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Original Research

SECURITY CONSTRAINED OPTIMAL POWER FLOW BASED ON AN ARTIFICIAL INTELLIGENCE TECHNIQUE

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Abstract: In the past, artificial intelligence techniques were successfully adopted for obtaining optimal power flow in a power system. However, this optimality is limited to the economic aspects of the system's operating conditions. The other aspects of the operation, like security conditions, have been given limited attention. Hence, this paper presents an attempt to dispatch the power generation in electrical power systems optimally by taking into consideration both economic and secure operations, so that modern power systems can operate reliably and effectively. Security-constrained optimal power flow is addressed in this paper as a multi-objective optimization problem, consisting of four objective functions: minimizing power generation costs; minimizing voltage deviation; minimizing power losses; and alleviating the overloading on transmission lines. A detailed steady-state generator model is adopted in the present formulation. A metaheuristic optimization technique, namely, differential evolution, is used to obtain the security constraint optimal power dispatch. Additionally, the operating states of a power system have been addressed in this paper. The identification of the operating states is vital to the assessment of the security of the EPS. Improvements and appropriate security assessments have been made in some cases. The proposed algorithm is applied to a typical power system with different operating strategies. The obtained results are compared to those obtained from previous studies in the literature to demonstrate the suggested method's validity and effectiveness.

Keywords: *Multi-objective optimization; power system security; differential evolution; economic dispatch*

1. Introduction

Optimal Power Flow (OPF) is a vital analysis in power system operation. The primary goal of an OPF study is to dispatch power generation in an economically efficient manner by making optimal modifications to control variables in electrical power systems EPS while meeting various equality (EqC) and inequality (IqC) constraints.

A lot of research has been carried out to tackle the OPF problem effectively by adopting traditional optimization techniques (successive linear programming as demonstrated in [1], sequential programming as in [2], and the Newton method as given in [3]). However, the above-mentioned approaches face difficulties when applied for continuous-discrete, non-linear functions in addition to the inherent limitations that come with account operations OPF, such as poor convergence characteristics, continuity, and trapping in the local minimum. A review of the OPF based on non-linear and quadratic programming approaches is given in [4]. Artificial optimization techniques have been adopted in other attempts (bacteria foraging, as in [5]; particle swarm optimization, as

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demonstrated in [6]). Mithun et al. [7] provide a review and survey of the most common optimization solutions for dealing with the OPF problem.

The economical operation of a power system in a normal state is maintained efficiently by using traditional OPF. Unfortunately, this optimal solution may influence the violation of the operation limits under some contingency conditions. These violations may include power flow limits in the lines and bus voltage violations. For this purpose, the security-constrained optimal power flow (SCOPF) plays an important role in maintaining a secure and economic operation of the system. In some cases, the SCOPF can be analyzed as a multi-objective function (MOF) in the normal state, in addition to the pre-contingency and post-contingency constraints, as illustrated in [8, 9].

Some of the previous studies dealt with the subject of SCOPF. Galvani et al. [10] use the Multi-Objective Genetic Algorithm to determine the exact relationship between operational cost and security constraints. Kucuktezcan et al. [11] propose an approach for optimizing preventative and corrective control operations to increase the dynamic security of a power system against transient instabilities. Ayan et al. in [12] and Saberi et al. in [13] present an approach for transient stability SCOPF solutions using a chaotic artificial bee colony algorithm based on chaos theory. while this study concentrates on steady-state security. The optimal coordination between preventive and corrective control was analyzed by Xu et al. [14]. Their analysis was based on utilizing a preventive/corrective SCOPF model and an artificial intelligence technique. Velloso et al. [15] gave a decomposition strategy that combines a column-and-constraint generation technique with numerical approaches to find accurate SCOPF issue solutions. As a result, heuristic search algorithms are a good fit for addressing the SCOPF problem and may be adapted for use in a contingency situation to improve security, as demonstrated in [16].

In this paper, an artificial intelligence technique, namely the differential evolution (DE) algorithm was used to conduct the SCOPF study. This algorithm was reported to be powerful in OPF studies, as illustrated in [17–20], by considering the single and multi-objective (S-MOF) optimization techniques, minimizing the total fuel costs (TFC) of the generation, active power transmission losses (APTLs), in addition to contingency constraints. The determinants that have been regarded as security limitations in this study include voltage deviations (VD) and overloaded transmission lines (OLTL).

This paper also addresses the operating states of a power system. These states are vital in the optimization process and the assessment of a secure operation of the power system.

In the normal state of operation, S-MOF are applied to obtain an optimized power flow in the operating system. In addition, a contingency analysis (CA) was employed to recognize the critical contingencies.

In the alert state, SCOPF is utilized to relieve the congestion of heavily loaded transmission lines and reduce the voltage deviations on the nodes to recover the system to a normal state before it goes into an emergency state. The overload on transmission lines is alleviated by minimizing SI through adjusting generator scheduling to redirect the power flows in the system. A suitable change in the generating schedule can cause a change in the power flows, allowing the remaining transmission lines to take the increased load while maintaining the limit.

This method was tested on the standard IEEE 30-bus system in a variety of scenarios. The simulation results are analyzed and show that the suggested method is effective when compared to other recently developed heuristic algorithms that have been discussed in the literature.

The rest of the paper is structured as follows: Section 2 states the problem formulation of a conventional optimal power flow and the objective function (OF) to be optimized. It also gives the structure of the optimization problem. The procedural steps for the proposed algorithm based on the DE technique are given in Section 3. Section 4 describes the results and discussions. Section 5 states the conclusions.

