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Adaptive Unified Differential Evolution Algorithm for Optimal Operation of Power Systems with Static Security, Transient Stability and Statcom Device

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Abstract: ***The complexity of a power system operating with transient stability/security constraints increases with increased interconnection of power transmission networks. Many of the power system's secure operations are affected with the voltage/transient instability problems. Thereby, the modern power systems have considered solving optimal power flow (OPF) problems using voltage/transient stability constraints as a tedious and challenging task. Algebraic and differential equations of the voltage/stability constraints are included in non-linear optimal power flow optimization problems. In this work, the OPF problems with voltage/stability constraints are solved using a newly developed reliable and robust technique. Moreover, the impact of a FACTS device such as STATCOM device was investigated to test its impact in the enhancement of power system performance. An adaptive unified differential evolution (AuDE) technique is proposed to search in the non-convex and nonlinear problems to obtain the global optimal solutions. Compared to other existing methods and basic DE, the proposed AuDE algorithm has achieved better results under simulation conditions. The power system's performance is considerably enhanced with STATCOM device. Efficiency of the proposed method in solving the transient and security constrained power systems for optimal operations were demonstrated using the numerical results obtained from IEEE 39-bus, 10-generator system and IEEE 30-bus, 6-generator system. Due to page limitation only 30-bus systems results are presented.***

Keywords: Adaptive unified differential evolution, power system transient stability, power system operation, power system security, optimal power flow.

I. INTRODUCTION

In current trend, maintaining flexibility and secured stability for the development of power system operation turns to be complex and challenging task. Electric power supply industries are now in demand to face the complexities due to increased power requirement for satisfying all-purpose environmental needs. Based on the generation patterns effects against stability of the system, the rapid changes were made to the power system to allow continuous power supply [1].

In secure and planning stage, the operators and planners of power system are currently supported using a powerful tool known as OPF. OPF program mainly aims to optimize simultaneously the objective function through meeting the operating and physical constraints. This optimization process is done in a power system for evaluating their optimal operating condition [2], [3]. Security and economic aspects of the power system are integrated better using the OPF model. Thereby, many researchers are highly interested with the OPF model due to its advanced mathematical formulation.

Optimizing the performance of static system has been analyzed limitedly in most of the conventional OPF problems. Furthermore, transient stability alone was dealt effectively using the existing OPF problems. But, the transient stability constraints are not considered by the existing OPF problems at the time of determining operation point of the system. Thereby, the crucial contingency in a system can produce unstable transient constraints. High expense and control loss are the main inadequacies faced with such kind of transient instabilities. Hence, dealing the transient constrained OPF problem through developing a reliable and robust technique is a significant challenging task in OPF study [4]. Power electronic converters are incorporated into the devices or controllers of Flexible Alternating Current Transmission System (FACTS) to make the power system highly stable and controllable through improving its stability, flexibility and performance. The FACTS controllers stabilize the transmission systems by increasing the transfer capability and reduce the risk of line trips [5]. The major requirement in power system is maintaining the steady acceptable system parameters under normal operation and abnormal operating conditions [6]. The development of power electronic based FACTS devices opened up new ways of controlling the power systems. They FACT devices have the capability of controlling both in steady state and dynamic control of power system [7].FACTS devices are incorporated for improving the power transfer capability, laudability of transmission lines, voltage stability, power loss reduction, damping of power oscillations, elimination of new transmission lines construction, and reactive power management etc., widely [8–18].

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By not delimiting the system security, the pre-fixed thermal limits are considered to load conventional transmission systems using an important tool called FACTs device [19]. Transmission line flows are controlled using these FACTs devices through varying the transmission system parameters.

Hence, it is suitable to implement the fast switching based high-gain type controllers. Voltage control and support in transmission grids are performed using the most famous voltage source converter (VSC) FACTs controller called static synchronous compensator (STATCOM) [20]. Voltage of transmission lines are increased or reduced as well as the reactive power is absorbed or supplied to operate the STATCOM devices in view of the steady-state point fact [21, 22]. For the transmission system, their location, number, size and type are considered to improve the goodness of FACTs devices [23].

From the past decades, the OPF problems were solved using various kinds of numerical optimization methods. Some of the commonly known OPF problems are quadratic programming (QP), nonlinear programming (NLP), and linear programming (LP). These problems have the ability to determine the global optimal solution through depending on the convexity and initial condition. In case of constraints in practical generators, these methods failed to determine the global optimum solution based on the convexity and initial condition. Works in [24-27], have detailed the literal studies and introduction of different conventional optimization methods.

At the time of initiating the conditions, the high sensitivity issues occurred are largely faced by the traditional TSCOPF and OPF based optimization methods [28]. Local optimum solutions are easily achieved by these methods [29]. Several restrictions are made to the transient stability limit of the OPF problems and to the objective functions due to different forms of computational complexities [30, 31].

Furthermore, the evolutionary algorithms (EAs) are applied to solve these kinds of limitations. The metaphor in the evaluation of natural biology is usually mimicked by the stochastic global search techniques called EAs. However, most of the power system optimization problems have adopted the EAs to yield optimal results [32-36].

Depending on the type of objective function and initial condition used, the main delimits of the used mathematical model can be identified. In order to withstand these delimits, the heuristic and stochastic aspects are followed to develop a new evolutionary optimization technique categories. They are as follows: Gravitational search algorithm (GSA) [50], Shuffled frog leaping algorithm (SFL) [49], A modified Artificial bee colony algorithm (MABCA) [48], Biogeography Based Optimization method (BBO) [46, 47], Artificial Bee Colony (ABC) [45], Harmony Search (HS) [44], Differential Evolution (DE) [43], Particle Swarm Optimization (PSO) [42], Evolutionary Programming (EP) [41], Simulated Annealing (SA) [40], Tabu Search (TS) [39], and Genetic Algorithm (GA) [37, 38]. However, the operation and control issues of power system were better solved using these evolutionary algorithms. Hybrid optimization and non-deterministic techniques were reviewed and has provided a valuable and significant introduction by the authors in the work [51]. Global optimal solutions can be searched effectively using the differential evolution (DE) algorithm of Storn and Price [52]. Work in [53] has suggested that, when compared to EAs the DE is simpler and has showed better performance. In DE, five different types of mutation strategies were proposed by Storn and Price [54]. The mutation operation properties have been improved using various new mutation strategy variants [55]. But, the implementation of DE algorithm becomes so complex with the usage of various mutation operation strategies. In this work, the global optimization process is done using the proposed adaptive unified differential evolution (AuDE) algorithm.

This algorithm has encompassed all used mutation strategies by means of applying alone a single expression of mutation. Compared to other existing algorithms, the mathematical operation of AuDE algorithm becomes simple further with the usage of multiple mutation strategies. In the optimization process, various new combinations of existing mutation strategies are explored by the users enabled using multiple mutation strategies. The proposed AuDE becomes self-adaptive while on using the crossover and mutation operation and its control parameters. Furthermore, during the optimization process, this allows the users to select an optimal set of control parameters.

The paper is organized as follows. This paper applies adaptive unified differential evolution in TSCOPF problems in order to deal with the limitations of existing techniques. The Section II presents the voltage stability computation. The Section III presents the brief overview of FACTS devices. The Section IV presents the fuzzy logic based static severity index. The formulation of TSCOPF problem is presented in Section V. The overview of standard differential evolution and the proposed adaptive unified differential evolution is presented in Section VI and Section VII respectively. The representation of transient stability constraints and the procedure of transient stability assessment in the implementation of AuDE technique for TSOPF are presented in Section VIII. The AuDE based TSCOPF is then studied on two test systems in Section IX. In Section IX, the implementation of the proposed AuDE method is presented and its effectiveness is also primarily investigated using the 6-generator, 30-bus system and 10-generator, 39-bus system. Finally, the paper gets completed up in Section X.

II. COMPUTATION OF VOLTAGE STABILITY INDEX (L-INDEX)

In normal operating conditions, each bus maintaining suitable levels of bus voltages defines the voltage stability of a power system. The power system enters into voltage instability condition when it is being subjected to different disturbances (system configuration changes, increase in load demand). Thereby, the uncontrollability in voltage reduction is experienced with these significant changes. As a result, one of the major tasks considered during power system operation is the good voltage stability maintenance in a power system. Proximities of voltage collapse condition are specified by the L-index of a bus. Equation (1) indicates the bus j^{th} corresponding L-index L_j condition [56].

$$L_j = \left| 1 - \sum_{i=1}^{h} F_{ji} \frac{V_i}{V_j} \right| \text{ where } j = g+1,\ldots,n \quad (1)$$

$$F_{ji} = -[y_1]^{-1}[y_2] \quad (2)$$

Number of load bus is indicated as N_{PQ} and number of PV bus is denoted as N_{PV}. The PQ and PV of the buses are separated to obtain y_1 and y_2 sub matrices of the YBUS system. It is indicated in Equation (3)

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \quad (3)$$

For all load buses, the voltage stability L-index is computed. Stable and no load case in a system is represented when L_j is closer to '0'. For bus 'j', the voltage collapse condition is determined when L_j is closer to 1, respectively. Equation (4) indicates the complete systems corresponding global stability indicator (L)

$$L = \max(L_j), \quad \text{where } j = 1,2,\ldots,NPQ \quad (4)$$

A stable system is identified with least 'L' value. In a system, the voltage instability will be experienced with increased L-index values when tuned the control variables of the OPF problem solutions.

