Jurnal
Teknologi

Full Paper

CLASSIFICATION OF ELECTRICAL FAULT SEVERITY IN A MODERN POWER SYSTEM OPERATING ENVIRONMENT

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Article history
Received
8 March 2023
Received in revised form
15 August 2023
Accepted
6 September 2023
Published Online
20 December 2023

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Graphical abstract

Abstract

Electrical power systems frequently experience different kinds of faults while they are used on a daily basis. Therefore, it is crucial to classify faults according to their severity in order to keep the system operating reliably. In this study, a novel method for categorising the severity of faults in the stability of the power system into three cases namely Minor, Moderate, and Major Fault was presented. This method is based on cutting-edge artificial intelligence algorithms. Under different types of faults, the suggested methodology was used in IEEE 9-bus. The study's findings give network operators important information that they can use to spot electrical system weaknesses during serious faults and maintain the power system's dependability and continuity of energy flow.

Keywords: Electrical power systems, faults, severity classification, artificial intelligence algorithms, reliability, IEEE 9-bus

1.0 INTRODUCTION

Electrical power systems in all sectors, including generation, transmission, distribution, and load systems, have grown and become more complex as a result of the significant changes in users' power requirements [1]. Due to its expansion, the electrical power system is now more susceptible to electrical faults, which can be brought on by a number of things including electrical overload, lightning, and improper wiring [2]. These faults have serious repercussions for the stability of the system [3] and the infrastructure of any nation [4] when they cause a disruption in the electrical power supply. The degree of loss can differ based on the duration and frequency of the interruptions, as well as the particular sectors and geographical areas impacted. According to some estimates, power outages can result in annual losses of billions of dollars [5]. This is caused by a variety of factors, such as decreased productivity, infrastructure and equipment damage, and higher energy costs.

When factors such as a short circuit or insulation failure disrupt the normal flow of electrical energy, it results in an electrical fault in the power system. The severity of these faults can range from minor, localised issues to major faults that can cause widespread power outages [6].

The power system is actually prone to a variety of faults, which can be categorised into two groups: short circuit faults and open circuit faults. In contrast to open circuit faults, which involve a break in the current path and are more dangerous for power systems, short circuit faults are more common in power systems. Asymmetrical faults and symmetrical faults are two different types of short circuit faults that can be distinguished by how severe they are and how frequently they occur in power systems. A malfunction that results in a circuit breaking down and continuity being lost is known as an open circuit fault, also known as a series fault. This can be brought on by problems like melted fuses or conductors in one or more phases, or failure of joints in cables or overhead lines. Figure 1 [7] illustrates further classification for both types of faults.

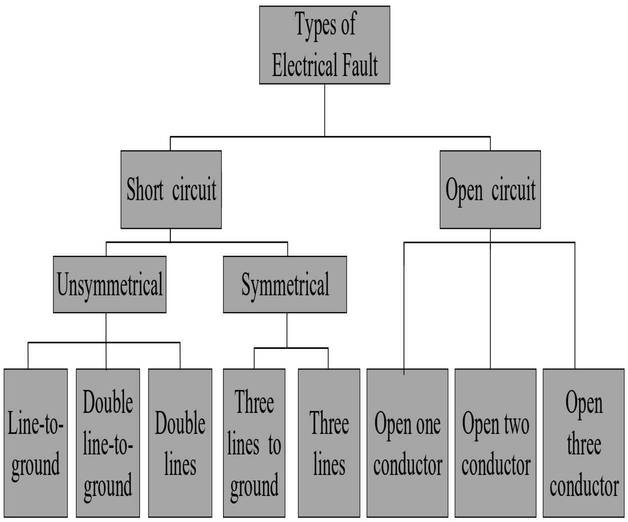

Figure 1 Various types of Electrical Fault

The choice of circuit breakers, as well as the size and ratings of switchgear, have a significant impact on the classification of electrical fault severity in today's power system operating environment. The selection of circuit breakers and switchgear to handle load requirements such as voltage, current, and frequency, as well as the anticipated maximum load including future expansions, is crucial for the safe and reliable operation of electrical systems. Consideration of ratings, flight curves, and coordination characteristics are necessary for protection coordination in order to isolate and safeguard defective components of the system while maintaining the functionality of the rest. The system voltage determines the type and ratings of circuit breakers and switchgear, with different specifications for low, medium, and high voltage systems. In order to prevent tripping or damage, it is also necessary to consider the current fault levels. Therefore, the proper selection of circuit breakers, the size of switchgear and their ratings, taking into account load requirements, protection coordination, system voltage and fault current levels for safety and security and reliable operation of electrical systems, are closely related to the classification of the severity of electrical faults in the modern power system operating environment.

