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A smart bi-objective two-stage algorithm for optimal transmission switching without islanding

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Abstract. In a deregulated environment, optimal transmission switching (OTS) plays an important role in coordination among power generating companies (GENCOs) and transmission company (TRANSCO) by minimizing operating costs. This paper solves ac OTS (ACOTS) in two different stages sequentially with ac optimal power flow (ACOPF) and transmission switching through ac power flows (TS-ACPF) for optimal power generation and efficient power transmission, respectively. The mutual dependency along with the coordination among these optimal problems are treated intelligently by adopting a metaheuristic based two-stage algorithm with a multi-objective approach to achieve an effective solution through maximum utilization of power in the existing system or for future expansion planning. Production cost optimization problem is taken care of in the first stage while transmission loss is optimized in the second stage with successive iterations of the proposed algorithm. MATLAB simulations to optimize both transmission loss and production cost for both the IEEE-30 bus system and the Indian Utility 62-bus real system are experimented. Results are provided to validate the proposed technique which satisfies several cases of load variations, N − 1 standards and other combinations of stressed security constraint conditions. The detailed investigation of the results prove the effectiveness of the proposed intelligent two-stage method over the existing methods in terms of automatic and cost-effective bi-objective solution relying on the flexibility of switching strategy and security by avoidance of islanding without any manual interaction in between.

Keywords. AC feasibility; Genetic Algorithm; optimal power flow; singular Jacobian matrix; transmission switching.

1. Introduction

In the present era of the electricity market, there is more than one market participant who plays to benefit the most from the physical flow of electricity. The GENCOs bid for its production while the TRANSCO maintains the transmission line. In the majority of the cases, manual coordination among their individual operations is maintained by system operators (SOs) to achieve optimized running conditions which remains apparent most of the time. Reconfiguration through switching has the ability to reduce the loss in a network further for a fixed production schedule. By opening a line, which may even be a congested one, the global re-routing of power flow may reduce the overall cost, and the concept of OTS is evolved. In OTS, proper switching strategies of the existing electrical network are made corresponding to an optimal generation schedule to maximize the resource utilization. Situations like line overloads, voltage profile, security, as well as meeting increased demand up to a certain limit are taken care of in OTS. The importance lies in maximizing the benefit of trading electricity to more than one partaker eventually benefitting the consumer.

The OTS is a mixed-integer problem to co-optimize unit commitment (UC) with transmission switching (TS) and has been solved in most of the early works with dc optimal power flow (DCOPF) to reduce the dispatch cost of the system. Savings in cost with OTS using mixed-integer linear program is reported in [1, 2] with load level variations and N-1 contingency analysis and extended in [3] considering the changes in generation cost along with nodal prices, load payment, revenue and rent, congestion rent and flow-gate price. N-1 reliability with decomposition and computational approach is adopted towards smart grid applications in [4]. In [5], the duration of the switched states is considered as a dual multi-period problem with fixed optimal values of the integer variables. The expansion planning problem is decomposed into a master problem and

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two sub-problems by optimizing investment cost along with operating cost using Benders decomposition in [6]. The expansion plan designed in master problem with candidate units and TS variables remains unaltered for feasibility and optimality check in the sub-problems. In [7] security-constrained UC (SCUC) is dealt with in the master problem with the feasibility checking of TS in sub-problem. In most of the cases, OTS is optimized by partitioning and parallel way of solving using CPLEX optimizer (which is a standard simplex optimizer in C programming language). Switching of a few particular lines produced cost savings and reduced computational burden, however, islanding situations is reported for certain cases in [1, 2].

The ACOTS is co-optimization of ACOPF considering real as well as reactive power flow along with TS. The market implications and economic efficiency of such OTS is studied in [8]. However, impediment to its use is the large computational burden which becomes more complicated with injection at nodes containing switches on each line along with their probable close and open operations. For a faster solution, two heuristic approaches based on linear programming and MIP is proposed in [9] but generation schedules are optimized with DCOPF. Heuristics are also proposed in [10] to prescreen switchable branches by ranking the transmission lines with the help of sensitivity factor and locational marginal prices so that the number of binary variables of switched states is reduced. Limiting switching operations to a smaller number of branches is further studied in [11] to reduce time complexity. Authors in [12] describe optimal TS based on ACOPF considering voltage security criteria and contingency analysis incorporating Bender's decomposition while a comparison on the behavior of OTS heuristics based on both DCOPF and ACOPF is made in [13, 14]. It found that for some cases DCOPF-based heuristic exhibits poor choice of switchable branches which even lead to increased cost. A new OTS model based on mixed integer second order cone programming with ac feasibility, however, is suggested in [15]. SCUC problem included in OTS with renewable generation is discussed in [16]. OTS as a multi-objective problem to minimize the generation cost and maximize the probabilistic reliability is suggested in [17] with the help of quasi Pareto-optimal solutions for transmission switching strategies. Monte Carlo simulation is employed to approximate the amount of load that could not be served for a concerned period of time using loss of load probability (LOLP) method. Reliability is translated to cost by multiplying the non-served energy with the amount of lost load and its effect on probabilistic security due to topology modifications is analyzed in [18]. However, transmission losses and generation costs are never explicitly optimized together with feasibility check in the optimized stages itself. Again, meta-heuristic evolutionary algorithms are not used for such a problem, except [17], which may give a solution within an acceptable time frame even with no prescreening of branches.

The multi-objective optimization generally has two different ways of solving a specific problem with the need for manual intervention in either of the ways. With two or more disagreeing objectives a set of non-inferior/ Pareto-optimal solutions within the feasible region of solutions are to be identified instead of a single optimal solution [17]. Thus a decision-maker (DM) is needed to categorize the subset of feasible solutions which is much more complex than that of a single objective solution producing a single best design [19, 20]. The other way to solve multi-objective problems is to represent both the objectives together as a weighted sum of single objective fitness function. In this case, to create this global function all criteria must be converted to a similar scale where the frequently used method to convert them into costs is usually complicated and often erroneous in operation. A solution is possible only if scaling is done perfectly [21]. The difficulty also arises due to the introduction of weight factors for different criteria which again depends on the operator or DM and may be a prejudiced one.

This paper proposes an intelligent algorithm with a cascaded two-stage metaheuristic approach to optimize the generation schedule in one stage and transmission switching in another. The interdependent input and output variables of each stage are optimized using this iterative method keeping the output variables of one stage unaltered while processing the input variables in other stage to gradually reach a state with almost no further changes in them. Use of evolutionary optimization technique at each stage enables itself to check its feasibility. The algorithm is designed as a background program to take care of different changes in the network like load variations and congestion. The proposed metaheuristic approach provides the following specific contributions:

1) It does not require any manual intervention to achieve multi-objectivity thus fully *automating* the process.
2) It deals with full network configuration that requires no pre-screening of branches giving maximum *flexibility* to choose the desired topology. Islanding is avoided through the singularity test of the Jacobian matrix maintaining the *security*.

