Probabilistic Decision Making for the Bulk Power System Optimal Topology Control

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***Abstract*—Power system topology control through transmission line switching for economic gains and reliability benefits has been recently considered in day to day operations. This paper introduces a probabilistic formulation for a more efficient application of topology control strategies in real world scenarios with anticipated increase in the presence of highly variable renewable generation and uncertain loads. Such uncertainties are modeled via the point estimation method embedded into the dc optimal power flow-based formulations for optimal switching solutions. Hourly and daily advantages of the proposed probabilistic framework, compared with the conventional operations and deterministic formulations, are discussed. As the anticipated economic gains would increase through sequential implementation of several switching actions, a new probabilistic decision making approach to identify the optimal number of switching actions at each hour is also proposed. This decision support tool uses the probabilistic reliability cost/value analytics in which not only the financial benefits, but also the costs of reliability risks, are taken into account. The approach is tested through various scenarios on the modified IEEE 118-bus test system, with and without renewables integration, and the results revealed its applicability and efficiency.**

***Index Terms*—Decision making, optimization, probabilistic, reliability, risk, switching, topology control.**

Nomenclature

Sets

$n \in \Omega_B$	Set of system buses.
$d \in \Omega_D$	Set of system load types at a bus.
$g \in \Omega_G$	Set of system generators.
$h \in \Omega_H$	Set of system probable contingencies.
$k \in \Omega_{K'}$	Set of optimal line switching candidates.
$k \in \Omega_L$	Set of system transmission lines.
$x \in \Omega_X$	Set of failed components in a contingency state.
$y \in \Omega_Y$	Set of online components in a contingency state.
$z \in \Omega_Z$	Set of uncertain variables.

Variables and Functions

$f_X(.)$	Probability density function of variable X.
$\overline{\mathrm{GC}^t}$	Expected total system generation dispatch cost probabilistically realized at time t.
G_W	Output wind power of a wind turbine (in MW).
$\mathrm{IL}^t_{n,h,k}$	Interrupted load at bus n (MW) due to contingency h in the optimal topology k at time t.
$\mathbf{P_{D_n}}$	Vector of demand (in MW) at load bus n.
$\overline{P^t_{d_n}}$	Expected active power of bus n at time t.
$\overline{P^{t,\mathrm{supplied}}_{d_n,h}}$	Expected active power (in MW) survived at bus n during contingency h at time t.
$\overline{P^t_{g_n}}$	Expected power output of generator g at bus n at time t.
$P^{Wind}_{g,n}$	Wind generation output at bus n.
P^t_h	Probability of contingency h at time t.
P^t_{knm}	Power flow through line k (connecting bus n to m) at time t.
$P_{z,i}$, $\lambda_{z,i}$	Probability and Skewness of concentration i for random variable k.
v	Wind speed (m/s).
$\mathbf{X}$, $\mathbf{Y}$	Vectors of random input and output variables.
α_k	Switch action for line k (1: no switch, 0: switch).
θ_n	Voltage angle at bus n.
τ^t_h	Duration of contingency h at time t.
$x_{(.),(.)}$	Concentrations of X.
σ_x, μ_x	Standard deviation and mean value of variable x.

Dual Variables

$\boldsymbol{\eta}$	Lagrange multipliers for equality constraints.
$\boldsymbol{\pi}$	Lagrange multipliers for inequality constraints.

Parameters

B_k	Susceptance of link k.
c_{g_n}	Linear generation cost of generator g at bus n.
$E(.)$	Expected value.
K, K', K''	Parameters of wind turbine.
M_k	Big M-Value for line k.
$P^{\min}_{g_n}, P^{\max}_{g_n}$	Min. and max. generation limit of generator g at bus n.
$P^{\min}_k, P^{\max}_k$	Min. and max. limit on the power flow of line k.
P_r	Rated power of a wind turbine (in MW).
v_i, v_r, v_o	Cut-in, rated, and cut-out wind speed (m/s).
VOLL_n	Value of lost load at bus n.
r	Number of input random variables in PEM.
Γ_x, γ_x	Failure rate and repair rate of component x.

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$\xi_{(.),(.)}$ Location of concentrations.
$\theta_n^{\min}, \theta_n^{\max}$ Min. and max. voltage angle at bus n.
ψ, β Shaping and scaling coefficients of the Weibull probability distribution.
χ Maximum number of switching possibilities.

Performance Indices

$\overline{\text{EENS}}_{n,k}^{t}$ Expected energy not supplied at bus n when optimal topology plan k is adopted at time t.
$\overline{\text{RC}}_{TS,k}^{t}$ Expected risk cost of the transmission system accommodated with optimal topology k at time t.

I. Introduction

POWER system *topology control* or *transmission line switching* has been acknowledged as an effective enhancement in hour- and day-ahead operations in exploiting the network infrastructure resources for significant operational cost reduction in normal operating state. It is also recognized as a promising corrective action for reliability improvements in face of critical contingencies [1], [2]. The applicability and efficiency of transmission topology control under the uncertainties originated from the variability of the demand and the growing trend in penetration of intermittent renewable energy resources is of particular interest. An efficient and flexible decision making support tool needs to be developed to account for the risks associated with switching out transmission lines under such uncertainties.

Since 1980s, there have been some notable contributions in the literature that introduced and extensively studied the theoretical background of the deterministic approaches for transmission line switching in power systems. Topology control as a corrective tool in dealing with system emergency operating conditions is reported for the following: mitigation of voltage violations [3], [4], alleviating the line overloads [5], [6], ensuring system security [7], [8], congestion management [9], [10], and recovering the load shed in the cases of critical contingencies [11], [12]. Application of topology control for network loss reductions is also studied in [13] and [14]. Transmission switching formulations based on the line outage distribution factors are proposed in [15] and [16].

Among the most recent works, a data mining approach for real-time corrective switching is proposed in [17]. A day-ahead corrective transmission topology control incorporated with the contingency analysis is presented in [18]. Real-time contingency analysis with transmission switching to improve the system reliability in emergency scenarios is suggested in [19] and successfully implemented using actual power system data. A deterministic approximation approach coupled to chance-constrained optimizations in order to investigate the possibility of topology control deployment to accommodate higher utilization of wind generations is suggested in [20]. The above references have neither modeled nor incorporated the uncertainties into the topology control formulations. Robust optimization for corrective switching decisions in response to system contingencies is employed in [21] where the switching solutions are found considering the worst case uncertainty realization resulting in the most conservative solution. The use of such robust optimization models introduces additional complexities to the topology control optimization as finding approximate models with tractable size is typically not a trivial task when facing real-world practical problems. Day-ahead methods to determine the maximum uncertainty in renewable resources in terms of the do-not-exceed limits combined with robust corrective topology control is suggested in [22] and [23], and the algorithms to solve for the do-not-exceed limits of renewable resources are further evaluated in [24].