III. FACTS DEVICES

Presently, the improvement in voltage stability and transmission congestion reduction is achieved greatly with FACTs devices. Furthermore, the advanced FACTs have used the synchronous sources as the Voltage Sourced Converter (VSC) [57]. Some of the commonly known synchronous sources such as, a combined series shunt type device, Unified Power Flow Controller (UPFC), a series type device called Static Series Compensator (SSSC), a shunt type device called (STATCOM) are employed as VSC by the FACTs devices. Among all these synchronous sources, the STATCOM device is the commonly used VSC device. It provides the reactive power for bus voltage magnitude control. More commonly, the power system properties such as, re-scheduling generation [61], load shedding reduction [59, 60], power loss reduction, and congestion management are handled well using the FACTs devices. Thereby, the cost of expense required for the operation of power system is potentially reduced. Customized security constrained optimal power flow (SCOPF) programs can be used to optimize the power dispatch of each plant as well as the operation and deployment mode of FACTs devices. But, a global optimal solution is obtained only by developing new methods due to the existence of a non-convex problem (i.e. optimization process of FACTs devices) [62].

A. STATCOM Device

Depending on the environment factors, the optimal process for the power system networks is developed. By the fact, this process can be performed well using the shunt FACTs devices. Generally, these FACTs devices are utilized to enhance the stability and performance of power system. Self-commutated DC to AC converters based GTO thyristors are included in the STATCOM device which corresponds to the VSC type. This device can be employed to control the usage of reactor or capacitor banks and compensation of transmission lines. In order to obtain an independent controllable reactive power, an energy storage device was equipped into the converter. Thereby, the stability and security of power system is highly improved [63]. A synchronous voltage amended with phase angle, controllable magnitude, and fundamental frequency is generated using a voltage source converter equipped in the STATCOM device. As shown in Fig. 1, the STATCOM device is formed through coupling a transformer via the VSC (i.e. a system connected with shunt device). The bus connected to STATCOM device helps them for regulating the bus voltage magnitude by means of injecting or absorbing the reactive power [63]. This model is otherwise called as Power Injection Model (PIM) or Voltage Source Model (VSM). At the polar co-ordinates, the Newton-Raphson methods working associated to the steady state model of STATCOM device is indicated as follows:

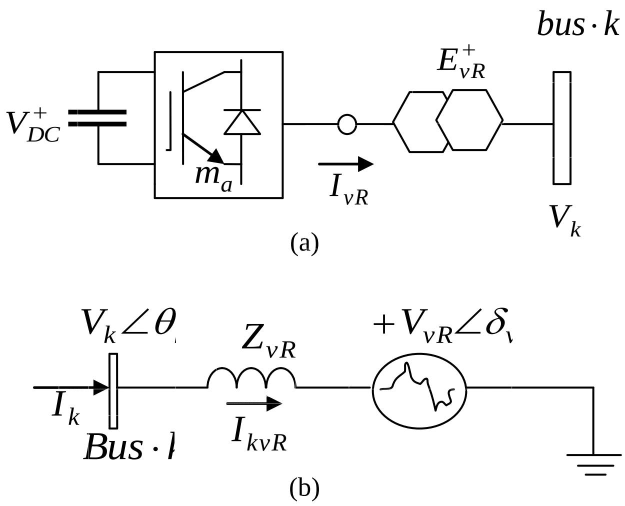

Figure 1: Static compensator of STATCOM model: (a) Association of shunt connected transformer and AC network into the voltage source converter (VSC); b) Voltage source of shunt solid state.

Figure 1 has indicated the Thevenin's equivalent circuit representing the transformer of switched-mode voltage sourced converter and its fundamental frequency operation.

$$V_{vR} = V_k + Z_{vR} I_{vR} \quad (5)$$

Equation (5) represents the Norton equivalent form

$$I_{vR} = I_N - Y_{vR} V_{vR} \quad (6)$$

Here, $I_N = Y_{vR} V_{vR}$

Where, the k voltage of bus is indicated as V_k, the voltage source inverter as V_{vR}, inverter's current as I_{vR} and Norton's current as I_N, respectively. Also, the admittance of short circuit and the transformers impedance are denoted as Y_{vR} and Z_{vR}, correspondingly.

The bound constraints of STATCOM voltage injection (V_{vR}) is expressed as:

$$V_{vR\min} \le V_{vR} \le V_{vR\max} \quad (7)$$

where, the maximum and minimum voltages of STATCOM's are represented as $V_{vR\max}$ and $V_{vR\min}$, respectively.

Using VSC, the power expression is formed through transforming the current expression indicated in (6). Equations (8) and (9) denote the bus 'k' containing the injected power.

$$S_{vR} = V_{vR} I_{vR}^* = V_{vR}^2 Y_{vR}^* - V_{vR} Y_{vR}^* V_k^* \quad (8)$$

$$S_k = V_k I_{vR}^* = V_{vR} Y_{vR}^* V_k^* - V_k^2 Y_{vR}^* \quad (9)$$

where $|V_{vR}|$ and δ_{vR} are the STATCOM voltage magnitude and angle respectively.

For bus k and STATCOM device, the reactive and active power equations derived are represented as follows:

$$P_{vR} = V_{vR}^2 G_{vR} + V_{vR} V_k [G_{vR} \cos(\delta_{vR} - \theta_k) + B_{vR} \sin(\delta_{vR} - \theta_k)], \quad (10)$$

$$Q_{vR} = -V_{vR}^2 B_{vR} + V_{vR} V_k [G_{vR} \sin(\delta_{vR} - \theta_k) - B_{vR} \cos(\delta_{vR} - \theta_k)] \quad (11)$$

$$P_k = V_k^2 G_{vR} + V_k V_{vR} [G_{vR} \cos(\theta_k - \delta_{vR}) + B_{vR} \sin(\theta_k - \delta_{vR})], \quad (12)$$

$$Q_k = -V_k^2 B_{vR} + V_k V_{vR} [G_{vR} \sin(\theta_k - \delta_{vR}) - B_{vR} \cos(\theta_k - \delta_{vR})] \quad (13)$$

Load flow solution has included the linearized STATCOM model based on these above derived power equations. Here, the state variables are considered to be the phase angle (δ_{vR}) and voltage magnitude (V_{vR}), respectively.

IV. STATIC SEVERITY INDEX (SSI) USING FUZZY LOGIC

From the past decades, a rapid growth is evident with the usage of fuzzy logic applications. Reasoning modes can be applied effectively using fuzzy logic (FL). Instead numbers, the words are considered to define the mapping rule of fuzzy logic. Tolerance and impression are explored using the words computed by the FL. Furthermore, the output and input spaces can be mapped effectively using FL. Nonetheless, the multi-output and multi-input systems are modeled accurately using FL tool.

In the literature, different types of objective functions were used for optimization of power system operation. But, no one has evaluated the impact of the optimization of a particular objective function on the power system severity/security. Therefore, in order to evaluate the impact of optimization of power system operation, a fuzzy logic composite criteria based severity index is proposed in this case. Using this FL based static severity index, the impact on network contingency ranking is also evaluated.

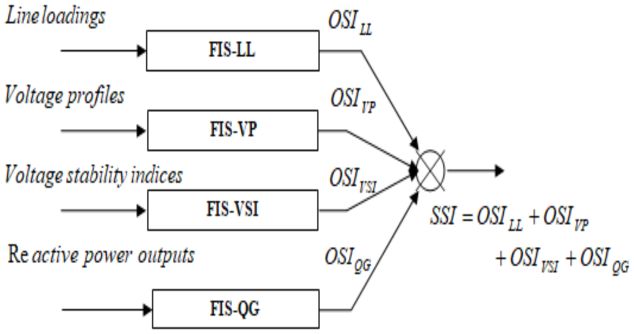

Figure 2: Parallel operated fuzzy inference systems

FL based static security/severity index: As indicated in Fig 2, the parallel operated fuzzy inference systems (FIS) has adopted the severity index to obtain the total fuzzy logic composite criteria. For contingency, the static severity index is computed. When compared to the pre-fixed value, the severity index showing higher value is ranked after listing out [64].

V. OPF PROBLEM FORMULATION

Formulation of transient stability constrained standard OPF problem is as follows:

$$\text{Min} \quad f(\mathbf{u}, \mathbf{x}) \quad (14)$$

$$\text{Subject to} \quad g(\mathbf{u}, \mathbf{x}) = 0 \quad (15)$$

$$h(\mathbf{u}, \mathbf{x}) \leq 0 \quad (16)$$

Here, the control variables vector is indicated as $\mathbf{u}$ and the variable that corresponds to the dependent variable vector is indicated as $\mathbf{x}$, respectively.

