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Optimal Relocating of Compensators for Real-Reactive Power Management in Distributed Systems

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Abstract – Congestion Management (CM) is an attractive research area in the electrical power transmission with the power compensation abilities. Reconfiguration and the Flexible Alternating Current Transmission Systems (FACTS) devices utilization relieve the congestion in transmission lines. The lack of optimal power (real and reactive) usage with the better transfer capability and minimum cost is still challenging issue in the CM. The prediction of suitable place for the energy resources to control the power flow is the major requirement for power handling scenario. This paper proposes the novel optimization principle to select the best location for the energy resources to achieve the real-reactive power compensation. The parameters estimation and the selection of values with the best fitness through the Symmetrical Distance Travelling Optimization (SDTO) algorithm establishes the proper controlling of optimal power flow in the transmission lines. The modified fitness function formulation based on the bus parameters, index estimation correspond to the optimal reactive power usage enhances the power transfer capability with the minimum cost. The comparative analysis between the proposed method with the existing power management techniques regarding the parameters of power loss, cost value, load power and energy loss confirms the effectiveness of proposed work in the distributed renewable energy systems.

Keywords: Congestion Management (CM), Distributed Energy Resources (DER), Flexible Alternating Current Transmission System (FACTS), Optimal Power Flow (OPF), Optimization

1. Introduction

Recently, the transition of minimum carbon-energy consumption and the evolution of Renewable Energy Sources (RES) increase the utilization of weather-driven sources utilization such as solar and wind energy resources. The introduction of the smart grid concept facilitates the demand responsiveness, ability of load shift and the low-price elasticity of the electricity demand. The dependency of wholesale price with the instantaneous load and electricity production increases the decorrelation between the electricity demand and the wholesale price. The employment of high wind or solar energy generation reduced the wholesale price with the increase in demand. Hence, the cost minimization, regulation of the operating frequencies and the provision of balancing services under the grid constraints are the major issues in smart-grid applications [1].

The existence of network constraints dictates the flow of finite amount of power among the grid points. Besides, the violation of the operating constraints (voltage and power flow limits) affects the delivery of the power among the bilateral and multi-lateral contracts to meet the electricity demand. The presence of above limitation (a violation of operating conditions) in smart-grids is referred as congestion. The preservation of relationship between the generation and transmission companies plays the major role in congestion management. The reconfiguration of the network and the operation of the transformer taps and the Flexible Alternating Current Transmission System (FACTS) relieve the congestion effectively. In addition to the trust in the changes of electricity prices, the demand response is modeled by the two factors such as incentives and the penalty factors. With these factors, the reliability and the response rate are increased with minimum cost [2]. The Optimal Power Flow (OPF) calculations are highly critical to model the modern power system engineering nowadays in the RES. The OPF formulation concentrated into the economic-security processes in the power system operations and they can be considered as the sub-function of a large problem in security constrained environment. The anticipation of the requirements for modeling and solution for the prospective power system users increases the system complexity. The formulation of traditional OPF deterministic problems as the single static objective [3] requires the optimization in control variables. The system operational limits and their sensitivities, infeasible problem constraints and the convergence of solution are the major implications in the secure OPF

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formulation. The operation of controllable loads and the Distributed Energy Resources (DER) with the OPF formulation in the islanded or grid-connected modes makes the energy management as the non-linear optimization problem. The solution to the demand-supply matching problem requires the following assumptions [4]:

- All the generations and the loads are connected to one bus
- Ignoring the power distribution network, associated power flow and the system operational constraints

Practically, these assumptions are not feasible due to the violation of constraints adversely. The consideration of underlying power distribution with the constraints provides the solution to the above issues. The deployment of the flexible and adaptive transmission networks enables the implementation of the smart grid for the dynamic optimization of transmission assets. The major impact of the FACTS devices on the transmission system is the maximum set point which is dynamically controllable in nature. The enhancement in power transfer capability does not require any changes in set point. Hence, the regulation of operational abilities of FACTS devices in addition to the controlling of the transmission assets to maximize the system benefit [5]. Besides, the replacement of vertical structure of power system industry with the market assessment models [6, 7] supports the utilization of transmission system by the multiple generation and distribution entities. The tracing of power flows in the transmission lines using two major methods such as commons and node are not perfect and more time consumption. The sharing principle-based power flow tracing models with the assessment topology also consume more time. Hence, the power flow tracing is performed with the matrix manipulation based on directed path increases the complexity. The employment of evolutionary optimization techniques allocates the losses and the application of generated power to the loads under the satisfaction of power constraints. But, the identification of the origin of losses (transmission line responsible) was the difficult task. The controlling of transmission system by periodical observation of transfer limits (congestion management) is the major problem in the competitive power markets [8]. With the increasing number of links between the buses, the joint and power admission control problem is formulated as the NP-hard problem and then devised it into the linear program. The removal of interfering links via joint optimization problem [9, 10] reduces the computational complexities that minimize the time consumption effectively. The brief review of traditional models conveys that the optimal usage of real and reactive power flows with the enhanced transfer capability is the major requirement [11] to meet the demand under minimum cost. The technical contributions of proposed work are listed as follows:

- The provision of proper controlling to the system based on the parameter estimation and the reactive power utilization yields the better power management compared to the existing power flow models.
- The periodical extraction of bus parameters and the computation of best fitness by using the Symmetrical Distance Travelling Optimization (SDTO) algorithm with the new objective function formulation handle the power demand conditions effectively.
- The index estimation corresponds to the best optimal reactive power usage is helpful to place the energy sources at the desired location maintains the power usage with the reactive power charging capacity effectively.
- The analysis of power loss, cost, load power and the energy losses in bus and lines of IEEE-bus systems (14 and 30) highly contributes to the transfer of real power capability if the reactive power is greater than the real power flow.