In addition to the effective use of transmission line switching as a corrective mechanism, optimal topology control technology is also introduced in normal operating conditions for gaining economic and financial benefits [25], [26]. Some authors deterministically investigated the impact of optimal switching solutions on the market features, with and without considering the N-1 reliability criterion [27], [28]. Sensitivity analysis is conducted in other studies with various percentages of system load to validate the optimal switching solutions in different scenarios [29], [30]. A novel AC solution method for optimal topology control problem with N-1 reliability through which human interface is also incorporated is suggested in [31]. A probabilistic security analysis taking into account the socio-economic cost of disruptions and economic benefits of topology control solutions is suggested in [32] where two types of security aspects were studied integrated with the topology control program: cascading failures due to overloaded lines and steady-state voltage instability.

Additional literature addressed other topology control implementation concerns in practice: system stability issues after switching implementation are discussed in [33]–[35]; The reliability and stability issues of the robust corrective topology control formulation, as a congestion management tool to facilitate the integration of renewable resources, are discussed and extensively studied in [36]. Practical implementation concerns and impacts on circuit breaker reliability are studied in [37]–[40]; AC formulation of topology control optimization is approached in [41] and [42]; Out-of-market corrections of the AC infeasible market solutions for day-ahead accommodation of transmission line switching is investigated in [43] and [44]. Scalability concerns of topology control implementations in real-world power systems are addressed in [19] and [45]–[49]. And computational complexities and some optimization heuristics are presented in [50]–[52].

Decisions for transmission line switching are currently either not frequently adopted in practice by the transmission operator or are made in an ad-hoc manner through a manual operator intervention. The reasons are multiple: lack of systematic decision-making tools, lack of proper training and, a lack of the mindset that will trust that such rather complex and critical decisions can be automated and systematically applied. For this practice to be frequently realized in every-day operation, attempts need to be made to further develop robust tools for the operator decision making taking into account practical implementation concerns when exposed to various uncertainties originated from renewables, loads, and other unpredictable grid disruptions. Different from the former studies, this paper: (1) proposes a general probabilistic topology control formulation that can efficiently capture major uncertainties in generation/load and incorporate such probabilistic features in power system topology control optimizations; (2) designs a probabilistic decision making framework to quantify the risks associated with switching out transmission lines for economic gains under such uncertainties and define, in an automated manner, the optimal number of switching actions per hour for final implementations.

The remainder of the paper is structured as follows. System uncertainty modeling and the proposed probabilistic formulations for power system optimal topology control are introduced in Section II. The new probabilistic reliability cost/value decision making framework for switching implementation is introduced in Section III. Application of the suggested framework is demonstrated through several case studies on the modified IEEE 118-bus test system in Section IV followed by discussions on computational complexities and future works in Section V. The conclusions of the paper are eventually presented in Section VI.

II. Probabilistic Optimal Topology Control

A. General Framework

Fig. 1 depicts a general idea of the proposed framework. We first model the hourly uncertainty in renewable (wind) generation and the variability of the system loads. Random behaviors of predicted load as well as the wind speed are modeled using the probability distribution functions. The proposed approach employs a robust probabilistic technique, the Point Estimation Method (PEM), to incorporate the uncertainties into the DC and AC optimal power flow (OPF) formulations. The probabilistic DCOPF-based switching optimization framework is developed to find the day-ahead optimal solutions of network topology and generation dispatch for economic savings. As the topology control optimization based on DCOPF does not take into account the reactive power and voltage constraints, the resulting optimal solutions may or may not be AC feasible. As a result, it is suggested that the AC feasibility be conducted in the next step for each topology control plan obtained earlier through the PEM. If the AC power flow does not converge, different adjustments may be tried (known as out-of-market corrections) to aid the convergence with the available reactive power sources such as further tuning of shunts, generator voltage set points, transformer tap settings, and so on [43], [44]. If AC feasibility is confirmed with all the adjustments satisfying the generator reactive power constraints or if the optimal topology control plans are originally decided using the ACOPF solvers, the system transient stability check is performed using the output of the AC load flow as the initial conditions for the machines. The optimized generation schedules and loading patterns corresponding to the topology control actions are employed for the system-wide transient stability checks. The switching solutions that cannot pass the AC feasibility and stability checks (even after the out-of-market corrections and with all the reactive power resources at their maximum limits)

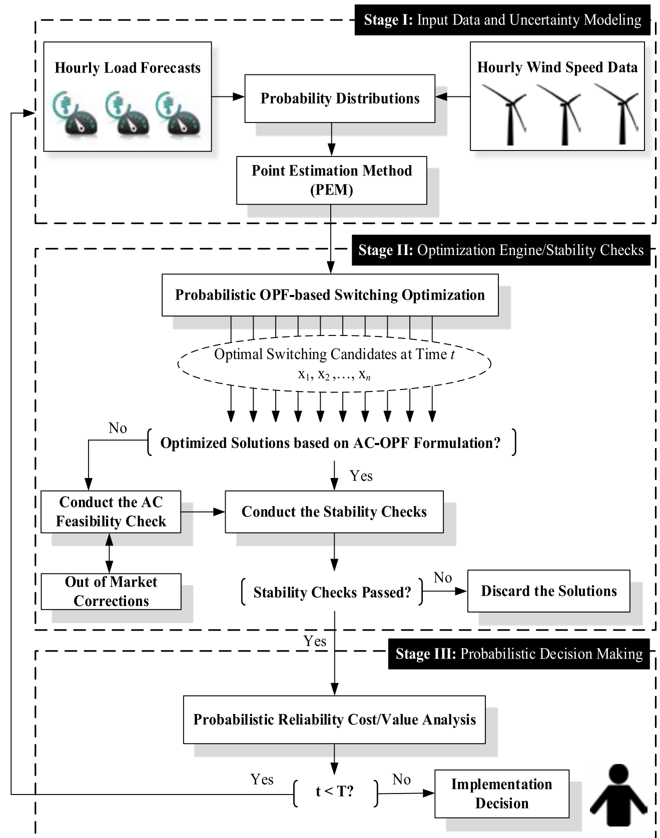

Fig. 1. Proposed framework for probabilistic power system topology control: overall architecture.

are considered not viable for implementation and are discarded from the rest of the framework.