Objective functions: Three different forms of objective functions included in the OPF problem are as follows:

Objective Function I :

$Min \quad f_1 = F_T = \sum (a_i P_{gi}^2 + b_i P_{gi} + c_i)$ is the cost of generation

Objective Function II :

$Min \quad f_2 = Ploss = \sum_{\substack{k \in N_l \\ k=(i,j)}} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij})$, is the power loss

Objective Function III :

$Min \quad f_3 = Lj2s = \sum_{j=g+1}^{nb} L_j^2$ is the sum of squared voltage stability indices

Constraints: The OPF problem constraints are categorized into two forms:

Equality Constraints: These constraints represent the sets of nonlinear equations for power flows, which means,

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (17)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (18)$$

where P_{Gi} and Q_{Gi} are the real and reactive power outputs injected at bus i respectively, the load demand at the same bus is represented by P_{Di} and Q_{Di}, and elements of the bus admittance matrix are represented by $|Y_{ij}|$ and θ_{ij}.

nequality Constraints: These constraints that represent the power system operational and security limits such as the bounds on the following:

Generators real and reactive power outputs

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max}, i = 1, \ldots, N \quad (19)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, i = 1, \ldots, N \quad (20)$$

Voltage magnitudes at each bus in the network

$$V_i^{\min} \leq V_i \leq V_i^{\max}, i = 1, \ldots, NL \quad (21)$$

Transformer tap settings

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1, \ldots, NT \quad (22)$$

Reactive power injections due to capacitor banks

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, i = 1, \ldots, CS \quad (23)$$

Transmission lines loading

$$S_i \le S_i^{\max}, i = 1, \ldots, nl \quad (24)$$

Voltage stability index:

$$L_j \le L_j^{\max}, \quad j = 1, \ldots, NL \quad (25)$$

FACTS device constraint:

STATCOM voltage magnitude

$$V_{vR}^{\min} \le V_{vR} \le V_{vR}^{\max} \quad (26a)$$

STATCOM voltage angle

$$\delta_{vR}^{\min} \le \delta_{vR} \le \delta_{vR}^{\max} \quad (26b)$$

Transient stability constraint

$$\left|\delta_i - \delta_{COI}\right|_{max} \le \delta_{max} \qquad i = 1 \ldots N_g, \quad (27)$$

A system maintaining stability followed with contingency 'k' is implied using the transient stability associated constraints as indicated in Equation (27). Power system ability is indicated using the term Transient stability index (TSI), which can be used to return back a new stable equilibrium by maintaining itself in its stable domain.

Transient stability constraints: Wide scopes of algebraic equations are used to explain the transient stability problem of power system. For the generator, the oscillation equations derived are as follows:

$$\dot{\delta_\iota} = w_i - w_0 \qquad i=1\ldots N_g \quad (28)$$

$$M_i\dot{\omega_\iota} = \omega_0(P_{m\iota} - P_{e\iota} - D_\iota\omega_\iota) \quad (29)$$

Here, the synchronous speed is indicated as ω_o, for the i^{th} generator, the electrical output power is denoted as P_{ci}, mechanical input power as P_{mi}, damping constant as D_i, moment of inertia as M_i, rotor speed as ω_i, and rotor angle as δ_i, respectively.

Likely, the center of inertia (COI) position is expressed as follows:

$$\delta_{COI} = \frac{\sum_{i=1}^{N_g} M_i\delta_i}{\sum_{i=1}^{N_g} M_i}. \quad (30)$$

Equation (31) indicates the formulation of transient stability's inequality constraints.

$$\left|\delta_i - \delta_{COI}\right|_{max} \le \delta_{max} \qquad i = 1 \ldots N_g, \quad (31)$$

For the i^{th} generator, the rotor angles maximum deviation from the COI is indicated as $\left|\delta_i - \delta_{COI}\right|_{max}$ and based on the experience the maximum value allowed by the rotor angle is denoted as δ_{max}. In this study, the trial and error method is used to determine the value of δ_{max}. Most of the past literal works have shown different values for each system.

Fitness value computation: To the fuel cost, the state variables violations are added to determine the fitness value of an individual. Normally, using Newton-Raphson algorithm, the fuel cost value is evaluated. Consequently, for each solution, the fitness value is evaluated as follows:

$$f(x,u) = f_i + K_Q \sum_{i=1}^{N_g}(Q_{gi} - Q_{gi}^{lim})^2 + K_V \sum_{i=1}^{N_{pq}}(V_i - Vilim)2+Ksi=1Nl(Sl- \quad Sllim)2+KLi=1Npq(Lj- Ljlim)2+KTi=1Ng(|\delta i- \delta COI|max- \delta lim)2. \quad (32)$$

Q_{gi}^{lim}, V_i^{lim}, S_i^{lim}, L_j^{lim}, and δ_i^{lim} are defined as follows:

$$Q_{gi}^{lim} = \begin{cases} Q_{gi}^{max}; \ Q_{gi} > Q_{gi}^{max} \\ Q_{gi}^{min}; Q_{gi} < Q_{gi}^{min} \end{cases}. \quad (33a)$$

$$V_i^{lim} = \begin{cases} V_i^{max}; \ V_i > V_i^{max} \\ V_i^{min}; V_i < V_i^{min} \end{cases}. \quad (33b)$$

$$L_j^{lim} = \begin{cases} L_j^{max}; \ L_j > L_j^{max} \\ L_j^{min}; L_j < L_j^{min} \end{cases}. \quad (34)$$

$$S_l^{lim} = \begin{cases} S_l^{max}; \ S_l > S_l^{max} \\ S_l^{min}; S_l < S_l^{min} \end{cases}. \quad (35)$$

$$\delta_i^{lim} = \begin{cases} \delta_{max}; \ \left|\delta_i - \delta_{COI}\right|_{max} > \delta_{max} \\ 0: \ \left|\delta_i - \delta_{COI}\right|_{max} < \delta_{max} \end{cases}. \quad (36)$$

Here, the fitness function is indicated as $f(x,u)$. The transient stability limit, load bus voltage, the generator bus reactive power output, the slack bus reactive power output are indicated as K_T, K_L, K_S, K_V and K_Q, respectively. For the related variables, their upper or lower limits violations are indicated as Q_i^{lim}, V_i^{lim}, S_l^{lim} and L_j^{lim}, respectively. The number of load buses is indicated as N_{pq}, respectively. The penalty value is assumed to be zero when, the constraints relay within their lower and upper limits.

VI. STANDARD DIFFERENTIAL EVOLUTION (DE) ALGORITHMS

Population initialization is the first step of DE algorithm. Initial population is formed through random generation of NP solutions group included in the control parametric space. Update of population from one cycle to the next cycle is performed soon after completing the initialization step. When reached maximum number of cycles, the repetition of process is stopped; otherwise, the process is continued until the termination criterion is attained. However, the mutation, crossover, and selection are the three kinds of operations used for updating the populations at each cycle or generations. Both crossover and mutation operations are applied to generate new solutions in every generation/iteration. Then, the appropriate solutions from these generated new solutions are obtained through applying the selection operation [65].

Individuals are referred to be the NP populations that are evolved using DE algorithm. In D-dimensional parametric space, the candidate solutions are encoded to achieve the global optimum (i.e. $X_{i,G} = \{X_{i,G}^1, \ldots\ldots, X_{i,G}^D\}, i = 1, \ldots\ldots, NP$). Inside the search space, the individuals are randomized uniformly considering the maximum and minimum parametric limits $X_{min} = \{X_{min}^1, \ldots\ldots, X_{min}^D\}$ and $X_{max} = \{X_{max}^1, \ldots\ldots, X_{max}^D\}$, respectively. For instance, at generation G=0, the ith individual containing the initial value of jth parameter is as follows:

$$x_{i,0}^{j} = x_{min}^{j} + rand(0,1) \cdot (x_{max}^{j} - x_{min}^{j}), \quad j = 1,2,3, \ldots, D \qquad (37)$$

Here, the limit [0, 1] considered for uniform distribution of random variables is indicated as $rand(0,1)$.

Mutation Operation: Considering each individual $X_{i,G}$ (target vector) in the current population, the mutant vector $V_{i,G}$ is generated using the mutation operation applied by the DE algorithm after completing the initialization of population or solutions. From the below given mutation strategies, any one of them can be selected to generate the mutant vector $V_{i,G} = \{v_{i,G}^1, v_{i,G}^2, \ldots, v_{i,G}^D\}$ corresponding to each target vector $X_{i,G}$ at each cycle.

In DE algorithm, the commonly used mutation operation strategies are provided below:

"DE/rand/1"

$$V_{i,G} = X_{r_1^i,G} + F \cdot \left(X_{r_2^i,G} - X_{r_3^i,G}\right) \qquad (38)$$

"DE/best/1":

$$V_{i,G} = X_{best,G} + F \cdot \left(X_{r_1^i,G} - X_{r_2^i,G}\right) \qquad (39)$$

"DE/rand − to − best/1":

$$V_{i,G} = X_{i,G} + F \cdot \left(X_{best,G} - X_{i,G}\right) + F \cdot \left(X_{r_1^i,G} - X_{r_2^i,G}\right) \qquad (40)$$

4) *"DE/best/2"*:

$$V_{i,G} = X_{best,G} + F \cdot \left(X_{r_1^i,G} - X_{r_2^i,G}\right) + F \cdot \left(X_{r_3^i,G} - X_{r_4^i,G}\right) \qquad (41)$$

5) "DE/rand/2":

$$V_{i,G} = X_{r_1^i,G} + F \cdot \left(X_{r_2^i,G} - X_{r_3^i,G}\right) + F \cdot \left(X_{r_4^i,G} - X_{r_5^i,G}\right) \qquad (42)$$

Here, the indices generated are represented as $r_1^i, r_2^i, r_3^i, r_4^i,$ and r_5^i, respectively. They are called exclusive integers generated in mutual and random manner. For each mutant vector, the random generation of these indices is performed. Vector difference is scaled using a positive control and scaling factor denoted as F. In a specific generation, the best fitness value containing individual vector is represented as $X_{best,G}$.

