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# FUZZY MULTI-OBJECTIVE OPTIMAL POWER FLOW CONSIDERING UPFC

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Abstract. *This paper presents a fuzzy optimization method to enhance the Optimal Power Flow (OPF) considering Unified Power Flow Controller (UPFC). The OPF problem is formulated as a nonlinear programming optimization problem using multiobjective framework wherein the total generation fuel cost and active power losses are considered as objective functions of the optimization problem. In the proposed approach, firstly, the total fuel cost generation and active power losses are optimized individually in order to obtain the fuzzy membership functions of the objectives, and then, the multi-objective problem is reformulated as a new standard nonlinear problem using the fuzzy sets theory and max-min operator. Finally, it is solved by nonlinear programming by means of discontinuous derivatives method. The simulation results of the IEEE 30-bus test system show the performance of the proposed method.*
**Keywords:** Fuzzy optimization, Optimal power flow, Decision making, UPFC

1. **Introduction.** Formerly, Carpentier [1] introduced a generalized, nonlinear programming formulation of the economic dispatch problem including voltage and other operating constraints. This formulation was later named the Optimal Power Flow problem (OPF) [2]. The main aim of the OPF is to determine the optimal steady state operation of a power system, which simultaneously minimizes the value of a chosen objective function and satisfies certain physical and operating constraints. Thus, the economic dispatch (ED) and power flow (PF) calculation have been ideally integrated into OPF problem. Today, any problem that involves the determination of the instantaneous "optimal" steady state of an electric power system is an OPF problem [3-5]. Different classes of the OPF problems, tailored towards special-purpose applications, are defined by selecting different functions to be optimized, different sets of controls and different sets of constraints.

In multi-objective OPF, due to being poor collaboration among design objectives and poor resolution of design conflicts, relations are complex and system operator (decision maker) encounters more uncertainty in planning to satisfy system preferences. To handle these problems, a fuzzy multi-objective optimization model is applied. Fuzzy set theory represents an attractive tool to aid research in optimization techniques when uncertain relationships or inconsistent measurements among model parameters limit the specification of model objective functions and constraints. Recently, fuzzy set theory has been successfully applied in solving power system optimization problems because it provides a new approach to coordinating multiple conflicting objectives of the problem. In this paper, constraints are classified into two parts: soft constraints and hard constraints. The OPF problem is formulated with fuzzy objective and fuzzy soft constraints. In the other words, security considerations of the network are considered as fuzzy soft constraint. An efficient nonlinear programming with discontinuous derivatives (DNLP) method is then modified to solve this new formulation. The numerical results show that the fuzzy OPF can be equivalent to the crisp OPF where a feasible solution exists. When there is no feasible solution for the crisp OPF, the fuzzy OPF can obtain a more realistic solution that "evenly" distributes violations of the limits, rather than violates a single normal limit excessively.

Also, security and reliability are the major concerns in the deregulated and unbundled electricity supply industry due to the increased number of market participants and the changing demand patterns. Congestion management has been debated much for increasing competition electricity power generation in both pool and bilateral dispatch models [6]. In this paper, congestion is corrected by corrective actions using FACTS devices. Indeed, while system security constraints are softened using fuzzy approach, in return, FACTS devices are considered in the network to facilitate power system security control by the system operator.

Many conventional optimization techniques were developed to solve the OPF problem; the most popular approaches are linear programming, sequential quadratic programming, generalized reduced gradient method and the Newton method. [7-9] offer a complete list of the most commonly used conventional optimization algorithms with regard to the OPF. Despite the fact that some of these techniques have excellent convergence characteristics and various among them are widely used in the industry, some of their drawbacks are [10]:

1. Convergence to the global or local solution is highly dependant on the selected initial guess; i.e., they might converge to local solutions instead of global ones if the initial guess happens to be in the vicinity of a local solution.
2. Each technique is tailored to suit a specific OPF optimization problem based on the mathematical nature of the objectives and/or constraints.
3. They are developed with some theoretical assumptions, such as convexity, differentiability and continuity, among other things, which may not be suitable for the actual OPF conditions.