The paper organized as follows: The detailed description about the related works on optimal power flow strategies with the merits and demerits is discussed in section II. The implementation process of Symmetrical Distance Travelling (SDT) optimization algorithm and update in index corresponds to the optimal power usage is described in section III. The comparative analysis of proposed approach with existing approaches under various IEEE bus systems provided in section IV. Finally, the conclusions about the proposed SDT optimization algorithm for the location prediction and their analysis presented in section V.

2. Related Work

Selling more power to the customers with high profit to the consumers is the major task in the competitive electricity markets. The violations in the operational constraints made the transmission network were unable to accommodate the market desired actions. *Esmaili et al* proposed the multi-objective framework [12] to manage the congestion in three aspects such as total cost, optimization of voltage and transient stability margins. The location and the number of FACTS devices were predicted on the basis of Locational Marginal Prices (LMP) under the multi-objective framework. The lack of integrated methods to derive the closed loop solution depends on the demand elasticity and the shifting characteristics. *Li et al* [13] extended LMP into the Distributed LMP to alleviate the congestion generated by the Electric Vehicles (EV). With the consideration aggregators and price takers in the Distribution System Operator (DSO) market, the derivation of the solution to the social welfare optimization model achieved the required efficiency. In traditional assessment models, the transmission assets of bulk power flow are modeled as fixed models did not allow the reconfiguration of the transmission grid for performance improvement. *Hedman et al* [14] provided the overview of the optimal transmission switching to demonstrate the substantial benefit according to the reliability requirements. The implications causing from network topology co-optimization on the LMPs. The hierarchical control paradigm for optimal transmission switching was unsuitable with an increase of the network complexity, hardware redundancy and the data storage resources. *Loia et al* [15] addressed the voltage control problem in the smart grids by the integration of fuzzy agents with the theoretically distributed parameters. The controlling of agents decided the injection of the useful reactive power flow effectively. The unbalanced nature of distribution network caused the overload and voltage violation risks. *Cao et al* formulated the chance constrained optimization-based multi-objective OPF model [16] which considered the forecast errors in the Renewable Energy Generation (REG). The minimization in contingencies and the inequality constraints in the normal state are under the pre-defined probability level. Hence, the profitability and the security were balanced in presence of stochastic REG.

The divergence in the centralized DSO optimization and the decentralized aggregator optimization models addressed the multi-solution issue, unique solution to the optimization problem. *Huang et al* [17] presented the DLMP method through the Quadratic Programming (QP) alleviated the congestion under the flexible demands. The employment of convex optimization theory with the aggregator optimization problem in Karush-Kuhn-Tucker (KKT) conditions provided the unique solution. The extensive sensing and communications increased the numerous complexities such as high-cost, deployment and operational risks. *Sansawatt et al* [18] offered the alternative and decentralized approach to manage the real-time voltage and thermal constraints. The controlling process of real and reactive power flows alleviated the voltage and thermal issues for the near-end connection. The utilization of the time-series analysis revealed the effectiveness of the decentralized approach. In addition to the active and reactive power flow controls, the prediction of location for placement of devices was also the major task. *Reddy* and *Singh* [19] utilized the two major approaches such as sensitivity-based and the pricing-based to determine the specific location for the compensator called Unified Power Flow Controller (UPFC). With these two methods, the losses in the total system and the determination of suitable location for UPFC were achieved. The effective congestion management depends on the minimization of rescheduling cost in various operating conditions respectively. The mathematical modeling of the evolutionary approaches and the provision of balance between the global and local exploitations were the difficult processes. *Ling et al* [20] presented the novel Fuzzy Particle Swarm Optimization with Cross-Mutated (FPSOCM) in accordance with the swarm intelligence to determine the inertia weight. The improvement in quality and robustness of the two real-world systems called economic load dispatch and self-provisioning system was achieved. The operation of the generation and consumption systems beyond the limits leads to the congestion problems. *Ushasurendra et al* [21] proposed the fuzzy technique to determine the optimal location for the compensators. The congestion level measurement was dependent on the two factors namely, line utilization factor (LUF) and real power performance index (RPPI) factor.

The evolution of restructuring process in the electric power market leads to the congestion problems. Besides, the instant power exchanges and the power flow scheduling were the major issues in the congestion management systems. *Mishra et al* [22, 23] proposed the factor called Disparity Line Utilisation Factor (DLUF) to search the optimal place for the Interline Power Flow Controller (IPFC) in order to manage the congestion in transmission lines. The optimal tuning by the differential evolution algorithm provided the minimum power loss, voltage deviations, security margin and the installed IPFC capacity. With the increase in multi-objectives, the variables involved in the circuit design were large that leads to the design problems. *Yang* [24] extended the optimization algorithm to solve the multi-objective problems. The selected subset of the test functions and application of them to solve the design optimization benchmarks validated the optimization algorithm effectively. The optimal ranges for the various optimization problems were identified by using the parametric studies. Transmission congestion management plays the significant role in the deregulated energy market. The lack of proper modeling according to the voltage and transient limits caused the vulnerable power to the system. *Hosseini et al* [25] included the cost of congestion management and stability margins and modeled the problems as the multi-objective problem. Under the Normalized Normal Constraint (NNC), the new and effective Multiobjective Mathematical Programming (MMP) generated the well-distributed and the Pareto Frontier for congestion management. The convergence point of the multi-objective formulation was high-sensitive to the starting point and its computational effort was high. Hence, the integration of local and global search methods was the major issue in the power flow handling problems. *Joorabian* and *Afzalan* [26] provided the solution to the optimal power flow problem by combining the Particle Swarm Optimization (PSO) with the Nelder-Mead (NM) algorithm which is called as Hybrid formulations.

