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Bayesian Network for Composite Power Systems using Hybrid Mutual Information Measure

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B. Abstract

The development of effective reliability-based evaluation approaches for assessment of power system component importance is very crucial in the planning and operational decision-making processes of power systems. Bayesian Network (BN) is one of the most powerful tools that have been used for this purpose. Generally, a BN may be constructed based on expert beliefs, casual-effect, or learning methods. In this chapter as a contribution to the previous literature, a new learning-based hybrid mutual information-oriented measure is developed for constructing the BN model for a Composite Power System (CPS) with emphasis on the involvement of the transmission components. Whilst, in the previous literature, because of the lower failure probability of transmission components compared to generating units, transmission components have not been accurately involved in the BN model. The presented approach is implemented on IEEE 24-bus Reliability Test System. The analysis shows that the constructed BN of the case study based on the proposed hybrid mutual information measure provides the importance evaluation of transmission system components more precisely.

C. Composite power system, Reliability, Transmission, Bayesian Network, Normalized Mutual Information

D. Introduction

Power system reliability issue has been received more attention in the recent years [1, 2]. From the reliability viewpoint, evaluation of the importance measure of power system components is essential in long-and short-term power system decision-making procedures such as, but not limited to, transmission expansion planning, generation expansion planning, maintenance scheduling, and network reinforcement. In recent years, the need for a fast and reliable evaluation technique is receiving more attention due to the higher mutual interactions of different components in the smart grid environment, and in the case of cascading events that lead to blackouts [3]. Two approaches are used for assessing the importance of system components: analytical models and simulation-based approaches. Applying the analytical models such as Reliability Block Diagram (RBD), structure-function, Fault Tree Analysis (FTA), and Markov Modeling for complex systems, such as the CPS, is not effective nor practical. Among simulation based-approaches, Monte Carlo (MC) method has been frequently used in the previous literature [4]. For importance evaluation of each component via MC simulation, the MC procedure should be repeated for large number of iterations. Hence, the evaluation of the importance of components via MC simulation is time-consuming and difficult to be implemented. To tackle this problem, BN is developed. Generally, a BN is a graphical probabilistic model that has been used successfully to study the probabilistic relations between lots of variables in large scale systems. A BN represents the conditional dependencies between a variable set via a Directed Acyclic Graph (DAG) known as BN structure and conditional probability distributions assigned to each node of DAG known as BN parameters. In BN structure, if an edge from node X to node Y exists, X is called as the parent of Y

[5]. BNs have been applied for various areas of power system studies such as fault diagnosis of three-phase inverters [6], reliability assessment of grid-connected photovoltaic systems with intermittent faults [7], incorporating of protection system failures in reliability studies [8], and agent-based modeling of electrical energy markets [9]. In [10], the BN has been used for assessing system resilience and is applied to study an interdependent electrical infrastructure system. In [11], a BN-based unified model has been presented for the performance and reliability study of the radial multi-microgrids.

Two steps should be taken to design an appropriate BN: a) constructing a proper structure for the BN, b) assigning precise parameters to the corresponding nodes: In [12], the BN of the CPS is constructed based on the physical topology of the system and the corresponding fault tree, or the minimal cut-sets. This approach was applied to a small CPS having a simple fault tree. In [13], an approach is employed to determine the minimal cut-sets and then they are used to construct the BN. Since using cut-sets for reliability analysis of systems with multi-state components is not a simple task, implementation of this method in CPS containing multi-state components such as derated generators is not practical for large power systems. Also, incorporation of protection system failures in reliability assessment of CPS, proposed in [8], suffers the same difficulty. Apart from time-consuming problem, in [8, 13], the cut sets of the system are determined in condition of fixed load, while with varying the system load, the cut sets may be changed. In [14], a BN is constructed for a CPS based on a learning approach. However, due to its generality of the employed learning algorithm, a relatively large burden of computation is required. Also in the final structure of the BN, the transmission components do not exist. In [15], to construct the BN, a novel learning-based approach has been adopted for a CPS. In [15], an initial structure is considered for the BN based on the causal relations and then it is modified using the Mutual Information measures between variables. In [16], it has been shown that due to the low failure probability of transmission system components, to reach the BN structure of the electric transmission system, a very large training data set is required that the structure learning becomes difficult. To overcome this problem, in [16] the Importance Sampling (IS) has been used to provide a weighted training data set with lower number of data. Afterwards, to construct the BN, the MI based approach presented in [15] with weighted training data is employed.

In [16], it is shown that by utilizing IS, the BN associated with the only transmission system can be obtained effectively. As the motivation of this research, it is shown in this study that the structure of BN of the power system consisting of both the generation and transmission systems based on MI measure is very sensitive to the threshold value selected for comparing MI values with it. Hence, the BN obtained based on MI measure may not be accurate enough. As it will be shown in this study, the cause of inaccuracy is due to considerable difference between Forced Outage Rate (FOR) of generation and transmission components.

Although transmission system components compared with generating units almost have low failure probabilities, their outages may have constructive effects on reliability of system. In this regard, transmission components need to be accurately involved in the designed BN.

