Multi-objective optimal location of Optimal Unified Power Flow Controller (OUPFC) through a fuzzy interactive method

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Received 24 June 2014; received in revised form 28 March 2015; accepted 16 June 2015

KEYWORDS
OUPFC;
UPFC;
FACTS;
Optimal location;
Multi-objective;
Fuzzy interactive method.

Abstract. This paper presents a fuzzy interactive approach to find the optimal location of Optimal Unified Power Flow Controller (OUPFC) device as a multi-objective optimization problem. The problem formulation is based on Optimal Power Flow (OPF) problem while the metric function and weighting method are added to ensure the collaboration among objective functions. The objective functions are the total fuel cost, power losses, and system loadability with and without the minimum cost of OUPFC installation. The proposed algorithm is implemented on IEEE 14- and 118-bus systems. The solution procedure uses nonlinear programming with discontinuous derivatives (DNLP) to solve the optimal location and settings of OUPFC device to enable power system dispatcher to improve the power system operation. The optimization problem is modeled in General Algebraic Modelling System (GAMS) software using CONOPT solver. Furthermore, the results obtained by OUPFC are compared with those of the Unified Power Flow Controller (UPFC) device. The OUPFC is outperformed by UPFC in the power system operation from the economic and technical point of view.

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1. Introduction

The optimum operation of an interconnected power system involves dispatcher concerns such as optimal choice and allocation of Flexible AC Transmission Systems (FACTS) devices as power flow controllers. Optimal Unified Power Flow Controller (OUPFC) is a member of FACTS controllers that can provide the necessary functional flexibility for optimal power flow control through phase angle control. It is composed of a conventional Phase Shifting Transformer (PST) and a scale-down Unified Power Flow Controller (UPFC).

The steady-state model of OUPFC and its operational characteristics are introduced in [1].

The multi-objective OPF problem considering FACTS devices is addressed in many technical literature. In [2], the best location of PSTs has been determined by genetic algorithm to reduce the flows in heavily loaded lines resulting in increased system loadability and reduced generation costs. The best optimal location of FACTS devices, in order to reduce the generation costs along with the device’s cost using real power flow performance index, has been reported [3]. A hybrid tabu search and simulated annealing has been proposed to minimize the generator fuel cost in OPF control with multi-type FACTS devices [4]. The optimal location of FACTS devices has been found using the Particle Swarm Optimization (PSO) technique for considering system loadability and installation cost [5].
In [6], the multi-objective optimal location of PST, UPFC, and OUPFC has been considered using the ε-constraint method. The contingency-based optimal location of UPFC and OUPFC has been investigated under a single-line contingency [7].

Several different methods have been widely applied for solving various power system problems such as optimal location and OPF problems. These methods can be divided into two main categories:

(i) Mathematical methods that include nonlinear programming [8], quadratic programming [9,10], linear programming [11,12], Newton-based techniques [13,14], sequential unconstrained minimization [15], interior point [16,17], and minimum cut algorithm [18].

(ii) Intelligent methods that include Evolutionary Programming (EP) [19], Genetic Algorithm (GA) [20-22], Differential Evolution (DE) [23], Artificial Neural Network (ANN) [24], Simulated Annealing (SA) [25,26], Artificial Bee Colony algorithm (ABC) [27], PSO [28], harmony search algorithm [29], and gravitational search algorithm [30].

Although some of the mathematical methods have excellent convergence characteristics, some drawbacks of these methods are [31]:

- The solution converges to a local optimum instead of a global optimum, depending on the selected initial values;
- Each technique is suitable for a specific kind of optimization problem based on the mathematical nature of the objectives and/or constraints;
- Some theoretical assumptions, such as convexity, differentiability, and continuity, are built into these methods which may not be suitable for the OPF problem;
- They are not able to interact with the decision-maker through optimization process.

In addition, the intelligent methods have been successfully used to solve the optimization problems in which global solutions are more preferred than local ones, or when the problem has non-differentiable regions. But these methods have some drawbacks, too, such as:

- These methods require significantly large computations and are not efficient enough for real-time systems that need to quickly change the system;
- Implementation of these methods is difficult;
- They generate a Pareto solution set; the decision-maker must select the best compromise solution through Pareto solutions by a decision-making approach;
- They are stochastic and cannot strictly figure on solutions optimally;
- They are not able to interact with the decision-maker through optimization process.

In order to handle the mentioned problems, the fuzzy optimization approach is used to solve the multi-objective optimization problems. The objective functions and constraints are considered as modified constraints in terms of their fuzzy membership functions. The model is constructed by definition of sets of membership functions for each constraint and objective function. Therefore, the main purpose of a fuzzy optimization problem is to maximize all membership functions at the same time. This is usually done using a formulation similar to the min–max formulation for the multi-objective optimization [32]. Consequently, fuzzy optimization lends itself to multi-objective optimization where additional objective functions are modeled as constraints. Moreover, the conflicting degree among objectives and the designer’s preferences are nearly neglected in many fuzzy multi-objective optimization models; however, they are still an ongoing research topic.