Those survived sets of AC feasible and stable topology control plans, which may embrace one or several switching actions, would be entered into the proposed probabilistic decision making module. Although economically attractive, switching solutions might have different system-wide impacts as their implementation would migrate the system previous topology to the operating states with different levels of risk and reliability performance. The probabilistic reliability cost/value analysis is conducted to evaluate the optimal number of switching actions per hour for final implementation. The probabilistic decision support tool helps the operator in deciding whether to adopt (or select among) the economically-attractive switching plan(s) depending on how the system risk and reliability are affected in the new system topology.

B. Renewable Generation and Load Uncertainty Modeling

While different notable approaches are employed in the literature, e.g., time series, artificial neural network, and regression techniques among the others [53]–[55], uncertainties introduced through high penetration of wind generation as well as the variable behavior of loads in the system are characterized in this paper using probability density functions (PDFs) and historical data. In order to account for the chronological characteristics of the wind velocity and its impact on the output power of wind turbines, wind speed at each hour is statistically modeled via the Weibull probability distribution with the PDF presented in (1) [56]. The Weibull distribution is utilized to characterize the wind speed since (1) it is widely proved to provide the best fit to wind speed applications in many countries and (2) its parameters could be easily determined from the observed wind speed summaries [56]–[58]. Employing the curve fitting techniques and maximum likelihood estimations, the PDF parameters are statistically estimated using the historical wind speed data. The output power of the wind generator, which is a function of the wind speed, is probabilistically calculated as formulated in (2).

$$f_\nu(\nu) = \left(\frac{\psi}{\beta}\right)\left(\frac{\nu}{\beta}\right)^{\psi-1} e^{-\left(\frac{\nu}{\beta}\right)^{\psi}} \quad 0 \leq \nu \leq \infty \tag{1}$$

$$G_W = \begin{cases} 0 & 0 \leq \nu \leq \nu_i,\ \nu > \nu_o \\ \left(K + K' \times \nu + K'' \times \nu^2\right) \times P_r & \nu_i \leq \nu \leq \nu_r \\ P_r & \nu_r \leq \nu \leq \nu_o \end{cases} \tag{2}$$

The other main source of uncertainties in power system operation is the actual load of the system as it fluctuates as a function of time, season, weather condition, electricity price, etc. Similarly, the random variation of loads is statistically modeled via Gaussian distribution with the PDF in (3).

$$f_{P_D}(P_D) = \frac{1}{\sqrt{2\pi\sigma_{P_D}^2}} \exp\left[-\frac{\left(P_D - \mu_{P_D}\right)^2}{2\sigma_{P_D}^2}\right]. \tag{3}$$

C. Probabilistic Topology Control Optimization

As the deterministic OPF evaluations cannot fully reveal the state of the system, probabilistic analysis is becoming of considerable importance and interest due to the increasing trend of facing many random distortions or uncertainties arisen from measurement errors, forecasting errors, variation of system variables due to adoption of renewable generation resources and load uncertainties. Performing OPF analysis for every possible or probable combination of loads, generation, and network topology is impractical or at least computationally cumbersome. As an analytical tool with tractable computation burden and acceptable level of accuracy, the PEM is suggested in this paper to be used for probabilistic formulation of the problem. Using the PEM method for probabilistic OPF analysis, the impact of uncertain input variables and the propagation of such uncertainties over the output parameters would be well captured. The PEM method is selected over the other probabilistic techniques as it is easier to implement and imposes less computational complexities for large-scale scenarios [58], [59]. Vectors of input and output random variables as well as corresponding nonlinear functions are presented in (4)-(6), respectively.

$$\mathbf{X} = \left[P_{g,n}^{Wind}, \mathbf{P_{D_n}}\right] \tag{4}$$

$$\mathbf{Y} = h(\mathbf{X}) = h(x_1, x_2) \tag{5}$$

$$Y = \left[\eta, \pi,\ \mathrm{GC}^t\right] \tag{6}$$

The probabilistic DCOPF-based optimization for transmission topology control problem is formulated below, where the objective function is introduced in (7) subject to system and security constraints in (8)-(13)[1] [25]–[27].

$$\min\ \overline{\mathrm{GC}^t} = \sum_{\substack{g\in\Omega_G \\ n\in\Omega_B}} c_{g_n}\overline{P^t_{g_n}} \tag{7}$$

$$P_{g_n}^{\min} \leq \overline{P^t_{g_n}} \leq P_{g_n}^{\max} \qquad \forall g \in \Omega_G \tag{8}$$

$$P_k^{\min}.\alpha_k \leq P^t_{knm} \leq P_k^{\max}.\alpha_k \qquad \forall k \in \Omega_L \tag{9}$$

$$\sum_{g\in\Omega_G}\overline{P^t_{g_n}} - \sum_{m\in\Omega_B} P^t_{knm} = \sum_{d\in\Omega_D}\overline{P^t_{d_n}} \qquad \forall n \in \Omega_B \tag{10}$$

$$B_k.(\theta_n - \theta_m) - P^t_{knm} + (1-\alpha_k).\mathrm{M}_k \geq 0 \qquad \forall k \in \Omega_L \tag{11}$$

$$B_k.(\theta_n - \theta_m) - P^t_{knm} - (1-\alpha_k).\mathrm{M}_k \leq 0 \qquad \forall k \in \Omega_L \tag{12}$$

$$\alpha_k \in \{0, 1\} \qquad \forall k \in \Omega_L \tag{13}$$

The output power of generator g at node n is limited to its physical capacities in (8). Constraint (9) limits the power flow across line k within the minimum and maximum line capacities. Power balance at each node is enforced by (10) and Kirchhoff's laws are incorporated in (11) and (12). The status of any line k of the system is identified via an integer variable in (13). Parameter M_k is a user-specified large number greater than or equal to $|B_k(\theta^{\max} - \theta^{\min})|$ which is selected to make the constraints nonbinding and relax those associated with Kirchhoff's laws when a line is removed from service regardless of the difference in the bus angles [29], [30]. Parameter χ introduced in (14) limits the number of open lines in the optimal reconfigured network.

$$\sum_k (1-\alpha_k) \leq \chi \qquad k \in \Omega_L \tag{14}$$

The optimization engine is able to provide several sets of optimal solutions for any selection of χ. In doing so, the probabilistic optimization algorithm is first simulated to suggest the best optimal solution for the topology control problem. A Not-To-Switch (NTS) list is designed where the obtained best optimal solution is stored. The optimization engine is simulated again neglecting the solutions previously stored in the NTS box and the process will continue to obtain the second best, third best, etc. optimal switching solution. Such implementation design would not only increase the chance that at least one set of the solutions would survive all the subsequent AC feasibility/stability tests and other operational concerns, but also would provide the operator with more flexibility in final decision making [12].