2. Formulation of the Optimal Power Flow Problem

In this study, the following four OFs are looked at as both S-MOF. These goals represent major interests in planning and operation for EPS [21].

2.1. Minimizing the Total Fuel Cost (TFC)

The actual power output of the generators, P_G, can be used to calculate the TFC for generators. The cost curves of generators are represented by quadratic functions, and TFC in dollars per hour ($/h) is represented as [21]:

$$OF1 = \sum_{i=1}^{N_G} (a_i + b_i P_{G_i} + c_i {P_{Gi}}^2) \ \$/h \qquad (1)$$

$i = 1,2,3 \ldots, N_G$

Where a_i, b_i and c_i are the cost factors of the i^{th} generating unit; P_{G_i} is the actual active power produced by the ith generating unit in MW; N_G is the total number of generators.

2.2. Active Power Transmission Losses (APTLs) Minimization

The APTLs can be minimized through the adjustment of the appropriate control parameters. For this purpose, the objective function is described as follows [21]:

$$OF2 = \sum_{i=1}^{N_{TL}} G_{ij} \left(\left|{V_i}^2\right| + \left|{V_j}^2\right| - 2\left|V_i V_j\right| \cos \delta_{ij} \right) \ MW \qquad i = 1, \ldots, N_{TL} \qquad (2)$$

Where G_{ij} is a conductance of line connecting bus i to bus j, δ_{ij} is a voltage angle difference, V_i & V_j are the voltage magnitude, and N_{TL} is the total is the total number of lines in the system

2.3. Minimization of the Voltage Deviation (VD)

Voltage magnitude constancy is one of the important security and quality indicators. The voltage magnitude should be maintained within permissible limits. To this end, the deviation in voltage is used as an objective function [21]:

$$OF3 = \sum_{k=1}^{N_{PQ}} \left|V_k - {V_k}^{ref}\right|^2 \quad k = 1,2, \ldots, N_{PQ} \quad (3)$$

Where, V_k is voltage load bus, N_{PQ} is the number of load buses, and ${V_k}^{ref}$ is the specified reference value of the voltage magnitude at load bus k, which is typically set to 1.0 p.u.

2.4. Severity Index (SI)

SI quantifies the severity of OLTL, which describes the power system's post-contingency state as follows [24].

$$OF4 = \sum_{l \in L_\circ}^{NTL} \left(\frac{S_l}{{S_l}^{max}}\right)^{2m} \qquad (4)$$

Where S_l is MVA power flow in transmission lines, ${S_l}^{max}$ is a line rating (MVA), $L_\circ$ set of overloaded transmission lines, and m is an integer exponent fixed at 1.

By adjusting generator scheduling, the SI is reduced, which is calculated by conducting a Newton-Raphson power flow study. Thus, it is possible to obtain the least amount of overload in transmission lines. The severity index's higher value indicates that the contingency is more insecure.

2.5. System Operational Constraints

The following transmission system constraints are considered [20]:

2.5.1. Equality Constraints (EQC)

The following are the balanced power flow equations that the equality constraints represent:

$$\sum_{i=1}^{N_G} P_{G_i} = P_{Load_i} + P_{Loss} \qquad i = 1, \dots, N_B \quad (5)$$

$$P_i = P_{G_i} - P_{Load_i} = \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_{ij}) \;\; i = 1,2..,N_B \quad (6)$$

$$Q_i = Q_{G_i} - Q_{Load_i} = -\sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \sin(-\theta_{ij} - \delta_{ij}) \;\; i = 1,..,N_B \quad (7)$$

Where P_i is the net active power injection. Q_i is the net reactive power injection, P_{G_i} is the produced active power at bus i , $Q_{G_i}$is the produced reactive power at bus i , Q_{Load_i} and P_{Load_i}stand for the reactive power and active power demand at a bus i , P_{Loss} is the active power losses, V is the voltage magnitude, N_G the total number of generator buses, N_B represents the total number of nodes, Y_{ij} is the Ybus (mho) admittance matrix, and i, j are the from and to buses, θ_{ij} The phase angle of Ybus' Yij element is ij (radian), while δ_{ij} The voltage angle difference between buses i and j is denoted as ij (radian).

2.5.2. Inequality Constraints (IQC)

There are two types of IQC in the system:

2.5.2.1. The inequality constraints on control variables

The following are the minimum and maximum IQC values for control variables:

- Generation constraints for active power output P_G:

$$P_{Gi}{}^{min} \le P_{Gi} \le P_{Gi}{}^{max} \quad i = 1,2,3 \dots, N_G \quad (8)$$

- Generation constraints for bus voltages V_G:

$$V_{Gi}{}^{min} \le V_{Gi} \le V_{Gi}{}^{max} \quad i = 1,2,3 \dots, N_G \quad (9)$$

N_G refers to the number of generation buses.

- Transformer tapping constraints TT_i:

$$TT^{min} \le TT_i \le TT_i{}^{max} \quad i = 1,2,3 \dots, N_T \quad (10)$$

N_T refers to the number of transformers.

- The reactive power VAR injected from a particular VAR source Q_{ci}:

$$Q_{ci}{}^{min} \le Q_{ci} \le Q_{ci}{}^{max} \quad i = 1,2, \dots, N_c \quad (11)$$

N_c refers to the number of shunt compensators.

