TÜBİTAK

Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2018) 26: 2104 – 2116

doi:10.3906/elk-1705-268

Real-time power system dynamic security assessment based on advanced feature selection for decision tree classifiers

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Received: 23.05.2017 • **Accepted/Published Online:** 14.11.2018 • **Final Version:** 27.07.2018

Abstract: This paper proposes a novel algorithm based on an advanced feature selection technique for the decision tree (DT) classifier to assess the dynamic security in a power system. The proposed methodology utilizes symmetrical uncertainty (SU) to reduce the data redundancy in a dataset for DT classifier-based dynamic security assessment (DSA) tools. The results show that SU reduces the dimension of the dataset used for DSA significantly. Subsequently, the approach improves the performance of the DT classifier. The effectiveness of the proposed technique is demonstrated on the modified IEEE 30-bus test system model. The results show that the DT classifier with SU outperforms the DT classifier without SU. The performance of the proposed algorithm indicates that the DT classifier with SU is able to assess the dynamic security of the system in near real time. Therefore, it is able to provide vital information for protection and control applications in power system operation.

Key words: Dynamic security assessment, data mining, decision tree, advanced feature selection, symmetrical uncertainty

1. Introduction

Forced by increasing demand and electricity market deregulation, a power system has to operate close to its stability limits by narrowing the operation security margin. Operating under a narrow security margin means that the system is operating under stressed operating conditions. Consequently, severe disturbances occur during stressed operating conditions that may trigger sequential tripping within the system and lead to catastrophic blackout [1]. Realizing the calamitous impact of a blackout for society, electrical engineers and researchers have proposed various solutions to address this challenge while allowing the system to operate close to its stability limit securely. Adaptive protection [2], self-healing grids [3], and advanced control strategies [4] are state-of-the-art solutions to address this challenge. However, all these techniques require an accurate monitoring parameter that monitors the security margin of the system to function effectively. Real-time dynamic security assessment (DSA) tools provide an elegant solution to this limitation.

Conventionally, DSA is developed offline based on the heuristic assumption of the system operating situation and load demand forecasting [5]. However, increasing the uncertainties in the network operating situation necessitates online DSA for continuous monitoring of the security state of the system. The development of online DSA is catalyzed with the advent of wide area measurement systems, providing various time-synchronized measurements in the system [6]. This measurement system enables the assessment of the system security state

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online. However, the application of the online DSA is limited. It is not suitable for real-time protection and remedial control action [7–9] following a disturbance in the system. This is due to the fact that the power system is characterized by a large number of dynamic and nonlinear algebraic equations [10]. Thus, computational complexity and time are very high to assess the dynamic security of the system. It is crucial to provide the real-time security index of the system instantaneously in order to provide ample time for the protection and control applications to analyze, make a decision, and provide remedial control action accurately. This paper proposes a new algorithm to address this challenge.

This paper reports a new novel algorithm for dynamic security assessment using advanced feature selection based on the decision tree (DT) classifier. The idea presented in this paper is instigated by the work reported in [11,12]. In [11], the DT classifier demonstrated satisfactory performance in assessing the dynamic security of the system. However, the computational burden increased exponentially with the size and complexity of the system. The work presented in [12,13] demonstrated that the advanced feature selection approach is capable of addressing this problem by reducing the dimensions of the dataset developed for the classifier. In this paper, the symmetrical uncertainty (SU) algorithm and the logistic model tree (LMT) algorithm are considered as the advanced feature selection and the DT classifier, respectively. These two methods are combined to overcome the challenge in minimizing the computational time for DSA tools for real-time power system protection and control applications without jeopardizing the accuracy of the assessment.

Following this introduction, the remainder of this paper is organized into five sections. Section 2 reports on recent research efforts in DSA. Section 3 explains the feature selection algorithm used. Section 4 presents the methodology proposed in this paper. Section 5 describes the application, analysis, and discussion of the proposed method for the modified IEEE 30-bus test model system. Finally, Section 6 concludes this study.

2. The state of the art

A DSA approach is an analytical tool that takes a snapshot of the system operating conditions and consequently performs a comprehensive security assessment in order to warn the system operators about any abnormal operation situations [14]. DSA also provides a remedial control recommendation corresponding to the situation. Recently, the urgent need for the DSA technique combined with the ever-increasing power-to-cost ratio of computers has led to a significant number of implementations of online DSA in practice. DSA systems are in use or in the implementation phases in power systems worldwide [15].