Three major categories can be drawn from a thorough analysis of the numerous studies used for finding and fixing faults in electrical systems: fault detection, fault location estimation, and fault classification. These studies employed various methodologies, including conventional and artificial intelligence techniques, to arrive at their results.

The process of identifying and locating an abnormal condition in the electrical network, such as a short circuit or a broken conductor, is known as fault detection in a power system [8]. Protective relays are frequently used for this, which monitor the electrical characteristics of the system and trip circuit breakers when a fault is discovered, isolating the malfunctioning area of the network and preventing equipment damage [9–11]. Fault detection in power systems can also be accomplished using additional techniques, such as remote monitoring and power system analysis software [12–15].

Finding the location of a fault (like a short circuit) on a transmission or distribution line is the process of fault location estimation in power systems. Analysing data from protective relays and other devices that keep an eye on the electrical conditions on the line is how this is accomplished. It is possible to quickly isolate the fault and restore power to unaffected areas using the estimated fault location. Different techniques are employed for fault location estimation, such as distance protection, impedance based [16], and traveling wave based [11, 17, 18].

The process of determining the precise type of fault that has occurred on the electrical network is known as fault classification in the power system. This is typically done by looking at the electrical parameters during the fault event, such as the voltage and current [19, 20]. Different techniques, including signal processing [21], machine learning, and other cutting-edge methodologies [22], can be used to categorise faults.

Electrical faults can range from minor problems that are simple to fix to major failures that can seriously harm equipment, disrupt the power supply, and pose a risk to safety. Therefore, it is essential for power system operators and engineers to identify and classify the severity of electrical faults in order to prioritise fault resolution and maintenance tasks, reduce downtime, and guarantee the power system's safe and reliable operation.

The word "severity" in the article title here refers to the extent to which electrical faults can affect the efficiency and security of power systems. The article concentrates on categorising faults according to their level of severity to better comprehend and reduce potential risks.

It is crucial to have a system in place for assessing the severity of faults that occur regularly over an extended period of time in order to protect power system reliability and avoid service interruptions. In addition to safeguarding the stability of the system, this will assist in designing areas vulnerable to serious faults, ensuring a more stable power flow. This is what the study aims to accomplish by systematically and thoroughly identifying and categorising the severity of electrical faults.

The remainder of this essay is structured as follows: The different degrees of severity for electrical faults are described in Section 2. The specifics of the suggested strategy, including its methodology and guiding principles, are covered in Section 3. In Section 4, the results and findings of this study are presented and analysed. A summary of the most important findings and contributions from this research are presented in Section 5.

1.1 Types of Electrical Fault Severity

Electrical faults in a modern power system can be categorised based on their severity, which establishes the proper course of action. Here are some typical categories of electrical fault severity, as determined by literature reviews:

i. Minor fault: Typically, this kind of fault is not severe and does not seriously harm the power system. Voltage dips, temporary overloads, and tiny ground faults are a few examples of minor faults. These faults typically do not require immediate attention because the power system's protective devices can handle them.

ii. Moderate fault: A moderate fault is more serious than a minor fault and, if left unattended, could harm the power system. Phase-to-phase faults, large ground faults, and sustained overloads are a few examples of moderate faults. In order to isolate these faults and stop further damage, protective devices like circuit breakers may need to be used.

iii. An electrical fault that can seriously harm the power system and necessitate pricey repairs is referred to as a major fault. Lightning strikes, transformer failures, and transmission line failures are a few examples of major faults. The power system may need to be shut down in order to address these faults right away and prevent further damage.

The severity of electrical faults in a power system must be properly classified because this determines the appropriate course of action.

