Congestion Management Using Optimal Transmission Switching

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***Abstract*—In this paper, a multiobjective-based congestion management (CM) methodology is proposed using the optimal transmission switching (OTS) strategies considering the minimization of the total operating cost and the maximization of probabilistic reliability as two conflicting objectives. To improve the efficiency of the transmission network, this paper considers the possibility of changing the topology of the transmission system using the transmission switching strategy. The OTS can increase the economic efficiency of power dispatch with the existing infrastructure. The objective of OTS is to find the most influential lines as candidate lines for the disconnection. System operators can change the network topology to increase the transfer capacity, to improve voltage profiles, and also to improve the reliability of the power system. In this paper, the loss of load probability reliability index is used to indicate the probability that an electrical power system is not able to serve the prescribed load within the concerned period of time. Here, the transmission lines that should be switched are determined by using the security-constrained ac optimal power flow. The proposed optimization problem is solved using the hybrid of evolutionary and stochastic programming approaches. The output of the proposed OTS is to find the transmission lines that have to be switched so that the congestion in the system can be relieved. A multiobjective optimization approach is used to generate the Pareto optimal solutions. The suitability and effectiveness of the proposed CM approach have been examined on IEEE 30- and 300-bus test systems.**

***Index Terms*—Multiobjective optimization (MOO), power generation dispatch, power transmission economics, reliability, transmission switching, transmission congestion.**

I. Introduction

IN RECENT years, the objective of electrical power industry has been to develop a smarter electrical grid. A smarter electrical grid applies available technologies and tools to bring the knowledge to power. Optimizing the use of transmission and the development of advanced transmission technologies is also an important aspect to develop the smarter and more flexible electrical grid [1]. This improves not only the market surplus, but also the system reliability. Making the new transmission infrastructure is expensive and very hard to locate. Hence, there is a requirement for the optimal use of the existing transmission system.

Usually, the system operator (SO) treats the transmission assets (i.e., transmission lines and transformers) as static in the optimal power flow formulation. However, the SO can change the transmission network topology to increase the transfer capability to improve the voltage profile and reliability. This network topology optimization increases the grid flexibility and efficiency into the day-ahead (DA) dispatch problems. The operational efficiency can be obtained by the joint optimization of generation scheduling/dispatch and the network topology. In the market environment, day-ahead security-constrained unit commitment (SCUC) performs a simultaneous solution of minimizing the cost of commitment for resources to meet forecasted load subjected to system constraints and activated transmission constraints for each hour of the scheduling period. The electrical power requirement in today's world is increasing day by day. To meet this growing demand, it is difficult to construct new transmission lines. In this paper, we propose an optimal generation dispatch and transmission switching to meet the load demand. In this paper, an optimal transmission switching (OTS) is considered as a tool to change the grid topology, which, in turn, improves the market efficiency. When the congestion occurs in the system, the most economical generating units cannot be dispatched fully to its capacity to meet the load demand. Hence, the expensive generating units have to be dispatched, which leads to the market inefficiency. In Pennsylvania–New Jersey–Maryland Interconnection, the special protection schemes (SPSs) allow the SO to disconnect a transmission line during normal operating conditions but return it to service during a contingency. Some SPSs open lines during the emergency situations, demonstrating that it can be beneficial to change the topology during emergency conditions. In this paper, we used the OTS to alleviate congestion in the system for use it in the real-time operation and control.

A review of network topology optimization and transmission switching is described in [2]. In [3], a network reduction approach based on the modified Jacobian–Newton–Raphson load flow considering the switchable line is used for speeding up the calculation, simplicity, and efficiency. A mixed-integer linear formulation to determine an optimum network topology that minimizes the resistive losses for a significant period is proposed in [4]. In [5], a new approach is proposed to determine the best transmission line and bus-bar switching action for relieving the voltage and overload violations caused by the contingencies based on fast decoupled load flow and a sparse inverse technique with a limited iteration count. The optimal topological configuration of a system providing the SOs with a

Manuscript received January 30, 2017; revised June 11, 2017, October 14, 2017, and December 19, 2017; accepted February 11, 2018. Date of publication March 21, 2018; date of current version November 22, 2018. This work was supported by 2017 Woosong University Academic Research Funding.

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Digital Object Identifier 10.1109/JSYST.2018.2808260

tool for congestion management (CM) is proposed in [6]. A joint energy and reserve scheduling model incorporating the network capability to switch transmission lines as a corrective action to enhance the system capability to circumvent contingency events is proposed in [7]. Fisher *et al.* [8] use the mixed-integer programming to determine the optimal transmission topology and generation dispatch to meet a specific inflexible demand in the system. The application of transmission switching in the SCUC for the DA scheduling problem is proposed in [9].

A stochastic mixed-integer linear programming model for the OTS considering joint optimization of energy and reserves is proposed in [10]. Torres and Castro [11] present an efficient and simple method based on the backward technique to solve the OTS problem, both in its parallel and serial versions. Mousavian *et al.* [12] propose a linear programming technique to find the optimal phasor measurement unit placement plan in two investment phases. A security-constrained OTS is proposed in [13] to relieve the congestion in the system, considering the ac constraints and also the generator rotor shaft impact caused by the switching. Khanabadi and Ghasemi [14] propose an approach to relieve the congestion in the system using the OTS approach to change the network topology, which, in turn, leads to the lower energy prices and higher market efficiently. A joint optimization of generating unit commitment and transmission switching problem considering the $N-1$ reliability is proposed in [15]. In [16], an OTS is used as a CM tool to change the grid topology to improve the market efficiency. Qiu and Wang [17] present a model of changing the transmission topology by using the OTS to include higher utilization of wind power and to reduce the thermal generation cost. Zhang and Wang [18] propose a multiobjective optimization (MOO) approach for the OTS strategies considering the minimization of generating cost and maximization of probabilistic reliability as objectives to be optimized. The objective of [19] is to present different types of corrective control schemes during the emergency and apply these actions to restore the secure operation of the system.