The solutions to the optimal power flow under normal and contingency conditions with the consideration of benchmark mathematical formulations and the successive objective functions. *Nesamalar et al* [27] extended the NM into the fuzzy adaptive method to solve the Multi-Line Congestion Management (MLCM) problem. Based on the power sensitivity factor, the generators were rescheduled through the hybrid methods. The utilization of fuzzy inference system updated the inertia weight dynamically to avoid the premature convergence problem in PSO. The quantification and the mitigation of risks of congestions occurred in distributed network by the penetration of the DER. *Huang et al* [28] designed the Dynamic Tariff (DT) method to handle the uncertainty problem due to the high penetration of distributed sources. The aggregators-based day ahead energy planning with forecasted parameters lead to problems in uncertainty management. *Koukoula et al* [29] proposed the gossip algorithm-based architecture to manage the power flows on the radial distribution grids. The critical physical quantities by reaching the global consensus were estimated by using the gossip algorithm. The congestion-free transmission without degrading the security level depends on the post-deregulation schemes. The Independent System Operator (ISO) enabled the correct methods by using the reliability and security maintenance relieved the transmission congestion effectively. *Gope et al* [30] presented the optimization model for the congestion management based on the two factors like Generator Sensitivity Factor (GSF) and the Bus Sensitivity Factor (BSF). Based on these factors, the optimal location for the pumped storage element was identified with minimal computation cost. Even though the congestion cost was minimum, the voltage and active power loss were maximum by using the factors-based congestion management. The trade-off between the effective congestion management and the minimal cost was the major deficiency in the restructured power system. *Verma* and *Mukherjee* [31] proposed the generation rescheduling-based approach for the congestion manage-ment in electricity market using the nature-inspired algorithm called Ant Lion Optimizer (ALO) algorithm. The load bus voltage and the line loading impact were considered for ALO-based congestion management. The rapid, secure and reliable operation was achieved with lesser fitness evaluations. The brief review of traditional methods conveyed that the proper bus location prediction for the compensators placement to minimize the losses and provide the necessary compensation to the reactive power with minimum cost is the major issue in distributed systems. This paper discusses the new optimization technique to select the best bus for compensators to alleviate the issues in existing studies.

3. Symmetrical Distance Travelling Optimization-based Relocating of Compensators

This section illustrates the implementation process of the proposed Symmetrical Distance Travelling Optimi-zation (SDTO)-based bus selection for the relocating compensators. The prior estimation of bus parameters decides the reactive power usage limit and provides the proper controlling of real-reactive power flows in the transmission lines. Fig. 1 shows the workflow of proposed optimal relocating compensators. The overall workflow

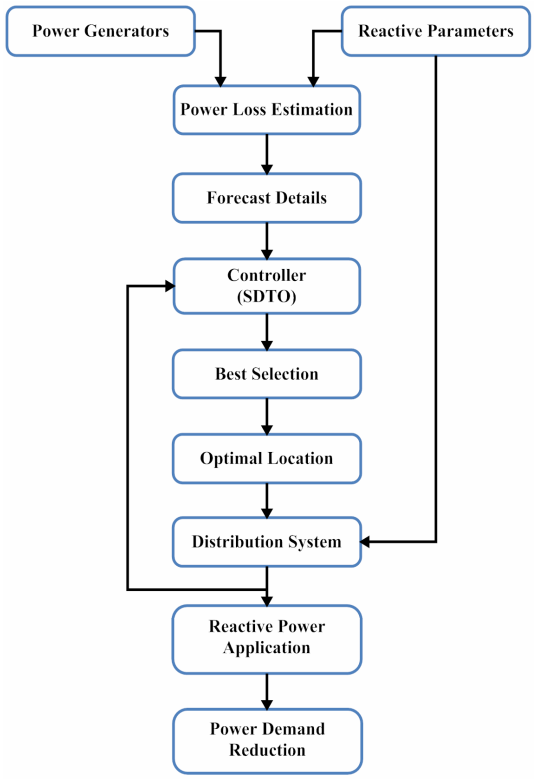

Fig. 1 Overall flow of proposed work

comprises the following major processes to locate the compensators in the suitable location.

- Power loss estimation for each bus
- SDTO-based best fitness selection

To validate the effectiveness of proposed relocating strategy, the IEEE-39 [30], 30 [22] and 14 [21] bus system is considered without and with compensators. The modification in the fitness function in terms of power loss and the cost of installed FACTS device assures the effective compensation with minimum cost.

3.1. Modeling of FACTS devices

3.1.1. Modeling of TCSC

The controllable reactance inserted in series with the transmission line monitors the power flow in the network. The active power flow through the compensated transmission line maintained in the specified level over the wide range of operating conditions. The static model is formed by using the set of mathematical formulations for TCSC are investigated in this section.

The firing angle (α), inductive (X_{LC}) capacitive reactance (X_C) and their relationship decide the TCSC reactance as follows:

$$X_{TCSC}=-X_c+C_1\{2(\pi-\alpha)+\sin[2(\pi-\alpha)]\}-C_2\cos^2(\pi-\alpha)\{\omega(\pi-\alpha)-\tan(\pi-\alpha)\} \tag{1}$$

$$C_1 = \frac{X_C + X_{LC}}{\pi}$$

$$C_2 = \frac{4X_{LC}^{\ 2}}{\pi X_L}$$

$$C_2 = \frac{4X_{LC}^{\ 2}}{\pi X_L}$$

$$X_{LC} = \frac{X_C X_L}{X_C - X_L}$$

$$w = \frac{X_C^{\ 2}}{X_L^{\ 2}}$$

where,

X_{TCSC} : TCSC Reactance
X_C : Capacitor Reactance
X_{LC} : Inductor Reactance
α : Firing Angle

3.1.2. Modeling of SVC

The appropriate power system models and the corresponding study methods are needed to handle the SVC application. The load flow studies, small or large disturbance studies, harmonic studies, electromagnetic transient studies and the fault studies are the necessary studies in SVC modeling. The provision of initial conditions for transient analysis, prediction of appropriate locations of FACTS devices and the information of effects SVCs on the voltage and power flows was the necessary stage in the load flow studies. The rating of SVC and the control parameter variations to achieve the transient and damping performance was the necessary stages in the small and large signal disturbances.