2.0 METHODOLOGY

Fluctuations in frequency on each bus can be caused by faults in electrical systems. The degree to which these fluctuations are severe depends on a number of variables, including the type of fault, its location, and the size and composition of the load [23]. As a result, severe faults will cause the frequency of buses to fluctuate more. Our research methodology involves keeping track of and recording the difference between the highest and lowest frequency fluctuations at each bus to assess the severity of a fault.

The study concentrated on three typical faults that can occur during routine operations: disconnecting loads, opening transmission lines, and causing three-phase faults in order to investigate the effects of typical electrical malfunctions on power systems. The frequency stability of power systems is known to be significantly impacted by these faults, so they were chosen.

The frequency value at each bus was recorded for three minutes with a very small time step (parts of a second) after each electrical fault was applied in order to analyse the effects and severity of these faults. This method enables a thorough comprehension of the system's behaviour after each fault, and the outcomes were documented in an Excel spreadsheet.

It's important to note that this approach differs from transient and dynamic studies, which only consider the behaviour of the system over a short period of time [24, 25]. In this study, a longer time frame is required to evaluate the stability of the system following the impact of the electrical fault [26]. The effects of the fault on the entire system can be more thoroughly examined thanks to the longer time frame.

This study highlights the importance of ongoing monitoring and maintenance to maintain the stability and dependability of power systems and offers significant new insights into the effects of common electrical faults on power systems. Power system operators can better comprehend the effects of faults and take the necessary action to reduce disruptions and avert potential system failures with the aid of detailed, time-based analysis.

The IEEE 9 bus test system was used as the testbed for our research methodology for a number of reasons. In the power systems community, it is first and foremost a well-known and widely used benchmark system. Second, it represents a power system at a small scale, with only 9 buses, 3 generators, and 3 loads [27], making it simpler to model and simulate than larger systems. As a result, we can concentrate on creating and validating our suggested approach without having to deal with the complexity of larger systems. Thirdly, the IEEE 9 bus test system is particularly helpful for testing and assessing novel approaches and innovations in the field of power systems, including distributed generation, the integration of renewable energy sources, and advanced control systems. As a result, it makes for a great starting point for our suggested methodology's investigation of fault classification in power systems. Overall, the IEEE 9 bus test system serves as a solid foundation for our research, and we are optimistic that the findings will advance fault classification methods in power systems.

The method for determining the severity of electrical faults in a power system is described in this passage. The data is gathered in a single file as follows after applying various electrical faults and noting the total differences in the results:

Sum for $case_m$= the difference between the highest and lowest value of frequency for bus1+the difference between the highest and lowest value of frequency for bus2+.... +the difference for between the highest and lowest value of frequency bus_n

Where
n=number of buses (1-9)
m=number of case

Based on the extent of the results' differences, the study assessed the faults' seriousness. A small difference indicates a minor fault and is represented by symbol (A), a moderate difference represents a moderate fault and is represented by symbol (B), and a large difference represents a major fault and is represented by symbol (C).

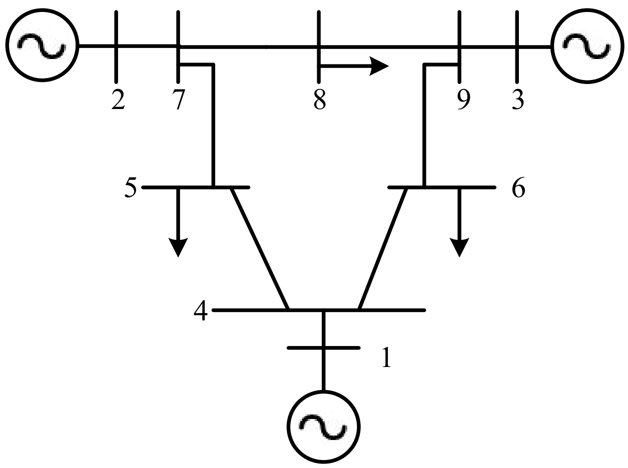

Figure 2. IEEE 9 bus test system

3.0 RESULTS AND DISCUSSION

The frequency values at each bus prior to an electrical fault are displayed in the OriginalHZ field of Tables 1, 2, and 3 in the second column. The third and fourth columns, MinHz and MaxHz, display the minimum and maximum frequency values, respectively, at each bus following the fault. In the fifth column, the max-MinHz field indicates the difference between the MinHz and MaxHz values. The case is classified based on the sum of the Max-MinHz values, which is displayed under the field labeled "sum for case". '

The outcomes of the symmetrical three-phase faults on the transmission line connecting bus 7-8 are shown in Table 1. As a result of the low sum of the Max-MinHz values, it is categorised as a minor fault (A). As shown in Table 2, the sum of the Max-MinHz values, on the other hand, is moderate, classifying it as a moderate fault (B). A serious fault (C) is indicated by the high sum of the Max-MinHz values as displayed in Table 3.

