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Placement of Combined Heat, Power and Hydrogen Production Fuel Cell Power Plants in a Distribution Network

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Abstract: This paper presents a new Fuzzy Adaptive Modified Particle Swarm Optimization algorithm (FAMPSO) for the placement of Fuel Cell Power Plants (FCPPs) in distribution systems. FCPPs, as Distributed Generation (DG) units, can be considered as Combined sources of Heat, Power, and Hydrogen (CHPH). CHPH operation of FCPPs can improve overall system efficiency, as well as produce hydrogen which can be stored for the future use of FCPPs or can be sold for profit. The objective functions investigated are minimizing the operating costs of electrical energy generation of distribution substations and FCPPs, minimizing the voltage deviation and minimizing the total emission. In this regard, this paper just considers the placement of CHPH FCPPs while investment cost of devices is not considered. Considering the fact that the objectives are different, non-commensurable and nonlinear, it is difficult to solve the problem using conventional approaches that may optimize a single objective. Moreover, the placement of FCPPs in distribution systems is a mixed integer problem. Therefore, this paper uses the FAMPSO algorithm to overcome these problems. For solving the proposed multi-objective problem, this paper utilizes the Pareto Optimality idea to obtain a set of solution in the multi-objective problem instead of only one. Also, a fuzzy system is used to tune parameters of FAMPSO algorithm such as inertia weight. The efficacy of the proposed approach is validated on a 69-bus distribution system.

Nomenclature:

P_{Sub}^t	active power produced by the substation of network	e_{grid,NO_x}	emission coefficient of grid
P_{FCPPj}^t	active power generated by *FCPPj* during time *t*	e_{FCPP,SO_2}	emission coefficient of FCPP units
C_{n1}	price of purchasing natural gas for FCPPs	e_{FCPP,NO_x}	emission coefficient of FCPP units
C_{n2}	fuel price for thermal loads	V_{ref}	nominal voltage
$P_{Max,FCPP}$	maximum power of FCPP	V_i^t	voltage magnitude of the bus *i* during time *t*
P_{Hj}^t	equivalent electric power for hydrogen production during time *t*	V_{Min}	lowest voltages of each bus
η_j^t	efficiency of *FCPPj* during time *t*	V_{Max}	highest voltages of each bus
N_{FCPP}	total number of FCPPs	$P_{FCPP,j}^{t,min}$	minimum of active power produced by *FCPPj* during time *t*
N_{bus}	total number of buses	$P_{FCPP,j}^{t,max}$	maximum of active power produced by *FCPPj* during time *t*
L_{thi}	thermal load demand of bus *i*	f_i^{min}	lower bound of each objective function
P_{thi}^t	produced thermal by FCPP in bus *i* if there is a FCPP in this bus during time *t*	f_i^{max}	upper bounds of each objective function
OM	operation and maintenance cost of FCPPs	$\mu_{f_i(X)}$	membership function of each objective function
C_{Sub}	cost of substation active power	$N_\mu(X_i)$	normalized membership value of each particle in the repository
C_{HS}	hydrogen selling price	h	number of objective function
T	the total time	m	number of non-dominated solutions in the repository
$location_n$	the location of *FCPPn*	w_k	weight of kth objective function

r_{TEj}	thermal energy to electrical energy ratio	Vel_j^k	current velocity of particle j at iteration k
PLR_j	part load ratio of *FCPPj* (equal to electrical generated power/maximum power)	Vel_j^{k+1}	modified velocity of particle j at iteration $k+1$
H_{factor}	a conversion factor (kg of hydrogen/kW of electric power), where $H_{factor} = 1.05 \times 10^{-8} / v_{cell}$ and v_{cell} is the cell operating voltage, $v_{cell} = 0.6 \ volt$	$rand(.)$	random number between 0 and 1
X	optimization variable	X_j^k	current position of particle j at iteration k
E_{grid}^t	emission produced by grid during time t	$X_{mut,j}^k$	mutant vector of particle j at iteration k
E_{FCPPj}^t	emission produced by *FCPPj* units during time t	$X_{new,j}^k$	the trial vector
e_{grid,SO_2}	emission coefficient of grid	NFV	normalized fitness value

1. Introduction

1.1. Literature Review

In recent years, the attention to Distributed Generation (DG) units connected to the distribution network has increased [1]. Modular generating systems sized from less than a kilowatt to tens of megawatts and placed at or near consumer locations are considered as DG units [2]. Fuel Cell Power Plants (FCPPs) have advanced the electrochemical energy conversion of devices operating at high temperature and changing the chemical energy of fuel into electrical energy at high efficiency compared with diesel or gas engines. Considering the increasing concerns about the environmental effects in recent years, it is important to generate electrical power with minimum emission and contamination. Since FCPPs generate less pollution with respect to the other generation units, it is very desirable to reduce emission in power systems. Furthermore, FCPPs have less noise compared with internal combustion engines. Also, the maintenance of FCPPs is simple; since there are few moving parts in the system [3].

Many researchers have investigated the placement of DG units in distribution systems. For instance, El-Khattam and colleagues presented a new integrated model to achieve optimal sizing and siting of DG units and considered cost and loss as minimized objectives [4]. Jabr and Pal developed an ordinal optimization method for determining the location and size of DG units [5]. They applied a hybrid genetic algorithm for locating and sizing DG units. A new formulation for the optimum DG unit placement problem was proposed in [6]. This paper considered a hybrid combination of technical factors as minimization of the line losses, the voltage sag problem, *etc.*, as well as the economical factors such as the installation and maintenance costs of the DG units. AlRashidi and AlHajri

presented an improved Particle Swarm Optimization (PSO) algorithm for optimal planning of multiple DG units [7]. They divided the problem into two parts: continuous and discrete optimization for optimal sizing and localizing respectively in order to minimize real power losses. A method based on the analysis of power flow continuation and determination of most sensitive buses to voltage collapse was used for placement of DG units in [8]. Celli *et al*. presented a multi-objective evolutionary algorithm for sizing and locating DG units. Their technique is based on a genetic algorithm and an epsilon-constraint method that produces a set of non inferior solutions [9]. Niknam *et al*. used a modified honey bee mating optimization algorithm for multi-objective placement of renewable energy resources [10]. They considered conflicting objectives such as the total cost, deviation of the bus voltage, power losses and emission. In order to minimize the power losses and maximizing the profitability, in [11] a new method was proposed which investigated the optimal size and location of biomass fuelled gas turbines in distribution systems. Application and comparison of several metaheuristic techniques for optimizing the placement and supplying the area of biomass-fueled power plants was presented in [12]. In all the above papers, the placement of CHPH FCPPs has not been investigated. Therefore, this problem is assessed in this paper.

This paper assesses the proper cost function for CHPH FCPPs which is essential for the optimal operation and placement of these devices in distributed networks. El-Sharkh *et al*. perused the optimal cost of CHPH operation of FCPP in different models of cost functions [13,14]. In fact, they used these models to determine the optimal operation strategy that yields the minimum operating cost. Optimal operation management of distribution networks with regard to FCPPs using effective evolutionary algorithms has been investigated by Niknam *et al*. in [15,16]. Nanaeda *et al*. considered some operating strategies including optimal sizing of the FCPP, thermal energy storage for dispatching the heat, and operation of FCPP to provide flexible grid power [17]. Ren and Gao evaluated two micro CHP systems including gas engine and FCPP for residential buildings in terms of minimum-cost operation and minimum-emission operation [18]. They showed that the FCPP system is a better option for residential buildings both economically and environmentally.

Since the load flow is the bare bone essential for calculating the objective functions, the proposed problem can be considered as a mixed integer nonlinear optimization problem. Therefore, this paper utilizes a new evolutionary algorithm called Fuzzy Adaptive Modified Particle Swarm Optimization (FAMPSO) for the placement of CHPH FCPPs in the distribution networks. The PSO algorithm is an evolutionary algorithm first proposed by Kennedy and Eberhart [19,20]. It is used for solving the nonlinear mixed integer and the complex optimization problem [21–25]. The performance of the PSO algorithm is highly dependent on its parameters such as inertia weight and learning factors. Therefore, a fuzzy system is used to adjust the inertia weight [22,26].

Nowadays, as the result of the increase in fuel prices and consequently the augment in electrical power costs, it is important to find a way to produce electricity for distribution networks and customers with lower operating costs. The CHPH operation of FCPP can decrease operating costs. Also, considering the increasing concern over environmental protection in recent years, it is important to generate electricity with minimum emissions. Moreover, the power quality is an important issue in transmission and distribution networks, and this issue is becoming more significant. Voltage deviation can satisfy the power quality concern and improve it. Therefore, the operating cost, voltage deviation and emission are considered simultaneously as objective functions in this paper. Since the objectives

are different, non-commensurable and nonlinear, it is difficult to solve the problem using conventional approaches that may optimize a single objective. Therefore, this paper modifies the mentioned algorithm for enhancing the performance of the algorithm to eliminate these conflictions. During the optimization process, a set of obtained non-dominated solutions, called Pareto optimal solutions, is stored in an external memory called repository.

1.2. Contributions

In the mentioned papers, the placement of the FCPPs and the effect of CHPH operation of FCPPs are considered independently while they have a direct influence on each other. Therefore, in the proposed approach, both of the issues are investigated simultaneously. In this paper will be shown that considering the effect of CHPH operation of FCPPs is very effective in reducing the cost.

