Universitat de Girona

DISCOVERING FREQUENT AND SIGNIFICANT EPISODES. APPLICATION TO SEQUENCES OF EVENTS RECORDED IN POWER DISTRIBUTION NETWORKS

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PhD Thesis

Discovering frequent and significant episodes. Application to sequences of events recorded in power distribution networks

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Thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy at the University of Girona. Doctoral Programme in Technology.

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Resum

En aquesta tesi es proposa un formalisme per analitzar conjunts de dades d'esdeveniments relacionats amb les fallades que es produeixen en les xarxes de distribució elèctrica, i explotar automàticament seqüències d'esdeveniments registrats pels monitors de qualitat d'ona instal ·lats en subestacions. Aquest formalisme permet cercar dependències o relacions entre esdeveniments per trobar patrons significatius. Quan els patrons es troben, es poden utilitzar per descriure millor les situacions de fallada i la seva evolució. Els patrons també poden ser útils per a predir fallades futures mitjançant el reconeixement dels successos que coincideixin amb les primeres etapes d'un patrò.

Un conjunt d'esdeveniments datats i registrats en un sol punt de la xarxa durant un període de temps específic es pot considerar com una seqüència d'esdeveniments. Aquesta pot contenir diversos esdeveniments, però només són d'interès alguns dels subconjunts que apareixen formant estructures locals al llarg de la seqüència. Aquests subconjunts d'esdeveniments significatius en una seqüència s'anomenen episodis i s'espera que descriguin alguns patrons. L'existència d'aquests patrons s'explota en base al criteri d'episodis freqüents, aprofitant algorismes de descobriment de patrons.

Diversos algorismes han estat proposats en la literatura per fer front a les particularitats de diferents dominis d'aplicació, com ara l'anàlisi de seqüències d'alarmes en xarxes de telecomunicacions, el descobriment de patrons en accessos web, el pronòstic de fallades sobre la base dels registres de les plantes de fabricació o seguiment de patrons en esdeveniments registrats a les noticies. Els resultats del procés de mineria de dades poden variar entre els diferents algorismes, però el recompte o reducció del nombre de casos dels patrons són problemes comuns en aquests mètodes. Per tant, en aquesta tesi es proposa un mètode alternatiu per resoldre algunes limitacions dels algorismes existents.

La freqüència és el criteri comú que es fa servir per discriminar la importància d'un episodi en una seqüència d'esdeveniments. No obstant això, aquest criteri no és suficient per avaluar la força de l'associació entre els esdeveniments d'un episodi. La tesi descriu els índexs i mètodes més comuns per avaluar la qualitat dels episodis. Es proposen nous índexs i estratègies, derivats de la informació dels episodis, s'aprofiten els coneixements sobre esdeveniments prioritaris en la seqüència i la seva aplicació s'il·lustra amb exemples.

Aquests mètodes i estratègies proposats per descobrir patrons significatius freqüents estan adaptats per fer mineria a seqüències d'esdeveniments registrats en les xarxes de distribució elèctrica. Els tipus d'esdeveniments són bàsicament els sots de tensió (disminució en el voltatge RMS registrat pels monitors de qualitat d'ona) i els incidents recollits per l'operador de la xarxa elèctrica. Els algorismes proposats permeten descobrir relacions significatives en ambdós conjunts de dades i se'n dicuteix el significat físic. La tesi mostra que és possible trobar regularitats en aquests conjunts de dades que permeten comprendre millor l'aparició de fallades i avaries en les xarxes de distribució elèctrica.

Paraules clau: seqüències d'esdeveniments, diagnòstic de fallades, pronòstic de fallades, mineria de dades, fallades del sistema de potència, episodis, mineria de patrons.

Abstract

This thesis proposes a formalism to analyse and automatically exploit sequences of events, which are related with faults occurred in power distribution networks and are recorded by power quality monitors at substations. This formalism allows to find dependencies or relationships among events, looking for meaningful patterns. Once those patterns are found, they can be used to better describe fault situations and their temporal evolution or can be also useful to predict future failures by recognising the events that match the early stages of a pattern.

A set of dated events recorded at a single point of the network during a specific period of time can be considered as a sequence of events. It can contain several events, but only some subsets of them, which appear together forming local structures along the sequence, are of interest. These subsets of significant events in a sequence are called episodes and are expected to describe some patterns. The existence of those patterns is exploited based on the criterion of frequent episodes, taking advantage of pattern discovery algorithms.

Different algorithms have been proposed in the literature to cope with the particularities of different application domains such as analysis of alarm sequences in telecommunication networks, web access pattern discovery, fault prognosis based on logs of manufacturing plants or event tracking problems for news stories. Results of the mining process can vary among these different algorithms, but over-count or missed of occurrences of patterns are common problems in these methods. So, an alternative method that solves some weakness of existing algorithms is proposed in this work.

Frequency is the common criterion used to discriminate importance of an episode with respect to others. However, this criterion is not enough to assess the strength of the associations between events in an episode. The thesis describes indexes and methods for assessing the quality of the episodes and new indexes and strategies, derived from information of the episodes and taking advantage of the knowledge about priority events in the sequence, are proposed and illustrated with application examples.

These methods and strategies proposed for discovering significant frequent patterns are adapted for mining event sequences related to the occurrence of faults in power networks. Basically, this events are voltage dips (decrease in RMS voltage recorded by power quality monitors) and incidents collected by the network operator. Meaningful relationships are discovered in these data sets through the proposed algorithms and their physical meaning is discussed. The thesis shows that it is possible to find regularities in these data sets of events that allow to better understand the occurrence of faults in power distribution networks.

Keywords: event sequences, fault diagnosis, fault prognosis, data mining, power system faults, episodes, pattern mining.

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Oscar A. Quiroga Q.

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Introduction

Power networks are submitted to continuous changes during their operation (load and capacitors commutation, activation of protections during faults, transformer regulations, etc.) that provoke the apparition of disturbances, or events, that flow through the networks affecting quality of supply. Power quality monitoring is the discipline that deals with those disturbances to better know how the network is performing and providing inputs to maintenance and planning departments. However, the increase of high performance equipment (PQ –Power Quality monitors– and/or PMUs –Phasor Meassuring units–) being installed in substations and consumers provokes the necessity of new methods to process these registers and sets of them automatically with monitoring and diagnosis purposes. The application of Data Mining and Knowledge Discovery approaches to model network behaviours and the exploitation of these models for different power quality purposes is usually known as Intelligent Power Quality Monitoring.

This thesis focus on proposing and using sequence pattern discovery algorithm to identify and learn network behaviours from sequences of events collected in substations. Special emphasis is put on voltage dips generated during faults and in analysing episodes of them previous the occurrence of failures.

This chapter introduces motivation, objectives and background of the work.

1.1 Motivation of the work

The huge number and variety of components in power networks (overhead lines, cables, circuit breakers, transformers, fuses, insulators, relays, etc.) that can be affected by failures makes impossible to deploy condition monitoring strategies to individually supervise all of these elements. Consequently, new paradigms to assist maintenance policies are needed. These paradigms should be oriented to extract, model and exploit useful information from historical data (call centers, event repositories and power quality data bases, control center data bases,etc.) and on-line events generated during both, normal and abnormal conditions (Meléndez et al., 2012).

The monitoring of power distribution networks takes place mainly in the distribution substations where the distribution lines, feeders or loads are derived. Events, caused by faults or normal/abnormal operation of equipment, devices and customer loads are recorded by sensing instruments such as digital relays or power quality monitors and reported to control rooms by supervisory control and data acquisition (SCADA) systems or directly stored in data bases for further exploitation. This information is recorded to support the network management and it is useful for several purposes such as: to assess the levels of power quality, to know the network behaviour or to assist maintenance. However, current systems do not provide the tools to automatically analise dependencies or relationships among events, and set of them, when these links really exists. The systematic analysis and characterization of these events, and sequences of them, is a challenging task and many research works have addressed it (Anis Ibrahim and Morcos, 2002; Cai et al., 2010; Khosravi et al., 2009). An accurate analysis of fault events can provide useful information to better understand how protective system performs, to carry out cause-effect analysis, to anticipate outages or to improve predictive maintenance policies.

Consider as example the events recorded in a power distribution substation plotted in Fig. 1.1 according to their time stamp. The figure represents the elapsed time between events plotted in a logarithmic scale and the time stamp with respect to their occurring order. An accurate analysis of such sequence reveals that those events occurring in short periods of time follows a pattern (linked by square marks in Fig. 1.1). A possible interpretation is that they are caused by permanent faults. The actuation of protective systems (automatic reclosing) provokes the apparition of such consecutive events with the same elapsed time between them.

The tendency is to increase observability of the power distribution networks, increasing also the collection of large data bases of power quality events, in part motivated by the necessity to adapt their management towards the Smart Grid concept which

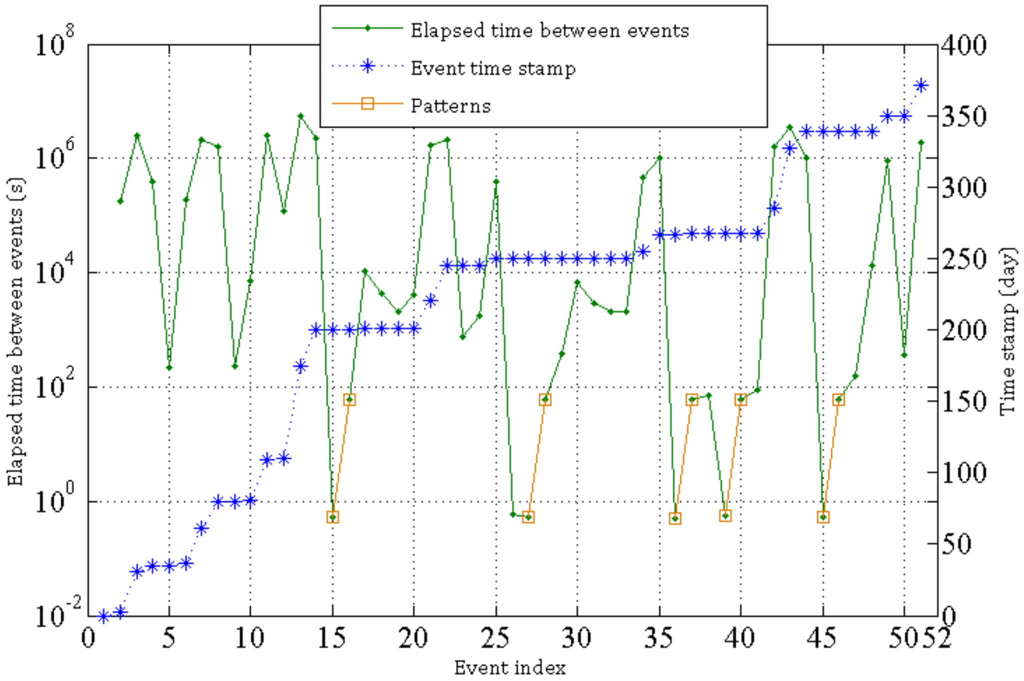


Figure 1.1: Patterns observed on the elapsed time between events.

involves aspects such as distributed generation, electric vehicle and flexible networks. So, adoption of strategies to deal with those event data bases and tools to automatically extract useful information are required. The use of data mining and knowledge discovery techniques can contribute to these challenging goals.