A new category of computational intelligence tools has emerged to cope with some of the traditional optimization algorithms' shortcomings. The main modern techniques include evolutionary programming (EP) [11,12], genetic algorithm (GA) [13,14], evolutionary strategies (ES) [15], artificial neural network (NN) [16,17], simulated annealing (SA) [18], ant colony optimization (ACO) [19] and particle swarm optimization (PSO) [20,21]. Most of these relatively new developed tools mimic a certain natural phenomenon in its search for an optimal solution like species evolution (EP, GA and ES), human neural systems (NN), thermal dynamics of a metal cooling process (SA), data processing and interpretation in human brain (FST), or social behavior (ACO and PSO). They have been successfully applied to a wide range of optimization problems in which global solutions are more preferred than local ones or when the problem has non-differentiable regions. However, these methods have some drawbacks too, such as:

1. These methods require significantly large computations and are not efficient enough for real-time use energy management system. Hence, there is a need of an alternative approach, which can quickly respond to changes of power system conditions in possible shortest time.
2. Implementation of these methods is difficult.

3. Intelligence methods generate a Pareto solution set and decision maker must select best compromise solution through Pareto solutions by a decision making approach.
4. Intelligence methods are stochastic and cannot strictly figure on solutions optimality.

To handle the mentioned problems, fuzzy optimization approach, as a mathematical method which does not have problems of traditional mathematical optimization and yet covers intelligent methods problems, can be an effective key in solving multi-objective optimization problems.

Some of its advantages are expressed as follows:

1. All objectives and constraints are considered as fuzzy form, simultaneously.
2. Using Generalized Algebraic Modeling of System (GAMS) software for solving fuzzy multi-objective model reduces computation time.
3. Fuzzy optimization generates an optimal solution in the end of algorithm and so do not need a decision making approach.

The remainder of this paper is organized as follows: UPFC model is presented in Section 2. In Section 3, the proposed mathematical formulations of the multiobjective OPF are expressed in the form of a nonlinear programming problem concerning system's physical and technical constraints. In Section 4, solution approach of the fuzzy optimization framework is mentioned. In the next section, the IEEE 30-bus test system is studied to demonstrate effectiveness of the proposed scheme. Some relevant conclusions are drawn in Section 6.

2. **UPFC Model.** The basic schematic of the UPFC is presented in Figure 1. The power injection model of the UPFC is shown in Figure 2.

$$P_{ss} = -\, b_s r V_i V_j \sin(\theta_i - \theta_j + \gamma) \tag{1}$$

$$Q_{ss} = -\, b_s r V_i^2 (r + 2\cos(\gamma)) + b_s r V_i V_j \cos(\theta_i - \theta_j + \gamma) \tag{2}$$

$$P_{sr} = -P_{ss} \tag{3}$$

$$Q_{sr} = +\, b_s r V_i V_j \cos(\theta_i - \theta_j + \gamma) \tag{4}$$

here $r$ is the radius of the UPFC operating region; $\gamma$ is the UPFC phase angle; $b_s$ is $1/(X_S + X_B)$ where $X_S$ is the transmission line reactance and $X_B$ is the series transformer leakage reactance [22].

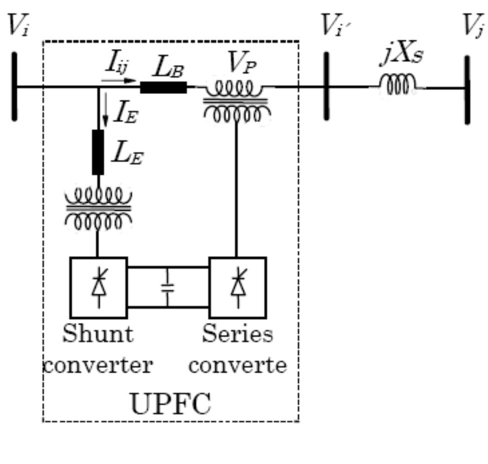



Figure 1. Basic schematic diagram of UPFC

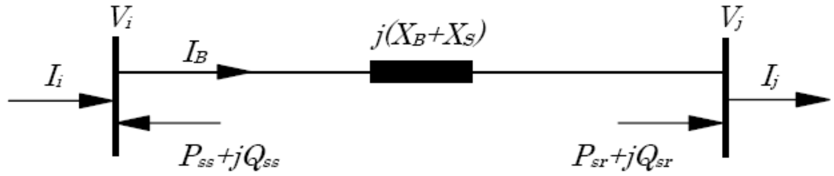



FIGURE 2. The power injection model of UPFC

3. **Problem Formulation.** The economic optimal operation of power systems, considering transmission constraints and supplying load demand, requires to minimize two objective functions (total generation fuel cost and active power losses) while satisfying several equality and inequality constraints. Generally the optimal operation problem which named OPF can be formulated as follows.