The other highlights of this work involve solving the OTS problem with ACOPF feasibility and TS-ACPF where line congestions are avoided and the voltage profile maintained. Section 2 elaborates on the methodology with mathematical formulations. It establishes security, automation, and flexibility along with restrictions. The simulated and compared results for various cases are demonstrated in section 3. Modified IEEE 30-bus system and an Indian Utility 62-bus system are considered as test networks to analyze and validate the algorithm. $N-1$ contingency standards along with stressed conditions are satisfied. Section 4 summarizes the outcome and scope of this paper.

2. Materials and methodology

To identify the best network configuration with suitable removal of transmission lines for a mutually dependent generation schedule, the proposed algorithm runs as a background program. The network data depending on load variations or contingencies are fed as input data. This type of automatic optimization through multi-objective OTS is smart enough to take care of the system operation without any manual settings or solutions to choose from.

Figure 1 represents a basic meshed network model on which the algorithm is applicable. It has *ng* number of generators and *nb* number of buses interconnected with each other. Switches are embedded in each line and each bus is connected with one or more than one bus. Opening switches between buses 6 and 8 or buses *nb* and 10 or both between buses 2 and 9 and buses *nb* and 9 cause dead islands with no generation at all. Again, the opening of lines between buses 4 and 5 and buses 6 and 5 also cause an island which is also to be avoided if Gen 5 is not able to meet load at bus 5 or if Gen 5 is not a slack bus.

2.1 *Mathematical formulation for two stages of algorithm*

OTS is a combination of OPF and TS which has been logically arranged in this work and the final output of the algorithm gives the optimization result. In the first processing stage of the proposed technique, the ACOPF model is used to produce a specific power generation profile such that the cost of production becomes minimum for a given transmission topology. In the second stage, ACPF is used based on logics with TS variables to minimize the real power loss with the first stage specific power generation profile taken as input. The concept of optimization of both the loss and cost is governed by the power balance equation for the whole of the system as in eq. (1). That is, for a particular demand, with any change in generation (and hence the cost of generation), there will be a corresponding change in the total loss.

$$\sum_{i}\sum_{g\in\emptyset_i} P_g - \sum_{i} P_{di} = T_L \tag{1}$$

The mathematical representations of the problem at each stage are as follows:

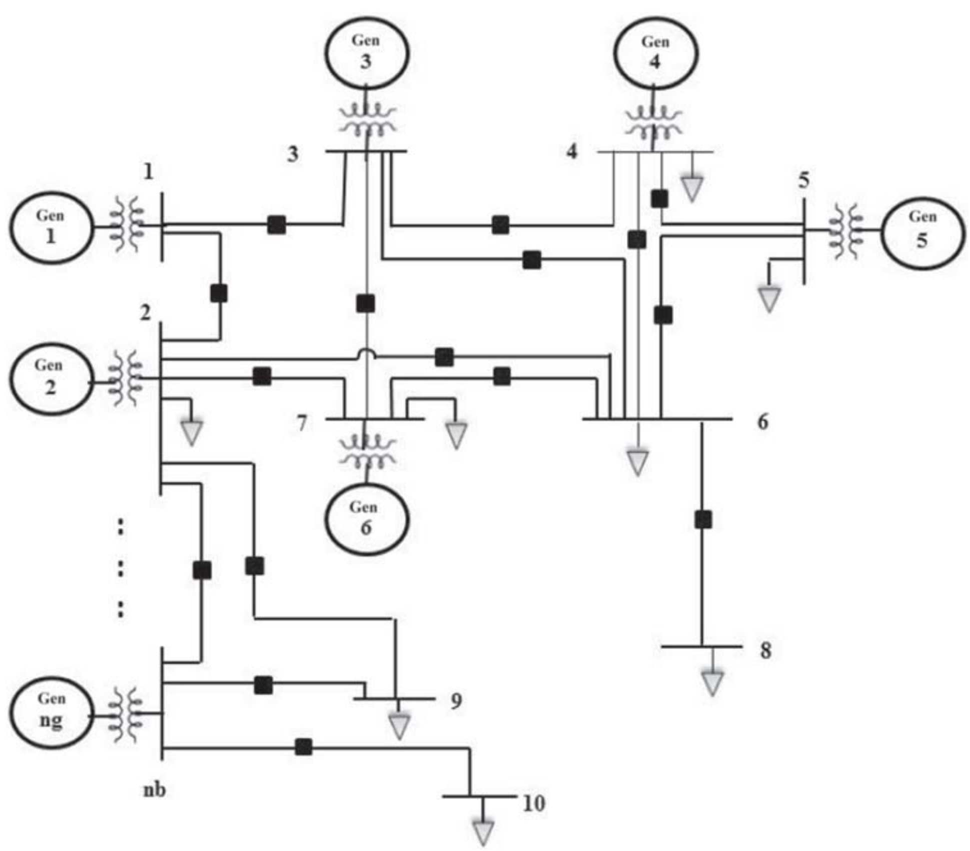

Figure 1. Basic network model.

2.1a *The First Stage*: *Cost optimization by ACOPF*: ACOPF yields an optimized real and reactive generation schedule minimizing the production cost and calculates corresponding losses. The objective function of the meta-heuristic method used is formulated as

$$\text{Min } C_G = \sum_g f(P_g) = \sum_g (c_{1g}P_g^2 + c_{2g}P_g + c_{3g}) \quad (2)$$

where c_{1g}, c_{2g}, c_{3g} are the cost coefficients in \$/MW^2, \$/MW, \$ respectively, subject to the constraints:

$$\sum_{g\in\emptyset_i} P_g - \sum_k V_iV_k(G_{ik}\cos\delta_{ik} + B_{ik}\sin\delta_{ik}) = P_{di}, \forall i \, and \, X(p) \rightarrow G_{ik}, B_{ik}, \cos\delta_{ik}, \sin\delta_{ik} \quad (2a)$$

$$\sum_{g\in\emptyset_i} Q_g - \sum_k V_iV_k(G_{ik}\sin\delta_{ik} - B_{ik}\cos\delta_{ik}) = Q_{di}, \forall i \, and \, X(p) \rightarrow G_{ik}, B_{ik}, \cos\delta_{ik}, \sin\delta_{ik} \quad (2b)$$

$$P_g^{min} \le P_g \le P_g^{max}, \forall g \quad (2c)$$

$$Q_{lik} = V_iV_k(G_{ik}\sin\delta_{ik} - B_{ik}\cos\delta_{ik}) + V_i^2(B_{ik} - b_{ik}), \forall l \, and \, X(p) \rightarrow Q_{lik} \quad (2d)$$