In this paper, an interactive fuzzy multi-objective optimization method, incorporated in the metric function and weighting method, is proposed to enable the operator to interact with the algorithm through optimization process in contrast to other multi-objective methods.

To the best of our knowledge, no research work has been developed to locate and allocate the OUPFC device through the fuzzy interactive multi-objective optimization. The main contribution of this paper is to find the optimal location of OUPFC based on OPF problem incorporated in the metric function and weighting method as the multi-objective optimization problem. The objective functions are classified into four categories:

(i) The total fuel cost;
(ii) Active power losses;
(iii) System loadability;
(iv) Installation cost of the FACTS device.

The optimal location and settings of OUPFC are determined on the IEEE 14-, and 118-bus test systems to optimize these objective functions simultaneously. The optimization problem is modeled as a nonlinear programming with discontinuous derivatives (DNLP) problem in General Algebraic Modeling System (GAMS) software and solved using CONOPT solver [33]. Furthermore, in order to highlight the performance and applicability of the OUPFC, its results are compared with those of UPFC.

This paper is organized as follows. The mod-
eling of FACTS controllers are studied in details in Section 2. Section 3 contains the problem formulation of OPF incorporated in the FACTS device, including variables, objective functions, and constraints. The multi-objective optimization problem is presented in Section 4. The simulation results and the optimal settings and the best location of OUPFC and UPFC are reported in Section 5.

2. Modeling of FACTS devices

2.1. Modeling of OUPFC [1]
The OUPFC is comprised of a PST and a UPFC, as shown in Figure 1. The power injection model of the OUPFC is shown in Figure 2 where:

\[
P_{ss} = -b_k r V_i V_j \sin(\theta_i - \theta_j + \sigma) \]
\[-b_r r V_i V_j \sin(\theta_i - \theta_j + \rho).
\]

\[
Q_{ss} = -b_k r^2 V_i^2 (L^2 + r^2) - 2b_k r V_i^2 \cos(\sigma - \rho) 
- 2b_r r V_i^2 \cos(\rho) + b_k r V_i V_j \cos(\theta_i - \theta_j + \sigma) 
+ b_r r V_i V_j \cos(\theta_i - \theta_j + \rho).
\]

\[
P_{sr} = -P_{ss},
\]

\[
Q_{sr} = b_k r V_i V_j \cos(\theta_i - \theta_j + \sigma) 
+ b_r r V_i V_j \cos(\theta_i - \theta_j + \rho).
\]

where \( k \) is the transfer ratio of PST; \( \sigma \) is the PST phase angle; \( r \) is the radius of the UPFC operating region; \( \rho \) is the UPFC phase angle; \( b_k \) is \( 1/(X_S + X_B) \) where \( X_S \) is the transmission line reactance; and \( X_B \) is the series transformer leakage reactance.

2.2. Modeling of UPFC
The basic schematic of the UPFC is shown in Figure 3. The power injection model of the UPFC is same as the OUPFC of Figure 2 where:

\[
P_{ss} = -b_k r V_i V_j \sin(\theta_i - \theta_j + \sigma),
\]

\[
Q_{ss} = -b_k r V_i^2 (r + 2 \cos(\gamma)) 
+ b_r r V_i V_j \cos(\theta_i - \theta_j + \gamma),
\]

\[
P_{sr} = -P_{ss},
\]

\[
Q_{sr} = b_r r V_i V_j \cos(\theta_i - \theta_j + \gamma).
\]

where \( r \) is radius of the UPFC operating region; and \( \gamma \) is the UPFC phase angle [34].

3. Problem formulation
The problem formulation is based on a multi-objective OPF problem to make trade-off between objective functions and optimize four objective functions simultaneously while satisfying several equality and inequality constraints. The objective functions and constraints are explained in the following.

3.1. Objective functions
The objective functions are dependent on the system requirements and on the system operator concerns. Therefore, the objective functions of this paper are the total fuel cost, active power losses, system loadability, and installation cost of the FACTS device.
3.1.1. Total fuel cost
The quadratic fuel cost functions are used to minimize the total operating cost as the objective function. The objective function of the total fuel cost can be formulated as follows [35]:

\[ F_1(P_i) = \sum_{i=1}^{NG} C_i(P_{Gi}) = \sum_{i=1}^{NG} a_{oi} + a_{1i}P_{Gi} + a_{2i}P_{Gi}^2 \text{ ($$/h$)}, \]  

where \( P_{Gi} \) is generator active power output at bus \( i \); \( a_{oi}, a_{1i}, \) and \( a_{2i} \) are cost coefficients of unit \( i \); and \( NG \) is number of generators.

3.1.2. Active power losses
Loss minimization is very important in the power system operation and tends to reduce the reactive power flow in the power system. It can be expressed as follows [36]:

\[ F_2(V, \theta) = \sum_{i=1}^{n} \sum_{j=1}^{n} V_i V_j \text{loss}(\alpha_{ij} + \theta_j - \theta_i), \]  

where \( V_i \) and \( \theta_i \) are voltage magnitude and angle of bus \( i \); \( V_{ij} \) and \( \alpha_{ij} \) are the elements of admittance matrix magnitude and angle in row \( i \) and column \( j \), respectively; and \( n \) is number of buses.