Crossover Operation: A trial vector $U_{i,G} = \left(u_{i,G}^1, u_{i,G}^2, \ldots, u_{i,G}^D\right)$ is generated from the mutant vector $V_{i,G}$ and its relative target vector $X_{i,G}$ by means of applying the crossover operation. This process is done after finishing the mutation operation. Uniform (binomial) crossover employed for the basic DE algorithm is as follows:

$$u_{i,G}^{j} = \begin{cases} v_{i,G}^{j}, & if\left(rand_j[0,1) \le CR\right) or\ (j = j_{rand}) \\ x_{i,G}^{j}, & otherwise \\ & j = 1,2, \ldots, D. \end{cases} \qquad (43)$$

Usually, the mutant vector is observed to copy the fraction of parameter values. These values are then controlled using a significant constant called crossover rate CR relaying in the limit [0,1] (as indicated in (43). In case, if $rand_j[0,1) \le CR$ or $j = j_{rand}$ then to the trial vector element $U_{i,G}$, the mutant vectors $V_{i,G}$ jth parameter is copied by the binomial crossover operator. If this is not the case, then the corresponding target vector $X_{i,G}$ is considered to copy the jth mutant vector parameter. Also, considering the target vector $X_{i,G}$, the trial vectors $U_{i,G}$ residual parameters are copied. Condition j_{rand} ensures that the trial vector $U_{i,G}$ will be different from its corresponding target vector $X_{i,G}$ by at least one parameter.

Selection Operation: Best population is obtained after employing the selection operation. Target vector $f(X_{i,G})$ is used to compare each trial vector $f(U_{i,G})$ and its relative objective function value. Compared to the target vector, the equal or less objective function value obtained by the trial vector can take place in the next cycle as an individual by replacing the target vector. If this is not the case then, the next cycle is continued with the target vector. Equation (44) indicates the selection operation.

$$X_{i,G+1} = \begin{cases} U_{i,G}, & iff\left(U_{i,G}\right) \le f\left(X_{i,G}\right) \\ X_{i,G}, & otherwise \end{cases} \qquad (44)$$

After reaching the termination criterion, the repetition of the process is stopped. Table 1 summarizes the pseudo-code of DE.

VII. ADAPTIVE UNIFIED DIFFERENTIAL EVOLUTION (AUDE) ALGORITHM

Standard differential evolution algorithm has been improved using the newly proposed ten various forms of mutation strategies. When quantified numerous test samples of different optimization problems, the "DE/best /1/bin" has achieved good performance compared to "DE/ rand/1 bin". However, the ICEC96 contest has suggested using the DE/best /2/bin due to its excellent performance [67]. Usage of differential evolution algorithm can cause difficulties with the existence of multiple mutation strategies. Works in [68-70] have proposed the techniques of combining different forms of multiple mutation strategies.

In this work, the differential evolution algorithm using many of the traditional mutation strategies are unified through developing a new single mutation expression. This can be expressed as follows:

$$v_i = x_i + F_1(x_b - x_i) + F_2(x_{r1} - x_i) + F_3(x_{r2} - x_{r3}) + F_4(x_{r4} - x_{r5}) \qquad (45)$$

In the current iteration (generation), the best solution identified is indicated in the right side of Eq. (45) (i.e. in second term). From the random solution, the rational invariant contributions obtained are indicated in third term [71]. As similar to the normal differential evolution algorithm, the parent solutions differences are indicated in the 4th and 5th terms.

From the best solution, the mutated solutions are diverted away using the final three terms. This helps in the improvement of exploration process of the algorithm during making decision in the parametric space.

The weights obtained are represented using four parameters such as, F_1, F_2, F_3 and F_4. In order to produce a new mutant solution, the exploration and exploitation are combined using mutation expression operation. Mutation operators space is explored widely using an opportunity provided by this new expression. It is possible to achieve a new mutation strategy during applying a differential set of parameters such as, F_1, F_2, F_3, and F_4. Compared to the most of the traditional standard differential evolution algorithms, a better optimization solution can be obtained using a unified mutation strategy.

During performing different optimization stages, various combinations of mutation strategies can be applied through adjusting the differential set of parameters at each evolution of the optimization process. Hence, the simplicity in mathematical expressions is enjoyed in these unified mutation operations.

Different mutation strategies are used and combined using a method provided by the unified mutation strategy. Thereby, the application users have considered the selection of suitable control parameters F_1, F_2, F_3, and F_4 is a time consuming and tedious process. Performance of the algorithm is highly improved and the computational burden of the application users is reduced on selecting the control parameters using a self-adaptive method.

In past studies, a number of parameters control methods were used for the conventional differential evolution algorithm [72-76]. The proposed unified differential algorithm in this work is developed through evolving dynamically the five control parameters F_1, F_2, F_3, F_4 and C_r of classical self-adaptive method [73]. In most of the experimental tests, the good performance was achieved using this simple self-adaptive scheme.

In this study, a set of control parameters $x_i, i = 1,2,3,....NP$ are comprised in each individual solution during the generation G of the mutation process in self-adaptive method. A new control parameter sets $F_{1,i}^{G+1}, F_{2,i}^{G+1}, F_{3,i}^{G+1}, F_{4,i}^{G+1} and C_{r_i}^{G+1}$ are computed prior to the adaptation of unified differential evolution expressions for producing a new mutant solution.

$$F_{j,i}^{G+1} = \begin{cases} F_{jmin} + r_{j1}(F_{jmax} - F_{min}), & if r_{j2} < \tau_j \\ F_{1,iotherwise}^{G} \end{cases} \quad (46)$$

$$C_{r_i}^{G+1} = \begin{cases} C_{r_{min}} + r_3(C_{r_{max}} - C_{r_{min}}), & if r_4 < \tau_5 \\ C_{r_{i,}}^{G} & otherwise \end{cases} \quad (47)$$

Maximum and minimum values of the control parameters are expressed as $F_{jmin} and F_{jmax}$ for j=1, 2, 3, 4; whereas, the uniform random values distributed in the interval [0,1] are indicated as r_{j1}, r_{j2}, $j = 1,2,3$, r_3, r_4 , respectively. Subsequently, the maximum and minimum cross over probability of the control parameters are denoted as $C_{r_{max}}$ and $C_{r_{min}}$. For the j^{th} control parameter, the probability of old value and new value used is indicated as τ_j, j=1, 2,3,4,5. Notably, it is important to maintain the value of τ_j to be smaller for further generating the new trial solutions by means of reusing the survived solutions. In this work, the value of τ_j is fixed to 0.1 [73]. Also, the values 0 and 1 are fixed to $F_{jmin} and F_{jmax}$, respectively. The control parameters values are fixed to $C_{r_{max}}$=1 and $C_{r_{min}}$ =0. Based on different traditional mutation strategies, the values for these parameters are selected. However, the mutant solution is generated using this new control parameter step. In between the minimum and maximum values, the initial values for the control parameters are assigned. Pseudo-code of the AuDE algorithm is indicated below as follows:

Pseudo-code of AuDE algorithm: Based on uniform samplings distributed randomly in the interval [0,1], the initial control parameters F_1, F_2, F_3, F_4, C_r are generated. The NP points are sampled randomly inside the feasible control parametric space x to generate a set of initial population. Then, their corresponding objective function values f(x) are evaluated.

Initialize the generation number as G=0
While not attained the stopping criteria, Do:
For i=1to NP (for each parent solutions target x_i):
Mutation
Determine a set of control parameters (for j=1, 2, 3, and 4):

$$F_{j,i}^{G+1} = \begin{cases} F_{jmin} + r_{j1}(F_{jmax} - F_{min}), & if r_{j2} < \tau_j \\ F_{1,iotherwise}^{G} \end{cases}$$

$$C_{r_i}^{G+1} = \begin{cases} C_{r_{min}} + r_3(C_{r_{max}} - C_{r_{min}}), & if r_4 < \tau_5 \\ C_{r_{i,}}^{G} & otherwise \end{cases}$$

Using AuDE mutation strategy to determine a mutant solution vector:

$$v_i = x_i + F_1(x_b - x_i) + F_2(x_{r1} - x_i) + F_3(x_{r2} - x_{r3}) + F_4(x_{r4} - x_{r5})$$

Crossover
Generate a new trial solution $U_i\,(u_{i1}, u_{i2}, \dots\dots\ \dots, u_{iD})$ through binomial crossover scheme:
u_{ij}=u_{ij} if $rand_{ij}[0,1] \leq C_{r_i}^{G+1}$or j=$j_{rand,}$
Otherwise $u_{ij} = x_{ij}$
Selection
For the trial solution $f(U_i)$ compute the objective functions
If $f(U_i) \leq f(x_i)$ then $x_{i,G+1} = U_i$
else $x_{i,G+1} = x_{i,G}$
Find For
G=G+1
End While

VIII. IMPLEMENTATION OF AUDE ALGORITHM (46) FOR OPF PROBLEM

Number of populations (N_p) is significantly adopted by the natural evolution algorithm called differential evolution to attain an optimal solution through repeating the iterations. In this section, the adaptive unified differential evolution algorithm is applied to solve TSCOPF problem. Initialization, selection, and evaluation of solutions are the three most important strategies introduced by the differential evolution algorithm (DEA). However, these strategies mainly aimed for the minimization of computational time. The flow chart of the proposed AuDE algorithm for solving the TSCOPF problem is illustrated in Fig.3. Detailed explanation is provided in this section.