1.2 Objectives

The final objective is to recognise the existence of faulty behaviours in a power network from the automatic analysis of sequences of events collected in the system. These sequences could be for example power quality registers (voltage dips) or incidents collected in the network operation center. This general objective is supported by the following assumptions:

- Faults at nearby points of the network can induce failures of aged elements located in the path of the overcurrent between the transformer and the affected point.
- A permanent fault, caused for example by component failure, can cause multiples

events on the network. This behaviour is due to the actuation of the power system protections. Actuation of protective systems can produce sequences of events at time intervals defined by predefined acting conditions. Duration of events is also related with the response time of these protective relays.

- Faults usually are reflected as voltage dip events whose magnitude is related with the fault location in the network. Voltage dips with similarities in magnitude and duration occur in a nearby region of the network.

- Transient faults are reflected as single voltage dip on the network. Usually these events do not have similarities with other unrelated events occurred in their temporal neighborhood. For example, several transient faults caused by lightnings can occur during a storm in a short period of time, but their pinpoint location on the network is different.

In order to achieve this goal a data mining approach and knowledge discovery is proposed. So, the selection of features to describe events and the use of appropriate pattern discovery algorithms is the backbone of this thesis. The following subgoals have been fixed:

- To adapt existing formalisms to describe sequences of events occurring in power systems.

- To analyse existing frequent pattern discovery algorithms and propose improvements to focus on power events.

- To propose new strategies to discriminate significant episodes that are consistent with faulty behaviours in the power system.

- To validate the proposed algorithms and strategies with real data from power distribution networks.

For this purpose power quality events (mainly voltage dips) recorded in power distribution substations and incidents collected in operation control centers are considered.

1.3 Faults and events in power distribution networks

While faults usually are short circuits caused by dielectric breakdown of the insulation system, failures are the termination of the ability of the components to perform their required functions. A fault is often the result of a failure of a component, but it may exist without prior failure (IEC60050-161, 1990). A direct effect of faults is the apparition of sudden disturbances (voltage dips) that flow along the network affecting the quality of supply. These disturbances and others (swells, interruptions, etc) that are generated during the operation of the network are known as events and can usually affect both currents and voltages. Each fault, failure or other misbehaviour of the network have associated root causes which can be internal or external to the network, and it is reflected as one or several events that affect the power quality.

The faults are reflected as temporary electromagnetic disturbances in the voltage and/or current in a monitored point. They can be monitored as long interruptions, short interruptions, dips and swells, outages or overcurrents. Deviations in voltages or currents in the power system such as imbalances, voltage fluctuations, harmonics or flikers are due to other factors such as load variations or nonlinear loads.

Voltage dips are the main event associated with faults (short-circuits) occurring in the power network, but they also are related with other causes resulting in overcurrent due to normal network operations such as motor starting, transformer energising or load commutation (Olguin, 2005).

Voltage dips are defined as a sudden reduction of the voltage at a point in the electrical system, followed by a voltage recovery after a short period of time, from half a cycle to a few seconds (IEC61000-2-1, 1990) or a reduction in the *rms* voltage at the power frequency for durations of 0.5 cycle to 1 minute, which is named as voltage sag in (IEEE-Std-1346, 1998) (voltage sag is an alternative name for the phenomenon voltage dip). Swells are a temporary increase in the *rms* voltage. Outages occur when permanent faults take place in the direct path feeding the monitoring point. Short interruptions (with a duration ranging from few tenths of seconds up to 3 minutes (UNE-EN50160, 2011)) are usually the result of temporary faults cleared by the successful operation of breakers or reclosers. Voltage dips and swells occur during faults on the system that does not interrupt the supply of the monitoring point and can be observed upstream of the fault, in consumers fed by the same transformer and also in other substations (fed by the same transmission network).

Other types of disturbances as partial discharges or arcing components usually occur in previous stages of faults. They are incipient faults due to degradation of material and can be detected using high frequency methods and specific software.

1.4 Power quality monitoring in power distribution networks

Power quality monitoring is concerned with measurement, analysis and treatment of electromagnetic compatibility problems induced by deviations of voltage and/or current from the ideal. The ideal voltage and/or current is a single-frequency sine wave of constant frequency and constant magnitude. An additional requirement for the ideal current is that its sine wave is in phase with the supply voltage (Bollen, 1999).

Development of automatic strategies for dealing with power quality monitoring problems in power distribution systems include topics such as: disturbance recognition and classification, failure analysis and forecasting, and fault location. In this field there are two main work approaches. The first one includes the design of strategies in order to understand the behavior of faults and the power network under faults from a power quality point of view. The second one brings together the designed strategies to avoid the occurrence of future faults and support the maintenance of the power network.

1.4.1 Modeling of the network performance in terms of power quality

Considering that the majority of faults occurring in power distribution systems are reflected in the system as voltage dips, several approaches have been developed for power quality monitoring in terms of voltage dips activity, to evaluate the compatibility of customer equipment as well as predict the severity of future faults under a probabilistic point of view. Power quality surveys, for example, are summaries of large power quality campaigns (one year or more) that represent voltage dips collected in an area. They use depth-duration cumulative tables to establish comparative studies in terms of number and severity of dips. The accuracy of the results depends on the duration of the monitoring campaign. Extrapolation of results it is not always convenient since the network topology and load profiles varies with time (Bollen, 1999; Olguin, 2005).

Another alternative for estimating the behavior of voltage dips in the network is using stochastic prediction methods (Gopi et al., 2009; Khanh et al., 2008; Milanovic et al., 2005; Olguin, 2005). A complete estimation of the number of voltage dips and their magnitude and duration can be obtained for the different regions of a network. The evaluation can be made even if the power system does not exist yet because only a network model is required.

The approaches described before are designed to know the effects of the faults on the network. That knowledge is useful for designing mitigation strategies to reduce the impact of faults on customers. In these approaches the voltage dip events are treated as independent, i.e, occurring at a random process. However, other studies show that this independence is not always true. This is for example the case of failure components caused by natural degradation (Kim et al., 2004) or the effect of aging due to cumulative stress (Zhang and Gockenbach, 2007). Multiple types of faults related to the gradual degradation of different components of lines collected using advanced equipment monitoring and data logging, are documented in (Benner and Russell, 2004, 2009; Bowers et al., 2008; EPRI, 2001).

1.4.2 Strategies to support the power network maintenance through the prognosis of future faults

Incipient fault detection and analysis of failures is a topic of great interest for the development of predictive maintenance policies of the electrical system. For example, the continuous monitoring of high frequency signatures, that are characteristic of specific types of failures, is proposed in (EPRI, 2001). A solution, described in (Faisal and Mohamed, 2009), consists in analysing the presence of partial discharge currents caused by insulation degradation before the failure occurs. Other works propose to analyse the trend of significant parameters extracted from events occurred at a monitored point to identify fault-pattern behaviours (Kim et al., 2004; Moghe and Mousavi, 2009). One of the most used indices for determining that statistical trend is the occurrence time of events. The Laplace test statistic (LTS) is used to identify the trend of incipient failures in the system based on learned patterns from precursor events as voltage and current disturbances in a feeder. When the LTS value reaches a certain threshold, normally a percentage of the maximum LTS value, an alarm is activated to forecast a possible failure with a given level of confidence. This method is used in (Kim et al., 2004) using high-frequency components to deal with incipient faults. It links the presence and evolution of high frequency components with the existence of incipient faults and, consequently, the prediction of possible failures. However, these methods require hardware capable of capturing high frequency components and, if it is necessary to locate the fault, multiple monitors –at the substation and several locations on the feeders– must be installed as proposed in (Bowers et al., 2008). An artificial intelligence method to predict and detect faults at an early stage in power systems components was used in (Wong et al., 1996). ANNs are employed to monitor the states of some components in power networks, such as switchgears and transformers with the aim of detecting and alerting the operator before a catastrophic fault occurs.

An interesting approach is to consider the analysis and classification of faults as sequences of events. Patterns built by a sequence of events can be exploited for predictive purposes. The analysis of sequences of events is a novel approach for the diagnosis and detection of faults in complex systems. However, few applications have been documented in the area of power networks. For example, in (Liao et al., 2003) faulty components of a high-voltage transmission line are identified based on real-time alarms provided during accidents. The idea is to build a set of patterns based on sequences of alarms fixed during representative incidents and failures. Then, when a new fault occurs, the sequence of alarms is compared with the set of patterns. A cost function is used to find the most similar pattern. This allows identifying the source of the problem. At a different time scale, consequences of the propagation of outages in cascading failures are studied in (Ren and Dobson, 2008). The paper focuses on 220 kV and 500 kV lines and it establishes a method to predict the probability distribution of the size of cascading outages given an initial distribution. A branching process is used in the search and only independent outages (not associated with the same fault) are considered. The previous scenario is different from what is considered in this thesis, since we focus on distribution power systems and sequences of events generated by faults and reclosing actions.

A major effort should be made to infer complete prognosis from single monitoring points and take advantage of standard equipment already installed in many substations. This implies the extraction and selection of adequate features from existing recorders and the use of appropriate data mining and processing techniques capable of identifying useful features.

1.5 Fault classification and episodes

Faults occurring in power networks can be classified according to different criteria as duration, roots causes, number of affected phases, impedance, etc. For example, if the duration is considered, then faults will be classified as permanent, temporary or self-clearing (Olguin, 2005), while when root causes are considered then they can be classified as internal or external (Barrera, 2012). Permanent faults are short circuits that will persist until they are repaired by human intervention. Temporary faults are those that will clear after the faulted component (typically an overhead line) is de-energized and reenergized, and self-clearing faults are short circuits extinguished themselves without any external intervention. External faults are those caused by factors do not own the network such as environment (animal, tree contacts, vehicle accidents, etc.) and weather (wind, snow, lightnings, etc.), while internal faults are those derived from factors related to the proper condition of the network or its components such as components breakdown by degradation, network normal operations (starting motors, energising transformers) or components malfunction. Fig. 1.2 shows fault classification based on the most common criteria. Nevertheless, in the literature other attributes, groups and subgroups can be found. For example, in (IDC-Technologies, 2000) faults are classified into two main areas: active and passive. The active fault is when fault current flows from one phase conductor to another (phase-to-phase) or alternatively from one phase conductor to earth (phase-to-earth). This type of fault can also be further classified into two groups, namely the solid fault and the incipient fault. The solid fault occurs as a result of an immediate complete breakdown of insulation as would happen if, say, a pick struck an underground cable, bridging conductors etc. or the cable was dug up by a bulldozer. In these circumstances the fault current would be very high, resulting in an electrical explosion. Incipient faults are those that start from very small beginnings, from say some partial discharge (excessive electronic activity often referred to as Corona) in a void in the insulation, increasing and developing over an extended period, until such time as it burns away adjacent insulation, eventually running away and developing into a solid fault. Passive faults are conditions that are stressing the system beyond its design capacity, so that ultimately active faults will occur. Typical examples are: overloading –leading to overheating of insulation (deteriorating quality, reduced life and ultimate failure). Overvoltage –stressing the insulation beyond its limits. Under frequency –causing plant to behave incorrectly. Power swings –generators going out-of-step or synchronism with each other.