2.5.2.2 The inequality constraints on state variables.

The following are the minimum and maximum IQC values for state variables:

- The maximum and minimum reactive power output that can be produced P_G:

$$Q_{Gi}{}^{min} \le Q_{Gi} \le Q_{Gi}{}^{max} \quad i = 1,2, \dots, N_G \quad (12)$$

- The permissible voltage magnitude at load buses:

$$V_{Li}{}^{min} \le V_{Li} \le V_{Li}{}^{max} \quad i = 1,2,3 \dots, N_{PQ} \quad (13)$$

N_{PQ} refers to the number of load buses.

- The maximum and minimum active power output that can be produced at the Slack bus P_{Gs}:

$$P_{Gs}{}^{min} \leq P_{Gs} \leq P_{Gs}{}^{max} \quad i = 1,2, \ldots, N_{Gs} \quad (14)$$

N_{Gs} refers to the number of slack bus generators.

In addition to EQC and IQC, transmission line overloading should not exceed the allowable limit for the system to be healthy, which is as follows:

- Transmission line power capacity constraints:

$$S_{Li} \leq S_{Li}{}^{max} \quad i = 1,2,3 \ldots, N_{TL} \quad (15)$$

2.6. Mathematical Structure of The Optimization Process

The security constraint optimal power flow problem is treated mathematically as a single and multi-objective function subjected to a non-linear constraint as shown below:

2.6.1 Single objective function [20]

$$minimize\ [CF_i(x,u) \quad i = 1, \ldots, N_{obj}] \quad (16)$$

Subject to:

$$g1_j\,(x,u) = 0 \quad j = 1,2,3 \ldots, n \quad (17)$$

$$g2_k(x,u) = 0 \quad k = 1,2,3 \ldots, m \quad (18)$$

Where: The nonlinear EQC and IQC are represented by $g1$ and $g2$, respectively, while CF represents the objective function.

The vector x consists of the following state variables:

1. Active power generated from the slack bus P_{Gs}.
2. Load buses' voltage V_L.
3. Reactive power output for generators Q_G.
4. Bus voltage angles θ.
5. Transmission line loading S_{Li}.

Hence, x may be written as:

$$x^T = \begin{bmatrix} P_{G1}, V_{L1} \ldots V_{L_{NL}},\ Q_{G1} \ldots\ Q_{G_{NG}}, \\ \theta_1 \ldots \theta_{N_B}, SL_1 \ldots SL_{NL} \end{bmatrix} \quad (19)$$

The vector u contains control variables such as:

1. Bus voltages for generators V_G.
2. Real power output for generators P_G at PV buses except at the slack bus P_{Gs}.
3. Transformer tap ratio T.
4. Reactive power compensator Q_c

Hence, u may be written as:

$$u^T = \begin{bmatrix} P_{G2} \ldots P_{G_{NG}}, V_{G1} \ldots V_{G_{NG}} \\ , Q_{c1} \ldots\ Q_{C_{NC}}, T_1 \ldots T_{NT} \end{bmatrix} \quad (20)$$

2.6.2. Multi-Objective Function (MOF)

The importance of considering several objectives stems from the fact that the mathematical model of the optimization process becomes more realistic. The power system runs efficiently under different constraints. This may be applied in the normal and alert state of the power system's actual operation.

The MOF may be realized as follows [25]:

$$minimize,\ JF_i(x,u) = \sum_{i=1}^{N} W_i CF_i(x,u)$$

$$= W_1 CF_1 + \ldots, + W_i CF_i \quad i = 1, \ldots, N_{obj} \quad (21)$$

Subject to the nonlinear equality and inequality constraints.

Where JF denotes a MOF with i functions, CF represents a single objective function, and W represents a scalar weight multiplied by each objective. The range of W is from (0-1) with a total summation equal to one.

The MOF problem was resolved in this paper by using the weighted sum of the OFs. For the case of conflicting OFs, the SCOPF may effectively solved as a single objective function to manage such adversary objectives at the same time. In general, MOF optimization can be solved with or without giving objective preferences. According to the author's conclusions in [25], the author found through the research [25] that the acquired solution has no substantial compromising results for a variety of combinations of weight values considered. Therefore, all objectives are weighted equally without prioritizing any of the objectives in the minimization process.

2.6.3. Bounds scaling

Since the control variables to be optimized vary in a wide range. For example, TFC can vary between 900 $/h and 700 $/h, while bus voltages can vary between 0.95 V and 1.05 V. It is important to standardize these ranges between 0 and 1 by a procedure called boundary scaling or normalization. This normalization can be achieved by using the following equation [27]:

$$OF_i^{normalized} = \frac{OF_i - OF_{i_{min}}}{OF_{i_{max}} - OF_{i_{min}}} \qquad (22)$$

2.7. Power System Security

The elements of the power system must operate within the security limits defined for them in order to maintain the secure operation of the power system. These elements are protected and switched out when these limits are violated. A secure operation of an EPS requires the system to not only run within a specified limit in a steady state but also be capable of surviving contingencies.

2.8. Contingency Analysis (CA)

CA is one of the many functions included in energy management systems (EMS) used to control EPS operation. Contingency analysis is a tool that indicates the impact of system elements outage. This outage may be due to a particular disturbance that occurs in the power system, its evaluation, and prioritization. Contingency analysis can also be used to assess the effect of N-1 contingencies, evaluate the performance indices of the system, and compare results to operating limits for each EPS element.