3.1. **Objective functions.**

3.1.1. *Minimization of total generation fuel cost.* The generation cost function is represented by a quadratic polynomial function as follows [23]:

$$F_1 = \sum_{i=1}^{g} C_i(P_{Gi}) = \sum_{i=1}^{g} \alpha_{0i} + \alpha_{1i} P_{Gi} + \alpha_{2i} P_{Gi}^2 \ \ (\$/h) \tag{5}$$

where $P_{Gi}$ is the real power generation of unit $i$. Also, $\alpha_{0i}$, $\alpha_{1i}$ and $\alpha_{2i}$ are cost coefficients of unit $i$; $g$ is the number of generators.

3.1.2. *Active power losses.* The total power loss to be minimized is as follows [24]:

$$F_2 = F(V, \delta) = \sum_{i=1}^{n} \sum_{j=1}^{n} V_i V_j Y_{ij} \cdot \cos(\alpha_{ij} + \theta_j - \theta_i) \tag{6}$$

3.2. **Constraints.**

3.2.1. *Generation real power limits.* The real power output limits of generator $i$ are formulated as:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \quad \forall i \in NG \tag{7}$$

3.2.2. *Voltage control and reactive support.* The voltage limits and reactive power output limits assuming constant power factor for loads can be expressed using following inequalities:

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad \forall i \in NG \tag{8}$$

$$\left|V_i^{\min}\right| \le |V_i| \le |V_i^{\max}| \quad \forall i \in n \tag{9}$$

where $Q_{Gi}$, $Q_{Gi}^{\min}$, $Q_{Gi}^{\min}$ are stand for reactive power output, maximum and minimum reactive limits of generating unit $i$, respectively. Also, $|V_i|$, $\left|V_i^{\min}\right|$ and $|V_i^{\max}|$ are related to bus voltage, minimum and maximum limits of voltage of $i^{\text{th}}$ bus, respectively.

3.2.3. *Power balance equations.* Real and reactive power balance equations of $i^{\text{th}}$ bus considering injected active and reactive power of FACTS devices can be expressed as [22]:

$$P_{Gi} + P_{FACTS} = P_{Di} + \sum_{j=1}^{n} V_i V_j Y_{ij} \cos(\alpha_{ij} + \theta_j - \theta_i) \quad \forall i, j \in n \tag{10}$$

$$Q_{Gi} + Q_{FACTS} = Q_{Di} + \sum_{j=1}^{n} V_i V_j Y_{ij} \sin(\alpha_{ij} + \theta_j - \theta_i) \quad \forall i, j \in n \tag{11}$$

where $i = 1, 2, \cdots, n$; and $n$ is the number of buses, $P_{Gi}$ and $Q_{Gi}$ are the generated real and reactive power of unit located at bus $i$, respectively; $P_{Di}$ and $Q_{Di}$ are the real and reactive power of load located at bus $i$, respectively; $P_{FACTS}$ and $Q_{FACTS}$ are active and reactive power injected by FACTS devices to the specific bus, respectively.

3.2.4. *Transmission constraints.*

$$|S_l| \le |S_l^{\max}| \quad \forall i \in NB \tag{12}$$

where $|S_l|$, $|S_l^{\max}|$ are stand for the apparent power flow and the capacity of $l^{\text{th}}$ transmission line.

3.2.5. *UPFC constraints.*

$$0 \le r \le r_{\max} \tag{13}$$

$$-\pi \le \gamma \le \pi \tag{14}$$

In (13) and (14) represent the limits of the parameters of UPFC, i.e., $r$ and $\gamma$, parameters, respectively.