In this study, as a major contribution, a new dependency measure named Hybrid Mutual Information (HMI) measure is developed that is used in the learning-based approach of constructing the BN associated with a CPS which is consisting both transmission and generation sectors. Since transmission components' FOR is low, the number of samples with transmission component outage is low. To have a richer data-set containing the failure of transmission components and with lower number of data, IS is deployed in data generation of MC simulation.

Generally, the structure learning of a BN is a NP-hard problem and different algorithms are proposed for it. But the special learning based approach proposed in [15] simplify constructing the BN associated with power system and it does not require much computational effort. It can be applicable for power systems with complex topologies and it is not required to system cut-sets be identified. Also, the multi state components and variation of load can be considered easily and it can be developed to consider other items in reliability studies of power systems. However, by introducing the HMI measure, while maintaining the advantages of constructing the BN from the learning based approach proposed in [15], a precise analysis of transmission components simultaneous with generation system components is *provided and the effectiveness of the proposed approach is shown in the modified IEEE 24-bus Reliability Test System. Table 1 presents a taxonomy of a few studies related to BN construction for a CPS's reliability studies.*

E. Introducing the HMI measure and its using to construct the BN associated with composite power system

1. The BN Construction Procedure

The procedure for constructing the BN is based on an initial structure. Afterward, it is modified using the BN's possibility of learning from data. MC simulation is utilized for training data set production in a non-sequential way. The procedure to create the BN and using it for reliability analysis of the CPS is briefly presented in Fig.1. In the following, at first the approach to produce training data is reviewed and then the general approach to create the BN is briefly presented [15, 16].

Table 1. Taxonomy of studies related to BN construction for a CPS

	Generation Sector	Transmission Sector	Multi/single state components	BN-construction approach	Possibility of component outage evaluation		Scalability
					Generation	Transmission	
[11]	✓	✗	Single	minimal cut-set	✓	✓	✗
[12]	✓	✓	Single	minimal cut-set/ fault tree	✓	✓	✗
[13]	✓	✓	Single	minimal cut-set	✓	✓	✗
[14]	✓	✗	Multi	typical learning algorithms	✓	✗	✗
[15]	✓	✓	Multi	learning with MI measure	✓	✗	✓
[16]	✗	✓	Multi	learning with MI measure	✗	✓	✓
Proposed approach	✓	✓	Multi	learning with HMI measure	✓	✓	✓

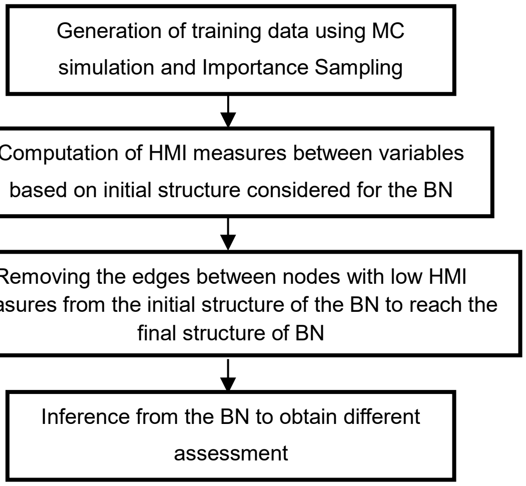

Fig. 1. The procedure to construct the BN with the application for reliability analysis

1.1. Training data Generation

As mentioned in the previous sections, to create the BN, we need a training data set. The training data includes state vectors as $S=[G_1,\ldots,G_{ng},L_1,\ldots,L_{nl},L_{i-j},L_{k-n},\ldots,Bus_1,\ldots,Bus_m,SF]$ *where* G_i *points to the ith set of generation units located on the same bus which are similar. The generating units related to* G_i *variable is considered as a derated generation unit and the value is equal to the number of its related generation units in the failure state.* L_i *is related to the state of the transmission line or power transformer i and its value is equal to 1 if it is in failure state, otherwise, it is zero.* L_{i-j} *denotes parallel transmission components i and j, having the same specification and its value equals the number of corresponding components in outage state. SF variable is devoted to represent the system state in supplying load. Its value equals to zero, unless the loss of load is occurred that it will be one. Variable* Bus_k *is similar to SF; however, it is devoted to the load point k. The value of* Bus_k *is equal to one, if the loss of load is occurred in bus k; otherwise, it is equal to zero.* ng *and* nl *are the numbers of generating units sets and individual transmission system components, respectively. Also, m is the number of load buses. MC simulation is used to generate training dataset. To evaluate and specify the sampled states and the values of variables* Bus_k*'s and SF variables in vector S, DC Optimal Power Flow (OPF) is used. In the OPF model, the branch flow constraints and real power generation limitations are considered. As corrective the actions to establish operational constraints, generation rescheduling and load shedding are applied. To perform a more accurate analysis of the transmission system, as suggested in [16], the IS scheme is used in the data generation stage. Using the IS results in a weighted training data set.*

1.2. BN Construction

The components outage might cause load loss in some load points. Load loss in each bus means the system load loss. So, the initial BN structure based on the independence assumption of the components' outages and the casual relationships between variables is considered as shown in Fig. 2. However, it is clear that all of components do not equally affect all of the load points. In this regard, to identify more critical relations between load points and components, a dependency measure should be used. After the BN structure is specified, the parameters of BN are determined as pointed in [15, 16]. In the next section, a new dependency measure is proposed to identify the effective links between nodes.