The two point estimation method (2-PEM) decomposes (5) into several sub problems by taking only two deterministic values of each uncertain variable located on the two sides of its mean value. The deterministic switching optimization (7)-(13) is then simulated twice for each uncertain variable, one for the value below and the other for the value above the mean, while keeping the other variables constant at their mean values. These two points may or may not be selected symmetrically around the mean of a given variable [59]. As each set of the selected sample points undergoes the optimization problem to obtain the transformed samples, the mean and standard deviation of output variables (e.g., the generation dispatch cost)

[1] The bar notation over variables show the probabilistic (expected) values.

as well as the status of each line would be calculated at each scenario. The probabilistic optimal topology control formulation would eventually result in the probability distribution function (PDF) of the generation dispatch cost as well as the final status for each transmission line which would be selected as the most repeated status over the studied probabilistic scenarios. Note that the transmission line switching embedded in the probabilistic ACOPF formulation can be also approached, if the computational facilities allow, by adding the voltage magnitude and reactive power constraints.

D. The 2-PEM Core Algorithm

The algorithm of the 2-PEM procedure for the above optimization formulation is as follows [58], [59]; the requisite variables of the 2-PEM are initialized in ***Step 1*** using (15):

$$E(Y)^{(1)} = 0 \tag{15.a}$$

$$E\left(Y^2\right)^{(1)} = 0 \tag{15.b}$$

In ***Step 2***, the locations and probability of concentrations are calculated through (16.a)-(16.d) as follows:

$$\xi_{z,1} = \frac{\lambda_{z,3}}{2} + \sqrt{r + \left(\frac{\lambda_{z,3}}{2}\right)^2} \quad \forall z \in \Omega_Z \tag{16.a}$$

$$\xi_{z,2} = \frac{\lambda_{z,3}}{2} - \sqrt{r + \left(\frac{\lambda_{z,3}}{2}\right)^2} \quad \forall z \in \Omega_Z \tag{16.b}$$

$$P_{z,1} = \frac{-\xi_{z,2}}{2r \cdot \sqrt{r + \left(\frac{\lambda_{z,3}}{2}\right)^2}} \quad \forall z \in \Omega_Z \tag{16.c}$$

$$P_{z,2} = \frac{\xi_{z,1}}{2r \cdot \sqrt{r + \left(\frac{\lambda_{z,3}}{2}\right)^2}} \quad \forall z \in \Omega_Z \tag{16.d}$$

The two concentrations $x_{z,1}$ and $x_{z,1}$ are determined in ***Step 3*** using the following formulations:

$$x_{z,1} = \mu_{x,z} + \xi_{z,1} \cdot \sigma_{x,z} \tag{17.a}$$

$$x_{z,2} = \mu_{x,z} + \xi_{z,2} \cdot \sigma_{x,z} \tag{17.b}$$

In ***Step 4***, the deterministic topology control optimization is solved for both concentrations $x_{z,i}$ with respect to vector $\mathbf{X}$ presented in (18).

$$X = [\mu_{z,1}, \mu_{z,2}, \ldots, x_{z,i}, \ldots, \mu_{z,r}] \quad i = 1, 2 \tag{18}$$

Equations (19.a) and (19.b) are updated in ***Step 5*** as follows:

$$E(Y)^{(z+1)} \cong E(Y)^{(z)} + \sum_{i=1}^{2} P_{z,i} \cdot h(\mathbf{X}) \tag{19.a}$$

$$E\left(Y^2\right)^{(z+1)} \cong E\left(Y^2\right)^{(z)} + \sum_{i=1}^{2} P_{z,i} \cdot h^2(\mathbf{X}) \tag{19.b}$$

And eventually in ***Step 6***, the output mean value and the associated standard deviation would be estimated in (20).

$$\mu_Y = E(Y) \tag{20.a}$$

$$\sigma_Y = \sqrt{E\left(Y^2\right) - E^2(Y)} \tag{20.b}$$

Detailed background on the mathematical proofs of the 2-PEM technique is provided in [60].

III. Probabilistic Reliability Cost/Value Framework for Optimal Topology Control Decision Making

The output of the above probabilistic topology control optimization engine would be the economically optimal switching plans that may involve one or several switching actions per hour. Such optimal switching plans would be different in that: (1) each provides different percentage of economic benefits (denoted as *value*); (2) each would lead to different states with different operational risk and reliability performance (translated as *risk cost*). In order to identify an efficient selection among the optimal topology control plans, a probabilistic reliability cost/value decision making technique is suggested. This day-ahead support tool would help the operators to (1) decide whether there is any optimal switching plan at each hour with substantial economic benefits and at the same time high system reliability performance, and (2) if the former condition is confirmed, select the best plan for final implementation among multiple sets of optimal switching solutions suggested per hour.