The dataset is organised and exported as an Excel file and consists of differences and the classifications that go with them. After that, it is fed into Orange Data Mining, an artificial intelligence programme, for data classification training. 66% of the data is used for training, and the remaining 34% is set aside for testing. Open-source and created in the Python programming language, Orange Data Mining is a tool for data visualisation and analysis. For creating interactive data analysis workflows, it provides a range of machine learning and data mining algorithms as well as a range of visualisation tools and widgets [28].

Table 1 Three-phase faults on transmission line 7-8 (Minor fault)

Name	OriginalHz	MinHz	MaxHz	Max-MinHz
Bus1	50	49.9752	50.2072	0.232
Bus 2	50	49.9785	50.41	0.4315
Bus 3	50	49.9822	50.3321	0.3499
Bus 4	50	49.9806	50.1833	0.2027
Bus 5	50	49.9834	50.1648	0.1814
Bus 6	50	49.9834	50.1659	0.1825
Bus 7	50	49.981	50.3247	0.3437
Bus 8	50	49.9816	50.3052	0.3236
Bus 9	50	49.9828	50.2782	0.2954
	Sum for case=			**2.5427**
	Classification:			**Minor fault (A)**

Table 2 Fault on transmission line 4-5 and 4-6 (Moderate fault)

Name	OriginalHz	MinHz	MaxHz	Max-MinHz
Bus1	50	50	52.2547	2.2547
Bus 2	50	48.3878	50.0055	1.6177
Bus 3	50	48.3878	50.0012	1.6134
Bus 4	50	50	52.2547	2.2547
Bus 5	50	48.3878	50.0045	1.6167
Bus 6	50	48.3878	50.002	1.6142
Bus 7	50	48.3878	50.0045	1.6167
Bus 8	50	48.3878	50.0035	1.6157
Bus 9	50	48.3878	50.002	1.6142
	Sum for case=			**15.818**
	Classification:			**Moderate fault (B)**

Table 3 Fault on transmission line 3-9 (Major fault)

Name	OriginalHz	MinHz	MaxHz	Max-MinHz
Bus1	50	48.1729	50	1.8271
Bus 2	50	48.1726	50	1.8274
Bus 3	50	50	63.7362	13.7362
Bus 4	50	48.1728	50	1.8272
Bus 5	50	48.1728	50	1.8272
Bus 6	50	48.1728	50	1.8272
Bus 7	50	48.1726	50	1.8274
Bus 8	50	48.1727	50	1.8273
Bus 9	50	48.1727	50	1.8273
	Sum for case=			**28.3543**
	Classification:			**Major fault (C)**

Multiple algorithms, including Support Vector Machine, K-Nearest Neighbours, and AdaBoost (Adaptive Boosting), were employed in order to achieve optimal results for fault severity classification. By utilising a variety of algorithms, we were able to compare and ultimately select the one that performed the best for this task.

Where the Support Vector Machine (SVM) algorithm is a supervised learning technique that can be used for classification or regression purposes [29]. In the context of classification, the SVM algorithm identifies the hyperplane in high-dimensional space that most effectively separates distinct classes. This enables the algorithm to effectively classify examples it has never encountered before. In regression tasks, SVM attempts to identify the hyperplane that best fits a dataset. Even when the number of training examples is small, SVM is known for its ability to handle high-dimensional data and make accurate generalisations in both instances. It is a potent and widely-applied machine learning algorithm that has proven effective in numerous real-world applications.

K-Nearest Neighbours (KNN) is a type of machine learning algorithm that does not require a great deal of prior data knowledge and is referred to as "lazy" because it does not create an explicit model and instead waits for an input before making a prediction. This algorithm is applicable to classification and regression problems. In both cases, the input consists of the k data points from the training set that are closest to the input in the feature space. Depending on the given task, the algorithm will produce a distinct output. The output of K-NN classification is the class to which the input belongs, as determined by the majority vote of the k closest data points. The input is assigned to the class to which the majority of its immediate neighbours also belong [30].