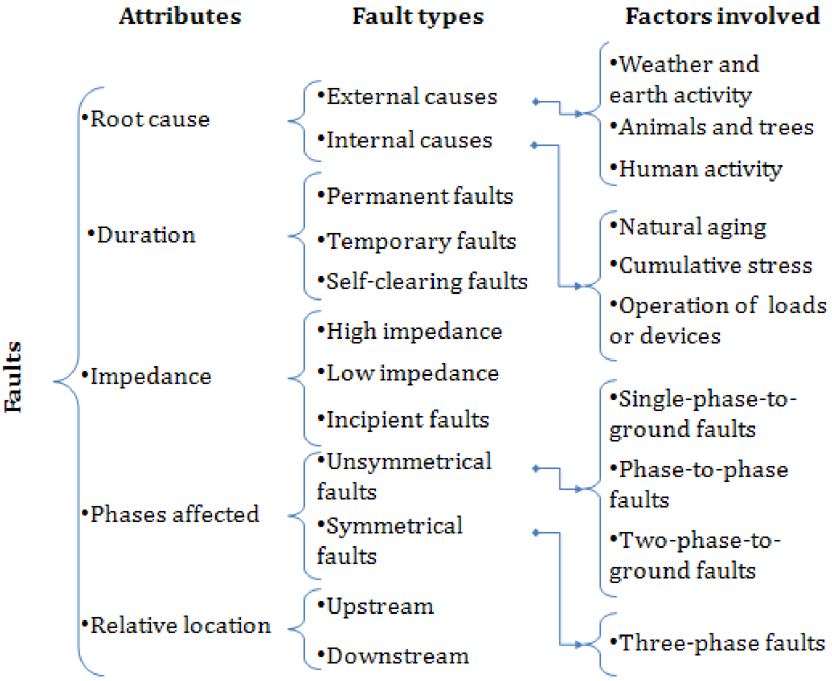


Figure 1.2: Classification of fault occurring in power networks.

Some type of faults can generate more than a single event. For example the activation of protective systems in presence a short circuit can generate several events as consequence of the automatic reclosing actions. These sequences of ordered events that have special sense all together are known as episodes. Automatic discovery of episodes that frequently occur in sequences of events recorded in distribution networks is the main objective of this work. In the following subsections these type of faults are analysed from the perspective of the episodes they can generate.

1.5.1 According to their root cause

Refers to the factors, actions or conditions that give rise to the faults. Two main groups can be distinguished: external factors due to the environment where the network is located and internal factors due to the network operation and operation of its components.

1.5.1.1 Externals causes

These are all factors do not own the network, capable of causing faults. Environment and weather are the main external causes of faults in power networks.

- **Trees and animals:** Animal contacts or tree contacts usually cause short circuits especially in overhead lines. While animal contacts take place during daytime and usually imply the apparition of events with significant arc voltage, tree contact events take place at the end of the year (fall) and have low zero sequence voltage values (Barrera, 2012).
- **Weather and earth activities:** Voltage events resulting from external causes are highly influenced by weather conditions. It includes fault caused by agents such as wind, snow, storms or lightning, but also others factors as landslides, floods, fire or earthquakes. Lightning induced events occur mainly during night as well as in the first two-thirds of the year (Barrera, 2012).
- **Human activities:** Excavations, vandalism and other activities of individuals are also important causes of faults in power distribution networks.

1.5.1.2 Internals causes

Includes all factors related to the proper condition of the network or its components that can cause faults.

- **Component aging:** These faults are caused by the degradation of materials and/or components, that under certain environmental conditions produce partial discharges (Zhang and Gockenbach, 2007). This type of fault evolves and develops over an extended period of time (days or months), and the rate of occurrence increases due to the acceleration of the degradation process (Kim et al., 2004; Moghe and Mousavi, 2009). When these phenomena happen, the disturbances generated are usually not detected by the protective systems, and specific devices such as power quality monitors, must be installed to capture such events (Bowers et al., 2008). Their evolution is expected to end as a permanent failure; so the recognition and monitoring of these events can prevent the occurrence of permanent faults.

- **Cumulative stress on electrical components:** Failures in electrical components may occur from electrical and mechanical stress (Zhang and Gockenbach, 2007). This stress may be originated during the occurrence of previous faults at other points of the network or by an intensive use of the infrastructure during long periods of time. In the first case, a sequence of events produced by subsequent faults in a feeder can be considered as a predictive episode that alerts of possible failures in components located in the path between the transformer and the location of previous faults associated with the events in the episode.

- **Normal operation of important loads:** Several events are caused by the operation of the equipment itself or significant loads connected to the network, mainly when connecting and disconnecting manoeuvres are performed. The switching of large loads can be viewed as voltage or current events. The regular occurrence of similar events may be indicative of this type of situation and their appearance probably follows patterns associated with the operation of those loads, so their characterisation could be used as a filtering method to separate them from events due to fault situations.

- **Abnormal operation of devices or equipment on the network:** Equipment connected to the network inappropriately can cause intermittent variations in current or voltage during short periods of time and even activate the protective system. For example, the incorrect connection of capacitor banks can produce transient overvoltage during the energising process that are reproduced every time a new energising is done. The identification and characterisation of this events would allow them to be filtered from the ones due to fault conditions.

1.5.2 According to their duration

The duration of faults is related with extent of damage on the network or its components and the time required to restore normal conditions of power supply.

1.5.2.1 Permanent faults

These faults are usually associated with short circuits or a breakdown of insulation between two or more conductors that cause the actuation of protective systems to isolate, locate and restore the fault. Permanent fault are short circuits that will persist until they are repaired by human intervention. As a consequence of these faults, several voltage dips similar in shape and duration are generated at time intervals that depend on the settings of protective systems, fault location and restoration strategies (Quiroga et al., 2010b). Examples of permanent faults include insulators damaged by flashover, underground cable breakdown and surge arrester damage.

1.5.2.2 Temporary faults

These are short circuits that will clear after the faulted component (typically an overhead line) is de-energized and reenergized. In this category low impedance faults produced by the interaction of external agents with the network (lightning strikes, wind, transient tree contacts, etc.) during a short period of time are included. They activate protective systems, allowing the circuit to be re-energised (fault clearing) after a reclosing operation. Although they are not associated with fault components of the power system, they can affect their performance. Moreover, the events generated by this type of fault are expected to be independent of each other.

1.5.2.3 Self-clearing faults

These are short circuits extinguished themselves without any external intervention. This type of faults can occur for example in the degradation process of cables due to insulation breakdown from water penetrating into splices (Stringer and Kojovic, 2001). When water accumulates in a cable splice, it leads to an insulation breakdown followed by an arc. Arcing causes rapid water evaporation and develops high pressures inside the splice which extinguishes the arc and interrupts the current. Because the fault current is interrupted by water vapor pressure developed from fault current, these types of faults are called self-clearing. Their frequency of occurrence increases over time. At first, they occur infrequently, once a month, then several times a week, then several times a day, and finally several times an hour until the splice fails, damaging the cable.

1.5.3 According to their impedance

The magnitude of faults is usually related with the severity of the short circuit and the current values during their occurrence. Bolted or solid faults cause more severe faults than impedance faults.

1.5.3.1 Low impedance faults

These are fault conditions in which the fault current magnitude is enough to be detected by conventional overcurrent relays or fuses, so they activate the protective system of the networks.

1.5.3.2 High impedance faults

These are fault conditions in which the fault current magnitude is not high enough to be detected by conventional overcurrent relays or fuses, so they do not activate any protection. A high impedance fault results when an energised primary conductor comes in contact with a quasi-insulating object, for example a tree, a structure or equipment, or falls to the ground. Often this leaves an energised conductor on the ground posing a danger to the public as well as a risk of arcing ignition of fires. The diagnosis of such faults is based on the detection of some abnormal features (harmonics, arcing, etc.) that can be extracted from the current and/or voltage but requires the installation of specific devices to be detected (Vico et al., 2010). They are associated with unpredictable phenomena, so it is very difficult to forecast them and only detection can be addressed.

1.5.3.3 Incipient faults

Misbehaviours in the power system typically associated with leakage current in electrical components. They are an intermittent and transient phenomena that only take place under specific conditions, usually related with symptoms of component failures. Despite not producing energy variations capable of activating protections, they generate disturbances of low magnitude that propagate across the network.

1.5.4 According to the number of affected phases

Given that distribution systems are three-phase systems, a fault can involve one or several phases of the systems. Two main groups can be distinguished: symmetrical and unsymmetrical faults. The fault impedance are related with the number of phases affected by the fault. This attribute is useful to estimate the magnitude and the pinpoint location of the fault.

1.5.4.1 Symmetrical faults

It refers to faults that affect simultaneously the three phases. Three-phase faults are more severe than unsymmetrical faults, but the latter are much more frequent.

1.5.4.2 Unsymmetrical faults

It refers to faults where not all phases of the power system are involved.

- **Single-phase-to-ground faults:** These are the more frequent faults, they represent more than 80% of the total faults in the system.
- **Phase-to-phase faults:** Two phases of the system are involved but they are isolated with respect to ground.
- **Phase-to-phase-to-ground faults:** A two-phase-to-ground fault is similar to a phase-to-phase fault, but current flows from phase to ground during the fault.

In general, the distribution probability of faults is around 80%, 10%, 5% and 5% for single-phase-to-ground, two-phase-to-ground, phase-to-phase and three-phase faults, respectively (Olguin, 2005).

1.5.5 According to their relative location

It refers to the fault source relative location from a monitored point in the network. Usually power quality monitors are installed at the bus bar of the distribution substation. So, they can distinguish between fault occurred in distribution system or downstream and transmission system or upstream.

1.5.6 Evolution of failures and faults

If we consider the analysis of a set of faults monitored in an individual point of the distribution network such as feeder head, probable dependency relationships among some of the fault situations described previously would be found. For example, an insulator under successive overvoltages caused by faults in the network may fail due to the accumulated stress, then successive transient o permanent faults may cause a new fault by cumulative stress in other point of the network. Possible influences are summarised in the schema of Fig. 1.3. Blocks are used to indicate faulty states, arrows causal dependencies among faulty states and circles represent the combination of effects. Thus, arrows indicate possible transitions between faulty states.

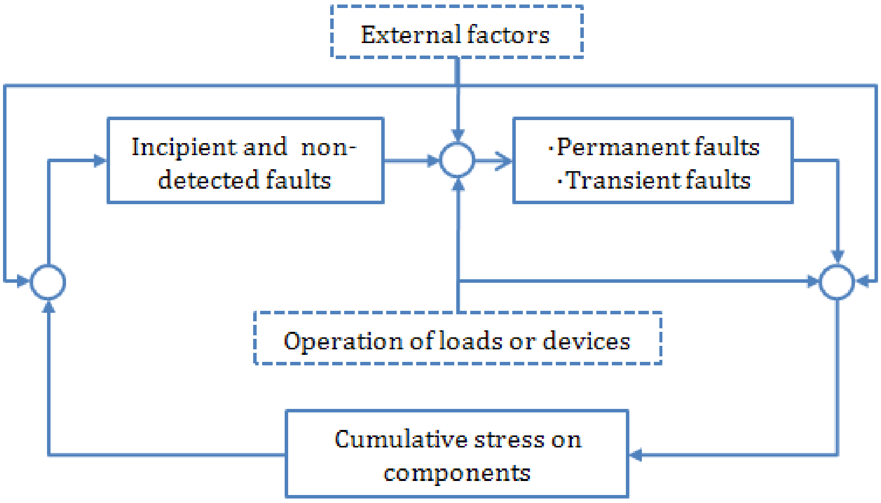

External factors
Incipient and non-detected faults
·Permanent faults
·Transient faults
Operation of loads or devices
Cumulative stress on components

Figure 1.3: Links between different fault situations.