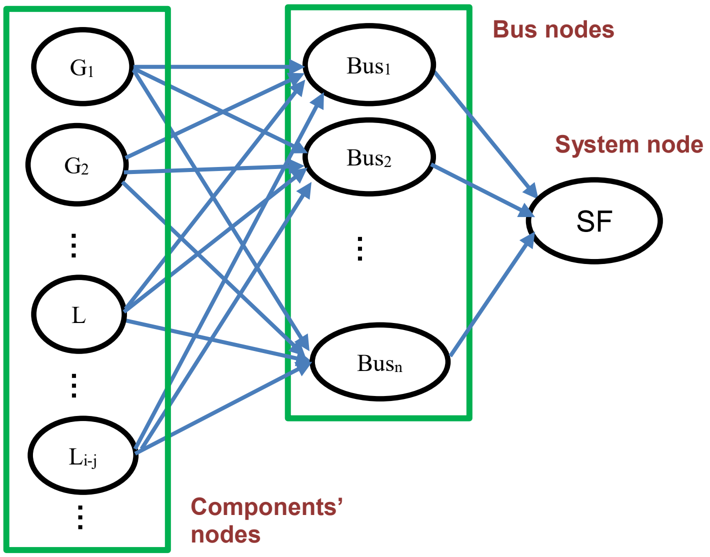

Fig. 2. The initial structure of the BN associated with the CPS

2. Mutual Information and Normalized Mutual Information Measures

One of the simple indices for measuring the dependency between random variables is Mutual Information index. For random variables X and Y with marginal probabilities p(x) and p(y), and joint probabilities p(x, y), MI is defined as:

$$MI\left(X;Y\right)=\sum_{x,y}p\left(x,y\right)\log\frac{p\left(x,y\right)}{p\left(x\right)p\left(y\right)} \qquad (1)$$

MI measure is always non-negative. If X and Y are independent, p(X, Y) = p(X).p(Y) and therefore MI measure is equal to zero. The higher value of MI indicates the stronger dependency between X and Y variables. The Mutual Information can be represented as the following equation in terms of variable entropies [17]:

$$MI\left(X,Y\right)=H(X)-H(X\mid Y)=H(Y)-H(Y\mid X) \qquad (2)$$

where, H(X) is the entropy of variable X that measures the uncertainty on variable X and is defined as

$$H\left(X\right)=-\sum_{x}P(x)\log P(x) \qquad (3)$$

The Mutual Information on the basis of Eq. (2) indicates the uncertainty reduction about X (or Y) through observing of Y (or X). The conditional entropy H(X|Y) is defined as:

$$\begin{aligned}H\left(X\mid Y\right)&=\sum_{y}P(y)H(X\mid y)=\\&=-\sum_{y}P(y)\sum_{x}P(x\mid y)\log P(x\mid y)\\&=-\sum_{x,y}P(x,y)\log P(x\mid y)\end{aligned} \qquad (4)$$

Joint entropy of random variables X and Y is defined as:

$$H(X,Y) = -\sum_{x,y} P(x,y) \log P(x,y) \tag{5}$$

Also, the MI measure is represented as:

$$MI(X,Y) = H(X) + H(Y) - H(X,Y) \tag{6}$$

The relation between MI measures and entropies is shown in Fig. 3., Eq. (6) implies that:

$$0 \leq MI(X < Y) \leq min(H(X), H(Y)) \leq \frac{1}{2}(H(X) + H(Y)) \tag{7}$$

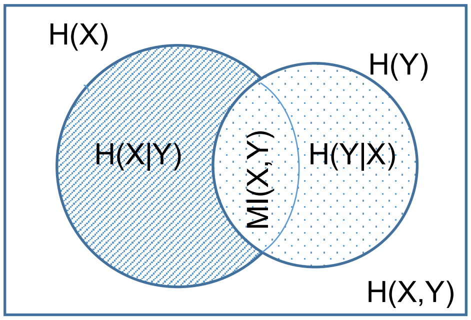

Fig. 3. Relations between MI measure and entropies

MI has been normalized in [18] in a way that the its maximum is 1. Four types of normalized NI are as following:

$$NI_{\min xy}(X,Y) = \frac{MI(X,Y)}{\min(H(X),H(Y))} \tag{8}$$

$$NI_{\overline{xy}}(X,Y) = \frac{2MI(X,Y)}{H(X)+H(Y)} \tag{9}$$

$$NI_{x}(X,Y) = \frac{MI(X,Y)}{H(X)} \tag{10}$$

$$NI_{y}(X,Y) = \frac{MI(X,Y)}{H(Y)} \tag{11}$$

3. A new hybrid dependency measure

Although, it is not expected that the BN structure consists of all components, it is expected that the BN comprises the most critical components. In the MI based approach proposed for constructing the BN, MI measure is used to measure the dependency between components outages events and load loss in different load points. After the computation of MI measures, they are compared with a threshold value to decide about the existence of edges in the BN.

