Probabilistic Method for Estimation of Spinning Reserves in Multi-connected Power Systems with Bayesian Network-based Rescheduling Algorithm

Yerzhigit Bapin[1] and Vasileios Zarikas[1,2]
[1]*School of Engineering, Nazarbayev University, 56 Kabanbay Batyr ave., Astana, Kazakhstan*
[2]*Department of Engineering Informatics, University of Thessaly, Greece*

Keywords: Spinning Reserve, Interconnected Power Systems, Bayesian Network, Probabilistic Reserve Estimation, Power System Reliability.

Abstract: This study proposes a new stochastic spinning reserve estimation model applicable to multi-connected energy systems with reserve rescheduling algorithm based on Bayesian Networks. The general structure of the model is developed based on the probabilistic reserve estimation model that considers random generator outages as well as load and renewable energy forecast errors. The novelty of the present work concerns the additional Bayesian layer which is linked to the general model. It conducts reserve rescheduling based on the actual net demand realization and other reserve requirements. The results show that the proposed model improves estimation of reserve requirements by reducing the total cost of the system associated with reserve schedule.

1 INTRODUCTION

Reduction of the greenhouse gas emissions is considered as one of the main issues faced by modern society. Global warming and deteriorating ecological situation on the planet require drastic changes to the energy production technologies. Undoubtedly, renewable energy and smart grid technologies have crucial impacts in this transformation. During the last decade, the total installed capacity of renewable energy in the world has increased from 1.058 TW to 2.012 TW (Whiteman et al., 2017). It is expected that the overall share of renewable energy will reach 40% by 2040 (IEA, 2017). Nevertheless, to successfully reach the renewable energy targets, many challenging tasks need to be overcome in the near future. Because of highly stochastic nature of renewable power, accommodating large amounts of renewable generation requires to have flexible grid from the technical and operational perspectives.

Smooth integration of renewable energy sources into the market and grid infrastructure will require reconsideration of conventional operating practices. Especially, significant attention should be paid to the operational reliability of power systems. Currently, there are two major reliability assessment approaches prevailing in the electric power industry, namely deterministic and probabilistic. Under deterministic approach the reliability criteria are set such that the grid system would be capable of withstanding the loss of a single unit (N-1), or even simultaneous loss of several power generating units (N-k). The power system reliability evaluation based on pure deterministic approach does not consider stochastic processes occurring in the grid; however, most of the present-day reliability criteria are based on deterministic techniques. One of the reasons for the widespread of deterministic reliability evaluation methods is their relative simplicity and the lower requirements applied to its input data (Billinton and Allan, 1996). On contrary, reliability assessment based on probabilistic techniques are more sophisticated and require detailed information about system characteristics such as generator outage rates, load and renewable forecast errors, etc. The advantage of probabilistic methods, as compared with deterministic ones, is the ability to capture system uncertainties and evaluate the magnitudes and effects of these uncertainties on the operation of power systems (Morales et al., 2014). Consequently, in probabilistic reliability assessment methods, the events are treated based on the likelihood of their occurrence and the degree of their severity (Grigsby, 2013).

Bapin, Y. and Zarikas, V.
Probabilistic Method for Estimation of Spinning Reserves in Multi-connected Power Systems with Bayesian Network-based Rescheduling Algorithm.
DOI: 10.5220/0007577308400849
In *Proceedings of the 11th International Conference on Agents and Artificial Intelligence (ICAART 2019)*, pages 840-849
ISBN: 978-989-758-350-6

The interest in utilization of the power system reliability assessment using probabilistic methods has been increasing with the growth of stochastic power generation. Various reserve estimation methodologies considering stochastic generation have been proposed in the last few years. Consideration of stochastic events in most of these methodologies is conducted in two distinct ways: one way requires imposing an upper limit to reliability metrics determining the loss of load or loss of energy expectation; another way includes an economic penalty into the objective function. Conventional probabilistic reliability assessment methods are generally based on analytical or Monte-Carlo (MC) techniques. Application of Bayesian network theory in probabilistic reliability assessment has its advantages over conventional analytical or MC-based probabilistic methods. Particularly, Bayesian Networks (BNs) aim to model conditional dependence of system components and states, which in turn allows making inference on the events of the interest (Zarikas and Tursynbek, 2017). The BN-based power system reliability assessment models provide powerful and mathematically sound framework to analyse complex and stochastic domains making them an effective decision-making tool for the grid system operators.