In [20], a cooptimization problem of unit commitment and transmission switching over a 24-h period is presented for solving the CM problem and to evaluate the impacts of topology control on the European electricity network. The current methodology for controlling congestion in the Central Western European market and quantify the benefits of topology control is presented in [21]. Nikoobakht *et al.* [22] investigate the challenges of increasing the penetration of wind energy sources in an ac network (i.e., ac feasibility, the ability to handle large-scale real power systems, and computational complexity) by developing the transmission switching based on a linearized ac network model. Esmaili *et al.* [23] propose a two-stage method using a modified Benders decomposition technique for solving the CM problem in hybrid electricity markets including pool and bilateral transactions. Conejo *et al.* [24] propose the CM problem avoiding offline transmission capacity limits related to stability. A CM method based on a new transient stability criterion using the sensitivity of corrected transient stability margin with respect to generations and demands is proposed in [25]. Esmaili *et al.* [26] propose a CM method based on the voltage stability margin sensitivities. Transmission switching as a corrective mechanism to help the system to achieve $N-1-1$ reliability considering the loss of a single element and also a second major element after an adjustment period is proposed in [27]. Bai *et al.* [28] propose a new OTS approach, which uses a two-level iterative framework, in which a mixed-integer second-order cone programming OTS model provides candidate solutions at the upper level, while the ac feasibility check is conducted at the lower level. In [29], the efficacy and value of using corrective control supported by transient assistive measures is quantified in terms of the cost savings due to less constrained operation of the system. Tiwari *et al.* [30] present a computer package for solving multiple contingency constrained reactive power planning, and to reduce the complexity of the optimization problem due to the consideration of multiple contingencies, a new methodology is proposed, where the overall problem is solved in two phases.

From the literature, it can be observed that most of the works use the dc optimal power flow (DC-OPF), which deals only with the active power generation used in the transmission dispatch problems. However, the solutions obtained using the DC-OPF are not acceptable when verified with the nonlinear power flow equations. Most of the previous literature works do not respect the voltage security criteria in the OTS problem. Therefore, here, an OTS is considered as a tool to change the transmission topology, which leads to the higher market efficiency. In the electricity markets, it is always necessary to transmit power to all parts of the transmission network without violating the system security constraints. The SO can use the OTS methods to partially or fully remove the congestion in the system. The output of this OTS problem is to identify the transmission lines that have to be switched so that the transmission congestion can be removed. This paper proposes a novel CM methodology by optimizing both the generation dispatch and the network topology simultaneously; this allows the SO to select the network topology with the generation.

In this paper, a MOO methodology is proposed to develop the OTS strategies with the minimum operating cost of generators and the maximum probabilistic reliability of the system. The proposed OTS can increase the economic efficiency of the system dispatch with the existing infrastructure. The objective of OTS is to determine the most influence lines as candidates for disconnection. The transmission lines that are opened during the OTS strategy may be available to be switched back into the network when required. In this paper, the transmission lines that must be switched are determined by means of security-constrained ac optimal power flow (AC-OPF). The main contributions of this paper are as follows.

1) An OTS strategy is proposed to reduce the extra generation cost without degradation in the system reliability.
2) The transmission switching strategy is embedded in the AC-OPF and formulated as a mixed-integer nonlinear programming (MINLP) problem, and then, it is solved by using the Benders decomposition method.
3) Monte Carlo simulation (MCS) is used to capture the probabilistic nature of system component failures.
4) The impact of transmission switching on system bus voltages and transmission losses is examined.

5) A MOO-based approach is proposed to determine the OTS strategies with the minimum generation cost and the maximum probabilistic reliability.
6) A multiobjective artificial immune algorithm (MO-AIA) is used to generate the optimal solutions.

The remainder of this paper is organized as follows. Section II presents the problem formulation of the proposed CM approach using the OTS strategy. The proposed solution methodology is described in Section III. Section IV presents the simulation results and discussion. Finally, Section V brings out the contributions with concluding remarks.

II. CM Using OTS: Problem Formulation

Here, the SO uses the transmission switching strategy to relieve the congestion in the system. The optimization algorithm identifies the transmission lines that need to be removed, so that the congestion can be relieved. In this paper, a multiobjective-based CM approach is proposed to determine the optimal switching strategies with the minimum generation cost and the maximum probabilistic reliability. The formulation of different objective functions are described next.

A. Total Generation Cost Minimization Objective

The main purpose of this objective is to minimize the total generation cost of the power system subjected to the physical constraints such as bus voltage limits and transmission line flow limits. In this paper, the quadratic supply bidding price function is used. However, the proposed approach is a generic one, and any other kind of supply bidding price function can be used, if deemed appropriate. The line(s) that required to be switched can be determined by running the following AC-OPF:

Minimize

$$\text{Total generation cost } (TC) = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (1)$$

where P_{Gi} is the active power generation of the ith generating unit (i.e., GenCo), N_G is the number of generating units in the system, and a_i, b_i, and c_i are the supply bidding price coefficients of the ith generating unit (i.e., GenCo).

B. Probabilistic Reliability Objective

In this paper, the maximum probabilistic reliability is considered as another objective to be optimized for the proposed MOO problem. Here, the loss of load probability (LOLP) reliability index is used to indicate the probability that the system is not able to serve the prescribed load demand within the scheduling period. Every transmission line has a certain probability of being out of service, and this leads to the possibility of unserved load demand. Therefore, the minimization of LOLP leads to the maximization of the system reliability

$$\text{minimize} \quad \text{LOLP}(\xi) \quad (2)$$

where $\xi = (\xi_1, \xi_2, \xi_3, ..., \xi_N)$ denotes a feasible transmission switching strategy.

The MCS-based approach shown in Fig. 1 is used to approximate the LOLP reliability index value of a transmission system topology, which is determined by each line switching strategy. In Fig. 1, OR_k is the outage rate of the kth transmission line. m_1 is the iteration index of the simulation. M_1 is the total number of iterations. M_0 is the number of iterations with unserved load demand. This MCS is used to generate the prespecified number of potential transmission line switching strategies based on the vector of appearance probabilities (i.e., $\rho = (\rho_1, \rho_2, \ldots, \rho_N)$) that each transmission line "k" appears in the solution, i.e., ρ_k = Probability($\xi_k = 0$), which represents that the probability of line "k" is selected to be switched. MCS is used to generate a specified number (i.e., N_S) of potential transmission switching strategies based on a vector of appearance probabilities (i.e., ρ). To generate a strategy, for each branch k, generate a random number (q_k). Transmission line "k" is switched (i.e., $\xi_k = 0$) if $q_k \leq \rho_k$.

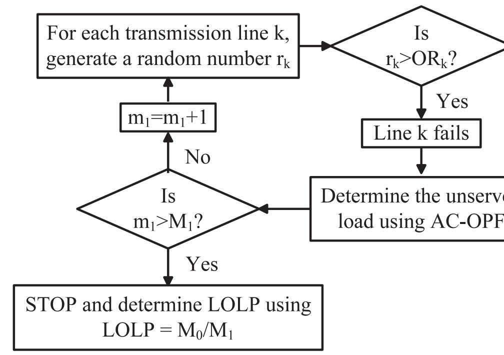

Fig. 1. MCS approach to determine the LOLP reliability index.

For each strategy generated, the AC-OPF is solved to get the optimum generation cost (TC) and LOLP(ξ) of each strategy using the MCS, and it is depicted in Fig. 1. For each transmission line (k), generate a random number (r_k). Check the condition ($r_k > \text{OR}_k$). If this condition is satisfied, then it indicates that line "k" fails to serve the load. Then, determine the unserved load using the AC-OPF. Now check the condition ($m_1 > M_1$). If this condition is satisfied, then determine the LOLP using

$$\text{LOLP}(\xi) = \frac{M_0}{M_1}. \quad (3)$$

The above objective functions are solved subjected to the following constraints.