Using individuals (populations) to encode the control variables: In order to withstand the TSCOPF issues, the differential algorithm should be applied only after identifying the number of control variables from the problem that are need to be optimized. Here, Q_{ci} indicates the shunt reactive power, T_{ti} as tap changing transformers, V_{gi} as voltage magnitudes generator, and P_{g1} is the slack unit not considered in P_{gi} known as the outputs of the active power generator. Therefore, u can be expressed as

$$u^T=[P_{g2}, \ldots\ldots .P_{gNg}, V_{g1}, \ldots\ldots .V_{gNg}, T_{t1}, \ldots\ldots .T_{tNt}, Q_{C1}, \ldots\ldots .Q_{CNc}] \quad (48)$$

Selecting the size of population:- Problem size is adopted for accurate selection of the population size (N_p).

Considering C as the control variables in most of the real world engineering problems, then obtaining optimal solutions with $N_p < 2C$ is a complex process and easier with $N_p = 20C$ condition [77]. Furthermore, the possible optimal solutions are obtained using the population size $N_p = 3-5C$.

In AuDE algorithm, the populations are initialized through employing the OBL scheme. This process is done to improve the solution quality.

Based on Eq. (49), an individual u containing the control variables are generated randomly within a specific limit. However, the first iteration has used these randomly generated individuals as the root (parent) population.

$$u_{i,j}^0 = rand(0,1) * \left(u_j^{max} - u_j^{min}\right) + u_j^{min} \quad (49)$$

$$ou_{i,j}^0 = u_j^{min} + u_j^{max} - u_{i,j}$$ //opposition-based learning

Selecting N_P fittest individuals from set the $\{u_{i,j}^0, ou_{i,j}^0\}$ as initial population;

At the kth generation, the control variables j in a population i is indicated as $u_{i,j}^k$ representing $i \in \{1,2,3,\ldots, N_p\}$ and $j \in \{1,2,3,\ldots, N_p\}$, respectively. For the control variable j, their upper and lower limits are indicated as u_j^{min} and u_j^{max}.

Below said procedures are followed for satisfying the constraints in slack bust active power. Consider P_L as the total active load of the system, P_{ds} be the power summed through not including the slack unit as well as dispatching from all the generators. Subsequently, the slack bus generator active power is assigned with a value obtained by means of subtracting P_{ds} from P_L. In case, if the slack bus generators upper or lower limits are exceeded by the value assigned to the slack bus active power, then the limits P_{slack}^{max} or P_{slack}^{min} are fixed to its active power. The other generators are assigned with the residual active power, proportionally.

Implementing load flow technique: In order to compute the power flow solutions, the Newton-Raphson power flow program is implemented for each population (individual). Indices of voltage stability, line flows, load bus voltages, outputs of the reactive power are considered as the constraints of power system operation. These constraints are verified and the slack bus (independent generator) generations are calculated during evaluating the power flow solutions.

Fitness Computation: Each individual's quality can be measured by evaluating every individual solution using penalty functions included in the fitness measure F_i as shown below:

$$F_i = 1/(f_i + K_Q F_{Qi} + K_V F_{Vi} + K_S F_{Si} + K_L F_{Li} + K_T F_{Ti}) \quad (50)$$

$$F_{Qi} = \sum_{l=1}^{N_g} (|Q_{Gil} - Q_{Gil}^{lim}|)^2 \quad (51a)$$

$$F_{Vi} = \sum_{l=1}^{N_{pq}} (|V_{il} - V_{il}^{lim}|)^2 \quad (51b)$$

$$F_{Si} = \sum_{l=1}^{Nl} (|S_{li} - S_{li}^{lim}|)^2 \quad (53a)$$

$$F_{Li} = \sum_{l=1}^{Npq} (|L_j - L_j^{lim}|)^2 \quad (53b)$$

$$F_{Ti} = \sum_{i=1}^{N_g} (|\, \delta_i - \delta_{COI}|_{max} - \delta^{lim})^2 \quad (54)$$

Here, the fuel costs (f_i) generated by the system is represented as F_{Qi}, F_{Vi}, F_{Si}, F_{Li} and F_{Ti}, respectively. For each individual i, the outputs of reactive power generators corresponding normalized violations summations, rotor angles generator, voltage stability indices, and PQ-bus voltages are also shown in Eq. (54)

N_{pq} is the total number of PQ buses, N_g is the total number of generator, N_l is the total number of lines; Q_{gil}^{lim}, V_{il}^{lim}, S_{il}^{lim}, L_{jil}^{lim} and δ^{lim} denote the violated upper and lower limits of the generator reactive power outputs, voltages of the load buses, line flows, voltage stability indices of load buses and generator rotor angle respectively; K_Q, $K_V K_S K_L$ and K_T are the corresponding penalty coefficients. Ultimately, if obtained higher the fitness value, then better the individual is generated.

Assessment of transient stability: Actually, the TSCOPF optimization problems have large searching space; thereby, it is a time-consuming process to assess the transient stability constraints. Hence, during TSA computation process, the populations (individuals) with good fitness alone are allowed to determine the stable and feasible optimal solutions. This process has reduced the computational burden by not delimiting the evolutions reproduction abilities. By the fact, the fitness function has included in the transient stability to satisfy its conditions neither for satisfying the optimization objectives. Therefore, before going to the evaluation of transient stability, each individual is evaluated for the SSI values whose value is less than or equal to the specified value. During evolution, the selection process will be maintained effectively through handling the system stability in a chosen contingency using that specific individual.

Global best individual: From all generations, the best individual obtained is indicated as u_{best}(i.e. the global best individual).

To find u_{best} individuals, two individuals u_a and u_b are compared in a particular generation, u_a is defined" better" than u_b if matched any one of the below given criterions:

Higher fitness value is for u_a and both of them are stable

Higher fitness value is for u_a and both of them are unstable

Instability is for u_b and stability for u_a

Mutation operation: Different evolution algorithms that have used few traditional mutation strategies are unified with the aid of a single mutation expression. This is expressed as follows:

$$v_i = x_i + F_1^{G+1}(x_b - x_i) + F_2^{G+1}(x_{r1} - x_i) + F_3^{G+1}(x_{r2} - x_{r3}) + F_4^{G+1}(x_{r4} - x_{r5}) \quad (55)$$

In order to produce a new mutant solution, the exploration and exploitation are combined using mutation expression operation. Mutation operators space is explored widely using an opportunity provided by this new expression. It is possible to achieve a new mutation strategy during applying a differential set of parameters such as, F_1, F_2, F_3, and F_4. Compared to the most of the traditional standard differential evolution algorithms, a better optimization solution can be obtained using a unified mutation strategy.

At the time of performing different optimization stages, various combinations of mutation strategies can be applied through adjusting the differential set parameters during each evolution of the optimization process. Hence, the simplicity in mathematical expressions is enjoyed in these unified mutation operations. The proposed unified differential algorithm in this work is developed through evolving dynamically the five control parameters F_1, F_2, F_3, F_4 and C_r of classical self-adaptive method [73]. In most of the experimental tests, the good performance was achieved using this simple self-adaptive scheme.

In this study, a set of control parameters $x_i, i = 1,2,3,....NP$ are comprised in each individual solution during the generation G of the mutation process in self-adaptive method. A new control parameter sets $F_{1,i}^{G+1}, F_{2,i}^{G+1}, F_{3,i}^{G+1}, F_{4,i}^{G+1} and C_{r_i}^{G+1}$ are computed prior to the adaptation of unified differential evolution expressions for producing a new mutant solution.

$$F_{j,i}^{G+1} = \begin{cases} F_{jmin} + r_{j1}(F_{jmax} - F_{min}), & if r_{j2} < \tau_j \\ F_{1,i otherwise}^{G} \end{cases} \quad (56)$$

$$C_{r_i}^{G+1} = \begin{cases} C_{r_{min}} + r_3(C_{r_{max}} - C_{r_{min}}), & if r_4 < \tau_5 \\ C_{r_i,}^{G} & otherwise \end{cases} \quad (57)$$

Maximum and minimum values of the control parameters are expressed as $F_{jmin} and F_{jmax}$ for j=1, 2, 3, 4; whereas, the uniform random values distributed in the interval [0,1] are indicated as r_{j1}, r_{j2}, $j = 1,2,3$, r_3, r_4, respectively. Subsequently, the maximum and minimum cross over probability of the control parameters are denoted as $C_{r_{max}}$ and $C_{r_{min}}$. For the j^{th} control parameter, the probability of old value and new value used is indicated as τ_j, j=1, 2,3,4,5. Notably, it is important to maintain the value of τ_j to be smaller for further generating the new trial solutions by means of reusing the survived solutions.