The rated line-to-line inductive reactance X_{Lrated} depends on the ratio of square of rated line-to-line voltage $U_{Lrated}^{\ 2}$ and the MVA rating of Thyristor Controlled Reactor (TCR) Q_{Lrated} as follows;

$$X_{Lrated} = \frac{U_{rated}^{\ 2}}{Q_{Lrated}} \tag{2}$$

Similarly, the transformer inductive reactance X_{Ltrans} depends on the ratio of square of rated line-to-line voltage Q_{Lrated} with the MVA rating of the transformer Q_{trans}.

$$X_{Ltrans} = \frac{U_{rated}^{\ 2}}{Q_{trans}} \tag{3}$$

The total inductive reactance for the TCR is expressed as

$$X_{L(TCR)} = X_{Lrated} - X_{Ltrans} \tag{4}$$

The capacitance value used in TSC (Thyristor Switching Capacitor) is determined based on the ratio of rated line-to-line voltage variations U_{Lrated} with the MVA rating of the capacitor Q_{Crated} as follows:

$$X_{Crated} = \frac{U_{rated}^{\ 2}}{Q_{Crated}} \tag{5}$$

$$C = \frac{1}{2\pi f X_{Crated}} \tag{6}$$

3.1.3. Modeling of STATCOMM

The static replacement of synchronous condenser is the basic principle for STATCOMM. The modelling of STATCOMM depends on the following assumptions

- The switches used in STATCOMM are identical
- Balanced source voltage
- The losses occurred in converter and coupling inductor are modelled as R_S.
- Harmonic contents are negligible.

The imaginary part in the mathematical representation of voltage-impedance relationship decides the reactance of the STATCOMM as follows:

$$X_{Statcom} = \mathrm{Im}\left(\frac{V_{sh}.Z_{sh}}{V_i.V_{sh}}\right) \tag{7}$$

where, V_{sh} Shunt Voltage
Z_{sh} Shunt Impedance
V_i Input Voltage

The major objective of the proposed approach is to find the suitable bus location for the compensator placement for proper controlling with minimum congestion cost. The mathematical formulation for the Congestion Management (CM) problem with the minimum cost [32] is as follows:

$$C_t = \sum_{j \in N_G} \left(C_{tG} \Delta P_{Gj}^{+} + D_{tG} \Delta P_{Gj}^{-} \right) \$ / h \tag{8}$$

where

C_t : Total cost incurred for the change in real power flow
C_{tG} : Incremental price bids by the generator company
D_{tG} : Decremental price bids by the generator company
ΔP_{Gj}^{+} : Real power increment of j th generator
ΔP_{Gj}^{-} : Real power decrement of j th generator
N_G : Total number of generators

The cost optimization should satisfy the equality and inequality constraints listed in the following subsections. Prior to the overview of constraints, the table 1 shows the description of the symbols used in the proposed work.

Table 1. Symbols and description

S. No	Symbols	Description
1	P_{Gk}	Generated active power at k^{th} bus
2	P_{Dk}	Active power at k^{th} bus
3	Q_{Gk}	Generated reactive power at k^{th} bus
4	Q_{Dk}	Reactive power at k^{th} bus
5	V_j	Voltage at j^{th} bus
6	V_k	Voltage at k^{th} bus
7	Y_{kj}	Mutual admittance between j^{th} and at k^{th} buses
8	δ_j	Bus voltage angle at j^{th} bus
9	δ_k	Bus voltage angle at k^{th} bus
10	θ_{kj}	Admittance angle of the line connecting j^{th} and k^{th} buses
11	N_b	Number of buses
12	N_g	Number of generators
13	N_d	Number of loads used
14	P_{Gk}^{C}	Real power produced by k^{th} generators
15	P_{Dj}^{C}	Active power consumed by the j^{th} load bus

Equality Constraints

The mathematical formulation of equality constraints corresponding to the CM to represent the power flow equation is stated as follows:

$$P_{Gk} - P_{Dk} = \sum_j |V_j||V_k||Y_{kj}|\cos(\delta_k - \delta_j - \theta_{kj}); \quad j = 1,2...N_b \tag{9}$$

$$Q_{Gk} - Q_{Dk} = \sum_j |V_j||V_k||Y_{kj}|\sin(\delta_k - \delta_j - \theta_{kj}); \quad j = 1,2...N_b \tag{10}$$

$$P_{Gk} = P_{Gk}^{C} + \Delta P_{GK}^{+} - \Delta P_{GK}^{-} \quad k = 1,2...N_g \tag{11}$$

$$P_{Dj} = P_{Dj}^{C}; \mathrm{j} = 1,2...N_d \tag{12}$$

The equations discussed from (9) and (10) show the balancing of real and reactive power flows in the transmission line and (11) and (12) show the final power estimated value.

