

FEATURE EXTRACTION OF POWER DISTURBANCE SIGNAL
USING TIME FREQUENCY ANALYSIS

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Master of Engineering
(Electric-Electronic & Telecommunication)

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

APRIL 2006

To my beloved mother, father, husband and families

ACKNOWLEDGEMENT

In preparing this thesis, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my very sincere appreciation to my thesis supervisor, Professor Ir. Dr. Sheikh Hussain Shaikh Salleh, for encouragement, guidance, advices and motivation. I am also very thankful to my co-supervisors Mr. Kamarulafizam Ismail for his guidance, advices, motivation and friendship. Without his continued support and interest, this thesis would not have been the same as presented here.

I am also indebted to Universiti Teknologi Mara (UiTM) for funding my M.Eng. study under the Young Lecturer Scheme.

My fellow postgraduate students should also be recognised for their support. My sincere appreciation also extends to all my colleagues and others who have provided assistance at various occasions. Their views and tips are useful indeed.

Unfortunately, it is not possible to list all of them in this very limited space. Finally, I am grateful to my beloved husband and all my family members for their support and understanding.

ABSTRACT

Power Quality has been one of the great concerns recently; it due to the increasing number of loads which sensitive to the power disturbance. One of the main issues in power quality problems includes how to localize each disturbance event and recognize its respective type of disturbance more efficiently. Another problem is harmonics problem which is due to nonlinear loads and the source of fault is difficult to detect and diagnose. Thus, it is important to propose an effective feature extraction method in order to build a system with DSP approach to overcome this problem as well as to maintain the power quality. This thesis utilized the concepts of time frequency analysis (TFA), which provides information of the disturbance signal as a function of time and frequency in order to analyze the power disturbance signals due to those signals is finite energy or non-stationary signals. By choosing real and simulated power signals, this study has been carried out over 30 normal signals and 90 signals with power disturbance including sag, swell, interruption, harmonics, transient and frequency variation. Those signals are transformed into time frequency plane using B-distribution algorithm. Then the important feature vectors or components are extracted using Singular Value Decomposition (SVD) and Principle Component Analysis (PCA). Finally, the distance metric, J , as class separability between two classes of vectors can be measured using Maximum Margin Criterion (MMC). From the results obtained, the most two of the right singular vector (SVs) become most powerful feature vectors to describe the TFD. The lowest SVs have cyclic structure becomes less significant feature vector which contains noise or redundancy. Furthermore, the projection between two SVs of normal power signal and disturbance power signal shows the plotting of these vectors are overlap or not overlap respectively. If the last two SVs (or either one is last SV) are projected, the plotting almost approached to zero. The most discriminates vectors is the distance between them, MMC shown either that vectors are close to those in the same class (ranges of J is 0.0006 to 0.0045) or far from those in different classes (ranges of J is 0.0045 to 0.0426). The accuracy of using these methods is 95.24%, the sensitivity (or normal signal performance) is 100% and the specificity (performance of power disturbance signal) is 94.4%. As a conclusion, SVD and PCA are useful to apply in TFD to extract important feature vectors then MMC can measure the distance metric between those mean vectors. Furthermore, all the features obtained are useful features and can be used for power disturbance classification and recognition with DSP approach as well as to maintain power quality.

