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Evaluation of Components Reliability Importance Measures of Electric Transmission Systems Using the Bayesian Network

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Abstract In this article, a novel approach is presented for the determination of reliability importance measures in electric transmission systems implementing the Bayesian network. By this method, the Bayesian network associated with a given power system is first constructed where the generation units are assumed fully reliable and the required training data is provided by using the state sampling method of Monte Carlo simulation. When the Bayesian network is constructed, it is readily used to determine the various reliability importance measures and to investigate their physical interpretations for the proposed transmission system.

Keywords Bayesian network, component reliability importance measure, transmission system

1. Introduction

Component importance measures quantify the impact of components failure and are valuable for identifying system weaknesses and prioritizing reliability improvement activities and, thus, detailed reliability assessments. These measures, if readily available, may be used for a variety of purposes, such as determination of the outages background, improvement of the operating methods, system reconfiguration, maintenance scheduling, expansion planning to improve system reliability, and so on.

Two groups of measures are usually defined—structural importance (SI) [1, 2] and reliability importance (RI) [3, 4]. The former measures represent the importance of a component to the system operation by virtue of its position in the system without considering the reliability of the component, while the latter considers both the component’s position and its reliability and provide more information [5]. This article focuses on the RI measures.

Component importance measures are also applied to electric power system analysis [4, 6–13]. These measures may relate the overall system reliability, cost of customer interruption, maintenance, etc. to the system structure and individual component reliability. Some approaches were presented in [6, 7] to rank the components of the high-voltage transmission station and customer delivery systems, respectively, based on frequency and duration indices. Some importance indices were proposed in [8, 9] for defining the...
importance of individual components in an electrical network with respect to the total interruption cost. In [10], a probabilistic approach was presented for ranking various components of a bulk transmission system in the deregulated environment based on the cost of supplied and unsupplied energy. New measures of component importance for all-digital protection systems were proposed in [11], which related the total cost consisting of both manufacturing and failure costs to the component failure rate. Some RI measures for electric transmission systems were proposed in [12] that related the overall system reliability to the failure rate of components. These measures are applied to some common electrical station configurations.

Calculation of RI measures in all of the above-mentioned references is based on analytical expressions, minimal cut sets, or fault trees of the given system. But providing these analytical models for a complex system, such as a relatively large transmission system, is not a simple task. In [13], Monte Carlo (MC) simulation was used to calculate RI measures of complex systems, and some new RI measures were introduced. Using MC simulation was also suggested for obtaining the RI measures of multi-state systems with multi-state components in [14, 15]. By this approach, it is necessary to run the MC simulation many times to compute various RI measures of each component individually, which is computationally expensive and time consuming.

RI measures relate the overall system reliability to individual component states in failure or operation modes. In this article, RI measures are defined based on availability, and so they are related to conditional probabilities describing the system and its components in different operation modes. In this article, the Bayesian network (BN) as an appropriate probabilistic graphical model will be used efficiently to evaluate various marginal and conditional probabilities required in probabilistic analysis and different inferences. In this study, the BN associated with the power system is constructed and used to compute RI measures for transmission system components.

The rest of this article is organized as follows. In Section 2, some component RI measures are reviewed, and their physical interpretation is presented; it is also shown that all these measures can be presented based on the conditional and marginal probabilities that can easily be obtained from the BN. An introduction to the BN and the approach of its construction are briefly presented in Section 3. RI measures are obtained for the IEEE reliability test system (RTS) in Section 4, and they are compared with actual values obtained directly from simulation. Finally, the conclusion is presented in Section 5.

2. Component RI Measures

Different RI measures are proposed for ranking components according to their importance in the system. In Table 1, the definitions of some of the most important RI measures are presented that relate the overall system reliability to the system structure and individual component reliabilities [2, 3, 16]. In the definition of these measures, \( S \) denotes the failure event of the system, \( e_k \) denotes the failure event of the \( k \)th component, and \( \overline{e_k} \) is the complement event of \( e_k \).