C. Equality and Inequality Constraints

1) Power Balance Constraints: These include the active and reactive power balance equations, and they are expressed as

$$P_{Gi} - (1+\gamma)P_{Di} = V_i \sum_{j=1}^{n} [V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)]] \quad (4)$$

$$Q_{Gi} - (1+\gamma)Q_{Di} = V_i \sum_{j=1}^{n} [V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)]] \quad (5)$$

where $i = 1, 2, ..., n$. n is the number of buses in the system and γ is the loading margin.

2) Generating Unit Constraints: The active power generation (P_{Gi}), reactive power generation (Q_{Gi}), and voltage magnitudes (V_{Gi}) of the ith generating unit are restricted by their minimum and maximum limits. These constraints are expressed as

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \qquad i = 1, 2, ..., N_G \tag{6}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \qquad i = 1, 2, ..., N_G \tag{7}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \qquad i = 1, 2, ..., N_G. \tag{8}$$

3) Security Constraints: These constraints include the limits on load bus voltage magnitudes and transmission line flows

$$V_{Di}^{\min} \le V_{Di} \le V_{Di}^{\max}, \qquad i = 1, 2, ..., N_D \tag{9}$$

$$|S_{ij}| \le S_{ij}^{\max} \beta_k \tag{10}$$

where S_{ij} is the line flow and $S_{ij}^{\max}$ is the stability/thermal limit of the line connected between bus i and bus j. β_k is the state of line k, which is a binary variable 0 or 1 (0: line is open, 1: line is closed). The power flow of an open line must be zero (i.e., an open circuit or the line without any power transmit).

4) Voltage Angle Constraint: The voltage angle at each bus in the system is limited by

$$\delta_i^{\min} \le \delta_i \le \delta_i^{\max}, \qquad i = 1, 2, ..., n. \tag{11}$$

The voltage angle at each bus is selected between +0.6 and − 0.6 rad.

5) Constraint on the Number of Switching Actions: This constraint is required to limit the number of transmission lines opened in the optimal network. The number of switching actions in the OTS strategy is expressed as

$$N_S \ge \sum_{k=1}^{N_l} (1 - \beta_k) \tag{12}$$

where N_S is the number of switching actions and N_l is the number of transmission lines in the system.

From the above objective functions and constraints (ac power balance constraints and binary variables), it is clear that this is an MINLP problem. Usually, opening of lines may deteriorate the voltage stability of the power system. For example, some unstable transients may get triggered and/or the voltage stability margin for the posttransmission switching system may not meet the criteria specified by the system operational requirements. The main objective of this problem is to minimize the total generation cost with regard to line thermal and bus voltage limits. For example, the bus voltages across the system should not exceed certain levels, and the bus angles across the system have to be maintained between upper and lower limits.

III. Solution Methodology

Fig. 2 shows the flowchart of the proposed multiobjective-based optimal transmission line switching strategy to solve the CM problem. As shown in this figure, first, the AC-OPF is performed with no transmission line switching. If there is no congestion in the system, then there is no action is required. If any lines are congested, i.e., some line flows are reached to their maximum limits, then this leads to inefficient use of generators. Therefore, in this paper, the OTS is used to relieve the congestion in the system, which, in turn, leads to the higher market efficiency. Using this optimization, the SO identifies the transmission lines that need to be outaged to remove congestion in the system.

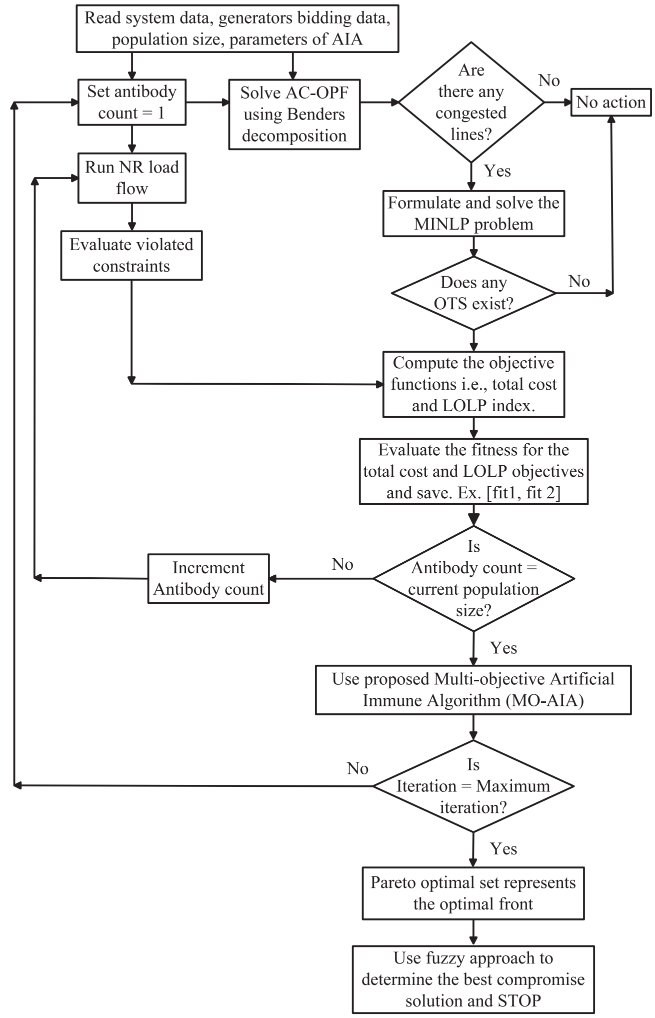

Fig. 2. Flowchart of the proposed multiobjective-based optimization algorithm for solving the CM using the OTS strategy.