Crossover Operation: A trial vector $U_{i,G} = (u_{i,G}^1, u_{i,G}^2, ..., u_{i,G}^D)$ is generated after performing the mutation operation. In other words, this trial vector is generated through applying crossover operation to the mutant vector $V_{i,G}$ and to its target vector pairs $X_{i,G}$. Uniform (binomial) crossover is employed to the AuDE as follows:

$$u_{i,G}^j = \begin{cases} v_{i,G}^j, & if(rand_j[0,1) \le CR) or\ (j = j_{rand}) \\ x_{i,G}^j, & otherwise \end{cases} \quad j = 1,2,....,D. \quad (58)$$

In case, if $rand_j[0,1) \le CR$ or $j = j_{rand}$ then to the trial vector element $U_{i,G}$, the mutant vectors $V_{i,G}$ jth parameter is copied by the binomial crossover operator. If this is not the case, then the corresponding target vector $X_{i,G}$ is considered to copy the jth mutant vector parameter. Also, considering the target vector $X_{i,G}$, the trial vectors $U_{i,G}$ residual parameters are copied. Condition j_{rand} ensures that the trial vector $U_{i,G}$ will be different from its corresponding target vector $X_{i,G}$ by at least one parameter.

Verifying the boundary limits: During evaluating the evolutionary based optimization algorithms, their unavoidable constraints are handled in numerous ways. In case, if any of the individual element in the AUDE algorithm drops its corresponding inequality constraints, then the minimum/maximum operating point is fixed based on the individual position.

Analysis of power flow to offspring individuals: Each offspring individuals power flow solutions are computed using a Newton-Raphson power flow program. The slack bus generators corresponding generations are calculated during this process. Then, the fitness function is evaluated through verifying the constraints of power system operation (voltage stability indices, line flows, load bus voltages, and reactive power outputs).

Transient stability assessment: By the fact, the fitness function has included in the transient stability to satisfy its conditions neither for satisfying the optimization objectives. Therefore, before going to the evaluation of transient stability, each individual is evaluated for the SSI values whose value is less than or equal to the specified value. During evolution, the selection process will be maintained effectively through handling the system stability in a chosen contingency using that specific individual.

Selection: A "one- to-one" selection process actually indicates this selection scheme. Ultimately, the best individual is selected by comparing the parent individual u_i^k to its offspring individual $u^{'k}$. In the next generation, the parent population was obtained from the previous updated population of generation 'k' (i.e. the selected individuals).

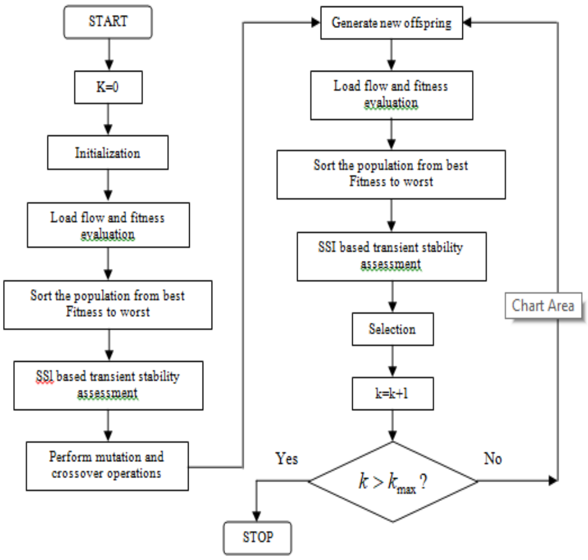

Figure 3: Flow chart for solution of TS-OPF problem

Updating the global best individual: From the generation k, the updated population's best individuals are determined and denoted asu_{best}^k. When compared to u_{best}, if found the better one is u_{best}^k then, using u_{best}^k the term u_{best} is replaced.

Verifying end condition: The iteration process is repeated continuously until the end condition is attained. In this work, after satisfying the given criterion, the iteration of AuDE is stopped: At any time a pre-determined generations are achieved, then it is possible to stop the optimization process

IX. SIMULATION RESULTS

The IEEE test systems such as, 39-bus system, New England ten-generator, and 30-bus system, ix-generator are used to test the effectiveness of proposed AuDE method. Constant impedance models of the loads and synchronous generators are modeled using the traditional generator model. Here, the simulation period is fixed to 2.0s and transient stability simulation is performed using 0.01s (integration time step). Reliability and robustness of the proposed AuDE method is verified through performing 20 trial runs for each test case. Implementation is done using MATLAB 7.8 software. The hardware components adopted for implementation are 2.0GB RAM PC, and Intel Core 2 Duo of 2 GHz.

A. Results of IEEE 30-bus system

The 30-bus test system consists of a transmission network of 41 branches with interconnection of six generating units as shown in Fig. 4. However, the total real and reactive power loads in the transmission network is 283.4 MW and 126.2 MVAR respectively. Ref. [79] is used to obtain the branch and bus data. Here, off-nominal tap ratio is included in 4 transformers. For buses 10, 12, 15, 17, 20, 21, 23, 24 and 29, the shunt injections are applied. In this work, the swing bus is assumed to be bus 1. Also, it is used to consider the real power generations with its minimum and maximum limits, and cost coefficients [79]. The value 0.9 and 1.1 pu is fixed to be the minimum and maximum limits of the control variables of tap changing transformer. Conversely, the value 0.9 and 1.1 pu is fixed to be the minimum and maximum limits of voltage generator. For load buses, their minimum and maximum voltages used are 0.95 and 1.1, respectively. Ref [80] is used to fix the limits of line flows.

In the simulation studies of Case 1, a fuzzy logic based SSI for network contingency ranking is carried out to determine the rank-1 network contingency. The FL based network contingency method takes the pre/post contingency line loadings, load bus voltages, voltage stability indices, and reactive power outputs of generators for ranking. Instead of assessing the transient stability under the randomly selected network contingency, The TSA is done under the rank-1 network contingency for testing the effectiveness of the proposed algorithm. In Case 2 simulation studies, the proposed AuDE method is applied for solving the transient stability constrained optimal power flow problem without and with STATCOM device under the rank-1 network contingency condition. Various equality and inequality constraints, including the voltage stability and transient stability constraints are considered during the solution of the TS-OPF problem.

Case 1: Using fuzzy approach for contingency ranking: Network contingencies are ranked by means of applying the proposed FL based SSI approach. Thereby, the most threatening contingencies are identified from the base-load conditions included in base-case control variables

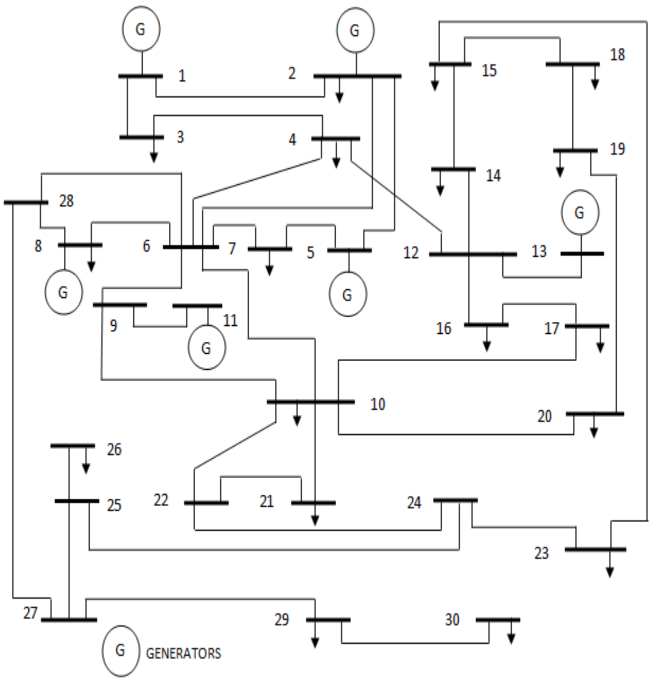

Figure 4: IEEE 30-bus test system indicated using single line diagram

Given input values are taken into account by the parallel operated fuzzy inference systems to find the network contingency and its total fuzzy logic based SSI (Fig. 2). Work in [64] has detailed the FL based SSI approach. Tables 1 and 2 provided the contingency analysis results. The other lines with heavy overload are resultant from the line outages 8-11, 27-30, 27-29, 9-10, and 10-20. On the other hand, Table 1 has shown ranking of top 5 contingencies. Moreover, the table also depicts the outcomes of top 5 network contingencies namely, outputs of generator reactive power, voltage stability indices, voltage profiles, and line loading of severity indices.

For network contingencies, different forms of severity indices (number of load buses, number of lines) determined are illustrated in Table 2. Highest total severity index (i.e. the most severe line outage 8-11) can be observed from both the Tables 1 and 2.