2.9. Contingency Ranking (CR)

Since only a few of the outages might alter the normal operation of the system. The CR is a short list of those contingencies that are likely to overload some transmission lines or violate the permissible voltage limit. This contingency ranking is accomplished by computing the severity index SI.

2.10. Operating States of a Power System

Identification of the power system operating states is important in the optimization and evaluation of the security of the system. The system might operate in one of the five states shown in Fig. 1 [26].

In the normal state, the system running with no constraints is violated. All variables are within the allowable limits. In this case, S-MOF can be treated as minimizing TFC, APTLs, VD, and OLTL. additionally, the critical contingencies can be identified by using CA. Another important state is the alert state. In this state, the system state variables are within the acceptable ranges and all operating constraints are fulfilled. However, the system becomes weaker to a level that any emergency renders the remaining elements running out of limits, putting the system in a contingency state. In this case, the focus is on improving security by minimizing the SI and VD as OFs, to alleviate the OLTL and reduce the VD on the buses and did not give the other objectives more priority (minimize TFC costs and APTLs). This is because the alert state is short, and the operator's priority is to return the system to a normal state before it goes into an emergency state.

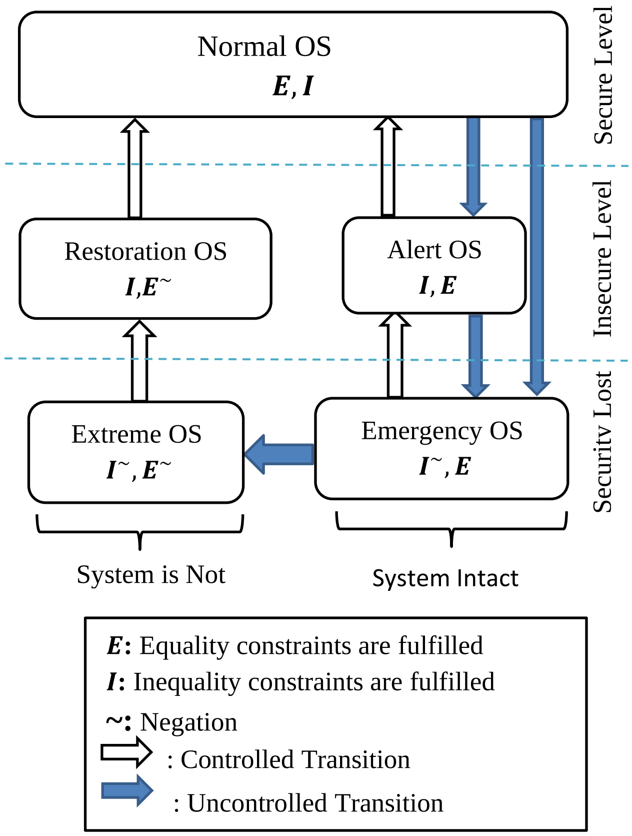


Figure 1. Classification of power system operating states

3. Proposed Approach

To solve the formulated single and multi-objective SCOPF problems, the approach suggested in this study employs a technique known as "differential evolution" (DE) [17]. The search for an optimum solution in an EPS faces difficulties due to the large size of the EPS, complexity, and wide geographical dispersion. The problem is exacerbated by the existence of many nonlinear equality and inequality constraints [27]. Storn and Price (1995) presented DE, a new evolution-inspired optimization approach that is simple but powerful for solving large optimization problems [17]. The DE algorithm can manage the following problems: non-linear, non-differentiable, non-convex, non-continuous, and multi-objective functions [19]. The search in this algorithm is based on a stochastic technique that is capable of achieving optimization globally [20].

The DE algorithm's stages are as follows:

$X = [x_1, x_2, \dots \dots, x_D]$, which represents a vector of control variables.

$P = [X_1, X_2, \dots \dots, X_{NP}]$, which represents a population-searching space.

NP: the size of a population; D: Dimension of problem, D represents the number of control variables; G: generation numbers.

The control parameters of the algorithms are:

- F : The mutation constant.
- C_R: The crossover constant.
- NP: The population size.

3.1. Structure of the DE Algorithm

The Differential algorithm consists of the following main steps as follows [20]:

3.1.1. Initialization:

In this step, the initialization of a population is realized. The parameter vectors are created based on a stochastic process by selecting elements inside the search space of the problem randomly to transform a group of control variables into the vector of target variables X. This is achieved by using the equation below Within its minimum and maximum limits:

$$X_i = X_i^{min} + rand\left(X_i^{max} - X_i^{min}\right) \qquad (23)$$

Where: i; $rand$ is an integer selected randomly between 0 and 1, X_i is a target vector, while X_i^{min} and X_i^{max} are the minimum and maximum limits of the control.