It is worth noting that all these importance measures are basically dependent to the time \( t \) at which the system and its components are observed. Due to the relatively long life times of power system components, their failure rate can be assumed constant over short periods. Thus, in this article, unreliability is replaced with unavailability in definitions of RI measures, and so their dependency on time is omitted. In the following, \( P(S = 0) \) and \( P(e_k = 0) \) denote the long-run unavailability of system and component \( k \), respectively.
### Table 1
Definition of certain RI measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Formula</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birnbaum measure (BM)</td>
<td>$I_{BM}^k = \frac{\partial P(S = 0)}{\partial P(e_k = 0)}$</td>
<td>Gives an indication of how system unavailability will change with changes in component unavailability</td>
</tr>
<tr>
<td>Critically importance factor (CIF)</td>
<td>$I_{CIF}^k = \frac{P(e_k = 0)}{P(S = 0)} I_{BM}^k$</td>
<td>Is an extension of the BM that includes component failure; thus, a less reliable component is more critical</td>
</tr>
<tr>
<td>Diagnostic importance factor (DIF)</td>
<td>$I_{DIF}^k = P(e_k = 0</td>
<td>S = 0)$</td>
</tr>
<tr>
<td>Risk achievement worth (RAW)</td>
<td>$I_{RAW}^k = \frac{P(S = 0</td>
<td>e_k = 0)}{P(S = 0)}$</td>
</tr>
<tr>
<td>Risk reduction worth (RRW)</td>
<td>$I_{RRW}^k = \frac{P(S = 0)}{P(S = 0</td>
<td>e_k = 1)}$</td>
</tr>
</tbody>
</table>

#### 2.1. Representation of RI Measures on the Basis of Conditional Probabilities

As it is observed in Table 1, the calculation of all the mentioned measures, except the Birnbaum, are directly related to the marginal or conditional probabilities. The Birnbaum measure (BM) is the partial differentiation of the system unreliability with respect to the probability of component failure. Having said this, $P(S)$ can be written as

$$P(S) = P(S | e = 0)P(e = 0) + P(S | e = 1)(1 - P(e = 1)),$$

(1)

and so,

$$I_{BM}^k = \frac{\partial P(S = 0)}{\partial P(e_k = 0)} = \Pr[S = 0 | e = 0] - P(S = 0 | e = 1).$$

(2)

Therefore, all the above RI measures are related to conditional and marginal probabilities that can be easily computed using the BN associated with the given system that will be described in the next sections.

#### 2.2. Physical Interpretation of RI Measures

RI measures may provide different rankings for the system components. So, their physical interpretations should be considered to employ them correctly. Generally, RI measures may indicate the following aspects [14]:

- **Birnbaum Measure (BM)**: Indicates the increase in system unavailability when a given component, say component $k$, fails.
- **Critically Importance Factor (CIF)**: Indicates the fraction of system unavailability that involves the component failure.
- **Diagnostic Importance Factor (DIF)**: Indicates the decrease in system unavailability when a given component, say component $k$, never fails.
1. the potential for reliability improvement and risk reduction that would be useful for studies aiming to determine which components should be upgraded or replaced with a newer and more reliable one,
2. the worst-case events that may be appropriate to select components for inspection or for preventive maintenance, and
3. the sensitivity of system reliability to component reliability that is valuable in designing a system that is robust and non-sensitive to its components

With attention to the definitions of RI measures presented in Table 1 and according to the above discussions, the risk reduction worth (RRW) is appropriate to replace or upgrade components for reliability improvement and the diagnostic importance factor (DIF) and risk achievement worth (RAW) may be used for inspection and preventive maintenance. In [17], the RAW is used as one of the measures to identify potentially safety-significant components for reliability centered maintenance (RCM). However, the DIF measure is more suitable for this purpose [5]. This priority is due to the relation in Eq. (3) that holds between these two measures:

\[ I_{DIF}^k = P(e_k = 0 | S = 0) = \frac{P(S = 0 | e_k = 0)P(e_k = 0)}{P(S = 0)} \]

Therefore, the failure probability of component \( k \) is also included in the definition of DIF measure, and so it is more appropriate and informative.

The BM can be interpreted in different ways.

1. The BM is the rate of increasing system unreliability to increasing component unreliability. This measure can, therefore, be used to develop a robust system where its reliability is not sensitive to any component [14].
2. The BM of a component (say, component \( k \)) represents the probability that a system is in a critical state with respect to that component; i.e., it indicates the probability that the failure of component \( k \) causes the system to fail, whereas the system is initially in the desired working state [18].
3. According to Eq. (2), the BM may be expressed as a difference of system failure probability while the component fails and the probability of system failure while it operates. Thus, this measure indicates the criticality of the component for system operation from the structural point of view [3].