$$V_i^{min} \le V_i \le V_i^{max}, \forall i \quad (2e)$$

$$\delta^{min} \le \delta_{ik} \le \delta^{max}, \forall i \, connected \, to \, k \, and \, X(p) \rightarrow \delta_{ik} \quad (2f)$$

$$P_{lik}^2 + Q_{lik}^2 \le \left(S_{lik}^{max}\right)^2, \forall l \, and \, X(p) \rightarrow P_{lik}, Q_{lik}, S_{lik} \quad (2g)$$

$$P_{lik} = V_iV_k(G_{ik}\cos\delta_{ik} + B_{ik}\sin\delta_{ik}) - G_{ik}V_i^2, \forall l \, and \, X(p) \rightarrow P_{lik} \quad (2h)$$

$$Q_g^{min} \le Q_g \le Q_g^{max}, \forall g \quad (2i)$$

The constraints in eqs. (2b), (2d), (2g) and (2i) are related to the reactive powers and that in eq. (2e) is the limitation to the voltage magnitude which is absent in DCOPF. The eq. (3) represents matrix $X(p)$ containing the binary values for prevailing switch status of the network indicated by the variable w_{lik}, where $lik = 1, 2, \ldots N$ for all i and all k. The symbol $\rightarrow$ denotes that the right side elements related to line flow depends on the left side variables.

$$X(p) = [w_1, w_2, \cdots, w_N] \quad (3)$$

2.1b *The Second Stage*: *Reconfiguration through TS-ACPF*: Removal of certain lines may further reduce the real power loss even after the generation schedule is optimized in the first stage. Reconfiguration with ACPF is thus approached to find the new switching strategy with chromosomes of the Genetic Algorithm (GA) representing the switch status. Each set of binary-coded chromosome is evaluated through Newton-Raphson power flow method to generate the system real loss with fitness function as

$$Min \, T_L = \sum_k Real(S_{lik} + S_{lki}), \forall i \, when \, i \ne k \, and \, w_{lik} \ne 0 \quad (4)$$

Subject to: eqs. (2e), (2f) and

$$I_{lik} \cdot w_{lik} \le I_{lik}^{max} \quad (4a)$$

$$\sum_{g\in\emptyset_i} P_g - w_{lik} \cdot \left(\sum_k V_iV_k(G_{ik}\cos\delta_{ik} + B_{ik}\sin\delta_{ik})\right) = P_{di}, \forall i \, and \, P_g \in M(p) \quad (4b)$$

$$\sum_{g\in\emptyset_i} Q_g - w_{lik} \cdot \left(\sum_k V_iV_k(G_{ik}\sin\delta_{ik} - B_{ik}\cos\delta_{ik})\right) = Q_{di}, \forall i \, and \, Q_g \in MV(p) \quad (4c)$$

$$(P_{lik} \cdot w_{lik})^2 + (Q_{lik} \cdot w_{lik})^2 \le \left(S_{lik}^{max} \cdot w_{lik}\right)^2, \forall l \quad (4d)$$

$$(nb - 1) \le \sum_{lik=1}^{N} w_{lik} \le N \quad (4e)$$

In eqs. (4a)–(4d) the possible switch status is incorporated through variable w_{lik}, where subscript *lik* indicates the line between i and k. The matrices $M(p)$ and $MV(p)$ holds the value of the scheduled real and reactive generation from the immediately previous stage 1 where all elements are summation of total generation in a particular bus. It is taken as the input schedule for the reconfiguration problem. Though all the lines are switchable, with *nb* number of total bus, a minimum of $(nb - 1)$ closed lines are required to maintain connectivity as reflected in eq. (4e).

$$M(p) = \left[P_{g1}, P_{g2}, \cdots P_{gng}\right] \quad (5)$$

$$MV(p) = \left[Q_{g1}, Q_{g2}, \cdots Q_{gng}\right] \quad (6)$$

2.2 *The flowchart for cascaded two-stage OTS algorithm*

The flowchart as shown in figure 2 represents steady-state operation of the system and is explained below in four steps for no congestion condition. The real and reactive generation schedule obtained in the first stage is kept unaltered and taken as an input for the second stage. The line switching profile obtained in the second stage is incorporated in the first stage in the following iteration for any possibility of further optimization. The complex problem is separately solved as a single-objective optimization problem in the respective stages and sequentially combined through algorithmic loop iterations with a feasibility check at each stage itself. The binary switch variables of TS-ACPF do not overlap with the continuous variables of ACOPF. The solution for individual utilities, that is, GENCOs and TRANSCO, are clearly identified with final output as the optimized result.