As explained earlier in this paper, the optimization problem (AC-OPF) is formulated as an MINLP problem, and then, it is solved by using the Benders decomposition approach. It should be noted that the available solvers for MINLP problems, in particular DICOPT and BARON, do not perform well for solving the proposed optimization problem in terms of convergence characteristics and computational time. And also, the solution might not be a global one. To avoid this issue, in this paper, the MINLP problem is solved by using the Benders decomposition method. In this method, the main optimization problem is decomposed into a master problem and a subproblem as a two-stage procedure [23]. Suppose the optimization problem is defined as

$$\text{minimize} \qquad f(x, y) \tag{13}$$

TABLE I
SUPPLY BIDDING INFORMATION AND POWER LIMITS OF THE GENERATOR IN THE IEEE 30-BUS SYSTEM

Generator number	Bus number	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/MW^{2}h)	$P_{Gi}^{\min}$ (MW)	$P_{Gi}^{\max}$ (MW)	$Q_{Gi}^{\min}$ (MVAr)	$Q_{Gi}^{\max}$ (MVAr)
1	1	0	2.0	0.0037	50	200	– 20	200
2	2	0	2.75	0.0175	20	80	–20	100
3	5	0	1.0	0.0625	15	50	–15	80
4	8	0	3.25	0.0083	10	35	–15	60
5	11	0	3.0	0.0250	10	30	–10	50
6	13	0	3.0	0.0250	12	40	–15	60

subjected to

$$g(y) \geq 0 \tag{14}$$

$$h(x) \geq 0 \tag{15}$$

$$A_1 x + A_2 y \geq a \tag{16}$$

where x and y are decision variables, $h(x)$ and $g(y)$ are constants in which x or y variables appear, and A_1 and A_2 are the coefficient matrices. By applying the Benders decomposition technique, the master problem is formulated as

$$\text{minimize} \qquad f(x, y) \tag{17}$$

subjected to

$$g(y) \geq 0 \tag{18}$$

$$(a - A_2 \tilde{y})^T \tilde{u}^r \leq 0 \tag{19}$$

where $\tilde{y}$ is the y value obtained from the previous iteration of master problem solution. $\tilde{u}^r$ is the marginal value of constraints with slack variables obtained from the previous iteration of the subproblem of the solution. The subproblem is formulated as

$$\text{minimize} \qquad R_v^T s \tag{20}$$

subjected to

$$(A_1 x + R_v s) \geq (a - A_2 \tilde{y}) \tag{21}$$

$$h(x) \geq 0 \tag{22}$$

where s represents the penalty/slack variables added to the constraint to make the solution feasible. R_v^T indicates a row vector with entries of 1. The objective function of the subproblem is to minimize the sum of penalty variables. The marginal value of constraints with penalty/slack variables will be used in constructing the infeasible cut constraints $(\tilde{u}^r)$ in the master problem. The reader may refer to [23] for the detailed algorithm of the Benders decomposition technique.

The master problem determines the system configuration and the active power output of each generator. In the master problem, only active power flow limits are checked; reactive power distribution and bus voltage limits are considered in this problem. The subproblem checks the feasibility of the master problem solution from the viewpoint of ac constraints. These violations could be relieved by modifying the lines to be switched or by controlling the power generation. The objective of the master problem is to minimize the total generation cost, where the objective of the subproblem is to check the feasibility and security analysis. For more details of the Benders decomposition approach applied for solving the OTS problem, the reader may refer to [16]. As mentioned, the MINLP is used to identify the OTS strategy, and the MO-AIA is used to generate the Pareto optimal front/Pareto optimal solutions.

In the recent years, a new branch of science called artificial immune system (AIS) has been developed replicating the workings of the human immune system. The applications discovered go beyond the area of biology and medicine. With some modifications, the AIS is found to be adaptable to many other applications such as optimization, pattern recognition, neural networking, and machine learning problems in different fields [31]. The authors of [32]–[36] present the application of the artificial immune algorithm for solving the various MOO problems. The advantages of this algorithm include excellent individual diversity maintaining mechanism, strength of multimodal function optimization ability, and strong get rid of local extreme value and global search ability. The reader may refer to [35] for more details of the MO-AIA. The brief description of the MO-AIA is presented in the Appendix.

After having the Pareto-optimal set of the nondominated solution using the MO-AIA, the fuzzy approach [37], [38] described here presents a best compromise solution to the SO.

IV. RESULTS AND DISCUSSION

The applicability and effectiveness of the proposed CM approach have been examined on standard IEEE 30- and 300-bus systems. These test systems data are presented in [39]. In this paper, ρ_k (i.e., probability of line "k" selected to be switched) is 0.5 for all the lines. The outage rates of transmission lines are selected randomly between 0 and 0.003. All the optimization programs are coded in MATLAB R20016a and implemented on a PC-Core2 Quad Personal Computer with 2.93 GHz and a RAM of 8 GB. The parameters of the MO-AIA algorithm are the following: the population size is 100, the Pareto optimal set size is 30, the clonal selection operator is 0.4, the memory cell threshold is 100, the refresh ratio is 0.2, the mutation operator is 0.1, and the maximum number of iterations selected is 100. The simulation results on two test systems are presented next.

A. Simulation Results on the IEEE 30-Bus Test System

The generator power limits and supply bid information of the IEEE 30-bus system are presented in Table I. The IEEE 30-bus test system consists of six generator buses, 21 load buses, and

41 lines. The active power load in this system is 283.4 MW and the reactive power demand is 126.2 MVAr. In order to simulate the congestion in the system, the loading in the system has been increased to 130% (i.e., $\gamma = 0.3$). Hence, the system active power has been changed to 368.42 MW, and the reactive power demand has been changed to 164.06 MVAr. Here, first, the AC-OPF is performed to identify the lines, which are violating their constraints, i.e., congested lines in the system. The simulation results of the AC-OPF indicate that line numbers 1 and 10, i.e., the transmission lines connected between buses 1 and 2 and buses 6 and 8, are congested in the system, which results in utilizing the more expensive generators to meet the load demand. In this paper, the proposed OTS strategy is used to relieve the congestion in the system.

As mentioned earlier, first, the proposed optimization problem (i.e., total generation cost minimization objective) is solved independently using the Benders decomposition algorithm. By using the proposed transmission switching approach, we can determine the transmission lines that are required to be opened to relieve the congestion in the system. In the proposed problem formulation, each transmission line is assigned a binary variable (β_k) that represents whether the line is included in the system (i.e., circuit breaker on that transmission line is closed) or not (i.e., circuit breaker on that transmission line is open). Due to the peculiar characteristics of electricity, it is possible to improve the total cost by removing a transmission line from the network. The proposed optimization problem will either return the result that no lines are switched OFF without any change in the objective function value or one or more transmission lines are opened with an improved/optimum objective function value. There is no general trend in physical characteristics of optimally opening the lines, i.e., the lines that are switched OFF. The decision to open a transmission line or keep it closed depends on specific operating conditions, generation costs, and load demands. It is not necessary to switch many transmission lines to get the economic benefit from the OTS problem. However, the number of transmission lines to be switched would need to be defined *a priori* in the proposed optimization model to achieve the most economic benefit. Performing the full optimization problem and then selecting only some transmission lines to switched OFF would not be the best way to operate the power system optimally. One possible way is to define a subset of transmission lines that are eligible for switching in the optimization problem based on the reliability studies.

