Decision Tree Analysis to Identify Harmful Contingencies and Estimate Blackout Indices for Predicting System Vulnerability

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Abstract

Cascading failure is the main mechanism for progressing large blackouts in power systems. Following an initial event, it is challenging to predict whether there is a potential for starting cascading failure. In fact, the potential of an event for starting a cascading failure depends on many factors such as network structure, system operating point and nature of the event. In this paper, based on the application of decision tree, a new approach is proposed for identifying harmful line outages with the potential of starting and propagating cascading failures. For this purpose, associated with each trajectory of the cascading failure, a blackout index is defined that determines the potential of the initial event for triggering cascading failures towards power system blackout. In order to estimate the blackout indices associated with a line outage, a three stages harmful estimator decision tree (HEDT) is proposed. The proposed HEDT works based on the online operating data provided by a wide area monitoring system (WAMS). The New England 39-bus test system is utilized to show the worthiness of the proposed algorithm.

Keywords*:* Blackout; cascading failure; decision tree; harmful line outage.

1. Introduction

Security assessment with respect to critical contingency with the potential for triggering cascading failure leading to blackout is the main concern for complex modern power systems. Cascading failure is recognized as one of the major threats for a blackout in power systems. Cascading failures successively weaken the system and make further failures more likely so that a blackout can propagate to disable large portions of the electric power system. The failure can be due to a variety of means, including action or malfunction of the protection system, automatic or manual controls, and physical breakdown. Long, intricate cascades of events were the main cause of the August 2003 blackout in Northeastern America that disconnected 61,800 MW of power [1], and cascading failures from Germany to eastern Europe resulted in Europe blackout in 2006 [2].

Typical contingency analysis based on the n-1 security is not able to reveal system vulnerability and harmful contingencies with the potential for developing blackout. Therefore, a blackout based security assessment is necessary for revealing harmful contingencies and vulnerable operating conditions. For this purpose, simulation of the cascading failure is a vital requirement. However, the process of cascading failure is very complex and time consuming to be implemented in the context of a contingency analysis algorithm.

There are two approaches for modeling dynamic of cascading events and blackout in power systems. The first one is deterministic approaches in which each component is modeled in detail. Complete dynamical description of power system involves detailed knowledge of each component and its coupling to the rest of the system. Because all of the components and the physical laws governing their interactions are known, the simulation of the process for cascading blackouts and events would be possible. The second one is probabilistic approaches in which events and process of cascading events and blackout are probabilistically modeled based on the random characteristic of the events [3].

DC load flow analysis is an approximate method for the determination of static flows within a power system. The method is useful due to the fact that it produces approximate flows in a system with a linear non-iterative method. This is in comparison to the use of AC load flow analysis which makes use of iterative procedures, such as the Gauss-Seidel and Newton-Raphson methods, in order to find solutions [4], [5]. The DC load flow analysis is less accurate than a full AC load flow due to the fact that it is based on assumptions. These assumptions give good approximations to the flow distributions that occur after contingencies and therefore the large increase in the tractability, and a number of cascading events that can be analyzed, make the DC load flow approximation a useful tool in cascading failure modeling for power systems. In [6], a modified DC power flow-based cascading failure simulator to evaluate its utilization in the contingencies triggered by both bus and branch failures is presented in which simulation results of DC are compared and validated against the transient stability analysis based approach. In [7], by using “DC” load flow and analysis of hidden failures of the network, the blackout is modeled. In [8], the effect of the choice of DCOPF solution at each stage on the risk of cascading failures is shown. Using DC power flow, Ref. [9] proposes an open source MATLAB based package for academic purposes to analyze cascading failures due to line overloads in a power grid.

In Ref. [10] a variety of methods are emerged to study the mechanism of cascading outages, and the theory can be divided into four categories: self-organized criticality, complex network theory, operational reliability theory, power system simulation theory. Carreras et al. have produced comprehensive work on self-organized criticality [11]-[13] in cascading failures using the AC power flow-based Manchester model [14], [15] and CASCADE model [16]. In [17], transmission grid reliability concerning cascading line overloads and outages is studied. In [18] the system reliability of the cascading models is analyzed. In [19] angle stability of power system with multiple operating conditions considering cascading failure is proposed. In [20], a new method in detecting power system islanding contingencies using both the system's topological structure and real-time system dynamic state variables is presented. A probabilistic framework for online identification of post fault dynamic behavior of power systems with renewable generation based on decision trees is introduced in [21]. In [22], illustrates how complex network theory can be applied to modern smart grids in structural vulnerability assessment, cascading blackouts, grid synchronization, network reconfigurations, distributed droop control, pinning control for micro-grid autonomous operations, and effective grid expansions. In [23], a decision tree assisted scheme is presented to determine the timing of controlled islanding in real time by using phasor measurements. The objective of [24] is to develop adaptive controlled islanding as a component of an emergency power system control strategy. In [25], a unified framework is proposed to clarify the important concepts related to DSE, forecasting-aided state estimation, tracking state estimation, and static state estimation.

While a wide variety of models are proposed for modeling blackouts, but to the authors' knowledge, rare studies are done in the prediction of blackouts. It demonstrates the importance of this paper. For instance, in Ref. [26] the stochastic processes in the dynamics of cascading failure propagations in power systems is studied which can provide predictive information for the failure spreading in the network. Ref. [27] proposes a probabilistic approach for prediction of cascading failure in power system, which predicts the next transmission line to trip based on the initial triggering event by considering the thermal limit of each line as a constraint.