Case 2: TSOPF with STATCOM device: In this Case 2, the transient stability constrained optimal power flow issues are solved using the proposed algorithm, which was tested through minimizing the number of objective functions. Sum of squared voltage stability indices, real power loss, and quadratic fuel cost function are considered as the objective functions. Using the power constraints such as, voltage stability, inequality, and equality, the augmentation of objective functions is performed. The proposed AuDE algorithm have used STATCOM device to solve the transient stability constrained optimal power flow issues. The STACOM device is located at bus 24 which is having a low voltage magnitude under base case operation.

Value 150 is fixed as the required number of maximum generation and the size of population is fixed to 50. For TSA, the individual population whose SSI value is less than the specified value can make the transient stability assessment under the rank-1 contingency case which is obtained in the previous section.

A large disturbance is experienced with tripping line 8-11. Line flow limits and reactive power generation limit constraints are highly achieved using these solutions.

Figs.5-7 show the convergence of the cost of generation, power loss and sum of squared voltage stability indices with the AuDE algorithm for the best run with STATCOM device. From the Figs.5-7 it can be observed that the AuDE algorithm reaches the best solution within 100 iterations with STATCOM during minimization of cost objective function. Also, it can be observed that during the iterative process, the proposed AuDE algorithm converges to global solution within 150 iterations of the algorithm during minimization of power loss and voltage stability index.

The optimal settings of the control variables for the best result of OPF problem obtained by the AuDE method without and with STATCOM are given in Table 3 respectively. The cost of generation, real power loss, maximum voltage stability index, and computation time are also given in Table 3. It can be found that the proposed AuDE method gives lower values for cost of generation, power loss and voltage stability index than the values obtained without and with STATCOM device. Also the cost of generation, power loss and voltage stability index are increased with the STATCOM and transient stability constraints.

The Figs. 11-13 show the stable trajectories of relative rotor angles of best solutions obtained with AuDE algorithm with STATCOM device. The load bus voltages, voltage stability indices and percentage line loadings with STATCOM device are maintained within their lower and upper limits after optimization with STATCOM device and are shown Figs.8-10 respectively. The comparison of the cost of generation for base case OPF with other methods reported in the literature is given in Table 4. It can be seen from the Table 4 that the proposed AuDE algorithm gives best cost of generation for base case OPF (neglecting voltage/transient stability constraints) compared with other methods reported in the literature.

The classification of transmission lines/transformers, load bus voltage profiles, voltage stability indices and generator reactive power outputs under different severity category before optimization and after optimization is given in Table 5 without and with STATCOM device respectively. From the Table 5 it can be observed that the number of lines/buses under different severity categories and the FL based severity index are increased after optimization with the proposed AuDE algorithm. The reason behind this is that the numbers of voltage profiles/buses under AS severity category are more after optimization than before optimization.

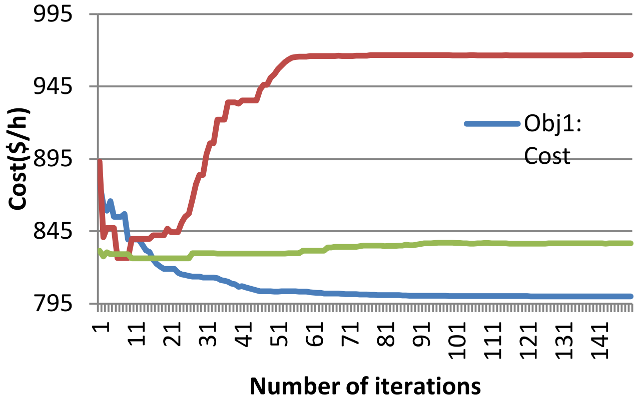

Figure 5: Convergence of cost of generation of IEEE 30-bus during optimization of different objective functions

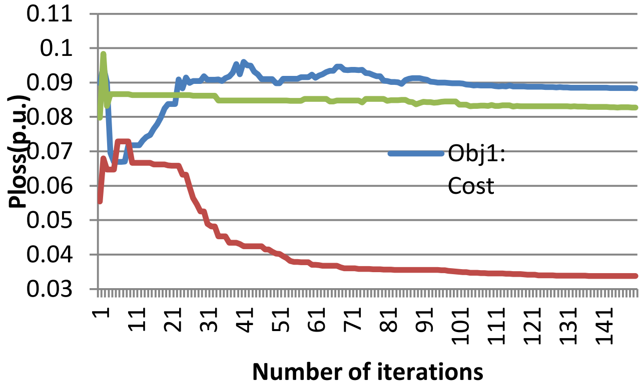

Figure 6: Convergence of real power loss of IEEE 30-bus during optimization of different objective functions

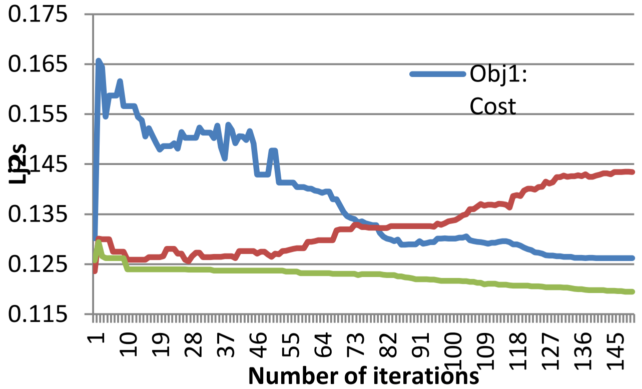

Figure 7: Convergence of sum of squared voltage stability indices of IEEE 30-bus during optimization of different objective functions

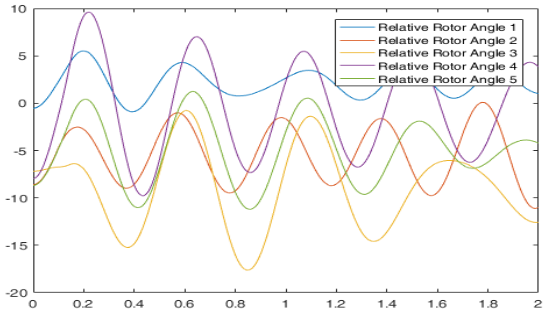

Figure8: Stable trajectories of rotor angles of IEEE 30-bus with fuel cost optimization

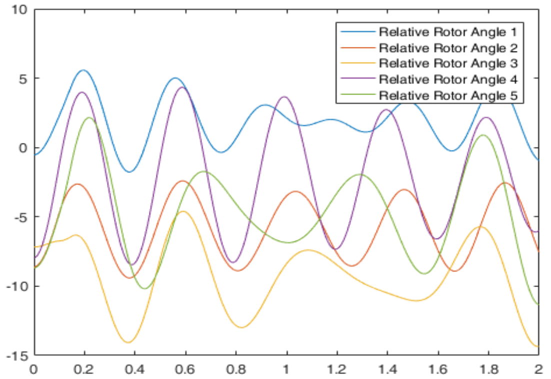

Figure9: Stable trajectories of rotor angles of IEEE 30-bus for real power loss optimization

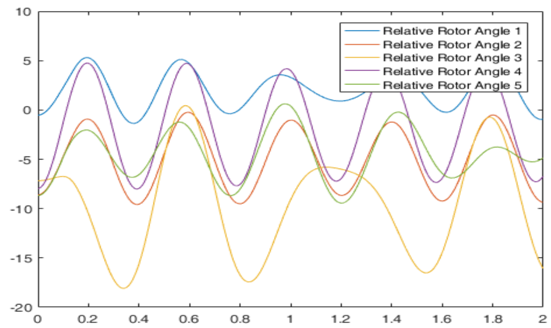

Figure10: Stable trajectories of rotor angles of IEEE 30-bus for voltage stability optimization

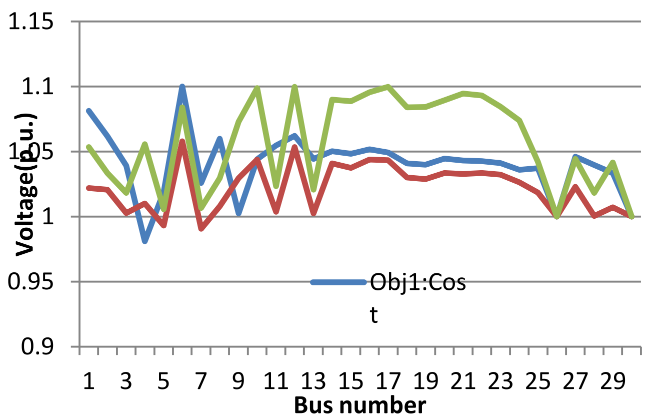

Figure 11: Voltage profiles of IEEE 30-bus system after optimization of different objective functions

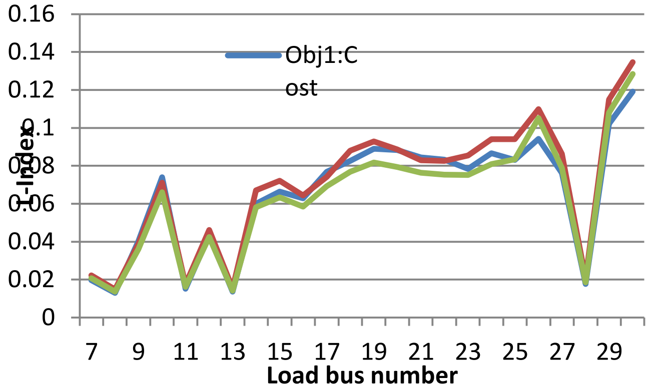

Figure 12: Voltage stability indices IEEE 30-bus system after optimization of different objective functions

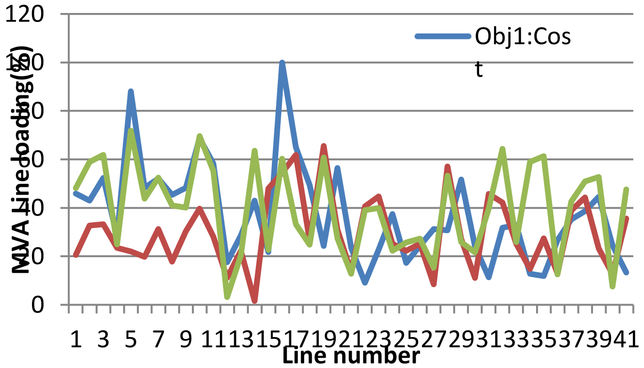

Figure 13: Percentage line loadings of IEEE 30-bus system after optimization of different objective functions

X. RESULT AND DISCUSSION

The following are the critical problems addressed/issues resolved/contributed in this paper.