In conclusion, the main contributions of this paper are as follows: (i) the placement of FCPPs considering the effect of CHPH operation of FCPPs is investigated; (ii) the problem is solved in a multi-objective framework with different strategies for considering the effect of produced hydrogen and thermal energy; (iii) the idea of non-dominated solutions called Pareto optimal solutions is utilized to find all optimal solutions; and (iv) the performance of the algorithm is improved using a new mutation operator and a fuzzy-based adjustment technique.

2. Placement of FCPPs in Distributed Networks

The main goal of this paper is to determine the best location for FCPPs by a trade-off between the different and conflicting objective functions. Therefore, this section introduces objective functions as well as the main constraints for solving the problem.

2.1. Objective Functions

2.1.1. Operating Cost of Energy

The operating cost function includes the cost of electrical energy generated by substation bus and FCPPs, the cost of thermal energy generated by FCPPs, and the cost of hydrogen produced. This paper considers thermal and electrical loads that FCPPs can supply them. If the FCPP is not able to supply all the thermal loads, the amount of thermal loads that are not supplied should be fed by natural gas. The operating cost function is modeled as follows [13,14]:

$$f_1(X) = \sum_{t=1}^{T} (P_{Sub}^t \times C_{Sub} + C_{n1} \sum_{j}^{N_{FCPP}} (\frac{P_{FCPPj}^t + P_{Hj}^t}{\eta_j}) + C_{n2} \sum_{i}^{N_{bus}} \max(L_{thi} - P_{thi}^t, 0) + OM$$

$$-C_{Hs} \sum_{j}^{N_{FCPP}} (P_{Hj}^t \times H_{factor}))$$

(1)

$$X = [L_{FCPP} \quad P_{FCPP}]_{1 \times n \times (1+T)}$$

(2)

$$L_{FCPP} = [location_1 \quad location_2 \quad ... \quad location_n]_{1 \times n}$$

(3)

$$P_{FCPP} = [P_{FCPP1} \quad P_{FCPP2} \quad ... \quad P_{FCPPn}]_{1 \times n \times T}$$

(4)

$$P_{FCPPj} = [P_{FCPPj}^1 \quad P_{FCPPj}^2 \quad \cdots \quad P_{FCPPj}^t \quad \cdots \quad P_{FCPPj}^T]_{1 \times T} \tag{5}$$

The cost objective function includes five terms: (1) cost of energy prepared by substation bus ($); (2) overall fuel cost for FCPPs ($); (3) cost of purchased gas for thermal load if the thermal energy produced by FCPPs is not enough to meet the thermal energy demand ($); (4) the operation and maintenance cost of the FCPPs ($); and (5) the income from the sale of the generated hydrogen by FCPPs ($). The amount of heat generated by FCPP has been developed in [13,14], as follows:

$$PLR_j = \frac{P_{FCPPj}^t}{P_{Max,FCPP}}$$

$$For \quad PLR_j \prec 0.05,$$

$$\eta_j = 0.2716, \quad r_{TEj} = 0.6801 \tag{6}$$

$$For \quad PLR_j \succ 0.05,$$

$$\eta_j = 0.9033 PLR_j^5 - 2.999 PLR_j^4 + 3.6503 PLR_j^3$$
$$- 2.0704 PLR_j^2 + 0.4623 PLR_j + 0.3747 \tag{7}$$

$$r_{TEj} = 1.0785 PLR_j^4 - 1.9739 PLR_j^3 + 1.5005 PLR_j^2$$
$$- 0.2817 PLR_j + 0.6938 \tag{8}$$

The efficiency value and the ratio of thermal energy to electrical energy are both functions of the *PLR*. The amount of thermal energy generated by FCPP is based on the amount of the output electrical energy and is calculated as follows [13,14]:

$$P_{thi}^t = r_{TEj}(P_{PCPPj}^t + P_{Hj}^t) \tag{9}$$

$$P_{Max,FCPP} = P_{PCPPj}^t + P_{Hj}^t \tag{10}$$

2.1.2. Emission

Summation of FCPPs and substation bus emissions is one of the major objectives of the placement of FCPPs problem that can be described as follows [15]:

$$f_2(X) = \sum_{t=1}^{T} (E_{grid}^t + \sum_{j=1}^{N_{FCPP}} E_{FCPP,j}^t) \tag{11}$$

$$E_{grid}^t = P_{Sub}^t \times e_{grid,SO_2} + P_{Sub}^t \times e_{grid,NO_x} \tag{12}$$

$$E_{FCPPj}^t = P_{FCPPj}^t \times e_{FCPP,SO_2} + P_{FCPPj}^t \times e_{FCPP,NO_x} \tag{13}$$

where E_{grid}^t and E_{FCPPj}^t are the emission produced by grid and *FCPPj* units during time *t*, respectively; e_{grid,SO_2} and e_{grid,NO_x} are the emission coefficients of the grid; e_{FCPP,SO_2} and e_{FCPP,NO_x} are the emission coefficients of FCPP units.

2.1.3. Voltage Deviation

Decreasing the voltage deviation can enhance the power quality. Mathematically, it can be defined as follows [15]:

$$f_3(X) = \frac{\sum_{t=1}^{T}\sum_{i=1}^{N_{bus}}(\frac{\left|V_{ref} - V_i^t\right|}{V_{ref}}) \times \Delta t}{N_{Bus}} \tag{14}$$

where V_{ref} and V_i^t are nominal voltage and voltage magnitude of the bus i during time t respectively. N_{bus} and T are the total number of buses and total time, respectively.

2.2. Constraints

2.2.1. Bus Voltage Limits

The voltage profile is maintained within specified limits, as follows [16]:

$$V_{Min} \leq \left|V_i^t\right| \leq V_{Max} \tag{15}$$

where V_{Min} and V_{Max} are the lowest and the highest voltage levels of each bus respectively. Also $\left|V_i^t\right|$ is the magnitude of voltage in the bus i.

2.2.2. Active Power Output of FCPPs

The amount of active power output of each FCPP is limited, as follows [16]:

$$P_{FCPP,j}^{t,\min} \leq P_{FCPP,j}^t \leq P_{FCPP,j}^{t,\max} \tag{16}$$

where $P_{FCPP,j}^{t,\min}$ and $P_{FCPP,j}^{t,\max}$ are the minimum and the maximum active power produced by *FCPPj* during time t respectively.

3. Multi-Objective Approach for Pareto Optimal Solutions

The optimum Pareto method includes a set of solutions. In fact, all dominant solutions are shown in a graph which is called Pareto graph. One solution (X_1) can dominate another solution (X_2) if the below equation is satisfied [10]:

$$\begin{cases} \forall i = 1,...,m & f_i(X_1) \leq f_i(X_2) \\ \exists i & f_i(X_1) \prec f_i(X_2) \end{cases} \tag{17}$$

If X_1 dominates X_2, X_1 is stored in the repository as a non-dominate solution. Solutions in the repository make up the Pareto graph. One solution can go into the repository if it can satisfy the following conditions:

- Repository is not full
- The answer is not dominated by any of the solutions in the repository.

4. Best Compromise Solution

The decision maker needs to select one solution as the best compromise solution among the Pareto optimal set of non-dominated solutions. Since the mentioned objective functions are imprecise, they are formulated as fuzzy sets. In this procedure, a fuzzy membership function is used to specify the best compromise solution. For any particle in the repository, the membership function of each objective function is defined as follows [10]:

$$\mu_{f_i(X)} = \begin{cases} 0 & f_i(X) \geq f_i^{\max} \\ \dfrac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \leq f_i(X) \leq f_i^{\max} \\ 1 & f_i(X) \leq f_i^{\min} \end{cases} \tag{18}$$

where $f_i^{\min}$ and $f_i^{\max}$ are the lower and the upper bounds of the ith objective function. In the proposed algorithm, the values of $f_i^{\min}$ and $f_i^{\max}$ are evaluated using the results obtained by optimizing each objective, separately.

The normalized membership value is calculated for each particle in the repository as follows [10]:

$$N_\mu(X_i) = \frac{\displaystyle\sum_{k=1}^{h} w_k \times \mu_{f_k}(X_i)}{\displaystyle\sum_{i}^{m} \sum_{k}^{h} w_k \times \mu_{f_k}(X_i)} \tag{19}$$

where h is the number of objective functions, m is the number of non-dominated solutions in the repository and w_k is the weight of the kth objective function. The best compromise solution is the one which has the maximum value of N_μ.

5. PSO Algorithm

5.1. Original PSO Algorithm

PSO algorithm is a population-based stochastic optimization method. The algorithm is derived by the social behavior of bird flocks, colonies of insects, schools of fishes, and groups of animals feeding and traveling together. The algorithm is started by initializing a population of random solutions called particles and searches for the best position by updating production through the following velocity and position update equations. The velocity and position are updated by the following equations:

$$Vel_j^{k+1} = \omega \times Vel_j^k + C_1 \times rand(.) \times (P_{Best,j}^k - X_j^k) + C_2 \times rand(.) \times (G_{Best}^k - X_j^k) \tag{20}$$

$$X_j^{k+1} = X_j^k + Vel_j^{k+1} \tag{21}$$

where Vel_j^k is the current velocity of particle j at iteration k, Vel_j^{k+1} is the modified velocity of particle j at iteration $k+1$, $rand(.)$ is the random number between 0 and 1, X_j^k is the current position of particle j at iteration k. The particles have memory and each particle keeps track of its previous best position (called the P_{Best}^k) and its corresponding fitness. There exist a number of P_{Best}^k for the respective

particles in the swarm and the particle with the greatest fitness is called the global best (G_{Best}^k) of the swarm. The learning factors C_1 and C_2 can control each particle to move in a single iteration. Typically, these are both set to a value of 2.0 [20]. The inertia weight ω is used to control the convergence behavior of the PSO. Typical implementations of the PSO adapt the value of ω during the training stage, e.g., linearly decreasing it from 1.0 to near 0 over the execution. Convergence can be obtained with fixed values, as shown in [20]. Since in this method the initial population is generated randomly similar to the other optimization methods, so the program may be not robust. The lower convergence rate is a disadvantage in this method rather than the classical and gradient-based methods.