Although, the implementation of BNs in power system analysis is relatively new approach, several valuable works have been published during the last decades. In one of the earliest studies on BN-based power system reliability assessment (Yu et al., 1999), the authors proposed the BN model for reliability assessment of multi-area power systems. In this study, the BN representation of a grid system is conducted via system components, such as, power generating capacity, tie-line capacity, interconnected capacity etc. The information provided by the system components is used to determine the system state variable – Loss of Load (LOL). Here, LOL serves as a binary variable identifying the states when demand exceeds available power. The overall reliability of a power system is evaluated in terms of the Loss of Load Probability (LOLP). The methodology was applied to the Three-Area IEEE Reliability Test System (RTS). The reported LOLP results show close proximity with the analytical method. Somewhat similar approach presented in the study by (Limin et al., 2002). The study constructs the BN of a grid system in two steps. First, the fault tree graph is created for each node using bucket elimination (Dechter, 1996). During the second step, the minimal path set is determined by using the graph search technique. The study by (Yongli et al, 2006) proposes an approximate inference algorithm on BN for reliability assessment of power systems by time-sequence simulation. The system components are modeled using two-state Markov model. The methodology constructs the fault tree graph and corresponding BN for a system of interest using the bucket elimination method. In the study by (Ebrahimi and Daemi, 2009) the authors present a novel BN-based grid system reliability assessment method. The methodology uses the MC-based data sampling technique to generate training data. The training data is used to construct BN representing the power system of interest. The methodology assesses the reliability level of a system in terms of LOLP. The methodology has been tested on the IEEE RTS. The reported LOLP results are very close to those obtained using conventional probabilistic techniques.

The main contribution of this paper is to present a hybrid method for estimation of optimal amount of spinning reserves in multi-connected power systems using traditional probabilistic cost-benefit analysis in conjunction with the BN-based reserve rescheduling algorithm.

2 METHODOLOGY

The proposed methodology is carried out in three phases. The flowchart of the proposed methodology is presented in figure 1.

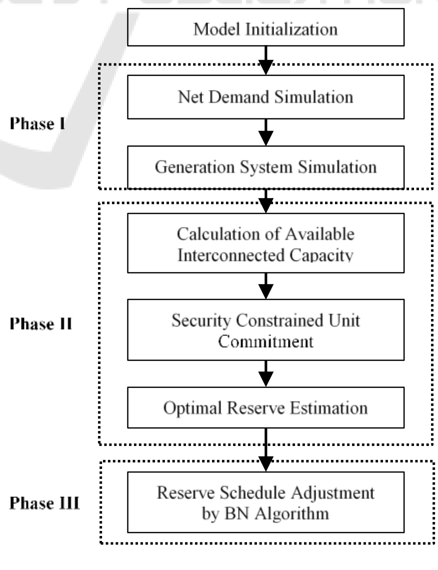

Figure 1: Flowchart of proposed model.

During the first phase, the reliability of the power system of interest is evaluated neglecting its interconnection with neighbouring systems. At the second phase, the Capacity Outage Probability Tables (COPT) of the assisting power systems are obtained using recursive algorithm and incorporated into COPT of the assisted system. The reliability evaluation is performed in terms of the Expected Energy Not Supplied (EENS), which serves as a metric for potential shortfall in supply of electricity to consumers. As a result, the required amount of spinning reserves is calculated based on the level of reliability of the system and the capacity that is available at a given time-period. At the final phase, the BN-based algorithm is used to adjust the reserve schedules based on the intra-hour actual data. The detailed description of calculations conducted during the first, second and third phases are described below.

2.1 Phase I

2.1.1 Net Demand Model

The proposed methodology considers renewable power as negative load, and the net demand is defined as the difference between load and renewable power generation given by:

$$D^t = L^t - R^t \tag{1}$$

where D^t is the net demand at period t, L_t and R^t are the actual load and renewable energy production at time period t. The forecast uncertainty is taken into consideration by implementation of parametric assumptions. Namely, the forecast error distribution at time period t is given by:

$$Y^t \sim F(y;\theta_t) \tag{2}$$

where Y^t is the forecast error at time period t, F is the distribution function of forecast error, y and θ_t is the set of parameters characterizing F (Morales et al., 2014).

It should be noted that throughout this paper the superscript t denotes the time periods and subscripts i, j, l and k denote the power generating units, interconnected reserve units, power transmission lines and energy system areas respectively.

In this study, we assume that the load and renewable forecast errors follow Normal distribution with zero mean and the standard deviation given by the following formulas (Ortega-Vazquez and Kirschen, 2009):

Standard deviation of load forecast error:

$$\sigma_L^t = \tfrac{k}{100} L_F^t \tag{3}$$

where σ_L^t is the standard deviation of the load forecast error distribution, k is a function depending on the accuracy of the forecasting software and the forecasted load at time period t.

Standard deviation of renewable forecast error:

$$\sigma_R^t = \tfrac{1}{5} R_F^t + \tfrac{1}{50} R_I \tag{4}$$

where σ_R^t is the standard deviation of renewable power forecast error distribution at time period t, R_F^t is the forecasted renewable power at period t and R_I is the total installed capacity of renewable power. The former term stays constant throughout the simulation horizon.

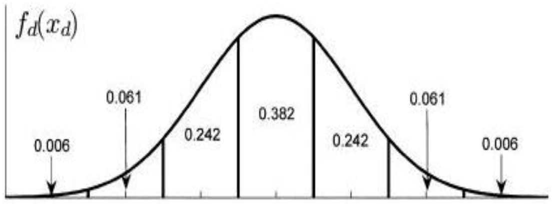

Figure 2: Seven-interval approximation of normal distribution.