In the literature, various DSA techniques have been reported. These methods aim either to improve computational time or improve the accuracy of the DSA results. Researchers in [16] assessed the dynamic security of the system by using the cascading three-stage fuzzy interference system. The study aimed to reduce the computational time in assessing the dynamic security of the system. Although the results showed a satisfactory reduction of computational time, the technique required a high number of processing units in order to achieve desirable results. In [17], the dynamic security of a system was assessed by using an intelligent system based on an extreme learning machine. The work reported there focused on improving the computational efficiency of the assessment tools for DSA. Nonetheless, the training time and mean absolute error in this method were relatively higher than in other methods reported in the literature. On the other hand, the work presented in [18] improved the performance of DSA tools by reducing the misclassification errors in the DT training process. This was realized by using adaptive ensemble DT training. Researchers in [19] adopted the advanced pattern discovery-based fuzzy classification method. The method improved the accuracy of DSA up to 98.1%.

The methods reported in the literature show that the research efforts for DSA advancements are focused on improving the accuracy or/and computational effort of the assessments. However, in the new environment for modern power systems, the size of the power grid has been increased. Thus, the numbers and types of contingencies have also increased. With the advantages of the PMU unit, which could take 60 to 120 snapshots per second for a current operation system, the amount of data that need to be analyzed has increased. All of these challenges have forced the control center to seek an accurate and fast DSA tool, especially in real time, to keep the power system in a secure state. The basic idea for the improvements for the DSA tool can be divided into two stages. The first stage is related to the process of reducing the size of the DSA dataset without affecting the relevant and nonredundant features within the dataset and the second stage involves choosing a better classifier model that has the ability to interpret patterns in the dataset to reach a highly accurate result and consume less time.

This paper proposes an assessment tool based on the DT classifier. The DT classifier has been applied to assess the dynamic security of the system [18,20]. The performance of the DT algorithms for DSA is promising with further opportunities for improvement. The proposed methodology utilizes the advanced feature selection technique based on the SU algorithm to improve the performance of the DT classifier for DSA in a power system. The SU reduces the data redundancy in a dataset in order to improve the accuracy and reduce the computational effort of the DT classifier for DSA significantly. The idea presented in this paper is instigated by the utilization of SU for DT classifier-based applications in power systems as reported in [21,22].

3. Advanced feature selection

In this paper, the SU algorithm is considered to reduce the errors between the classification labels and the nonrelevant and nonredundant features within the dataset. It is considered due to its efficiency in processing the dataset [23]. SU is a correlation measuring test to evaluate the worth or value of a feature for classification [12]. This technique is able to investigate a dataset to embed or map data points from high-dimensional to low-dimensional variables while keeping all the relevant structures intact. The idea is based on the concept of entropy that measures the uncertainty of a random variable [24]. The entropy of a variable X is defined as:

$$H(X) = -\sum_i P(x_i) log_2(P(x_i)) \tag{1}$$

In Eq. (1), P (xi) is the previous probabilities for all values of X. Consequently, the entropy of X after observing values of other variables Y is written as:

$$H(X|Y) = -\sum_j P(y_j) \sum_i P(x_i|y_j) log_2(P(x_i|y_j)) \tag{2}$$

From Eq. (2) $P(xi|yj)$ is the posterior probabilities of X given the values of Y. The decrement of the entropy of X represents additional information about X provided by Y. This value is called information gain (IG) and it is formulated as in Eq. (3).

$$IG(X|Y) = H(X) - H(X|Y) \tag{3}$$

Based on IG, feature Y is considered more correlated to feature X than to feature Z if IG (Z, Y) $\prec$ IG (X|Y). This means that X is symmetrical to Y. Features with higher IG values provide an excellent indicator to reduce the errors between the classification labels and nonrelevant features within the dataset. Consequently, the IG is normalized with the corresponding entropies in order to reduce data redundancy and improve data visibility.

Here, SU (X, Y) is introduced, which represents the normalized information gain [24], and it is defined as in Eq. (4).

$$SU(XY) = 2\left[\frac{IG(X,Y)}{H(X)+H(Y)}\right] \tag{4}$$

The SU ranges from 0 to 1. SU = 0 means that feature X and feature Y are independent. On the other hand, SU = 1 means that feature X and feature Y are highly correlated. In the proposed method, this entropy-based measure is utilized to reduce the dimension of the dataset by choosing relevant and redundant and nonredundant features only as will be explained in the next section to enhance the performance of DT algorithms for power system DSA applications.

4. Proposed methodology

The methodology proposed in this paper combines the SU technique with the DT classifier for superior performance for DSA applications. While SU reduces the dimensions of the datasets, the DT offers an elegant solution to DSA classification challenges. SU is utilized to significantly improve the performance of the DT classifiers that suffer from high computational burdens and insufficient accuracy in the presence of high-dimensional data. Figure 1 summarizes the methodology proposed for DSA. It is segregated into three major stages to achieve the research objective. The first stage consists of constructing the dataset that represents the dynamic behaviors of a test system model. Following the first stage, advanced feature selection (FS) is utilized to reduce the redundancy in the dataset for data dimension reduction. In the third stage, the dimension-reduced dataset is applied to the DT classifier for DSA application.