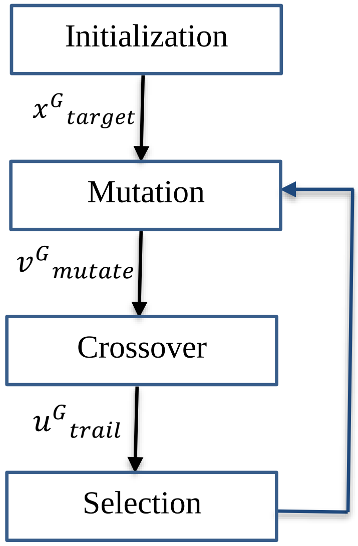


Figure 2. Differential Evolution Process

3.1.2. Mutation

The second step in the DE algorithm is mutation. This is simply a recombination of the members of the population by using a mutation operator. The mutation process led to the creation of a modified version of each individual. This can be implemented after normalizing the population randomly by collecting a third vector consisting of the difference between two vectors from the same population. This vector is referred to as a mutant vector. As a result, the differential mutation is mathematically described as follows:

$$v_i = X_{p1} + FS(X_{p2} - X_{p3}) \tag{24}$$

Where: v is a mutant vector; $p1 \neq \mathrm{p}2 \neq \mathrm{p}3$ are randomly selected numbers from the population search; $X_{p1}, X_{\mathrm{p}2}$ *and* X_{p3} are vectors picked randomly in the current generation's population; FS is the scaling factor, which takes values from 0 to 1.

3.1.3. Crossover

The function of this step is to enhance the diversity of each solution vector. This can be accomplished by generating a trail vector from the target and mutated vectors. Depending on the value of a random variable. If this value is smaller than the crossover constant, a mutant vector variable is considered; otherwise, the target vector variable is considered. This is realized through the comparison of the crossover constant and with a random number in the range of 0 to 1. as illustrated in Equation (25).

$$u^G{}_{trail} = \begin{cases} v^G{}_{mutate} & if\ (rand \leq C_R) \\ x^G{}_{target} & \dots\dots\dots otherwise \end{cases} \tag{25}$$

u_{trail} is the trailing vector of the control variable; v_{mutate} is the mutant vector of the control variable; x_{target} is the target vector of the control variable; C_R is the crossover constant.

3.1.4. Selection

This step is aimed at keeping the best-selected solutions in the population throughout the optimization process. To this end, the trial vector is a candidate to be included in the population if it meets the quality selection criterion. It can replace the previous one if it is found to provide the best answer; otherwise, the candidate retains the previous version, according to the following equation (26).

$$x_i{}^{G+1} = \begin{cases} u^G{}_{trail\_i}\ if \dots f(u^G{}_{trail\_i} \leq f x^G{}_{target\_i}) \\ x^G{}_{target\_i} \dots\dots\dots otherwise \end{cases} \tag{26}$$

Where $f(x)$ stands for the value of the fitness function of the vector x, x_i is the ith control variables, i ranges from 1 to the population size, while G is the generation number.

The algorithm does the mutation, crossover, and selection steps repeatedly for the control variables in the target vector and the trail vector, for the subsequent generation till the end of the total number of iterations. Fig.2 shows a flowchart of the DE process.

3.2. Implementation

In this work, the recommended DE approach was implemented using the MATLAB application. "Table 1" displays the algorithm's control settings.

Table 1. Differential Evolution parameters

F	0.8
C_R	0.5
NP	10
G_{max}	50

4. Simulation Results and Discussion

In this study, the DE algorithm is used to solve the SCOPF problem, and it was tested on the standard IEEE 30-bus system, whose data and operation constraints are given in Ref. [28,29]. A single-line diagram is shown in "Fig. 3" with the main characteristics specified in "Table 2."

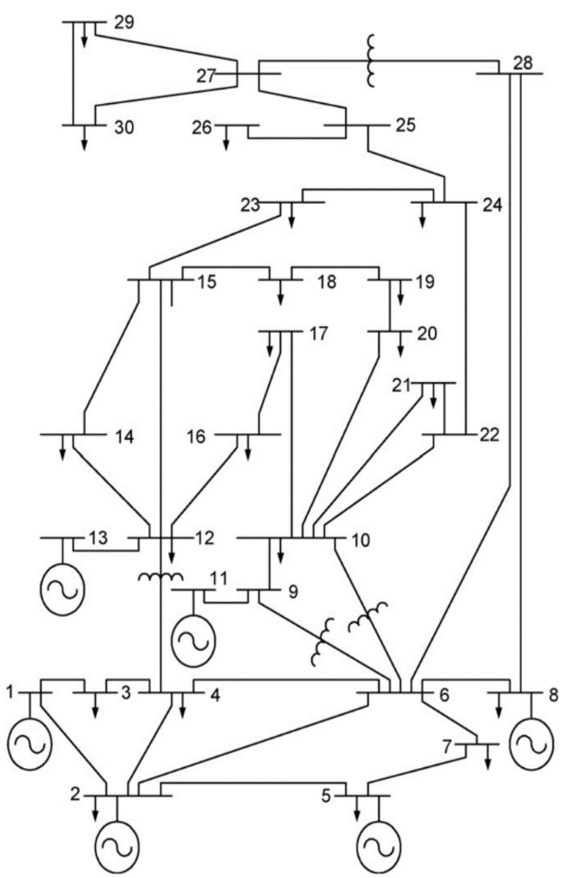


Figure 3. Single line diagram of IEEE 30-bus test system.