3.1.3. System loadability
The power system operator usually prefers some further loading margins to decrease the risk of load variations, particularly in weak connections of the network. Therefore, the objective function of the system loadability can approximately remedy the maximum loading limits of the transmission lines and the dynamic power oscillations of the system that can be described as [37,38]:

\[ F_3 = \rho(x, u), \]  

and \( \rho \) can be obtained by assuming constant power factor at each load in both real and reactive power balance equations as follows:

\[ P_G - \rho P_D = f_P(x, u), \]  

\[ Q_G - \rho Q_D = f_Q(x, u), \]  

where \( P_G \) and \( Q_G \) are the vectors of generators real and reactive power, respectively; \( P_D \) and \( Q_D \) are the vectors of loads real and reactive power, respectively; \( f_P \) and \( f_Q \) are the vectors of real and reactive power flow equations, respectively; and \( x \) and \( u \) are sets of dependent and control variables, respectively.

3.1.4. FACTS investment cost
Since the installation of FACTS device is an investment issue, it interests the operator to decrease the total operating cost including its cost while the other objectives are considered. Therefore, the cost of FACTS installation is minimized in the multi-objective optimization framework. It can be mathematically formulated as follows:

\[ F_4 = \frac{C_{FACTS}}{8760 \times 5} \text{ ($$/h$)}, \]  

where \( C_{FACTS} \) is the cost of FACTS installation in US$. The OUPFC and UPFC cost functions are taken [6,39] as follows:

\[ C_{OUPFC} = \left[(12 \times S_{PST}) + \left(0.0003S_{UPFC}^2 - 0.2691S_{UPFC} + 188.22\right) \times S_{UPFC}\right] \times 1000, \]  

\[ C_{UPFC} = \left(0.0003S_{UPFC}^2 - 0.2691S_{UPFC} + 188.22\right) \times S_{UPFC} \times 1000, \]  

where \( S_{FACTS} \) is the operating range of FACTS devices in MVA. In this paper, a five-year period is assumed to usefully apply FACTS devices.

3.2. Constraints
The constraints of OPF problem can be divided into two categories: equality and inequality constraints.

3.2.1. Equality constraints
The equality constraints include active and reactive power balance equations for each bus as follows [35]:

\[ P_{Gi} + P_{FACTS} = P_{Di} + \sum_{j=1}^{n} V_i V_j \text{loss}(\alpha_{ij} + \theta_j - \theta_i) \]

\[ \forall i \in 1, 2, \ldots, n, \]  

\[ Q_{Gi} + Q_{FACTS} = Q_{Di} + \sum_{j=1}^{n} V_i V_j \text{loss}(\alpha_{ij} + \theta_j - \theta_i) \]

\[ \forall i \in 1, 2, \ldots, n, \]  

where \( P_{Gi} \) and \( Q_{Gi} \) are the generator active and reactive power at bus-\( i \), respectively; \( P_{Di} \) and \( Q_{Di} \) are the load active and reactive power at bus-\( i \), respectively; \( P_{FACTS} \) and \( Q_{FACTS} \) are the injected active and reactive powers by the FACTS device, respectively.

3.2.2. Inequality constraints
Inequality constraints represent the following limits on the active and reactive output power of generators, bus voltages, transmission lines loadings, and FACTS operational parameters [31].

a. The generators active and reactive output power is restricted by its lower and upper limits as follows:
Voltage magnitude of the buses is limited in the region defined by the following form:

\[
|V_i^\text{min}| \leq |V_i| \leq |V_i^\text{max}|
\]

\forall i \in n.

(21)

4. Interactive fuzzy multi-objective optimization algorithm

Generally, the multi-objective optimization problem attempts to find feasible solutions to optimize a vector of objective functions \( F(x) = \{ F_1(x), F_2(x), \cdots, F_n(x) \} \) while the constraints are satisfied. The problem can be formulated as follows:

\[
\begin{align*}
\text{minimize or maximize:} \\
F(x) & = \{ F_1(x), F_2(x), \cdots, F_n(x) \}, \\
\text{subject to:} \\
h_i(x) & = 0, \quad i = 1, 2, \cdots, I, \\
g_j(x) & \leq 0, \quad j = 1, 2, \cdots, J, \\
X_k^u & \geq X_k \geq X_k^l, \quad k = 1, 2, \cdots, k,
\end{align*}
\]

where \( F(x) \) is a vector of objective functions which can be minimized or maximized simultaneously; \( h_i(x) \) and \( g_j(x) \) are equality and inequality constraints, respectively; \( X_k^u \) and \( X_k^l \) are upper and lower bounds of variables, respectively. It is noted that the problem should be modeled as the fuzzy optimization framework. Therefore, the process of fuzzy implementation is explained in the following.