The present research proposes a new method for identifying critical line contingency with the potential for developing cascading failure propelling power system toward blackout. This new approach is based on the Decision Tree Analysis. In this approach, at the pre-contingency steady state condition by online measurement of the active power of line by means of WAMS, the proposed DT is able to evaluate the harmfulness of the line outage for triggering cascading failure and blackout. The proposed method is based on the static model in which element overloading is considered as the main cause for creating and developing cascaded events. Finally, based on IEEE 39-bus test system, the simulations are conducted to demonstrate the effectiveness of the proposed model.

The rest sections of this research are organized as follows: Cascading failure model is introduced in Section II. In Section III, the structure of the proposed approach is described. The simulation study of the research is done in Section IV. Finally, the relevant conclusions are included in Section V.

2. Cascading failure modeling

The Cascading failure is one of the important mechanisms to develop the large blackouts in power networks. The term "failure" indicates the outage of elements in power system due to the action of protection devices to prevent damages to the components of the system. Following an initial event, e.g., a fault or outage of a line with heavy loading, the system may experience some violations like severe voltage drop, line overloading or generator swing. If these violations can activate protective relays, the process of cascading failure will start and continue according to system vulnerability. System potential for triggering and propagating cascading failures following an initial event is referred as the risk of power networks for the blackout.

The cascading failure process can be propagated and triggered based on the following characteristics of power networks.

1. Brittleness of system components (like a transmission line, transformer and generator) due to limit violations following each event.
2. Activation of protective relays plays a key role to trigger new component outage leading to propagation of cascading events.
3. The principal cause for bringing out new outage following an initial event is relay tripping of violated elements. Thus, the limit violation by system components accompanied by relay action is the prime reason for propagating cascading failure. On the developed stages of cascading failures, undesirable islands can propel power system into a blackout.

For modeling the phenomena of cascading failure in power systems, various methods and algorithms are proposed. In the Following the main four methods are described.

2.1. CASCADE model

The CASCADE model is an analytically tractable model for general systems with the potential of cascading failure [16]. This model does not incorporate the complicated nature of power systems and the interactions of components within the system. It qualitatively describes the nature of cascading events in power systems and therefore is an appropriate model to introduce the concept of cascading failure in power transmission systems. The model comprises of a system of n identical components with each given an independent random initial loading. Each component has a loading failure threshold at which the component fails. After a component fails it transfers a fixed amount of its load to the other components of the system. A disturbance has occurred in the system which results in random increases in the loadings of the components. If loading of any of the components goes above its threshold value it fails and its load will be transferred to the remaining system components. The secondary increase due to the failed component may cause more components to go above their threshold values which cause cascading failure to propagate more. The cascade stops when all of the components are tripped out or none of the components have a value above their threshold. This relatively simple model captures the essence of cascading failures in power transmission systems.

2.2. Hidden Failure Model

The Hidden Failure model is based on the idea that cascading failure within power systems can occur due to the failure of protective relays which are physically and electrically close to a transmission line which has been forced out [28]. The hypothesis is that a line failure exposes a hidden failure in the protective equipment of neighboring branches. If a line fails, its neighbors are given a probability of failure that is a function of the new loading of the line. As a result of this cascading mechanism, as each neighbor fails, the initial disturbance can propagate through the system resulting in diminished transmission capacity and load shedding. This model while diverging from the simpler CASCADE model, by including the transfers of loading in a manner that is more consistent with power system operation, still shows characteristics that are close to that of the CASCADE model

2.3. The Manchester Model

The Manchester model uses a full AC load flow analysis [29] to model cascading failures through sympathetic tripping of components including generator instabilities in response to disturbances with subsequent load shedding. It is again observed in this model that the risk of blackouts goes through a critical phase transition in response to an increase in the system loading.

2.4. OPA model

All of the above models simulate the evolution of cascades through a system in the short term and therefore model only is used for a given fixed topology, the full representation of real-world power transmission systems would include the engineering response to blackouts or perceived threats of blackout risk. The OPA model was developed to model this evolution of a power system to a dynamical state that is near a critical point [30-31]. The model represents in a very simplified manner the cascading dynamics of the electrical power transmission system, reduction in the generation capacity of the power system as well as the operation, maintenance and repair of the transmission system. These simplifications may lead to the behavior of the model to be unable to represent the actual dynamics of power systems appropriately.

3. The Proposed Approach

The conceptual structure of the proposed algorithm for identifying harmful line contingency with the potential for initiating and propagating cascading failures in power systems leading to blackout is shown in Fig. 1.

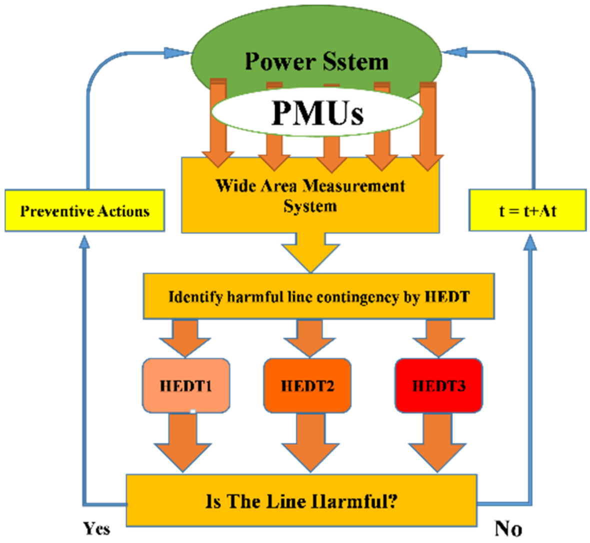

Fig. 1. The conceptual structure of the proposed algorithm for identifying harmful line outage.