Discretization of load and renewable forecast uncertainty can be done using seven-interval approximation technique described in (Billinton and Allan, 1996). Discretization is performed by dividing the probability distribution of an error into an odd number of equal intervals (Figure 2). These intervals are considered as scenarios with individual probabilities corresponding to the mid-point of each interval. The lack of correlation between these errors allows to calculate the net demand forecast error by summation of the load and renewable forecast errors.

2.1.2 Generation System Model

The random outages of conventional units are considered in the same fashion as it was done in (Bapin et al., 2018). A random unavailability of generating capacity can be modelled by representing it as a Markov process. The availability and unavailability of each generating unit in this case are given by (5) and (6) (Billinton and Allan, 1996):

$$A_i^t = \frac{\sum(up\ time)}{\sum(down\ time) + \sum(up\ time)} \tag{5}$$

$$U_i^t = 1 - A_i^t \tag{6}$$

where A_i^t and U_i^t represent availability and unavailability of unit i at time period t. Equations (5) and (6) represent the probability of finding the unit either available or on forced outage at a given period and can be used to create the Capacity Outage Probability Table (COPT). Creation of COPT is carried out using the recursive algorithm described in (Billinton and Allan, 1996) and includes information on available capacity and corresponding probabilities for each system state. It should be noted that throughout this paper the units' capacity and power production are denoted by capital P, whereas lowercase p denotes probability.

The Expected Energy Not Supplied (EENS) due to a random capacity outage m at time period t is given by (Billinton and Allan, 1996):

$$EENS^t = \sum_{m=1}^{M}\left(\sum_{s=1}^{S}[(D_s^t - \sum_{i=1}^{I} P_{i,m}^t)\times q_s]\right) q_m \qquad (7)$$

where s is an index representing the net demand scenario, $P_{i,m}^t$ is the available power when generation system is at state m during time period t, q_s and q_m are the probability of scenario of the net demand and generating system availability respectively. Finally, I, M and S are the total number of generating units, generation system states and net demand scenarios respectively. It is worth noting that, although variable $EENS_m^t$ highly depends on the level of capacity forced out of service, the probability of this outage may have even stronger impact on the loss of energy expectation. For instance, a simultaneous failure of two or more units may cause significant disruption of electricity supply. However, the probability of this event is very low, thus the overall loss of energy expectation would be lower as compared to the single unit outage event.

2.2 Phase II

2.2.1 Interconnected Capacity

It is very common for an electric grid to have interconnection with neighbouring systems, as most of the time grid interconnections improve reliability of the system and reduce its needs in reserve capacity (Watchorn, 1950). The cross-border electricity trading between interconnected systems is often done based on the contractual agreements, where the system operators define trading time, limits, ramp rates etc. To account for interconnected capacity, the proposed model utilizes the equivalent assisting unit method as described in (Billinton and Allan, 1996). The maximum assistance level provided by interconnected system at time period t is given by the minimum of available interconnected capacity and tie-line capacity (Allan et al., 1986):

$$IR_k^{\max,t} = \min\left\{\sum_{j=1}^{J}(IR_{j,k}^{inst} - IRe_{j,k}^{t} - IRr_{j,k}^{t}), \sum_{l}^{L} B_{l,k}^{\max}\right\} \qquad (8)$$

Where $IR_{j,k}^{inst}$ is the installed capacity of interconnected unit j located in the assisting system k, $IRe_{j,k}^t$ is the capacity committed for energy generation of interconnected unit j located at assisting system k during time period t, $IRr_{j,k}^t$ is the capacity of interconnected unit j committed for provision of spinning reserve at assisting system k during time period t and B_l^{max} is the maximum transmission capacity of transmission line l. Finally, J and L are the total number of interconnected reserve units and transmission lines respectively. The maximum capacity assistance level can be utilized to create a capacity model in the same way as it was described in the previous subsection. The resulting COPT is regarded as an equivalent multi-stage generator, which can be integrated in the existing capacity model of an assisted system. During this phase, the capacity assistance states are determined individually for all assisting systems and added to the COPT of the system of interest. It should be noted that in this paper we assume that the interconnected capacity can only participate in ancillary service market, thus it can only provide up-spinning reserve service.

2.2.2 Stochastic Security Constrained Unit Commitment

Objective Function.
In this study, the unit commitment problem is expressed as a two-stage stochastic MILP. The first stage involves conventional unit commitment with stochastic reliability criteria to find the most optimal energy production schedule. This stage is performed for the base case scenario. The base case implies no unit outage and results in the most economically efficient unit commitment. The first-stage optimization objective is to minimize the total cost of system operation, where the total system operation cost is given by:

$$C_{total}=\sum_{t=1}^{T}\left(\sum_{i=1}^{I}(C_iP_i^tu_i^t+CS_i^t)+\sum_{i=1}^{I}(Cup_i^tRup_i^t+Cdw_i^tRdw_i^t)+\sum_{k=1}^{K}\sum_{j=1}^{J}CIR_{j,k}^t\,IR_{j,k}^t+\sum_{m=1}^{M}SC_m^t\right) \quad (9)$$

