A Synchrophasor-based Decision Tree Approach for Identification of Most Coherent Generating Units

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***Abstract*— Identifying coherent generating units in power systems is an important step toward development of a reduced model for bulk electricity grid aiming at wide-area analysis and controlled islanding practices. In this paper, an approach for identification of the most coherent generating units is proposed which exploits a decision tree (DT) algorithm based on synchronized data measured by phasor measurement units (PMUs). Such DTs should be trained so as to provide accurate decisions for almost all possible disturbances in power systems. Three probabilistic parameters are, therefore, taken into account in a training stage including fault type, fault location, and the system load level at the time fault occurs. In order to generate the training dataset, different scenarios are simulated and appropriate attributes are extracted from voltage phasors. Furthermore, the most coherent generating units, which are the DT target, are determined in each scenario by evaluating the similarity between the frequency components existing in their speed variation signals. The effectiveness of the suggested approach is verified by its application to the 68-bus, 16-machine test system through which it reveals high accuracy in recognizing the most coherent generating units under various prevailing conditions in power grid.**

Keywords— coherency detection; decision tree; frequency component; phasor measurement unit (PMU); wide area measurement system.

I. INTRODUCTION

THE OPERATING POINT of the power system changes continuously following disturbances and other prevailing conditions highlighting the need to trace and analyze this transient behavior continuously to maintain the system stability. However, due to the increasing complexity and interconnections of modern power systems, the real-time system monitoring, control, and analysis is quite challenging. Therefore, a reduced dynamic model of the power grid can be helpful for such analysis potentially alleviating the associated computational burdens. The first application of coherency-based generators clustering was to achieve the reduced dynamic models of power systems for transient stability analyses. Later, with the advent and widespread deployment of synchronized measurement technologies, other applications such as wide area control [1] and controlled islanding [2] were introduced and applied in real world practices.

Deriving power system equivalence entails two main steps. The first step is to identify the coherent generating units and partitioning the system based on the generators' dynamic response. The focus on the second step is to determine a reduced equivalent model of the generating units in each coherent partition using different aggregation and reduction methods. The main idea for generator clustering is the similarity of dynamic response of generators in response to disturbances. In this regard, generating units that have the same post-disturbance rotor angle or speed variation are called *coherent* and are clustered in the same category. Some of the techniques and methods introduced and developed on the topic are as follows: weak links method [3], two time scale method [4], modal analysis-based method [5], and nonlinear methods [6]. Furthermore, the wavelet phase difference approach [7], subtractive clustering [8], Lyapunov function [9], projection pursuit [10], singular value decomposition [11], prony analysis [12] and, principal component analysis [13] are among the solution techniques applied in the literature.

Today, synchronized measurement technology (SMT), in which phasor measurement unit (PMU) is the main element, has been fully installed or is being deployed in many countries [14]. Recently, several efforts have been made on the coherent generator identification using measurement data captured by PMUs [7]-[21]. For instance, the authors in [15] utilized the correlation between time-varying signals for assessing the coherency between generating units or non-generating buses. In [13], principal component analysis (PCA) is applied on mono-components obtained from a digital filter bank. The concept of equivalent rotor speed in center of inertia (COI) is also employed in [10] to find the coherent generating units. In [19], coherent generating units are determined using a multiflock-based technique. A hierarchical approach to cluster the generating units into coherent groups are practiced in [20]. In general, there are several key problems and un-addressed challenges in most of the previous literature with regards to the measurement-based coherent generator identification, including complicacy, scalability, and high computational burdens, as well as its tight dependency on the data measured by PMUs. Additionally, while some of these studies have assumed that the generators clustering is fixed and static regardless of disturbance severity, this assumption was declined in [8], [21]. Note that each of the aforementioned methods suffers from one or more, but not all, pitfalls introduced. The main concern still remains to be an efficient method for coherency detection that needs to record the rotor angle or speed variations for a considerably long time after a disturbance occurs. This paper aims to go beyond the conventional online coherency detection methods by building models, which can predict and detect the coherency in a relatively shorter time frame compared to that practiced in the past. In so doing, the phasor data measured in the first seconds of disturbance occurrence are utilized to predict the most coherent generating units using decision trees (DTs) algorithm.