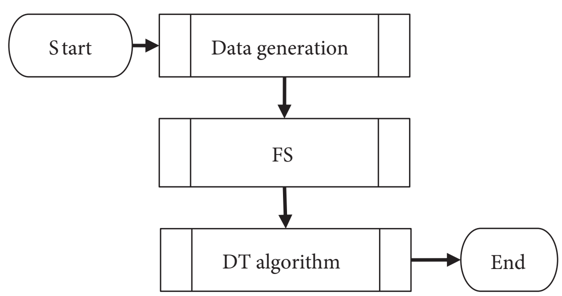

Figure 1. Summary of proposed research methodology.

Figure 2 illustrates the detailed process of the first stage of the proposed methodology. The behavior of the dynamic modeling of the power system elements in various operating conditions is investigated. The contingency cases considered to construct the dataset are as follows:

1. At normal load and for each transmission line, balanced three-phase faults are applied and then cleared after 0.1 s.
2. At normal and 110% load, respectively, one transmission line is open at each time.
3. At normal, 110%, and 120% load, respectively, two transmission lines are open simultaneously near the generation buses.

For all cases, rotor angle, voltage magnitude, and frequency at each bus are recorded. Based on these measurements, the security status of the corresponding scenario is set based on the criteria listed as follows:

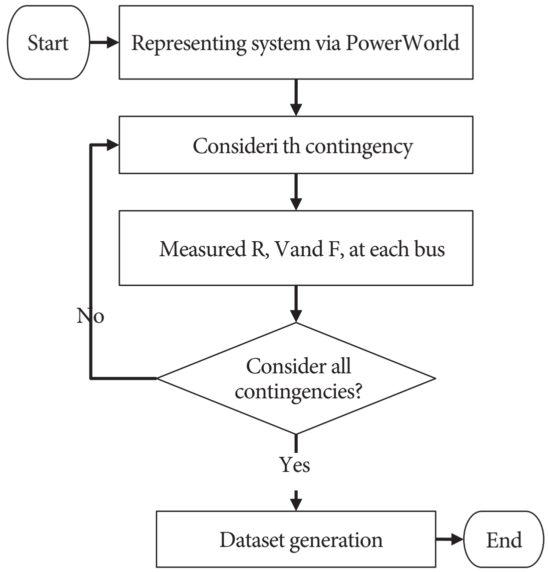

Figure 2. Dataset construction.

1. The system is considered secure if the maximum rotor angle separation of any two synchronous generators (or group of generators) following a disturbance is less than $180°$. Otherwise, the system is insecure.
2. The system is considered secure if the voltage magnitude at each bus is within $0.9 \leq V \leq 1.1$ per unit. Otherwise, the system is insecure.
3. The system is considered secure if the frequency at each bus fluctuates within $49.5 \leq f \leq 50.5$ Hz. Otherwise, the system is insecure.

Figure 3 provides the detailed process for the second stage of the methodology. This is explained as the DSA dataset having n features and c target classes for each instance. The SU algorithm measures the correlation among features and target classes to evaluate the weight of features for classification to determine whether this feature is relevant to the target class or nonrelevant. Then all calculated $SU_{n,c}$ are stored in matrix SU_{list}. They are sorted in descending order according to their SU values. Traditionally, the feature selection can help eliminate nonrelevant attributes, but it cannot remove redundant attributes because it is only looking at individual attributes within the target. In order to identify a redundant feature, the SU and the ranking search method are used in this paper. As explained in Figure 3, the first feature from the SU_{list} matrix, F_a, is set to have the highest relevance to the target class. Consequently, $SU_{a,b}$ is compared with $SU_{b,c}$. If $SU_{a,b} \geq SU_{b,c}$, then F_b is removed from SU_{list}. However, if $SU_{a,b} < SU_{b,c}$ then we keep F_b and take the next feature, F_c. To clarify this point, if two features A and B are highly relevant or correlated to each other, only one of the features is required. If A is selected, B may be removed because of similar feature A. Then we repeat the process by comparing F_a with the next one. This process will be continued until the last, F_z. This process results in a new SU_{list} matrix, SU_{new}. The same filtering processes are repeated until the last feature in the current SU_{list}. In SU_{new}, only the most relevant features remain to classify the target that has no redundancies with other relevant features.

Following the feature selection process, the process continues with the classification of the dataset using the DT technique. This process is shown in Figure 4. The result of feature selection with the ranking search method could sort features according to their evaluation; after that, the user could specify the number of features