ABSTRAK

Kualiti Kuasa telah mendapat perhatian kebelakangan ini, penambahan beban boleh mengakibatkan gangguan kuasa. Satu daripada isu utama dalam masalah kualiti kuasa adalah bagaimana untuk mengetahui dan mengenalpasti jenis gangguan dengan efisien. Antara masalah lain yang sama pentingnya adalah isyarat harmonik dimana ia disebabkan oleh ketidaklinearan beban dan menyebabkan gangguan kuasa yang mana puncanya sukar untuk dikenalpasti. Maka amat penting mencadangkan kaedah mendapatkan ciri yang berkesan dalam membina satu sistem berasaskan pemrosesan isyarat digital bagi mengatasi masalah ini seterusnya mengekalkan kualiti kuasa. Tesis ini lebih kepada konsep analisis masa-frekuensi, dimana memberi informasi mengenai isyarat gangguan dalam fungsi masa dan frekuensi serentak bagi menganalisa isyarat gangguan kuasa dimana ia amat sesuai bagi isyarat berubah atau tidak tetap. Dengan menggunakan isyarat kuasa yang sebenar dan simulasi, dimana 30 isyarat normal dan 90 isyarat gangguan kuasa seperti kurang voltage, lebih voltage, gangguan, harmonik, ketidaktetapan and variasi frekuensi. Kesemua isyarat ditukar kepada domain masa-frekuensi menggunakan algoritma taburan-B. Vektor ciri atau dikenali sebagai komponen dapat dikenalpasti dengan menggunakan kaedah Singular Value Decomposition (SVD) dan Analisis Prinsip Komponen (PCA). Kriteria Margin Maksima (MMC) sebagai kaedah mendapatkan jarak, J , di antara vektor-vektor. Dari keputusan yang didapati, dua vektor ganjil kanan (SVs) pertama adalah vektor terbaik bagi menerangkan taburan masa-frekuensi (TFD). Namun vektor ganjil kanan terakhir dengan struktur yang kompleks adalah vektor tidak penting dimana mengandungi pertindihan maklumat atau hingar. Manakala jika salah satu dari kedua-dua vektor adalah dari vektor yang terakhir maka kesemua plot adalah menumpu ke sifar. Apabila dua vektor pertama ini di plot dengan vektor kedua melawan vektor pertama, dapat dilihat bentuknya adalah bertindih atau tidak bertindih dengan merujuk kepada isyarat tersebut samada ia normal atau mengalami gangguan. Faktor membezakan antara vektor-vektor adalah jarak diantaranya, J , dan dapat ditentu ukur melalui kaedah Kriteria Margin Maksima (MMC). MMC boleh menentu ukur jarak antara vektor samada ia dekat jika didalam kelas yang sama iaitu antara 0.0006 to 0.0045 atau jauh jika dalam kelas yang berbeza 0.0045 to 0.0426 dan ketepatan adalah 95.24%. Manakala kepekaan (prestasi isyarat normal) dan (ketepatan) prestasi isyarat gangguan kuasa adalah masing-masing 100% dan 94.4%. Kesimpulannya SVD dan PCA amat baik untuk diadaptasi didalam TFD bagi mengenalpasti ciri-ciri TFD tersebut dalam bentuk vektor. Manakala, MMC dapat menentu ukur jarak min/purata antara vektor. Dengan ini kesemua ciri-ciri tadi boleh digunakan untuk tujuan klasifikasi gangguan isyarat bagi menentukan jenis gangguan kuasa dalam sistem kuasa dengan pendekatan pemrosesan isyarat digit dan seterusnya ia dapat mengekalkan kualiti kuasa.

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LIST OF ABBREVIATIONS

DSP	-	Digital Signal Processing
IF	-	Instantaneous Frequency
LDA	-	Linear Discriminant Analysis
MMC	-	Maximum Margin Criterion
PCA	-	Principle Component Analysis
PD	-	Power Disturbance
PDF	-	Probability Density Function
PQ	-	Power Quality
PU	-	Per Unit
RID	-	Reduced Interference Effect
STFT	-	Short-Time Fourier Transform
SV	-	Singular Vector
SVD	-	Singular Value Decomposition
TD	-	Time Delay
TF	-	Time Frequency
TFA	-	Time Frequency Analysis
TFD	-	Time Frequency Distribution
TFSA	-	Time Frequency Signal Analysis
TFSP	-	Time Frequency Signal Processing

LIST OF SYMBOLS

S_b	-	Between-class scatter matrix
n	-	Column
\mathbf{m}	-	Column mean
Φ_x	-	Covariance matrix
Σ	-	Diagonal matrix of eigenvalues
D, d	-	Dimension
σ_k	-	Eigenvalues
v_k	-	Eigenvector
f	-	Frequency
$\{u_k\}$	-	Left singular vector
m_i	-	Mean vector
c	-	Number of class
p_i	-	Probability
$\{v_k\}$	-	Right singular vector
m	-	Row
t	-	Time
Δt	-	Time interval
tr	-	Trace
σ^2	-	Variance
S_i	-	Within class scatter matrix of class i
S_w	-	Within-class scatter matrix

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Power Quality has been one of the great concerns recently, due to increase the number of loads which sensitive to power disturbance, whereby power disturbance corresponds to any deviation from the nominal value of the input AC power characteristics. One of the main issues in power quality problems is how to localize each disturbance event including recognize its respective type in the disturbance group more efficiently. Harmonics is one of the power quality problems due to non-linear load which this type of power disturbance is difficult to detect and diagnose the source of fault. These problems can be solved using signal processing approach.