As mentioned earlier, the OTS problem is formulated as an MINLP problem, and then, it is solved by using the Benders decomposition method. Here, the Benders decomposition method is converged when all congestions in the system are removed; then, the final value of the subproblem objective will become zero. The final solution of the master problem after converging the Benders decomposition represents the total generation cost by considering all the security constraints. Fig. 3 depicts the variation of the total overloads versus Benders decomposition iterations for pre- and posttransmission switching cases using the proposed AC-OPF-based OTS approach. Here, the total overloads represent the sum of all branch overloads in the system. From this figure, it can be observed that all the

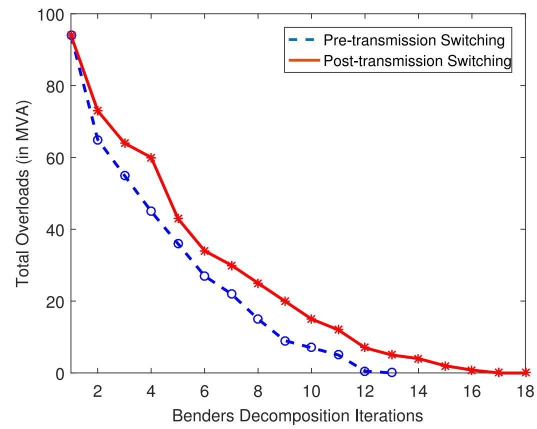

Fig. 3. Variation of the total overloads in Benders decomposition iterations.

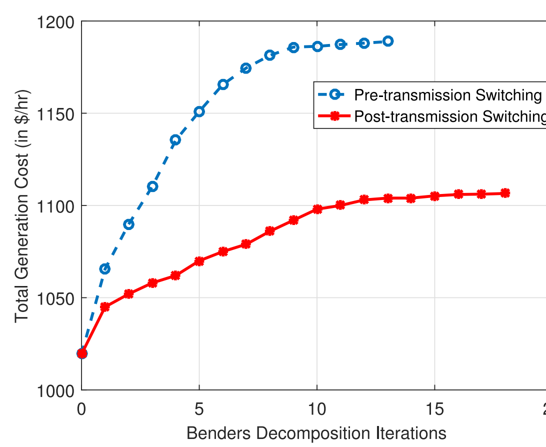

Fig. 4. Variation of the total generation cost in Benders decomposition iterations.

overloads are removed successfully for both the cases in their last iteration. Fig. 4 depicts the variation of the total generation cost versus Benders decomposition iterations for both pre- and posttransmission switching cases. Here, iteration "0" represents the master problem solution before starting the Benders decomposition iterations without any Benders infeasibility cut constraint.

The simulation results indicate that transmission lines connected between buses 2 and 4 and buses 10 and 22 are identified as the switchable lines, i.e., the lines to be outaged to remove the congestion in the system while satisfying all the ac and security constraints. Table II presents the optimum generation schedules and objective function values for the pre- and posttransmission switching operations. The optimum generation cost obtained before the transmission switching is 1188.83 $ /h, whereas after opening lines 2–4 and 10–22, the total generation cost has been decreased to 1106.51 $ /h, due to the higher dispatch of cheaper generators. The optimum generation cost obtained considering the transmission switching is 6.92% less than the optimum generation cost obtained without considering the OTS. However, the active and reactive power losses are increased in the post-transmission switching operation. This is because of the changes in the generation schedules. Although the losses are higher after the switching, the total generation cost is less compared to the

TABLE II
OPTIMUM GENERATION DISPATCH AND OBJECTIVE FUNCTION VALUES FOR THE PRE- AND POSTTRANSMISSION SWITCHING OPERATIONS FOR THE IEEE 30-BUS SYSTEM

Generator number and objective function values	Optimum generation schedules				
	Generation rescheduling approach	Pretransmission switching using DC-OPF [8]	Posttransmission switching using DC-OPF [8]	Pretransmission switching using the proposed AC-OPF	Posttransmission switching using the proposed AC-OPF
P_{G1} (MW)	174.46	191.43	198.34	184.92	196.35
P_{G2} (MW)	76.37	78.36	77.27	76.75	80.0
P_{G5} (MW)	42.08	46.44	31.62	46.50	50.0
P_{G8} (MW)	32.72	24.02	34.35	34.96	16.37
P_{G11} (MW)	28.79	14.34	15.22	21.92	28.9
P_{G13} (MW)	31.77	29.81	26.41	20.01	19.16
Total cost (in $/h)	**1196.35**	**1198.46**	**1134.93**	**1188.83**	**1106.51**
LOLP (in %)	—	9.92	9.65	9.86	9.32
Active power losses (MW)	17.76	15.98	16.81	16.65	22.36
Reactive power losses (MVAr)	20.93	21.84	27.69	20.58	31.64
Computational time (s)	2.16	2.75	3.21	8.52	12.64

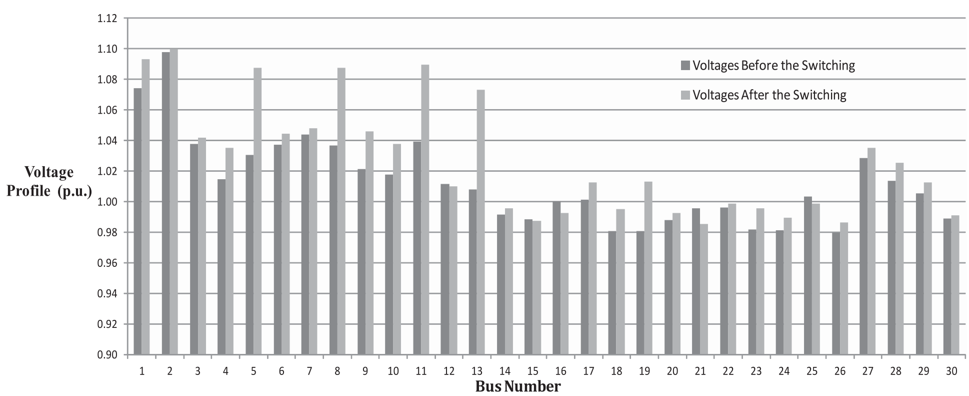

Fig. 5. Bus voltages before and after the OTS using the proposed AC-OPF approach for the IEEE 30-bus system.

pretransmission switching. The increase in losses are on the expected lines. For more details, the reader may refer to [40]. The computational times required for solving the pre- and posttransmission switching problem using the proposed approach are 8.52 and 12.64 s, respectively, and they are shown in Table II.

In this paper, for the comparison purpose, the CM problem is also solved using the conventional optimum generation rescheduling approach [41], without considering the OTS method. Table II also presents the optimum generation schedules and the total generation cost obtained using the optimum generation rescheduling approach. The total generation cost obtained using the generation rescheduling approach is 1196.35 $/h. But, this cost is 7.5% higher than the proposed posttransmission switching approach, which shows the superiority of the proposed CM approach considering the OTS method.