Table 2. Characteristics specified for standard IEEE 30-bus system

Test system [28,29]	IEEE 30-bus network
Number of buses	30
Number of lines	41
Number of generators	6
Number of transformers	4 (90–110% ± 1.25%)
off-nominal tap ratio at bus-to-bus lines	6-10, 4-12,6-9, 28- 27
Reactive power compensator on the buses	10, 12, 15, 17, 20, 21, 23, 24, 29 for (0-5) MVAR
Number of loads	21
Control variable	24
Total loads	283.40 + j126.20 MVA
Line load flow losses	5.849 + j 30.386 MVA
voltage PV bus limits	0.95-1.1 (pu)
voltage PQ bus limits	0.95-1.05 (pu)

A code is written in MATLAB environment to simulate the proposed algorithm. The execution is carried out on a laptop with an Intel (R) Core (TM) i7-6700QM CPU running at 2.60 GHz (8 CPUs), 8.192 GB of RAM, and a 64-bit operating system. The Newton-Raphson technique is used to compute the power flow in the IEEE-30 system. In this work, the (SCOPF) will be used to process S-MOF optimization techniques in the IEEE-30 system, as well as contingency limitations, in order to minimize TFC, APTLs, and VD as well as OLTL. The following detailed cases will be used to present this study:

4.1. Case study 1:

In this case, the DE algorithm optimizes OF1-OF3 consecutively as a single objective function, which may be used in the normal state of system operation.

“Table 3” illustrates the optimal OFs for TFC, APTLs, and VD. The convergence of the OFs is depicted in "Fig. 4(a)–4(c) ". The validity of the results was confirmed by comparing them with other results in previous studies, as illustrated in "Table 4". The proposed algorithm is effective in reducing the TFC, APTLs, and VD in comparison with previous studies.

4.2. Case study 2:

Case 2: In this case, OF_1–OF_3 are optimized as a MOF by the DE algorithm. All functions are given equal weight. The results of three OFs optimizations with equal weight values for TFC, APTLs, and VD are shown in "Table 3". "Fig. 5" illustrates the convergence characteristics for determining the optimal value.

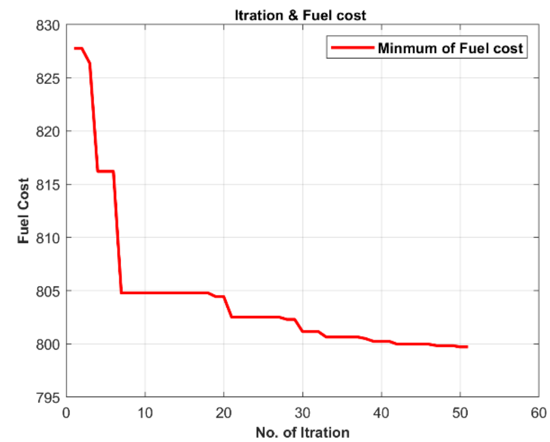
Despite improved TFCs, APTLs, and VDs in this case, overload is observed in some iterations on the TL6-TL8 transmission line while observing the security constraint for the OLTL. where, in this test, the TL6-TL8 is loaded with 44.8 MW, exceeding its maximum capacity of 32 MW. Because of the conflicting goals of the different OFs, the total cost in this case is (805.21 $/h), which is higher than the total cost in Case 1.

4.3 Case Study 3:

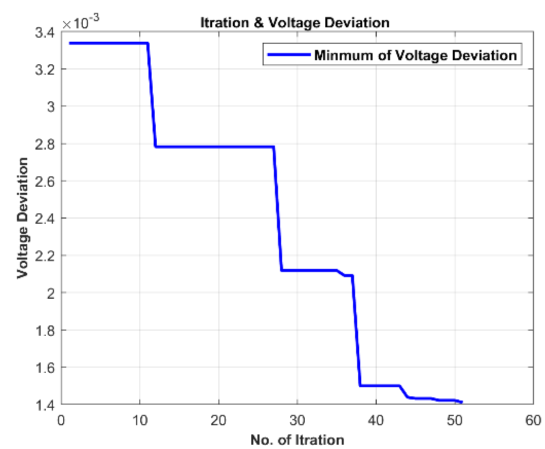
In this case, in addition to optimizing the OF_1–OF_3 as a MOF, the security optimization was applied to minimize the severity index OF_4 and then minimize overloading in transmission lines, which appears at some iterations during the optimizing process. All the four OFs are given an equal weight of (0.25). "Table 3" shows the results of four OFs optimizations for TFC, APTLs, VD, and OLTL. The convergence characteristics for determining the optimal value for it are shown in "Fig. 6".

4.4. Case study 4:

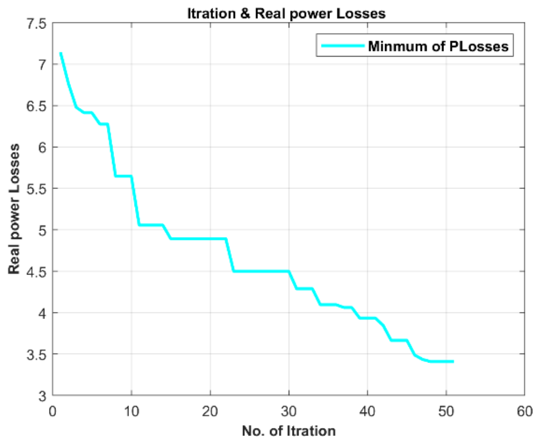
The (N-1) CA is used in normal operation in order to identify the critical contingencies. The line outage was considered in this work to be a critical contingency that caused the other elements to be overloaded. "Table 5" shortlists the critical contingencies as well as the generation initial value determined in this case and the generator output before rescheduling. The Rnk and power flow of the overloaded lines, as well as the SI, are shown in "Table 6". The results have been validated by comparing the results with previous studies [24] which identified four critical lines that cause overloading in the other lines when one is out. Unlike Ref [24], in this work, by performing a contingency analysis, seven critical lines were identified. Its effects on other parts of the system have been verified.