Based on the proposed approach, in a real-time environment, at any instant of system operation by using operational data gathered by WAMS through the system, the harmfulness of each line contingency for initiating cascading failure and propelling system to blackout is evaluated. For this purpose, a harmful estimator decision tree (HEDT) is designed and trained which can estimate the harmfulness of each line outage for initiating cascading failure leading to a blackout. The operational data required for HEDT consist of active power flow of lines which are measured directly by PMUs. If a line contingency is recognized as harmful with the potential for developing cascading failure and blackout, so, it remains to adopt proper preventive actions as remedial actions to mitigate line hazardously.

3.1. Cascading Failure simulation

In order to train harmful estimator decision tree (HEDT), it is required to prepare proper training data including cascading failures trajectories with the potential for creating a blackout in power system. Fig. 2 shows the process of the procedure used for evaluating blackout size associated with harmful cascading failures. The process can be explained in the following steps.

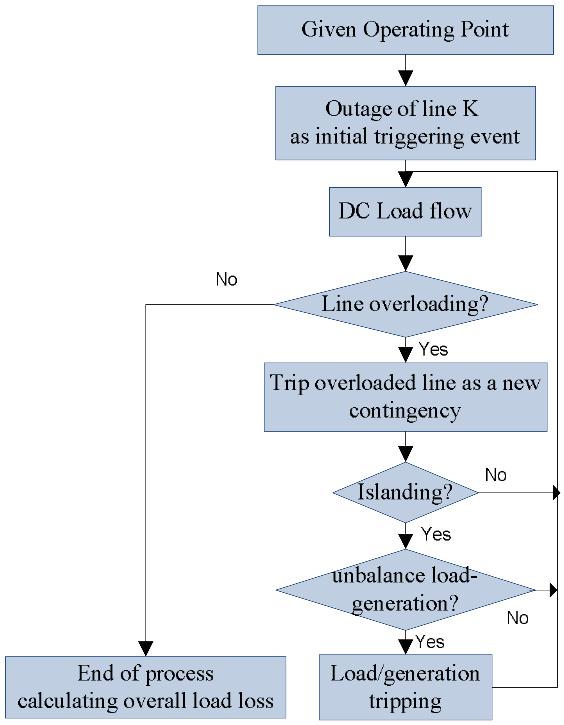

Fig. 2. The process of blackout evaluation due to cascading failure following an initial event.

A. Step1: Initiating cascading failures

The line outage, whose harmfulness for propagating cascading failure in the system is intended, is referred as the initial event. For all operating points with different network structures which are designed for training data preparation, the intended line is taken out as the initiating event, and its effect on the propagation of cascading failure in the system will be evaluated.

B. Step2: Tripping overloaded lines

Line tripping is one of the most general failures responsible for propagating cascading failures [4]. Each tripping element is referred to as a chain of the cascading failures, and the whole chain of the cascading failures following an initiating event leading to power system blackout is denoted as a blackout trajectory. When the initial event occurs, it may cause overloading on some of the transmission lines. The protective relays are activated by overloading and trip dangerously overloaded lines. Tripping an overloaded line is regarded as a new cascaded event. In this paper, only line outages are considered as initial events. Tripping time of relays is not considered. Therefore, at each instant as soon as lines get overloaded, the line with the maximum overloading will be tripped immediately without any delay. System dynamic behavior and generator outage are not considered.

C. Step3: DC load flow

In order to evaluate the change in line flow after each line outage, DC load flow is utilized which can be modeled as follows [5].

$$\begin{cases} P_{bus} = [A].\theta \\ P_{line} = [B].\theta \\ P_{line} = [B].[A]^{-1}.\,P_{bus} \end{cases} \tag{1}$$

where θ is phase angle of bus voltages, P_{bus} is net injection power at buses, P_{line} is line active power flow, $[A]$ is reduced Jacobean matrix, $[B]$ is an incident matrix, B_{ij} is susceptance of the line connecting buses i and j.

Equations (1) can be written as (2):

$$\begin{aligned} P_{line} &= [C].\,P_{bus} \\ [C] &= [B].[A]^{-1} \end{aligned} \tag{2}$$

D. Step4: Islanding due to cascading Failure

During the process of cascading failure, the initial network may be separated into several islands. Each island should be able to operate independently. In the case of unbalance load-generation the island may suffer from frequency or voltage instabilities, and it is necessary to shed excess generation or load. The amount of load/generation trip is regarded as a criterion for measuring criticality of the initial event.

3.2. Blackout index

In order to assess the harmfulness of the initial event, an index denoted as blackout index is defined. According to this index, the potential of line outage for creating cascading failures leading to blackout can be determined. Also one can rank the lines outage severity according to their associated blackout indices. In this paper, the total power loss created due to cascading failures following an outage of a line, is regarded as blackout index. It is worth noting that the blackout index associated with each line contingency is strongly dependent on the system operating condition and network structure.

In this paper, the technique of decision tree is used to evaluate the blackout index of each line contingency according to the current operating condition. Equation (3) shows blackout index in term of percentage of total load loss at the end of the process of cascading failure.

$$BI = \frac{P_{loss}}{P_{D_0}} \tag{3}$$

where P_{D_o} and P_{loss} are system initial load power and total loss respectively.

3.3. Harmful Estimator Decision tree

As it is mentioned, the harmfulness of a line contingency for initiating cascading failure and blackout strongly depends on the system operating condition. Therefore the blackout index associated with a line outage may vary in a wide range with respect to change in system condition including load level, load-generation patterns and network structure. In this paper, in order to have an online and fast estimator for evaluating the harmfulness of a line contingency, the technique of decision tree is utilized in which by using online data acquired from WAMS, harmfulness estimator decision trees HEDTs will predict the blackout indices of lines at the current pre-contingency operating condition.