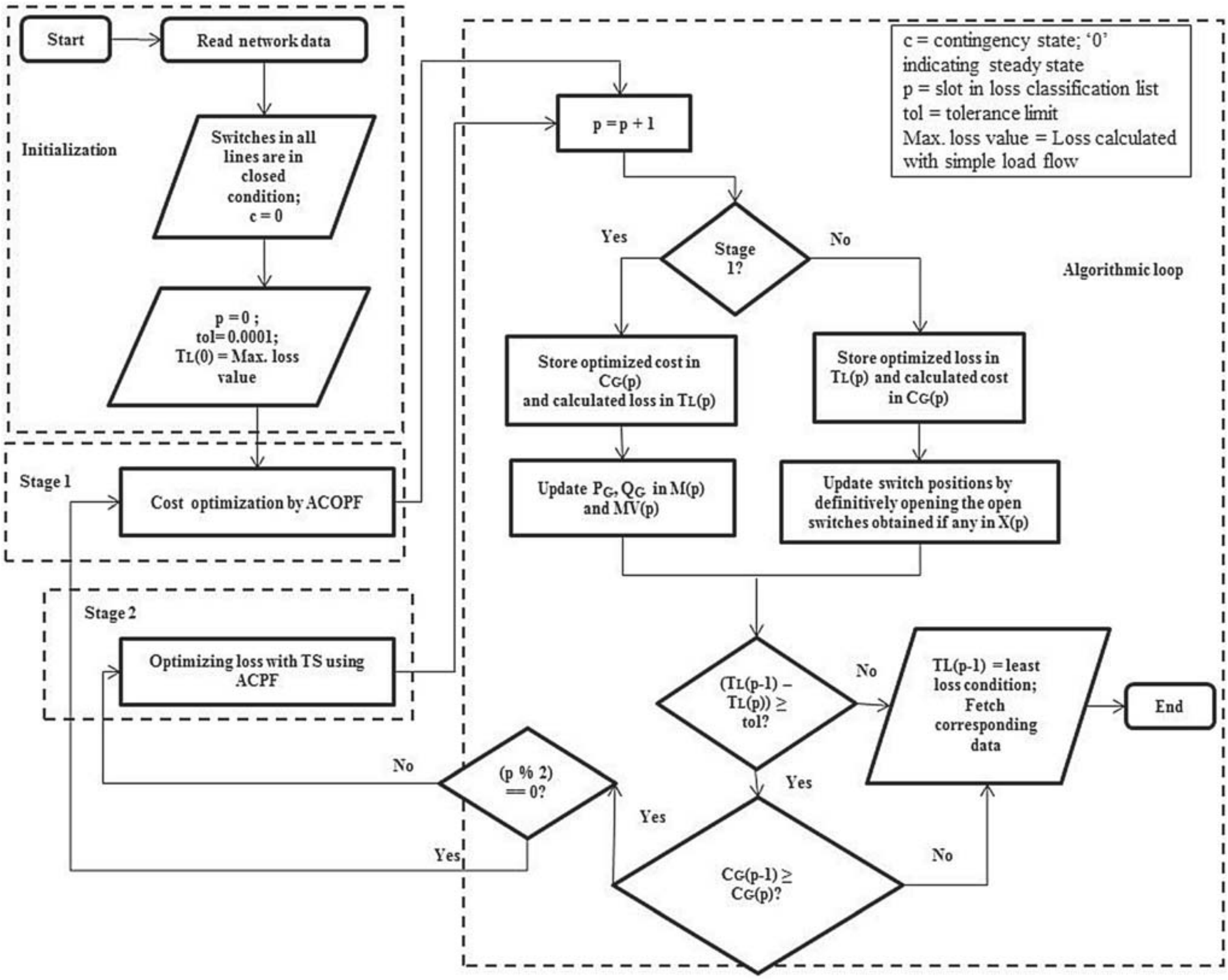

Figure 2. Flowchart of the proposed algorithm.

2.2a *Algorithm initialization*: The algorithm is initialized with network data considering that all the lines contain a switch and are in closed condition, that is, $w_{lik} = 1, \forall l$. Classified data storage is created for the loss T_L and corresponding cost C_G for each of the slots p as shown in figure 3. Slots are computational sequence numbers, and the optimized output values are stored in arrays with slots as its index number.

In this initialization step, the real power loss magnitude obtained from simple load flow analysis (considered as maximum in magnitude) is stored in the zeroth slot ($p = 0$) of the classified list denoted by $T_L(0)$ along with $C_G(0)$ as infinity. This maximum value of loss and cost is initialized to ensure that the algorithm at least completes one loop of both the stages if not more. A tolerance limit *tol* is the maximum pre-specified allowable error assumed to be 0.0001. A contingency state c is introduced while initializing the algorithm.

2.2b *ACOPF optimization in stage 1*: For the first iteration, with $p = 1$, ACOPF is performed considering all switches are in closed condition checking the feasibility in the stage itself. GA is used as a tool with objective function as mentioned in eq. (2), and the variables ranged between the maximum and minimum generation at the buses. In subsequent iterations, the switch states $X(p)$ updated in previous stage 2 are utilized to perform the ACOPF. This stage optimizes production cost while corresponding transmission loss is also calculated.

2.2c *TS-ACPF optimization in stage 2*: At the first iteration of this stage, with $p = 2$, reconfiguration of the network is performed considering all the lines are switchable with a limit as indicated by eq. (4e) and $M(1)$ and $MV(1)$ values are taken as input. Bit-string type of population is used to ensure the binary nature of the variables. Certain switching combinations may create islands that are discarded by the Jacobian Singularity test. TS-ACPF thus

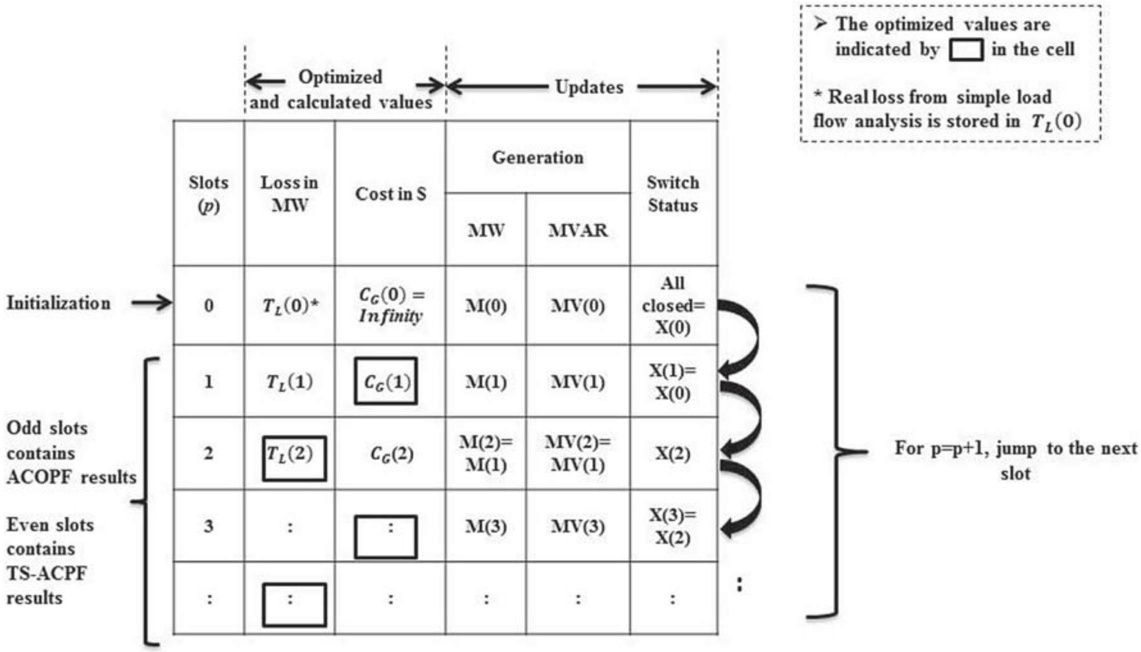

Figure 3. The classified data storage module.

utilizes unaltered generation schedule, $M(p)$ and $MV(p)$ from the immediately previous stage 1 and optimizes transmission losses with a combination of open and closed lines. It also re-calculates $C_G(p)$ for any change in dispatch caused due to switching.

In the subsequent iterations, with $p > 2$, the switch profile obtained from the earlier stage 2 is taken as input with open switches not changing their status during the process. Thus, any switch that is opened in a particular iteration will remain open till termination of the program.