AdaBoost (Adaptive Boosting) is a boosting algorithm used in machine learning to enhance the performance of weak learners (base models) through the combination of their predictions. It operates by iteratively training weak learners on the dataset, giving greater weight to examples misclassified by previous weak learners, and combining the predictions of all weak learners to make the final prediction. This process continues until the desired level of performance is achieved or until a maximum number of weak learners is reached. Typically, the final ensemble model is more accurate than any of the weak learners individually [31].

A schema for an Orange data mining program that investigates the categorization of electrical fault severity data is shown in Figure 3. SVM, KNN, and AdaBoost are the three classifier algorithms that are being used.

The F1 score is a metric used to evaluate a classification model's performance. It is computed as the harmonic mean of both precision and recall. The score ranges from 0 to 1, with 1 representing perfect precision and recall. The F1 score is useful when class labels are unbalanced because it gives equal weight to both precision and recall. It is frequently employed when the cost of false positives and false negatives differs. The ideal F1 score is 1, but in practise this is often difficult to achieve. Given the particular problem and data set, a good F1 score is one that is close to 1 and achievable.

Precision is a metric used to evaluate the performance of a classification model; it measures the ratio of true positive predictions to all positive predictions (true positives and false positives). A model with a high precision has a small number of false positives. The ratio of true positive predictions to the sum of true positives and false positives is used to calculate precision. A precision score of 1 is optimal, indicating that all positive predictions are accurate and there are no false positives. However, achieving or maintaining a precision score of 1 may not always be possible or practical.

Recall is a metric used to measure the accuracy of a classification model; it calculates the proportion of correctly predicted positive examples relative to the number of actual positive examples. It is the proportion of true positive predictions to the sum of true positives and false negatives. A high recall rate indicates few false negatives. The optimal recall value is 1, indicating that all positive examples are accurately predicted and there are no false negatives. However, achieving a perfect recall score of 1 is not always possible [32].

Table 4 Results of the Proposed Methodology

Algorithm	Classification accuracy	F1	Precision	Recall
kNN	0.875	0.875	0.8783	0.875
SVM	0.925	0.925	0.9437	0.925
AdaBoost	0.850	0.841	0.8535	0.85

The SVM algorithm outperformed the competition, achieving a 92.5% correct classification rate a 5% and 8% improvement over the KNN and AdaBoost algorithms, respectively. The results are shown in Table 4. In comparison to the other algorithms, the SVM algorithm also showed a higher ratio of F1, precision, and recall.

Incorporating more training cases will increase the accuracy of an SVM algorithm because it will give it more data to learn from, similar to using a large-scale test system. The best way to increase accuracy may not always be to simply use larger systems because doing so can increase computational complexity and overfitting. Dimensionality reduction, which can involve lowering the number of instances or features used to represent the data, is an efficient method for any test system for enhancing accuracy while lowering computational complexity. By doing so, it may be possible to keep the most useful elements while removing noise and unimportant data.

Principal component analysis (PCA), a widely used method for dimensionality reduction in SVM, can be used to convert high-dimensional data into a lower-dimensional space while preserving as much of the original information as possible.