where C_i is the cost of power of generating unit *i*, P_i^t is the power produced by unit *i* during time period *t*, u_i^t is the binary indicator of the status of generating unit *i* at time period *t* (0 – not operating, 1 – operating), CS_i^t is the start-up cost of unit *i* during time period *t*, Cup_i^t is the cost of power of unit *i*, during time period *t* for providing the up-spinning reserve, Rup_i^t is the up-spinning reserve service provided by unit *i* during time period *t*, Cdw_i^t is the cost of power of unit *i*, during time period *t* for providing the down-spinning reserve, Rdw_i^t is the down-spinning reserve service provided by unit *i* during time period *t*, $CIR_{j,k}^t$ is the cost of power provided by interconnected unit *j*, located at energy system *k*, during time period *t*, $IR_{j,k}^t$ is the amount of reserve provided by the interconnected unit *j*, located at energy system *k*, during time period *t*. SC_m^t is related to the second-stage decisions and is given by:

$$SC^t=\sum_{m=1}^{M}q_m\left(\sum_{i=1}^{I}C_i^tR_{i,m}^t+\sum_{j=1}^{J}\sum_{k=1}^{K}CIR_{j,k}^tIR_{j,m,k}^t+VOLL\times CE_m^t\right) \quad (10)$$

where C_i^t is the cost of providing the spinning reserve by intra-zonal unit *i* during time period *t*, $R_{i,m}^t$ is the reserve service provided by intra-zonal unit *i*, at system state *m*, during time period *t*, $IR_{j,m,k}^t$ is the amount of reserve provided by the interconnected unit *j*, located at energy system *k*, at system state *m*, during time period *t*. VOLL represents the value of lost load – the financial loss of consumers due to interruption in electricity supply, CE_m^t is the amount of curtailed energy when generation system is in state *m*, during time period *t*. The objective of the second-stage is to find the most optimal reserve schedule by comparing different scenarios.

First-Stage Constraints.
The objective function (9) must be minimized subject to the set of constraints specified below. Note that to reduce the computational burden and simplify the model, the transmission line constraints are neglected in this study. The equality between supply and demand of electric power is specified by the power balance constraint, which for all time instances is given by:

$$D^t=\sum_{i=1}^{I}(P_i^tu_i^t+Rup_i^tu_i^t-Rdw_i^tu_i^t)+\sum_{\kappa=1}^{K}\sum_{j=1}^{J}IR_{j,k}^tu_{j,k}^t \quad (11)$$

In addition to equation (11) the conventional units are subject to their operating constraints, such as minimum up and down time, ramping and capacity limits.

Second-Stage Constraints.
The second-stage constraints specifying all capacity outage states is presented below. For all time periods and scenarios, the power balance equation is given by:

$$\sum_{i=1}^{I}(q_mP_i^t+Rup_{i,m}^t+Rdw_{i,m}^t)+\sum_{k=1}^{K}\sum_{j=1}^{J}IR_{j,k,m}^t=\sum_{s=1}^{S}(D_s^t-CE_{s,m}^t) \quad (12)$$

Under this formulation of probabilistic reliability criteria, the optimal spinning reserve requirement is determined by counterweighting costs required to operate the reserves with socioeconomic costs of possible load curtailment. Reduction of spinning reserves will negatively affect reliability of a system, yet this reduction will be justified if the probability of capacity outage is insignificant, or the social value of curtailed load is very low.

2.3 Phase III

During recent years, rapid rise in computational efficiency triggered the introduction of complex machine learning algorithms into many different areas. The scope of application of these algorithms ranges from intellectual games, such as chess (David et al., 2014) or go (van den Werf et al., 2003), medical research (Eleftheriadou et al., 2009), (Deltsidou et al., 2017), (Zarikas et al., 2015) to the power system operation (Calabria et al., 2015) and (Steels and Hanappe, 2008).

Aside from other machine learning algorithms, BN-based algorithms have gained wide popularity among power system and electrical engineers. According to (Craciun et al., 2017) the application of

BNs by the power system engineering researchers include, but not limited to load forecasting, power system reliability assessment and stability analysis, electrical networks fault analysis and power system state estimation.

Generally speaking, BN is a probabilistic graphical model representing variables, their mutual dependencies and associated probabilities (Zarikas, 2007). BN models are usually expressed in terms of causal directed acrylic graphs (Jensen and Nielsen, 2011), where each variable has one or several directed links with other variables. The objective of BN models is to determine posterior conditional probability distribution of an event in question based on new evidence (Pearl, 2005). Equation (13) represents the Bayes' rule serving as the foundation for BNs.

$$p(A|B) = \frac{p(B|A)p(A)}{p(B)} \tag{13}$$

In this study, we propose a BN-based reserve rescheduling algorithm. The main purpose of this algorithm is to adjust the spinning reserve schedule that was calculated during the first and second phases of this methodology. The algorithm adjusts the reserve requirement of the next closest time period (*t+1*) based on the evidence received from the past closest time period (*t-1*). Other parameters considered by the algorithm during the adjustment procedure are hour type (peak, non-peak) and day type (weekday, weekend, holiday). The node specific properties, such as, conditional probabilities or reserve increase/decrease levels were set based on existing practice, nevertheless, these properties can be easily adjusted according to the user-specific preferences.