## 4. Fuzzy Multiobjective Algorithm.

### 4.1. Finding the optimum value of each objective function.

The optimization model to find the optimum value of each objective is given by [25]:

$$\begin{array}{lll} \text{Minimize} & F_t(X), & t = 1, 2 \\ \text{Subject to} & h_i(X) = 0, & i = 1, 2, \cdots, M \\ & g_j(X) \le 0, & j = 1, 2, \cdots, N \\ & X_k^l \le X_k \le X_k^u & \end{array} \tag{15}$$

where, $F_t(X)$ refers to the objective functions; Also, $h_i(X)$ and $g_j(X)$ are equality and inequality constraints. Finally, $X_k$ is the $k^{\text{th}}$ decision variable.

The solution of the above model is the optimum solution of each objective function, $X_t'$, and the optimal value of the objective function at the optimum solution, $X_t'$, can be written as:

$$F_t^u = F_t(X_t') \quad (t = 1, 2) \tag{16}$$

where, $F_t^u$ is the optimum value of $t^{\text{th}}$ objective function.

4.2. **Fuzzy multiobjective optimization model.** Due to the compromised nature of the solutions of multi-objective optimization problems, it is well-fitted to implement fuzzy decision making approach [26,27]. Because of the conflicting objective functions and the role of human decision on the final solution of the multiobjective optimization solutions, the fuzzy method can be implemented to solve the problem.

In the fuzzy set theory, membership functions are established to fuzzify the fuzzy sets. The membership function values vary between zero and one. The elements in a fuzzy set with membership value 1 reflect that they are in the core of the fuzzy set. The membership function value is zero for the element outside the fuzzy set. The elements with membership function value between zero and one construct the boundary of the fuzzy set. In order to use fuzzy set theory to solve the optimization problems, the fuzzy constraints have to be formed first. These constraints originated from the given crisp constraints by relaxing the bounds. A corresponding membership function is established to describe the fuzziness of each constraint. In addition to fuzzy constraints, fuzzy objective functions are also needed. Each objective function is converted into a pseudo-goal. A membership function is associated with the pseudo-goal. The pseudo-goal has membership function value one if the design is located at the optimum from the single-objective optimization problem with the same constraints for the multiobjective design. It is obvious that solving the multiobjective optimization problem is essential to simultaneously make all membership function values of the pseudo-goals as large as possible.

The above-mentioned procedure is summarized as follows:

(a) Finding the minimal and maximum feasible value of each objective function considering constraints:

$$m_i = \min_{1 \le l \le n} F_i(X_l^*) = F_i(X_i^*) \tag{17}$$

$$M_i = \max_{1 \le l \le n} f_i(X_l^*) \tag{18}$$

where, $m_i$ and $M_i$ are the minimum and maximum feasible value of $i^{\text{th}}$ objective function, respectively. Accordingly, using (16) and (17) for the OPF problem with individual objective functions, total generation fuel cost ($F_1$) or active power losses ($F_2$), the payoff table, Table 1, can be performed as follows:

$$m_1(\text{Minimum cost}) = F_1^*(X_1^*)$$

$$M_1(\text{Maximum cost}) = F_1(X_2^*)$$

$$m_2(\text{Minimum loss}) = F_2^*(X_2^*)$$

$$M_2(\text{Maximum loss}) = F_2(X_1^*)$$

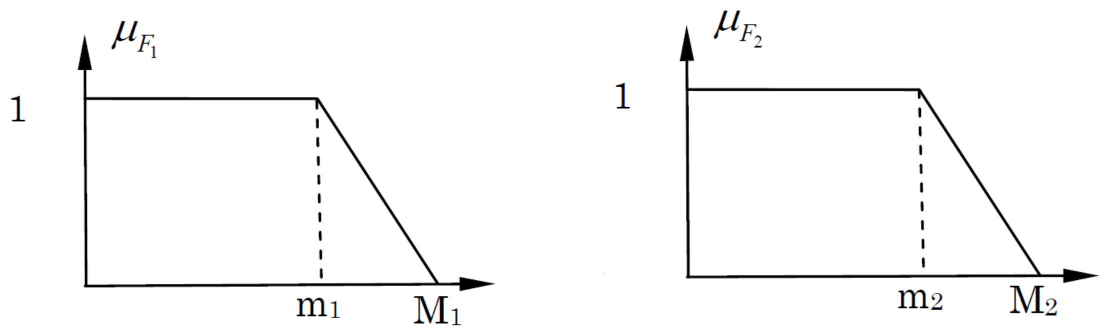
Table 1. Payoff table

| | $F_1$ | $F_2$ |
|---|---|---|
| $(\min F_1, F_2)$ | $F_1^*(X_1^*)$ | $F_2(X_1^*)$ |
| $(F_1, \min F_2)$ | $F_1(X_2^*)$ | $F_2^*(X_2^*)$ |