Power quality is a main concern because today's electricity equipments which ranging from personal computers in offices to automated manufacturing processes is much more susceptible to power quality problems than older equipments, such as conventional lighting and motors. The deviation of the power system is fundamental frequency from its specified nominal value. For example 50 or 60Hz which depends on the country specification. The U.S. electricity system is one of the examples which had been described as one of the most reliable in the world.

Power quality variations fall into two basic categories:

1. Disturbances

Disturbances are measured by triggering on an abnormality in the voltage or the current. Transient voltages may be detected when the peak magnitude exceeds a specified threshold. RMS voltage variations (e.g. sags or interruptions) may be can be detect when the RMS variation exceeds a specified level.

Electrical disturbances come in many forms and one of a reality to electrical distribution systems. Recommended Practice for Monitoring Electrical Power, IEEE Standard 1159-1995 (see appendix C) has been categorized by most of the disturbances into one of the following:

1. Short duration variations (i.e. interruptions, sags or swells)
2. Long duration variations (i.e. interruptions, sags or swells)
3. Transients
4. Voltage imbalance, and
5. Wave form distortion (i.e. harmonics).

Electrical disturbance which written above can not be over emphasized and these electrical phenomena will occur on all typical systems at some point and time. The impact of the phenomena depends on the sensitivity of the equipment. Every facility should consider the impact of electrical disturbances on the various equipments and implement the appropriate mitigation.

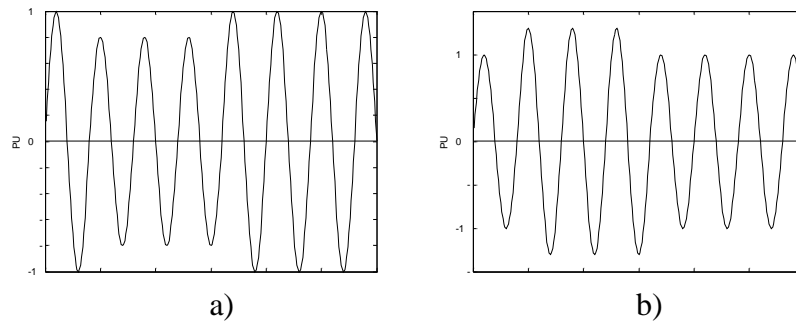


Figure 1.1 Short duration variation a) Voltage sags, and, b) Voltage swells

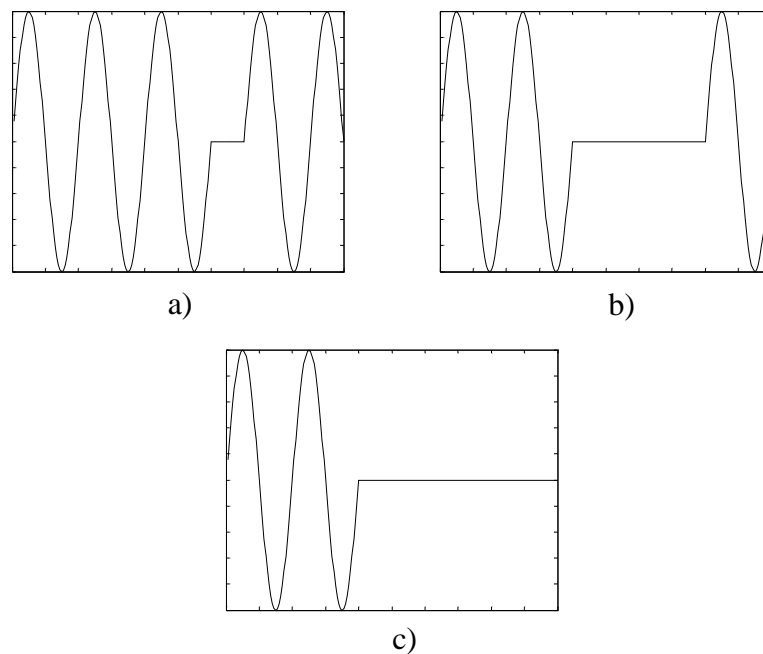


Figure 1.2 Interruptions a) Momentary interruptions, b) Temporary interruption, and c) Long term interruption