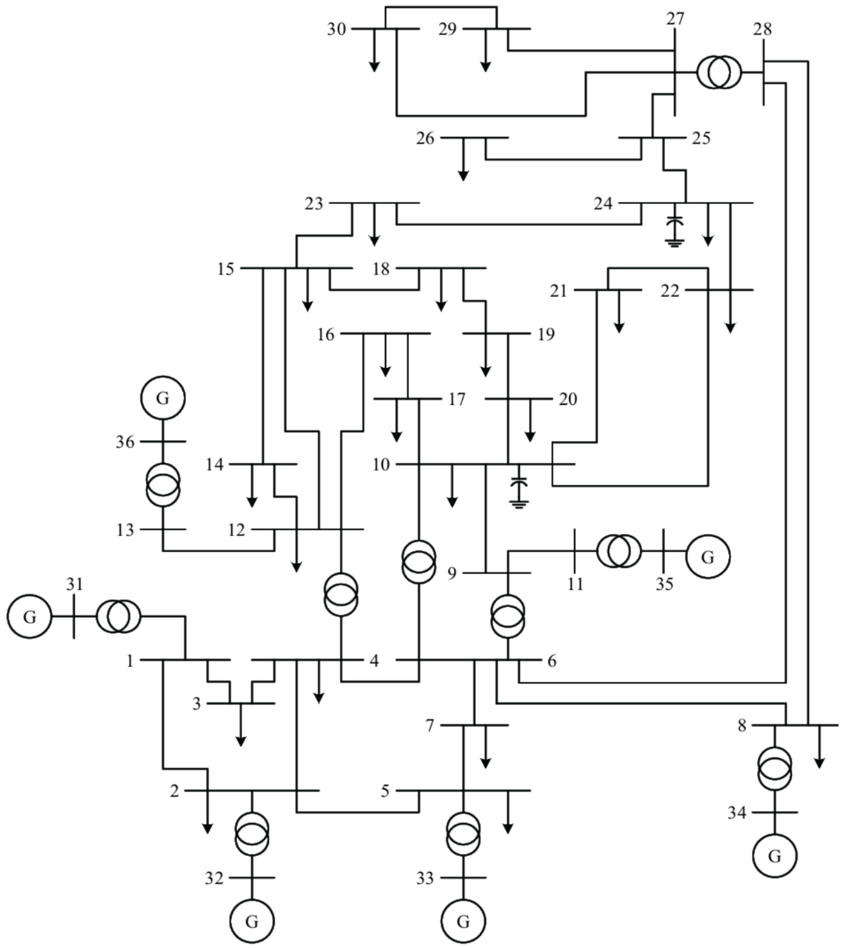

Figure 3. Feature selection processes.

in SU_{new} to retain by the DT technique based on the highest rank in SU_{new} and a predefined threshold. It is hard to specify a suitable cut-off for the number of retained features in each power system; therefore, the user needs to do experimentation to get the best results. Following this process, the reduced dataset is applied to the DT technique for classification. In this study, the logistic model tree (LMT) algorithm is considered to classify the dataset for the DSA of a power system. LMT is considered due to its performance in terms of accuracy and speed in classifying datasets for medical and image processing applications [25–27]. In comparison to a conventional DT, LMT replaces the terminal nodes of a DT with logistic regression functions [28]. Due to this improvement, it is able to classify the binary and multiclass target variables, numeric and nominal attributes, and missing values. When fitting the logistic regression functions at a node, LMT uses cross-validation to determine the number of iterations and employs the same number of iterations throughout the tree instead of cross-validating at every node. This heuristic approach improves the runtime considerably with little effect on accuracy.

5. Results, analysis, and discussion

The methodology described in Section 4 is applied to the modified IEEE 30-bus test system model. This test system model represents a simplified version of an actual power system network. For the IEEE 30-bus test

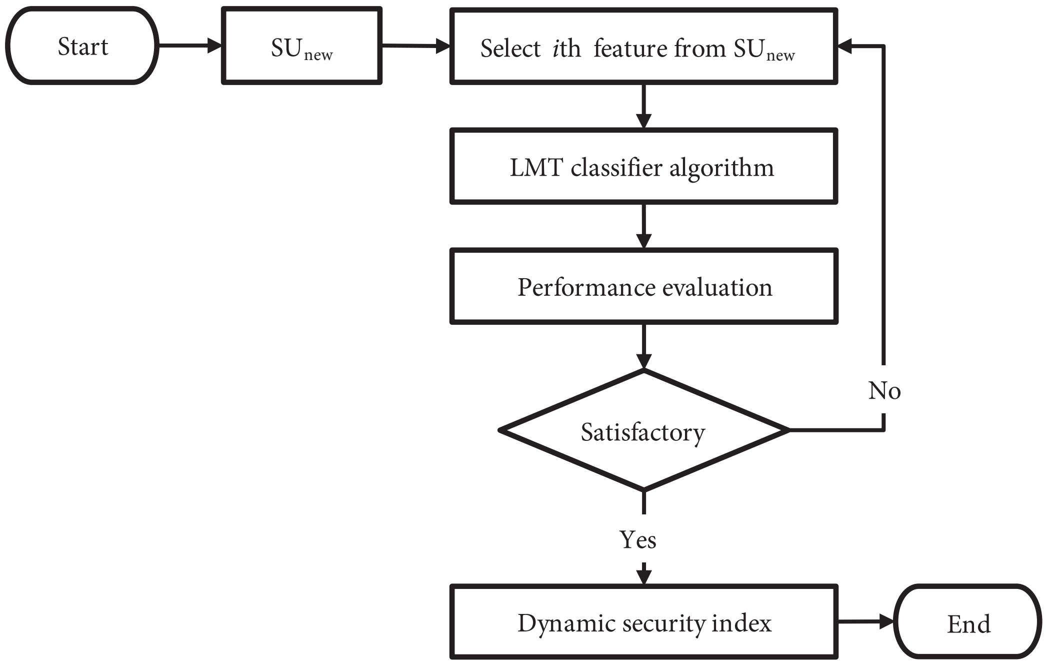

Figure 4. LMT classifier.