**4.1. Single objective optimization**

The search space of multi-objective optimization is usually well defined by single objective optimization. Therefore, each objective function is optimized while the corresponding values of other objective functions are calculated at the optimal point. Consequently, the payoff table is constructed as shown in Table 1.

| Table 1. Computed payoff table by single objective optimization for each function. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| \( F_1 \) | \( F_2 \) | \( F_3 \) | \( F_4 \) |
| \( m_i \) | \( F_i(x_i^*) \) | \( F_i(x_i^*) \) | \( F_i(x_i^*) \) | \( F_i(x_i^*) \) |
| \( M_i \) | \( \max_{j=1,2,3,4} \{ F_j(x_i^*) \} \) | \( \max_{j=1,2,3,4} \{ F_j(x_i^*) \} \) | \( \max_{j=1,2,3,4} \{ F_j(x_i^*) \} \) | \( \max_{j=1,2,3,4} \{ F_j(x_i^*) \} \) |
| \( i \) | 1, 2, 3, 4 | 1, 2, 3, 4 | 1, 2, 3, 4 | 1, 2, 3, 4 |

(26)

where \( x_i^* \) is the optimal solution of \( i \)th objective function as the Pareto optimal solution; \( m_i \) and \( M_i \) are the best and worst values of \( i \)th objective function, respectively.

**4.2. Developing the interactive constraint**

One of the most important features of a fuzzy multi-objective optimization is presentation of candidate solutions in an interactive process. The general idea of interactive methods is to determine a good compromise solution integrating preferences of the operator. The operator’s preferences can be consistently represented in the optimization model using the interactive process, although the objective functions naturally conflict with each other. In this paper, the interactive process is implemented by the metric function as defined by the following equation [40]:

\[
d(x) = \rho \left( \sum_{i=1}^{n} \frac{M_i - F_i(X)}{M_i - m_i} \right)
\]

(27)

where \( \rho \) belongs to the interval \([1, +\infty)\) and usually equals to 2; \( X \) is the vector of single objective solutions; the metric function is minimized to evaluate the optimum \( X \) using the common min-max method as follows:

\[
F(X) = \min_{x} \max_{i} \left( \frac{M_i - F_i(X)}{M_i - m_i} \right)
\]

The importance degree of each objective function de-
defined by the operator can be incorporated in the metric function as additional constraints in the optimization problem:

$$w_i \frac{M_i - F_i(X)}{M_i - m_i} \leq \varepsilon,$$

(29)

related to minimizing the $i$th objective function,

$$w_j \frac{F_j(X) - M_j}{m_j - M_j} \leq \varepsilon,$$

(30)

and to maximizing the $j$th objective function, and

$$\sum_{i=1}^{n} w_i = 1,$$

(31)

where $w_i$ is the importance degree of the $i$th objective function and $\varepsilon$ is the allowable degree of deviation from the optimal solution obtained by the single objective optimization.

The ideal value of the deviation degree is equal to 0. Therefore, the additional constraints, as equality constraints in the optimization problem, are equal to each other, i.e.:

$$w_i \frac{M_i - F_i(x)}{M_i - m_i} = w_j \frac{F_j(x) - M_j}{m_j - M_j},$$

(32)

and:

$$\sum_{i=1}^{4} w_i = 1.$$

The collaboration among objective functions and the importance of each objective function are considered by adding these equality constraints into the multi-objective optimization problem. Furthermore, the relative deviations of each objective function from its optimal value can be minimized.

4.3 Constituting membership functions

The main idea is to simultaneously optimize objective functions and constraints in the fuzzy optimization [41]. To implement this idea, the multi-objective optimization problem can be converted into a single-objective optimization by the fuzzy optimization strategy. Therefore, the objective functions and constraints are reformulated by using fuzzy membership functions to reflect the satisfaction degree of a given solution. The first step is a fuzzification process of the objective functions and the constraints. This procedure converts the objective functions $F_i(x)$ and constraints $g_j(x)$ into pseudogoods $\mu_{F_i}(x)$ and $\mu_{g_j}(x)$, respectively.

The membership functions for $F_1$, $F_2$, and $F_3$ are provided by linear monotonically decreasing function when these objectives are in between their maximum and minimum values obtained by Eq. (26). In other words, the degree of satisfaction decreases while these objectives increase from $m_i$ to $M_i$ ($i = 1, 2, 4$). The mathematical formulation is expressed as follows [40]:

$$\mu_{\hat{F}_i} = \begin{cases} 
1 & \frac{M_i - F_i(x)}{m_i - M_i} \leq 1, \\
\frac{F_i(x) - m_i}{M_i - m_i} & 1 < \frac{F_i(x)}{m_i} \leq M_i, \\
0 & F_i(x) \geq M_i.
\end{cases}$$

(33)

Similarly, the membership function of $F_3$ is determined by an increasing function when it is in the range between $M_2$ and $m_3$. These membership functions can be written as:

$$\mu_{\hat{F}_i} = \begin{cases} 
0 & \frac{F_i(x) - m_i}{M_i - m_i} \leq 1, \\
\frac{F_i(x) - M_i}{m_i - M_i} & m_i < F_i(x) < M_i, \\
1 & F_i(x) \geq m_i.
\end{cases}$$