2.2d *The state-of-the-art algorithmic loop*: Optimized solutions of each stage are stored in the respective slots of the storage list. In all odd slots of figure 3 results of stage 1 are stored. The optimized cost and calculated loss value are stored and generated MW and MVAR values are updated for the next stage in $M(p)$ and $MV(p)$ following equations (5) and (6), respectively. The updated switch positions are recorded in $X(p)$ as in eq. (3) after stage 2 in all even slots, along with optimized loss and calculated cost value.

At the end of each stage, if loss value in the present sequence is greater than the previous slot i.e., it does not satisfy $(T_L(p-1) - T_L(p) \geq tol)$, the preceding solution is taken as the best and algorithm is terminated. If the losses at the two corresponding slots are exactly equal, then the previous one is taken as the best. Otherwise, the cost value is checked to find whether $(C_G(p-1) \geq C_G(p))$ and the algorithm terminates if the present cost value is greater than the previous one. On the other hand, the process continues with iteration till the desired accuracy is obtained, with ACOPF in stage 1 and TS-ACPF in stage 2 depending on the odd and even slots, respectively.

Multi-objectivity is thus achieved without any multiple results to choose from Pareto front or setting weight factors after scaling them. The algorithmic iterative loop linking both the optimization stages intelligently, with a single objective at each stage, is the key to automatize the process without DM intervention making it a smart application.

2.3 *Security constraints*

Security analysis is demonstrated with loss of a transmission asset through N − 1 compliance check for which, a contingency state c is introduced as in [4] while initializing the algorithm. Except for certain changes in this initialization step, the rest of the three steps remain unchanged for such analysis. The steady-state operation of all elements is indicated by $c = 0$. The loss of a transmission element is reflected by $c > 0$. For each transmission element l and contingent state c, a binary parameter CN_{lc} is assigned. $CN_{lc} = 0$ for loss of a transmission element l and $CN_{lc} = CN_{l0} = 1$ indicate no contingency for all transmission elements. For each element and all $c > 0$,

$$CN_{lc} = \begin{cases} 0, & if\, c = l \\ 1, & otherwise \end{cases} \quad (7)$$

Thus, with N being the total number of transmission elements,

$$\sum_{\forall l} CN_{lc} = N-1, \forall c > 0 \tag{7a}$$

$$\sum_{\forall c>0} CN_{lc} = N-1, \forall l \tag{7b}$$

Contingent transmission line (/element) l is treated to be open when $CN_{lc} = 0$ during security analysis, just like $w_{lik} = 0$ with TS, while initializing the algorithm and kept so for the rest of the program. The parameter CN_{lc} forces the flow in such a line to zero through eqs. (8a) and (8b) which is modified from eqs. (2g) and (4d), respectively at different stages along with other constraints. The right side of eqs. (2d) and (2h) is also multiplied with CN_{lc}.

$$(P_{lik} \cdot CN_{lc})^2 + (Q_{lik} \cdot CN_{lc})^2 \le \left(S_{lik}^{max} \cdot CN_{lc}\right)^2, \forall l \tag{8a}$$

$$\begin{aligned}(P_{lik} \cdot w_{lik} \cdot CN_{lc})^2 + (Q_{lik} \cdot w_{lik} \cdot CN_{lc})^2 \\ \le \left(S_{lik}^{max} \cdot w_{lik} \cdot CN_{lc}\right)^2, \forall l\end{aligned} \tag{8b}$$

The limitation of this method is that, if the transmission line removed is connected to any load bus or Load Dispatch Center (LDC), which is not linked with any other line in the system, the bus gets islanded. In such cases, that bus data needs to be removed from the dataset in the initialization stage and algorithm simulated thereafter. Generator contingency forcing generator supply to become zero is not considered in this paper.

Other stressed conditions with decrease in generator output to check whether the system can still cater to all loads optimizing loss and cost is validated along with combination of many conditions.

2.4 *Jacobian singularity test to avoid islanding*

A network is said to be connected if all the buses can be reached from one arbitrarily chosen bus [22]. In this paper, network connectivity checking is incorporated in the Newton-based power flow code. Detection of formation of the island(s) or network splitting with no slack bus in it is done with the singularity test of the Jacobian matrix (J) as in eq. (9).

$$J = \begin{bmatrix} \dfrac{\partial P}{\partial \delta} & \dfrac{\partial P}{\partial V} \\ \dfrac{\partial Q}{\partial \delta} & \dfrac{\partial Q}{\partial V} \end{bmatrix} \tag{9}$$

Thus, the singularity occurs for two cases,

Case 1: The power flow equations are functions of voltage phase angular differences between two buses. Therefore, a network with at least one island would result in eq. (10). The sum of the columns of derivatives with respect to δ is zero for the islanded buses.

$$\sum_{k\epsilon Is} \frac{\partial P_i}{\partial \delta_k} = 0; \quad \sum_{k\epsilon Is} \frac{\partial Q_i}{\partial \delta_k} = 0 \tag{10}$$

The real/reactive powers at bus i are P_i / Q_i and δ_k is the voltage phase angle at bus k. The set of buses making part of the island is represented by Is.

Case 2: At least one column of J is linearly dependent on the preceding columns for one island, such that,

$$\hat{c}_m = \sum_{n=1}^{m-1} \eta_n \hat{c}_n, \, and \; \eta_n = \begin{cases} 0 \\ -1 \end{cases} \tag{11}$$

The m^{th} column of matrix J is denoted by $\hat{c}_m$. η_n are suitable coefficients (not all equal to zero) for the n^{th} column. Equation (11) holds for only two conditions:

1) If $\hat{c}_m$ is one of the columns of derivatives with respect to δ, all phase angles should be valid power flow variables, that is, none of them are constant, indicating no slack bus or existence of islands with no slack bus.
2) If $\hat{c}_m$ is one of the columns of derivatives with respect to V, for a particular value of δ and V variables under special conditions like absence of line charging, off-nominal transformer ratios, absence of any (reactive) slack bus, etc., which also occurs in case of islands with no slack bus in it.

Singularity test of the Jacobian matrix thus helps to ensure continuity of power supply [23, 24]. In this work to avoid islands a minimum singular value of J is considered as σ_m. If σ_m is zero, a solution cannot be obtained from load flow. It is different for each system and reduces as the system approaches the point of collapse and may vary with change in TS. Any switching combination, for which the value of σ_m obtained is less than the fixed value, is abandoned. This also helps to avoid critical loading conditions with absolute voltage collapse along with islands. The analysis helps to discard undesired solutions and thus increases the speed of optimization.

2.5 *Flexibility of switching strategy through the use of meta-heuristic method*

This paper utilizes evolutionary meta-heuristic based algorithm to solve the bi-objective problem. OTS in literature is solved by exact search methods like mixed-integer programming, branch-and-bound, and Benders decomposition. Though meta-heuristics have no mechanism to guarantee optimal condition over exact methods, it is used due to certain advantages [25].