5.2. Modified PSO Algorithm

In its part, a new mutation is applied to the PSO algorithm to increase the population diversity and preventing premature convergence. Inopportune convergence may happen under different situations: the population has converged to local optima of the objective function or the population has lost its variety or the search algorithm has proceeded slowly. Variegating the PSO population and amending its performance in a hindering inopportune convergence to local minima mutation are potent strategies. This paper uses a new mutation operator. In this method the algorithm selects three different particles from the initial population and mutates the population using these particles. To cover the whole searching region, in each iteration $X_{m1} \neq X_{m2} \neq X_{m3} \neq X_j$ are selected and are mutated by other particles within the population. A mutant vector $X_{mut,j}^k$ is generated as:

$$
\begin{aligned}
X_{mut,j}^k &= X_{m1}^k + rand(.) \times (X_{m2}^k - X_{m3}^k) \\
X_{mut,j}^k &= [x_{mut1}, x_{mut2}, ..., x_{mutD}]
\end{aligned}
\tag{22}
$$

Then the mutant vector is mixed with each swarm of population to obtain the trial vector as follows:

$$
\begin{aligned}
X_{new,j}^k &= [x_{new,1}^k, x_{new,2}^k, ..., x_{new,D}^k] \\
x_{new,z}^k &= \begin{cases} x_{mut,z}^k & if \quad Cr \leq rand(.) \\ x_{swarm,z}^k & otherwise \end{cases}
\end{aligned}
\tag{23}
$$

where *Cr* is a number between 0.1 and 0.9, and *rand*(.) is a random number between zero and one. If the problem is a kind of single objective optimization, $X_{new,j}^k$ and $X_{swarm,z}^k$ are compared in terms of cost function value, as follows:

$$
X_{swarm,j}^{k+1} = \begin{cases} X_{new,j}^k & if \quad f(X_{new,j}^k) \leq f(X_{swarm,j}^k) \\ X_{swarm,j}^k & otherwise \end{cases}
\tag{24}
$$

If the objective function value of $X_{new,j}^k$ ($f(X_{new,j}^k)$) is less than the objective function value of $X_{swarm,j}^k$ ($f(X_{swarm,j}^k)$), $X_{new,j}^k$ is replaced by $X_{swarm,j}^k$ in the next generation. When the problem is multi-objective, if $X_{new,j}^k$ dominates $X_{swarm,z}^k$, $X_{new,j}^k$ is replaces by $X_{swarm,j}^k$ in the next generation.

5.3. Fuzzy Adaptive PSO

The procedure of the proposed FAPSO begins like the standard PSO described in Section 4.2. The main difference is that the proposed FAPSO utilizes a fuzzy logic to adaptively adjust inertia weights instead of using the fixed constant in the original PSO. The parameters of PSO algorithm have a salient influence on the performance of the search process. Inertia weight directly affects the convergence of the algorithm. Large amounts of inertia weight cause the particle to search for new parts of space related to optimization problem; in other words they perform a global search. Also, the local search can be included for less values of inertia weight. Local search is suitable for increasing the accuracy of an existing answer while global search is used to find possible better answers in unknown places within the search space. To establish a better balance between global search and local search, the inertia weight needs to be adjusted. By appropriate selection of ω, the algorithm requires less iterations on average to locate the global optimum solution [22,26]. In this way, the process allows the swarm to explore the search space in the beginning of the run for finding global optimum, and still manages to shift towards a local search when fine-tuning is required. Based on the mentioned reasons, the best candidate for this process is using a fuzzy system to adjust the inertia weight.

The Mamdani-type fuzzy is a good candidate for dynamically tuning the inertia weight of the PSO. The current best performance evaluation and the current inertia weight are selected as input for the fuzzy system. Changing the inertia weight is the output of fuzzy system. The normalized fitness value *NFV* is used as an input variable between 0 and 1, and is defined as [27]:

$$NFV = \frac{FV - FV_{\min}}{FV_{\max} - FV_{\min}} \tag{25}$$

The calculated value of *NFV* from (25) at the first iteration may be used as $FV_{\min}$ for the next iterations. $FV_{\max}$ is a very large value, which is greater than any acceptable feasible solution. The typical inertia weight value is $0.4 \leq \omega \leq 0.9$, therefore, both positive and negative corrections are required for the inertia weight. So, a range of −0.1 to 0.1 has been chosen for the inertia weight correction values [27]:

$$\omega^{k+1} = \omega^k + \Delta\omega \tag{26}$$

The input fuzzy variables are classified in three fuzzy sets of linguistic values: S (small), M (medium) and L (large) with associated membership functions as shown in Figures 1(a,b). Also, the output variable is defined in three fuzzy sets of linguistic values: NE (negative), ZE (zero) and PE (positive) as shown in Figure 1(c). The Mamdani-type fuzzy rule is employed to formulate the conditional statements including fuzzy logic. For example:

$$R_i: \quad \textit{If } (NFV \textit{ is } S) \textit{ and } (\omega \textit{ is } M)$$
$$\textit{Then } (\Delta\omega \textit{ is } NE)$$

Each rule represents a mapping from the input into the output space and determines the inertia weight correction ($\Delta\omega$) in each iteration. These fuzzy rules are shown in Table 1.

Figure 1. Membership functions of inputs and outputs (**a**) *NFV* (**b**) ω (**c**) Δω.
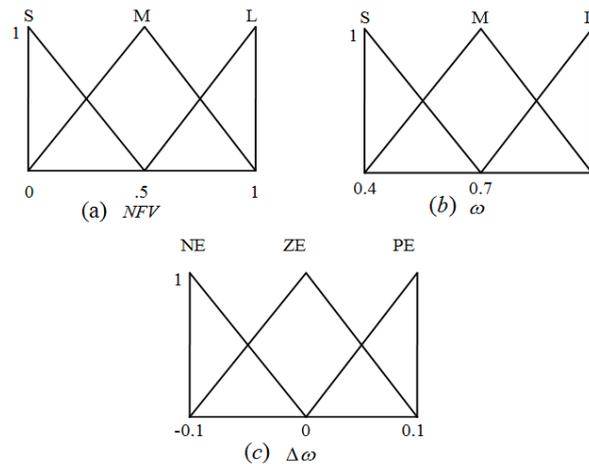
Table 1. Fuzzy rules for variations of the inertia weight.

Δω		Ω		
		S	M	L
NFV	S	ZE	NE	NE
	M	PE	NE	NE
	L	PE	ZE	NE

6. Implementing FAMPSO for Placement of FCPPs

In this section, the proposed FAMPSO algorithm for the placement of FCPP is described in detail:

Step 1: Data Input, including cost coefficients of FCPPs, emission coefficients of FCPPs, network data, thermal and electrical loads, number of population, initial value of inertia weight and values of learning factors.

Step 2: Generation of initial population X_j and an initial velocity Vel_j, which must satisfy constraints, as follows:

$$Population = \begin{bmatrix} X_1 \\ X_2 \\ ... \\ X_N \end{bmatrix}_{N \times n \times (1+T)} \tag{27}$$

$$X_j = [L_{FCPP} \quad P_{FCPP}]_{1 \times n \times (1+T)} \tag{28}$$

$$L_{FCPP} = [location_1 \quad location_2 \quad ... \quad location_n]_{1 \times n} \tag{29}$$

$$P_{FCPP} = [P_{FCPP1} \quad P_{FCPP2} \quad ... \quad P_{FCPPn}]_{1 \times n \times T} \tag{30}$$

$$P_{FCPPj} = [P_{FCPPj}^1 \quad P_{FCPPj}^2 \quad ... \quad P_{FCPPj}^t \quad ... \quad P_{FCPPj}^T]_{1 \times T} \tag{31}$$

$$Velocity = \begin{bmatrix} Vel_1 \\ Vel_2 \\ ... \\ Vel_N \end{bmatrix}_{N \times n \times (1+T)} \tag{32}$$

$$Vel_j = [Vel_{L_{FCPP}} \quad Vel_{P_{FCPP}}]_{1 \times n \times (1+T)} \tag{33}$$

$$Vel_{L_{FCPP}} = [Vel_{location_1} \quad Vel_{location_2} \quad .... \quad Vel_{location_n}]_{1 \times n} \tag{34}$$

$$Vel_{P_{FCPP}} = [Vel_{P_{FCPP1}} \quad Vel_{P_{FCPP2}} \quad .... \quad Vel_{P_{FCPPn}}]_{1 \times n \times T} \tag{35}$$

$$Vel_{P_{FCPPj}} = [Vel_{P_{FCPPj}^1} \quad Vel_{P_{FCPPj}^2} \quad ... \quad Vel_{P_{FCPPj}^t} \quad ... \quad Vel_{P_{FCPPj}^T}]_{1 \times T} \tag{36}$$

where N is the number swarms in the population and n is the number of *FCPPs*, $location_n$ is the location of *FCPPn*, P_{FCPPn}^t is active power generated by *FCPPn* during time t. $location_n$ changes between 1 and maximum number of the buses and P_{FCPPn}^t changes between 0 and maximum capacity of *FCPPn*. $Vel_{location_n}$ and $Vel_{P_{FCPPn}^t}$ are velocities of $location_n$ and P_{FCPPn}^t, respectively.