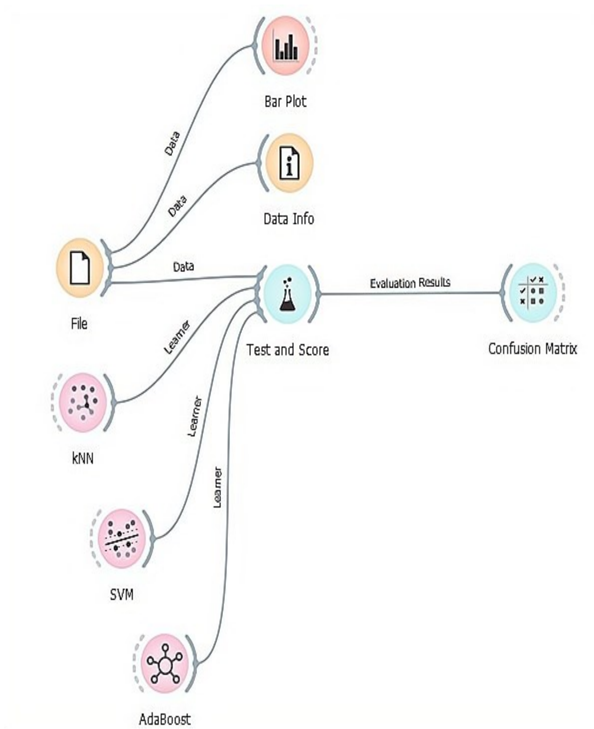

Figure 3 Orange Data Mining Program Interface for the Proposed Methodology

Overall, increasing the number of training cases and employing dimensionality reduction techniques can both be successful methods for enhancing an SVM algorithm's accuracy. The specifics of the dataset and the available computational resources will determine which approach should be used.

Our proposed fault classification severity methodology, which classifies faults based solely on the difference between the minimum and maximum frequency values across all buses, is superior to other fault classification methods previously examined in sources such as [19-22] which rely on additional system parameters as inputs. Our approach is distinguished by its simplicity and ease of implementation, making it a promising candidate for fault classification severity in real-world applications.

The findings of this study have significant engineering and scientific ramifications for the power systems industry. For the grid to remain reliable and stable, it is essential to determine the severity of electrical faults in power systems. By offering a more effective and efficient method of fault classification, the proposed fault classification methodology can help achieve this goal.

To address the shortcomings of current approaches and enhance the precision and effectiveness of fault detection and classification in power systems, further research and development are still required in the field of fault classification algorithms.

It is important to note that, for any power grid, there are differences in fault levels, types of faults, impact on customers, protection mechanisms, and repair/restoration processes between distribution systems and HV transmission grids. These differences are crucial to consider after determining the severity of the faults. Whereas, because of their greater power transfer capacity and longer transmission lines, HV transmission grids tend to have higher fault levels and a wider variety of fault types, such as lightning strikes and insulator failures. While faults in HV transmission grids can have broader area effects and result in widespread blackouts, faults in distribution systems are typically localised and affect a smaller number of customers. Distribution systems' protection mechanisms are less complicated, whereas HV transmission grids' protection mechanisms are more intricate. Distribution systems' repair and restoration procedures might go more quickly, whereas HV transmission grid faults might take longer to fix and restore because of their greater size and complexity.

Additionally, in power systems, reliability and electrical faults have the opposite relationships. The reliability of the power system is reduced when electrical faults like short circuits or equipment breakdowns happen because they can result in power outages or interruptions. The number of electrical faults that occur and their duration have a direct impact on how reliable the power system is; the more faults that occur, the less reliable the system becomes.

By maintaining and upgrading equipment, reducing the likelihood of electrical faults, and putting backup systems and procedures in place to swiftly restore power in the event of a fault, reliability can be increased. A high level of reliability is what most power systems aim to achieve, and it can be gauged using metrics like system availability, mean time between failures (MTBF), and mean time to repair (MTTR). The study's objective was to classify the severity of electrical faults in order to pinpoint the system's weak points and improve system performance by increasing backup power and upgrading equipment. This will lessen the MTBF and MTTR, as well as the severity of faults.

4.0 CONCLUSION

By comparing the difference between the highest and lowest value of the bass frequency after an electrical fault occurs, this study concluded that a new method for determining the severity of electrical faults that occur during routine operation could be developed. The study's findings demonstrated that classifying faults with an artificial intelligence technique—more specifically, the SVM algorithm—is possible with a high degree of accuracy (92.5%) and a low level of error.

Electrical fault severity classification is a crucial task for the reliability of electrical power systems because it helps engineers and technicians decide the best course of action for fixing the fault and minimising the risk of further damage. The method put forth in this study can be a useful instrument for determining how serious electrical faults are in power systems.

A large-scale test system, taking into account other system parameters, could provide a more accurate reflection of real-world issues for future research. Therefore, it is advised to take into account using an even larger test system in future work with the benefit of the principal component analysis (PCA) technique.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

Acknowledgement

The authors express their sincere gratitude to the University of Mosul Department of Electrical Engineering for their invaluable support during the completion of this work.

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