2. Steady State Variations.

Steady state variations are including normal RMS voltage variations and harmonic distortion. These variations must be measured by sampling the voltage or current over time. This information is best presented as a trend of the quantity (e.g. voltage distortion) over time and then analyzes using statistical methods (e.g. average distortion level, 95% probability of not being exceeded, etc.).

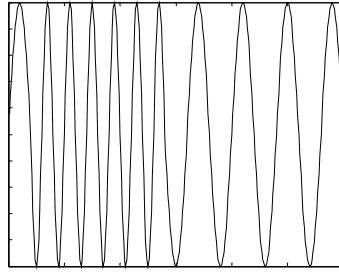
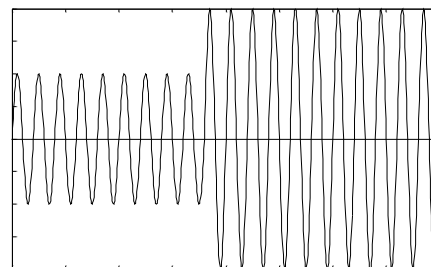
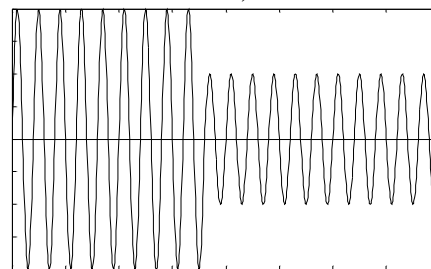


Figure 1.3 Frequency variations

There is no steady state on the power system. Loads are continually changing and the power system is continually adjusting to these changes. All of these changes and adjustments result in voltage variations which are referred to long duration voltage variations. These can be under voltages or over voltages, depending on the specific circuit conditions.



a)



b)

Figure 1.4 Long duration voltage variations a) Over voltage, and b) Under voltage

According to the American National Standard ANSI C84.1 (see appendix A) which proved that nominal voltage ratings and tolerances for 60-hertz (alternating current, AC) electric power systems is above 100 volts and within 230, 000 volts. Voltage operating ranges are recommended for two voltage categories:

- 1) The service voltage, typically the point of connection between utility and customer; and
- 2) The utilization voltage, typically the termination point to equipment.

The utilization voltage range takes into account that a voltage drop within the end user's distribution circuits. The ANSI C84.1 expects equipment to operate the service voltages from 95% to 105%, with utilization voltage ranges of 87% to 106% (120V to 600V). Refer to ANSI C84.1 for additional operating voltage ranges. Voltage levels outside this range may occur because of the conditions beyond the control of the supplier, user or both. Equipment may not operate satisfactorily under these conditions and protection devices may be utilized to protect against equipment damage.

ANSI C84.1–1995 specifies the steady state voltage tolerances for both magnitudes and unbalance expected on a power system. Long duration variations are considered to be present when the limits are exceeded and greater than 1 minute.

The characteristics of the steady state voltage are best expressed with long duration profiles and statistics. The important characteristics include the voltage magnitude and unbalance. Harmonic distortion is also a characteristic of the steady state voltage but this characteristic is treated separately because it does not involve variations in the fundamental frequency component of the voltage.

Harmonic distortion of the voltage (see figure 1.6) and current are results from the operation of nonlinear loads and devices on the power system. The nonlinear loads that cause harmonics can often be represented as current sources of harmonics. The system voltage appears stiff to individual loads and the loads draw distorted current waveforms.

The harmonic standard, IEEE 519-1992 (see appendix D), has proposed two way responsibilities for controlling harmonic levels on the power system.

1. End users must limit the harmonic currents injected onto the power system.
2. The power supplier will control the harmonic voltage distortion and make sure the system resonant conditions do not cause excessive magnification of the harmonic levels.