1) Exact algorithms can be extremely time-consuming for problems with large dimensions. The present problem is evaluated with no pre-screening of switchable lines giving maximum flexibility to select optimum topology.

It creates a huge range of switch variables with the possibility of many switching combinations. With the existing methods, handling such large variables requires a longer solution time [10, 11].

2) These algorithms are capable of handling numerous constraints and are much lesser strict in mathematics.

The present paper uses the basic Genetic Algorithm (GA) for ACOPF while binary-coded GA for TS-ACPF. It is a powerful tool that can successfully tackle difficult problems with large dimensions in reasonable time and give good quality solutions. Present solutions are tested numerous times with the most frequently occurring result considered to be the optimal solution. The algorithm is also tested with the tuning of crossover and mutation processes and changing the number of generations.

3. Simulation results and discussion

The proposed methodology is simulated for different cases as in table 1. It consists of normal, peak and off-peak load conditions along with stressed and contingent conditions. The system data to carry out case study of the IEEE-30 bus system is downloaded from the University of Washington Power Systems Test Case Archive and modified for different load demands. The generator variable costs of the six GENCOs are taken as reported in the appendices of [26]. The data of the practical 62-bus system which has nineteen GENCOs, forty-three LDCs along with the generator variable cost is taken as reported in appendices of [26]. The tests are performed for each chromosome at the second stage of reconfiguration with minimum singular value (σ_m) of 0.0193 and 0.0001 for IEEE and actual test systems, respectively in this paper. Simulated results are compared to evaluate the potential benefit of the OTS over OPF and to explicitly measure the benefit of both utilities.

3.1 *Implementation of algorithm for different load profiles*

The available data of the IEEE-30 bus system is considered the *Base* case. Different loading patterns are simulated as *Peak load* case with a 10% increase and *Off-Peak load* case with a decrease of demand by 10% individually on all LDCs. The detailed results including optimal topology with a comparison with that of ACOPF results are provided in table 2. The outcomes of ACOPF are obtained with the same network data with all switches closed after processing the first iteration of stage 1. The changes in generator output from this initial OPF condition are also presented, where positive and negative values indicate an increase and decrease in output, respectively. Both loss and cost are found to decrease in all the cases. However, in the second case, switching could not minimize any of them.

The results indicate that a network optimized for one particular pattern of load on a network is not necessarily optimal for another. It is not a good idea to open certain line(s) forever, even if their opening makes the system more efficient for a certain time span. This mandate that the topology must be changed based on real-time span, system conditions, load change or forecasts that can result in a lower loss and cost. To check this, the optimal TS strategy of the *Base* case has been applied to the *Peak load* condition, only to find that, with the opening of the line, the loss is increased by nearly 11%. To show this, the optimized losses for different loading conditions are compared with the *Base* case in figure 4. Coincidentally, the optimal topology for both *Base* and *Off-Peak load* cases are the same for this network.

To depict the advantage of incorporating TS with ACOPF, some OPF results from the literature are compared with the present work in table 3. Switching has the potential to reduce the cost further. Multi-objective OPF solution gives a varied range to choose from as presented in table 4 which necessitates DM's preferences and thus subjectivity

Table 1. List of cases simulated with the proposed algorithm.

System tested	Conditions evaluated	Sub-division
Modified IEEE-30 Bus	Change in load profile	Base case with normal consumption
		Peak load case with a 10% rise in all loads
		Off-peak load case with a 10% fall in all loads
	Analysis of security constraints	N − 1 contingency
		Stressed generator contingency
		N − 1 contingency with peak load
		N − 1 contingency with stressed generator
		Comparison with a case from literature
Indian utility-62 bus (Tamil Nadu Electricity Board (TNEB), India) [26]	Performance analysis of a real system	Base case with normal consumption
		Peak load case with a 20% rise in all loads
		Off-peak load case with a 20% fall in all loads

Table 2. Optimal network data for different load conditions (Modified IEEE 30-Bus System).

Problem	OPF results (with all switches closed)		Proposed algorithm results			Changes in generation from initial OPF to proposed technique		
	Generation cost ($/h)	P_{Loss} (MW)	Open lines	Generation cost ($/h)	P_{Loss} (MW)	GENCO	P_g (MW)	Q_g (MVAR)
Base case (283.4 MW 126.2 MVAR)	803.0758	9.8039	5–7	802.9870	9.5531	1	− 3.3812	0.7690
						2	0.2686	2.8040
						5	0.0914	− 4.9248
						8	1.1805	2.7769
						11	0.1438	0.3138
						13	0.4472	0.2828
Peak load case (311.74 MW 138.82 MVAR)	908.6166	11.2217	All closed	908.6166	11.2217	1	0.0	0.0
						2	0.0	0.0
						5	0.0	0.0
						8	0.0	0.0
						11	0.0	0.0
						13	0.0	0.0
Off-peak load case (255.06 MW 113.58 MVAR)	701.6985	8.1595	5–7	701.6957	7.9385	1	− 3.9341	0.9688
						2	1.9974	1.5194
						5	0.8280	− 3.6424
						8	0.3203	2.5946
						11	− 0.1477	0.2513
						13	0.7150	0.1977

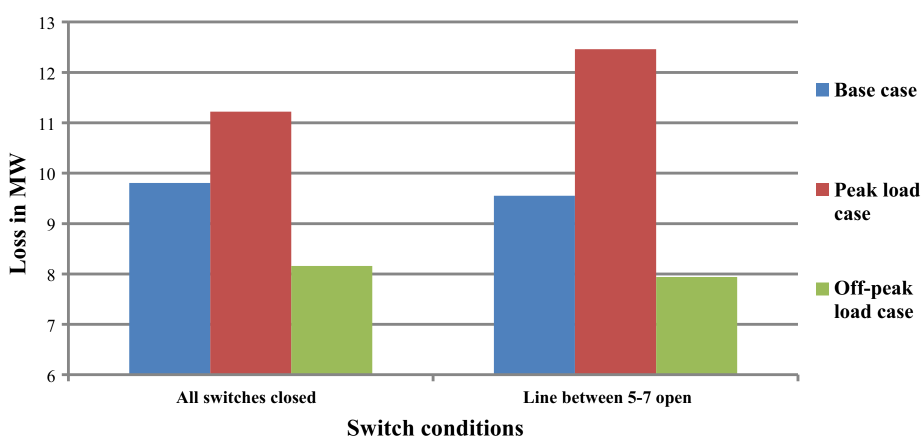

Figure 4. Comparison of loss for different load profile according to their optimal topology.

may appear. This shows the advantage of getting a definite result as in this paper.