system model, the total demands of active and reactive power are 283.4 MW and 126.2 MVAr, respectively. The details of these IEEE test system models are available in [29]. Figure 5 illustrates the single-line diagram of this test system model. From Figure 5, the modified IEEE 30-bus test system model consists of 36 buses.

In this study, the PowerWorld simulator program is used to simulate the test system model responses for all contingency scenarios. The methodology proposed in this paper requires voltage magnitude and frequency at all buses. Therefore, 72 measurements of voltage magnitude and frequency are taken at all buses for every instance and contingency. Additionally, the rotor angle measurements of all six generators are required for the proposed method as well.

As discussed in Section 4, each measurement is a feature or an attribute in a dataset. Therefore, this means that there are 72 + 6 = 78 features in each contingency scenario. Based on the proposed contingency scenario as explained in Section 4, 47 contingencies came from balanced three-phase faults at normal load, 94 contingencies came from the one open transmission line at normal and 110% load, and 45 contingencies came from the two open transmission lines simultaneously near the generation buses at normal, 110%, and 120% loads. Thus, the total number of contingency scenarios considered in this study was 186. Here, each contingency scenario is an instance. Consequently, the dataset for the modified IEEE 30-bus test system model consists of 78 features and 186 instances. Based on the security status of the system, each instance is assigned either "1" if the system is in a secure state or "0" if the system is in an insecure state of operation. The contingency scenario is defined as secure only if all criteria discussed in Section 4 are fulfilled. In this section, only selective samples of cases are discussed due to the limitation of space.

Figures 6, 7, and 8 illustrate the responses of the IEEE 30-bus test system model following an N − 1 contingency scenario. A bolted three-phase fault is applied at bus 2 at t = 1 s and the fault is cleared by opening line 2–6. Figures 6, 7, and 8 represent the generators' rotor angle, the voltage magnitude of all buses connected to bus 2, and the frequency of all buses connected to bus 2 of the test system model following the operating

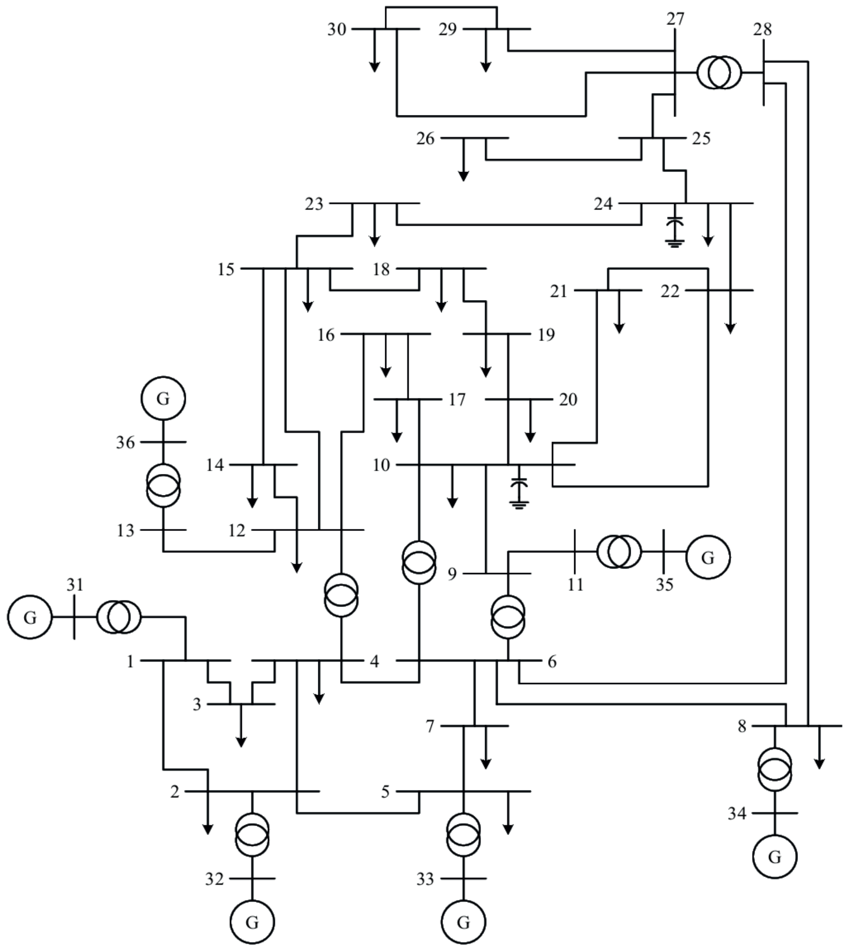

Figure 5. Single-line diagram of modified IEEE 30-bus test system model.