According to Fig. 1.3, the operation of loads or devices in the network, can lead to the emergence of permanent or transient faults, is the case for example of motor starting, transformer energization, capacitor banks operation, etc. In turn, the effects generated by these faults cause stress on other components such as switches, cables and insulators. This stress is manifested in the form of incipient faults which subsequently evolve into states of permanent faults. Likewise, the external factors influence the emergence of permanent faults, transient faults, incipient faults or by cumulative stress. Each of these types of faults can evolve to other states in the same or other network components. In summary, due of the physical connection and interaction between the different components of the power network, the condition of each component, is linked –to a greater or lesser extent– to the state of other components.

Notice that the events generated by those faults can present different shapes depending on factors such as the phases affected, including the number of phases or imbalance, the load (presence of laterals, affected load, etc.), fault impedance (high/low, resistive or none), type of affected line (aerial, cable or combination of the both), etc. The study of significant features for each type of fault and the episode associated with them offers possible ways of automatically discriminating according to fault causes or using them as prediction tools (Barrera et al., 2010).

1.6 Main contributions of this work

This thesis manuscript reports the research work developed by the author about the automatic discovery of meaningful patterns in sequences of events recorded in power distribution systems. Chapter 1 contains a basic review of the approaches related to treatment of events recorded in power distribution networks useful for power quality monitoring and assessment. Likewise, this chapter contains aspects related with the origin and nature of faults and other misbehaviours of the power distribution networks, their classification and relationships between events due to faults.

This thesis proposes the use of sequence pattern discovery algorithms to find relevant patterns in data bases of historical events recorded in power distribution networks. The main contributions of the work are summarised as follows:

1. Representation of power quality events as attribute-value tuples and sequences of them generated by faults and failures as episodes. Adaptation of pattern sequence discovery problem to deal with sequences of power events and its general formulation. This topics are presented in Chapters 1 and 2 of this thesis and they were partially published in (Meléndez et al., 2012).

2. A new algorithm for frequent episode discovery is proposed. A comprehensive review of existing algorithms was made. The proposed algorithm avoids overcount and missing of occurrences, which are common problems in other pattern sequence discovery algorithms. Chapter 2 contains the proposed algorithm and their main principles were published in (Quiroga et al., 2012a).

3. A strategy to guide the search of episodes related/unrelated with events predefined by the user is proposed. This strategy allows the extraction of significant episodes from the point of view of the priority events in the mining process. A particular case is given when the analysis focuses on episodes containing specific events, exploration of other unrelated episodes is avoided. This contribution is presented in Chapter 3 and also was published in (Quiroga et al., 2012b).

4. Two new indexes for assessing the causality of frequent episodes are proposed. They are suggested as complementary criteria to the confidence of the episode rule. The first one, named *cohesion of the episode*, is based on the comparison

of the number of serial and parallel occurrences, whereas the second, named *backward-confidence of the episode*, is analogous to the confidence of an episode rule but it focuses on the beginning of the episode instead of the end. The cited indexes are presented in Chapter 3 and they were published in (Quiroga et al., 2011b, 2012a).

5. Application of proposed methods (frequent episode discovery and significant episodes recognition) with voltage dips and incident data bases to discover relevant patterns. Episodes related with permanent and transient faults, as well as other interesting patterns from causes point of view, are found using the algorithms.

   The analysis of these data sets was part of the research projects 'Monitorización Inteligente de la Calidad de la Energía Eléctrica' (DPI2009-07891) and "ENERGOS, CEN20091048: Tecnologías para la gestión automatizada e inteligente de las redes de distribución energética del futuro" (PROGRAMA CENIT-2009). Chapters 4 and 5 are focused in the analysis of the cited data sets and results have been also reported in (Meléndez et al., 2012; Quiroga et al., 2010a, 2011b, 2012b, 2010b).

The manuscript is self contained and provides references that supported the contents of this research.

1.7 List of publications

This thesis is partially based on the work reported in the following publications.

- **Journals**

  1. **O. Quiroga**, J. Meléndez, S. Herraiz. *Pattern discovery in sequences of incidents collected in power distribution systems*, Engineering Applications of Artificial Intelligence.*Submitted on July 31, 2012.*
  2. J. Meléndez, **O. Quiroga**, S. Herraiz, *Analysis of sequences of events for the characterisation of faults in power systems*, Electric Power Systems Research (EPSR), DOI: 10.1016/j.epsr.2012.01.010, vol. 87, pp. 22 - 30, 2012, (Meléndez et al., 2012).

- **Conferences**

1. **O. Quiroga**, J. Meléndez and S. Herraiz, *Frequent and significant episodes in sequences of events: Computation of a new frequency measure based on individual occurrences of the events*, 4th International Conference on Knowledge Discovery and Information Retrieval KDIR 2012. Barcelona, Spain, 4-7 Oct. 2012, (Quiroga et al., 2012a).
2. **O. Quiroga**, J. Meléndez, S. Herraiz, Á. Ferreira, A. Muñoz. *Analysis of frequent episodes in sequences of incidents collected in power distribution systems*, 2nd. IEEE PES European Conference and Exhibition on Innovative Smart Grid Technologies (ISGT-EUROPE 2011). Manchester, UK, 5-7 Dec. 2011, (Quiroga et al., 2011b).
3. **O. Quiroga**, J. Meléndez, S. Herraiz. *Fault Causes Analysis in Feeders of Power Distribution Networks*, International Conference in Renewables Energies and Quality Power ICREP'11. Las Palmas de Gran Canaria, Spain, 13 -15 Apr. 2011, (Quiroga et al., 2011a).
4. **O. Quiroga**, J. Meléndez and S. Herraiz. *Fault-Pattern Discovery in Sequences of Voltage Sag Events*, in 14th IEEE International Conference on Harmonics and Quality of Power (ICHQP), Bergamo, Italy., 26-29 Sept. 2010, (Quiroga et al., 2010a).
5. **O. Quiroga**, J. Meléndez and S. Herraiz. *Sequence Pattern Discovery of Events Caused by Ground Fault Trips in Power Distribution Systems*, 18th Mediterranean Conference on Control and Automation, MED'10. Marrakech, Morocco, June 23-25, 2010, (Quiroga et al., 2010b).
6. **O. Quiroga**, J. Meléndez, S. Herraiz, J. Sánchez. *Analysis of Event sequences in Power Distribution Systems*, International Conference in Renewables Energies and Quality Power ICREP'10. Granada, Spain, 23 - 25 Mar. 2010, (Quiroga et al., 2010c).

1.8 Outline of the thesis

The thesis is organised in six chapters. Chapter 1 introduces the general background of the work, motivation and objectives. The rest of the thesis document is organised as follows.

- **Chapter 2 – Mining sequences of events:** This chapter presents the principles used for frequent pattern discovery in sequences of events. The main procedure used in the search for episodes and several algorithms to compute their frequency are described. A new algorithm to improve results of the mining process is proposed and validated using synthetic data sets.

- **Chapter 3 – Significant episodes in sequences of events:** This chapter presents different approaches for recognising significant events and meaningful patterns once the discovery algorithms have identified frequent patterns. Methods used to assess the quality of episodes are described and two new indexes for assessing the causality and the strength of the order relation expressed by frequent episodes are proposed and tested using synthetic data sets.

- **Chapter 4 – Mining voltage dip sequences recorded in power distribution substations:** This chapter adopts strategies proposed in previous chapters for discovering significant frequent patterns from data bases of events collected by power quality monitors installed in the secondary of distribution substations in a real network. A dataset of voltage dip events recorded in a power distribution network is analysed and different types of associations between events are discovered and their physical meaning is discussed.

- **Chapter 5 – Pattern discovery in sequences of incidents collected in power distribution networks:** This chapter presents the analysis of a dataset of incidents –faults or situations that affect the continuity of supply – collected in a power distribution network. Order relations between main causes of incidents on the network are discovered and their physical meaning is discussed.

- **Chapter 6 – Conclusions and future work:** Main conclusions and contributions of this thesis are emphasized in this chapter. Some research issues are identified and proposed for future work.

Finally, references and an appendix are included. The appendix presents a method for identification of transient faults events in sequences of voltage dips from their similarities in magnitude and duration, results are presented and discussed.

2

Mining sequences of events

This chapter presents the frequent pattern discovery fundamentals used for mining event sequences. General background, formal definitions and related concepts and procedures for mining sequences of events are introduced in the chapter. The majority of these algorithms are based on proposing candidates and finding the most frequent, in terms of number of counted occurrences, in a given sequence following an iterative procedure. Different methods proposed in the literature for the computation of frequency of episodes are presented and discussed. Besides, a new algorithm to extract frequent episodes is proposed. Improvements of this new method are includes the ability to deal with serial and parallel episodes and allowing different restrictions among events in the episode. Performance of the method is evaluated with synthetic data to quantify the benefits.

2.1 Introduction

Given the advances in monitoring systems and data storage, a new approach has become important for the prediction of failures in complex systems. This new approach includes the analysis of large blocks of information, which is known as data mining.

Data mining is the process of automatic or semiautomatic exploration and analysis of large amounts of stored data to discover useful structures hidden in the data such as regularities or correlations. In general, models or patterns are the two types of structures that can be found by data mining algorithms.

A *model* can be defined as a global summary of the data, which is often obtained in the form of some functional relationship among the variables (or attributes) in the data. The idea here is to understand the underlying data generation process. In contrast to a model, a *pattern* is a local structure or regularity in the data. The role of patterns in data mining would be to bring to the attention of some interesting structures in the data rather than provide summary information about the whole data generation process (Murthy, 2007).

Multivariate statistical techniques are widely used to model multi attributes data sets. These techniques can be classified into two main groups depending on the nature of the monitored variables: dependence methods and interdependence methods. Dependence methods are applied when the variables in the dataset are divided into two groups: dependent and independent. The objective is to discover the relationships between the sets of independent and dependent variables. This group includes techniques such as multi linear regression (MLR), multivariate analysis of variance (MANOVA), discriminant analysis (DA). Interdependence methods are applied when dependent and independent set of variables are not distinguished in the data set. The aim is to identify which variables are linked together and interpret how this relationship is established. Techniques such as principal component analysis (PCA), Cluster analysis (CA) or factor analysis (FA) are part of this group. Following this paradigm, other methods and algorithms coming from the Artificial Intelligence community have been proposed for learning such relationships using data sets. Examples of them are the artificial neural networks, Bayesian networks, decision trees, support vector machines and so on.

Patterns is the type of structures searched in many application domains such as clinical monitoring, alarm management systems, customer transactions, query databases. When this data has a time dimension or sequential order then they must be treated differently in order to recognize the existence of such temporary or causal structures. This research field is known as sequential data mining and/or temporal data mining (Roddick and Spiliopoulou, 2002). Depending on the nature of the data, there are two main approaches to automatically discover patterns in sequences using different order criteria between the elements of the sequence: sequential pattern mining (Agrawal and Srikant, 1995) and frequent episode discovery (Mannila et al., 1997). Both approaches are oriented to the analysis of sets of discrete events with time dependencies (Laxman and Sastry, 2006). The fundamentals of each one are described below.

2.1.1 Sequential pattern mining

This approach is applied when a dataset consists of a collection of sequences. Each sequence is an ordered list of itemsets and each itemset is a set of items. A frequent sequential pattern is defined as a sequence of itemsets, which is contained in sufficiently many sequences of the database. A sequence $\langle a_1, a_2, ..., a_n \rangle$ is contained in another sequence $\langle b_1, b_2, ..., b_m \rangle$ if there exist integers $1 \leq i_1 \leq i_2 < ... < i_n \leq m$ such the itemset $a_1 \subseteq b_{i_1}, a_2 \subseteq b_{i_2}, ..., a_n \subseteq b_{i_n}$ (Agrawal and Srikant, 1995).