(34)

In the conventional OPF, from other viewpoints, the equality and inequality constraints can be categorized into hard and soft constraints [42]. The hard constraints comprise the active and reactive power balance equations, output power of generators, bus voltages, and FACTS operational parameters. Because of technical and physical limitations, violations of these limits are not justifiable in any power system. On the other hand, the limits for the transmission line flows are soft constraints. The word “soft” signifies that the constraint is not absolutely enforced. Small violations of these limits sometimes can be acceptable, for example, when occurring special conditions such as line overloaded or contingency. Normal and emergency limits are two usual limits for each constraint of the transmission line flows. The operators desire to operate the system in optimum performance within normal limits while small violations of the normal limits are allowed. However, the emergency limits can never be violated and are considered as hard limits. These practical considerations of constraint limits are not satisfactorily formulated in a conventional OPF.

Soft constraints on membership functions are made based on the desired lowest limit ($b_j$) and the highest limit ($b_j + d_j$) as normal and emergency limits of the transmissions line flows. The membership functions of inequality constraints are characterized by trapezoidal functions as follows [40]:

$$\mu_{g_j} = \begin{cases} 
1 & g_j(x) \leq b_j, \\
\frac{g_j(x) - b_j}{d_j - b_j} & b_j \leq g_j(x) \leq b_j + d_j, \\
0 & g_j(x) \geq b_j + d_j.
\end{cases}$$

(35)

4.4 Fuzzy multi-objective optimization modeling

After the fuzzification process, membership of the optimal function can be found by the aggregation of
all the pseudo-goods and constraints. In the computation of fuzzy maximum function, the degree of satisfaction for fuzzy functions and fuzzy constraints can be represented by a membership variable $\lambda$. The membership variable $\lambda$ is defined as the minimum of all the membership functions of the fuzzy functions and fuzzy constraints. This procedure can be formulated through the following equations [41]:

$$\lambda = \mu_D(x) = \min \{ \mu_{F_1}(x), \ldots, \mu_{F_4}(x), \mu_{g_3}(x), \ldots, \mu_{g_n}(x) \}. \quad (36)$$

Using operator maximum, the optimal solution is computed as:

$$\max_{\lambda \in [0,1]} \lambda = \max_{\lambda \in [0,1]} \min \{ \mu_{F_1}(x), \ldots, \mu_{F_4}(x), \mu_{g_3}(x), \ldots, \mu_{g_n}(x) \}. \quad (37)$$

Finally, the interactive fuzzy multi-objective optimization is modeled as follows [46]:

maximize: $\lambda$,

subject to:

$$\lambda \leq \mu_{F_i}(x) \quad i = 1, 2, 3, 4,$$

$$\lambda \leq \mu_{g_j}(x) \quad i = 1, 2, \ldots, n,$$

$$w_i \left| \frac{M_i - F_i(x)}{M_i - m_i} \right| = w_j \left| \frac{F_j(x) - M_j}{m_j - M_j} \right|,$$

$$\sum_{i=1}^{4} w_i = 1,$$

$$0 \leq \lambda \leq 1,$$

$$X^u_k \geq X_k \geq X^l_k. \quad (38)$$

5. Case studies

The proposed method is applied to the IEEE 14-, and 118-bus test systems to verify its effectiveness to optimally locate OUPFC and UPFC devices. It is implemented in GAMS and modeled as a DNLP problem. The optimization problem is solved using CONOPT solver [33]. Data on the IEEE test systems are taken from [43]. Parameters and limits of the OUPFC and UPFC devices are given in Appendix A.

The CONOPT is used to solve static and dynamic large-scale nonlinearly constrained optimization problems. The GAMS/CONOPT solver is the link between the GAMS and CONOPT to solve the problem. It has a fast method for finding a first feasible solution that is particularly well suited for models with few degrees of freedom. It can also be used to solve square systems of equations without an objective function corresponding to the constrained nonlinear system model form [33].

The proposed algorithm is done for the optimum allocation of FACTS devices through individual optimization and various combinations of objective functions in IEEE 14- 118-bus test systems which can be expressed by the following frames:

Case 1: Minimizing total fuel cost and active power losses, simultaneously;

Case 2: Minimizing total fuel cost and maximizing system loadability at the same time;

Case 3: Minimizing active power losses and maximizing system loadability, concurrently;

Case 4: Minimizing total fuel cost, active power losses and maximizing system loadability, simultaneously.

In all cases, when the OPF problem is composed of the total fuel cost and FACTS investment cost as the objective functions, these functions are added together and become one objective, therefore take one weight in whole algorithm.