Step 3: Evaluation of objective functions. The objective functions (Equation (1), Equation (11), and Equation (14)) are calculated for each particle using the result of load flow distribution.

Step 4: Select P_{Best}^k.

The locations and real power output of all FCPPs are represented as the position of the particle in the swarm. The best position of a particle is P_{Best}^k.

Step 5: Non-dominated solutions of initial population are determined and stored in the repository.

Step 6: Select G_{Best}^k.

Normalized membership values are calculated [Equation (19)] for non-dominated solutions in the repository. The G_{Best}^k is a solution which has the biggest value of N_μ.

Step 7: Set $i = 1$.

Step 8: Update velocity and position.

To update the position of each individual, it is necessary to calculate the velocity of each individual in the next stage which is obtained from (20). The position of each individual is updated by (21).

Step 9: Implement mutation as described in Section 5.2.

Step 10: Select the non-dominate solutions. If the particle i is a non-dominated solution, it is stored in the repository.

Step 11: If all of the individuals are selected, go to Step 12, otherwise set up $i = i + 1$ and return to Step 8.

Step 12: Update P_{Best}^k. P_{Best}^k is updated when one of the following conditions is satisfied, otherwise it would be the same as the previous mentioned population:

I.   If the current individual dominates the former P_{Best}, it is considered as P_{Best}^k.

    II.   If no one dominates another, the one that its normalized membership function is greater will be considered as P_{Best}^{k}.

Step 13: Update G_{Best}^{k}. For updating G_{Best}^{k}, non-dominated solutions in the repository are sorted with respect to the value of N_{μ} and the solution which has the biggest value of N_{μ} is selected as G_{Best}^{k}.

Step 14: Update the inertia weight ω. In this algorithm, the suitable selection of inertia weight ω is updated by the fuzzy rules described in Section 5.3.

Step 15: Check the termination criteria. If the termination criterion is met, finish the algorithm, otherwise go to Step 7 and repeat the process.

7. Simulation Results

In this section, the mentioned optimization algorithm has been employed for placement of FCPPs on a 69-bus distribution system. This network consists of one source transformer and 68 load points. The total system load is 3802 (kW). The system base values are $V_b = 12.66$ kV and $S_b = 10$ MVA. The system data are given in [28] and the single line diagram of this system is shown in Figure 2. The thermal load is considered as 0.4 of the active load on each feeder. In this network, four FCPPs are placed and each of these sources can generate 250 kW. Information regarding the gas price, hydrogen selling price and the parameters of cost objective function are shown in Table 2 and the values of emission coefficients are shown in Table 3.

Figure 2. Single line diagram of distribution test system.
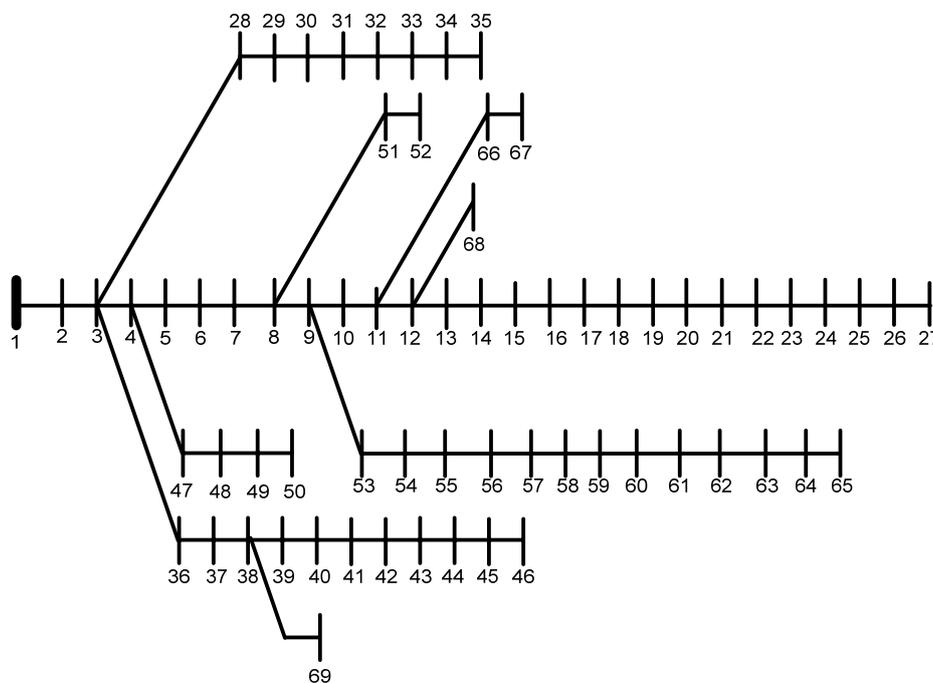
Table 2. Information of cost parameters.

Parameter	Value
Cost of substation active power C_{sub} ($/kWh)	0.035
Price of natural gas for FCPPs C_{n1} ($/kWh)	0.04
Fuel price for thermal loads C_{n2} ($/kWh)	0.05
operation and maintenance cost of FCPPs OM ($/h)	19.32
Hydrogen selling price C_{Hs} ($/kg)	1.8

Table 3. Emission coefficients related to NO_x and SO_2.

Emission coefficients (gr/kWh)		
Emission type	Substation	FCPP
NO_x	3	0.015
SO_2	6	0.024

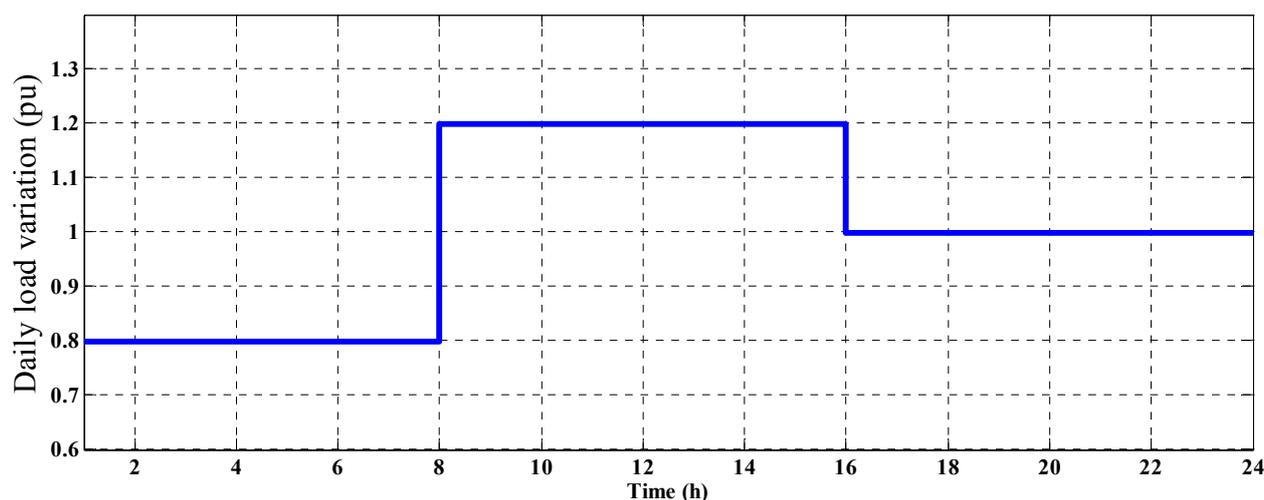Four strategies are considered for the cost objective function, as follows:

Strategy 1: Neglecting the effect of hydrogen and thermal energy produced by FCPPs and supplying thermal loads just with natural gas.

Strategy 2: Considering the effect of thermal energy on supplying thermal loads.

Strategy 3: Considering the effect of Hydrogen production by FCPP.

Strategy 4: Investigating the effect of both thermal supplement and hydrogen production.

The daily load variation in this problem is shown in Figure 3.

Figure 3. Daily load variation.

At first, all objective functions are optimized separately. Table 4 presents a comparison among the results obtained by FAMPSO algorithm for the placement of FCPPs considering four strategies for the cost objective function. Table 5 shows the value of thermal energy and hydrogen produced by each FCPP. As shown in Table 4, the lowest cost value is related to the strategy in which both thermal energy and hydrogen produced have been considered. The highest cost value is related to the strategy in which thermal energy and hydrogen produced by FCPPs are not considered. In the strategy which

considers the effect of thermal energy produced by FCPPs in the cost objective function, the cost value is less than that of the strategy which considers the effect of hydrogen produced by FCPPs on the cost objective function. In fact, the reason is that the value of thermal energy produced by FCPPs is more than the amount of hydrogen produced by FCPPs. Table 5 shows that the equivalent electrical energy generated by produced hydrogen of FCPPs is low. Because the maximum capacity of FCPP 1, 2&3 are used to generate electrical energy, the equivalent amount of electrical energy produced by hydrogen is zero for these FCPPs and only FCPP 4 produces electrical energy using hydrogen. In those strategies that don't use the thermal energy generated by FCPPs, thermal loads must be supplied by natural gas which can cause increase in cost value. Therefore, the CHPH operating of FCPP decreases cost objective function effectively and data in Table 4 confirm these results. The convergence plots of FAMPSO for four strategies of cost function are shown in Figures 4–7. The results for the placement of FCPPs considering emission and voltage deviation objective functions are presented in Table 6. The FCPPs are electrical power sources with extremely low amount of emission which can affect the emission objective function significantly. Table 6 shows that the voltage deviation objective function is placed at a very low level. Convergence plots of FAMPSO for emission and voltage deviation objective functions are shown in Figures 8 and 9.