Harmonic distortion levels can be categorized by the complete harmonic spectrum with magnitudes and phase angles of each individual harmonic component. It is also common to use a single quantity, the Total Harmonic Distortion, as a measure of the magnitude of harmonic distortion. For currents, the distortion values must be referred to a constant base (e.g. the rated load current or demand current) rather than the fundamental component. This provides a constant reference while the fundamental can vary over a wide range.

Harmonic distortion is a characteristic of the steady state voltage and current. It is not a disturbance. Therefore, characterizing harmonic distortion levels is accomplished with profiles of the harmonic distortion over time (e.g. 24 hours) and statistics.

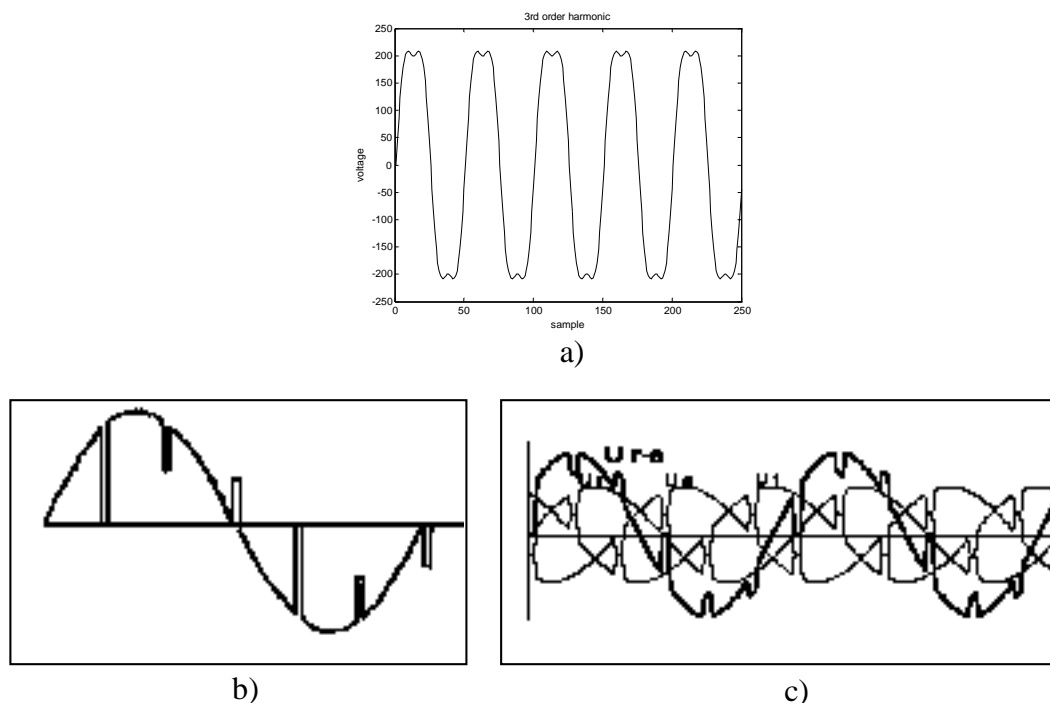


Figure 1.5 Waveform distortion a) Harmonic (3rd order), b) Notching, and c) Switching notches caused by a three-phase rectifier

The term transient is normally used to refer to fast changes in the system voltage or current. Transients are disturbances, rather than steady state variations such as harmonic distortion or voltage unbalance. Disturbances can be measured by triggering on the abnormality involved. For transients, this could be the peak magnitude, the rate of rise, or just the change in the waveform from one cycle to the next. Transients can be divided into two sub-categories, impulsive transients and oscillatory transients, depending on the characteristics.

Transients are normally characterized by the actual waveform, although summary descriptors can also be developed (peak magnitude, primary frequency, rate-of-rise, etc.). Capacitor switching transient waveform is one of the most important transients that is initiated on the utility supply system and can affect the operation of end user equipment.