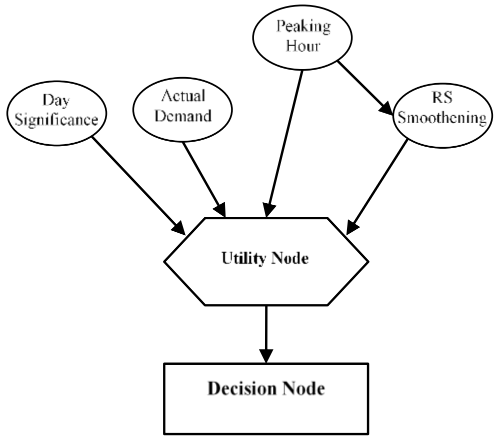

Figure 3: Part of the Influence Diagram of Proposed Algorithm.

The algorithm was implemented in BayesiaLab 7 (Bayesia S.A.A., 2018). Figure 3 shows a simplistic view of the decision influence diagram of the proposed algorithm. The implemented BN consists of 2 such graphs each of every hour of one day.

The diagram consists of probabilistic, utility and decision nodes each represented by elliptical, hexagonal and rectangular-shaped figures respectively. The detailed description of nodes is provided below.

Probabilistic Nodes.

The probabilistic nodes denote variables specified below:

Peaking Hour – denotes the variable containing information about hour type and affects *RS Smoothening* and *Utility nodes*. Usually, during peak-hours energy systems pass through tremendous stress, so the risk of electricity supply interruption is very high. One way of reducing the level of this risk is to increase the level of spinning reserve capacity. In this model, the spinning reserve schedule adjustment is set, such that, the reserve requirement is increased by 10% for peaking time. The off-peak hours do not affect previously calculated reserve schedule.

Day Significance – denotes the variable containing information about day types and their influence on spinning reserve schedule. In the proposed algorithm, three day types were considered, these are: weekdays, weekends and holidays. Weekends do not have any effect on reserve schedule, whereas weekends and holidays increase the reserve requirement by 10% and 20% respectively.

Actual Demand – denotes the variable containing information about the level of net demand forecast error and its influence on spinning reserve schedule. This node signals to adjust initial reserve schedule if the difference between the forecasted and actual net demand values exceed some predefined threshold. It should be reasonable to set this threshold equal to the expected value or the standard deviation of load/net demand forecast error. According to (Allan et al., 1986) it is suggested to model the load forecast uncertainty associated with IEEE RTS using normal distribution with a standard deviation equal to 5%. However, since the proposed model considers not only load, but also renewable forecast uncertainty the average threshold was set to be equal to 10% of forecasted value. The prior probabilities for this node do not have big importance. For completeness we note that there are five states in this node and the priors are P(same actual demand with forecast demand reserve power)=P(small positive difference between forecast and actual value)= P(small negative difference between forecast and actual value)=0.25.

"Small" means within the 10% variance as we have explained. The other priors P(big positive difference between forecast and actual value)=P(big negative difference between forecast and actual value)=0.125. "Big" means above 10% difference.

The important thing for this node is to determine how evidences are updated. The following description of this subsection is devoted to this issue; what are the conditional probabilities for updating the node.

Mathematically, the spinning reserve adjustment given the actual net demand of the previous hour is expressed as follows.

Increase by 10%:

$$p\,(R_{UU}^{t} \mid D_A^{t-1}, D_F^{t-1}) = \begin{Bmatrix} 0.8,\ (D_A^{t-1} - D_F^{t-1}) > 10\%\ D_F^{t-1} \\ 0.2,\ otherwise \end{Bmatrix} \tag{14}$$

where R_{UU}^t is the 10% increase in reserve requirement for time period *t*, D_A^{t-1} and D_F^{t-1} are the actual and forecasted values of net demand of time period *t-1*.

Increase by 5%:

$$p\,(R_{U}^{t} \mid D_A^{t-1}, D_F^{t-1}) = \begin{Bmatrix} 0.8,\ 5\%\ D_F^{t-1} < (D_A^{t-1} - D_F^{t-1}) \leq 10\%\ D_F^{t-1} \\ 0.2,\ otherwise \end{Bmatrix} \tag{15}$$

where R_U^t is the 5% increase in reserve requirement for time period *t*.

Decrease by 10%:

$$p\,(R_{DD}^{t} \mid D_A^{t-1}, D_F^{t-1}) = \begin{Bmatrix} 0.8,\ (D_F^{t-1} - D_A^{t-1}) > 10\%\ D_F^{t-1} \\ 0.2,\ otherwise \end{Bmatrix} \tag{16}$$

where R_{DD}^t is the 10% decrease in reserve requirement for time period *t*.

Decrease by 5%:

$$p\,(R_{D}^{t} \mid D_A^{t-1}, D_F^{t-1}) = \begin{Bmatrix} 0.8,\ 5\%\ D_F^{t-1} < (D_F^{t-1} - D_A^{t-1}) \leq 10\%\ D_F^{t-1} \\ 0.2,\ otherwise \end{Bmatrix} \tag{17}$$

where R_D^t is the 5% decrease in reserve requirement for time period *t*.