Table 4. Results obtained by optimizing the Cost.

Strategies	Cost ($)	CPU time (s)	FCCPs locations (Bus Number)	Total electrical energy generation in a day (kW)
Strategy 1	8.6574×10^3	176.3	64,61,62,65	$6 \times 10^3, 6 \times 10^3, 6 \times 10^3, 1.346 \times 10^3$
Strategy 2	7.6996×10^3	181.6	64.62,61,65	$6 \times 10^3, 6 \times 10^3, 6 \times 10^3, 1.716 \times 10^3$
Strategy 3	8.6569×10^3	179.4	64,61,62,65	$6 \times 10^3, 6 \times 10^3, 6 \times 10^3, 1.345 \times 10^3$
Strategy 4	7.5472×10^3	184.2	61,64,62,65	$6 \times 10^3, 6 \times 10^3, 6 \times 10^3, 1.404 \times 10^3$

Table 5. Results obtained for thermal energy & hydrogen production for FCPPs by optimizing the Cost.

Strategies	Total electrical energy generation by hydrogen production in a day (kW)				Total thermal energy generation in a day (kW)			
	FCCP1	FCCP1	FCCP1	FCCP4	FCCP1	FCCP2	FCCP3	FCCP 4
Strategy 1	0	0	0	0	0	0	0	0
Strategy 2	0	0	0	0	6.0432×10^3	6.0432×10^3	6.0432×10^3	1.1794×10^3
Strategy 3	0	0	0	4.6547×10^3	0	0	0	0
Strategy 4	0	0	0	4.5959×10^3	6.0432×10^3	6.0432×10^3	6.0432×10^3	4.067×10^3

Figure 4. Convergence plot of FAMPSO for cost function without considering CHPH.
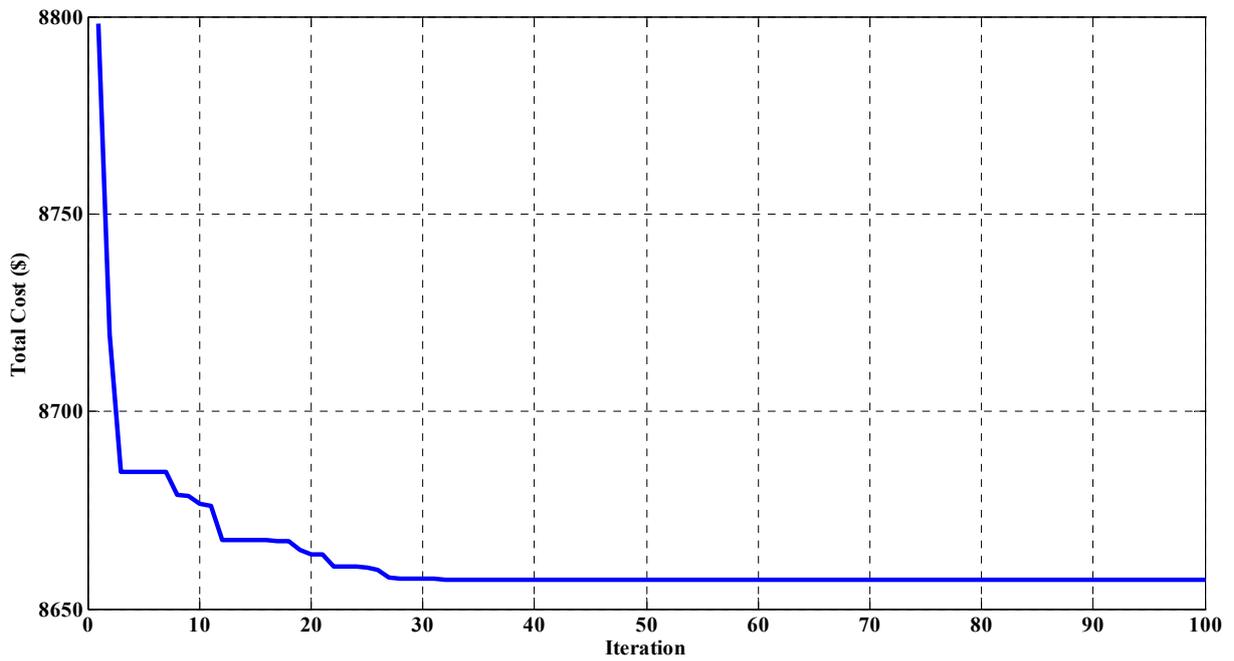

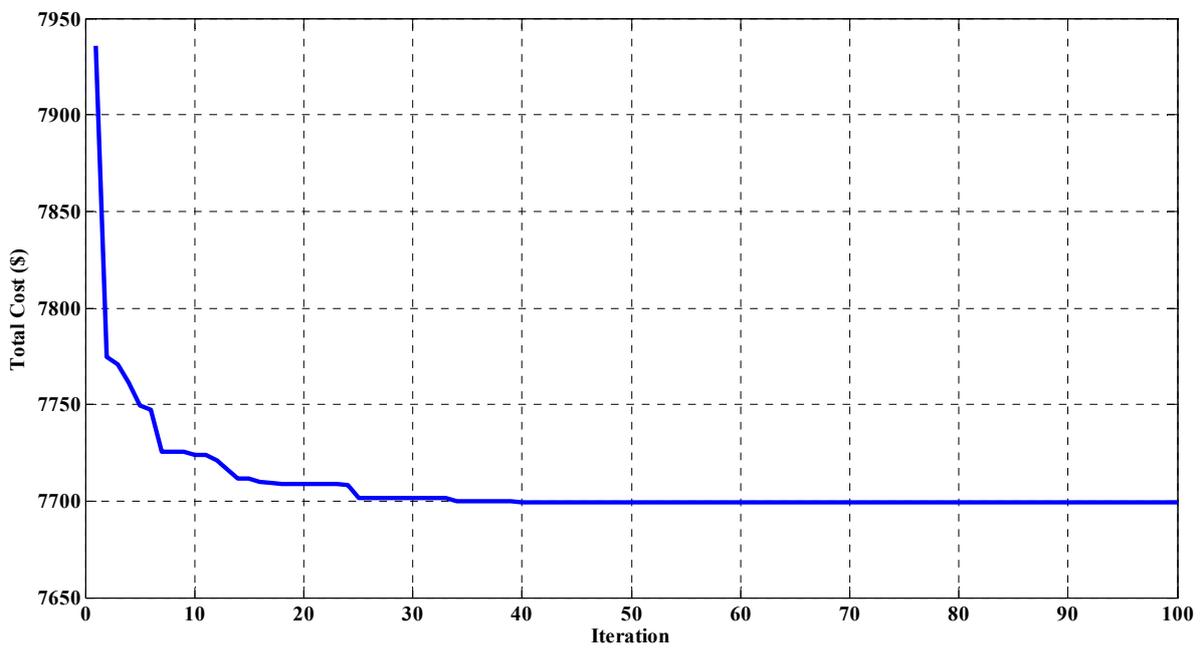**Figure 5.** Convergence plot of FAMPSO for cost function considering CHP.