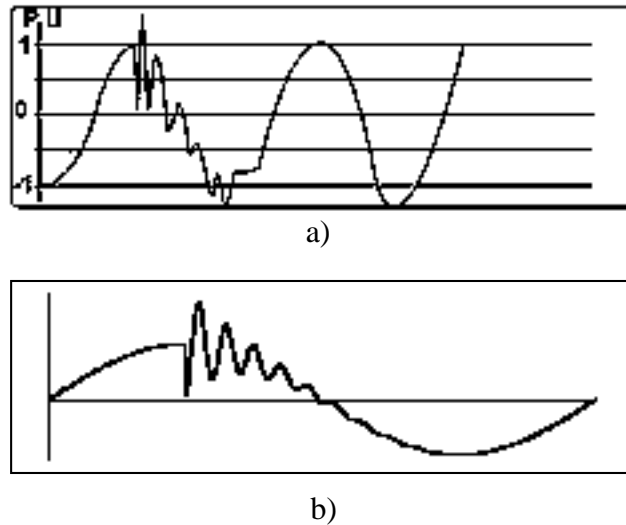


Figure 1.6 Transients a) Impulsive transient and b) Transient damped oscillation

A summary based on power quality variation categories and its criteria for the low voltage side of the supply network refer to the appendix E and appendix B respectively.

1.2 Project Objectives

The main objectives of this project are:

1. To understand the concepts of time frequency analysis (TFA).
2. To study an efficient feature extraction methods in time frequency distribution (TFD).
3. To extract the important feature from time frequency distribution of the power disturbance signals.

1.3 Scopes of Project

Power disturbances are finite energy transient or non stationary signals, it may not be sufficient to analyze them in the time-domain or frequency-domain alone. To solve such problems, signal processing approaches based on joint time-frequency signal representation can be used, where the time-frequency structure of each disturbance signals is exploited as its distinguish feature of respective types of power disturbances [2]. Being the two dimensional representation of a one dimensional signal, the time-frequency signal representation encodes in a redundant fashion in the information of one dimensional signal [26]. Thus, for effective use of joint time-frequency signal representations, it is practical important to apply a data compression to the time-frequency representations [2]. In this project, the B-Distribution (BD) is utilized as a bilinear or quadratic time frequency representation with multi resolution which can achieve a better time frequency of the input signal and it significantly to suppress the cross-terms [1]. The effective data compression is accomplished by employing matrices analysis called Singular Value Decomposition (SVD) of the B-Distribution and Principle Component Analysis (PCA). This results in an efficient feature vector extraction [27]. Finally, seven classes of disturbance data include the normal signals, are tested by using a method called Maximum Margin Criterion (MMC), where the distance metric or margin between each class of vectors can be represented. Finally, MMC outperformed the dissimilarity either those feature vectors are close to those in the same class or far from those in different classes within specific margin in order to represents types of power signals.

1.4 Thesis Outline

This thesis is organized in five chapters as follows: Chapter 1: Introduction; Chapter 2: Literature Review; Chapter 3: Research Methodology; Chapter 4: Result, Analysis and Discussion; and Chapter 5: Conclusion and Future Work. It follows by the references and appendices.

Chapter 1 provides a general introduction to the power disturbance and power quality including the project's objectives and scopes.

Chapter 2 deals with literature review of previous works which is close related to the time frequency analysis, matrix decomposition namely SVD/PCA and a method in order to determine the margin between groups of vectors that is MMC.

Chapter 3 more concentrates on project methodology. It covers all aspect in project's implementation process starting with time frequency analysis using TFSA 5.4 which is a time frequency signal analysis toolbox; matrix decomposition using SVD/PCA and margin determination by implement the maximum margin criterion (MMC).

Chapter 4 explains in detail results of tested signals. It illustrates how important feature vector can be extracted from time frequency distribution (TFD) from power disturbance signal. It also covers the accuracy, sensitivity, specificity and shows the probability density function (pdf) of the entire distance metrics or margin obtained from MMC. Moreover, some experiments on data with different constraint such as number of samples, per unit (pu) level, is discussed.

Chapter 5 is presents some recommendations related to this project for further interesting research topics.

All valuable references cited in this thesis have been listed in the list of references at the end of the last chapter.

Finally, appendix A, B, C, D and E represents some power quality standard such as ANSI C84.1, BS EN 50160:2000, IEEE 1159, IEEE 519 and etc.

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