Noting that evaluating load curtailment and the number of islands, following the outage of a critical line is possible only when the system has experienced the consequent of cascading events. However, for evaluating the harmfulness of a line contingency, it is necessary to estimate the consequent harmful results following the outage of the line in advance. The techniques of artificial intelligence are very prone to such applications. They are usually trained based on the offline data and then utilized in real time operational environment using online data.

In this paper, a three stages HEDT scheme is used for estimating harmfulness associated with each line contingency. Fig. 3 shows the overall structure of the proposed three-stage HEDT scheme. The proposed scheme uses pre-contingency lines active power flows and then estimates the severity and harmfulness of each line contingency in term of the amount of power loss which can be resulted due to cascading failure following the contingency. In fact, the proposed scheme is able to estimate the potential of each line contingency for initiating cascading failure and propelling system toward blackout. In order to simplify the training and estimating task of each DT, the process of harmfulness estimation is divided into three stages. The input data for all DTs is the active power flows of the line at the pre-contingency current operating point. Corresponding to each line contingency, a specific estimation scheme shown in Fig. 3 is designed and trained.

The first DT estimates whether following the outages of a line any blackout will occur or not. In the case of any potential for creating blackout, the second and third DTs estimate the size of the blackout in terms of MW loss. The classification of the harmfulness of the line contingency is depicted in Table 1.

Table 1. The output of HEDTs for estimating harmful contingency

Harmfulness of line contingency	HEDT1	HEDT2	HEDT3	The size of the Associated blackout (MW)
safe	0	0	0	0
Partial blackout	1	0	0	>0 & <500
critical blackout	1	1	0	>500 & <1000
Large blackout	1	1	1	>1000

4. Simulation studies

In order to show the ability of the proposed algorithm for estimating harmfulness of line contingency with the potential for triggering cascading failure and propelling the system toward blackout; it is applied on IEEE 39 bus test system consisting of 46 transmission lines, ten generating units and 19 load buses. In this study, the harmfulness of line #26 (bus16-bus17) is supposed to be examined. Therefore, according to the proposed algorithm a 3 stage HEDT scheme is trained to estimate harmfulness of line #26 as an initiating event for creating cascading failure and developing blackout. It is worth noting that for estimating harmfulness of each line contingency, an individual HEDT scheme is supposed to be trained.

4.1. Training data for HEDT

For training DTs of a HEDT scheme, proper training data should be provided. Provision of training data needs a wide range of system operating conditions including a versatile range of load level, load-generation pattern on buses. These operating conditions should contain different degrees of vulnerability including harmful line contingencies and safe contingencies with no potential for cascading failures and blackout. System base load is 6250 MW according to which, five loading level as 80%, 90%, 100%, 105%, and 110% are examined.

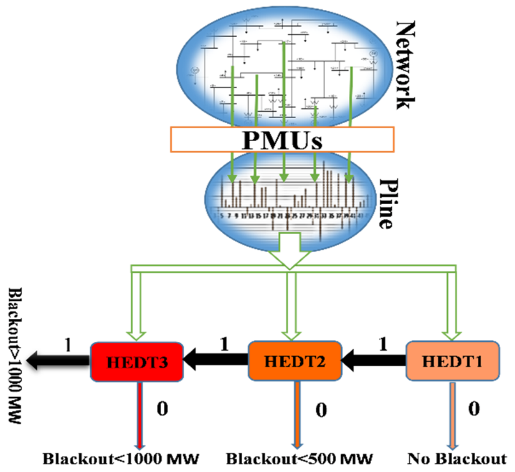

Fig. 3. Overall structure of the three stages HEDT scheme

Corresponding to each load level, there is a base load-generation pattern for which, around the corresponding base load-generation pattern, load and generation of all buses are changed randomly by ±15% by which 300 load-generation patterns are produced. In order to take into account the effect of network topology on the harmfulness of line contingencies, in addition to the basic structure of the network, single and double lines outage due to maintenance are considered in the network topology. In fact, by this way, the proposed HEDT will be robust with respect to topology change due to line maintenance. Table 2 shows the set of lines whose single and double outages are considered in the network topology. By combining these outages, as single or double outages, totally 90 different topology patterns are obtained.

Concerning each load-generation pattern, from 147 topology patterns, two maintenance patterns are adopted which resulted in total 600 operating scenarios from which 200 scenarios are for basic topology and 400 scenarios for maintenance topology with a versatile range of vulnerability from secure to worst cases. Pre-contingency steady state condition of each operating point is evaluated by power flow calculation.

Table 2. Lines whose outage are considered in the network topology.

No.	**Line No.**	**Bus i**	**Bus j**
1	1	1	2
2	3	2	3
3	6	3	4
4	7	3	18
5	8	4	5
6	9	4	14
7	11	5	8
8	15	7	8

4.2. Calculation of blackout index

With respect to the contingency of line #26 as the initial event whose harmfulness is intended to be evaluated by the proposed scheme, cascading failure simulation shown in Fig. 2 is performed for all operating scenarios. Corresponding to each operating scenario, the harmfulness of line #26 is evaluated. The active power flow of all lines at the pre-contingency steady state condition constitutes the input data for training HEDT associated to line #26, while the blackout (load loss) associated to the contingency of line #26 due to the cascading failure constitutes the output data of HEDT.