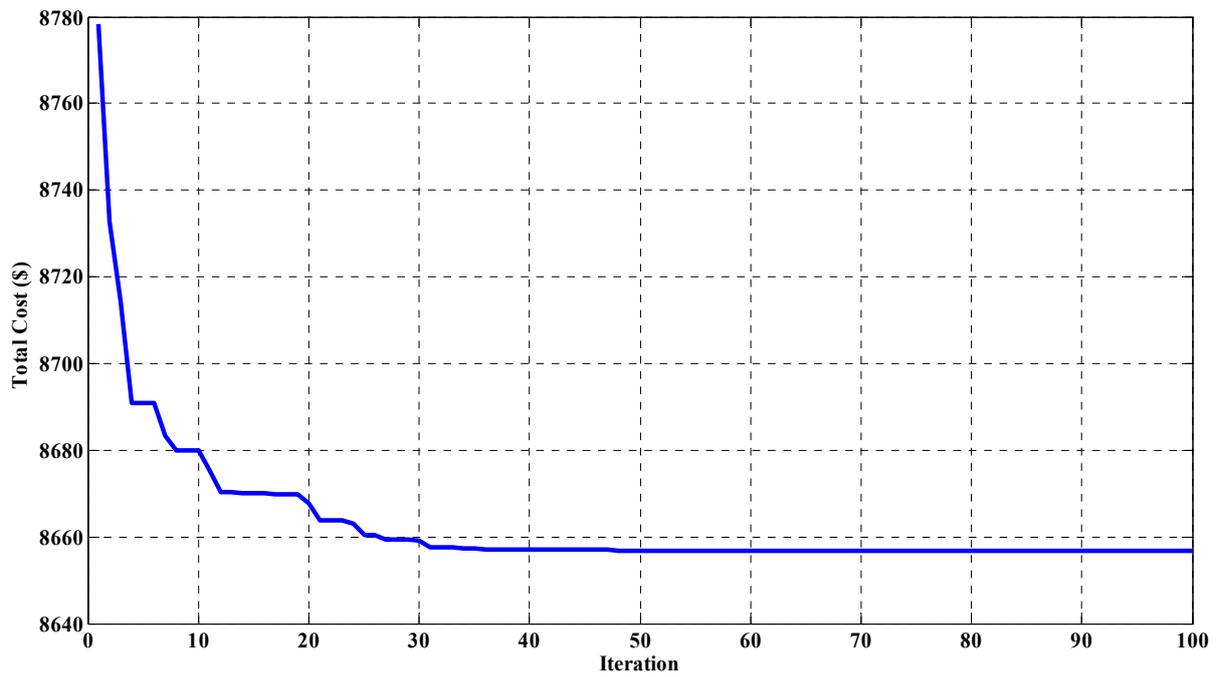**Figure 6.** Convergence plot of FAMPSO for cost function considering H.
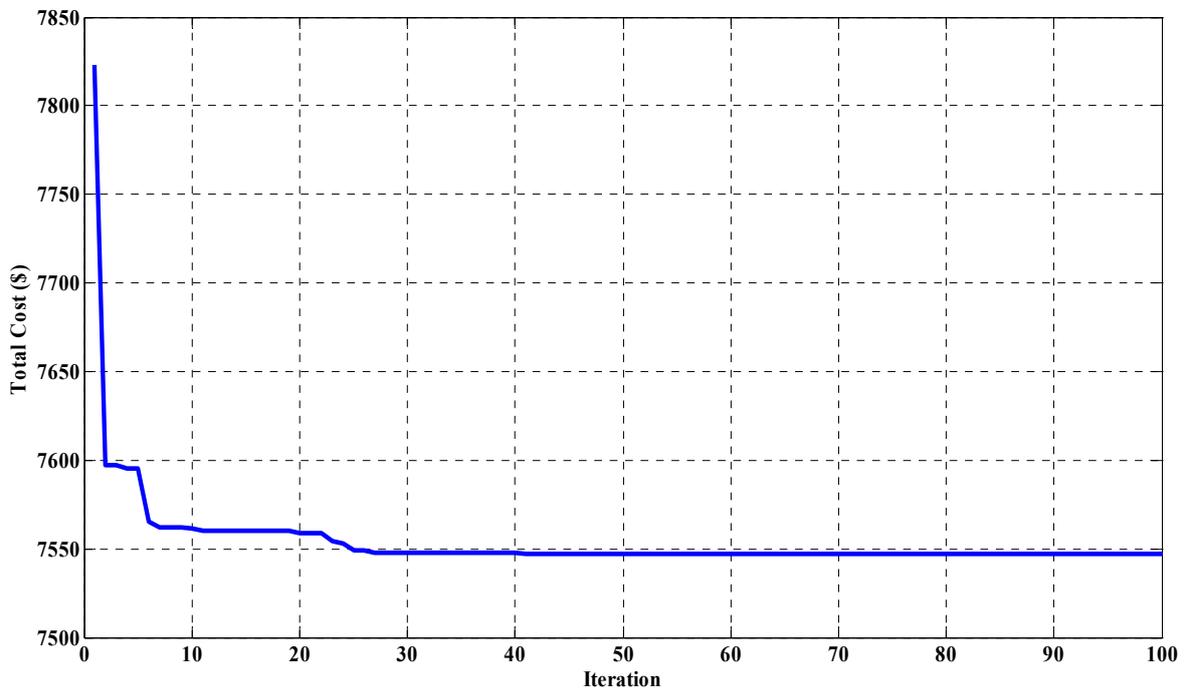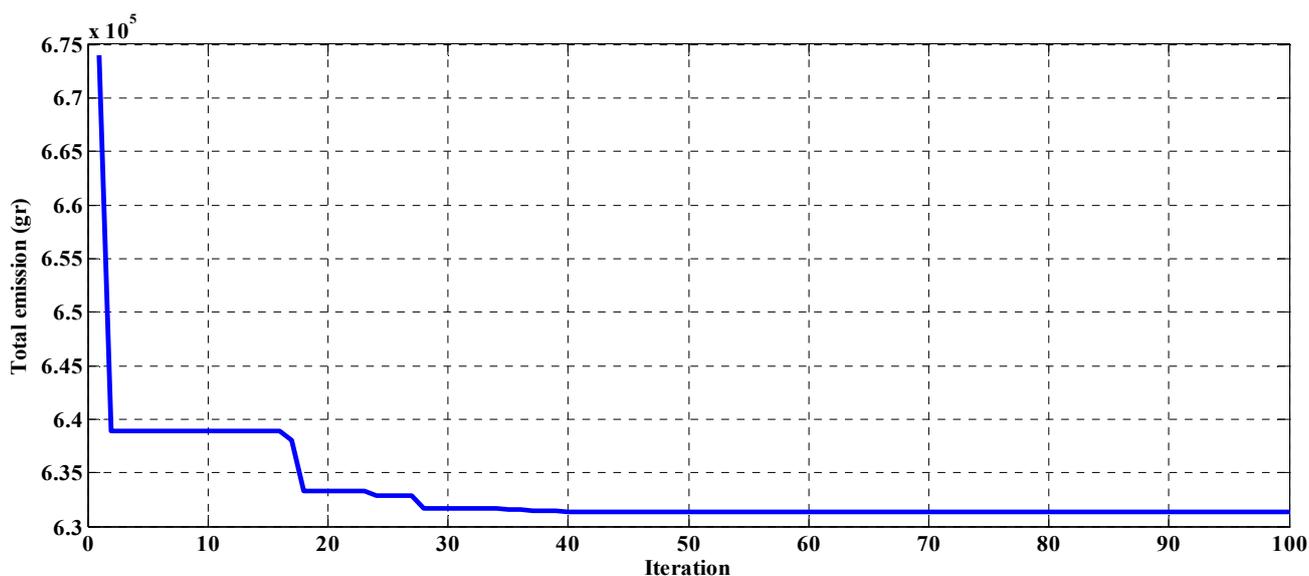

**Figure 7.** Convergence plot of FAMPSO for cost function considering CHPH.

Table 6. Results obtained by optimizing the emission and voltage deviation.

Objective	Emission (gr)	Voltage deviation (pu)	CPU time (s)	FCCPs locations (Bus Number)	Total electrical energy generation in a day (kW)
Emission	6.3132×10^5	…	129.2	62,64,63,61	$6 \times 10^3, 6 \times 10^3, 6 \times 10^3, 6 \times 10^3$
Voltage deviation	…	0.3636	126.4	25,27,65,26	$6 \times 10^3, 6 \times 10^3, 6 \times 10^3, 6 \times 10^3$

**Figure 8.** Convergence plot of FAMPSO for emission function.

**Figure 9.** Convergence plot of FAMPSO for Voltage deviation function.
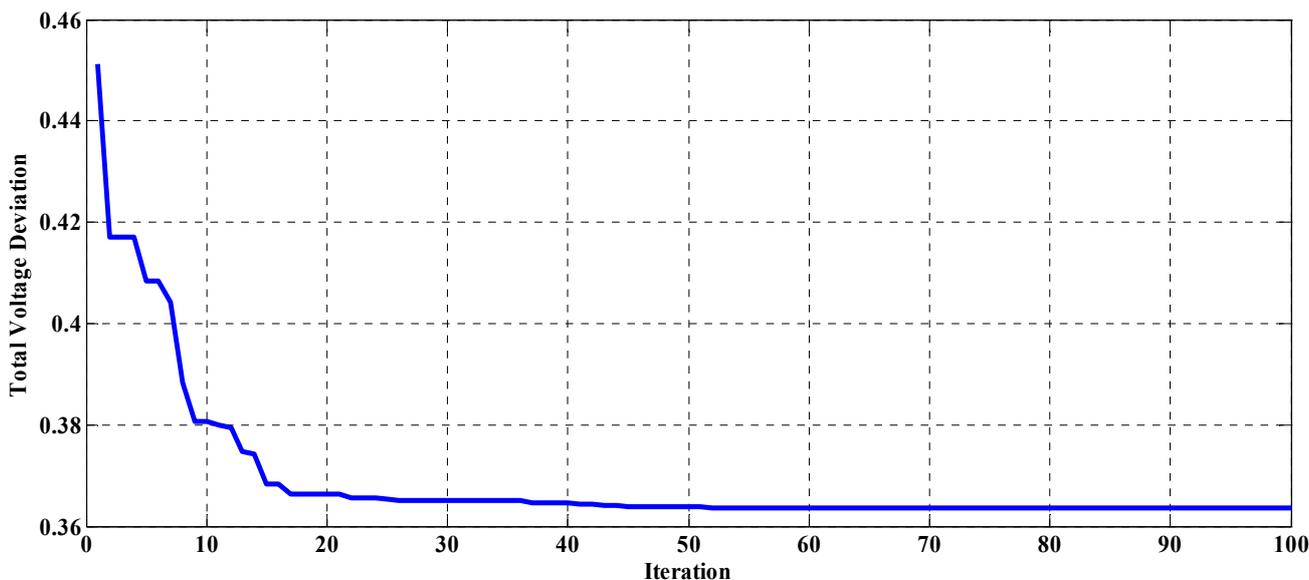
The proposed algorithm has been implemented to optimize the objective functions simultaneously. In Figures 10–13, the distribution of the Pareto optimal set over the trade-off surface for the three objectives using the four mentioned strategies considered for cost objective function are shown. In