Inequality Constraints

The specification of operating and the physical limits by the constraints of inequality defined as the set of following equations

$$P_{Gk}^{\min} \le P_{Gk} \le P_{GK}^{\max} \forall k \in N_g \tag{13}$$

$$Q_{GK}^{\min} \le Q_{Gk} \le Q_{GK}^{\max} \forall k \in N_g \tag{14}$$

$$(P_{Gk} - P_{Gk}^{\min}) = \Delta P_{GK}^{\min} \le \Delta P_{GK} \le \Delta P_{GK}^{\max} = (P_{Gk}^{\max} - P_{GK}) \tag{15}$$

$$V_n^{min} \le V_n \le V_n^{max} \tag{16}$$

$$P_{ij} \le P_{ij}^{max} \tag{17}$$

With the above constraints, the proposed work performs two major processes such as power loss estimation and the optimum bus location prediction for compensators.

3.2. Power loss estimation

The total power loss in the transmission line depends on the combination of complex power injected from current bus to next bus, next current and the voltage at the swing bus. Hence, the mathematical formulation of power loss in the current bus placed at the transmission line is expressed as

$$\Delta S_{ij} = S_{ij} + S_{ji} + W \tag{18}$$

where

ΔS_{ij} : Power loss variation between i and j buses
S_{ij}, S_{ji} : Complex power injected from bus i to bus j and vice versa
W : Power supply at the swing bus

The addition of all the losses defined in (18) for each bus decides the total power loss in the transmission line. But, the loss depends on the injected complex power. The polar form of the complex power containing voltage magnitude (V_{mag}) and phase angle (θ) (deg) represented as

$$U = V_{mag} * \left(cos\,\theta + j\,sin\,\theta\right) \tag{19}$$

With the combination of real, reactive power, admittance variables, the complex power is reformulated for the successive iterations as

$$U_i^{(k+1)} = \frac{\dfrac{P_i - jQ_i}{U_i^{(k)}} - \sum_{j=1}^{n} Y_{ij} U_j^{(k)}}{Y_{ii}} \quad i \ne j \tag{20}$$

where

$P_i Q_i$: Real and reactive power in i^{th} bus
Y_{ii} : Self admittance value for i^{th} bus
Y_{ij} : Mutual admittance between i^{th} and j^{th} buses
$U_j^{(k)}$: Complex power estimate of current state
$U_j^{(k+1)}$: Complex power estimate of future state

The algorithm to estimate the power loss is listed as follows:

Power Loss Estimation

Input : Bus data and Line Data i.e. B and L
Output : Total Power Loss, *S*

Step-1: Calculate bus and line admittance matrix calculation

$Y_{kk} = \sum_{i=1}^{n} Y_{ki}$ \\ Y_{kk} = Self Admittance at bus k

$Y_{ki} = -\sum_{i=1 \neq k}^{n} Y_{ki}$ \\ Y_{ki} = Mutual Admittance between bus k and bus i

Step-2: $Z_{line} = R + jX$ \\ Line Impedance Matrix

Step-3: $Y_{line} = 1 / Z_{line}$ \\ Line Admittance Matrix

Step-4: Represent the complex power in polar form

$U = V_{mag} * (\cos\theta + j\sin\theta)$

Step-5: $W = V_1(Y_{11}V_1 + Y_{12}V_2 + Y_{13}V_3 + \dots Y_{1n}V_n)$

N_b : Total number of buses; W- Power supply in swing bus

Step-6: Compute the power estimate

$U_i^{(k+1)} = \dfrac{\dfrac{P_i - jQ_i}{U_i^{(k)}} - \sum_{j=1}^{n} Y_{ij}U_j^{(k)}}{Y_{ii}} \quad i \neq j$ \\$k$→iteration count,

Step-7: Estimate the injected power among the buses

$S_{ij} = U_i^2 * \left[Y_{ij} + Y_{i0} - U_j U_i Y_{ij}\right]$ // Injected Complex Power from bus 'i' to bus 'j'

Step-8: $S_{ij} = U_i^2 * \left[Y_{ij} + Y_{i0} - U_j U_i Y_{ji}\right]$ // Injected Complex

Step-9: Estimate the power loss for transmission Line connecting two buses

$$\Delta S_{ij} = S_{ij} + S_{ji} + W$$

Step-10: All the transmission line power losses are added to get the total line power loss.

$$S = \sum_{i,j \in N_b} \Delta S_{ij}$$

Initially, the data (bus and line) from the IEEE bus system are extracted and the admittance value for the line is calculated. The self and mutual admittance among the buses are estimated which play the major role in the power loss estimates. The complex power is estimated using the equation (11) with real, reactive power flows. Then, the injected complex power between the buses is estimated and the power supply on the swing bus estimated as follows:

$$W = V_1(Y_{11}V_1 + Y_{12}V_2 + Y_{13}V_3 + \dots Y_{1n}V_n) \tag{21}$$

Finally, the injected complex power estimates (S_{ij}, S_{ji}) and the power supply corresponding to the swing bus (W) are added together to get the power loss among the two buses (ΔS_{ij}). The total power loss is the algebraic sum of all the losses occurred between the buses computed further to predict the location.

3.3 SDTO-based bus location information extraction

The suitable bus location prediction depends on the forecast details of bus data, FACTS device used and the cost of FACTS device. Here, the objective is to minimize the cost incurred and the loss. The objective or fitness function to represent the minimization problem represented as

$$\gamma = \frac{Sin(s) - Max(s)^2}{S - Max(\partial)^2} \tag{22}$$

where

γ : Fitness value

S : Total power loss in transmission line

∂ : Cost of FACTS device

The algorithm to predict the bus number for the compensators is listed as follows:

SDTO-based bus location prediction

Input: Bus data (B), Cost of FACTS device (∂), FACTS data (F), Power loss (S)

Output: Best bus number (b_{best})

Step 1: Initialize the total number of buses as particle size (Ps), coefficient for update ($coeff$) and maximum number of iterations (max)

$Ps = Total\ number\ of\ buses$

$coeff = 1$

$max = 50$

Location prediction through power injected by FACTS device by SDTO

Step 2: for ($i = 1\ to\ max$)