As a simple example, consider the purchases by five customers in a period of one month which are summarised in the list of 10 transactions of Table 2.1.

Table 2.1: Example of a set of customer transactions

Date	Id customer	Items
jun-10	2	a, b
jun-12	5	h
jun-15	2	c
jun-20	2	d,f,g
jun-25	1	c
jun-25	3	c,e,g
jun-25	4	c
jun-30	1	h
jun-30	4	d,g
jul-8	4	h

A transaction corresponds to an itemset. Each customer has a sequence of itemsets, which is obtained by ordering the set of transactions by id customer and by date. Table 2.2 shows the sequences corresponding to the set of transactions shown in Table 2.1.

Table 2.2: Sequences of customer transactions

Id customer	Sequence
1	$\langle (c)(h) \rangle$
2	$\langle (a, b)(c)(d, f, g) \rangle$
3	$\langle (c, e, g) \rangle$
4	$\langle (c)(d, g)(h) \rangle$
5	$\langle (h) \rangle$

The objective is to discover subsequences of ordered itemsets that appear simultaneously in several of these sequences. For example, consider the subsequences of *itemset* that appear in at least two sequences in Table 2.2, then the results are: $\langle(c)(h)\rangle$ and $\langle(c)(d,g)\rangle$. They constitute the sequential patterns of this dataset.

Several algorithms such as SPADE (Zaki, 2001), PrefixSpan (Prefix-projected Sequential pattern mining) (Pei et al., 2001), SaM (Split and Merge Algorithm) (Borgelt, 2010), Relim (Recursive Elimination Algorithm) (Borgelt, 2005), LCM (Linear Closet Item set Miner) (Uno et al., 2004), have been developed for the discovery of sequential patterns. This is an issue in continuous development that is part of the frequent itemset mining in transaction databases, research field that covered other topics such as structured pattern mining, correlation mining, associative classification, and frequent pattern-based clustering, as well as their broad applications (Han et al., 2007).

2.1.2 Frequent episode discovery

The starting point are data sets organised as a single long sequence of events where each event is described by its type and its time of occurrence.

Definition 2.1. Event. An event is defined by the pair *(e,t)* where t denotes the occurrence time (time stamp) and e represent the event attributes (one or several) that contain the information useful to characterise the event. Event attributes can be a single label or a vector of continuous/discrete attribute-value pairs defined in a given range or set of predefined values (Mannila et al., 1997).

Definition 2.2. Sequence of events. A sequence of events $\mathbf{S}$ is an ordered list of events or a n-tuple $\mathbf{S} = \langle(e_1,t_1),(e_2,t_2),...,(e_n,t_n)\rangle$ where $t_i \leq t_{i+1}$ for all $i \in \{1,2,...,n-1\}$. The length of $\mathbf{S}$, $|\mathbf{S}|$, is n. In single sequence mining, the events are represented categorically from a finite set A of event types where $e_i \in A$ (Mannila et al., 1997).

The following is an example of a sequence of events.

$$\mathbf{S1} = \langle(a,5),(d,10),(a,20),(b,25),(c,30),(b,36),(a,40),(d,51),(a,55),(b,60),(c,68)\rangle \tag{2.1}$$

In this example, the length of the sequence is 11, and A is a set of 4 different types of events, $A = \{a,b,c,d\}$. The sequence can be represented graphically as shown in Fig 2.1. In the basic framework, the events are essentially instantaneous; this means that events occur at a given instant and have not a duration associated.

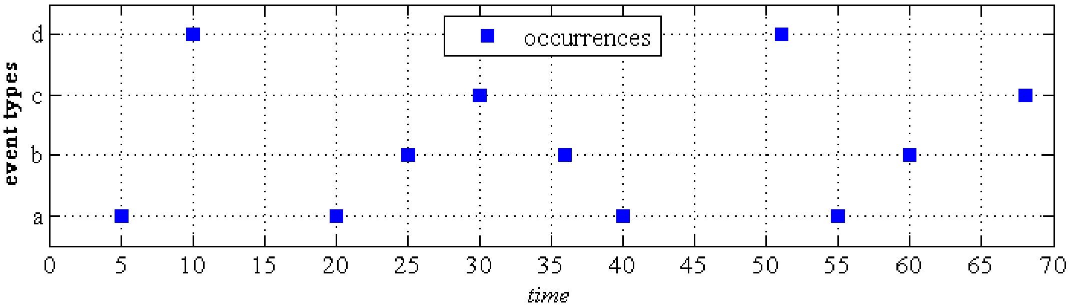


Figure 2.1: Graphic representation of an event sequence.

The mining objective is to find collections of partially ordered events occurring together within the sequence. This collection of events are called episodes.

Definition 2.3. Episode. An episode α is an ordered list formed by event types in A (set of event types) of the form $\alpha = \langle a_1, a_2, ..., a_m \rangle$ with $a_j \in A$ for all $j = 1, ..., m$. The size of α is the number of elements in α that is $|\alpha| = m$.

For example, in the sequence of Fig. 2.1 the events a, b and c can conform and episode, $\alpha = \langle a, b, c \rangle$, which have at least two occurrences along the sequences: $\langle (a, 20), (b, 25),\ (c, 30) \rangle$ and $\langle (a, 55), (b, 60), (c, 68) \rangle$. The frequency or support of an episode is equal to its number of occurrences and a minimum frequency threshold must be specified to consider an episode as frequent.

Definition 2.4. Occurrence of an episode. An episode $\alpha = \langle a_1, a_2, ..., a_m \rangle$ occurs in a sequence of events $\mathbf{S} = \langle (e_1, t_1), (e_2, t_2), ..., (e_n, t_n) \rangle$ if there is at least one ordered sequence of events $\mathbf{S}' = \langle (e_{i_1}, t_{i_1}), (e_{i_2}, t_{i_2}), ..., (e_{i_m}, t_{i_m}) \rangle$ such that $\mathbf{S}' \subseteq \mathbf{S}$ and $a_j = e_{i_j}$ for all $j = 1, 2, ..., m$. Usually an occurrence is denoted as $o = \langle i_1, i_2, ..., i_m \rangle$ where $o\,[j] = i_j$ and $j = 1, 2, ..., m$.

Definition 2.5. Frequency or support of an episode. It is the number of occurrences of an episode over a sequence of events. The frequency of an episode α is abbreviated as $fr(\alpha)$.

Definition 2.6. Frequent episode. An episode α is frequent if its number of occurrences $fr(\alpha)$ is equal or greater than a threshold (min_fr), i.e., α is frequent if $fr(\alpha) \geq min\_fr$.

2.2 Analysis of sequences of events registered in power distribution systems

The previous definitions have been adapted to deal with disturbances, i.e. power or electrical events, collected by power quality monitors installed in substations and/or consumers. A set of timestamped events recorded at a single point of the network during a power quality monitoring campaign is considered as a sequence of events.

Definition 2.7. Electrical event. An electrical event, $e_i(t_i)$, is a dated record of an electric variable, typically currents and voltages, that suffers a sudden variation in its value. It is defined by an (m+1)-tuple, $(a_1, \ldots, a_m, t_i)$, where t_i is the event time stamp (usually, the starting time) and a_j (with $j = 1, \ldots, m$) represents the value of each attribute, A_j, defined in its respective domain, $a_j \in Dom(A_j)$. Event attributes can be continuous (duration, magnitude, maximum peak, frequency content, etc.) or symbolic (type of incident, causes, affected phases, etc.). The attributes are selected according to their relevance with respect to the proposed goal.

A sequence of events can contain several events, but only some subsets of them are of interest, either because they present similar features (shape, duration, etc.) or because there is some relationship that allows them to be considered together (timing, periodicity, etc.), as for example, when they are originated by the same cause in an evolving fault. According to the nomenclature introduced in Section 2.1.2, these subsets of significant events in a sequence are called episodes and are expected to describe some patterns. The existence of those patterns is exploited, taking advantage of mining algorithms to automatically obtain those patterns from an existing sequence of events based on the criterion of frequent episodes. Once those patterns are known, they can be used to better describe fault situations and their evolution. They can also be used to predict future failures by recognising the events that match the early stages of a pattern.

In the remainder of this chapter, common terminology, fundamentals and main methods used in single sequence mining are presented. Likewise, a new algorithm to improve results of the mining process is proposed.

2.3 Background on event sequences mining

Frequent episodes mining in sequences of events has been applied in many application domains: analysing alarm sequences in telecommunication networks (Mannila et al., 1997), web access pattern discovery and family protein analysis (Casas-Garriga, 2003), fault prognosis based on logs of manufacturing plants (Laxman et al., 2007), study of multi-neuronal spike train recordings (Patnaik, 2006) or event tracking problems for news stories (Iwanuma et al., 2005).

Typically, methods for mining frequent episodes in a sequence follow an iterative procedure that starts searching for frequent events (single event episodes). The candidate episodes are generated by aggregating frequent events. Occurrence of these candidate episodes is evaluated to check if their frequency is over a minimum threshold to be considered a frequent pattern. This basic procedure shown in Algorithm 1, is based on the same general idea as the Apriori algorithm (Agrawal and Srikant, 1995).

Algorithm 1 General method for frequent episode discovery

Input: A sequence of events **S**, the set of event types or categories (E), and the minimum frequency threshold min_fr.

Output: Frequent episodes of length L, F^L.

Procedure:

```
1: Initialise a counter associated with the length of episodes ($L = 1$).
2: Generate the first set of candidate episodes $\mathbf{C}^L$ ($L = 1$) from the frequent events in $E$.
3: while $\mathbf{C}^L \neq \{\}$ do
4:     Compute the frequency ($fr$) of the candidate episodes of length $L$.
5:     Extract and store frequent episodes ($fr \geq min\_fr$) as $F^L$.
6:     Increase the counter in 1: $L \leftarrow L + 1$.
7:     Generate candidate episodes of length $L$, $\mathbf{C}^L$, from the frequent episodes in $F^{L-1}$.
```

The first set of candidate episodes C^1 (length $L = 1$) is generated by using the set of event types E that appears in the sequence (line 2). In the main function (line 4), the number of occurrences fr of each candidate episode is computed and those with fr over the threshold are classified as frequent episodes and stored as F^L (line 5). From frequent episodes in F^L, a new set of candidate episodes, C^L, of length $L = L + 1$, is build (line 7). The process continues iteratively until no candidate episodes are found ($C^L = \{\}$) (line 3). In the literature, frequent episode discovery algorithms differ mainly in the way of searching and computing the frequency of the candidate episodes (line 4).

2.3.1 Main characteristics of frequent episodes

There are three important factors that guide the search of frequent episodes. The first is related with the constraints among events in the episode that can be defined by relationships among attributes (similarity, duration, elapsed time between events, etc.). The second is the relationship between a pattern episode an the sub-episodes it contains. Monotonic (or anti-monotonic) property is expected in the indices used to guide the search. In that sense frequency is a good index because it presents and anti-monotonic behaviour (frequency of an episode can not be greater than frequency of their sub-episodes) and special care has to be done when defining it to preserve this property. The third factor aims to find all or at least the largest number of occurrences –maximum frequency– of an episode, without violating the two previous principles.