For all other cases, the probability of adjustment the reserve requirements equal to 0.

The conditional dependencies stated above are expanded by the example presented in table 1.

Table 1: Calculation of spinning reserve adjustment level given actual net demand value.

Variable	Observed/ forecasted value, MW	Difference/ adjustment, MW	Difference/ adjustment, %
D_A^{t-1}	1 467	129	10.47
D_F^{t-1}	1 328		
R_F^t	268	27	10
R_{Adj}^t	295		

The difference between the actual and forecasted net demand, in this example, is greater than 10% of forecasted net demand, therefore, the equation (14) must be used in further calculation. According to equation (14), for this particular case, the algorithm would assign the probability of increasing previously calculated spinning reserve by 295 MW equal to 0.8. Note that the adjustment procedure is not finished at this point, the final decision on the adjustment level would be made by the Decision Node.

Reserve Schedule (RS) Smoothening – denotes the variable containing information about spinning reserve requirements forecasted for previous (*t-1*), intra (*t*) and the next adjacent (*t+1*) time periods. As the name suggests, the main objective of this node is to smoothen the reserve schedule by increasing (positive smoothening) or decreasing (negative smoothening) reserve requirement for time period *t* based on the difference between forecasted reserve values of *t-1* and *t+1* time periods.

Mathematically the setting of new evidences for the smoothening procedure concerns the definition of the conditional probabilities. Thus, the update of of this node is as follows.

Positive 5% smoothening:

$$p\,(R_{U}^{t} \mid R_F^{t-1}, R_F^{t}, R_F^{t+1}) = \begin{Bmatrix} 0.8,\ R_F^{t+1} > 1.1R_F^{t}\ \&\ R_F^{t-1} > 1.1R_F^{t} \\ 0.2,\ otherwise \end{Bmatrix} \tag{18}$$

Negative 5% smoothening:

$$p\,(R_{D}^{t} \mid R_F^{t-1}, R_F^{t}, R_F^{t+1}) = \begin{Bmatrix} 0.8,\ R_F^{t+1} < 0.9R_F^{t}\ \&\ R_F^{t-1} < 0.9R_F^{t} \\ 0.2,\ otherwise \end{Bmatrix} \tag{19}$$

Thus, in this study, the probability of applying or not applying the smoothening given the forecasted values of spinning reserves for *t-1*, *t* and *t+1* time periods is set to 0.8 and 0.2 respectively. For all other cases, the probability of adjustment the reserve requirements equal to 0.

Table 2: Calculation of spinning reserve adjustment level given forecasted reserve requirements.

Variable	Reserve requirement, MW	Difference, MW	Difference, %	Assigned probability
R_F^{t-1}	232	36	13,43	-
R_F^t	268	-	-	-
R_F^{t+1}	256	8	4,48	-
R_{Adj}^t				0.2

The example presented in table 2 demonstrates calculation of conditional probability of smoothening given forecasted reserve requirements. The first step in the smoothening procedure is to evaluate the difference between initial reserve requirements calculated for time periods *t* and *t-1*. The same calculation should be conducted for time periods *t* and *t+1*. In this particular case, R_F^t greater than R_F^{t-1} and R_F^{t+1}, thus the equation (18) must be applied. According to the equation (18) the probability of increasing reserve requirement by 5% would be set to be equal to 0.2.

Utility Node.

In general, the utility node denotes a value that contains information about the decision maker's goals and objectives. Usually, these types of nodes express the decision maker's preferences over the outcomes over their direct predecessors.

In the proposed algorithm, the utility node contains information about all possible combination of relevant states of the parents, given the information provided by probabilistic nodes. The decision whether to adjust initial reserve schedule is made based on the weights that are set manually. The weights represent the strength of influence that each combination has on the final decision. The weights range on the scale from 0 to 10 indicating zero and maximum influence respectively. To save the paper space, only several combinations are presented in the table 3.

Table 3: Utility node conditional dependence table.

Day Significance	Weekend							
Actual Demand	Increase by 5%				Decrease by 10%			
RS Smoothening	Positive 5%		Negative 5%		Positive 5%		Negative 5%	
Peaking Hour	P	NP	P	NP	P	NP	P	NP
Value	9	7	2	4	5	4	4	7

Decision Node.

The decision node denotes a variable that is under decision maker's control and is used to model decision maker's options.

The objective of this algorithm is to find optimal spinning reserve adjustment actions based on the set of parameters described above. The set of decisions available to the decision maker through this algorithm is stated below:

1. Keep initially calculated reserve requirement;
2. Increase reserve requirement by 5%;
3. Increase reserve requirement by 10%;
4. Decrease reserve requirement by 5%;
5. Decrease reserve requirement by 10%.