In the similar lines, for the sake of comparison, the proposed AC-OPF-based OTS approach is also compared with the DC-OPF-based OTS approach [8], with and without considering the OTS (i.e., pre- and posttransmission switching) strategies. Table II also presents the optimum generation schedules, total generation cost, and LOLP values for pre- and posttransmission using the DC-OPF-based OTS strategy [8]. From Table II, it is clear that the results obtained using the proposed AC-OPF-based OTS are better compared to the results obtained from the DC-OPF-based OTS approach. The total generation cost obtained after the OTS using the DC-OPF approach is 1134.93 $/h, which is 2.5% higher than the cost obtained from the proposed AC-OPF-based OTS approach.

Fig. 5 depicts the voltage magnitudes of all the buses in the IEEE 30-bus test system before and after the OTS. From this figure, it can be observed that most of the voltages are increased after the transmission switching, while a few voltages are decreased. However, the average voltages of the entire system has been increased after the transmission switching. Fig. 5 also indicates that by including the ac constraints, the minimum voltage criterion has been respected at all the buses in the system. In this paper, we have considered that the lower and upper limits of generator bus voltages are 0.95 and 1.1 p.u., respectively, whereas the lower and upper limits of load bus voltages are 0.95 and 1.05 p.u., respectively.

Table II also presents the system reliability (i.e., LOLP) index. From the total generation cost and LOLP reliability index values

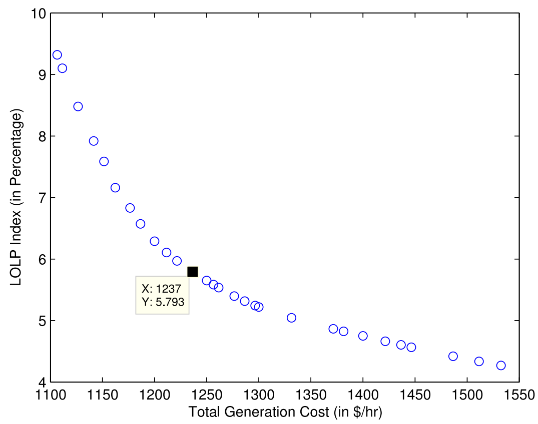

Fig. 6. Pareto optimal front for total generation cost and probabilistic reliability (LOLP index) objectives using the MO-AIA for the IEEE 30-bus system.

in Table II, it can be observed that the total generation cost is optimum, whereas the LOLP index value is deviated from the optimum. Therefore, there is a requirement for determining the tradeoff solution between the total generation cost and the system reliability considering the OTS strategies.

1) MOO Approach for Solving the OTS on the IEEE 30-Bus System: As explained earlier, when the total generation cost minimization objective function is optimized independently, the generation cost obtained is optimum, but the reliability index has been deviated from the optimum. Therefore, the cost-based optimization solutions are not attractive from the system reliability point of view. Hence, such optimization objectives cannot be treated independently. In this paper, an MO-AIA is used for solving the OTS problem considering the total generation cost and the probabilistic reliability (i.e., LOLP index) as the two conflicting objective functions. The flowchart of the proposed MOO algorithm for solving the CM problem using the OTS is presented in Fig. 2.

Fig. 6 depicts the Pareto optimal front of two objectives, i.e., the total generation cost and the probabilistic reliability. These Pareto optimal solutions can help the SOs to get the balance between two objectives of interest; based on this, the SO can determine the better informed decisions on transmission switching.

After obtaining the Pareto optimal front using the MO-AIA, the fuzzy min–max method is used to determine the best-compromised solution [37]–[38]. The best-compromised solution obtained using the fuzzy approach has the total generation cost of 1237.13 $/h and the LOLP index value of 5.793% (this can be seen from Fig. 6). The computational time required for solving the proposed CM problem using the MO-AIA is 152.80 s.

B. Simulation Results on the IEEE 300-Bus Test System

The IEEE 300-bus test system [39] consists of 69 generating units and 411 branches/transmission lines. The base case active and reactive power demands are 23246.86 MW and 7788 MVAr, respectively. In this paper, in order to simulate the congestion situation, the loading in the system has been increased to 115% (i.e., $\gamma = 0.15$). Therefore, the active and the reactive power demands of this system are 26733.89 MW and 8956.2 MVAr, respectively. Here, first, the AC-OPF is performed to identify the transmission lines that are congested in the system. The simulation results of the AC-OPF shows that the transmission lines connected between buses 11 and 28, 28 and 116, 91 and 92, 108 and 109, and 183 and 184 are overloaded in the system.

TABLE III
OPTIMUM OBJECTIVE FUNCTION VALUES FOR THE PRE- AND POSTTRANSMISSION SWITCHING FOR THE IEEE 300-BUS SYSTEM

Objective function values	Pretransmission Switching	Posttransmission Switching
Total cost (in $/h)	**391 509.62**	**380 108.46**
LOLP (in %)	6.14	5.52
Active power losses (MW)	627.08	634.72
Reactive power losses (MVAr)	6875.34	6943.31
Computational time (s)	125.57	136.92

Using the proposed OTS approach (i.e., total cost minimization is optimized independently), lines 12–20, 25–232, 54–123, and 198–216 are identified as the switchable lines. Table III presents the optimum objective function values for the pre- and posttransmission switching operations. The optimum generation cost obtained before the TS is 391509.62 $/h, whereas after opening the transmission lines 12–20, 25–232, 54–123, and 198–216, the total cost has decreased to 380 108.46 $ /h, due to the higher dispatch of cheaper generating units. The active and reactive power losses are increased a bit in the posttransmission switching case compared to the pretransmission switching case. Table III also shows the LOLP reliability index values. From this table, it can be observed that the LOLP value is deviated from the optimum as it is the single-objective (i.e., total cost minimization) optimization problem. The computational times required for solving the single-objective-based pre- and posttransmission switching problem using the proposed approach are 125.57 and 136.92 s, respectively, and they are shown in Table III.

1) MOO Approach for Solving the OTS Problem on the IEEE 300-Bus System: As mentioned earlier, the MO-AIA is used for solving the OTS problem considering the total generation cost and LOLP as the two conflicting objectives. Fig. 7 depicts the Pareto optimal front of the total generation cost and the probabilistic reliability for the IEEE 300-bus system. After obtaining the Pareto optimal front, the SO can use higher level information to make a choice. Higher level information is usually taken from domain expertise. However, in this paper, the fuzzy satisfaction maximization approach is used to determine the final optimum solution, i.e., best-compromised solution. The best-compromised solution obtained in this case has the total generation cost of 393 746.92 $ /h and the probabilistic reliability (LOLP) index of 3.61% (this can be seen from Fig. 7). The computational time required for solving the proposed CM problem using the MO-AIA is 581.34 s.