A weakness of the BM is that it does not depend on component reliability. The critically importance factor (CIF) measure is an extension of the BM that includes component unreliability. So, on the basis of CIF measure, a less reliable component is more critical [12].

3. **BN and Its Construction**

3.1. **BN**

A BN is a graphical probabilistic model consisting of two parts: structure and parameters. The structure of BN is a directed acyclic graph (DAG), the nodes of which are related
to random variables and directed arcs (from parent to child) represent influential and casual relationships between variables. The BN parameters are conditional probability distributions (CPDs) assigned to the nodes. The parameters define the probabilistic relationship between each node state with different states of its parents. The nodes without parents are described with their marginal probability distributions [18].

The structure and parameters of a BN is such that it defines a unique joint probability distribution of variables; thus, it lifts the need for a joint probability distribution table of variables whose size increases super-exponentially when the number of variables increases.

The structure and parameters of the BN associated with a given system may be generally specified by expert belief or casual relations between the system variables, or they may be obtained from employing different structure and parameter learning algorithms. When the number of system variables is too large, such as for large power systems, using the former approach is not so simple. In this article, the learning possibility of the BN from data is used for constructing the BN, and so a training data base is required.

3.2. Generation of Training Data

The training data is obtained from the state sampling method of MC simulation. In this way, it is assumed that every system component \( L_i \) has two states of operation and failure. The components considered are transmission lines and power transformers. The dataset for a system with \( n \) components and \( m \) load buses in each sample is considered as a vector of \([L_1, \ldots, L_n, Bus_1, \ldots, Bus_m, LOL] \). In this vector, variable \( Bus_j \) represents the ability of system in supplying the load of bus \( j \), and \( LOL \) indicates loss of load event in the whole of the system.

To specify the state vector of system, a uniformly random number is generated for each component, and by comparing it with the component forced outage rate (FOR), the state of components and, thus, the value of variables \( L_j \) are determined. If any component is in outage, the system is in a contingency state, and its adequacy in supplying the load should be evaluated. A DC optimal power flow model is used for adequacy evaluation of sampled states and specifying the value of variables \( Bus_j \) and \( LOL \). In this model, generation rescheduling and load shedding are considered to be corrective actions in contingency states, taking into account (considering) the branch flow and real power generation constraints. It should be noted that this study is performed for a specified load scenario.

Reliability of transmission system components is usually much higher than generating units, and so, generating units are almost the main cause of loss of load in stochastic contingency analysis. Therefore, the effect of transmission components due to their higher reliability is not considered properly in a composite system reliability assessment. To obtain more accurate results from the transmission system analysis, the generating components are assumed perfectly reliable. It means that the FOR values of generating units are assumed to be zero.

High reliability of transmission system components induces the need for a very large number of samples. To speed up the simulation convergence and also to achieve a more accurate model of the BN, importance sampling (IS) is employed. IS is a procedure for changing the probability density function of sampling in such a way that the events with greater effects on the simulation results have greater occurrence probabilities. Using IS provides a weighted training dataset. This concept was explained in detail in [19].
3.3. Constructing the BN

To construct the BN, an initial structure is assumed for the BN, as shown in Figure 1. Based on this structure, components nodes are parents of load point nodes, and the load points nodes are parents of the loss of load node. It is clear that all components do not have the same significance on different load points. To remove the edges between nodes with lower dependency, mutual information (MI) is used. MI is a criterion to measure the dependency of variables, and for variables $X$ and $Y$, it is defined as

$$MI(X; Y) = \sum_{x,y} \hat{P}(X, Y) \log \frac{\hat{P}(X, Y)}{\hat{P}(X)\hat{P}(Y)},$$

(4)

where $\hat{P}$ represents the observed frequency of samples in the dataset. The effect of weighting factors of samples can easily be inserted in computation of $\hat{P}$, required in the relation in Eq. (4), and also for specifying the BN parameters.

When the BN is constructed, it can easily be used to compute any conditional and marginal probability of events by using different inference algorithms [20]. In this article, the approach to construct the BN has been programmed in MATLAB (The MathWorks, Natick, Massachusetts, USA), and the bucket elimination algorithm implemented in BN toolbox (BNT) [21] is used for inference from the BN.

