Electrical Power and Energy Systems 43 (2012) 474–480

Contents lists available at SciVerse ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

# Constructing the Bayesian Network for components reliability importance ranking in composite power systems

T. Daemi [a,*], A. Ebrahimi [a], M. Fotuhi-Firuzabad [b]

[a] Department of Electrical & Computer Engineering, Isfahan University of Technology, Isfahan, Iran
[b] Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran

ARTICLE INFO

*Article history:*
Received 7 March 2011
Received in revised form 5 May 2012
Accepted 1 June 2012
Available online 5 July 2012

*Keywords:*
Bayesian Network
Power system reliability
Monte Carlo simulation
Component importance ranking

ABSTRACT

In this paper, Bayesian Network (BN) is used for reliability assessment of composite power systems with emphasis on the importance of system components. A simple approach is presented to construct the BN associated with a given power system. The approach is based on the capability of the BN to learn from data which makes it possible to be applied to large power systems. The required training data is provided by state sampling using the Monte Carlo simulation. The constructed BN is then used to perform different probabilistic assessments such as ranking the criticality and importance of system components from reliability perspective. The BN is also used to compute the frequency and duration-based indices without time sequential simulation based inferences. The proposed approach provides the possibility of assessing the components importance in view of different load points.

The validity and efficiency of the proposed approach is verified by application to the IEEE-Reliability Test System (RTS).



## 1. Introduction

The common purpose of power system reliability studies is to provide probabilistic analysis to determine various reliability indices to evaluate the adequacy of power system in supplying the total load. However, analyzing the effect of individual components in system reliability and ranking is also of high importance for a variety of purposes such as determining the background of outages, system reinforcement, maintenance scheduling, and expansion planning and so on, all performed to improve system reliability.

Bayesian Network is one of the most efficient probabilistic graphical models to represent uncertain information and inferences thereof. BNs have found wide applications in many fields and they especially have been used in power system studies [1–3]. BNs have recently been used as an appropriate probabilistic framework in reliability studies. Various applications of the BN are also reported in power system reliability assessments.

The first step in applying the BN in system study involves determining its structure and parameters. BN is mainly utilized for reliability assessment of generating systems [4] as well as power distribution systems [5–10]. In [11], the BN is used in reliability assessment of a small composite power system constructed on the basis of the system's physical topology interpreted by its fault tree and minimal cut-sets or tie-sets. Refs. [6–9] present methods based on time sequential simulation technique to perform inferences by the BN to compute frequency and duration based indices. A D–S evidence inference method with Bayesian Network is employed in [10] for reliability evaluation of distribution system in the case of lack of original data. This approach considers the impacts of uncertain information on the system reliability.

In these studies, the BN is constructed on the basis of expert beliefs, cause-and-effect relationships, and physical topology of systems. Particularly, constructing the BN associated with the composite power systems necessitates access to the fault tree, minimal cut-sets or tie-sets of the given system. But for a composite power system with a generally non-radial topology, identification of minimal cut-sets or tie-sets or constructing the fault tree of system, especially with regard to the different operational conditions in the system is not practical. In [12], the common structure learning algorithms were used to construct the BN for a power system with a relatively large burden of computation.

In this paper, a simple approach based on the learning capability of the BN from data is proposed to construct the BN associated with a composite electric power system. The required training data is generated by state sampling using the Monte Carlo simulation. The obtained BN is then used for importance ranking of individual system components, computation of frequency and duration-based reliability indices and to perform other probabilistic assessments that may not be easily handled by the conventional methods.

The rest of this paper is organized as follows. In Section 2, the BN is briefly introduced. The approach used for data generation

* Corresponding author. Tel.: +98 351 8280118; fax: +98 311 3912451.
*E-mail address:* t.daemi@ec.iut.ac.ir (T. Daemi).

0142-0615/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.ijepes.2012.06.010

**Nomenclature**

*Abbreviations*

| | |
|---|---|
| BN | Bayesian Network |
| MSMC | Multi-states Systems with Multi-states Component |
| FOR | Forced outage rate |
| CPD | Conditional probability distribution |
| P(.) | Probability |
| SF | System Failure event |
| $S^i$ | System state in the $i$th simulation (in sample $i$) |
| $e_j$ | Failure event of the component $j$. |
| $Bus_j$ | Loss of load event in bus $j$ and its corresponding node in BN |
| $\mathbf{T(S^i)}$ | Line flow vector under system state $S^i$ |
| $T^{\max}$ | Maximum capacity limit vector for the line flows $T(S^i)$ |
| $A(S^i)$ | Relation matrix between line flows and power injections under state $S^i$ |
| **PG** | Generation vector |
| **PD** | Load vector |
| NG | The set of generator buses |
| ND | The set of load buses |
| **C** | Load curtailment vector |
| **W** | Weighting factor vector related to a specified load shedding policy |
| $MI(X, Y)$ | Mutual Information between variables $X$ and $Y$ |
| *LOLP* | Loss of load probability |
| LOLF | Loss of load frequency |
| DIF | Diagnostic Importance Factor |
| $\lambda_{jl}$ | Transition rate form state $j$ to $l$ |
| $\mu$ | Repair rate |

is presented in Section 3. A method to construct the BN is proposed in Section 4 and then it is applied to the IEEE-RTS in Section 5. In this section, the obtained BN is used for different inferences and components ranking from different aspects. The paper is concluded in Section 6.