4(a) TFC convergence



4(b) VD convergence



4(c) APTLs convergence

Figure 4(a)-4(c). Objective function convergence for Case 1

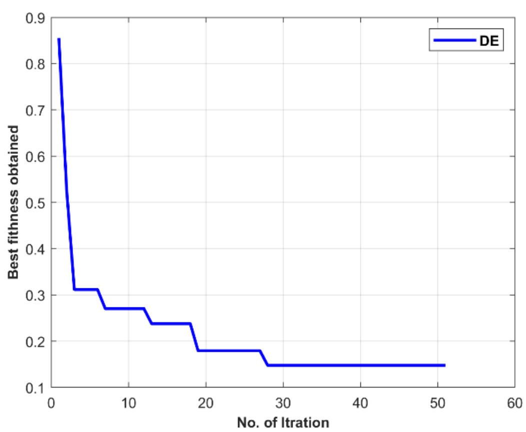


Figure 5. Convergence Characteristics for case.2

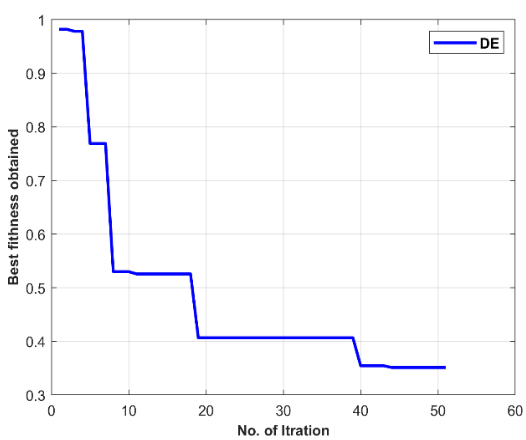


Figure 6. Convergence Characteristics for case.3

4.5 Case Study 5:

In this case, OLTL is alleviated by generator rescheduling using the suggested DE approach in order to achieve a minimal SI value that is near to or equal to zero. in addition to minimizing voltage violations by making the best modifications to the control variables for the system. "Table 7" illustrates the best control settings for all major contingencies, as well as the minimal SI and VD, in addition to the TFC and APTLs results. The results produced with the suggested approach outperform those obtained in Ref [24]. It is clear from the reduction in total TFC and taking VD into account.

Following generator rescheduling during the TL1-TL3 outage, the new line flows achieved for TL1-TL2, and TL4-TL6 are less than the acceptable limit, which alleviates the overloaded lines and thus the obtained SI of zero. Similarly,

for other element outages, the loading for elements after rescheduling is less than the allowable limit, demonstrating that the overloaded lines are eliminated.

Table 3. Simulation findings based on the DE algorithm

Control variable	Limits		Initial value	Case-1			Case-2	Case-3
	Max.	Min.		TFC	APTLs	VD		
VG1 (pu)	1.10	0.95	1.05	1.0893	1.085	1.0151	1.074	1.077
VG2 (pu)	1.10	0.95	1.04	1.0780	1.086	0.983	1.02	1.087
VG5 (pu)	1.10	0.95	1.01	1.0383	1.059	1.031	0.999	1.021
VG8 (pu)	1.10	0.95	1.01	1.0631	1.046	1.002	1.017	1.046
VG11 (pu)	1.10	0.95	1.05	1.0597	1.037	1.076	1.094	1.028
VG13 (pu)	1.10	0.95	1.05	1.0703	1.078	1.059	1.04	1.029
PG1 (MW)	200	50	0	173.768	65.955	166.79	148.72	137.68
PG2 (MW)	80	20	80	50.833	77.09	48.823	48.668	46.178
PG5 (MW)	50	15	50	21.737	49.176	21.079	23.151	42.101
PG8 (MW)	35	10	20	20.538	33.724	29.162	29.884	34.266
PG11 (MW)	30	10	20	13.106	28.009	15.502	17.16	11.317
PG13 (MW)	40	12	20	12.363	33.199	12.998	24.373	18.864
Qc 10 (MVAR)	5	0	0	2.705	2.295	3.243	3.869	1.837
Qc 12 (MVAR)	5	0	0	2.303	1.67	2.69	4.08	4.883
Qc 15 (MVAR)	5	0	0	2.058	2.304	4.755	0.882	0.788
Qc 17 (MVAR)	5	0	0	1.478	0.786	1.758	2.978	4.719
Qc 20 (MVAR)	5	0	0	2.689	2.03	4.185	1.869	2.216
Qc 21 (MVAR)	5	0	0	0.675	2.395	4.195	2.052	0.444
Qc 23 (MVAR)	5	0	0	2.911	3.94	3.8	3.697	3.555
Qc 24 (MVAR)	5	0	0	0.564	1.792	3.801	4.206	4.56
Qc 29 (MVAR)	5	0	0	3.238	2.206	3.288	1.753	2.687
T 6-9	1.10	0.9	1.078	0.968	1.003	1.041	1.032	1.067
T 6-10	1.10	0.9	1.069	1.031	0.984	0.966	0.976	0.964
T 4-12	1.10	0.9	1.032	1.080	1.042	1.08	0.963	0.964
T 27-28	1.10	0.9	1.068	1.026	1.006	0.958	0.999	0.984
TFC ($/h)			902.02	**799.06**	937.058	810.1	**805.21**	**810.1**
APTLs (MW)			5.849	8.927	**3.41**	10.942	**5.719**	**10.942**
VD (pu)			0.079	0.0234	0.0237	**0.0012**	**0.003**	**0.0012**
RPTLs (MVAR)			30.134	39.16	18.797	51.266	**26.666**	**51.266**
SI			0.157	----	----	----	----	**0.134**