each figure, the best compromise solution is shown by a red circle. Here, in Equation (19) w_i = 0.33, i = 1, 2, 3 for three objective functions.
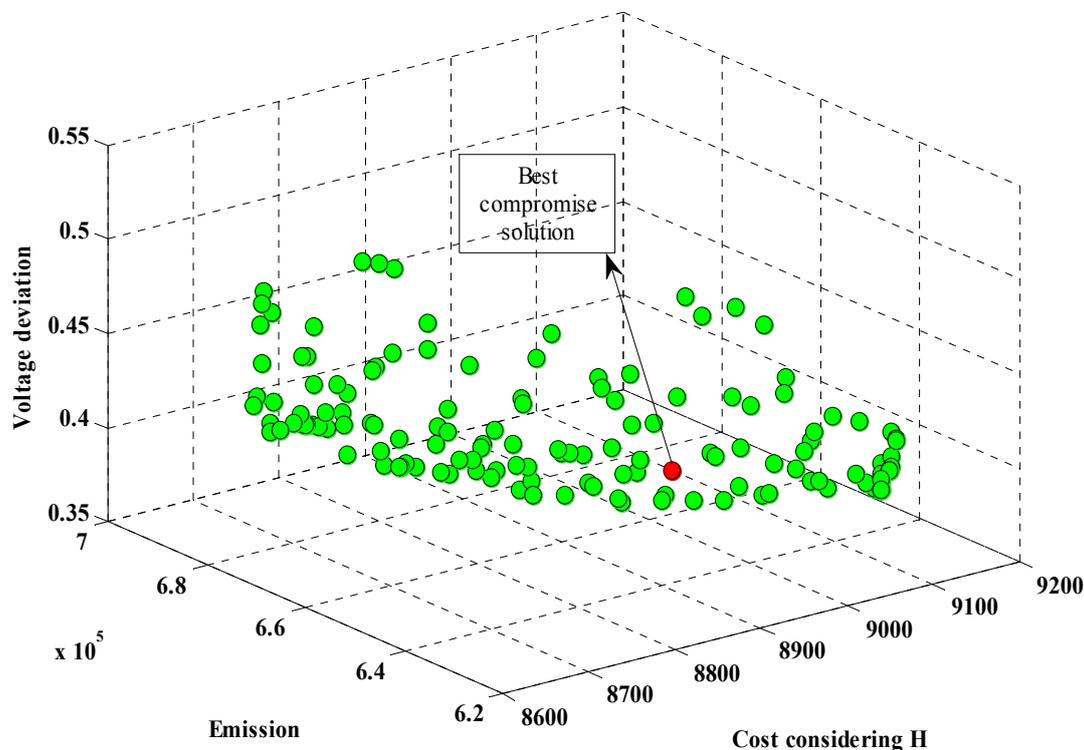
Figure 10. Pareto front for cost considering strategy 1, emission and voltage deviation objective functions.
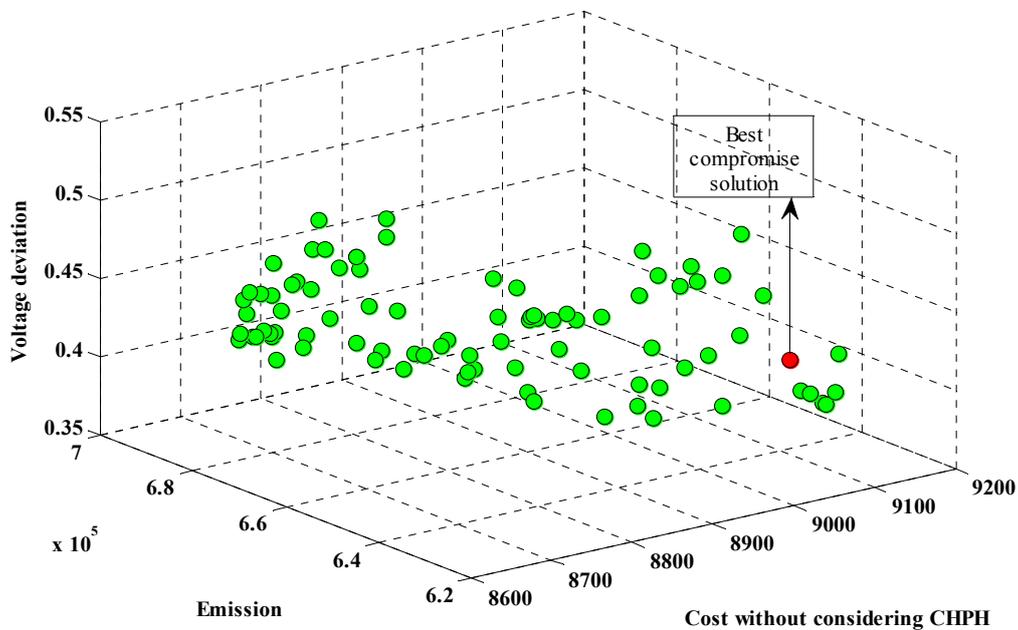
Figure 11. Pareto front for cost considering strategy 2, emission and voltage deviation objective functions.
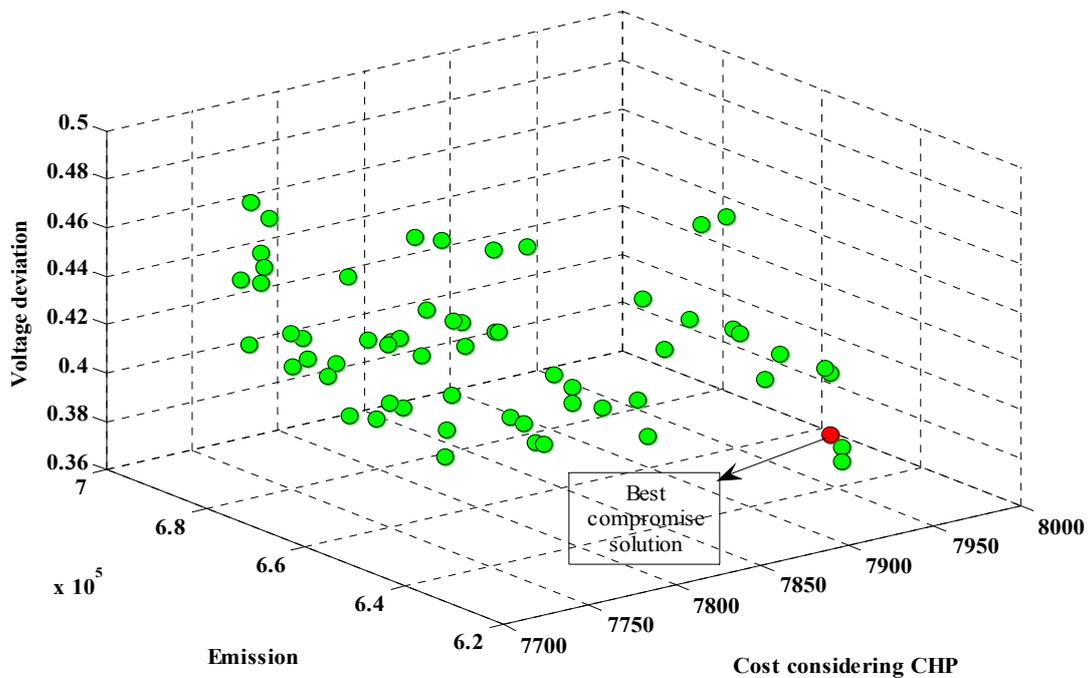
Figure 12. Pareto front for cost considering strategy 3, emission and voltage deviation objective functions.

Figure 13. Pareto front for cost considering strategy 4, emission and voltage deviation objective functions.
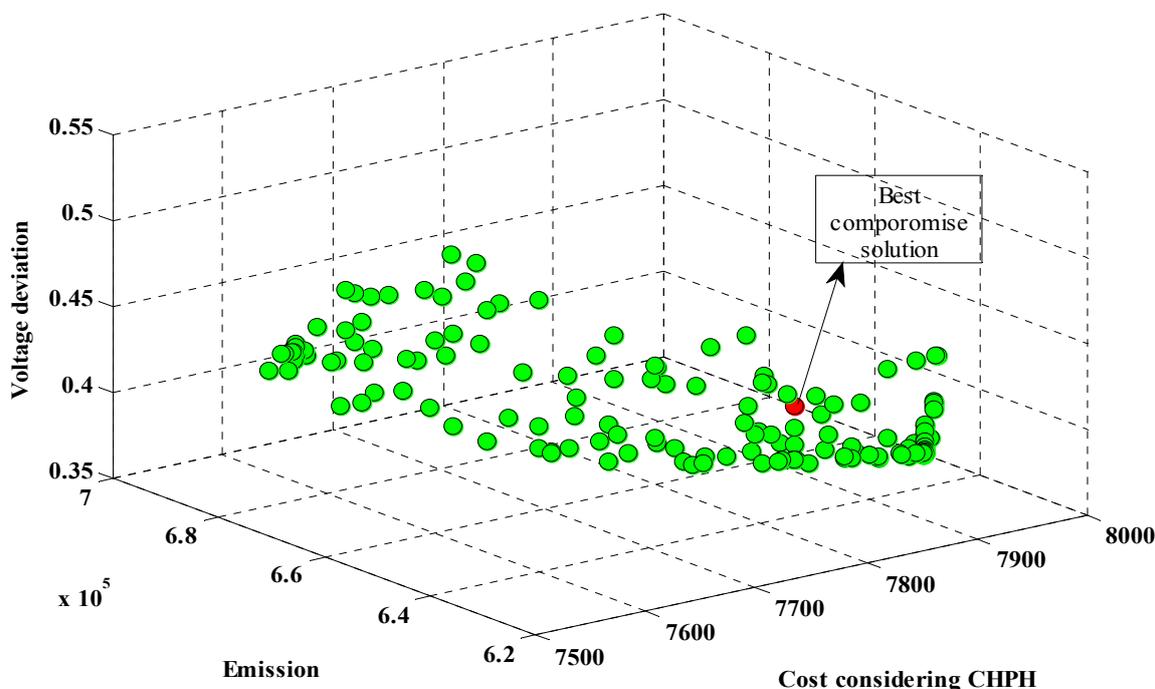