## 2. Bayesian Network

A Bayesian Network is a graphical probabilistic model consisting of two parts; the structure and the parameters. The structure of BN is a directed acyclic graph (DAG) which its nodes are related to random variables and directed arcs from parent to child representing influential and casual relationships between variables. The BN parameters are conditional probability distributions (CPDs) assigned to the nodes that define probabilistic relationship between each node and its parents. The nodes without parents, named roots, are described with their marginal probability distributions. The nodes without any child are known as leaf nodes [13].

The structure and parameters of a BN are such that it defines a unique joint probability distribution over variables and so it lifts the need for a joint probability distribution table of variables whose size increases super-exponentially when the number of variables increases. It is possible to compute any conditional and marginal probability of events by using different inference algorithms from the BN [14].

## 3. Generation of training data

As mentioned earlier, to construct the BN by the proposed approach, a training data set is required. The data set consists of state vectors $\boldsymbol{S} = [\boldsymbol{G_1}, \ldots, \boldsymbol{G_{ng}}, \boldsymbol{L_1}, \ldots, \boldsymbol{L_{nl}}, \boldsymbol{Bus_1}, \ldots, \boldsymbol{Bus_m}, \boldsymbol{SF}]$ where $G_i$ denotes the $i$th set of similar generators placed on the same bus considered as a derated generating unit and its value is equal to the number of its related generators in failure states. $L_i$ denotes the state of transmission line or power transformer $i$ and is equal to one if it is in the failed state, otherwise it is zero. *SF* represents the loss of load in the system. It is one unless the total load of the system is supplied in which case is zero. Variable $Bus_k$ is similar to *SF*, however it is devoted to load point $k$. The value of $Bus_k$ is equal to zero if the total load of bus $k$ is supplied; otherwise, it equals to one. $ng$, $nl$ and $m$ are the number of derated generating units, transmission system components and load points, respectively.

The training data is provided by state sampling using MC simulation [15]. The steps to generate the data can be summarized as:

1. The state of each component is determined by generating uniformly distributed random number $U_j$ within [0–1] and it is then compared with component forced outage rate (FOR). If $U_j$ is smaller than the FOR value of component $j$, the component is in outage state and the state of component $j$, denoted by $e_j$, is equal to one. Otherwise, the component is in the normal state and $e_j$ equals zero.

Based on the value of $e_j$ for all components, the values of variables $G_k$ and $L_k$ in vector $\boldsymbol{S}$ are determined. If for all of the components, $e_j$ is equal to zero, the system is in the normal state and the values of all variables *SF* and $Bus_i$ equal to zero. If at least the value of a variable $e_j$ is equal to one, the system is in a contingency state and the adequacy of system in supplying the load should be evaluated in the next step.

2. In contingency states, some corrective actions such as generation rescheduling, transformer tap adjustment, shunt capacitor switching and load shedding may be taken to maintain the generation-demand balance, alleviate line overloads and satisfy the system constraints. In this paper, generation rescheduling and load shedding are considered as the corrective actions. In this way, the following linear optimization load flow model is used [16]:

$$
\begin{aligned}
&\min \sum_{i \in NC} W_i C_i \\
&s.t.\,\mathbf{T}(\mathbf{S}^i) = \mathbf{A}(\mathbf{S}^i)(\mathbf{PG} + \mathbf{C} - \mathbf{PD}) \\
&\sum_{j \in NG} PG_j + \sum_{j \in NC} C_j = \sum_{j \in NC} PD_j \\
&\mathbf{PG}^{\min} \leqslant \mathbf{PG} \leqslant \mathbf{PG}^{\max} \\
&\mathbf{0} \leqslant \mathbf{C} \leqslant \mathbf{PD} \\
&|\mathbf{T}(\mathbf{S}^i)| \leqslant \mathbf{T}^{\max}
\end{aligned}
\tag{1}
$$

Although the load shedding policy does not affect the reliability indices of the overall system, it greatly affects the reliability assessment of a power system from the viewpoint of load buses [17]. In this model, some load curtailment policies can be incorporated in the model by using the weighting factors $W_i$. The load shedding policy used here is to curtail the loads at the buses that are more close to the element(s) on outage. The purpose of this load shedding policy is to localize the severity of an event within the area in which the component(s) failure occurs.

Based on the results obtained using the above optimization model for the load curtailment vector, **C**, the value of variables $Bus_j$ and *SF* are determined. It should be mentioned that in this study,