3.2 *Analysis of security constraint*

The performance of the network during contingencies and other stressed conditions demonstrates its reliability. The proposed technique not only alleviates the security conditions but also achieves the optimized results under such conditions and still provides power to all possible loads. The output of the conditions simulated by the proposed OTS compared with ACOPF results with all switches closed except the contingent lines are shown in table 5. The *N-1* compatibility analysis is done under normal demand conditions with a single asset loss between LDCs 12 and 15. Simulation is also done when both the P_g and Q_g limits of power producer at bus 2 is reduced by 75%. This condition is termed as *Stressed Generator* contingency. To further evaluate the system under stress, the $N-1$

Table 3. Comparison of generation cost.

Literature	Method	Generation cost ($/h)
Present work	ACOPF with TS	802.987
[27]	EP based algorithm	803.51
[28]	LP-programming algorithm	806.84
[19]	GA based OPF to reduce voltage stability index	815.51
[21]	PSO based OPF to minimize security margin	823.0009
[21]	PSO based OPF to minimize loss	967.7009

Table 4. Multi-objective OPF to optimize both loss and cost in [21].

MOOPF considering	Loss in between (MW)	Cost in between ($/h)
Two clusters	7.783–6.0492	805.4443–824.7188
Three clusters	8.3015–6.0492	804.0179–824.7188
Four clusters	9.1555–6.0492	804.8738–824.7188

contingency is also combined with *Peak Load* demand with line between LDCs 12 and 14 taken as a candidate for outage. *Stressed Generator* condition is also coupled with a single line outage between LDCs 18 and 19. The loss and cost are found to get minimized though the decrement is quite low. In the last case, however, switching has not been able to decrease the loss at all. Thus the initial OPF result is taken as the best possible result. In both the cases involving *Stressed Generator*, the GENCO at bus 2 is found to supply its full capacity, that is, its reduced power output of 20 MW.

3.2a *Steps of the Proposed Algorithm for N − 1 condition*: To explain the working of the proposed algorithm, loss and cost values changing in each step of it in the *N − 1* contingency condition is shown in figure 5. ACOPF application in stage 1 gave an optimal generation schedule followed by the opening of switch between LDCs 15 and 23 in stage 2. The bold and underlined values in the figure are the optimized values of that stage. The switching sequences in the next step opened lines between buses 16 and 17, and buses 15 and 18 with each of the optimum topology followed by cost optimization rearranging the best values of P_g and Q_g. An open line obtained is kept definitively open, thus, the optimum topology had three lines devoid of supply along with the single line outage. Further opening of the line between bus 21 and bus 22 though reduces the loss, the cost is increased and the previous condition is considered to be the ideal condition.

3.2b *Comparison with Literature* [29]: A special case is considered with a load of the 30-bus system increased by 30% creating two overloaded lines (refer [29]), which are not removed, but TS is performed to find the lines to be outaged to alleviate congestion along with decreasing the generation cost by higher dispatch from a cheaper source. In the present work, the incremented load using the same data when analyzed with ACOPF, shows the same lines to get congested. However, with the help of constraint equations and switching, the proposed method does relieve congestion with the removal of lines between buses 24 and 25 and buses 19 and 18 without removal of contingent lines. Optimal scheduling with opening lines as mentioned in [29] is also performed. Comparable results are therefore obtainable through evolutionary algorithm as shown in table 6. Though the objective function is different, MW loss is found to be quite less (ranging around 40%) than that calculated in [29] but the cost is more (ranging around 1%). The most important advantage is that a definite result is obtained instead of selecting from a Pareto front.

3.3 *Performance analysis in a real system (TNEB, India)*

The Indian utility with normal consumption is termed as the *Base* case. The analysis of the test system has been done considering V^{max} and V^{min} at each bus between 1.08 and 0.94 per unit, respectively. The various load profiles to meet the change in demand are simulated to find the optimal topology. The *Peak Load* and *Off-Peak Load* cases are considered this time with a hike and drop of 20% of the base demand on all the LDCs respectively. The optimized results are shown in table 7 which again establishes that switching strategy should be changed with change in demand. However, the lines between buses 14 and 15 and buses 34 and 37 are found to be open in all the three cases. Figure 6 depicts all the values that are converted to per unit based on the results of the *Base* case and alternately shows *Off-Peak Load* and *Peak Load* conditions with *Base* case in

Table 5. Different simulated cases for security analysis.

		OPF results				Results of the proposed algorithm				
Problem	GENCO	P_g (MW)	Q_g (MVAR)	Generation cost ($/h)	P_{Loss} (MW)	P_g (MW)	Q_g (MVAR)	Open lines in optimal network	Generation Cost ($/h)	P_{Loss} (MW)
N − 1 contingency	1	174.8385	0.4720	806.0580	10.4748	177.4040	− 0.6349	Between bus 15–23, 16–17, 15–18	805.3006	10.2042
	2	52.6685	30.8886			46.0758	34.0086			
	5	21.3171	27.8898			22.0162	28.7750			
	8	20.0672	27.2436			21.6583	33.4996			
	11	12.7432	23.7327			13.9781	21.3108			
	13	12.2404	10.4205			12.4700	4.3994			
Stressed generator contingency	1	195.5227	14.6052	819.8659	10.0904	191.1673	15.2886	Between bus 6–8	819.7607	9.6974
	2	20	8.8144			20	7.2391			
	5	21.3382	33.6657			23.7651	32.2781			
	8	28.9489	26.2644			28.5935	28.5371			
	11	14.1971	21.8769			16.1818	21.6395			
	13	13.4836	14.8490			13.3897	14.6235			
N − 1 contingency with peak load	1	191.9613	− 2.4427	909.7902	11.6274	188.7320	− 1.8923	Between bus 18–19	909.3139	11.4474
	2	50.3022	37.5841			52.1854	36.5544			
	5	23.7222	33.7466			23.5627	33.8225			
	8	29.5404	30.7255			28.7223	31.0206			
	11	14.5252	23.3843			14.1897	18.6299			
	13	13.3161	16.1711			15.6937	14.9708			
N − 1 contingency with stressed generator	1	192.2654	15.2069	819.7927	9.8313	192.2654	15.2069	All switches closed	819.7927	9.8313
	2	20.0000	8.2968			20.0000	8.2968			
	5	22.3257	33.3505			22.3257	33.3505			
	8	30.3983	26.1345			30.3983	26.1345			
	11	14.2954	22.6122			14.2954	22.6122			
	13	13.9464	13.6111			13.9464	13.6111			