(b) Establishing the membership function of each fuzzy objective function: Most applications that involve fuzzy set theory have a tendency to be independent of the specific shape of the membership functions. For total generation fuel cost and active power losses functions, it is suitable to use a membership function with trapezoidal form, as shown in

Figure 3; the membership function is as follows:

$$\mu_{\tilde{F}_i}(X) = \begin{cases} 1, & F_i(X) \le m_i, \\ \dfrac{M_i - F_i(X)}{M_i - m_i}, & m_i < F_i(X) < M_i, \quad (i = 1, 2) \\ 0, & F_i(X) \ge M_i \end{cases} . \tag{19}$$




(a) (b)

FIGURE 3. (a) Total fuel cost membership function; (b) active power losses membership function

(c) Establishing the membership function of each fuzzy constraint function: For simplicity, a linear membership function is used to reflect the smooth transition. Other types of the membership function can also be used depending on the problems under consideration. The linear membership function is given by:

$$\mu_{\tilde{g}_i}(X) = \begin{cases} 1, & g_j(X) \le b_j, \\ \dfrac{[(b_j + d_j) - g_j]}{d_j}, & b_i < g_j(X) < b_j + d_j, \\ 0, & g_j(X) \ge b_j + d_j. \end{cases} \tag{20}$$

where $b_j$ and $b_j + d_j$ form an allowable fuzzy transition interval for the $j^{\text{th}}$ inequality constraint. In this paper, constraints are classified into two parts: soft constraints (transmission power flow constraint, i.e., (12)) and hard constraints (such as active and reactive power balance, i.e., Equations (10) and (11), respectively). Therefore, the above membership function, (20), can be used to fuzzify power flow of lines, (12). In this regard, in the fuzzy optimization model, the power flow of a transmission line ($S_l$) can increase up to $1.1S_l^{\max}$. That is, $b_j = S_l^{\max}$ and $b_j + d_j = 1.1\,S_l^{\max}$.

(d) Establishing fuzzy multiobjective optimization model:

$$\begin{array}{lll} \text{Maximize} & \lambda & \\ \text{Subject to} & \lambda \le \mu_{\tilde{F}_i}(X), & i = 1, 2 \\ & \lambda \le \mu_{\tilde{h}_i}(X), & i = 1, 2, \cdots, I \\ & \lambda \le \mu_{\tilde{g}_j}(X), & j = 1, 2, \cdots, J \\ & 1 \ge \lambda \ge 0 & \\ & X_k^u \ge X_k \ge X_k^l, & k = 1, 2, \cdots, k \end{array} \tag{21}$$

The flowchart of finding the best location for the UPFC in the network is illustrated in Figure 4. In this flowchart, UPFC is located in different lines and the mentioned model, (21), is executed. After searching all lines, the best line selected based on the fuzzy decision making approach [28].