The *value* of each topology control plan is considered as the economic benefits realized, compared to the base case condition, via co-optimizing the topology and the generation dispatch. Regarding the *risk cost* associated with each switching plan, probabilistic analytical state enumeration approach is employed for each optimal switching solution to assess the reliability of the topologically reconfigured transmission system. Up to the fourth order of contingencies are considered for calculation of reliability indices. The method employs the interrupted load probability for every contingency in each system topology to calculate the expected energy not supplied (EENS) index reflecting the system reliability performance. Mathematically speaking, the following linear programming optimization problem is run in each contingency state. The objective function is to minimize the system total interrupted load subject to the physical network constrains and security requirements [61].

$$\min_{h \in \Omega_H} \sum_{n \in \Omega_D} \left(\mathrm{IL}^t_{n,h,k} = \bar{P}^t_{d_n} - \bar{P}^{t,\mathrm{supplied}}_{d_n,h}\right) \tag{21}$$

$$P^{\min}_{g_n} \le \overline{P^t_{g_n}} \le P^{\max}_{g_n} \quad \forall g \in \Omega_G \tag{22}$$

$$\theta^{\min}_n \le \theta_n \le \theta^{\max}_n \quad \forall n \in \Omega_B \tag{23}$$

$$\sum_{g \in \Omega_G} \overline{P^t_{g_n}} - \sum_{m \in \Omega_B} P^t_{knm} = \sum_{d \in \Omega_D} \overline{P^t_{d_n}} - \mathrm{IL}^t_{n,h,k} \quad \forall n \in \Omega_B \tag{24}$$

$$P^t_{knm} = 0 \quad \forall k \in \Omega_{K'} \tag{25.a}$$

$$P^{\min}_k \le P^t_{knm} \le P^{\max}_k \quad \forall k \notin \Omega_{K'} \tag{25.b}$$

$$0 \le \mathrm{IL}^t_{n,h,k} \le \bar{P}^t_{d_n} \quad \forall n \in \Omega_B, \forall h \in \Omega_H \tag{26}$$

Probabilistically approached, the EENS index of reliability at each bus would be then calculated through (27).

$$\overline{\mathrm{EENS}}^t_{n,k} = \sum_{h \in \Omega_H} P^t_h . \tau^t_h . \mathrm{IL}^t_{n,h,k} \quad \forall n \in \Omega_B \tag{27}$$

$$P^t_h = \prod_{x \in \Omega_X} \frac{\Gamma_x}{(\gamma_x + \Gamma_x)} \times \prod_{y \in \Omega_Y} \frac{\gamma_y}{(\gamma_y + \Gamma_y)} \tag{28}$$

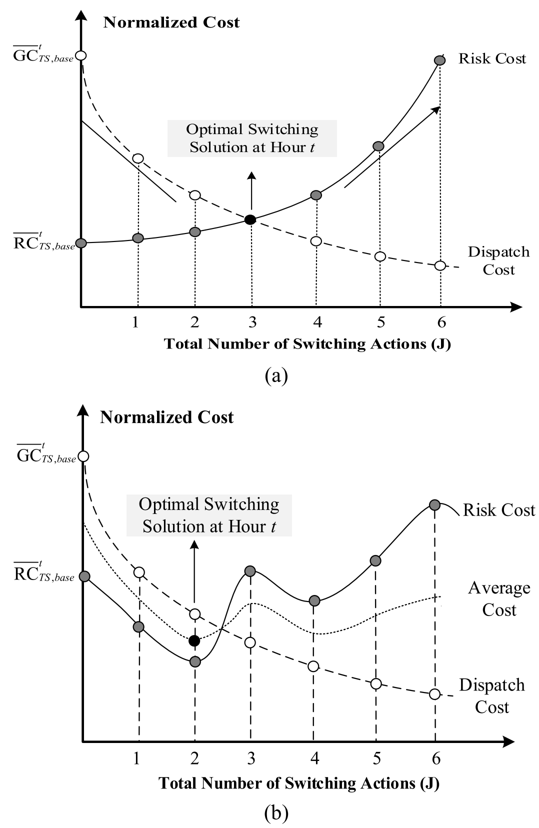

Fig. 2. Probabilistic cost/value framework for optimal topology control decision making at hour t: (a) monotonically degrading system reliability with line switching; (b) cases of reliability improvement through line switching.

$$\tau_h^t = \left(\sum_{x\in X}\gamma_x + \sum_{y\in Y}\Gamma_y\right)^{-1} \quad \forall h\in\Omega_H \tag{29}$$

where, P_h^t is obtained in (28) by multiplying the availability of online components and unavailability of the failed ones in a contingency state h; and τ_h^t is calculated in (29) using the failure rates of online components and repair rates of the failed ones in a given contingency state. Note that in all the above calculations, the common two-state Markov model for each system component is considered. Taking into account different types of loads and customers at each bus, the system total risk cost is assessed in (30) for each optimal topology control plan k at time t based on the corresponding EENS index and the value of lost load (VOLL) for each type of interrupted demand. The VOLL_n represents the unit interruption costs of different customer sectors served at load point n which is directly dependent on the duration of outage and is commonly determined through customer surveys and historical data [62].

$$\overline{\mathrm{RC}}^t_{TS,k} = \sum_{n\in\Omega_B} \overline{\mathrm{EENS}}^t_{n,k}.\mathrm{VOLL}_n \tag{30}$$

In order to determine the final topology control plan with an optimal number of switching actions involved, the probabilistic cost/value chart is utilized as illustrated in Fig. 2. As the number of switching actions increases, the higher economic benefit is expected. While transmission switching does often degrade the system reliability (and higher risk), there are cases where switching out some transmission lines for economic gains would help improving the system reliability performance. The reason lies in the fact that the suggested framework involves a probabilistic co-optimization of the generation dispatch along with the network topology. Moreover, system reliability may be affected by several other important factors in a given operating state (e.g., available generation capacity, generators' ramping capabilities, etc. in the new topology). Hence, lower/higher reliability performance (i.e., higher/lower risk) would be experienced in practice after switching a sequence of transmission lines out. Fig. 2(a) illustrates the case where system reliability degrades (translated to higher risk cost) as the number of switching actions increases. As indicated in Fig. 2(a), the optimal number of switching actions is determined when the risk cost and economic benefit curves intersect, which assures an efficient compromise between economic gains and system reliability and risk performance. Fig. 2(b) demonstrates the situation where switching out transmission lines, in some cases, may improve system reliability. In such circumstances, the optimal decision where the average costs are minimized is found. Note that while the two types of costs (dispatch and risk) may be in different orders of magnitude, such costs are translated into normalized values with regards to the corresponding maximum quantities so that the compromise could be made and a robust optimal number of switching actions for implementation could be decided.

IV. Case Study: Modified IEEE 118-Bus Test System

A. System Descriptions, Data, and Assumptions

The modified IEEE 118-bus test system contains 185 transmission lines and 19 generators with the installed capacity of 6859.2MW, serving a total demand of 6000 MW at peak load hour [63]. The demands are considered to be of 20% dispatchable load with the interruption cost of 0.2 VOLL and 80% firm load with the interruption cost of 0.8 VOLL. The system one line diagram as well as the required data including hourly generation and load profiles, historical wind data, transmission line parameters, generator variable costs and dynamic settings, and the reliability parameters of the system components and load points is all provided in [63].