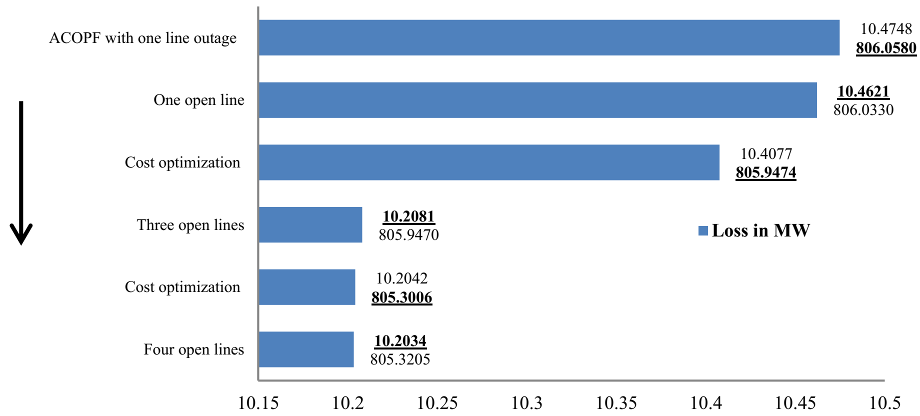

Figure 5. Step-wise performance analysis of N − 1 contingency case.

Table 6. Comparison of OTS results.

Literature	Post TS using ACOPF				
	Generation cost ($/h)	Active loss	Switchable lines	Percentage increase in cost	Percentage decrease in loss
Present work	1112.40	12.38	24–25, 19–18	0.53	44.63
	1119.82	13.37	2–4, 10–22	1.2	40.2
[29]	1106.51	22.36	2–4, 10–22	–	–

Table 7. Simulation results of 62-bus system.

Problem	Open lines in-between bus	Proposed two-stage optimization	
		Loss in MW	Generation cost in $/h
Base case	14–15, 34–37	74.0676	14832.98
Peak load case	14–15, 4–14, 34–37	92.7795	19636.75
Off-peak load case	14–15, 21–22, 34–37, 32–34, 55–58, 49–48	37.1259	11410.92

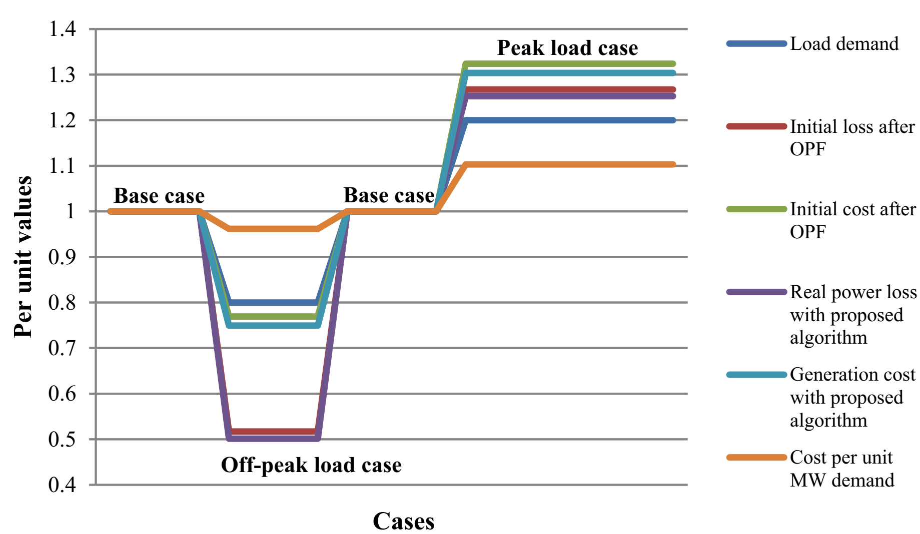

Figure 6. Comparison of per unit values of 62-bus system.

between. The cost per unit MW demand changes based on the load condition which may be flattened with encouraging usage of power during *Off-Peak* condition as an application of smart network.

4. Conclusions

OTS optimizes simultaneously the generation schedule and network topology and is used in this paper as a potential method to explicitly improve both loss and cost. Feasible ACOPF solutions with TS-ACPF prevent islanding with power reaching every bus without any pre-screening of branch connections even at contingency states ensuring security. The bi-objective optimization is done through the iterative process without any decision maker's interference giving a single certain solution automatizing the operation. The SOs need not chose the results from a set of non-inferior solutions, they only need to implement it.

The updates after reconfiguration in the loop decrease the number of variables gradually and speed up optimization by abandoning undesired solutions. Comparable results with literature in terms of cost and improvement in line loss is recognized. Although the standard existing methods to solve OTS are exact search algorithms, the proposed metaheuristic technique is advantageous in terms of flexibility of choosing the best topology through the switching strategy which requires a long time to achieve otherwise.

Load shedding is not allowed by the model. It not only meets the load growth (within possible limit) but also addresses the existing power system to function with increased efficiency. The algorithm may be applied to realize optimal and reliable conditions from forecasted network data. Another scope of the proposed method is that it may be generalized for any such mutually dependent bi-objective problem with no requirement of decision making.

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Nomenclature

Indices and sets

c	Operating state (steady-state, $c = 0$/contingent state, $c > 0$)
g	Index for generator
$\emptyset_i$	Set of generators at bus i
i, k	Index for bus
l	Transmission line (or element)
lik	Transmission line between bus i and bus k

Constant parameters

nb	Total number of bus
ng	Total number of generator bus
G_{ik}	Element ik from the real part of the admittance matrix
B_{ik}	Element ik from the imaginary part of the admittance matrix
b_{ik}	Shunt susceptance of line lik
P_{di}/Q_{di}	Real/Reactive power demand at bus i for a particular time period
P_g^{min}/P_g^{max}	Minimum/ maximum limit of real power from generator g
Q_g^{min}/Q_g^{max}	Minimum/ maximum limit of reactive power from generator g
V_i^{min}/V_i^{max}	Minimum/maximum limit of voltage magnitude at bus i
$\delta^{min}/\delta^{max}$	Minimum/maximum limit of voltage angle at bus i
S_{lik}^{max}	Maximum limit of apparent power flow of line lik
I_{lik}^{max}	Maximum current limit in line lik
CN_{lc}	Binary parameter representing contingency state of l
N	Total number of transmission elements

Variables

P_g	Real power from generator g for a particular time period
Q_g	Reactive power from generator g for a particular time period
V_i	Voltage magnitude at bus i
δ_{ik}	Voltage angle difference between bus i and bus k
P_{lik}/Q_{lik}	Real/Reactive power flow on line l from i to k
I_{lik}	Current in line lik
S_{lik}/S_{lki}	Apparent power flow at line l from bus i to k/ k to i
C_G	Total generation fuel cost
T_L	Total active power loss
w_{lik}	Binary variable indicating switch status of line lik

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