Table 3 shows a statistics overview of the harmfulness of line #26 within all 600 scenarios. As it can be seen, for example, 169 operating scenarios are within the load range 6000-6500 MW from which 69 scenarios are vulnerable concerning the contingency of line #26 as a harmful line. Total power loss associated with the outage of line #26 for all 69 vulnerable scenarios is 155453 MW. The average power loss corresponding to each scenario is 919.8 MW as shown in the last row. As it can be seen, by increasing system load level mean blackout index is showing harmfulness of line #26 will increase.

Table 3. Statistic of harmfulness of line #26 in all scenarios

	Load level 1	Load level 2	Load level 3	Load level 4	Load level 5
Loading (MW)	<5500	5500-6000	6000-6500	6500-7000	>7000
No. of scenarios	130	145	169	115	41
Critical scenarios	41	62	69	56	18
%Critical scenarios	31.5%	42.8%	40.1%	48.7%	44%
Total blackout (MW)	72640	129430	155453	117048	43118
Mean blackout (MW)	558.8	892.6	919.8	1017.8	1051.7

Table 4 shows the sequence of cascading failures which are automatically triggered following the outage of line #26 as an initial event for a typical scenario (#261) in which system loading is 5954 MW and line #9 (bus4-bus14) is out for maintenance. Blackout size associated with the contingency of line #26 at this scenario is evaluated to be 2239 MW.

Table 4. The sequence of cascading failures following an outage of line #26

No.	Event type	Line Outage	Bus i	Bus j	Pline before outage (MW)
1	**Initiating event**	26	16	17	-247
2	**1st cascaded failure**	10	5	6	763
3	**2nd cascaded failure**	12	6	7	-1094
4	**3rd cascaded failure**	24	14	15	-629
5	**4th cascaded failure**	6	3	4	-570
6	**5th cascaded failure**	2	1	39	-608

The pattern of line active power flow at the pre-contingency condition of this scenario which constitutes the input of HEDT is illustrated in Fig. 4.

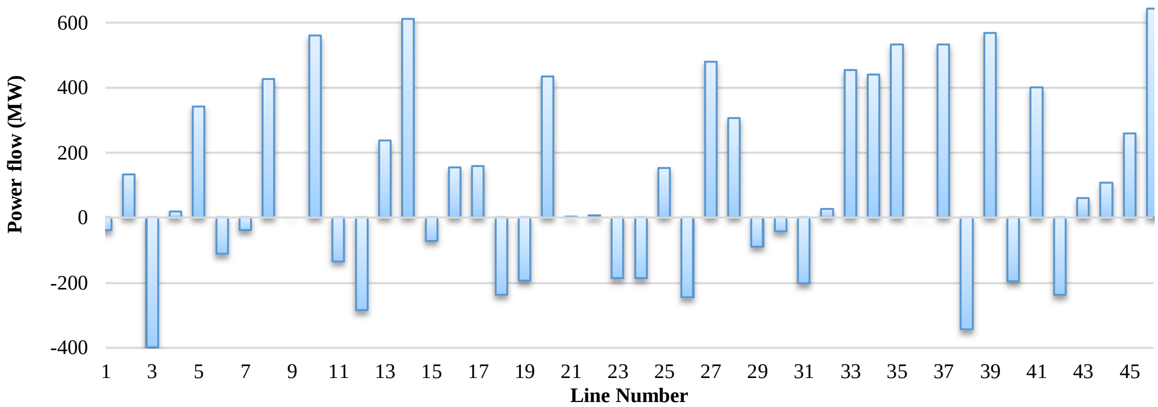

Fig. 4. Pattern of line active power flow for scenario #261

Fig. 5 shows islanding pattern created at the end of five cascading failures in Table 4. As it can be seen, the power grid is separated into four islands and finally after 2239 MW load loss, has been settled down in a new steady state condition.