3 CASE STUDY

This section presents a case study which was conducted by applying the model on the distribution system of Pavlodar, Kazakhstan. The main objective of the case study is to analyze the performance of the proposed BN-based rescheduling algorithm by comparing it to the conventional probabilistic reserve estimation model based on the cost-benefit analysis. The overall performance of the model is evaluated in terms of the total cost of reserve schedules given by the following equation:

$$CR_{total}^{t} = CR^{t} + SE^{t} \tag{20}$$

Figure 4 represents the costs of the test system presented in this case study calculated for one particular day using equation (20).

The analysis was conducted for a 24-hour operating horizon on 20 different days almost equally representing weekdays, weekends and holidays. The Value of Lost Load (VOLL) was set to 2 000 $/MWh.

The I and II Phase simulations were performed in MATLAB R2017a. The MILP optimization was done in IBM ILOG CPLEX Optimization Studio 12.7.1 using YALMIP. The computational efficiency of the model is achieved by considering the system state probabilities above 10^5. The III Phase calculations were conducted in BayesiaLab software.

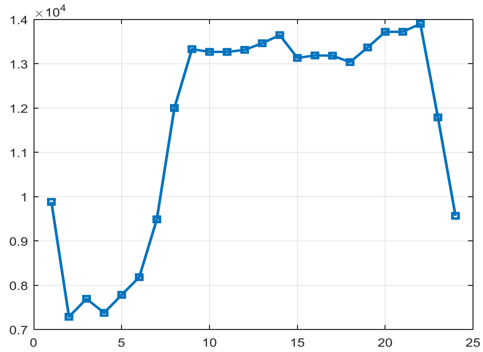

Figure 4: Total costs of reserve schedule calculated for the test system.

Table 4 represents the results obtained by the models. In this table CP represents conventional probabilistic model, whereas P represents the proposed model.

Table 4: Simulation results.

Day	CP	P	Day	CP	P
1	256	254	11	269	266
2	268	266	12	265	265
3	262	261	13	244	246
4	254	251	14	252	248
5	265	266	15	261	261
6	250	250	16	240	242
7	269	264	17	249	249
8	246	246	18	267	264
9	256	255	19	245	244
10	262	262	20	259	254

According to the simulation results, the proposed algorithm outperformed the conventional probabilistic reserve estimation model. The adjustments made by the proposed model resulted in 11 reserve schedules that were on average 1.05% cheaper than that of conventional probabilistic model. It's worth noting that out of 20 simulations 6 (30%) produced totally similar results. This can be explained by the fact that there are relatively fair number of scenarios that end up in unchanged reserve schedule.

4 CONCLUSION

A probabilistic model to estimate the spinning reserves in multi-connected systems with a BN-based spinning reserve rescheduling algorithm was discussed. The model accounts for random outages of conventional units as well as load and renewable forecast errors. Random unavailability of generating capacity was modeled through a two-state Markov process. The load and renewable forecast errors were modeled assuming that they are normally distributed. The model considers the interconnected capacity of multiple energy systems through utilization of the equivalent assisting multi-state unit approach. The two-stage unit commitment problem was formulated such that the mixed integer linear program could be applied to conduct the optimization. Furthermore, to minimize the total cost associated with spinning reserve schedule the BN-based reserve rescheduling algorithm was implemented. The algorithm takes into account actual net demand, forecasted reserve requirement of previous and next hours as well as the day and hour types. The objective of the algorithm is to perform reserve rescheduling if significant deviations in actual versus predicted net demand have occurred or there is a big difference between reserve requirements of adjacent hours.

The proposed model was evaluated on the energy system of Pavlodar, Kazakhstan. The goal of the case study was to estimate the performance of the proposed model by comparing it to the conventional probabilistic reserve estimation model that is based on the cost-benefit analysis. The test was conducted for 20 different days almost equally representing three groups (weekdays, weekends and holidays). The results show that 11 (55%) out of 20 simulations resulted in reserve schedules that were on average 1.05% cheaper compared to those obtained by conventional probabilistic reserve estimation model.

ACKNOWLEDGEMENTS

This work was supported by NUIG Grant funded by Nazarbayev University.

REFERENCES

Whiteman, J. Esparrago, and T. Rinke. 2017. *Renewable Energy Statistics 2017*, Abu Dhabi, The International Renewable Energy Agency.

International Energy Agency. 2017. *World Energy Outlook 2017*, Paris, France. [Online]. Available: https://www.iea.org/weo2017/

Billinton, R., and Allan, N. R. 1996. *Reliability Evaluation of Power Systems*, 2nd ed., New York: Plenum.

Morales, J. M., Conejo, A. J., Madsen, H., Pinson, P., and Zugno, M. 2014. *Integrating Renewables in Electricity Markets: Operational Problems*, vol. 205, New York: Springer.

Grigsby, L., Power Systems. 2013. *Electric Power Engineering Handbook*, 3rd ed., CRC Press.

Zarikas V., Tursynbek N., *Intelligent Elevators in a Smart Building*, FTC 2017 - Future Technologies Conference 2017. 29-30 November 2017. Vancouver, BC, Canada.

Bouffard, F., and Galiana, F. 2004. *An electricity market with a probabilistic spinning reserve criterion*, IEEE Trans. Power Syst., vol. 19, no. 1, pp. 300–307.

