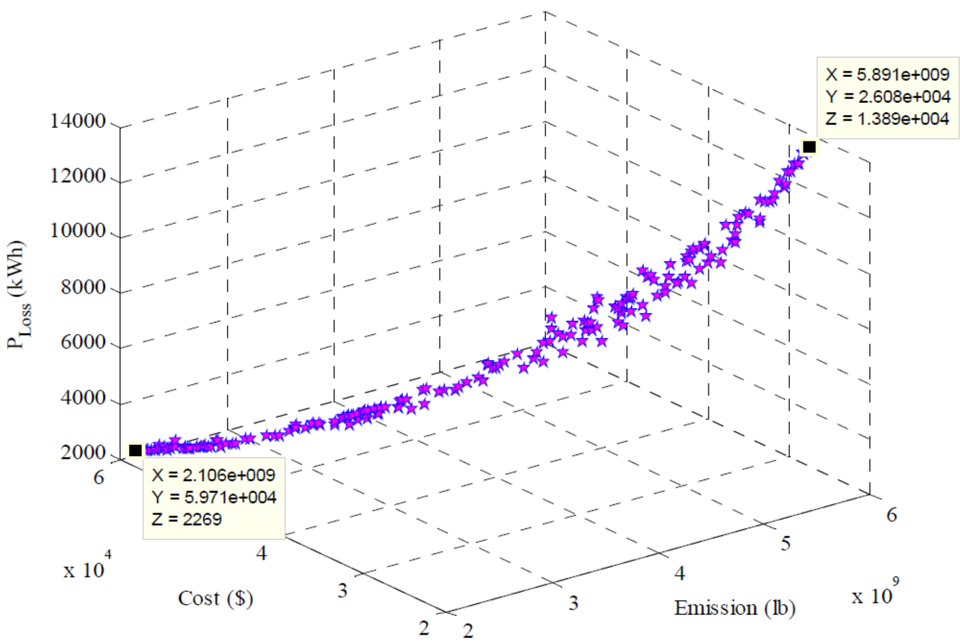

FIGURE 3. Three-dimentional Pareto front of CCPSO algorithm (Emission, Cost, P_{Loss})

The non-dominated solutions that represent the best solutions of objective functions (given in Tables 1-4) are shown in Figures 3-6 with cursor. These solutions are quite close to those of individual optimization in terms of objective function values. The best solutions for objectives *Emission*, *Cost*, P_{Loss} and *Voltage deviation* are closely 2.106E+09

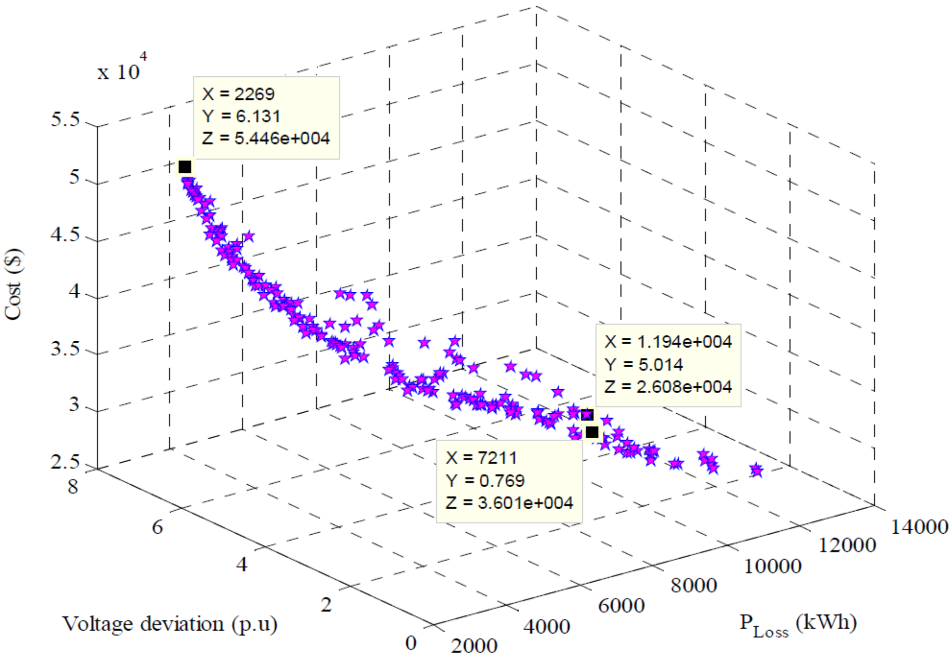

FIGURE 4. Three-dimentional Pareto front of CCPSO algorithm (P_{Loss}, Voltage deviation, Cost)