The proposed multiobjective-based CM approach is not sensitive to the selected starting point/initial values, and also, the

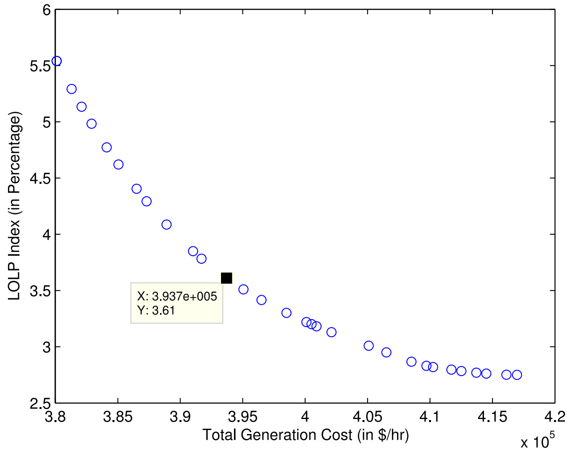

Fig. 7. Pareto optimal front for the total generation cost and LOLP reliability index objectives using the MO-AIA for the IEEE 300-bus system.

changes in the solution point are consistent with changes in the operating constraints. These factors make the proposed approach robust and reliable. From the simulation results on two test systems, it can be observed that by using the proposed multiobjective-based OTS approach, substantial cost savings can be obtained without degradation in the system reliability. And also, the voltage profile of the system has improved and line loadings were balanced, thus making the proposed approach appropriate for using in real-time power system operation and control.

V. Conclusion

In this paper, the CM problem is solved using the proposed OTS strategy considering the total generation cost and the system reliability index as the multiple objectives. Here, the proposed OTS problem is formulated as the MINLP problem and then solved using the Benders decomposition approach to identify the switchable lines to relieve the congestion in the system. In this paper, the LOLP reliability index is used to indicate the probabilistic reliability of the system. Here, the MCS is used to approximate the LOLP index value of a transmission network topology. The MO-AIA is used to determine the tradeoff solutions between the total generation cost and the probabilistic reliability. This paper has evaluated the proposed CM methodology on two (IEEE 30- and 300-bus) test systems to access the potential benefits of OTS and its effects on the system reliability. From the simulation results, it can be observed that by using the proposed OTS approach, substantial cost savings can be obtained without degradation in the system reliability. Considering the tradeoff between switching transmission line OFF versus turning ON, a shunt capacitor at the receiving end of the line is a scope for future research.

Appendix
Multiobjective Artificial Immune Algorithm

The immune system is an adaptive, self-organizing, and distributed system. In addition, it is a complex functional system that defends the human body from foreign agents such as

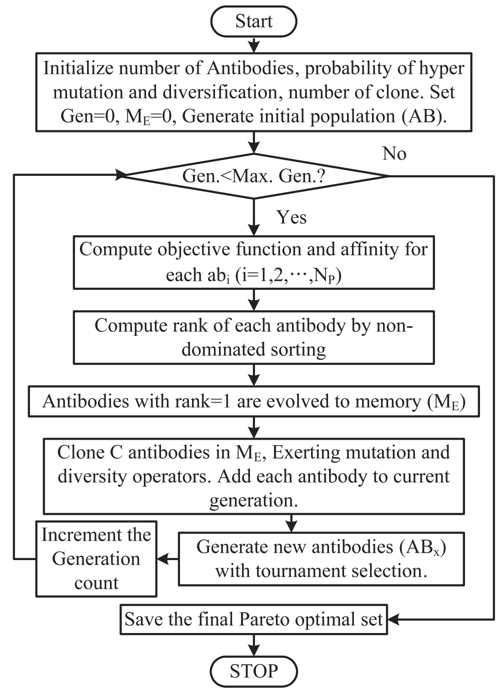

Fig. 8. Flowchart of the MO-AIA.

viruses or bacteria called pathogens. It categorizes all cells or molecules into two kinds within the body: first are those that belong to its own kind (self-cell) and second are those that have a foreign origin (nonself-cell). Patterns expressed on pathogens are called antigens. The immune system contains cells for recognizing them. These cells are called antibodies. The AIS has two important processes: cloning and affinity maturation. The combination of them is known as the clonal selection principle [42]. When a pathogen invades the human body, a number of cells that recognize pathogens proliferate. These cells can be classified into two kinds: first are effecter cells and second are memory cells. The effecter cells secrete antibodies in large numbers, and the memory cells have long lifespans so as to act faster and more effectively in future exposures to the same or a similar pathogen. During cellular reproduction, the cells suffer somatic mutations at high rates, together with a selective force; the cells with higher affinity to the invading pathogen differentiate into memory cells. This whole process of somatic mutation plus selection is known as affinity maturation.

Suppose there are a set of antibodies $AB = [AB_1, AB_2, ..., AB_{N_P}]$ in the population, where N_P represents the size of population. Each antibody represents a solution to the optimization problem. The flowchart of the MO-AIA is depicted in Fig. 8.

The reader may refer to [35] and [42] for more details of the AIA and the MO-AIA.

References

[1] May 2010. [Online]. Available: http://www.cse.wustl.edu/∼jain/cse574-10/ftp/grid/index.html
[2] K. W. Hedman, S. S. Oren, and R. P. O'Neill, "A review of transmission switching and network topology optimization," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, San Diego, CA, USA, 2011, pp. 1–7.