scenario, respectively. Based on the generators' rotor angle responses shown in Figure 6, the system is able to find a new equilibrium point following the disturbance in the system. Therefore, the system is transiently stable. Consequently, Figure 7 shows that the voltage magnitude of all buses connected to bus 2 oscillates between 0.9 and 1.1 pu, while Figure 8 shows that the frequency of all buses connected to bus 2 oscillates between 49.5 and 50.5 Hz following the N – 1 contingency scenario. Since all three criteria of system dynamic security are fulfilled, the system is assigned as secured.

Figures 9, 10, and 11 depict the system responses of the IEEE 30-bus test system model following an N – 2 contingency scenario. Similar to the N – 1 contingency, a bolted three-phase fault is applied at bus 2 at t = 1 s and the fault is cleared by opening line 2–6. However, an additional line, 2–32, is opened as well following the fault in the system. This situation may occur in practice due to relay maloperation that causes unnecessary tripping of the line [1]. Figures 9, 10, and 11 represent the generators' rotor angle, the voltage magnitude of all buses connected to bus 2, and the frequency of all buses connected to bus 2 of the test system model following the operating scenario, respectively. Based on the generators' rotor angle responses shown in Figure 9, generator 32 accelerates compared to the rest of generators in the system. The separation angle between generator 32 and the rest of the system exceeds 180° after t = 1.5 s. This implies that the system is transiently unstable because it is unable to find a new equilibrium point following a disturbance in the system. Subsequently, Figure

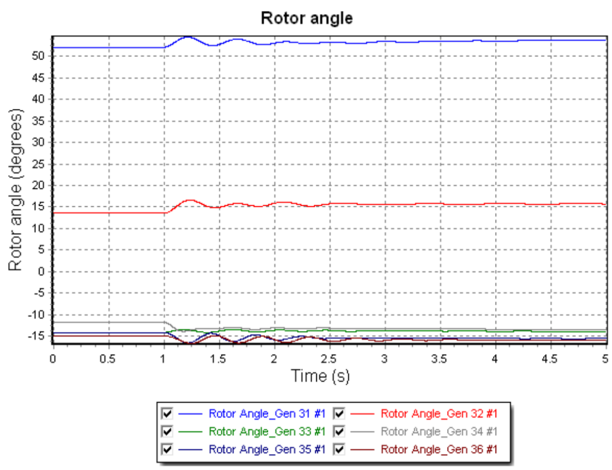

Figure 6. Generators' rotor angle responses (N – 1 contingency scenario).

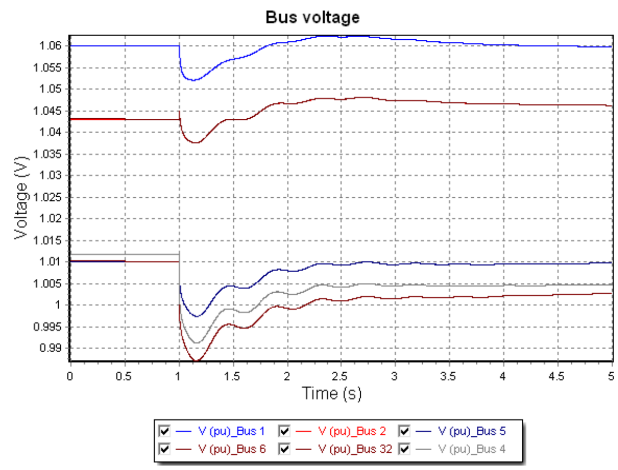

Figure 7. Voltage magnitude of all buses connected to bus 2 (N – 1 contingency scenario).

10 shows that the oscillation of voltage magnitude of all buses connected to bus 2 exceeds the minimum and the maximum limits of 0.9 and 1.1 pu, respectively. Figure 11 illustrates that the oscillation of frequency of all buses connected to bus 2 also exceeds the limit between 49.5 and 50.5 Hz following this contingency scenario. Based on these responses, the system is assigned as insecure following this contingency scenario. It is worth noting that, given a similar disturbance in the system, different remedial actions may cause huge differences in the system security's state of operation.