Based on inequality (7), MI measure is always less than variables entropies. The variations curve of H(X) for variable X having a binomial distribution with parameter p, for different values of p is shown in Fig. 4.

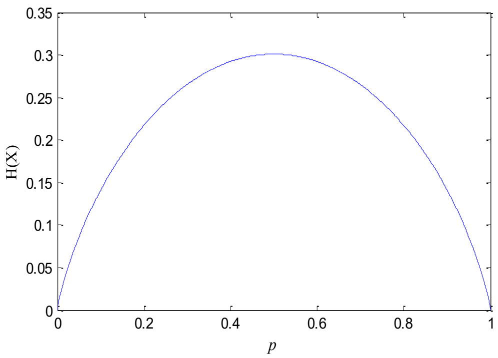

Fig. 4. The curve of H(X), X having binomial distribution with parameter p

It is observed that for p=0.5, H(X) is maximum. Also, for values near to zero or one, H(X) is very small and near to zero. Therefore, for components such as transmission system components that their Forced Outage Rate (FOR) values are very low, their entropies are very small and so, even if their outages cause to certainly loss of load in some load points, the MI measure will be very small and depending on the chosen threshold value, such components may or not be appeared in the BN.

To ensure the existence of the edges between load points and components having very low FOR values that their outages affect the reliability of load points considerably, it seems that using the MI measure is not effective. Applying Eq. (10) can solve the problem, since in that equation the normalization is done based on entropy of components. On the other hand, for components with high FOR values, such as generating units, corresponding values of NI_x *are low. Therefore, a hybrid mutual information measure (HMI) to measure the dependency between components* X_i *and load point* Bus_j *is proposed as:*

$$HMI(X_i, Bus_j) = \max\left\{\frac{MI(X_i, Bus_j)}{\max \mathbf{MI}_\mathrm{j}}, \frac{NI_x(X_i, Bus_j)}{\max \mathbf{NI}_\mathrm{xj}}\right\} \qquad (12)$$

In Eq. (12), $\mathbf{MI_j}$ *and* $\mathbf{NI_{xj}}$ *are respectively the vectors of MI and NI measures between* Bus_j *and all of the system components. Since the variation range of MI and NI measures are different, to improve their comparison, they are normalized on the basis of their maximum values on each bus. The value of HMI measure is limited to [0, 1], so the threshold value can be specified easily (e.g. 0.05).*

4. Component ranking

One of the main application of BN in power system is component ranking. A question that may be raised is why the BN is constructed, while the critical components can be identified using the MI, NI, or HMI. It should be noted that the BN provides the possibility of various probabilistic inferences and the importance of components can be evaluated from different aspects as is done in [15, 16, 19, 20]. For example in [15], it is shown that the BN can be used to components ranking on the basis of frequency and duration indices. So, having the BN for the power system can be useful. Although these evaluations can be done by other approaches such as MC simulation, they will be very time consuming.

In the next section, Birnbaum Mesure (BM) is used for component ranking. BM indicates how system unavailability will change with changes in component unavailability and is defined as

$$BM_k = \frac{\partial P_{SF=1}}{\partial P_{x_k=1}} \qquad (13)$$

where SF denotes system failure event and x_k points to the number of component in failure state related to the kth component. So, $P_{SF=1}$indicates the system failure probability and $P_{x_k=1}$ indicates the failure probability of component k. Considering the conditional probability rule, Eq. (13) can be represented as:

$$BM_k = P(SF=1 \mid x_k=1) - P(SF=1 \mid x_k=0) \qquad (14)$$

The BM of component k represents the criticality state of system in view of probability with respect to that component. Based on Eq. (11), this measure indicates the importance of the component for system operation from the structural point of view and so sometimes is known as structural importance index [21].

In this study, with regard to considering the similar components in the same position with one multi-state variable and so with one multi-state node in the BN, the definition of BM will be different. For a multi-state system with multi-state components, the Composite Importance Measures (CIM) are developed [22]. On this base, for a two-state system with multi-state components, BM measure will be as:

$$BM_k^{CIM} = \frac{1}{m_k - 1} \sum_{j=1}^{m_k} \left| P(SF=1 \mid x_k = j) - P(SF=1) \right| \qquad (15)$$

where m_k is the number of state of x_k.

5. Case Study

In this study to more obviously show the importance and efficiency of the new proposed dependency measure, a moderate size power system as IEEE- 24 bus Reliability Test System (RTS) is selected for the case study. But to put the transmission section in more stress, the load of the system is increased by 40% and the capacity of transmission components is decreased