The method presented in this paper is founded based on phasors measured by PMUs and employs DT as a powerful pattern recognition mechanism to predict the most coherent generating units. The most coherent generating units are identified through calculating the similarity between frequency components that exist in generators' speed signals. Noteworthy is that these frequencies and their amplitudes represent the contribution of each generating unit in the dynamic response of power system in the face of disturbances or other prevailing conditions. To train the DTs, different scenarios are generated and applied to a test power system, each pertinent to a certain fault type occurred in a specific location and at a certain load level in the system. These scenarios are selected in such a way that they serve as a fairly accurate and reasonable representation of all possible fault scenarios in the system.

II. Coherency in Power Systems

Following a disturbance occurrence, the power system can be partitioned into clusters of generating units based on the similarity of their swing curve variations. In this regard, generating units that have the same swing curves are placed in the same cluster and are called "*coherent*". It is apparent that the deviation in the rotor angle or speed of a generating unit after a disturbance represents its contribution to the system overall dynamic behavior and response. This can be characterized through extracting and investigating the frequency components that exist in the rotor angle or speed variation signals of generating units. These components can be extracted using fast Fourier transform (FFT) as follows.

$$F_i(\omega) = FFT\{\omega_i(k)\} \qquad i = 1,\dots,N_G \tag{1}$$

$$\omega_i(k) = \frac{\theta_i(k) - \theta_i(k-1)}{\Delta t} \tag{2}$$

where, ω_i (k) and θ_i (k) are the speed and rotor angle of generating unit i at time instant k, and F_i (ω) represents the Fourier transform of the speed signal. Δt is the time interval between two executive samples, which is constant in all simulations; N_G is the number of generating units in the system. In order to identify the most coherent generators, the similarity matrix is constructed as follows.

$$C = \begin{bmatrix} c_{1,1} & \cdots & c_{1,N_G} \\ \vdots & \ddots & \vdots \\ c_{N_G,1} & \cdots & c_{N_G,N_G} \end{bmatrix} \tag{3}$$

$$c_{i,j} = \sum_{\omega=1}^{n} \left(F_i(\omega) - F_j(\omega) \right) \tag{4}$$

In (4), $c_{i,j}$ is the similarity index between generators i and j. As described above, the frequency components of angular speeds can provide a good representation of each generator's contribution to the system dynamic response and, therefore, handful to identify the coherent generating units. The similarity matrix elements in (3) is normalized in (5) as identification of the most coherent generating units is easier in this way.

$$\bar{c}_{i,j} = \frac{c_{i,j}}{\max\{C\}} \tag{5}$$

III. The Proposed Methodology

Data mining methods and analytics have been utilized in many different applications in power systems studies and simulations, where the data are gathered from all over the system historically. Then, hidden patterns between these data and the target parameters are recognized using different types of data mining tools and techniques. Among different types of data mining methods, decision tree (DT) seems to be suitable for generating unit coherency detection due to its powerful ability for classification. Therefore, this paper suggests a methodology based on DTs to predict the most coherent generating units after a disturbance occurs in power systems. A simple decision tree structure is illustrated in Fig 1. Each decision tree consists of two types of nodes namely *decision* and *terminal* nodes. The input to the DT includes several attributes, which should be tested and verified in the corresponding decision nodes.

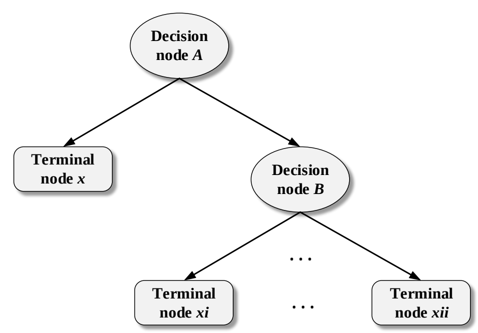

Figure 1. General structure of a simple decision tree.

The most coherent generating units are defined based on the similarity between the frequency components that exist in generators' angular speeds. The flowchart for the proposed methodology is illustrated in Fig. 2, where each decision tree is trained offline. In so doing, N_S number of scenarios are defined based on the possibilities for disturbance severities and locations as well as system conditions. In other words, each scenario is associated with a specific type of fault occurs when the test system is in a given operating condition. It should be noted that these scenarios should be selected inclusively and in such a way that they can be a good representation of all possible situations that can happen in power systems.