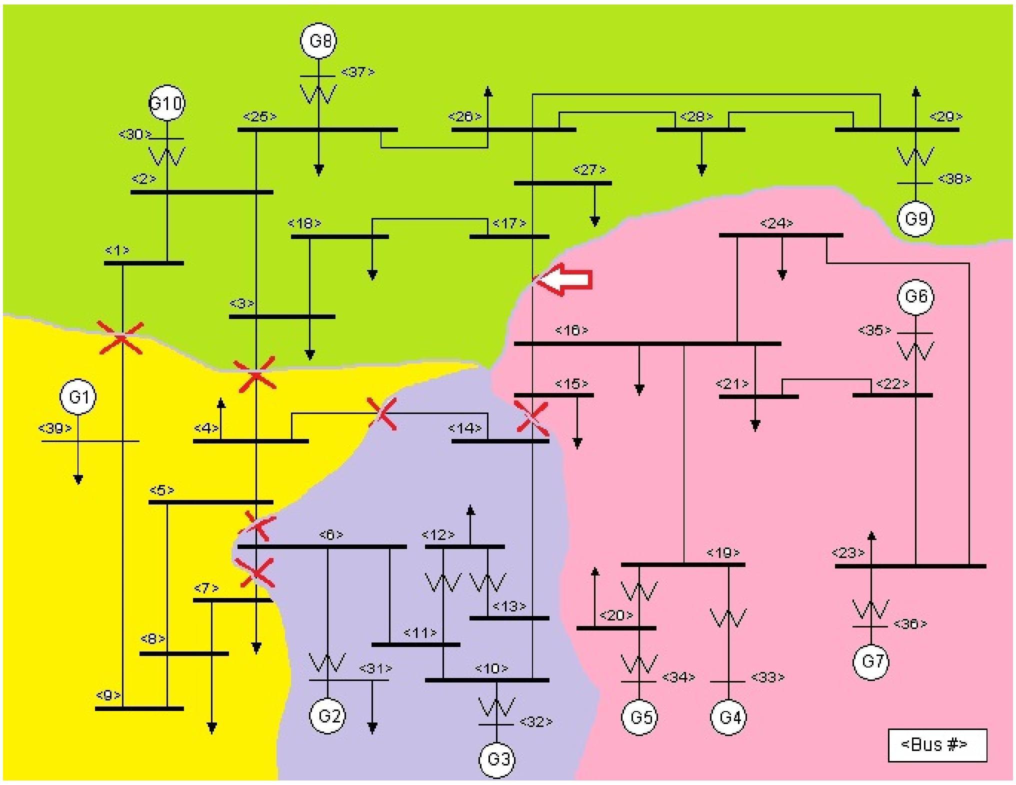

Fig. 5. Islanding pattern due to cascading failures initiated by the contingency of line #26 at scenario #261

Regarding all 246 vulnerable scenarios (out of 600), there are 246 corresponding blackout trajectories, each consisting of a chain of cascading failures. In order to rank the contribution of each line outage for participating in the chains of cascading failure, a contribution factor (CF) can be defined for each line #j as follows.

$$CF_j = \frac{NC_j}{N_{max}} \tag{4}$$

where NC_j is the total number of times which line #j has participated in all blackout trajectories as a chain of outages. N_{max} is the total number of blackout trajectories which is here 246.

The contribution factor of a line shows the number of times whose trip participates in the chains of cascading failures. As big as CF of a line, it will become more critical for propagating cascading failures following the initial outage of line #26. Fig. 7. shows the contribution factor of each line for participating in the cascading failures of 246 blackout trajectories following an outage of line #26 as initiating the event.

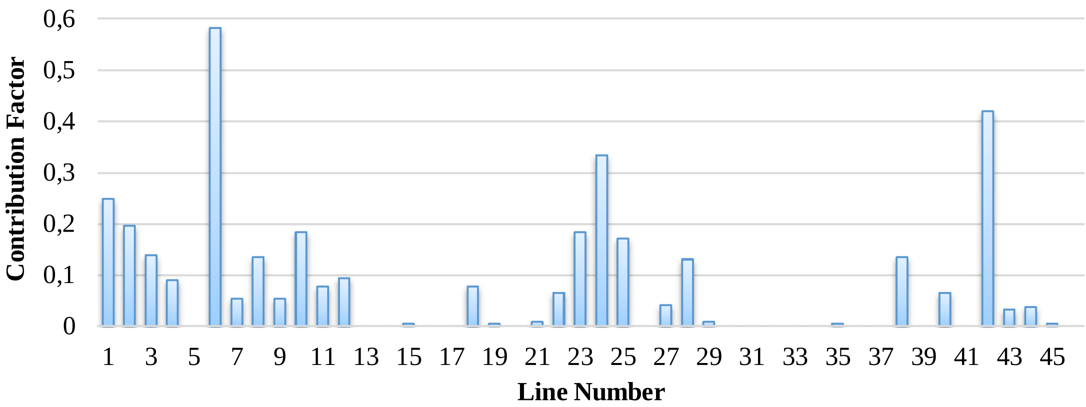

Fig. 6. Contribution factor of lines for participating in cascading failures within 246 blackout trajectories triggering by the outage of line #26 as the initial event

Fig. 7 shows a number of times by which each line trip has participated in the chain of cascading failure of all blackout trajectories as the first cascaded outage. For example, the trip to line #6 (bus3-bus4) has participated 42 times out of 246 blackout trajectories as the first cascaded outage after the initial outage of line #26. So, the line #6 can be regarded as a critical line for propagating blackout through the network.

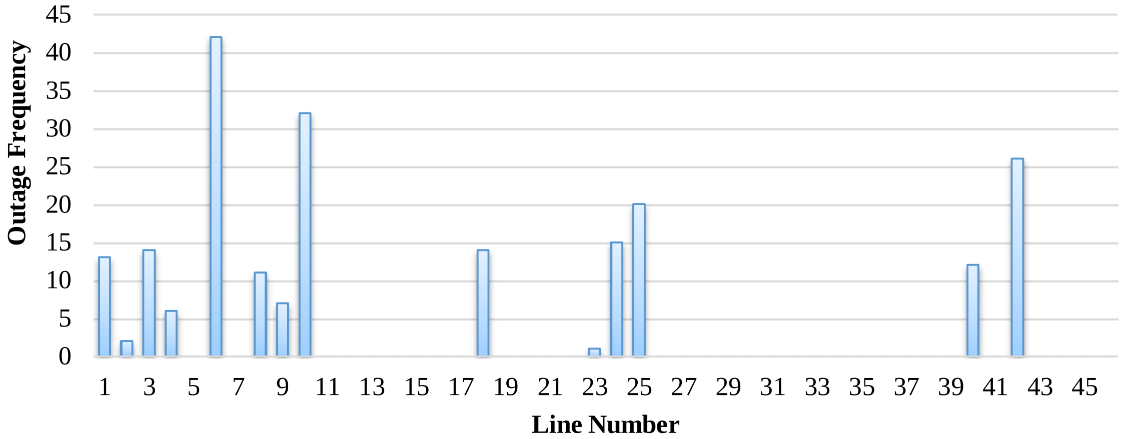

Fig. 7. Frequency of lines trip as the 1st cascaded event within 589 blackout trajectories following the initial outage of line #26

4.3. Input vector of HEDT

The input vector of each DT of the proposed HEDT scheme consists of lines active power flow at the pre-contingency condition as shown in Fig. 4 for a sample scenario. This vector can be prepared online using data from WAMS. The negative value shows a reverse direction of power on the line.

$$\underline{P} = [\, P_{L1}, P_{L2}, \dots, P_{Li}, \ \dots, P_{L46} \,] \tag{4}$$

where P_{Li} is the active power of line #i.