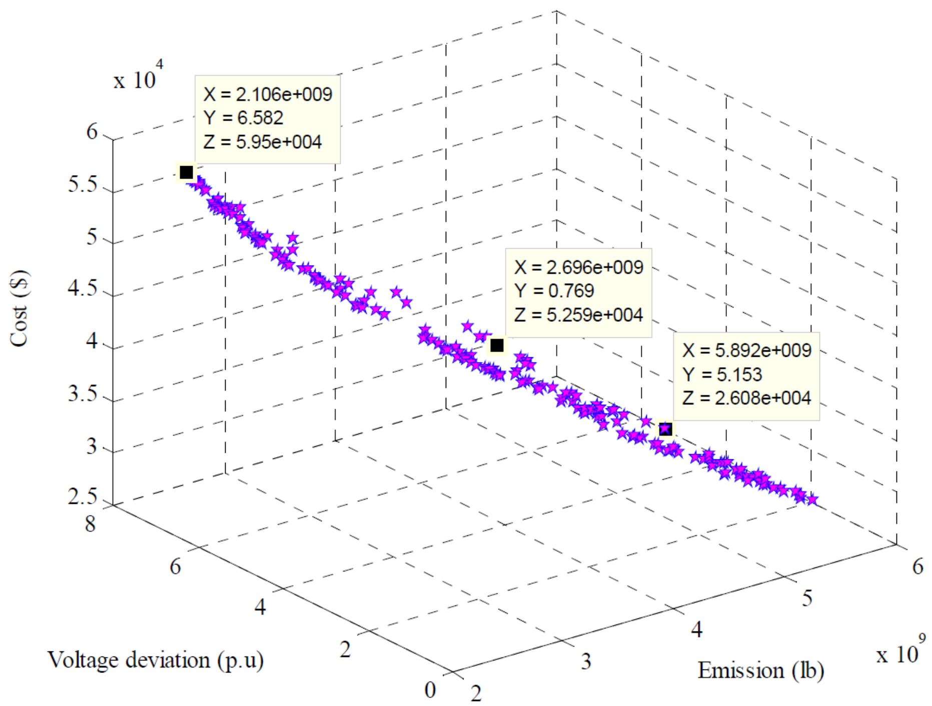

FIGURE 5. Three-dimentional Pareto front of CCPSO algorithm (Emission, Voltage deviation, Cost)

(lb), 2.608E+04 ($), 2269 (kWh) and 0.769 (p.u) respectively, which shown in Figures 3-6 with cursor.

It can be seen that the proposed technique preserves the diversity of the non-dominated solutions over the Pareto-optimal front and solve the problem effectively.

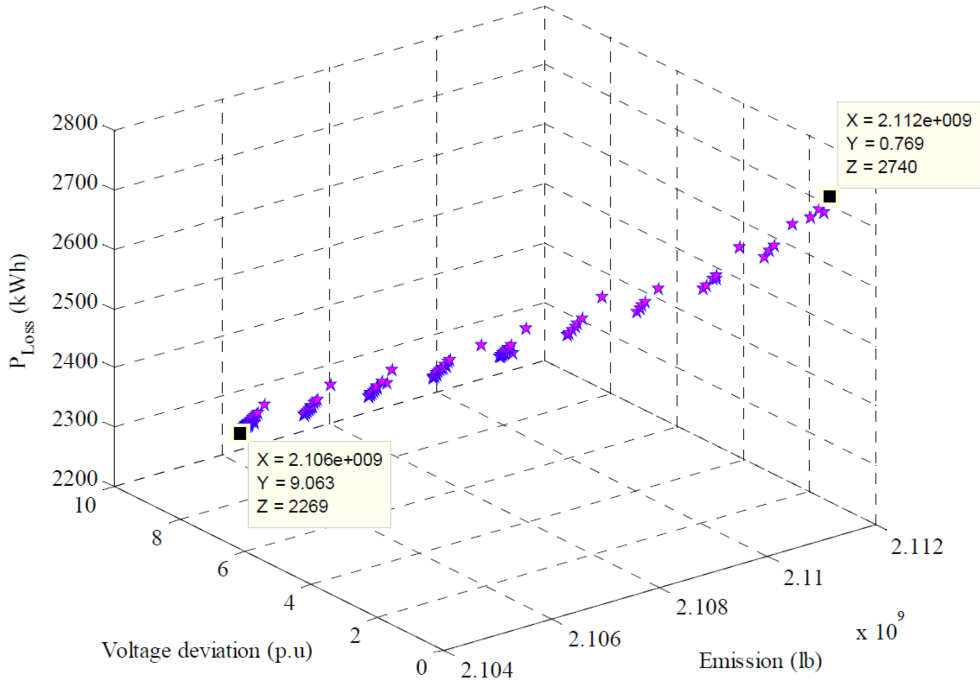

FIGURE 6. Three-dimentional Pareto front of CCPSO algorithm (Emission, Voltage deviation, P_{Loss})

The close agreement of the results shows clearly the capability of the proposed technique to handle multi-objective optimization problems as the best solution of each objective along with a manageable set of non-dominated solutions can be obtained in one single run.

7. **Conclusion.** Multi-objective daily Optimal Operation Management (MOOM) problem is proposed in this study, which is then handled by a novel multi-objective CCPSO optimization technique for searching out a set of Pareto-optimal solutions. One of the most important advantages of the multi-objective formulation is that it obtains several non-dominated solutions allowing the system operator to use his personal preference in selecting any one of those solutions for implementation. In order to control the size of the repository, a fuzzy-based clustering has been used. The results show that the proposed approach is efficient for solving multi-objective optimization where multiple Pareto-optimal solutions can be found in one simulation run. In addition, the non-dominated solutions in the obtained Pareto-optimal set are well distributed and have acceptable diversity characteristics.

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