Step 3: for (j= 1 to F_T) // F_T - Total FACTS devices

Step 4: Initialize the maximum loss as previous value for the optimization

$Prev = S_{max}$

Step 5: for (k=1 to L_T) // L_T – Total number of lines

Step 6: Extract the real (F_P) and reactive power (F_Q) value injected from the FACTS data (F)

Step 7: Extract the real (S_P) and reactive power loss (S_Q) before injection from total power loss estimate (S)

Step 8: Compute the real and reactive power loss after the injection

$I_P(k) = \sum S_P - F_P$

$I_Q(k) = \sum S_Q - F_P$

Step 9: $\beta(k) = \sum I_{real} + jI_{reactive}$

Step 10: If $(\beta(k) < \Pr ev)$

$\Pr ev = \beta(k)$

$\gamma = \dfrac{\sin(s) - \text{Max}(s)^2}{S - Max(\partial)^2}$

End if

Step 11: End for

Step 12: End for

Step 13: End for

Step 14: $b_{best} = \gamma$ \\ b_{best} - Best fitness for bus number corresponding to FACTS placement

Initially, the total number of buses in the transmission line is regarded as the size of particles traveled. Then, the variables governing the optimization are initialized. The real and reactive power injected by the FACTS devices are extracted from the FACTS data, total power loss estimates before injection. The real and reactive power loss after the injection is estimated by using the following equations

$$I_P(k) = \sum S_P - F_P \tag{23}$$

$$I_Q(k) = \Sigma S_Q - F_Q \tag{24}$$

The values estimated from the above equation are organized into the single term as follows:

$$\beta(k) = \Sigma I_{real} + jI_{reactive} \tag{25}$$

Then, the value from (18) is compared with the previous maximum loss estimated value. If it is less than the maximum value, then the current estimated value is regarded as the previous value and estimate the fitness value. The fitness value after the maximum iteration is reached decides the bus number for compensator placement. The placement of FACTS device at this location assures the effective congestion management with minimum cost.

4. Performance Analysis

The proposed SDTO is tested with the three IEEE bus systems such as 14 [21], 30 [22] and 39[30] with the objective of cost minimization. The algorithms are implemented in MATLAB R2013b programming language and the code is executed in 2.70 GHz, 2 GB RAM, Intel (R) Pentium (R) CPU.

4.1. Case study 1: IEEE 14-bus system

The IEEE-14 bus system is the approximate American Electrical Power System that contains the 14 buses, 5 generators and 11 loads. Besides, it contains the 5 synchronous machines with IEEE type-I exciters. The real and reactive power losses for the IEEE-14 bus system with and without FACTS devices (series capacitor, a shunt capacitor, Static Volt-Ampere Reactive Compensators (SVC), Thyristor Controlled Series Compensator (TCSC) and Static Synchronous Compensator (STATCOM)) are discussed in Table 2.

Table 2. Real and reactive power loss

Power Loss	Without FACTS Devices	With FACTS Devices
Real power loss	0.046	0.044
Reactive power loss	0.031	-0.016

Table 3. Real power loss with load variations

Load	Real Power Loss (MW)	
	Without FACTS	With FACTS
+5%	0.050	0.042
-5%	0.041	0.035
+10 %	0.055	0.045
-10 %	0.037	0.027

Table 4. Reactive power loss with load variations

Load	Real Power Loss (MW)	
	Without FACTS	With FACTS
+5%	0.034	-0.028
-5%	0.028	-0.004
+10 %	0.037	-0.071
-10 %	0.025	0.007

The real power loss without FACTS devices is 0.046 MW and the application of FACTS devices reduces the loss into 0.044 MW which confirms the 4.34 % reduction in loss. Similarly, the reactive power loss reduction with FACTS devices is 48.39 % compared to the absence of FACTS devices. The individual real and reactive power loss variations according to the load variations ($\pm 5\%$, $\pm 10\%$) are illustrated in Table 3 and 4 respectively.

With the increase or decrease of the load along the lines, the power loss variation depicts that the proposed SDTO-based location prediction for compensators reduces the real and reactive power loss variations effectively. The Line Utilization Factor (LUF) is the factor or index (LUF_{ij}) denotes the congestion in the transmission line which is defined as the ratio of actual Mega Volt Ampere (MVA) rating (MVA_{ij}) of the line between the buses to the maximum MVA rating (MVA_{ijmax}) of the line between the two buses (i, j) as follows:

$$LUF_{ij} = \frac{MVA_{ij}}{MVA_{ij\,max}} \tag{19}$$

The line 4-2 in the IEEE-14 bus system has the LUF values of 0.04 and 0.012 corresponding to before and after compensator placement. The type of FACTS devices with corresponding locations in the line and the reduction of line losses are presented in Table 5.

Table 5. Reduction of line losses with location

Line	Before placement	After placement	Facts device
1-2	0.055	0.009	STATCOM
2-3	0.040	0.003	TCSC
1-5	0.037	0.003	STATCOM
3-4	0.034	0	SVC
5-6	0.087	-0.004	Series Capacitor
7-8	0.046	-0.004	Shunt Capacitor
4-9	0.002	-0.002	SVC
6-11	0.020	-0.020	Shunt Capacitor
2-4	0.029	0.007	TCSC
4-7	0.046	0.004	Series Capacitor