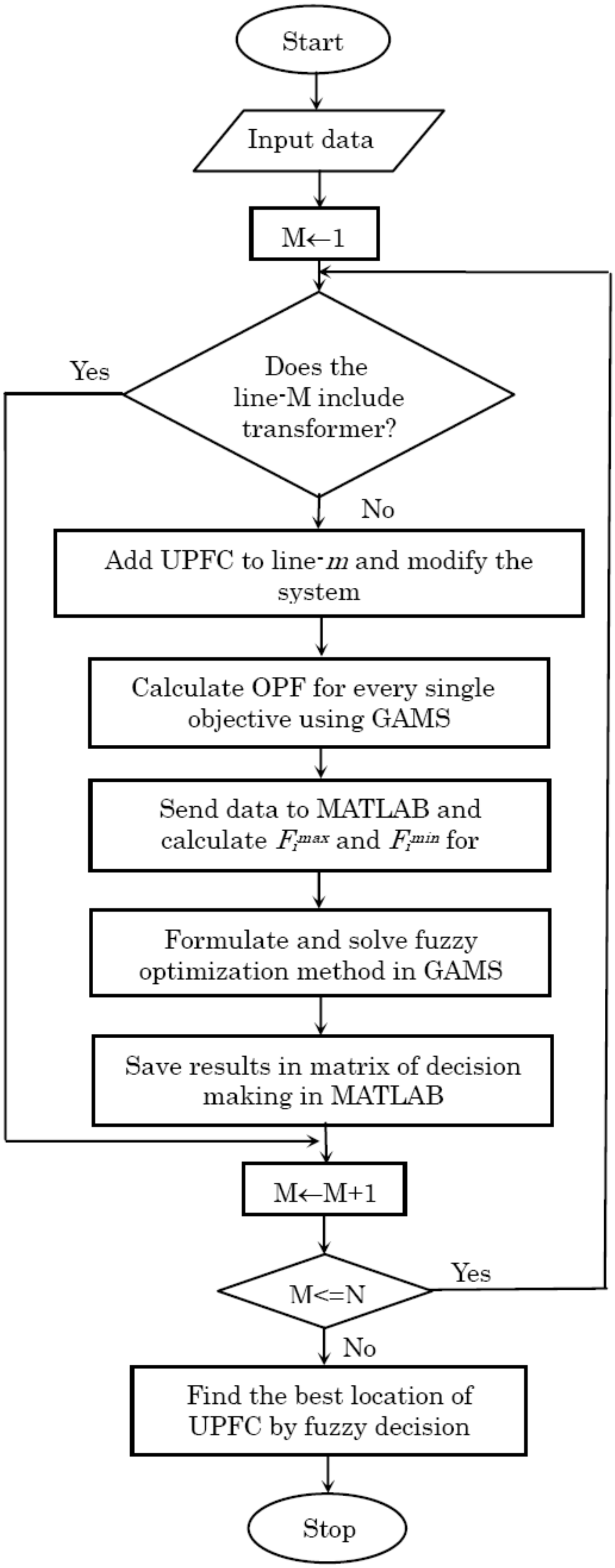



Figure 4. Flowchart of fuzzy multiobjective optimization

5. **Case Study.** The optimal power flow problem using the proposed fuzzy optimization algorithm is implemented in MATLAB and GAMS software which handles nonlinear programming with discontinuous derivatives (DNLP) method to minimize total generation fuel cost and active power losses of the system, simultaneously. The UPFC performance is tested on the IEEE 30-bus [29] and optimal settings of the UPFC and its best location are determined. To demonstrate the effectiveness of the proposed approach, different cases with various objectives are considered as follow:

- Case 1: Total generation fuel cost is minimized
- Case 2: Active power losses are minimized
- Case 3: Total fuel cost and active power losses are minimized simultaneously

In the case 1, the total fuel cost is 802.252 ($/h) and 790.820 ($/h) for cases without UPFC and with UPFC, respectively. The investment cost of UPFC is 383.19 ($/h) as shown in the fourth column of Table 2. The aim of the case 2 is to minimize total active power losses with optimal placement of UPFC. The results of Table 2 show that total active power losses are decreased from 3.290 MW to 2.032 MW while the investment cost of utilizing UPFC is 270.44 ($/h). In the case 3, the active power losses and the cost of UPFC are simultaneously minimized. It can be seen in the Table 2 that the total fuel cost of this case has a value between the corresponding values of the other cases, i.e. 802.25 $ < 849.947 $ < 968.11 $ and 790.83 $ < 833.648 $ <965.12 $ for the states with and without installing UPFC, respectively. Also in case 3 active power losses are in the middle of the respective value for the cases 1 and 2.