It should be noted that the obtained BN will not necessarily consist of all of components and load points; rather, the most critical and most important of them will be in the BN. So, it is not possible to assess the effects of components that are not in the BN on system reliability, although, as it is clear and will be shown, their importance, compared to other components, is rather negligible. So, it can be concluded that in highly reliable systems that have less critical components, the BN will be simpler. The procedure proposed for construction of the BN was explained in more detail in [19].

4. Case Study

In this section, the RI measures are computed for the IEEE RTS. This power system (shown in Figure 2) consists of 24 buses (including 17 load buses), 32 generating units, 33 transmission lines, and 5 transformers [22]. In this study, the system is analyzed for
the peak load condition. It was observed that the generation of training data using the MC simulation takes about 220 sec. The time for constructing the BN was about 1.5 sec, and it was obtained as shown in Figure 3. It should be noted that the stages of providing training data and constructing the BN are only executed once; the BN may then be used for different inferences many times. This figure shows that some load buses do not appear in the BN. This is because of the high reliability of these load points due to the existence of local generation or multiple power lines connected to them. Also, some lines, such as lines 1, 24, 25, 26, 32, and 33, do not appear in the BN. Figure 2 declares the reason as the existence of multiple parallel paths for these lines.

As previously mentioned, any probability of the events occurring in the power test system may be specified by using different inference algorithms. With attention to the definitions of considered RI measures in this article, it is observed that they are based

Figure 2. One-line diagram of IEEE RTS.
on some conditional probabilities, such as $P(S = 0 \mid e_k = 0)$ and $P(e_k = 0 \mid S = 0)$, that can easily be obtained by applying inference algorithms on the associated BN.

It was observed that the inference time from the BN is on average less than 1 sec, although it may be much shorter by using more efficient inference algorithms. As it was presented in Section 1, MC simulation is a common approach to obtain RI measures of complex systems, such as electric transmission systems. However, the time of obtaining these probabilities by MC simulation, even with low precision, is much larger.

In the next subsection, the results obtained for these RI measures are presented, and their accuracy is verified.

4.1. Component Ranking Based on Different Component RI Measures

The RI measures calculated for transmission system components of the RTS and their ranking are shown in Table 2, in which the first 15 important components are shown. Table 2 indicates that line 11 is the most critical component from the viewpoint of all RI measures. Note that this line is the only path for supplying the load of bus 7, and its outage certainly causes loss of load.

From the values of the RRW, it can be concluded that except for line 11, improving the reliability of other components does not have any significant effect on the system reliability. Considering the very low FOR values for components, this result is admissible. So, for more improvement in the system reliability, other actions, such as reconfiguration or system expansion, would be considered.

As it was mentioned earlier, either the RAW or DIF may be used to select components for inspection or for preventive maintenance, although the DIF is more suitable. Therefore, after line 11, components 7, 2, 6, 10, 5, and 27 have higher priorities for preventive maintenance.

According to the rankings based on the BM, components 2, 6, and 5, following line 11, are structurally more important, and they should be more attended in order to design a robust system due to the changes in the unreliability of components. If the failure
Table 2
RI measures for transmission system components of RTS