In order to investigate the impacts of different probabilistic scenarios on the performance of the suggested framework, three different numerical studies are conducted. Case 1 is the base case condition with no wind penetration where the conventional generating units are utilized. The modified IEEE 118-bus test system in presence of large-scale wind farms is studied in Case 2 and Case 3. In Case 2, a large-scale wind farm, comprised of 100 wind turbines with the overall capacity of 300MW, is directly added to bus 90 where the wind energy penetration is expected to be 5% of overall system generation capacities. Similarly in Case 3, two wind farms each of which carrying a capacity of 300MW are directly connected to buses 90 and 91 where the wind penetration is supposed to be 10% of the system entire generation capacities.

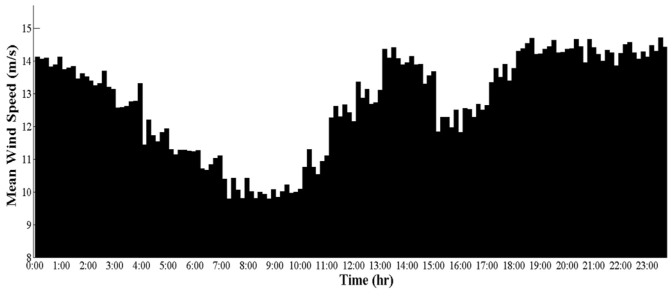

Fig. 3. Real diurnal wind speed at Manjil wind farm: October 10, 2008 [63].

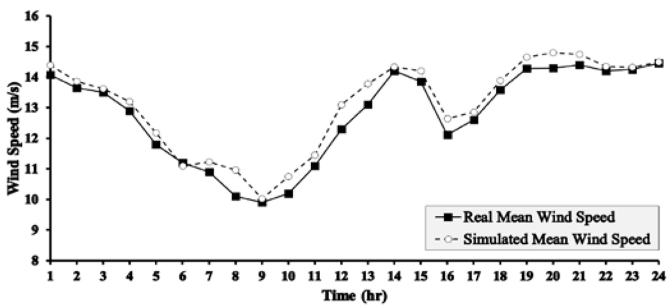

Fig. 4. Simulated mean values for the wind speed diurnal distribution at Manjil wind farm: October 10, 2008.

B. Wind Speed Modeling

The random Monte Carlo simulation is hourly implemented to probabilistically simulate the variations of the wind speed. The real hourly wind speed data of two wind farms located in North of Iran (Manjil and Binaloud) in a five-year period of January 1, 2005 to December 31, 2009 are employed as the historical data [63]. The simulation engine is able to accurately capture the chronological and intermittent characteristics of the wind speed over time. Fig. 3 demonstrates the real wind speed data during a day at Manjil wind farm and Fig. 4 illustrates how the developed framework can trace the real wind speed diurnal distribution. The wind power generated at time t corresponding to a given hourly wind speed distribution is then evaluated using (2). The wind farm total generation is the sum of all generations from all the online turbines in the farm. The hourly wind farm generation is fed into the probabilistic topology control optimization as an input random variable.

C. Results and Discussions: 24-Hour Period (Oct. 10, 2008)

The probabilistic mixed integer linear programing (MILP) optimization formulations in (4)-(13) are employed in the MATLAB environment applying the MATPOWER operating functions [64] and using the system hourly generation and load profiles. The optimization problem is run on a Dell PowerEdge R815 with 4 AMD Opteron 6174 Processors (48 2.2 GHz cores) and 256 GB of Memory running CentOS 5.7.

First, we demonstrate the necessity of employing a probabilistic framework vs. the conventional deterministic formulations for optimal topology control problem. The test results for having just one switching possibility at each hour (on October 10, 2008) are demonstrated in Fig. 5 to Fig. 7 corresponding to Cases 1-3, respectively. In each case, three

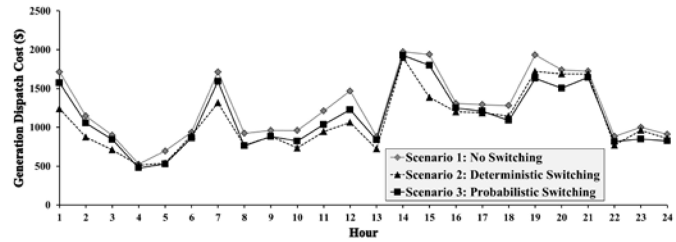

Fig. 5. Hourly dispatch costs in the studied scenarios on Oct. 10, 2008: Case 1.

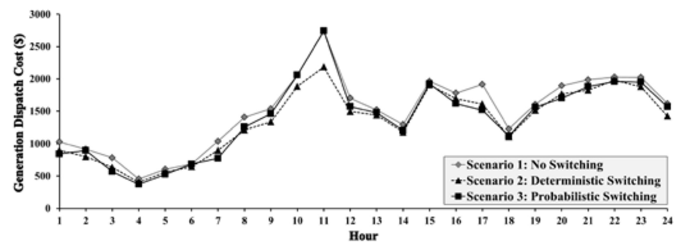

Fig. 6. Hourly dispatch costs in the studied scenarios on Oct. 10, 2008: Case 2.

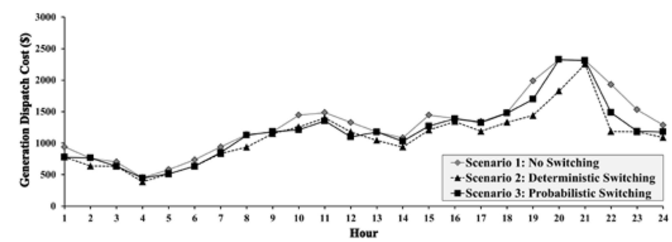

Fig. 7. Hourly dispatch costs in the studied scenarios on Oct. 10, 2008: Case 3.