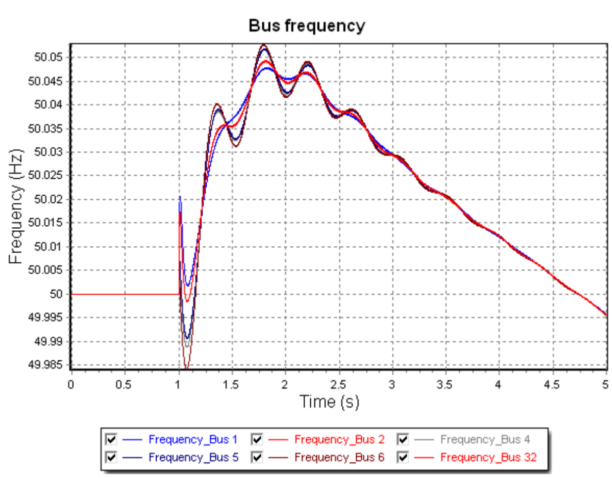

Figure 8. Frequency of all buses connected to bus 2 (N – 1 contingency scenario).

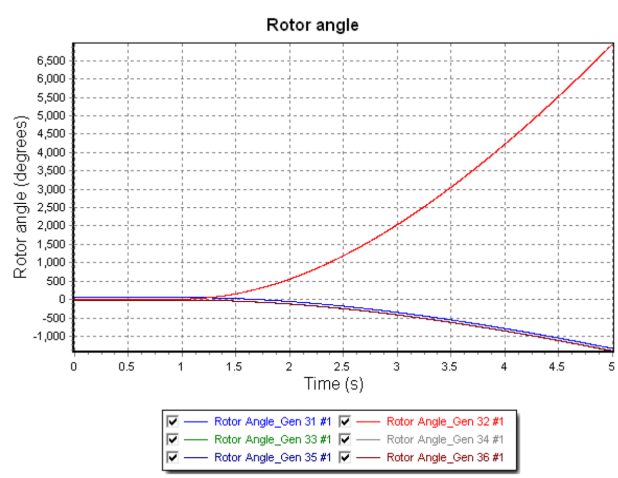

Figure 9. Generators' rotor angle responses (N – 2 contingency scenario).

These processes are repeated for all instances in the dataset. For the test system model considered in this study, 123 instances are assigned as secure and 63 instances are assigned as insecure, respectively. Consequently, the SU algorithm is applied to reduce information redundancy in the dataset. Then the reduced dataset is applied for DSA using the LMT algorithm. The accuracy and the computational time using the proposed method are recorded. Consequently, the performance of DSA using the proposed methodology is compared with the performance of DSA using the LMT algorithm. Table 1 summarizes the results obtained using the LMT algorithm with and without SU.

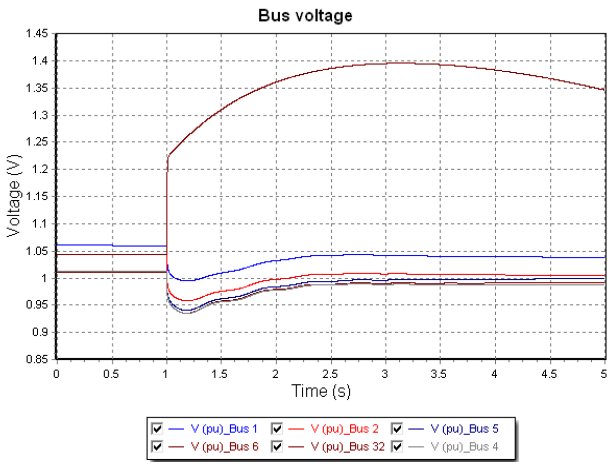

Figure 10. Voltage magnitude of all buses connected to bus 2 (N – 2 contingency scenario).

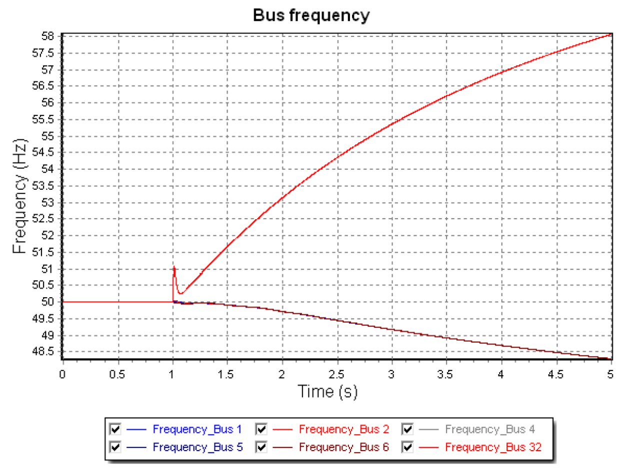

Figure 11. Frequency of all buses connected to bus 2 (N – 2 contingency scenario).

Table 1. Performance of decision tree techniques via LMT using SU.