2.3.1.1 Partial order

An episode $\alpha = \langle a_1, a_2, ..., a_m \rangle$ imposes a constraint on relative order of its occurrences a_j. According with this order, there are three types of episodes: serial episodes, parallel and hybrid episodes (Mannila et al., 1997).

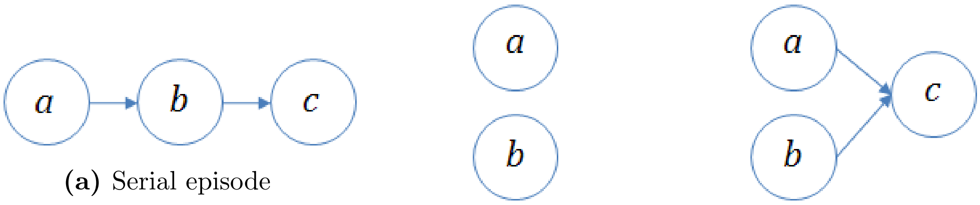
Definition 2.8. Serial episode. It is an episode $\langle a_1, a_2, ..., a_m \rangle$ where the event a_j occurs before event a_{j+1} for all $j = 1, ..., m-1$.

Definition 2.9. Parallel episode. It is an episode $\langle a_1, a_2, ..., a_m \rangle$ where the event a_j can occurs before or after of the event a_{j+1} for all $j = 1, ..., m-1$. In this document a parallel episode is represented as $\langle a_1 \cdot a_2 \cdot ... \cdot a_m \rangle$.

Definition 2.10. Hybrid episode. It is a combination of serial and parallel episodes.

Fig. 2.2 shows a schematic of each type of episodes according to their partial order.

Serial episode $\langle a, b, c \rangle$ in Fig. 2.2a indicates that event a occurs before event b, and b before event c. In contrast, parallel episode $\langle a \cdot b \rangle$ in Fig. 2.2b indicates that events a and b occur together but it does not distinguish which one comes first. Finally, hybrid episode in Fig. 2.2c shows a combination between the parallel episode $\langle a \cdot b \rangle$ and the event c. It indicates that episode $\langle a \cdot b \rangle$ occurs before the event c.



(a) Serial episode

(b) Parallel episode

(c) Hybrid episode

Figure 2.2: Types of episodes according to their partial order

2.3.1.2 Duration of an episode

Since a sequence of events can last for long periods, it is necessary to bound proximity between both, consecutive events in an episode and delay between the first and the last event within the episode. An episode usually occurs in shorter and realistic periods of time over a sequence. There are two basic strategies to define the duration of the episodes: the first one is using an observation window of fixed width also called expiry-time constraint and the second one is defining a gap between consecutive events also named inter-event time constraint.

Definition 2.11. Expiry-time constraint. It is the maximal elapsed time allowable between the first and the last event of and episode which is abbreviated as t_x. In the literature, an observation window of fixed width win is also used to define the expiry-time of an episode, i.e, t_x and win are equivalent terms.

Definition 2.12. Inter-event time constraint. It is the maximum elapsed time allowable (maximal gap) between two consecutive events of an episode which can be a fixed value t_{max} also abbreviated as max_gap or an interval $(t_{min}, t_{max}]$.

Consider as example the serial episode $\alpha = \langle a, b, c \rangle$. If a expiry-time constraint t_x is used, then for each occurrence of α the elapsed time between the occurrence of a and the occurrence of c must be less than or equal to t_x. If the inter-event time constraint t_{max} is used, for each occurrence of α the elapsed time between the corresponding occurrences of a, b and b, c must be less than or equal to t_{max}. If an interval $(t_{min}, t_{max}]$ is used, then the elapsed time between the corresponding occurrences of a, b and b, c must be located within the defined interval.

An alternative strategy is to establish a variable expiry-time in function of the episode size. Using the previous nomenclature, a possible definition of this variable expiry-time t_x of an episode α can be $t_x = (|\alpha| - 1) \times t_{max}$. In this case, for episodes of size greater than two, the elapsed time between successive events is not constrained (Casas-Garriga, 2003).

2.3.1.3 Derivations or extensions of an episode

Sub-episodes and super-episodes are the most common derivations and extensions of an episode, respectively.

Definition 2.13. Sub-episode, super episode. An episode $\beta = \langle b_1, b_2, ..., b_m \rangle$ is a sub-episode of another episode $\alpha = \langle a_1, a_2, ..., a_n \rangle$ if $m < n$ and there exist $1 \leq i_1 < i_2 < ... < i_m \leq n$ such that $b_j = a_{i_j}$ for all $j = 1, 2, \ldots, m$. In this case, α is a super episode of β.

In turn, the episode α in Definition 2.13 can be classified within three types of super episodes of β, depending of the location of β within α: forward-extension super episode, backward-extension super episode and middle-extension super episode (Zhou et al., 2010).

Definition 2.14. Forward-extension super episode. The episode α in Definition 2.13 is called the forward-extension super episode of β if there exist $i_1 = 1, i_2 = 2, \cdots, i_m = m$.

Definition 2.15. Backward-extension super episode. The episode α in Definition 2.13 is called the backward-extension super episode of β if there exist $i_1 = n-m+1, i_2 = n-m+2, \cdots, i_m = n$.

Definition 2.16. Middle-extension super episode. The episode α in Definition 2.13 is called the middle-extension super episode of β if α is neither a forward-extension nor backward-extension super episode of β.

2.3.1.4 Parts of an episode

The parts of an episode are related with the relative location of the event within it. Suffix and prefix are the most important parts.

Definition 2.17. Suffix of an episode. The suffix of an episode α is defined as the last event in the episode and it is abbreviated $suffix(\alpha)$, i.e., if $\alpha = \langle a_1, a_2, ..., a_m \rangle$, then $suffix(\alpha) = \langle a_m \rangle$,

Definition 2.18. Prefix of an episode. The prefix of α is the episode composed by all elements in α without the last one. It is abbreviated as $prefix(\alpha)$. I.e., if $\alpha = \langle a_1, a_2, ..., a_m \rangle$, then $prefix(\alpha) = \langle a_1, a_2, ..., a_{m-1} \rangle$.

Definition 2.19. Large suffix of an episode. The large suffix of an episode is defined in this work as the episode composed by the elements in α without the first one and it is abbreviates as $lsuffix(\alpha)$. If $\alpha = \langle a_1, a_2, ..., a_m \rangle$, then $lsuffix(\alpha) = \langle a_2, ..., a_m \rangle$.

2.3.1.5 Types of occurrences

After defining the limits of duration of episodes (Definitions 2.11 or 2.12), the occurrences of an episode refer to parts of the sequence containing the episode. Such occurrences can be normal occurrences as shown in Definition 2.4 or minimal occurrences.

Definition 2.20. Minimal occurrence. An occurrence of α, $o = \langle i_1, i_2, ..., i_m \rangle$, is minimal if no other occurrence $o' = \langle i'_1, i'_2, ..., i'_m \rangle$ exists in a sequence of events $\mathbf{S}$, between the intervals $[i_1, i_m)$ or $(i_1, i_m]$ with $[i'_1, i'_m] \subset [i_1, i_m]$. A minimal occurrence of an episode α is denoted as $mo(\alpha)$.

In turn, a set of occurrences, or minimal occurrences, of an episode can be classified as redundant or non-redundant, if different occurrences have or do not have elements in common, respectively.

Definition 2.21. Redundant occurrences, non-redundant occurrences. A set of occurrences of an episode α is called non-redundant if for any two occurrences $o = \langle i_1, i_2, ..., i_m \rangle$ and $o' = \langle i'_1, i'_2, ..., i'_m \rangle$ no event occurs simultaneously in both, i. e., $e_{i_j} \neq e_{i'_j}$ $for\ all$ $j \in \{1, 2, ..., m\}$. Otherwise, this set of occurrences is redundant.

Likewise, a set of occurrences can be overlapped or non-overlapped depending of the location of these occurrences over a sequence.

Definition 2.22. Overlapped occurrences, non-overlapped occurrences. Two occurrences of an episode α in a sequence of events $\mathbf{S}$, $o = \langle i_1, i_2, ..., i_m \rangle$ and $o' = \langle i'_1, i'_2, ..., i'_m \rangle$, are non-overlapped if $o[1] > o'[m]$ or $o'[1] > o[m]$, where $m = |\alpha|$. Otherwise, these two occurrences are overlapped.

2.3.1.6 Anti-monotonicity property

Anti-monotonicity property is a common principle that frequency measure methods should obey in frequent pattern mining.

Definition 2.23. Anti-monotonicity of an episode. An episode is anti-monotonic if its frequency is no greater than the frequency of its sub-episodes i.e., any two episodes α and β, $\alpha \supseteq \beta$ follow the principle of anti-monotonicity if $fr(\alpha) \leq fr(\beta)$.

The anti-monotonicity property guarantees that a candidate episode can be pruned safely if any of its sub-episodes is infrequent, and any infrequent episode need to be extended. However, when the strategy of inter-event time constraint (Definition 2.12) is used for the duration of the episodes, the anti-monotonicity property of an episode can not be applied based on the frequency of all its sub-episodes. Only the frequency of its non-overlapped sub-episodes must be considered (Casas-Garriga, 2003). For example, given the serial episode $\langle a, b, c \rangle$, and its sub-episode $\langle a, c \rangle$. The two episodes are extracted using a maximal gap between events t_{max}. While in $\langle a, b, c \rangle$, events a and c can be separated for $2 \times t_{max}$ time units, in its sub-episode $\langle a, c \rangle$ the events have only a maximum gap of t_{max} time units. Since the gap between events is different in both episodes, the sub-episode $\langle a, c \rangle$ may be less frequent than the episode $\langle a, b, c \rangle$.

2.3.1.7 Maximum frequency of an episode

Maximum frequency refers to the fact of finding all the occurrences of an episode under a strategy of duration constraint and an anti-monotonic measure.

Definition 2.24. Maximum frequency. Given a sequence of events S, a strategy of duration constraint (Section 2.3.1.2) and an anti-monotonic measure, then the frequency (Definition 2.5) $fr \ \forall \ \ \alpha$ and $\forall \ \ \mathbf{S}$, $\neg\exists \ \ fr^*$ such that $fr^*(\alpha) > fr(\alpha)$. It ensures that no proper occurrences are missed in the computation of the frequency of and episode (Gan and Dai, 2010).

2.3.2 Frequency measure methods

How occurrences of a candidate episode α are counted varies among the different algorithms. Results depend on the duration constraint (Section 2.3.1.2) used to obtain the episodes and the occurrences selected (Section 2.3.1.5). Beyond the duration, different methods have been proposed to cope with particularities of the occurrences of an episode. The occurrences within an observation window (Definition 2.11), to count only the minimal occurrences (Definition 2.20), to consider only non-overlapped occurrences (Definition 2.22), etc., are strategies implemented to select the most properly occurrences of an episode. According to the types of occurrences selected, there are two main groups of methods to compute the frequency of an episode: methods based on occurrences and methods based on minimal occurrences. Next, a short description of the most common algorithms is presented.

2.3.2.1 Methods based on occurrences

The most used strategy to compute the frequency of an episode consists in counting the number of occurrences. However, once the duration of a candidate episode α has been defined, there are different ways to count the associated occurrences:

- **Fixed-width window frequency measure:** This method, exposed in (Mannila et al., 1997), uses a sliding window w of fixed width t_x predefined by the user. The original sequence $\mathbf{S}$ is transformed in a set of overlapped fixed-width windows and the fraction of windows that contain the episode corresponds to its frequency.

  $$fr(\alpha, \mathbf{S}, t_x) = \frac{|\{w \in W(S, t_x) \text{ such that } \alpha \text{ occurs in } w\}|}{|W(\mathbf{S}, t_x)|} \tag{2.2}$$

  where $W(\mathbf{S}, t_x)$ is the set of all windows w on $\mathbf{S}$.