scenarios (S) have been studied at each hour: (S1) the system is operated with no topology control program; (S2) the system generation is deterministically dispatched enforced by the topology control; (S3) the suggested probabilistic topology control formulation is applied. As can be seen in the results of Fig. 5–7, in all the studied cases and scenarios, the optimal one-line-switch topology control solutions in both deterministic and probabilistic formulations have resulted in considerable economic benefits (lower generation dispatch costs) in almost 91% of the entire 24-hour period compared to the base case condition (where there is no switching actions adopted). However, a main observation is that contrary to the deterministic approach, the probabilistic topology control framework does not always propagate into optimal switching solutions at each hour (day-ahead comparisons). For instance, one can take hour 11 in Case 2 as an example, where the deterministic optimal solution would be switching out line 151 (S2) while in S3, there is no optimal solution found at this hour considering the variable response of load and generation (i.e., the generation dispatch cost is the same as that in S1). The same observation is repeated at hours 6 and 10, too. The other main observation is that, at most hours (but not all), the optimal hourly topology control plans are different when employing the probabilistic formulation compared to

TABLE I
NUMERICAL RESULTS ON DAY-AHEAD TOPOLOGY CONTROL SOLUTIONS CONSIDERING DIFFERENT CASES AND SCENARIOS ON OCT. 10, 2008

Cases	Case 1			Case 2			Case 3		
Scenarios	S1	S2	S3	S1	S2	S3	S1	S2	S3
min GC^t ($)	524.76	512.74	477.50	456.15	403.85	373.18	452.09	386.43	446.23
max GC^t ($)	1973.38	1900	1927.73	2743.60	2186.25	2743.60	2326.16	2255.22	2326.16
Daily GC ($)	30028	25728.91	27052.12	35820.55	32279.74	33254.06	31012.42	26387.51	28469.21
Daily Savings (%)	0	14.32	9.91	0	9.88	7.16	0	14.91	8.20

TABLE II
COMPARISON OF MULTIPLE TOPOLOGY CONTROL SOLUTIONS AT HOUR 24 CONSIDERING DIFFERENT CASES AND SCENARIOS ON OCT. 10, 2008

	J	$\overline{GC}_k^{24}$ ($)		Savings (%)		AC Feasibility Check		Stability Check		$\overline{EENS}_{TS,k}^{24}$ (MWh./yr.)		$\overline{RC}_{TS,k}^{24}$ (k$/yr.)	
		S2	S3	S2	S3	S2	S3	S2	S3	S2	S3	S2	S3
Case 1	1	858.387	839.596	5.67	7.72	✓	✓	✓	✓	46.754	48.135	153.344	157.875
	2	803.235	800.093	11.72	12.06	✓	✓	✓	✓	47.856	49.185	160.956	165.425
	3	760.652	741.887	16.39	15.16	✓	✓	✓	✓	49.353	53.923	165.893	250.145
	4	749.996	766.797	17.46	15.72	✓	✓	✓	✓	50.756	55.156	193.434	300.456
	5	730.365	760.996	19.73	16.36	✓	✓	✓	✓	51.755	53.908	345.825	410.231
Case 2	1	1422.630	1769.085	12.06	3.67	✓	✓	✓	✓	46.826	50.965	153.579	167.155
	2	1365.572	1680.531	15.58	8.49	✓	✓	✓	✓	48.112	52.365	161.819	176.121
	3	1356.326	1638.427	16.16	10.79	✓	×	✓	×	50.531	N/A	169.855	N/A
	4	1340.456	1616.253	17.14	11.96	✓	✓	✓	✓	53.546	58.235	204.067	221.937
	5	1330.897	1590.230	17.73	13.41	✓	×	✓	×	59.245	N/A	395.877	N/A
Case 3	1	1129.767	1278.315	12.19	10.00	✓	✓	✓	✓	51.001	56.523	167.274	185.385
	2	1070.934	1242.207	16.76	12.55	✓	✓	✓	✓	54.963	60.489	184.860	203.445
	3	945.635	1221.366	26.49	14.02	✓	×	✓	×	58.147	N/A	195.454	N/A
	4	897.965	1211.789	30.20	14.69	✓	✓	✓	×	60.248	62.859	229.608	N/A
	5	852.633	1192.369	33.73	16.06	✓	✓	×	×	63.453	63.789	N/A	N/A

those deterministically found. As a result, the economic benefits through switching actions obtained using the suggested probabilistic framework for topology control (S3) vary at each hour (either less, equal, or higher) compared to the results from the conventional deterministic methods (S2). To put a figure on this, take Case 1 as an example. The minimum generation dispatch cost in S2 is $512.74 at hour 4 (corresponding to switching line 85) while in S3, it is $477.5 at hour 4 (corresponding to switching line 155). Table I provides further details on the numerical results in various studied cases and scenarios. In Case 1, the total daily generation dispatch cost on Oct. 10, 2008 is $27,052.12 in S3 (+9.91% saving compared to S1) which is 4.89% more than $25,728.91 in S2. Similar observations are valid from the results in Cases 2 and 3. It can be concluded from such day-ahead comparisons that the daily economic savings obtained through application of the probabilistic topology control framework on the studied system is generally less than conventional deterministic approaches.

Let us now compare the day-ahead probabilistic results (S3) in Case 2 and Case 3 where there is large-scale wind generation included vs. the results in Case 1. The probabilistic topology control approach has resulted in higher economic saving at some specific hours (e.g., 1, 10, and 11). However, the total daily generation dispatch cost enforced with optimal switching actions has been increased ($33,254.06 in Case 2 and $28,469.21 in Case 3) compared to Case 1 ($27,052.12), resulting in relatively lower daily economic savings expected from the topology control optimization (9.91%, 7.16%, and 8.20% corresponding to Case 1, Case 2, and Case 3, respectively). It can be seen that as the stochastic wind generation is increased, the possibility of finding optimal topology control solutions has been decreased in some hours. Taking Case 3 with large scale wind integration into account: the optimization engine could not find any optimal switching solution at hours 9, 13, 20, and 21 when performing the probabilistic analysis while the optimal topology control plans were found at every hour if deterministically approached.