The set of vectors of active power flow corresponding to different scenarios constitutes the input matrix [P] for training HEDT. The number of rows is equal to the number of training patterns. Each vector of active power flow corresponds to a particular operating condition of the power system.

4.4. Training HEDT

In the proposed scheme, the first HEDT1 is responsible just for detecting the potential of the blackout. The second HEDT2 classifies vulnerable scenarios with respect to smaller or bigger than 500MW blackout, and the third HEDT3 classifies vulnerable scenarios concerning smaller or bigger than 1000MW blackout. All HEDTs are trained and tested by 60% and 40% of prepared scenarios respectively. The proposed HEDTs are trained based on top-down search method for data classification. In this method by starting from a root node, samples are classified by submitting a series of questions about the properties associated with the data. A node is bisected into two sub-branches on the basis of the feasible answers for its question. Table 5 shows the training/test performance of HEDT1 in which from 360 training scenarios, 135 scenarios experienced a blackout and perfect classification is achieved.

Table 5. Training/Test Performance of HEDT1

	Training			Test		
Blackout risk	**No. of training scenarios**	**False learning**	**%correct learning**	**No. of test scenarios**	**False estimate**	**%Correct estimate**
Vulnerable	135	0	100	142	0	100
Secure	225	0	100	98	0	100

Table 6 shows the training/test performance of HEDT2 in which from 600 scenarios, 136 and 86 training and test scenarios respectively experienced blackout greater than 500 MW. The corresponding accuracy of training and test are %97.8 and %98.8 respectively.

Table 6. Training/Test Performance of HEDT2

	Training			Test		
Blackout risk (MW)	**No. of training scenarios**	**False learning**	**%correct learning**	**No. of test scenarios**	**False estimate**	**%Correct estimate**
<500	224	2	%99.1	154	2	%98.7
>500	136	3	%97.8	86	1	%98.8

Table 7 shows the training/test performance of HEDT3 in which from 600 scenarios, 114 and 74 training and test scenarios respectively experienced blackout greater than 1000 MW. The corresponding accuracy of training and test are %98.2 and %98.6 respectively.

Table 7. Training/Test Performance of HEDT3

	Training			Test		
Blackout risk (MW)	**No. of training scenarios**	**False learning**	**%Correct learning**	**No. of training scenarios**	**False estimate**	**%Correct estimate**
<1000	246	3	%98.8	166	3	%98.2
>1000	114	2	%98.2	74	1	%98.6

5. Conclusion

In this paper, an approach for predicting system vulnerability with respect to an outage of a line with the potential for cascading failures was established in the decision tree theory. In fact, the proposed scheme was able to estimate the potential of each line contingency for initiating cascading failure and propelling system toward blackout. A three stages HEDT scheme was used for estimating the harmfulness associated with each line contingency. DC power flow was used for modeling cascading failures. The procured results revealed that the proposed method was a powerful technique for online identification of critical branches. A large collection of system operating conditions including a versatile range of load level, load-generation pattern on buses was used for decision tree construction. The capability of the proposed algorithm was assessed through a 39-bus test system. The proposed decision tree was a valuable technique that was deemed robust under topological changes. The one of the most interesting topics for future work would be to develop precise models for blackout problem.

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References

[1] Final Report on the August 14th Blackout in the United States and Canada, United States Department of Energy and National Resources Canada, U.S.-Canada Power System Outage Task Force, 2004.

[2] Final Report, System Disturbance, Union for the Coordination of Transmission of Electricity (UCTE), 2006. [Online]. Available: http://www.ucte.org

[3] B. A. Carreras, V. E. Lynch, M. L. Sachtjen, I. Dobson, and D. E. Newman, "Modeling blackout dynamics in power transmission networks with simple structure," 34th Hawaii International Conference on System Sciences, Maui, Hawaii, January 2001.

[4] M. Vaiman, K. Bell, Y. Chen, B. Chowdhury, I. Dobson, P. Hines, M. Papic, S. Miller, and P. Zhang, "Risk assessment of cascading outages: Methodologies and challenges," IEEE Trans. Power Syst., vol. 27, no. 2, pp. 631–641, May 2012.

[5] B. Stott, J. Jardim, and O. Alsac, "Dc power flow revisited," IEEE Trans. Power Syst., vol. 24, no. 3, pp. 1290–1300, Aug. 2009.

[6] J. Yan, Y. Tang, H. He, Y. Sun, "Cascading failure analysis with dc power flow model and transient stability analysis," IEEE Trans. Power Syst., vol. 30, no. 1, pp. 285-297, 2015.

[7] J. Chen and J. S. Thorp, "A reliability study of transmission system protection via a hidden failure DC load flow model," IEEE Fifth International Conference on Power System Management and Control, pp. 384–389, April 2002.

[8] Liu X, Li Z. "Revealing the impact of multiple solutions in DCOPF on the risk assessment of line cascading failure in OPA model," IEEE Trans. Power Systems, vol. 35, pp. 4159-60, 2016.

[9] Koc Y, Verma T, Araujo NA, Warnier M. Matcasc: "A tool to analyse cascading line outages in power grids." Intelligent Energy Systems (IWIES), IEEE International Workshop, pp. 143-148, Nov 2013.