Having defined the scenarios, the required data for generating the training dataset should be collected. Hence, each scenario is simulated in a time domain platform and the required data are measured and stored. These data includes

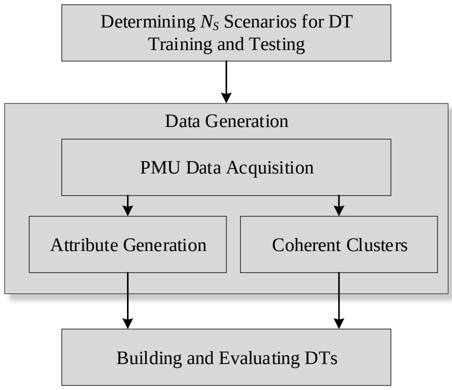

Figure 2. Flowchart of the proposed method.

voltage phasors variations at all buses as well as the rotor angle variations of all generating units during the time period of simulations, which are obtained through wide area measurement system (WAMS).

Two sets of parameters have to be calculated in each scenario. First, the most coherent generating units need to be determined. In the proposed method, the similarity between the frequency components of generating units' angular speed is calculated and the dissimilarity matrix is constructed and normalized using (3)-(5). Within the i^{th} row of matrix C (which corresponds to generator i), the lowest dissimilarity index c_{ij}, which should also be lower than a threshold λ, indicates that generator j is the one that is most coherent with generator i. The Second set of parameters are the appropriate attributes that are extracted from voltage phasors measured by PMUs. In this paper, the first peak of amplitude and phase angle of voltage phasors are selected as the attributes which are illustrated in Fig. 3. Note that the selection of appropriate features as the input to the pattern recognition algorithm is entirely a target-based decision. Coherency from a measurement-based point of view is the similarity of dynamic responses, represented by swing curves. These dynamic responses might cause variations in voltage magnitudes and phase angles. Therefore, coherency can be assessed through investigating the voltage phasor variations, especially the shape of variations. Furthermore, the variations associated with an individual bus are different for various disturbance types, locations and other probabilistic parameters defined in the paper. These probabilistic parameters cause the frequency and magnitude of voltage variations to be stochastic in nature. Utilizing these attributes help develop predictive models which results in faster identification of the most coherent generators in the partitioned system. It should be noted that the error in PMU measurements or PMU missing data will affect the accuracy of DTs. However, in this paper, it is assumed that the system is fully observable and the required PMU data are continuously available without any data loss or any significant error in measurements.

In this paper, N_G number of DTs are considered for N_G number of generating units. Each DT is aimed to predict the generator that is most coherent with the corresponding generator. Therefore, each DT will be created based on its own dataset. As earlier mentioned, the generating dataset consists of

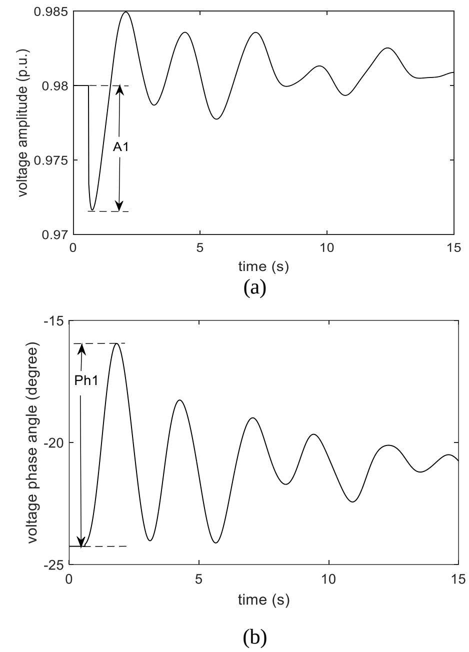

Figure 3. First peak in (a) amplitude and (b) phase angle of a voltage phasor

two sets of parameters, including the *attributes* and the *target parameters*. However, the attribute values in all generating datasets are the same, while the only difference between datasets will be the target. A generating dataset used in this paper is presented in Fig. 4.

IV. Results and Discussions

The proposed approach is simulated on a 68-bus, 16-machine test system [22]. Simulations are performed in 3 different platforms. First, the test power system is simulated using DIgSILENT Power Factory. Then, different scenarios are applied to this system and the required data are stored. The data are processed in the MATLAB environment for further analysis and finally, WEKA is employed as the data mining software tool to build the DTs algorithm.