Chattopadhyay, D., and Baldick, R. 2002. *Unit commitment with probabilistic reserve*. In IEEE Power Engineering Society Winter Meeting, New York, NY, USA.

Ortega-Vazquez M., and Kirschen, D. 2009. *Estimating the spinning reserve requirements in systems with significant wind power generation penetration*. IEEE Trans. Power Syst., vol. 24, no. 1, pp. 114-124.

Liu, G., and Tomsovic, K., 2012. *Quantifying Spinning Reserve in Systems With Significant Wind Power Penetration*. IEEE Trans. Power Syst., vol. 27, no. 4, p. 2385–2393.

Bapin, Y., Mussard, M., and Bagheri, M. 2018. *Estimation of Operating Reserve Capacity in Interconnected Systems with Variable Renewable Energy Using Probabilistic Approach.* In 18th Conference on Probabilistic Methods Applied to Power Systems, Boise, ID, USA. IEEE Xplore.

Yu, D., Nguyen, T., Haddaway, P. 1999. *Bayesian network model for reliability assessment of power system*. IEEE Transaction on Power Systems, vol. 14, no. 2, pp. 426-432.

Limin, H., Yongli, Z., Gaofeng, F. 2002. *Reliability Assessment of Power Systems by Bayesian Networks*. In Powercon'02. International Conference on Power System Technology. IEEE Xplore.

Yongli, Z., Limin, H., Liguo, Z., Yan, W. 2008. *Bayesian Network Based Time-sequence Simulation for Power System Reliability Assessment*. In MICAI'07. 7th Mexican International Conference on Artificial Intelligence. IEEE Xplore.

Dechter, R., 1996. *Bucket Elimination: A Unifying Framework for Probabilistic Inference*. In UAI'96. 12th Conference on Uncertainty in Artificial Intelligence.

Ebrahimi, A., Daemi, T. 2009. *A novel method for constructing the Bayesian network for detailed reliability assessment of power systems*. In EPECS'09. 1st International Conference of Electric Power and Energy Conversion Systems. IEEE Xplore.

C. W. Watchorn, *The Determination and Allocation of the Capacity Benefits Resulting from Interconnecting Two or More Generating Systems*, Transactions of the American Institute of Electrical Engineers, vol. 69, no. 2, p. 1180–1186, Jan. 1950.

David, E., van den Herik, H., J., Koppel, M., Netanyahu, N., S. 2014. *Genetic Algorithms for Evolving Computer Chess Programs*. IEEE Transactions on Evolutionary Computation, vol. 18, no. 5, pp.779–789.

Van den Werf, E., C., D., van den Herik, H., J., Uiterwijk, J., W., H., M. 2003. Solving Go On Small Boards. ICGA Journal, vol. 26, no. 2, pp.92–107.

Eleftheriadou A, Deftereos S, Zarikas Vasilios, Panagopoulos G, Korres S, Sfetsos S, Karageorgiou C, Ferekidou E, Kandiloros. 2009. *Test - retest Reliability. VEMP eliciting in normal subjects. Normative data of Vestibular Evoked Myogenic Potential Stimulation (VEMPS) in a large healthy population*, J Otolaryngol Head Neck Surg., vol. 38, no .4, pp. 462-473.

Deltsidou, A., Zarikas, V., Mastrogiannis, D., Kapreli, E., Bourdas, D., Papageorgiou, E., Raftopoulos, V., Noula, M., Lambadiari, M. and Lykeridou, K., 2017. *Reliability analysis of Finometer and AGE-Reader devices in a clinical research trial*. International Journal of Reliability and Safety, vol. 11, no. 1-2, pp.78-96.

Calabria, F.A., Saraiva, J.T. and Rocha, A.P., 2015. *A new electricity market design for power systems with large share of hydro: Improving flexibility and ensuring efficiency and security in the Brazilian case*. 2015 IEEE Eindhoven PowerTech.

Steels, L. and Hanappe, P., 2008. *Peer-to-peer transaction-based power supply methods and systems*. US 2008/0269953 A1

Craciun, M. et al., 2017. *Bayesian Networks Applications in Power System Engineering. A Review*. Journal of Sustainable Energy, vol. 8, no. 3, pp.99–105.

Zarikas, V., 2007. *Modeling decisions under uncertainty in adaptive user interfaces*. Universal Access in the Information Society, vol. 6, no. 1, pp.87-101.

Jensen, F.V. and Graven-Nielsen, T., 2011. *Bayesian networks and decision graphs*, New York: Springer.

Pearl, J., 2005. *Casuality: models, reasoning, and inference*, Cambridge: Cambridge University Press.

Allan, R.N., Billinton, R. and Abdel-Gawad, N.M.K., 1986. *The IEEE Reliability Test System - Extensions to and Evaluation of the Generating System*. IEEE Power Engineering Review, PER vol. 6, no. 11, pp.24–24.

Zarikas, V., Papageorgiou, E. and Regner, P., 2015. *Bayesian network construction using a fuzzy rule based approach for medical decision support*. Expert Systems, vol. 32, no. 3, pp.344-369.