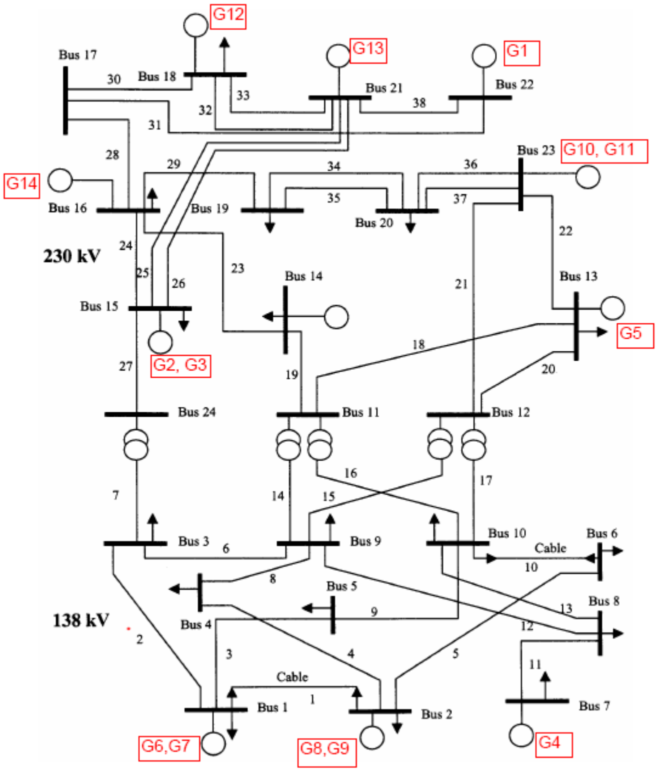

Fig.5. The single-line diagram of IEEE-RTS

10% and then the approach is applied to the Modified RTS (MRTS). The MRTS is depicted in Fig. 5 that has 24 buses, 32 generation units, 17 load points, 5 transformers , and 33 transmission lines [23]. As mentioned in Section III, similar generating units placed on a same bus are related to one variable G_i *in vector **S** and they are shown with one node in the BN. The variables* G_i ($\forall i = 1{:}ng$) *for the test system, with their specifications can be referred to Table 1 of [14]. As an example, in that Table, variable* G_1 *points to 6 generating units having the capacity of 50MW and FOR value of 0.01, located on Bus 22. It should be mentioned that the approach to generate data, and constructing the BN involving structure and parameter learning is done in MATLAB and for inference from the BN, GeNIe & SMILE developed at the University of Pittsburg [24]is employed.*

5.1. Comparison of MI, NI and HMI measures

Before showing the final structure of BN corresponding to the test system obtained using the HMI measure, it is appropriate to compare the MI, NI, and HMI measures between a load point and components. This is done for Bus 8 in Figs. 6 and 7. From Fig. 5, it is observed that transmission lines 11, 12, and 13 connect Bus 8 to the system. In this study, the used load shedding policy in contingency states is based on closeness to the component(s) on an outage. So, the outage of lines 11, 12, and 13 can affect the reliability of load point 8 and so it is expected that these lines are parents of node Bus_8 *in the BN.*

Fig. 6 shows that the MI measures between theses transmission lines and the load point 8 are low and so the existence of edges between these lines and node Bus_8 *in the BN, is highly affected by the chosen threshold value to compare with MI measures.*
However, the value of NI measures between transmission lines 11, 12, and 13 is high and so based on this measure, these lines certainly are chosen as parents of node Bus_8*.On the other hand, the NI measures between some variables that have large MI measures, are relatively low due to their high FOR values and so their high entropies. The curve of HMI measures between load point 8 and components is shown in Fig. 7. It is observed that the effective components on the reliability of this load point are well identified using this measure. It should be mentioned that the value of MI, NI, and HMI measures of the other components that have not appeared in Figs. 6 and 7, is very low and so they are not shown.*
In another illustration, the value MI and HMI measures between
Buses 1-6 and system components are respectively shown in Figs. 8 and 9. This can be done for all load points. But, for more clear view, here this is shown for only 6 load points. Also, some components that their related MI and HMI measures with all load points were very low are not considered in these figures.
Based on Fig. 8, it is shown that most of MI measures between load points and transmission system components are very low and so identification of effective transmission components on load points is highly dependent on the selected threshold value to compare them. But it is shown that based on Fig. 9, the effective transmission components can be suitably identified based on HMI measures.