A. *Generation of Training Dataset*

In order to generate the training data set, 365 different scenarios are defined and applied to the test system. These scenarios are chosen so that they can provide a sufficient representation of the possible faults that might occur in the system. This is achieved by considering three probabilistic parameters described in Section 3 to generate the training data set. The probability of fault types is listed in Table I [23]. In

Attributes

Scenarios

Case No.	Att. #1	Att. #2	...	Att. #N_{Att}	Target
1	$a_{1,1}$	$a_{1,2}$	...	$a_{1,Natt}$	Generator No.
2	$a_{2,1}$	$a_{2,2}$	...	$a_{2,Natt}$	Generator No.
...	...	...	...	...	Generator No.
N_S	$a_{NS,1}$	$a_{NS,2}$	...	$a_{NS,Natt}$	Generator No.

Figure 4. The training dataset

TABLE I
THE PROBABILITIES ASSIGNED TO DIFFERENT FAULT TYPES

Fault type	Probability (%)
Single line to ground (SLG)	70
Line to line (LL)	15
Line to line to ground (LLG)	10
Three phase	5

TABLE II
THE PROBABILITIES REPRESENTING SYSTEM LOAD LEVELS

Load level [%]	Probability (%)
100	5
94	10
86	30
77	30
71	15
65	10

this paper, all 68 buses and 86 lines are considered as the probable fault locations. The probabilities corresponding to various fault locations should be obtained historically. However, due to the unavailability of data regarding the transmission line outages, these probabilities are considered to be identical for all buses and lines in the system. In this paper, six load levels are defined to reflect the annual variations of load demand. These load levels, shown in Table II, are all arbitrary and defined as percentage of maximum loadability of the studied system.

In each of the 365 generated scenarios, one individual fault is applied to the test system. Each scenario is simulated for 30 s, which is enough to find the coherency between generating units. The sampling rate of voltage signals is considered to be 200 Hz, i.e. a time interval of 0.005 s. To assess the coherency of generators, speed signals are used. In this regard, for generator *i*, the most coherent generator among other generators is the one which has the highest correlation value between its speed signal and the speed signal of generator *i*. However, this correlation is assumed to be more than 0.9. In each scenario, voltage phasors at all buses as well as rotor angles of all generating units are stored to be used for extracting the attributes and targets. Then, a training dataset, as the one shown in Fig. 4, is generated for each generating unit.

B. *Building the Classifiers' Models*

In the proposed approach, 16 DTs, which are related to 16 generating units that exist in the test power system, are defined. The output corresponding to the i^{th} DT will determine the generator that is most coherent with generator *i*. One of the best algorithms, which has been used in literature to build a DT as a classifier model, is the C4.5 algorithm [24], [25]. This algorithm, which is a developed version of earlier algorithms ID3 and CLS, has been implemented in WEKA and named as J48. However, ensemble classifiers, whether generated by techniques such as bagging or boosting, offer better accuracy. Therefore, Random Forest, which uses bagging to construct a collection of DTs, is employed in this paper. A detailed description of these methods and their performance characteristics is available in [24], [25]. It should be noted that, in this paper, λ is considered to be 0.1. Furthermore, among different methods for training and testing a DT, cross-validation is adopted due to its superior performance compared to others. In so doing, for all simulations, the DTs' evaluation is performed using a 10-fold cross-validation method.

The results of 16 decision trees generated are detailed in Table III. As it can be seen, the accuracy of DTs are very high. Table III reflects the fact that the measured voltage phasors of 60 buses are sufficient to determine the coherency of generating units concluded as the output of DTs. This highlights that it is essential to obtain the voltage phasors of these buses directly or indirectly. Ideally, it is essential to monitor the voltage phasors at all buses to achieve a full observability of the grid. However, it is not cost-effective to install PMUs at all buses. Therefore, there have been numerous methods proposed to determine the optimum number and locations of PMUs. In this regard, in a wide area measurement system, the voltage phasors at PMU buses are measured directly by PMUs, while the voltage phasors at buses with no