[10] Xiaohui, Ye, Zhong Wuzhi, Song Xinli, Wu Guoyang, Liu Tao, and Su Zhida. "Review on power system cascading failure theories and studies," In Probabilistic Methods Applied to Power Systems (PMAPS), International Conference on, pp. 1-6. IEEE, 2016.

[11] B. Carreras, D. Newman, I. Dobson, and A. Poole, "Evidence for self-organized criticality in a time series of electric power system blackouts," IEEE Trans. Circuits Syst. I: Reg. Papers, vol. 51, no. 9, pp. 1733–1740, 2004.

[12] I. Dobson, B. A. Carreras, V. E. Lynch, and D. E. Newman, "Complex systems analysis of series of blackouts: Cascading failure, critical points, and self-organization," Chaos: Interdiscipl. J. Nonlin. Sci., vol. 17, no. 2, pp. 1-14, Jun 2007.

[13] B. A. Carreras, V. E. Lynch, I. Dobson, and D. E. Newman, "Critical points and transitions in an electric power transmission model for cascading failure blackouts," Chaos: Interdiscipl. J. Nonlin. Sci., vol. 12, no. 4, pp. 985–994, 2002.

[14] M. Rios, D. Kirschen, D. Jayaweera, D. Nedic, and R. Allan, "Value of security: Modeling time-dependent phenomena and weather conditions," IEEE Trans. Power Syst., vol. 17, no. 3, pp. 543–548, Aug. 2002.

[15] D.S. Kirschen, D. Jayaweera, D.P. Nedic, R.N. Allan, "A probabilistic indicator of system stress," IEEE Trans. Power Systems, vol. 19, no. 3, pp. 1650-1657, August 2004.

[16] I. Dobson, B. Carreras, and D. Newman, "A probabilistic loading-dependent model of cascading failure and possible implications for blackouts," In Proc. 36th Annu. Hawaii Int. Conf. System Sciences, vol. 19, no. 1, pp. 15–32, 2003.

[17] Ren, Hui, Ian Dobson, and Benjamin A. Carreras. "Long-term effect of the n-1 criterion on cascading line outages in an evolving power transmission grid", IEEE Trans. Power Systems, vol. 23, no. 3, pp. 1217-1225, 2008.

[18] Dong, Hui, and Lirong Cui, “System Reliability under Cascading Failure Models,” IEEE Transactions on Reliability, vol. 65, no. 2, 2016, pp. 929-940.

[19] Ma, Jing, Shangxing Wang, Yang Qiu, Yinan Li, Zengping Wang, and James S. Thorp. “Angle Stability Analysis of Power System With Multiple Operating Conditions Considering Cascading Failure,” IEEE Trans. Power Systems, vol. 32, no. 2, 2017, pp. 873-882.

[20] R. Sun, Z. Wu and V. A. Centeno, "Power system islanding detection & identification using topology approach and decision tree," IEEE Power and Energy Society General Meeting, San Diego, CA, 2011.

[21] Papadopoulos P N, Guo T, Milanovic J V., “Probabilistic Framework for Online Identification of Dynamic Behavior of Power Systems with Renewable Generation”, IEEE Transactions on Power Systems, vol. 33, no. 1, Jan. 2018.

[22] Chu C C, Iu H H C., “Complex Networks Theory For Modern Smart Grid Applications: A Survey”, IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 7, no. 2, pp. 177-191, 2017.

[23] R. Diao, V. Vittal, K. Sun, S. Kolluri, S. Mandal and F. Galvan, "Decision tree assisted controlled islanding for preventing cascading events," IEEE/PES Power Systems Conference and Exposition, Seattle, WA, 2009.

[24] N. Senroy, G. T. Heydt and V. Vittal, "Decision Tree Assisted Controlled Islanding," in IEEE Transactions on Power Systems, vol. 21, no. 4, pp. 1790-1797, Nov. 2006.

[25] J. Zhao, A. Gómez-Expósito, M. Netto, L. Mili, A. Abur, V. Terzija, I. Kamwa, B. Pal, A. K. Singh, J. Qi, Z. Huang and S. Meliopoulos, "Power System Dynamic State Estimation: Motivations, Definitions, Methodologies and Future Work," IEEE Transactions on Power Systems, vol. 34, no. 4 , July 2019.

[26] Zhang, Xi, Choujun Zhan, and K. Tse Chi, “Modeling the Dynamics of Cascading Failures in Power Systems,” IEEE Journal on Emerging and Selected Topics in Circuits and Systems, 2017.

[27] Chertkov, Michael, Feng Pan, and Mikhail G. Stepanov, “Predicting failures in power grids: The case of static overloads”, IEEE Transactions on Smart Grid, vol. 2, no. 1, pp. 162-172, 2011.

[28] Q. Chen, J.D. McCalley, “Identifying high risk n-k contingencies for online security assessment”, IEEE Trans. Power Systems, vol. 20, no. 2, pp. 823-834, May 2005.

[29] D.P. Nedic, I. Dobson, D.S. Kirschen, B.A. Carreras, V.E. Lynch, “Criticality in a cascading failure blackout model”, International Journal of Electrical Power and Energy Systems, vol. 28, pp. 627-633, 2006.

[30] B.A. Carreras, V.E. Lynch, I. Dobson, D.E. Newman, “Complex dynamics of blackouts in power transmission systems”, Chaos, vol. 14, no. 3, pp. 643-652, Sept 2004.

[31] S. Mei, F. He, X. Zhang, S. Wu, and G. Wang, “An improved OPA model and blackout risk assessment,” IEEE Trans. Power Syst., vol. 24,no. 2, pp. 814–823, May 2009.