D. Decision Making: Hour 24 (Oct. 10, 2008)

This section elaborates on the application of the suggested probabilistic decision making support tool which can identify multiple switching solutions at each hour that if implemented in a sequence, would offer higher economic gains. Take hour 24 time-frame as an example. Given the probabilistically modeled generation and load profile at this hour, the possibility of at most 5 line switchings is enforced in the optimization engine. The question would be which optimal plan with how many switching actions involved needs to be selected at this hour for final implementation. The numerical results for the obtained solutions in Case 1, Case 2, and Case 3 can be found in Table II (J is the total number of switching actions). The solutions obtained using the probabilistic models in S3 are also compared with those of the conventional deterministic approaches (S2). It can be seen that as the number of switching actions increases at this hour, the higher economic gains

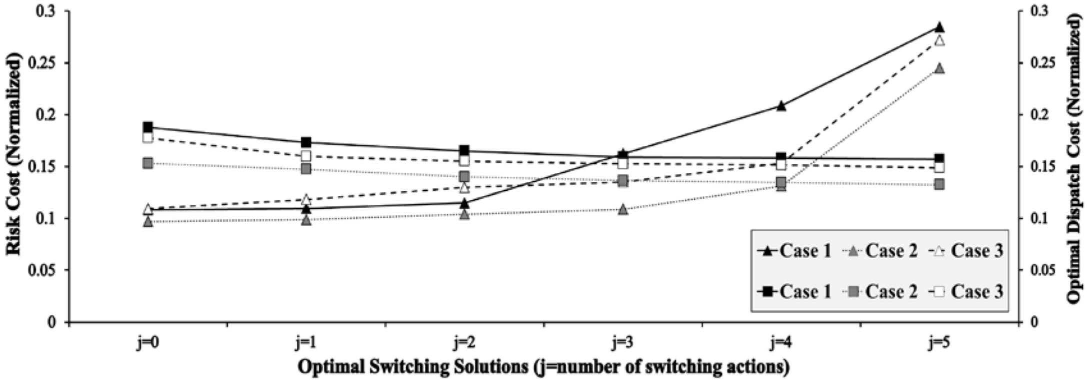

Fig. 8. Probabilistic decision making on the optimal number of switching actions for final implementation: Hour 24.

are generally obtained in all the studied cases. In order to identify the optimal topology control plan at this hour, the AC feasibility and stability checks are conducted on each solution. The aforementioned checks were successful in all the conducted tests in Case 1 and 77.5% of the tests in Case 2 and Case 3. So, it can be seen that as the probabilistic nature of load and generation is characterized, the possibility of facing unstable switching solutions would increase. As the optimization engine is able to suggest several sets of optimal plans, the second best optimal sequence of switching actions at this hour, which is both AC feasible and stable, was replaced (not shown in the Table). However, the operator might choose to exclude such infeasible solutions from the list and go on with the decision making steps using other available options. For final decision making, the financial benefits and probabilistic risk costs are calculated for each optimal plan. The probabilistic results for decision making at hour 24 are illustrated in Fig. 8 in all the studied cases in S3. As can be seen in this figure, the optimal dispatch cost and the risk cost curves intersect at different optimal points in different studied cases. In Case 1, it is shown that the optimal number of low-risk switching actions at this hour, which is not only economically attractive but also does not jeopardize the system reliability, is 3 while it is found to be 4 in Case 2 and Case 3. Similar process should be conducted at each hour to decide on the optimal topology control plan for final implementation.

V. Discussions

A. Computational Issues

Fig. 9 summarizes the computational requirements of implementing various segments of the proposed DCOPF-based probabilistic topology control optimization on the IEEE 118-bus test system at hour 24. Table III also presents a summary of the simulation run time for a complete implementation of the deterministic and the proposed probabilistic day-ahead topology control decision making on the studied system using the hourly information on October 10, 2008. Note that contrary to Fig. 9, the computational results presented in Table III include simulation of all modules within the proposed framework for up to 5 transmission line switching actions per hour over the studied 24-hour time frame on October 10, 2008.

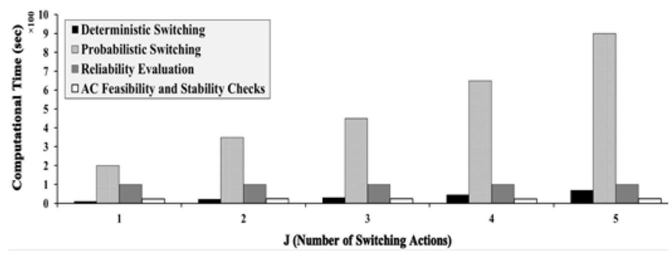

Fig. 9. Simulation run time for various modules of the suggested probabilistic decision making framework: Modified IEEE 118-bus test system at Hour 24.

TABLE III
Computational Time for Implementation of the Proposed Decision Making Framework: Deterministic vs. Probabilistic Formulations

October 10, 2008	Computational Time (min.)		
	Min	**Max**	**Average**
Deterministic	11.96	13.08	12.33
Probabilistic	42.47	45.39	44.35

Rapid advances in both computing hardware and computational performance of modern optimization solvers together with more efficient parallel computation techniques can further expedite the implementation of the proposed framework in large-scale real-world power systems.

B. Future Work

Ongoing and future work includes investigating the scalability and tractability of the proposed probabilistic framework as well as other efficient probabilistic techniques in large-scale real-world transmission systems. Another extension of the work may be focused on modifications of the DCOPF-based topology control optimizations with inclusions of realistic factors such as losses and nomogram constraints. Future works should also include the practical mechanisms for selection of an optimal switching sequence which is very critical as far as the system stability is concerned [12].

VI. Conclusion

This paper presents a probabilistic framework for recognizing the day-ahead optimal topology control plans that improve the system economic efficiency. The existing uncertainties of wind generation and load were statistically modeled, formulated, and incorporated in the probabilistic DCOPF-based topology control optimizations using the PEM technique. Hourly and daily economic analysis performed through various probabilistic cases and scenarios demonstrated the necessity of modeling and incorporating such uncertainties into the conventional transmission switching formulations. Results on the modified IEEE 118-bus test system indicated that contrary to the deterministic approaches, the probabilistic topology control framework does not always propagate into optimal switching solutions at each hour and the anticipated economic saving may not be as promising as for deterministic solutions. The paper also addressed a main question: if several topology control actions per hour bring about considerable economic savings, which optimal plan involving how many switching actions should be selected for final implementation. A probabilistic decision making framework to define the optimal number of switching actions per hour taking into account both economic gains and risk costs associated with the new system states after the topology change was formulated. Employing the suggested probabilistic framework, the operator will be offered the flexibility in making decisions as he/she is presented with the explicit expected benefits and risks associated with each optimal option. The operator can decide which one among various options to select depending on the risk-averse or risk-tolerant policies he/she is following.

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