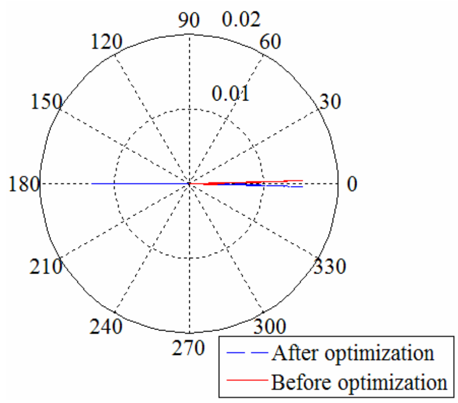

Fig. 2. Voltage profile analysis for IEEE -14 bus system

Table 6. Real and reactive power loss

Power loss	Without FACTS devices	With FACTS devices
Real power loss	0.064	0.056
Reactive power loss	0.180	-0.225

Table 7 Real power loss with load variations

Load	Real Power Loss (MW)	
	Without FACTS	With FACTS
+5%	0.071	0.066
-5%	0.058	0.046
+10 %	0.078	0.018
-10 %	0.052	0.036

Table 8. Reactive power loss with load variations

Load	Real Power Loss (MW)	
	Without FACTS	With FACTS
+5%	0.199	-0.254
-5%	0.163	-0.197
+10 %	0.218	-0.285
-10 %	0.146	-0.171

From the Table 5, it is observed that the combination of FACTS devices placed on the suitable location reduces the line losses, congestion with the minimum cost effectively. The voltage profile before and after the SDTO algorithm is illustrated in Fig. 2.

The prediction of suitable location using SDTO provides the good extent (blue line) compared to the before optimization (red line) in the IEEE-14 bus system.

4.2. System case study 2: IEEE-30 bus

The equivalent model for IEEE-30 bus system includes the set of 15 buses, 2 generators and 3 synchronous condensers with 11 kV or 1 kV base voltages. The real and reactive power losses for the IEEE-30 bus system with and without FACTS devices are discussed in Table 6.

The real power loss without FACTS devices is 0.064 MW and the application of FACTS devices reduces the loss into 0.056 MW which confirms the 12.5 % reduction in loss. Similarly, the reactive power loss reduction with FACTS devices is 17.78 % compared to the absence of FACTS devices. The individual real and reactive power loss variations according to the load variations ($\pm 5\%$, $\pm 10\%$) are illustrated in Table 7 and 8 respectively.

The prior power loss estimation to the location information prediction in proposed SDTO-based reduces the real and reactive power loss variations corresponding to the load variations effectively. The line 2-3 in the IEEE-30 bus system has the LUF values of 0.076 and 0.005 corresponding to before and after compensator placement. The type of FACTS devices with corresponding locations on the line and the reduction of line losses for IEEE-30 bus system are presented in Table 9.

Table 9. Reduction of line losses with location

Line	Before placement	After placement	Facts device
1-2	0.054	0.009	STATCOM
3-4	0.039	0.005	TCSC
2-5	0.039	0	STATCOM
5-7	0.020	0.001	SVC
6-8	0.007	0.002	Series capacitor
4-12	0.001	-0.001	Shunt capacitor
12-13	0.036	-0.036	SVC
6-9	0.002	-0.002	Shunt capacitor
9-11	0.032	-0.032	TCSC
1-3	0.025	0.003	Series capacitor

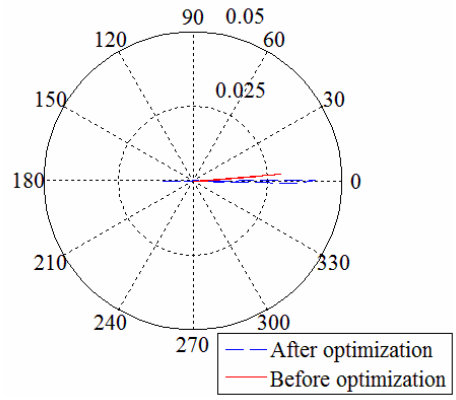

Fig. 3 Voltage profile analysis for IEEE-30 bus system

From the Table 9, it is observed that the combination of FACTS devices placed on the suitable location reduces the line losses, congestion with the minimum cost effectively. The voltage profile before and after the SDTO algorithm is illustrated in Fig. 3.

The prediction of suitable location using SDTO provides the good extent (blue line) compared to the before optimization (red line) in IEEE-30 bus system.

4.3. Case study 3: IEEE-39 bus system

The well-known 10-machine New-England power system known as IEEE-39 bus system and this is used to study both static and dynamic problems in power system effectively. The IEEE-39 bus system is organized into three areas as follows:

Area-1 : 2230 MW of generation and 2380 MW of load
Area-2 : 790 MW generation and 1120 MW of load
Area-3 : 3180 MW of generation and 2650 MW of load

The IEEE-39 bus system includes the 10 generators, 19 loads, 36 transmission lines and 12 transformers which are used to validate the proposed SDTO algorithm. The real and reactive power losses for the IEEE-39 bus system with and without FACTS devices are discussed in Table 10.

The real power loss without FACTS devices is 0.049 MW and the application of FACTS devices reduces the loss into 0.020 MW which confirms the 72.5 % reduction in loss. Similarly, the reactive power loss reduction with FACTS devices is 83.26 % compared to the absence of FACTS devices. The individual real and reactive power loss variations according to the load variations (±5%, ±10%) are illustrated in Table 11 and 12 respectively. The prior power loss estimation to the location information prediction in proposed SDTO-based reduces the real and reactive power loss variations corresponding to the load variations effectively. The line 3-4 in the IEEE-39 bus system has the LUF values of 0.0535 and 0.007 corresponding to before and after compensator placement.