TABLE III
RESULT OF DECISION TREES

Gen. No.	No. of leaves	No. of decision nodes	Decision nodes		Accuracy [%]
			Amplitude	*Phase angle*	
1	11	10	12, 16, 19, 22, 37, 39, 47, 48	8, 62	99.39
2	15	14	1, 13, 15, 20, 22, 29, 33, 40, 59	13, 39	99.08
3	7	6	9, 10, 16, 40, 42, 47	-	99.08
4	5	4	33	11, 51, 58	100
5	2	1	19	-	100
6	13	12	1, 3, 16, 30, 36, 66	1, 25, 27, 37, 48, 51	96.63
7	13	12	1, 9, 10, 14, 27, 29, 54, 66	11, 12, 31	97.85
8	10	9	2, 14, 16, 19, 22, 25, 37, 48	64	99.08
9	10	9	6, 11, 13, 19, 33, 40, 51	-	98.47
10	12	11	5, 10, 11, 12, 13, 20, 23, 50	6, 14	99.08
11	7	6	3, 21, 38	3, 14, 54	99.39
12	7	6	2,19	3, 17, 40, 51	98.16
13	12	11	2, 7, 13, 17, 20, 22, 36, 43, 54, 67	3	96.93
14	16	15	11, 13, 16, 18, 23, 24, 28, 35, 46, 49, 57	12, 38, 48	97.55
15	12	11	14, 15, 16, 17, 30, 32, 41, 54	25	97.55
16	18	17	1, 10, 12, 13, 16, 17, 22, 35, 42, 48, 59	3, 11, 49, 50	99.39

installed PMUs are calculated using the data measured at the neighboring buses with PMU. Furthermore, for some generators such as generator 2, nine amplitude and two phase angles are stated as the required data, while it has stated that the total number is 14 in the third column. The reason is that some of these data are compared with different thresholds in more than one decision node.

Unlike the first approach (detailed in Table III) in which DTs were trained using only the voltage phasors, another approach based on both voltage phasors and the results of other DTs can also be applied to predict the most coherent generating units. In this approach, each DT considers not only the voltage phasors, but also the final decision of other DTs in the training procedure. In contrast to the first approach, where all 16 DTs are constructed in parallel, DTs in the new approach are arranged in a multi-layer, hierarchical order architecture. Hence, DTs' performance will be dependent on the final decision of each other, meaning that there will be several loops in the overall coherent generator identification process. Therefore, an optimization problem needs to be solved to find the optimum hierarchical scheme for this problem. As an example, a typical scheme is selected and illustrated in Fig. 5. The detailed information of this approach is provided in Table IV. For instance, the final decision of the DT related to generator 2 depends on the group of generator 3 as well as the voltage amplitude at buses 25 and 42. It can be seen that, except for generators 2 and 16, the accuracy of DTs related to other generators are higher compared to the first approach.

As shown in Fig. 5, the hierarchical coherent generators identification approach includes 5 layers, in which layers 1-5 consist 6, 5, 1, 3 and1 DTs, respectively. In the first layer, the generators that are most coherent with each of generators 3, 4, 8, 9, 11 and 12 are identified using the DTs obtained for each of them. Then, the generators most coherent with each of generators [1, 2, 5, 7, 10]; [14]; [6, 13, 16] will be determined in the second, third and fourth layers, respectively, using their corresponding DTs. Finally, the DT in the fifth layer predicts the generator is going to be most coherent with generator 15. In order to make a comparison between these two coherency detection approaches in terms of calculation time and computational burdens, the number of decision nodes in the longest path from the root node to the farthest leaf in each individual DT is calculated. For instance, in the DT shown in Fig. 1, the longest path is the one which consists of two decision nodes including the decision nodes *A* and *B*. The longest path of each DT in both approaches is presented in Fig. 6. One can conclude, from Fig. 6, that in the first approach, the DT associated with generating unit 6 owns the longest path among all generating units. It highlights that in this approach, where all DTs are structured in parallel, most coherent generating units are identified after 8 comparisons are performed through this DT in the worst case scenario. However, in the second approach, which is shown in Fig. 5, the generating units are divided into five consecutive layers, and hence, it might be expected to perform a series of additional comparisons than the first approach to identify the most coherent generating units. From Fig. 5 and Fig. 6, it can be realized that the worst situation is where DTs associated with