5.1. IEEE 14-bus test system

The single-objective and multi-objective optimization problems are performed on IEEE 14-bus test system considering the total fuel cost, active power losses, and the system loadability as objective functions. The results of the single-objective optimization are shown in Table 2 with and without minimization of the investment cost of OUPFC and UPFC devices. In the case without minimization of the investment cost, two devices have a similar performance with different sizes while the OUPFC investment cost is less than that of UPFC as much as 80%, 78%, and 81% for optimization of the total fuel cost, active power losses, and the system loadability, respectively. In the case with minimization of the investment cost, OUPFC has better performance than UPFC with 71.1% less investment cost for minimizing the total fuel cost and the investment cost, simultaneously. Also, the UPFC improves investment 2% more than OUPFC to minimize active power losses while the investment cost of UPFC is 92.8% more than that of OUPFC. The results show that utilizing both UPFC and OUPFC enhances system loadability objective function almost equally, but with 75.1% reduction in investment cost of OUPFC compared to that of UPFC.

Using fuzzy optimization method in solving different combinations of stated objectives, the multi-objective optimization results with the same weighting coefficients are tabulated in Table 3. The simulation results indicate better performance of OUPFC compared
Table 2. Single objective optimization results in IEEE 14-bus system.

<table>
<thead>
<tr>
<th>Objective function</th>
<th>Parameters</th>
<th>Without FACTS</th>
<th>UPFC without investment cost</th>
<th>OUPFC without investment cost</th>
<th>UPFC with investment cost</th>
<th>OUPFC with investment cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>( F_1 )</td>
<td>Loadability index</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Investment cost ($/h)</td>
<td>-</td>
<td>236.89</td>
<td>47.42</td>
<td>42.36</td>
<td>12.0</td>
</tr>
<tr>
<td></td>
<td>FACTS size (MVA)</td>
<td>-</td>
<td>59.92</td>
<td>56.92</td>
<td>10.00</td>
<td>26.31</td>
</tr>
<tr>
<td></td>
<td>FACTS location</td>
<td>-</td>
<td>Line 1-5</td>
<td>Line 1-5</td>
<td>Line 3-2</td>
<td>Line 4-2</td>
</tr>
<tr>
<td></td>
<td>FACTS settings</td>
<td>-</td>
<td>( r = 0.135 )</td>
<td>( \gamma^p = -180 )</td>
<td>( \gamma^p = 85.15 )</td>
<td>( \sigma^p = 1.02 )</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.835</td>
<td>0.783</td>
<td></td>
</tr>
<tr>
<td>( \sum P_{loss} ) (MW)</td>
<td>1.128</td>
<td>0.799</td>
<td>0.799</td>
<td>0.859</td>
<td>0.878</td>
<td></td>
</tr>
<tr>
<td>Total fuel cost ($/h)</td>
<td>18186.61</td>
<td>18379.88</td>
<td>18379.88</td>
<td>18835.776</td>
<td>18884.398</td>
<td></td>
</tr>
<tr>
<td>( \sum Q_{loss} ) (MVAr)</td>
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<td>10.515</td>
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<td>( \gamma^p = 111.5 )</td>
<td>( \sigma^p = 3.94 )</td>
<td>( \gamma^p = 90.84 )</td>
<td>( \sigma^p = 0.007 )</td>
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<th>UPFC without investment cost</th>
<th>OUPFC without investment cost</th>
<th>UPFC with investment cost</th>
<th>OUPFC with investment cost</th>
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<td></td>
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<td>30700.10</td>
<td>30700.100</td>
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<td>4.33</td>
<td>6.679</td>
<td>6.101</td>
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<td></td>
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<td>30.287</td>
<td>26.189</td>
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<td>( \gamma^p = 88.08 )</td>
<td>( \sigma^p = -0.96 )</td>
<td>( \gamma^p = 72.77 )</td>
<td>( \sigma^p = 0.209 )</td>
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</tr>
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</table>

To that of UPFC with lower investment cost. According to Case 1, by placing OUPFC and minimizing its investment cost, the total fuel cost increases about 1.1% and active power losses decrease about 16% compared to that of UPFC, while without minimizing of investment cost, both OUPFC and UPFC give the same result. In Case 2, OUPFC improves system loadability in both modes of with and without minimizing investment cost, i.e. increasing system loadability, but increases the total fuel cost slightly. Also in Cases 3 and 4, OUPFC has greater impact in reducing active power losses and improving all objective functions with lower investment cost compared to that of UPFC.