Table 7 presents a comparison among the results obtained by the proposed FAMPSO algorithm for placement of FCPPs to optimize the objective functions simultaneously considering four strategies for the cost objective function. Table 8 shows the values of thermal energy and hydrogen produced by

each FCPP for different strategies of the cost objective function. In multi objective optimization, as shown in Table 7, the lowest cost value is related to strategy 4 and the highest cost value is related to strategy 1. Electrical energy produced by FCPPs releases less pollution in the environment and is very effective in reducing the voltage deviation. Therefore, in the multi objective optimization case, considering emission, voltage deviation, and cost as objective functions result in the FCPPs with higher capacity which are used to generate electrical energy as well as reduce the amount of electrical energy produced by hydrogen. Table 8 demonstrates the above statement where, using FCPPs with more capacity for producing electrical energy causes an increasing production of thermal energy. In this paper the output power of each FCPP is considered to be constant. Since the total capacity of FCPPs supplies a low percentage of the total load and considering the problems of distribution network such as high losses, it is more economical to use the total capacity of FCPPs. As the results show, FCPPs in different cases are used in their maximum or close to their nominal capacity.

Table 7. Results of best compromise solution for multi objective optimization.

Strategies	Cost ($)	Emission (gr)	Voltage deviation (pu)	CPU time (s)	FCCPs locations (Bus Number)	Total electrical generation in a day (kW)
Strategy 1	9.0838×10^3	6.3553×10^5	0.4156	236.2	20,65,63,59	6×10^3, 6×10^3, 6×10^3, 5.815×10^3
Strategy 1	7.9386×10^3	6.3687×10^5	0.3857	238.7	62,25,63,19	6×10^3, 6×10^3, 6×10^3, 6×10^3
Strategy 3	8.9432×10^3	6.4551×10^5	0.3993	240.8	64,17,18,63	6×10^3, 6×10^3, 6×10^3, 5.11×10^3
Strategy 4	7.8233×10^3	6.3856×10^5	0.4168	241.3	61,59,23,65	6×110^3, 6×10^3, 6×10^3, 5.505×10^3

Table 8. Results obtained for thermal energy & hydrogen production for FCPPs by multi objective optimization.

	Results obtained for thermal energy & hydrogen production for FCPPs by multi objective optimization.							
Strategies	Total electrical energy generation by hydrogen production in a day (kW)				Total thermal energy generation in a day (kW)			
	FCCP 1	FCCP 2	FCCP 3	FCCP 4	FCCP 1	FCCP 2	FCCP 3	FCCP 4
Strategy 1	0	0	0	0	0	0	0	0
Strategy 2	0	0	0	0	6.0432×10^3	6.0432×10^3	6.0432×10^3	6.0432×10^3
Strategy 3	0	0	0	889.4078	0	0	0	
Strategy 4	0	0	0	494.7211	6.0432×10^3	6.0432×10^3	6.0432×10^3	5.5693×10^3

Each Pareto optimal solution is an alternative choice for a decision maker. The decision maker can adopt one of them for the respective system based on objective function preferences. In fact, after obtaining the Pareto optimal solutions, the decision maker needs to choose one best compromise solution according to the specific preference for different applications. After generating the Pareto set by FAMPSO, the normalized fuzzy membership function, *i.e.*, Equation (19) is applied to select the best compromise solution of this set. It should be noted that in the fuzzy decision making approach, the importance of the objective functions should be determined. In this regard, w_i refers to the importance of the objective functions such that $\sum_{i=1}^{3} w_i = 1$ (in this paper w_1, w_2 and w_3 shows the importance of cost considering strategy 4 (f_1), emission (f_2), and voltage deviation (f_3) objective functions, respectively).

This paper includes four cases in order to better illustrating the multi-objective placement of FCCP units with CHPH operation problem. Three of the cases solve the proposed problem as a single objective and in the other case the proposed problem is solved as a multi-objective functions considering strategy 4. The results are classified into the following cases:

Case I: considering the f_1 function
Case II: considering the f_2 function
Case III: considering the f_3 function
Case IV: considering f_1, f_2 and f_3 functions

The results of executing the fuzzy decision making approach over Pareto optimal solutions in case IV are illustrated in Table 9. In this table some combinations of decision maker preferences in objective functions are considered as w_i. To compare single-objective with multi-objective optimization, cases I to IV are devoted to the single objective optimization results.

Table 9. Fuzzy decision making on Pareto optimal set.

Cases	Importance			f_1 (kW)	f_2 (gr)	f_3 (pu)
	w_1	w_2	w_3			
Case I	-	-	-	**7.5472×10^3**	6.7561×10^5	0.4716
Case II	-	-	-	7.9170×10^3	**6.3132×10^5**	0.4377
Case III	-	-	-	7.9656×10^3	6.4380×10^5	**0.3636**
Case IV	0.33	0.33	0.33	7.8233×10^3	6.3856×10^5	0.4168
	0.4	0.4	0.2	7.7192×10^3	6.4308×10^5	0.45
	0.4	0.2	0.4	7.6783×10^3	6.4972×10^5	0.419
	0.2	0.4	0.4	7.9239×10^3	6.3310×10^5	0.4071
	0.8	0.1	0.1	7.5620×10^3	6.7642×10^5	0.4431
	0.1	0.8	0.1	7.9184×10^3	6.3168×10^5	0.4408
	0.1	0.1	0.8	7.9636×10^3	6.4328×10^5	0.3638

Analyzing the results outcomes the following points:

- In Cases I–III, when each objective is minimized individually, its value is the best one among the cases. Also, it can be seen that when each objective reaches its minimum value, the value of the other objectives will increase with respect to their minimum (when they are minimized in a single objective optimization process).

- Objectives f_1 and f_2 are conflicting. To minimize the emissions, FCPPs should generate more active power, so the energy costs will be increased. The results of Cases I, II, and IV-3, 4, 5 and 6 support this fact.

- Objectives f_1 and f_3 are conflicting. For instance, in case IV when $w_1 = 0.8$ and $w_3 = 0.1$, the cost function and voltage deviation are 7.5620×10^3 \$ and 0.4431 pu, respectively; in contrast when $w_1 = 0.1$ and $w_3 = 0.8$, the cost and voltage deviation are 7.9636×10^3 \$ and 0.3638 pu, respectively. The results of cases I, III and IV 2 and 4 confirm the above statements.

- The objectives f_2 and f_3 have similar interests. In cases IV-3 and 4 when the importance of f_2 is fixed and the importance of f_3 is increased, the value of f_2 decreases.

- In cases I and II when the value of f_2 is decreased, the value of f_3 is also decreased.
- In case IV when the importance of f_1 is decreased the values of f_2 and f_3 are increased.
- Case IV-1 has a suitable tradeoff between all objective functions.

8. Conclusions

In this paper, a multi-objective FAMPSO algorithm was proposed and applied to locate FCPPs in distribution systems. The objective functions consists of the total cost of the system (including the CHPH FCPP units), the total emission produced by the system and the voltage deviation of each bus from its nominal value. The mentioned algorithm uses the concept of Pareto optimality. One of the most important privileges of the multi-objective formulation is that it allows the decision maker to apply his personal experiences in selecting any of the non-dominated solutions called Pareto optimal solutions in the repository. To improve the original PSO algorithm, the mating process is enhanced to improve the exploration ability of the algorithm in the entire search space. In this paper, the effect of hydrogen production and thermal recovery on the optimal cost of FCPP units in a distribution network was investigated. Results show that considering the effect of heat and hydrogen produced by FCPPs reduces the cost extremely, which obviously causes in a significant cost savings. Using FCPPs in distributed networks reduces emission and voltage deviation, which are benefits for the grid operator. Due to the increase in the energy demand all over the World, reducing the cost is crucial. In this regard, the cost objective function includes the production cost, thermal recovery, hydrogen production and the charge of buying natural gas to satisfy the thermal loads. In this paper the proposed procedure gives the decision maker a very good point of view for selecting the best solution between the Pareto optimal solutions. In conclusion, this paper introduces an efficient algorithm with a low convergence time while investigating the actual model of grid and FCPPs. The simulation results show the satisfying and good performance of the proposed method.

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