[3] R. Aazami, M. R. Haghifam, F. Soltanian, and M. Moradkhani, "A comprehensive strategy for transmission switching action in simultaneous clearing of energy and spinning reserve markets," *Int. J. Elect. Power Energy Syst.*, vol. 64, pp. 408–418, Jan. 2015.
[4] S. Fliscounakis, F. Zaoui, G. Simeant, and R. Gonzalez, "Topology influence on loss reduction as a mixed integer linear programming problem," in *Proc. IEEE Lausanne Power Tech*, Lausanne, Switzerland, 2007, pp. 1987–1990.
[5] W. Shao and V. Vittal, "Corrective switching algorithm for relieving overloads and voltage violations," *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1877–1885, Nov. 2005.
[6] G. Granelli, M. Montagna, F. Zanellini, P. Bresesti, R. Vailati, and M. Innorta, "Optimal network reconfiguration for congestion management by deterministic and genetic algorithms," *Electr. Power Syst. Res.*, vol. 76, nos. 6/7, pp. 549–556, Apr. 2006.
[7] G. Ayala and A. Street, "Energy and reserve scheduling with post-contingency transmission switching," *Electr. Power Syst. Res.*, vol. 111, pp. 133–140, Jun. 2014.
[8] E. B. Fisher, R. P. O'Neill, and M. C. Ferris, "Optimal transmission switching," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1346–1355, Aug. 2008.
[9] A. Khodaei and M. Shahidehpour, "Security-constrained transmission switching with voltage constraints," *Int. J. Elect. Power Energy Syst.*, vol. 35, no. 1, pp. 74–82, Feb. 2012.
[10] R. Aazami, M. R. Haghifam, and K. Aflaki, "Stochastic energy and spinning reserve market with considering smart transmission switching action," in *Proc. IEEE PES Innovative Smart Grid Technol.*, Washington, DC, USA, 2012, pp. 1–6.
[11] S. P. Torres and C. A. Castro, "Practical heuristic approach to solve the optimal transmission switching problem for smart grids," in *Proc. IEEE PES Transmiss. Distrib. Conf. Expo.—Latin Amer.*, Medellin, Colombia, 2014, pp. 1–6.
[12] S. Mousavian, J. Valenzuela, and J. Wang, "A two-phase investment model for optimal allocation of phasor measurement units considering transmission switching," *Electr. Power Syst. Res.*, vol. 119, pp. 492–498, Feb. 2015.
[13] E. Nasrolahpour and H. Ghasemi, "Congestion management through rotor stress controlled optimal transmission switching," *IET Gener., Transmiss. Distrib.*, vol. 9, no. 12, pp. 1369–1376, 2015.
[14] M. Khanabadi and H. Ghasemi, "Transmission congestion management through optimal transmission switching," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, San Diego, CA, USA, 2011, pp. 1–5.
[15] K. W. Hedman, M. C. Ferris, R. P. O'Neill, E. B. Fisher, and S. S. Oren, "Co-optimization of generation unit commitment and transmission switching with N-1 reliability," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1052–1063, May 2010.
[16] M. Khanabadi, H. Ghasemi, and M. Doostizadeh, "Optimal transmission switching considering voltage security and N-1 contingency analysis," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 542–550, Feb. 2013.
[17] F. Qiu and J. Wang, "Chance-constrained transmission switching with guaranteed wind power utilization," *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1270–1278, May 2015.
[18] C. Zhang and J. Wang, "Optimal transmission switching considering probabilistic reliability," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 974–975, Mar. 2014.
[19] A. A. Abou, E. L. Ela, and S. R. Spea, "Optimal corrective actions for power systems using multi-objective genetic algorithms," *Electr. Power Syst. Res.*, vol. 79, no. 5, pp. 722–733, May 2009.
[20] J. Han and A. Papavasiliou, "The impacts of transmission topology control on the european electricity network," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 496–507, Jan. 2016.
[21] J. Han and A. Papavasilioua, "Congestion management through topological corrections: A case study of Central Western Europe," *Energy Policy*, vol. 86, pp. 470–482, Nov. 2015.
[22] A. Nikoobakht, J. Aghaei, and M. Mardaneh, "Securing highly penetrated wind energy systems using linearized transmission switching mechanism," *Appl. Energy*, vol. 190, pp. 1207–1220, Mar. 2017.
[23] M. Esmaili, F. Ebadi, H. A. Shayanfar, and S. Jadid, "Congestion management in hybrid power markets using modified Benders decomposition," *Appl. Energy*, vol. 102, pp. 1004–1012, Feb. 2013.
[24] A. J. Conejo, F. Milano, and R. Garcia-Bertrand, "Congestion management ensuring voltage stability," *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 357–364, Feb. 2006.
[25] M. Esmaili, H. A. Shayanfar, and N. Amjady, "Congestion management enhancing transient stability of power systems," *Appl. Energy*, vol. 87, no. 3, pp. 971–981, Mar. 2010.
[26] M. Esmaili, H. A. Shayanfar, and N. Amjady, "Congestion management considering voltage security of power systems," *Energy Convers. Manage.*, vol. 50, no. 10, pp. 2562–2569, Oct. 2009.
[27] M. Abdi-Khorsand, M. Sahraei-Ardakani, and Y. M. Al-Abdullah, "Corrective transmission switching for N-1-1 contingency analysis," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1606–1615, Mar. 2017.
[28] Y. Bai, H. Zhong, Q. Xia, and C. Kang, "A two-level approach to AC optimal transmission switching with an accelerating technique," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1616–1625, Mar. 2017.
[29] Y. Pipelzadeh, R. Moreno, B. Chaudhuri, G. Strbac, and T. C. Green, "Corrective control with transient assistive measures: Value assessment for great britain transmission system," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1638–1650, Mar. 2017.
[30] A. Tiwari and V. Ajjarapu, "A computer package for multi-contingency constrained reactive power planning,," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Denver, CO, USA, 2015, pp. 1–5.
[31] D. Dasgupta, *Artificial Immune Systems and Their Applications*. New York, NY, USA: Springer, 1999.
[32] A. Lanaridis and A. Stafylopatis, "An artificial immune network for multiobjective optimization problems," *Eng. Optim.*, vol. 46, no. 8, pp. 1008–1031, 2014.
[33] C. A. C. Coello and N. C. Cortes, "Solving multi-objective optimization problems using an artificial immune system," *Genetic Program. Evolvable Mach.*, vol. 6, no. 2, pp. 163–190, 2005.
[34] Y. Qi, Z. Hou, M. Yin, H. Sunb, and J. Huangcet, "An immune multi-objective optimization algorithm with differential evolution inspired recombination," *Appl. Soft Comput.*, vol. 29, pp. 395–410, 2015.
[35] X. Hugang, C. Haozhong, and L. Haiyu, "Optimal reactive power flow incorporating static voltage stability based on multi-objective adaptive immune algorithm," *Energy Convers. Manage.*, vol. 49, no. 5, pp. 1175–1181, 2008.
[36] F. R. Alonso, D. Q. Oliveira, and A. C. Zambroni de Souza, "Artificial immune systems optimization approach for multi-objective distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 840–847, Mar. 2015.
[37] M. A. Abido and J. M. Bakhashwain, "Optimal VAR dispatch using a multi-objective evolutionary algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 27, no. 1, pp. 13–20, 2005.
[38] M. S. Kumari and S. Maheswarapu, "Enhanced genetic algorithm based computation technique for multi-objective optimal power flow solution," *Int. J. Elect. Power Energy Syst.*, vol. 32, no. 6, pp. 736–742, Jul. 2010.
[39] Power System Test Case Archive, Dept. Elect. Eng., Univ. Washington, Seattle, WA, USA, 2007. [Online]. Available: https://www.ee.washington.edu/research/pstca/
[40] D. S. Kirchen and G. Strbac, *Fundamentals of Power System Economics*. Chichester, U.K.: Wiley, 2004.
[41] S. Dutta and S. P. Singh, "Optimal rescheduling of generators for congestion management based on particle swarm optimization," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1560–1569, Nov. 2008.
[42] Z. Davarzani, M. R. Akbarzadeh-T, and N. Khairdoost, "Multiobjective artificial immune algorithm for flexible job shop scheduling problem," *Int. J. Hybrid Inf. Technol.*, vol. 5, no. 3, pp. 75–88, Jul. 2012.

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