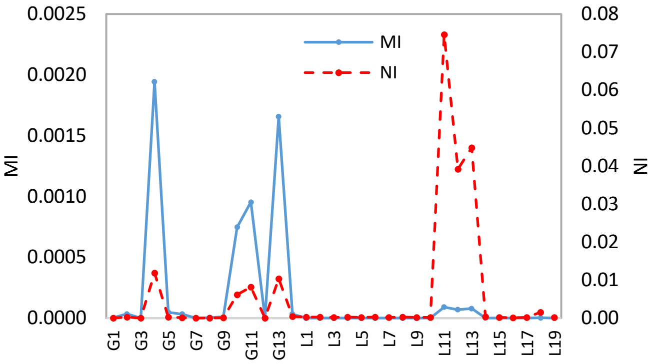

Fig. 6. MI and NI measure between Bus 8 and components

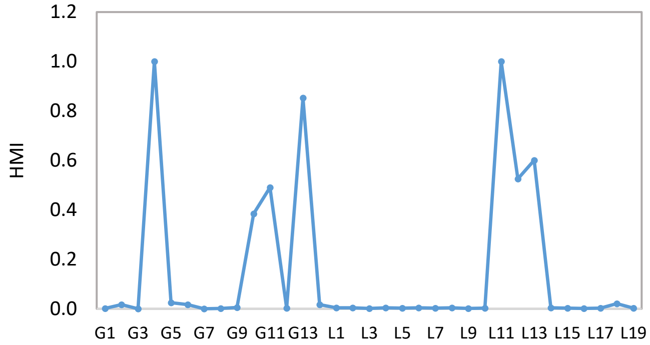

Fig. 7. HMI measure between Bus 8 and components

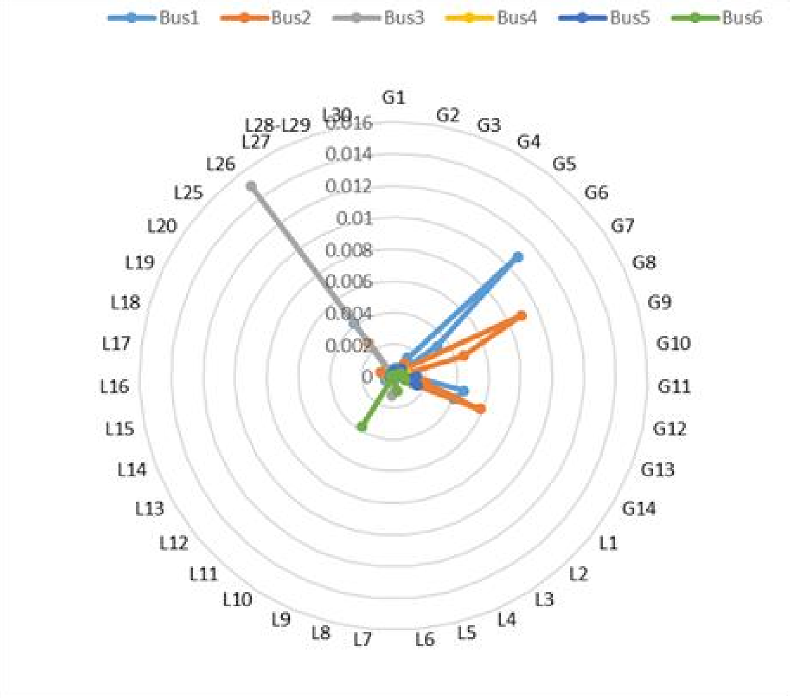

Fig. 8. MI measures between load point 1-6 with components

Table 2. Transmission system components which are parents of different load points

Bus No.	1	2	3	4	6	6	7	8	14	15	16	19	20
Transmission system components being buses' parents	L1 L2	L1 L4 L5	L2 L6 L7	L4 L8	L3 L9	L5 L10	L11	L11 L12 L13	L19 L23	L24	L23 L24 L28 L29	L29 L34-35	L34-35 L36-37

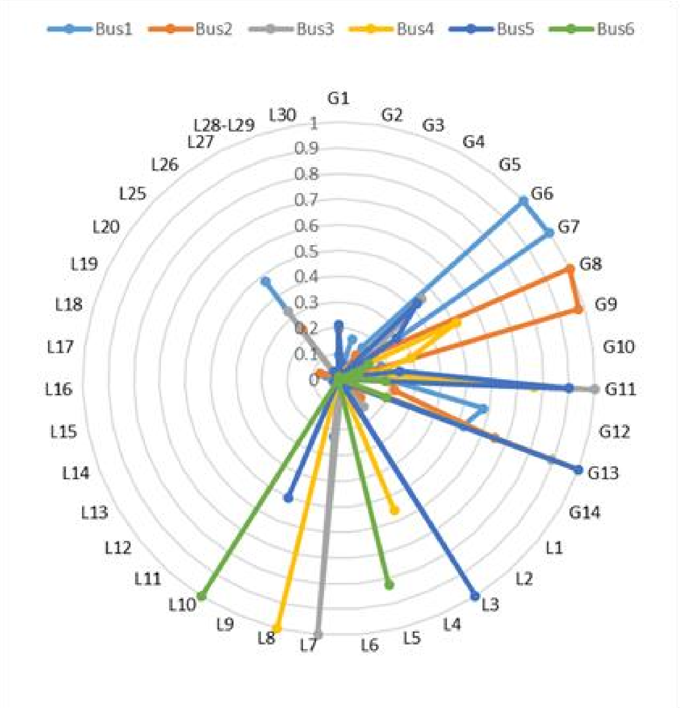

Fig. 9. HMI measures between load point 1-6 with components

5.2. Final structure of BN associated with MRTS

The final structure of the BN obtained using the HMI measure is shown in Fig. 10. Although the accuracy of the obtained BN can be evaluated by different quantitative probabilistic inferences from the BN, the BN structure also involves information and so it can be evaluated intuitionally. In Table 2 the transmission system components that are parents of each loads point are shown. Referring to Fig. 5 and with regard to load shedding policy, it is observed that the being parents of transmission system components for load points is expected. It may be thought that it is not required to determine the parents of load points using the HMI measure and they can be identified based on system topology. But it should be noted that in this study, the closeness to the component(s) on outage is considered as load shedding policy.