To illustrate flexibility and interactive properties of the proposed algorithm, Case 4 is investigated considering various weighting factors of objective functions. In Table 4, it is assumed that the weighting factor of the total fuel cost objective function is increased while the other weighting factors are decreased through four steps. Consequently, the total fuel cost
<table>
<thead>
<tr>
<th>Objective function</th>
<th>Parameters</th>
<th>Without</th>
<th>UPFC without</th>
<th>OUPFC without</th>
<th>UPFC with</th>
<th>OUPFC with</th>
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<td>cost</td>
<td>investment</td>
<td>cost</td>
<td>investment</td>
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<td>$\lambda$</td>
<td>0.712</td>
<td>0.771</td>
<td>0.771</td>
<td>0.716</td>
<td>0.592</td>
<td>0.928</td>
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<td>Total fuel cost ($$/h)</td>
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<td>17257.807</td>
<td>17326.078</td>
<td>17428.629</td>
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<td>$\sum P_{loss}$ (MW)</td>
<td>1.282</td>
<td>0.881</td>
<td>0.881</td>
<td>1.105</td>
<td>0.887</td>
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<td>$\sum Q_{loss}$ (MVAR)</td>
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<td>11.172</td>
<td>11.860</td>
<td>11.216</td>
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<td>1</td>
<td>1</td>
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<td>Case 1</td>
<td>Investment cost ($$/h)</td>
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<td>220.034</td>
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<td>128.351</td>
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<td>Total fuel cost ($$/h)</td>
<td>23609.050</td>
<td>23515.023</td>
<td>23563.741</td>
<td>23601.625</td>
<td>23607.898</td>
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<td>1.297</td>
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<td>$\sum P_{loss}$ (MW)</td>
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<td>2.539</td>
<td>4.029</td>
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<td>$\sum Q_{loss}$ (MVAR)</td>
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<td>16.030</td>
<td>16.080</td>
<td>22.160</td>
<td>19.005</td>
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<tr>
<td>Case 2</td>
<td>Investment cost ($$/h)</td>
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<td>323.250</td>
<td>62.597</td>
<td>13.176</td>
<td>31.229</td>
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<td>FACTS size (MVA)</td>
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<td>72.151</td>
<td>3.080</td>
<td>35.792</td>
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<td>Line 14-9</td>
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<td>0.588</td>
<td>0.570</td>
<td>0.583</td>
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<td>Total fuel cost ($$/h)</td>
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<td>24348.723</td>
<td>23662.438</td>
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<td>1.317</td>
<td>1.330</td>
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<td>$\sum Q_{loss}$ (MVAR)</td>
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<td>18.034</td>
<td>16.260</td>
<td>19.310</td>
<td>15.362</td>
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<td>Case 3</td>
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<td>62.153</td>
<td>73.332</td>
<td>28.225</td>
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<td>17.495</td>
<td>44.632</td>
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<td>Line 5-1</td>
<td>Line 3-2</td>
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<td>0.529</td>
<td>0.528</td>
<td>0.528</td>
<td>0.533</td>
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<tr>
<td>Total fuel cost ($$/h)</td>
<td>23615.607</td>
<td>23598.660</td>
<td>23575.906</td>
<td>23618.122</td>
<td>23636.588</td>
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<td>2.810</td>
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<tr>
<td>$\sum P_{loss}$ (MW)</td>
<td>1.294</td>
<td>1.296</td>
<td>1.296</td>
<td>1.296</td>
<td>1.300</td>
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<tr>
<td>$\sum Q_{loss}$ (MVAR)</td>
<td>21.055</td>
<td>19.437</td>
<td>17.696</td>
<td>19.341</td>
<td>17.186</td>
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<td>51.767</td>
<td>177.005</td>
<td>33.859</td>
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<td>43.825</td>
<td>49.620</td>
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<td>$\gamma^s = 122.2$</td>
<td>$\gamma^s = 89.10$</td>
<td>$\sigma^s = 3.76$</td>
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Table 4. Interactive results in Case 4 of IEEE 14-bus system.

<table>
<thead>
<tr>
<th>Objective functions (Case 4)</th>
<th>$w_1(w_1, w_2, w_3)$</th>
<th>$\lambda$</th>
<th>Total fuel cost ($$/h)</th>
<th>$\sum P_{loss}$ (MW)</th>
<th>Loadability index</th>
<th>$\sum Q_{loss}$ (MVAr)</th>
<th>Investment cost ($$/h)</th>
<th>FACTS size (MVA)</th>
<th>FACTS location</th>
<th>FACTS settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without FACTS</td>
<td>$(0.333, 0.333, 0.333)$</td>
<td>0.528</td>
<td>23615.607</td>
<td>3.896</td>
<td>1.294</td>
<td>21.095</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UPFC without investment cost</td>
<td>$(0.6, 0.2, 0.2)$</td>
<td>0.272</td>
<td>20118.203</td>
<td>4.580</td>
<td>1.152</td>
<td>24.933</td>
<td>574.640</td>
<td>165.749</td>
<td>Line 2-1</td>
<td></td>
</tr>
<tr>
<td>OUPFC without investment cost</td>
<td>$(0.7, 0.15, 0.15)$</td>
<td>0.190</td>
<td>19558.692</td>
<td>4.232</td>
<td>1.107</td>
<td>25.542</td>
<td>65.578</td>
<td>75.628</td>
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<td></td>
</tr>
<tr>
<td>UPFC with investment cost</td>
<td>$(0.333, 0.333, 0.333)$</td>
<td>0.528</td>
<td>23618.122</td>
<td>3.356</td>
<td>1.290</td>
<td>19.341</td>
<td>177.095</td>
<td>43.825</td>
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</tr>
<tr>
<td>OUPFC with investment cost</td>
<td>$(0.6, 0.2, 0.2)$</td>
<td>0.266</td>
<td>20466.682</td>
<td>4.608</td>
<td>1.149</td>
<td>27.959</td>
<td>213.730</td>
<td>53.601</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

function approaches its ideal solution value and two other functions are kept out of their ideal solution values.