Table 2. Results implementing the proposed method in IEEE 30-bus test system

| CASE | Parameters | Status 1 (without UPFC) | Status 2 (with UPFC) |
|---|---|---|---|
| CASE 1 | Active power losses (MW) | 802.25 | 790.83 |
| | $\sum P_{loss}$ (MW) | 9.447 | 6.362 |
| | Reactive power losses (MVAr) | 37.789 | 25.715 |
| | Investment cost ($/h) | – | 383.19 |
| | FACTS Size (MVA) | – | 102.47 |
| | FACTS Location | – | Line 2-5 |
| | FACTS Settings | – | $r = 20.44$, $\gamma = 85.17$ |
| CASE 2 | Active power losses (MW) | 3.29 | 2.031 |
| | Total Fuel Cost ($/h) | 968.11 | 965.12 |
| | Reactive power losses (MVAr) | 16.245 | 11.668 |
| | Investment cost ($/h) | – | 270.44 |
| | FACTS Size (MVA) | – | 69.27 |
| | FACTS Location | – | Line 2-5 |
| | FACTS Settings | – | $r = 0.137$, $\gamma = 66.12$ |
| CASE 3 | Total Fuel Cost ($/h) | 849.947 | 833.648 |
| | Active power losses (MW) | 5.061 | 3.096 |
| | Reactive power losses (MVAr) | 22.318 | 14.863 |
| | Investment cost ($/h) | – | 346.151 |
| | FACTS Size (MVA) | – | 91.248 |
| | FACTS Location | – | Line 2-5 |
| | FACTS Settings | – | $r = 0.180$, $\gamma = 78.658$ |

Most of literatures in the area of OPF refer to special single objective optimization problem (considering generators fuel cost function) [30-35]; however, in this paper, to concurrently minimize generators fuel cost and active power loss of power systems in presence of FACTS devices, the multi-objective OPF is adopted. In fact, a system operator can profit by the proposed flexible multiobjective optimization framework considering its preferences in the operation conditions of the network. To show this subject, numerical results of single (based on the previous works in the area [30-35]) and multiobjective OPF on IEEE 30-bus are presented and compared with each other. In case 1, generator fuel cost function is considered as the objective function and the OPF optimized in the form of single objective optimization problem wherein values of fuel cost and active power losses are equal to 802.25 \$/h and 9.447 MW, respectively. In this status, the optimal solution has the minimum fuel cost and the maximum active power losses. Correspondingly, in case 2, the active power loss is adopted as the objective function. Accordingly, the obtained values for active power losses and fuel cost are equal to 3.29 MW and 968.11 \$/h, respectively. In case 2, in contrast with case 1, active power losses and generator fuel cost have their minimum and maximum values, respectively. Both of the above-mentioned cases will not satisfy all of the system operators' concerns, simultaneously. System operators want to profit by the scheme that it is capable of compromising between their objective functions. To get access to this goal, multiobjective optimization framework is an essential requirement. By the way, in case 3, generator fuel cost and active power losses are considered simultaneously in the multiobjective optimization framework. Hence, the proposed multiobjective OPF is solved and values of total fuel cost and active power losses are achieved 849.947 \$/h and 5.061 MW, respectively. Comparing the results of case 3 with respect to cases 1 and 2, it can be inferred that the results of proposed multiobjective framework is trade-off between the results of single objective cases (case 1 and 2). In the other words, optimized operation of the power system as one of the main responsibilities of the system operators are incorporated in the multiobjective OPF considering an extra objective function, i.e. total active power losses. The proposed method can compromise the conflicting objectives of the scheduling of generating units in such a way that the system operators' concerns about the system operation are relieved with tolerable and reasonable total generation cost. Additionally, this paper has shown the economic benefits of implementing FACTS devices which efficiently manage power flows in the network. Therefore, it can be inferred that the multiobjective approach can lead to a more efficient utilization of generating units as well as transmission lines and it permits the system operator to estimate how likely system security are and what are the possible actions to cope with congestion in the system.

6. **Conclusion.** This paper presents a new multiobjective optimal power flow method while UPFC is considered. The equations for the inclusion of the UPFC devices are presented with an appropriate circuit model. A mathematical model is presented with a fuzzy optimization formulation. The solution of the fuzzy problem through a nonlinear programming using DNLP method is presented. The method is tested on the IEEE 30-bus system and its results are presented. The results of implementing fuzzy approach shows that using multiobjective optimization problem leads to enhance flexible framework for solving optimal power flow problems while meeting the uncertainty of some parameters of the model. In other words, the system operator can relax some of its constraints and limitations using fuzzy approach. Therefore the optimization problem of network operation can be solved with more feasible region of candidate solutions. Consequently, the proposed method with respect to the crisp optimization makes more flexible optimization solution for the operator in the system.

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