  With this method some occurrences of the episodes could be over-counted because several windows could contain the same occurrence. The method is limited to discover episodes with duration no greater than the window width.

- **Total frequency measure:** This method, described in (Iwanuma et al., 2005), also uses a sliding window of fixed width to search the episodes, but only windows headed by the first event of the candidate episode are taken into account for the frequency measure. This constraint aims to avoid over-counting occurrences of episodes. The anti-monotonic property is assured by defining the frequency of an episode as the lower frequency of its sub-episodes.

  This method can be summarised as follows: given a sequence of events $\mathbf{S} = \langle (e_1, t_1), (e_2, t_2), ..., (e_n, t_n) \rangle$ and the length of the window win, the frequency of each candidate episode $\alpha = \langle a_1, ..., a_m \rangle$ is evaluated in two steps. First, the Head frequency (*H–freq*) is computed as:

$$H\text{-}freq(\mathbf{S}, \alpha, win) = \sum_{i=1}^{n} \delta(\mathbf{S}(t_i, t_j)), \alpha) \tag{2.3}$$

where $\mathbf{S}(t_i, t_j) = \langle (e_i, t_i), ..., (e_j, t_j) \rangle$ and $t_j - t_i \leq win$. The function δ of Equation 2.3 is defined as:

$$\begin{aligned} &\delta(\langle (e_i, t_i), ..., (e_j, t_j) \rangle, \langle a_1, ..., a_m \rangle) = \\ &\quad \begin{cases} 1 & \text{if } a_1 \subseteq e_i \text{ and } \langle a_2, ..., a_m \rangle \subseteq \langle e_{i+1}, ..., e_j \rangle, \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \tag{2.4}$$

The measure *H–freq*$(\mathbf{S}, \alpha, win)$ counts the number of occurrences for the first element a_1 of α in $\mathbf{S}$, whereas, for the second and later elements $a_2, ..., a_m$, *H–freq*$(\mathbf{S}, \alpha, win)$ just checks whether each of $a_2, ..., a_m$ occurs in $\mathbf{S}$ or not. Then, frequency of α may be greater than the frequency of some of its sub-episodes.

To ensure the anti-monotonicity of an episode, the Total frequency (*T–freq*) is calculated in the next step considering also the Head frequency of their corresponding sub-episodes, as:

$$T\text{–}freq(\mathbf{S}, \alpha, win) = min\,\{H\text{–}freq(\mathbf{S}, \beta, win)\} \tag{2.5}$$

where $\beta \subseteq \alpha$.

The algorithm in (Iwanuma et al., 2005) was formulated only for serial episodes. We propose an adaptation for this method, to count parallel occurrences.

Given a sequence of events $\mathbf{S} = \langle (e_1, t_1), (e_2, t_2), ..., (e_n, t_n) \rangle$ and the length of the window *win*, the *Head parallel frequency* (*H-pfreq*) of each candidate episode $\alpha = \langle a_1 \cdot ... \cdot a_m \rangle$ can be evaluated as:

$$H\text{-}pfreq(\mathbf{S}, \alpha, win) = \sum_{i=1}^{n} \delta_p(\mathbf{S}(t_i, t_j)), \alpha) \tag{2.6}$$

where $\mathbf{S}(t_i, t_j) = \langle (e_i, t_i), ..., (e_j, t_j) \rangle$ and $t_j - t_i \leq win$. The function δ_p of Equation 2.6 is defined as:

$$\delta_p(\langle(e_i,t_i),...,(e_j,t_j)\rangle,\langle a_1\cdot...\cdot a_m\rangle)= \begin{cases} 1 & \text{if } e_i\subseteq\langle a_1\cdot...\cdot a_m\rangle \text{ and } \langle a_1\cdot...\cdot a_m\rangle\ \subseteq\ \langle e_i,...,e_j\rangle, \\ 0 & \text{otherwise.}\end{cases} \tag{2.7}$$

Finally, the total parallel frequency measure (*T-pfreq*) is obtained from the head parallel frequency as:

$$\textit{T-pfreq}(\mathbf{S},\alpha,win)=min\left\{\textit{H-pfreq}(\mathbf{S},\beta,win)\right\} \tag{2.8}$$

where $\beta\subseteq\alpha$.

Redefining the function δ_p in Equation 2.7, the adaptation of the method to count parallel occurrences is performed. Equations 2.6 and 2.8 are similar to Equations 2.3 and 2.5, respectively.

- **Bounded list of occurrences:** This algorithm, proposed by Huang and Chang (Huang and Chang, 2008), also uses a sliding window of fixed-width. They define the support of an episode as the number of windows that start with the first element of the episode. When windows are overlapped this support can be anti-monotonic, then they define an episode as frequent if and only if the supports of the episode and its sub-episodes are at least greater than threshold specified by the user.

- **Variable-width window:** In this method, exposed in (Casas-Garriga, 2003), the search of an occurrence is constrained to a maximal gap (max_gap) between consecutive events in the episode. This maximal gap is a parameters specified by the user. Then, the frequency is calculated following the same procedure introduced for the fixed-width window method but in this case the width of the window is updated according to the length of the candidate episode $|\alpha|$ as: $win=(|\alpha|-1)\times max\_gap$. The frequency of α in $\mathbf{S}$ is defined as:

$$fr(\alpha,\mathbf{S},max\_gap)=\frac{|\{w \text{ such that } w\in W(S,win)\wedge\alpha \text{ occurs in } w\}|}{|W(\mathbf{S},win)|} \tag{2.9}$$

where $W(\mathbf{S},win)$ is the set of all windows w in $\mathbf{S}$ with width win and $|W(\mathbf{S},win)|=|\mathbf{S}|-1+win-1$.

- **Frequency based on maximal non-redundant sets of occurrences:** This method uses as constraint the maximal gap between events (Gan and Dai, 2010). The occurrences of a candidate episode are constructed recursively appending to the occurrence of its *prefix* the leftmost occurrence of its *suffix* considering the maximal gap constraint.

2.3.2.2 Methods based on minimal occurrences

The other methodology used to compute the frequency of an episode is by its minimal occurrences. Each minimal occurrence must follow the duration constraint. There are several ways to group these minimal occurrences:

- **Minimal occurrences within a fixed window width:** This method, also introduced by Mannila et al. (Mannila et al., 1997), considers only the minimal occurrences of an episode. Given an episode α and an event sequence $\mathbf{S}$, they say that the interval $[t_s, t_e)$ is a minimal occurrence of α in $\mathbf{S}$, if α occurs in the window $\mathbf{w} = (w, t_s, t_e)$, and if α does not occur in any proper subwindow on $\mathbf{w}$. For each frequent episode, information about the location of its minimal occurrences is stored, then the locations of minimal occurrences of a candidate episode α, are computed as a temporal join of the minimal occurrences of two sub-episodes of α. The first sub-episode is the prefix of α, $prefix(\alpha)$ and the second one is the large suffix of α, $lsuffix(\alpha)$. This method avoids counting non-minimal occurrences.

- **Minimal occurrences with maximal gap:** This method forces two constraints during the search (Méger and Rigotti, 2004): a maximal window width and a maximal gap between events. The frequency of an episode is calculated as the sum of all minimum occurrences between a variant window width whose value increase between one and the maximal window width. With this method non-minimal occurrences are not counted and the bound of window restricts the width of occurrences.

- **Non-overlapped frequency measure:** This method defines the frequency of an episode as the maximal cardinality of the sets of the non-overlapped occurrences (Laxman et al., 2007). Non-overlapped occurrences means that an occurrence must be finished before starting a new one (Definition 2.22).

2.3.3 Discussion about the frequency measure methods

Frequency measure methods aims to find all the occurrences of candidate episodes. However, the episodes extracted for all of them have dissimilar characteristics in duration and in the number of occurrences extracted. Some occurrences can be over-counted or omitted under the described methods. Given a candidate episode and a duration constraint, to find its maximal number of non-redundant occurrences implies to consider not only its minimal occurrences but also, their overlapped and non-minimal occurrences.

Methods based on minimal occurrences are useful to plot the occurrences of an episode. They locate each occurrence in the process of computing frequency. Methods that use observation windows only show the index of the windows where are located the occurrences. Some methods find the occurrences of the episodes from the sub-episodes locations (indexes). Such algorithms are faster, but can propagate errors due to the improper selection of the sub-episode occurrences. Consequently, proper occurrences of an episode would be ignored (missed).

Table 2.3 summarise the main characteristics of the methods described in Section 2.3.2. A list of five features for the episodes is shown. Partial order is abbreviated as (S) or (P) for serial and parallel episodes, respectively. Duration is abbreviated as (1), (2) or (3) for expiry-time constraint, inter-event time constraint or combination of both, respectively. Likewise, four aspects about the occurrences is indicated: (R) over-count occurrences , (M) missed or omit occurrences, (L) index or locate the occurrences and (B) if the algorithm use the indexes of sub-episodes.

According with Table 2.3, methods of total frequency measure, maximal non-redundant set of occurrences, minimal occurrences within a fixed-width window and minimal occurrences with a maximal gap, are not defined for parallel occurrences. However, for the total frequency measure method an adaptation to count parallel occurrences is proposed in Section 2.3.2.1 of this thesis.

Likewise, all review methods (except the method of non-overlapped occurrences) are defined for episodes with expiry-time constraint or inter-event time constraint and all of them over-count or missed occurrences. Moreover, occurrences can be located by methods based on minimal occurrences and by the method of maximal non-redundant

Table 2.3: Characteristics of the episodes according with the method used in the discovery process.

Frequency measure method	Episode characteristics					Occurrences			
	Order		Duration			extraction			
	S	P	1	2	3	R	M	L	B
Methods based on occurrences:									
–Fixed window width frequency measure (Mannila et al., 1997)	✓	✓	✓			✓			
–Variable-width window (Casas-Garriga, 2003)	✓	✓		✓			✓		
–Total frequency measure (Iwanuma et al., 2005)	✓		✓			✓			
–Bound list of occurrences (Huang and Chang, 2008)	✓	✓	✓			✓			
–Maximal non-redundant sets of occurrences (Gan and Dai, 2010)	✓			✓			✓	✓	✓
–Fminevent[1] (Quiroga et al., 2012a)	✓	✓	✓	✓	✓			✓	
Methods based on minimal occurrences:									
–Within a fixed window width (Mannila et al., 1997)	✓		✓				✓	✓	✓
–With maximal gap (Méger and Rigotti, 2004)	✓			✓			✓	✓	
–Non-overlapped occurrences (Laxman et al., 2007)	✓	✓	✓	✓	✓		✓	✓	

–Episode characteristics: (S) serial episodes, (P) parallel episodes, (1) expiry-time constraint, (2) inter-event time constraint , (3) combination of the two time constraint.

–Occurrences extraction: (R) over-count occurrences , (M) missed occurrences, (L) locate or index the occurrences, (B) require sub-episodes indexes.

[1] This algorithm has been proposed in this thesis and it is described in Section 2.4.

set of occurrences, while the method of minimal occurrences within a fixed-width window and maximal non-redundant set of occurrences require sub-episodes indexes in the search process.