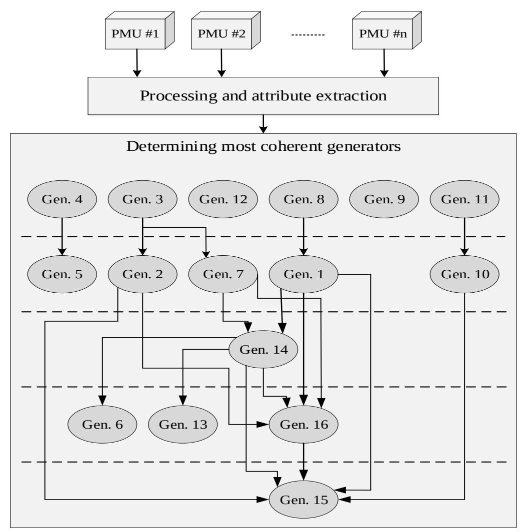

Figure 5. Hierarchical scheme for most coherent generators determination

TABLE IV
RESULT OF DECISION TREES FOR THE TYPICAL HIERARCHICAL APPROACH

Gen. No.	**No. of leaves**	**No. of decision nodes**	**Decision nodes**			**Accuracy [%]**
			Generator	***Bus***		
				Amplitude	***Phase angle***	
1	3	1	8	-	-	100
2	4	3	3	25, 42	-	98.47
3	7	6	-	9, 10, 16, 40, 42, 47	-	99.08
4	5	4	-	33	11, 51, 58	100
5	4	1	4	-	-	100
6	13	8	14	12, 20, 22, 25, 50, 67	-	97.55
7	13	12	3	10, 25, 31, 33, 47, 54	15, 36, 42, 46, 57	98.47
8	10	9	-	2, 14, 16, 19, 22, 25, 37, 48	64	99.08
9	10	9	-	6, 11, 13, 19, 33, 40, 51	-	98.47
10	4	3	11	11, 56	-	100
11	7	6	-	3, 21, 38	3, 14, 54	99.39
12	7	6	-	2, 19	3, 17, 40, 51	98.16
13	11	6	14	9, 10, 22, 41, 42	-	99.39
14	14	10	1, 7	6, 12, 16, 40, 43, 45	13, 14	98.16
15	18	8	1, 2, 10, 14, 16	1, 12	-	99.08
16	17	8	1, 2, 7, 14	28, 67, 52	13	96.01

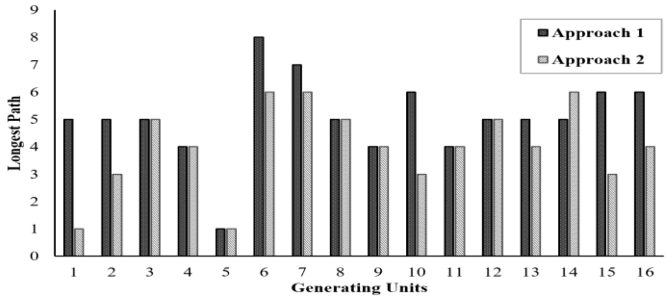

Figure 6. Longest path of all DTs: comparison of approaches

generating units 3, 7, 14, 16 and 15 use their longest paths to determine their coherent groups. In such a circumstance, 24 comparison are needed.

It should be noted that in some circumstances, several generating units in the system may swing together. For example, generating unit 1 and 8 in the studied system are coherent in almost all cases. Another such example relates to generating units 4 and 5 or, generating units 2 and 3. On the other hand, there are generating units such as generating unit 10 that may swap from one group to another for different scenarios. Therefore, it is not needed to build and use DTs for all generating units. However, we showed, in this paper, that one can obtain such DTs for all generating units.

V. Conclusion

In this paper, a synchrophasor-based approach for predicting the most coherent generating units in power systems was proposed. This method utilized decision trees to predict the most coherent generators after a disturbance occurs. It was suggested to use the similarity between frequency components that exist in the generators' angular speed as an index for identifying the degree of coherency between generating units. Simulation results of the proposed method applied to a 68-bus 16-machine test system demonstrated that these methods can be used for online applications due to its low computational burden. A comparison between two different approaches for DT formation for coherency assessment showed that although using a hierarchical approach increases the overall detection time of coherent generators, it reduces the quantity of the required data for such assessments especially in an online setting.

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