1) A new evolutionary algorithm namely adaptive unified differential evolution is developed for solving the TS-OPF problems to meet the pressing need of the vertically integrated power systems.
2) An OPF problem formulation was made with both voltage stability and transient stability constraints along with various equality and inequality constraints.
3) A maiden attempt has been made to include the SSI as a security level before going to TS assessment.
4) A fuzzy logic based SSI for network contingency ranking method is developed to identify the critical network contingencies.
5) The proposed AuDE algorithm gives the best results without and with STATCOM compared to the other methods reported in the literature
6) The presence of STATCOM is reducing the little bit cost of generation, power loss and maximum of voltage stability L-index.
7) The SSI based severity indices are increased after optimization which means that the stress on the system has been increased after optimization.
8) From the case studies, it was observed that the proposed AuDE method has achieved good results while on using STATCOM device to solve the transient stability and voltage stability constraints included in the OPF problem.

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9) Evaluation of transient stability using time-domain simulation is a time consuming process for the proposed AuDE approach based OPF problem. But, when compared to New England 39-bus-10-genertor system, the IEEE 30-bus-6-generator system has shown moderate time consumption.

XI. CONCLUSION

In this paper, a fuzzy logic based SSI for network contingency ranking was presented. Modern power systems pressing needs were addressed using the AuDE method adopting STATCOM device to solve the TS-OPF problems. Compared to other past works in literature, the installation of FACTs devices advantages was accurately evaluated by the proposed method. This optimization process has been done using three different objective functions of optimal power flow solutions of formulated a large-scale optimization problem. Efficiency of proposed method in determining the optimal solution was validated and tested through analyzing the impacts of FACTs device (e.g. STATCOM device). Using 39–bus test systems and IEEE 30–bus systems, the implementation of proposed approach was achieved successfully. Better maintenance of transient stability and low fuel cost solution was the goodness achieved with proposed method when compared to the abilities of other existing methods. Also, the STATCOM device is adopted to improve the performance of power system.

Table 1
Contingency Ranking of IEEE 30-bus system

Contingency	OSI_{LL}	OSI_{VP}	OSI_{VSI}	OSI_{QG}	FLCC	Ploss(p.u.)	Ljmax	Rank
8-11	362.5	306.9996	96.0019	144.9996	910.5011	0.0718	0.1473	1
27-30	393.75	306.9996	108.0018	54	862.7515	0.0586	0.2389	2
27-29	375	302.9649	120.0017	54	851.9666	0.0573	0.2719	3
9-10	456.25	216	96.0019	54	822.2519	0.0586	0.1681	4
10-20	456.2496	216	96.0019	54	822.2515	0..582	0.1562	5

Table 2
Number of lines/buses under different severity category before optimization

Contingency	Line Loading				Voltage Profile			Voltage Stability Indices					Reactive power outputs			Rank
	LS	BS	AS	MS	BS	AS	MS	VLS	LS	BS	AS	MS	BS	AS	MS	
8-11	34	6	0	0	23	0	1	24	0	0	0	0	5	0	1	1
27-30	34	5	1	0	23	0	1	23	1	0	0	0	6	0	0	2
27-29	35	4	1	0	23	0	1	22	2	0	0	0	6	0	0	3
9-10	29	11	0	0	24	0	0	24	0	0	0	0	6	0	0	4
10-20	33	6	0	1	24	0	0	24	0	0	0	0	6	0	0	5

Table 3
Optimal Setting of control variables for IEEE 30-bus system with STATCOM

Control variables(p.u.)	Base Case	OPF (without TS constraint and STATCOM)	Objective functions		
			Cost	P Loss	Lj2s
P_{g1}	0.9873	1.7730	1.7719	0.5282	1.5036
P_{g2}	0.80	0.4871	0.4883	0.8000	0.6014
P_{g3}	0.20	0.2084	0.2265	0.3398	0.1000
P_{g4}	0.20	0.1180	0.1000	0.3000	0.1186
P_{g5}	0.50	0.2135	0.2157	0.5000	0.4131
P_{g6}	0.20	0.1200	0.1200	0.3998	0.1801
V_{g1}	1.050	1.1000	1.0813	1.0220	1.0535
V_{g2}	1.045	1.0877	1.0619	1.0406	0.9034
V_{g3}	1.010	1.0689	1.0391	0.9827	1.0782
V_{g4}	1.050	1.1000	0.9809	0.9000	0.9856
V_{g5}	1.010	1.0613	1.0190	0.9831	1.0256
V_{g6}	1.050	1.1000	1.1000	1.0579	1.0140
T_{t1}	0.978	0.9760	1.0848	1.0629	0.9648

T_{t2}	0.969	1.0512	1.0023	0.9000	1.0056
T_{t3}	0.932	0.9813	1.0637	0.9808	0.9912
T_{t4}	0.968	0.9590	0.9821	1.0749	0.9789
Q_{c10}	0	0.0020	0.1472	0.1022	0.1104
Q_{c12}	0	0.1425	0.1530	0	0.2000
Q_{c15}	0	0	0.0273	0	0.0297
Q_{c17}	0	0.0493	0.1380	0.0767	0.1245
Q_{c21}	0	0.0431	0.0893	0.0356	0.0498
Q_{c22}	0	0.1040	0.2000	0	0.2000
Q_{c23}	0	0.0252	0.0151	0.0300	0.0523
Q_{c24}	0	0.0291	0.0581	0.0326	0.0148
Q_{c29}	0	0.0228	0.0235	0	0.1110
Cost($/hr)	900.5995	798.9124	**799.9126**	966.7993	836.5424
Power Loss(p.u.)	0.0533	0.0858	0.0883	**0.0338**	0.0827
Lj2s	-	0.1154	0.1262	0.1434	**0.1195**
t(s)	0.1456	156.8580	202.1020	203.8340	204.0670

Table 4
Comparison of fuel costs

Method	Base Case	MATPOWER [81]	IPM	GA	EP	PSO	IEP [82]	DE	AuDE
Cost($/h)	900.5995	804.0600	803.986	805.3076	801.1315	800.3484	802.4650	800.2241	798.9124

Table 5a
Number of transmission lines/buses under different severity category before and after optimization without STATCOM device

			NLL				NVP			NVS					NQG			FLCC Index
			LS	BS	AS	MS	LS	BS	AS	VLS	LS	BS	AS	MS	LS	BS	AS	
Before Optimization			37	4	0	0	24	0	0	24	0	0	0	0	6	0	0	0697.2519
After Optimization	Without TS Constraints		34	6	1	0	0	0	24	24	0	0	0	0	6	0	0	2968.7000
	With TS Constraints	Cost	33	7	1	0	18	0	6	24	0	0	0	0	6	0	0	1349.5000
		Ploss	35	6	0	0	24	0	0	24	0	0	0	0	5	0	1	0761.1393
		Lj2s	32	9	0	0	5	0	19	24	0	0	0	0	6	0	0	2520.0000

Table 5b
Number of transmission lines/buses under different severity category before and after optimization with STATCOM device

			NLL				NVP			NVS					NQG			FLCC Index
			LS	BS	AS	MS	LS	BS	AS	VLS	LS	BS	AS	MS	LS	BS	AS	
Before Optimization			37	4	0	0	24	0	0	24	0	0	0	0	6	0	0	0697.2519
After Optimization	Without TS Constraints		34	6	1	0	0	0	24	24	0	0	0	0	6	0	0	2968.7000
	With TS Constraints	Cost	31	9	1	0	7	0	17	24	0	0	0	0	4	0	2	2570.0000
		Ploss	32	9	0	0	19	0	5	24	0	0	0	0	2	0	4	1610.0000
		Lj2s	26	9	2	4	14	0	10	24	0	0	0	0	0	0	6	2693.7000

where
NLL=Number of lines/transformers loadings;
NVP=Number of bus voltages
NVS=Number of voltage stability indices
NVQ=Number of generator reactive power outputs

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