<table>
<thead>
<tr>
<th></th>
<th>BM</th>
<th>CIF</th>
<th>DIF</th>
<th>RAW</th>
<th>RRW</th>
</tr>
</thead>
<tbody>
<tr>
<td>L11</td>
<td>0.999997</td>
<td>L11</td>
<td>1.12614</td>
<td>L11</td>
<td>0.987</td>
</tr>
<tr>
<td>L2</td>
<td>0.002248</td>
<td>L7</td>
<td>0.00632</td>
<td>L7</td>
<td>0.00807</td>
</tr>
<tr>
<td>L6</td>
<td>0.002247</td>
<td>L2</td>
<td>0.00430</td>
<td>L2</td>
<td>0.00503</td>
</tr>
<tr>
<td>L5</td>
<td>0.001297</td>
<td>L6</td>
<td>0.00405</td>
<td>L6</td>
<td>0.00419</td>
</tr>
<tr>
<td>L7</td>
<td>0.001098</td>
<td>L10</td>
<td>0.00217</td>
<td>L10</td>
<td>0.00344</td>
</tr>
<tr>
<td>L27</td>
<td>0.001097</td>
<td>L5</td>
<td>0.00190</td>
<td>L5</td>
<td>0.00264</td>
</tr>
<tr>
<td>L13</td>
<td>0.000503</td>
<td>L27</td>
<td>0.00186</td>
<td>L27</td>
<td>0.00231</td>
</tr>
<tr>
<td>L23</td>
<td>0.000503</td>
<td>L13</td>
<td>0.00083</td>
<td>L17</td>
<td>0.00178</td>
</tr>
<tr>
<td>L12</td>
<td>0.000502</td>
<td>L12</td>
<td>0.00083</td>
<td>L16</td>
<td>0.00177</td>
</tr>
<tr>
<td>L10</td>
<td>0.000500</td>
<td>L19</td>
<td>0.00081</td>
<td>L14</td>
<td>0.00175</td>
</tr>
<tr>
<td>L19</td>
<td>0.000500</td>
<td>L23</td>
<td>0.00079</td>
<td>L15</td>
<td>0.00175</td>
</tr>
<tr>
<td>L8</td>
<td>0.000400</td>
<td>L4</td>
<td>0.00058</td>
<td>L12</td>
<td>0.00133</td>
</tr>
<tr>
<td>L9</td>
<td>0.000400</td>
<td>L8</td>
<td>0.00054</td>
<td>L13</td>
<td>0.00133</td>
</tr>
<tr>
<td>L3</td>
<td>0.000399</td>
<td>L9</td>
<td>0.00051</td>
<td>L23</td>
<td>0.00133</td>
</tr>
<tr>
<td>L4</td>
<td>0.000399</td>
<td>L3</td>
<td>0.00049</td>
<td>L19</td>
<td>0.00132</td>
</tr>
</tbody>
</table>

probability of a component is attended, as it is considered in the CIF measure, a different ranking will result, as shown in Table 2.

In order to verify the obtained RI measures from the BN, they are also computed directly using MC simulation. The comparison of the results for measures of the BM, CIF, DIF, and RAW is shown in Figures 4–7. These figures show that the results obtained easily by the constructed BN of Figure 3 are the same in component ranking and are very close in values to the exact results obtained by the direct simulation method obtained.

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**Figure 4.** BM measures obtained from BN and direct approach. (color figure available online)
with a large amount of computational efforts. This comparison is performed for other RI measures that verify the proposed approach, although it is not shown here.

4.2. Component Ranking from the Viewpoint of Different Load Buses

Some buses in a power system have special loads with a higher order of reliability requirements, and it may be desirable to improve the reliability of these load points. So, it is valuable to rank the components from the viewpoint of a load bus based on different RI measures. For this purpose, it is sufficient to consider the event $S$ in the definitions of RI measures as a loss of load event in that bus. As an example, this analysis is performed for bus 9, and the results are shown in Table 3. It is seen that in terms of all

![Figure 5. CIF measures obtained from BN and direct approach. (color figure available online)](image)

![Figure 6. DIF measures obtained from BN and direct approach. (color figure available online)](image)
RI measures, line 23 is the most critical component for this load bus. Also, it is observed that the rankings on the basis of the RRW and DIF are identical. So this ranking is suitable for inspection and preventive maintenance and also for improving the reliability of this load bus.

5. Conclusion

RI measures quantify the impact of system components failure on the system operation. Different RI measures have different physical interpretations, and so the ranking resulted from these measures may be used for making various decisions, such as reliability improvement actions, preventive maintenance scheduling, or designing a robust system that is not sensitive to variations in component reliability. These actions may be performed for the overall system or may be applied for improving the reliability of certain buses.

The calculation of RI measures is usually based on physical expressions, minimal cut/tie sets, or fault trees of the given system. But implementing these analytical models for a complex and relatively large system is not a simple task. MC simulation is also used to calculate RI measures of complex systems. But by this approach, MC simulation
must be run many times to compute various RI measures of each component, which is very time consuming.

In this article, the BN associated with an electric transmission system is constructed and used for computing its component RI measures. The constructed BN makes it possible to evaluate various importance measures of system components from different aspects, in view of different load points without much computational effort. Importance evaluation of different components in the viewpoint of load buses using MC simulation due to higher reliability of load points is computationally very time consuming.

As a case study, the RI measures of the IEEE reliability test system were computed and analyzed by the proposed method. In order to verify the method, the obtained results for RI measures from the BN are compared with those obtained directly using MC simulation. The comparison shows that the results obtained easily by the BN are the same in components ranking and very close in values to the results obtained by the direct simulation method obtained with a large amount of computational effort.

References