	LMT without SU	LMT with SU
Number of instances	186	186
Number of features	78	7
Accuracy (%)	98.3871	100
Computational time (s)	0.13	0.09

From Table 1, the number of features in the dataset for the application of DSA to the IEEE 30-bus test system model is 78. However, using the proposed method, the number of features has been significantly reduced to seven. This implies that 78 – 7 = 71 features are highly correlated to these seven features. In other words, only these seven features are significant within the dataset. Therefore, these 71 features can be ignored because they are representing similar characteristics to the significant features. Therefore, these significant features are sufficient to represent the dynamic responses following a disturbance in the system. In addition, the instances to be considered are maintained at 186. This implies that the proposed method does not neglect any contingencies for the DT training process. Reducing the number of features in the dataset improves the performance of the LMT algorithm. The results also show that the LMT algorithm with SU outpaces the LMT algorithm without SU. The LMT only requires 0.09 s to achieve 100% accuracy using the dataset reduced by SU compared to 0.13 s to achieve only 98.3871% accuracy using the initial dataset to assess the dynamic security of the IEEE 30-bus test system model. This implies that the proposed algorithm improves the performance of the DT via the LMT algorithm for DSA application by reducing the instances in the dataset.

To compare the effectiveness of the SU feature selection with other feature selection algorithms in other machine learning applications, four feature selection algorithms were used in the same dataset with the LMT algorithm, namely correlation-based, gain ratio, information gain, and RELIEFF algorithms. Details of these algorithms are available in [30]. Table 2 shows the comparable results for each feature selection algorithm. From the table, SU is clearly superior to all other algorithms in terms of accuracy. This superiority is due to its high performance because the SU algorithm chooses only the most important feature and excludes the redundant features. Consequently, this leads to the reduction of error and noise to the minimum limit and improves the results of the LMT classifier.

Table 2. Comparison of results between SU and 4 different feature selection algorithms for the same dataset with LMT.

LMT with	SU	Correlation-based	Gain Ratio	Information gain	RELIEFF
Accuracy (%)	100	94.086	99.4622	99.4624	96.7742

The machine learning technique shows high efficiency in various applications for DSA compared with traditional techniques. However, a modern power system would have to deal with massive changes in the volume of the data coming per millisecond from measuring devices, such as PMUs. Thus, it is vital to reduce the size of the data and to remove any irrelevant or redundant features from the dataset, which could reduce analysis time and increase the accuracy of the machine learning algorithms. Unlike the traditional application of the DT classification methods for DSA, this study has combined the advantages of the SU feature selection algorithm with the benefits of the LMT classifier algorithm. This combination has been effective in achieving the target of online DSA applications (high accuracy and short timeframe) because SU turned the LMT learning process into a highly effective and faster operation.

The advantage of this approach, in terms of a cost-effective solution, is that this methodology could remove the nonrelevant and redundant features for the DSA dataset. This could reduce the size of the data that need to be analyzed by the DSA tool, thus enhancing the performance of the classification algorithm and reducing the additional computational cost. Additionally, highly accurate assessments for the operator could reduce the cost of the protection process.

Security and stability are time-varying features that could be measured by monitoring the power system's performance under a contingency scenario. In the event of a contingency, the survival of the power system will depend on the nature and site of the fault, as well as the rapid clearance of faults by protective devices. Any delays in the protection device or unsatisfactory operation of that device could lead to changes in the stability of the power system, which could lead to an unstable and thus insecure state in a short period. The high accuracy and shorter timeframe offered by this proposed methodology could be helpful in the efficiency assessment of the security and stability state of a power system.

Based on the methodology, this proposed method is suitable for a postfault event when the DSA tool has determined that a specific contingency may lead to an insecure situation. Then the control center should implement effective remedial measures, such as generator tripping, load shedding, capacitor bank switching, and an automatic reactor, to keep the system in a secure state. Although these remedial control actions are costly, they are necessary to avoid blackouts.

6. Conclusions

This paper reports a novel algorithm for power system dynamic security assessment using advanced feature selection based on the DT classifier. The method combines the dataset reduction technique with the DT classifier. The proposed method uses the SU algorithm, a variant of the advanced feature selection technique, to reduce the dimensions of the dataset. Subsequently, the reduced dataset is applied to the LMT algorithm to assess the dynamic security of the power system. The proposed methodology is applied to the IEEE 30-bus test system model to demonstrate its effectiveness in improving the performance of the DT classifier for power system DSA applications. The results show that the SU algorithm is able to decrease the computational time by 30.76% while improving the accuracy of the LMT algorithm to 100% for DSA of the IEEE 30-bus test system model.

This method could be quite valuable for real-time protection and control applications. Finally, evaluating the effectiveness of this method by computing in a larger and more complex system with renewable energy sources is essential to demonstrate the superiority of the proposed method, with a state-of-the-art DSA power system, based on the DT classifier technique. This will be pursued as an immediate future activity.

Acknowledgments

The authors would like to thank Universiti Tun Hussein Onn Malaysia (UTHM) for the award that enabled this research under Grant U424 and the Ministry of Communications (Iraq) for technical support.

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