However, the other load shedding policies may be used in a power system and so identification of effective components on

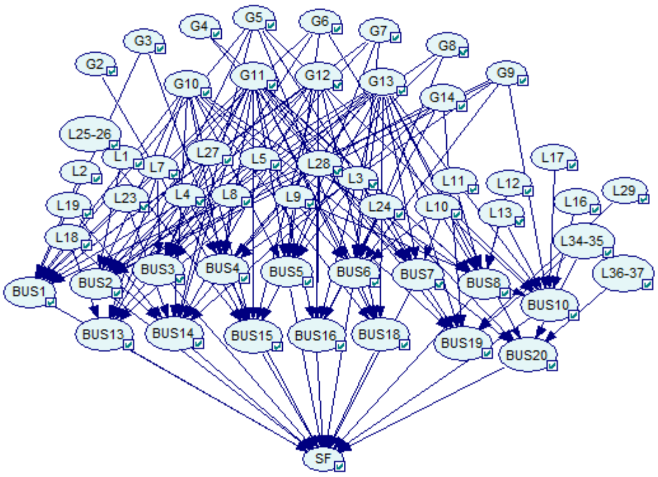

Fig. 10. The BN structure associated with MRTS

load points will not be so easy, generally. The results in Table 2 verify the accuracy of the proposed dependency measure in constructing the BN.

5.3. Numerical Evaluation of component ranking

The ranking of components based on the BM measure is performed. The results are shown in Fig. 11. For computation of BM of each component with m_k states, m_k MC simulation is run. MC should be repeated for each component which is very time-consuming. While, these assessments can be easily done using the obtained BN. The results of MC simulation is also depicted in Fig. 11.

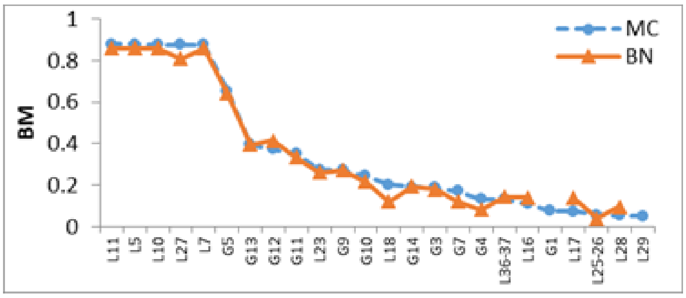

Fig. 11. Components ranking based in Birnbaum measure

As another assessment, here, the Loss of Load Probability (LOLP) of Bus$_3$, given some components in outage states is shown in Fig. 12.

To show the accuracy of the results, this analysis is also done using the Monte Carlo simulation. For this purpose, it is required to set the state of each component individually to failure state and then run MC simulation to obtain the LOLP of buses or system. It is clear that it is time-consuming, but it can be easily performed by inference from the BN. However, the comparison of results obtained from the BN and MC verifies the accuracy of the BN model. In this study the BN is applied to assess the CPS in view of loss of load probabilities and components ranking.

It is noted that the approach is applicable for larger power system. A BN may be generally large. But it is suitable that the number of parents for each node is not so numerous. For every load point, there are some components that have more effect on their reliability and so the number of parents of the load point nodes in the BN will be limited. But when the power system is large size, the parents' number of node SF will be large that it will not be suitable. For the large size power system, the nodes

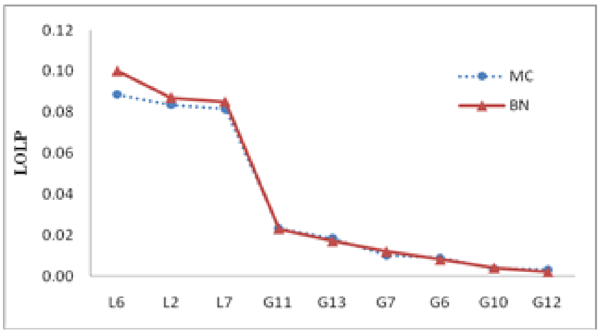

Fig. 12. Loss of load probability of Bus 3 given components outage

associated with load points can be divided to some groups, each group connect to one node and then the new nodes associated with groups connect to SF nodes and so it can be employed for the large power system.

F. Conclusion

In this chapter, a new dependency measure was suggested to be used in constructing the BN associated with the power system considering both generation and transmission sections with the aim of achieving the more precise BN and so more accurate analysis of transmission system components effects on the system reliability. The proposed measure was a combination of Mutual Information and a special normalized Mutual Information measure. Using the new proposed measure in the process of special BN structure learning provided the possibility of accurate analysis of the transmission system components while taking advantage of using the BN in detailed reliability evaluation of CPS. As a case study, the proposed measure was applied to the modified IEEE 24-bus test system, although it was applicable for larger CPS. The simulation results showed that using the new dependency measure in constructing the BN could provide a more precise evaluation of transmission system components on system and load points reliability in comparison with the BN constructed based on MI measure. As future work, it is suggested that the state of load points in the BN is selected based on the measure of curtailed load or energy not supplied to provide more reliability analysis of CPS on the basis of energy indices. Also, the application of the proposed approach to renewable-based power systems, hybrid AC/DC systems and micro-grids is suggested.

G. References

[1] K. Varnavskiy, Q. Chen, and F. Nepsha, "Structure orderliness assessment of grid development to improve the reliability of coal mine external electrical power supply," Electric Power Systems Research, vol. 183, p. 106283, 2020.