5.2. IEEE 118-bus test system

The IEEE 118-bus test system is used to examine the performance capability of the proposed algorithm in locating UPFC and OUPFC, individually, in order to improve objective functions. Single- and multi-objective optimization results are shown in Tables 5 and 6, respectively. Although UPFC has better performances compared to OUPFC in some cases, the OUPFC investment cost is low compared to that of UPFC.
Table 5. Single objective optimization results in IEEE 118-bus system.

<table>
<thead>
<tr>
<th>Objective function</th>
<th>Parameters</th>
<th>Without FACTS</th>
<th>UPFC without investment cost</th>
<th>OUPFC without investment cost</th>
<th>UPFC with investment cost</th>
<th>OUPFC with investment cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_1$</td>
<td>Total fuel cost ($$/h$)</td>
<td>129660.997</td>
<td>129315.89</td>
<td>129378.1</td>
<td>129629.85</td>
<td>129656.15</td>
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<tr>
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<td>$\sum P_{\text{loss}}$ (MW)</td>
<td>74.408</td>
<td>70.479</td>
<td>71.075</td>
<td>76.755</td>
<td>77.287</td>
</tr>
<tr>
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<td>$\sum Q_{\text{loss}}$ (MVAr)</td>
<td>507.25</td>
<td>480.66</td>
<td>465.114</td>
<td>504.036</td>
<td>506.91</td>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Investment cost ($$/h$)</td>
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<td>170.141</td>
<td>42.36</td>
<td>3.97</td>
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<td>200.00</td>
<td>10.00</td>
<td>12.64</td>
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<td>$\lambda$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.998</td>
<td>0.999</td>
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</tr>
<tr>
<td>$\sum P_{\text{loss}}$ (MW)</td>
<td>9.2476</td>
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<td>7.9387</td>
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<td>Total fuel cost ($$/h$)</td>
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<td>166514.67</td>
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<td>$\sum Q_{\text{loss}}$ (MVAr)</td>
<td>69.38</td>
<td>64.07</td>
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<td>63.510</td>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Investment cost ($$/h$)</td>
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<td>406.72</td>
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<td>1.746</td>
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<td>Line 49-48</td>
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<td>$\sigma^* = -0.016$</td>
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<td>2.28</td>
<td>2.053</td>
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<td>Total fuel cost ($$/h$)</td>
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<td>417113.21</td>
<td>417113.21</td>
<td>351906.276</td>
<td>361074.973</td>
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<tr>
<td>$\sum P_{\text{loss}}$ (MW)</td>
<td>198.577</td>
<td>275.547</td>
<td>275.767</td>
<td>211.28</td>
<td>215.844</td>
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<td>$\sum Q_{\text{loss}}$ (MVAr)</td>
<td>1141.87</td>
<td>1542.681</td>
<td>1543.39</td>
<td>1215.03</td>
<td>1254.67</td>
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<td>$\gamma^* = 117.65$</td>
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<td>$\gamma^* = 18.00$</td>
<td>$\sigma^* = 0.83$</td>
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6. Conclusions

Power system optimization is one of the most important off-line tools in the field of operation, planning, and control of power systems. This paper made an attempt to find the optimal location of OUPFC and UPFC devices to simultaneously optimize total fuel cost, power losses, and system loadability as a multi-objective optimization problem to enable power system dispatcher to operate the power system reliably and economically. The multi-objective optimization problem was performed by a fuzzy interactive approach. The fuzzy method is preferable to common methods of multi-objective optimization since it is able to interact with the decision-maker through the optimization process. The proposed algorithm was implemented in GAMS software and solved using CONOPT solver as a DNLP problem. Simulations were performed on IEEE 14- and 118-bus test systems. Simulation results show that OUPFC is more capable of improving the
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<th>Total fuel cost ($/h)</th>
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</table>

Table 6. Multi-objective optimization results in IEEE 118-bus system.
dispatcher's ability to effectively operate power systems compared to UPFC, while the cost of OUPFC is less than the one of UPFC.

References


32. Baylasoglu, A. and Sevim, T. “A review and classification of fuzzy approaches to multi objective optimization”, *International XII Turkish Symposium on Artificial Intelligence and Neural Networks-TA1NN 2003*.


**Appendix A**

**OUPFC data**

\[
\begin{align*}
-20^\circ & \leq \sigma \leq 20^\circ , & 0 \leq r & \leq 0.15 , \\
-\pi & \leq \rho \leq \pi , & X_B = 0.007 \text{ p.u.} , \\
X_E = 0.001 \text{ p.u.} , & S_{\text{base}} = 100 \text{ MVA} .
\end{align*}
\]

**UPFC data**

\[
\begin{align*}
0 \leq r & \leq 1 , & X_B = 0.007 \text{ p.u.} , \\
X_E = 0.001 \text{ p.u.} , & -\pi \leq \gamma \leq \pi , \\
S_{\text{base}} = 100 \text{ MVA} .
\end{align*}
\]

**Biographies**

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