Table 4. Comparison of the objectives with other optimization methods

Optimization Techniques		TFC	APTLs	VD	Iterations	Ref
Initial Value	--	902.02	5.849	0.079	-----	-----
Differential Evolution	**DE**	**799.06**	**3.41**	**0.0012**	50	**proposed method**
Ant Colony Optimization	ACO	801.4	3.417	0.119	50	[22]
Flower Pollination Algorithm	FPA	800.161	3.115	0.1845	500	[21]
Particle Swarm Optimization	PSO	799.704	3.026	0.1506	500	[21]
Artificial Bee Colony	ABC	799.3862	2.8864	0.1017	100	[23]
Moth-Flame Optimizer	MFO	799.072	2.853	0.1065	500	[21]

Table 5. Generators Output (MW) for IEEE 30-bus system (without rescheduling)

Control Variables		Initial value	Outage Elements						
			TL1-TL2	TL1-TL3	TL3-TL4	TL2-TL5	TL4-TL6	TL9-TL10	TL10-TL20
Generators Output (MW)	PG1	0	**190.81**	**180.04**	**179.70**	**183.91**	**177.04**	**176.74**	**176.05**
	PG2	50	50	50	50	50	50	50	50
	PG5	22	22	22	22	22	22	22	22
	PG8	22	22	22	22	22	22	22	22
	PG11	12	12	12	12	12	12	12	12
	PG13	12	12	12	12	12	12	12	12

Table 6. Power flow and Contingency ranking of the overloaded lines

Outage Elements	Overload Line	Power Flow (MVA)	Acceptable Limit (MVA)	SI
TL1-TL2	TL1-TL3	**191.0875**	130	**5.5465**
	TL3-TL4	**181.1595**	130	
	TL4-TL6	**108.148**	90	
TL1-TL3	TL1-TL2	**182.9055**	130	**3.0251**
	TL2-TL6	**66.4641**	65	
TL3-TL4	TL1-TL2	**180.0979**	130	**2.9359**
	TL2-TL6	**65.5402**	65	
TL2-TL5	TL2-TL6	**76.8172**	65	**2.8237**
	TL5-TL7	**83.6204**	70	
TL4-TL6	TL1-TL2	**133.6409**	130	**2.2132**
	TL2-TL6	**69.8978**	65	
TL9-TL10	TL16-TL17	**16.8038**	16	**1.103**
TL10-TL20	TL15-TL18	**16.4377**	16	**1.0555**

Table 7. Generator rescheduling (MW) using DE algorithm under critical contingencies

Outage Elements	Critical Line	Power Flow (MVA) before	Power Flow (MVA) after	Power Flow Limit (MVA)	SI	TFC ($/h)	APTLs (MW)	VD (pu)
TL1-TL2	TL1-TL3	191.0875	119.998	130	0	859.4235	11.0626	0.0033
	TL3-TL4	181.1595	110.722	130				
	TL4-TL6	108.148	69.738	90				
TL1-TL3	TL1-TL2	182.9055	119.775	130	0	837.0058	7.6451	0.0015
	TL2-TL6	66.4641	47.456	65				
TL3-TL4	TL1-TL2	180.0979	112.669	130	0	848.3814	5.6864	0.0021
	TL2-TL6	65.5402	39.402	65				
TL2-TL5	TL2-TL6	76.8172	60.632	65	0	846.1312	9.7193	0.0018
	TL5-TL7	83.6204	53.933	70				
TL4-TL6	TL1-TL2	133.6409	88.59	130	0	824.5084	7.0307	0.0051
	TL2-TL6	69.8978	53.177	65				
TL9-TL10	TL16-TL17	16.8038	12.563	16	0	822.4431	7.7838	0.0046
TL10-TL20	TL15-TL18	16.4377	15.273	16	0	817.6163	7.6035	0.0044

5. Conclusions

In this study, the power generation and other control variables (VAR sources and tap changers) were dispatched optimally by taking into consideration both the economic and security aspects of the operation. The problem was modelled as a multi-objective optimization one with quality and inequality operating constraints.

The objective functions that have been considered were the fuel cost, active power losses, and voltage deviation. A contingency analysis was successfully applied to shortlist the critical contingencies. The proposed algorithm was based on a metaheuristic technique (namely, DE). The proposed algorithm was applied to IEEE 30 bus test system with various cases of the power system operation. An appropriate security assessment and improvement were made by taking into account the security restrictions assigned to each case. The results obtained were compared to other previous studies. The findings reveal the effectiveness of the proposed algorithm in dispatching the generation optimally with the satisfaction of the operation equality and inequality constraints.

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Conflict of interest

The authors state that the publication of this work does not involve any conflicts of interest.

Author Contribution Statement

The second author proposed the research problem, which included using artificial intelligence technologies to solve the SCOPF problem. The first author used an evolutionary technique known as differential evolution (DE) to solve the SCOPF problem and applied it to various operating stages of a typical power system. The authors confirmed the study findings by comparing them to the results of other investigations and confirming their validity and efficacy. The authors contributed to the final manuscript and discussed the results.

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