[2] Y. Xiang, Y. Wang, Y. Su, W. Sun, Y. Huang, and J. Liu, "Reliability correlated optimal planning of distribution network with distributed generation," Electric Power Systems Research, vol. 186, p. 106391, 2020.

[3] L. Li, H. Wu, Y. Song, and Y. Liu, "A state-failure-network method to identify critical components in power systems," Electric Power Systems Research, vol. 181, p. 106192, 2020/04/01/ 2020.

[4] W. Wendai, J. Loman, and P. Vassiliou, "Reliability importance of components in a complex system," in Annual Reliability and Maintainability Symposium, 2004, pp. 6-11.

[5] R. E. Neapolitan, Learning Bayesian networks. Pearson Prentice Hall, 2004.

[6] B. Cai, Y. Zhao, H. Liu, and M. Xie, "A Data-Driven Fault Diagnosis Methodology in Three-Phase Inverters for PMSM Drive Systems," IEEE Transactions on Power Electronics, vol. 32, no. 7, pp. 5590-5600, 2017.

[7] B. Cai, Y. Liu, Y. Ma, L. Huang, and Z. Liu, "A framework for the reliability evaluation of grid-connected photovoltaic systems in the presence of intermittent faults," Energy, vol. 93, pp. 1308-1320, 2015/12/15/ 2015.

[8] M. Eliassi, H. Seifi, and M. R. Haghifam, "Incorporation of protection system failures into bulk power

system reliability assessment by Bayesian networks," IET Generation, Transmission & Distribution, vol. 9, no. 11, pp. 1226-1234, 2015.

[9] K. Dehghanpour, M. H. Nehrir, J. W. Sheppard, and N. C. Kelly, "Agent-Based Modeling in Electrical Energy Markets Using Dynamic Bayesian Networks," IEEE Transactions on Power Systems, vol. 31, no. 6, pp. 4744-4754, 2016.

[10] R. Buchanan, N. U. Ibne Hossain, S. Hosseini, R. Jaradat, and M. Marufuzzaman, "A Framework for Modeling and Assessing System Resilience Using a Bayesian Network: A Case Study of An Interdependent Electrical Infrastructure System," International Journal of Critical Infrastructure Protection, vol. 25, 02/01 2019.

[11] Y. Ren et al., "A reliability evaluation method for radial multi-microgrid systems considering distribution network transmission capacity," Computers & Industrial Engineering, vol. 139, p. 106145, 2020/01/01/ 2020.

[12] L. Huo, Y. Zhu, and G. Fan., "Reliability assessment of power systems by Bayesian networks. in International Conference on Power System Technology," In proceeding of the PowerCon, 2002.

[13] M. Eliassi, A.K. Dashtaki, H. Seifi, M.R. Haghifam, and C. Singh, "Application of Bayesian networks in composite power system reliability assessment and reliability-based analysis," IET Generation, Transmission and Distribution, vol. 9, pp. 1755-1764, 2015.

[14] A. Ebrahimi and T. Daemi, "Novel Method for constructing the Bayesian Network for Detailed Reliability assessment of Power systems," in International Conference on Electric Power and Energy Conversion Systems, Sharjah, UAE, 2009.

[15] T. Daemi, A. Ebrahimi, and M. Firuzabad, "Constructing the Bayesian Network for Components Reliability Importance Ranking in Composite Power Systems," International Journal of Electrical Power and Energy Systems, vol. 43, pp. 474-480, 2012.

[16] A. Ebrahimi and T. Daemi, "A Simple Approach to Construct the Bayesian Network Associated with Electric Transmission Systems," Int. Review of Elec. Eng., vol. 5, pp. 180-184, 2010.

[17] Y. Y. Yao and P. Karmeshu, Information-Theoretic Measures for Knowledge Discovery and Data Mining, in Entropy Measures, Maximum Entropy Principle and Emerging Applications. Springer Berlin Heidelberg, 2003.

[18] I. Kojadinovic, "On the use of mutual information in data analysis: an overview," in 11th International Symposium on Applied Stochastic Models and Data Analysis, 2005.

[19] T. Daemi and A. Ebrahimi, "Evaluation of Components Reliability Importance Measures of Electric Transmission Systems Using the Bayesian Network," Electric Power Components and Systems, vol. 40, pp. 1377-1389, 2012.

[20] T. Daemi and A. Ebrahimi, "Detailed reliability assessment of composite power systems considering load variation and weather conditions using the Bayesian Network," International Transactions on Electrical Energy Systems, 2012.

[21] G. J. Anders, "Evaluation of Importance and Related Reliability Measures for Electric Power Systems," IEEE Trans. Power Appar. Syst., vol. PAS-102, no. 3, pp. 527-537, 1983.

[22] J. E. Ramirez-Marquez and D. W. Coit, "Composite importance measures for multi-state systems with multi-state components," IEEE Trans. Reliab., vol. 54, no. 3, pp. 517-529, 2005.

[23] Reliability Test System Task Force, "The IEEE reliability Test System-1996," IEEE Trans Power Syst, vol. 14, pp. 1010-1020, 1999.

[24] The Genie tool for Bayesian networks and influence diagrams, http://www2.sis.pitt.edu/~genie/