Table 10. Real and reactive power loss

Power loss	Without FACTS Devices	With FACTS Devices
Real power loss	0.049	0.020
Reactive power loss	21.362	3.577

Table 11. Real power loss with load variations

Load	Real Power Loss (MW)	
	Without FACTS	With FACTS
+5%	0.054	0.027
-5%	0.044	0.013
+10 %	0.059	0.034
-10 %	0.040	0.007

Table 12. Reactive power loss with load variations

Load	Reactive Power Loss (VAR)	
	Without FACTS	With FACTS
+5%	23.551	3.937
-5%	19.279	3.234
+10 %	25.848	4.315
-10 %	17.303	2.908

Table 13. Reduction of line losses with location

Line	Before placement	After placement	Facts device
1-2	1.521	0.009	STATCOM
3-4	0.426	0.006	TCSC
2-25	0.318	0.004	STATCOM
5-6	0.086	0	SVC
1-39	1.602	0.006	Series Capacitor
4-14	0.276	-0.004	Shunt Capacitor
12-13	0.005	-0.005	SVC
12-11	0.004	-0.004	Shunt Capacitor
10-32	0.057	-0.057	TCSC
2-3	0.535	0.007	Series Capacitor

The type of FACTS devices with corresponding locations in the line and the reduction of line losses for IEEE-39 bus system are presented in Table 13.

From the Table 13, it is observed that the combination of FACTS devices placed on the suitable location reduces the line losses, congestion with the minimum cost effectively. The voltage profile before and after the SDTO algorithm is illustrated in Fig. 4.

The prediction of suitable location using SDTO provides the good extent (blue line) compared to the before optimization (red line) in the IEEE-39 bus system.

4.4. Overall cost analysis

The proposed optimization-based location prediction focuses on the cost minimization for hybrid compensators used in the respective locations of the bus system. The cost spent for the utilization of individual compensator and the hybrid compensators are analyzed in detail in this sub-section. Table 14 presents the cost ($/h) analysis corresponding to the compensators used in the bus system.

From the table 14, it is observed that the single compensator used in the suitable locations either increases the cost or it provides the less compensation. For E.g., the TCSC provides the high-compensation with maximum cost and less cost shunt capacitor provides low compensation.

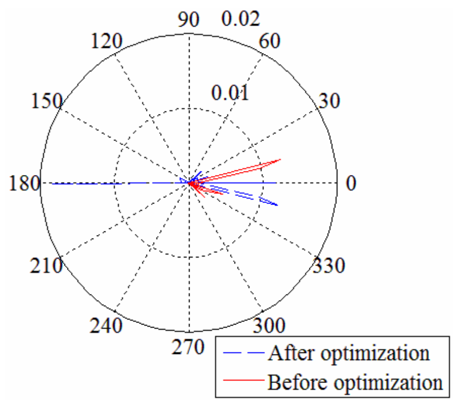

Fig. 4 Voltage profile analysis for IEEE-39 bus system

Table 14. Overall cost analysis

Bus system		Overall Cost ($/h)				
		Series capacitor	Shunt capacitor	STATCOM	SVC	TCSC
IEEE-14	Individual	2800	736	4450	3200	7800
	SDTO-hybrid	728				
IEEE-30	Individual	2980	688	4550	3200	8480
	SDTO-hybrid	1954				
IEEE-39	Individual	2040	368	2000	1440	6120
	SDTO-hybrid	1394				

Hence, the proposed optimization alleviates this issue effectively by placing these five compensators in ten different locations. The overall cost spent for the FACTS devices deployment in IEEE-14, 30 and 39 bus system for the proposed SDTO algorithm are 728, 1954 and 1394 $/h which are comparatively less to the individual devices utilization. Besides, the compensation provided to the reactive power is also high to provide the better output. Thus, the proposed system efficiently finds or relocates the FACTS devices on the respective bus locations responsible for the minimal real/reactive power loss, line losses and the cost spent on the design.

4.5. Comparative analysis

The effectiveness of the proposed approach is further investigated against the existing methods of Hybrid Nelder-Mead-Fuzzy Adaptive Particle Swarm Optimization (HNM-FAPSO)-based Multi-Line Congestion Management (MLCM) [27] and absence of MLCM in terms of real power losses. Table 15 presents the variation of line losses for the three methods.

Table 15. Line Loss Analysis for IEEE 30 bus system

Parameter	Before MLCM	HNM-FAPSO	SDTO
Line loss (MW)	12.353	11.811	10.809

From the Table 15, it is observed that the existing HNM-FAPSO offers 4.3876 % reduction in line losses and proposed SDTO offers 12.5 % reduction compared to the absence of MLCM. Table 16 shows the variations of real power losses for existing methods of pre-rescheduling, Firefly Algorithm (FA)-based post rescheduling[30] and proposed method of SDTO in detail.

Table 16. Line loss analysis for IEEE 39 bus system

Parameter	Pre-Rescheduling	FA	SDTO
Real Power loss (MW)	59.057	57.24	55.56

From the Table 16, it is observed that the existing FA-rescheduling offers 3.08 % reduction in real-power losses and proposed SDTO offers 5.92 % reduction compared to the absence of pre-rescheduling methods respectively.

5. Conclusion

This paper addressed the issues involved in CM topologies with FACTS devices employment. The challenging issues observed in the CM topologies are the lack of optimal power (real and reactive) usage with the better transfer capability and minimum cost. The prediction of the suitable place for the energy resources to control the power flow is the major requirement for power handling scenario. This paper proposed the novel optimization principle that selected the best location for the compensators or FACTS devices and achieved the real-reactive power compensation. The parameters estimation and the selection of values with the best fitness through the Symmetrical Distance Travelling Optimization (SDTO) algorithm established the proper controlling of optimal power flow in the transmission lines. The modified fitness function formulation based on the bus parameters, index estimation correspond to the optimal reactive power usage enhanced the power transfer capability with the minimum cost. The comparative analysis between the proposed method with the existing power management techniques regarding the parameters of power loss, cost value, load power and energy loss confirmed the effectiveness of proposed work in the distributed renewable energy systems.

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