Table 2.3 also includes a new method proposed in this thesis for the analysis of event sequences related with faults collected in power distribution systems, and it is described in Section 2.4. Fminevent is the short name of the proposed method, which uses the occurrences of the individual event types to search the occurrences of a candidate episode of any size, i.e., the occurrences of the sub-episodes are not required. As show in Table 2.3, this method avoids counting redundant occurrences and allows the existence of overlapped episodes. Inter-event time constraint is used to control the duration of the episodes but the method is flexible to constrain also the expiry time of the episodes, or both expiry time and inter-event time. Additional benefit is that the method also allows dealing with parallel occurrences and facilitates graphical representation because episodes are perfectly indexed.

2.4 New frequency measure based on individual occurrences of the events (Fminevent)

Novelty of this method is on the process of selection of the occurrences of a candidate episode. This follows an iterative procedure and it is made by combining occurrences of their event types instead of adding them to discovered sub-episodes. Serial and parallel occurrences are found using a similar strategy. The cardinality of these sets of occurrences constitutes the frequency of the episodes.

2.4.1 Serial occurrences with inter-event time constraint

Given a sequence of events $\mathbf{S} = \langle (e_1, t_1), (e_2, t_2), ..., (e_n, t_n) \rangle$, a candidate episode $\alpha = \langle a_1, a_2, ..., a_m \rangle$ and a maximal gap between events $max\_gap = k$, Algorithm 2 returns the set of maximal non-redundant occurrences, $maxnO$. First, for $m = 1$, the occurrences of the episode are the same minimal occurrences of the event a_1, $maxnO(\mathbf{S}, \alpha, k) = mo(a_1)$. Then, for $m > 1$, $maxnO(\mathbf{S}, \alpha, k)$ is obtained by joining each occurrence of a_1 with occurrences of $a_2, ..., a_m$ located between the corresponding t_1 to $t_1 + (m-1)k$.

For simplicity let each t_i in $\mathbf{S}$ take values from $j = 1, 2, ...,$ and $t_i = j$ means the i-th data element occurs at the j-th tiemestamp. The algorithm has a two-phase structure. In the first phase (lines 4-9), a *list* for each occurrence of a_1, $mo(a_1)(i)$, is created containing the occurrences of the other events (a_j) within the constraint max_gap, where $list.a_1 = mo(a_1)(i)$ and $list.a_j = mo(a_j)$ such that $list.a_{j-1}(1) < mo(a_j) \leq list.a_{j-1}(end) + k$ for $j = 2, ..., m$.

In the second phase (lines 11-17), the most proper serial occurrence sO is selected from the *list*. The most proper occurrence is composed by the most left occurrence of each event found in $list.a_j$ that meets the restrictions of max_gap between events. This is done starting with the first occurrence of the last event from the *list*, that is $list.a_m(1)$ (line 12) and in an iterative procedure the most left occurrence of the other events within k are located (lines 13-17). Each serial occurrence sO is added to $maxnO$ (line 18) and constitutes the output of the algorithm.

Algorithm 2 Fminevent: Serial occurrences with inter-event time constraint

Input: An event sequence $\mathbf{S}$, a candidate episode $\alpha = \langle a_1, a_2, ..., a_m \rangle$, the maximal gap k, occurrences of the events in α i.e, $mo(a_1), ..., mo(a_m)$.

Output: The maximal non-redundant occurrences of α, $maxnO(\mathbf{S}, \alpha, k)$.

Procedure:

```
Initialise $maxnO(\mathbf{S}, \alpha, k) \leftarrow \{\}$
for $i = 1$ to $|mo(a_1)|$ do
    //From each $mo(a_1)$ create a $list$ of candidate occurrences.
    if $mo(a_1)(i) \notin maxnO(\mathbf{S}, \alpha, k)$ then
        $list.a_1 \leftarrow mo(a_1)(i)$
        for $j = 2$ to $|\alpha|$ do
            $oc \leftarrow mo(a_j)$ such that $list.a_{j-1}(1) < mo(a_j) \leq list.a_{j-1}(end) + k$ and $mo(a_j) \notin maxnO(\mathbf{S}, \alpha, k)$
            if $oc \neq \{\}$ then
                $list.a_j \leftarrow mo(a_j)(oc)$
        //From $list$ select the most proper occurrence.
        if $size(list) = |\alpha|$ then
            $sO \leftarrow list.a_m(1)$
            for $j = m - 1$ to 1 do
                for $kk = 1$ to $|list.a_j|$ do
                    if $sO(1) - list.a_j(kk) \leq k$ then
                        $sO \leftarrow [list.a_j(kk)\ \ sO]$
                        break
            Add $sO$ to $maxnO(\mathbf{S}, \alpha, k)$
```

Note that to search the occurrences of an episode (any size), the method requires only the single event occurrences without using their sub-episodes.

Consider as example the sequence $\mathbf{S2} = \langle (a, 1), (b, 2), (b, 3), (c, 4), (c, 5), (a, 6), (d, 7), (d, 8) \rangle$. We are interested in the occurrences of the serial episode $\alpha = \langle a, b, c, d \rangle$, assuming the maximal gap between events $k = 2$. The search can be oriented as follows:

1. From the occurrences of the individual events $mo(a) = \{1, 6\}$, $mo(b) = \{2, 3\}$, $mo(c) = \{4, 5\}$ and $mo(d) = \{7, 8\}$, build a *list* for the first occurrence of $mo(a)(1) = 1$ as: $list.a = \{1\}$, $list.b = \{2, 3\}$, $list.c = \{4, 5\}$ and $list.d = \{7\}$.

2. Select from the *list* the most proper serial episode starting with the last event from the list ($list.d$) and add it to sO, that is $sO = \langle 7 \rangle$.

3. Complete sO searching the occurrence kk of the other events a_j within k in *list*, adding each one to sO as $sO = [list.a_j(kk)\ \ sO]$. Then, for $j = 3$: $sO = \langle 5, 7 \rangle$, for $j = 2$: $sO = \langle 3, 5, 7 \rangle$ and finally, for $j = 1$: $sO = \langle 1, 3, 5, 7 \rangle$.

4. For the other occurrence of a, $mo(a)(2) = \{6\}$ a new *list* can not be completed, whereby the process ends.

The output of the algorithm is the set of serial occurrences of α, $maxnO(\mathbf{S2}, \alpha, 2) = \{\langle 1, 3, 5, 7\rangle\}$. The frequency of α in **S2** is $fr(\alpha) = |maxnO(\mathbf{S2}, \alpha, 2)| = 1$.

Fig. 2.3 shows the search process of the occurrences of α in **S2**. In the first phase of the process, from $a, 1$ the occurrences of b, c and d are located recursively, taking into account the maximal gap between events $k = 2$ as shown the black arrows in the figure. Such occurrences are located between 1 (t_1) and 7 ($t_1 + (|\alpha| - 1)k$) time units. In the second phase, the best occurrence of α is selected from $d, 7$, choosing iteratively the more left occurrences of c, b and a as shown with the green arrows in the figure.

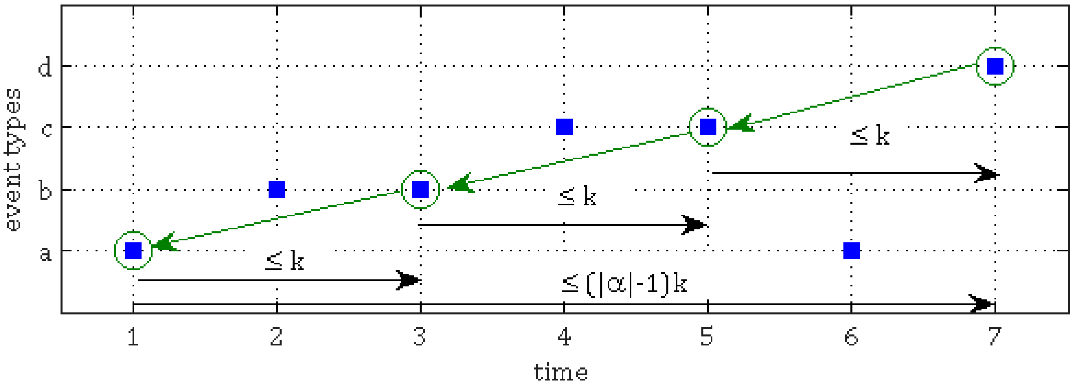


Figure 2.3: Search process of the occurrences of $\langle a, b, c, d\rangle$ in **S2**.

Algorithm 2 shows the extraction of serial occurrences of an episode using a inter-event time constraint (t_{max}) or maximal gap (max_gap) for the duration of the episodes. However, this algorithm can also be used for episodes with a expiry-time constraint, t_x or observation window, win, for episodes with inter-event time constraint defined as an interval $(t_{min}, t_{max}]$, and for episodes which duration is a combination of both.

2.4.1.1 Serial occurrences with expiry-time constraint

Occurrences of episodes which duration is defined by the maximal elapsed time allowable between the first and the last event, can be extracted of a sequence using the Algorithm 2 with the following adaptations:

1. Include in the input the expiry-time constraint, t_x or win defined by the user and set as maximal gap between events $k = t_x$ or $k = win$.

2. Add the instruction $mo(a_j) - list.a_1(1) \leq k$ at line 7 of Algorithm 2 as:

```
7: $oc \leftarrow mo(a_j)$ such that $list.a_{j-1}(1) < mo(a_j) \leq list.a_{j-1}(end) + k$ and $mo(a_j) - list.a_1(1) \leq k$
   and $mo(a_j) \notin maxnO(\mathbf{S}, \alpha, k)$
```

3. Add the instruction $sO(end) - list.a_j(kk) \leq k$ at line 15 of the Algorithm 2 as:

```
15: if $sO(1) - list.a_j(kk) \leq k$ and $sO(end) - list.a_j(kk) \leq k$ then
```

With these adaptations, the output of the algorithm is the set of serial occurrences of α with a maximal fixed duration without inter-event time constraint.

2.4.1.2 Serial occurrences with inter-event time constraint defined as an interval

Occurrences of episodes which elapsed time between two consecutive events is defined by an interval $(t_{min}, t_{max}]$, can be extracted of a sequence using the Algorithm 2 with the following adaptations:

1. In the input of the algorithm, set as maximal gap between events $k = [t_{min} \;\; t_{max}]$.

2. Replace the instruction $list.a_{j-1}(1) < mo(a_j) \leq list.a_{j-1}(end) + k$ with $list.a_{j-1}(1) < mo(a_j) - k(1) \leq list.a_{j-1}(end) + k(2)$ at line 7 of Algorithm 2 as:

```
7: $oc \leftarrow mo(a_j)$ such that $list.a_{j-1}(1) < mo(a_j) - k(1) \leq list.a_{j-1}(end) + k(2)$ and $mo(a_j) \notin$
   $maxnO(\mathbf{S}, \alpha, k)$
```

3. Replace the instruction $sO(1) - list.a_j(kk) \leq k$ with $k(1) < sO(1) - list.a_j(kk) \leq k(2)$ at line 15 of the Algorithm 2 as:

```
15: if $k(1) < sO(1) - list.a_j(kk) \leq k(2)$ then
```

With these adaptations, the output of the algorithm is the set of serial occurrences of α with inter-event time constraint defined as an interval without maximal duration constraint.

2.4.1.3 Serial occurrences with inter-event time constraint and expiry-time constraint

Occurrences of serial episode which duration is a combination of both, inter-event time constraint t_{max}, or an interval, $(t_{min}, t_{max}]$ and expiry-time constraint t_x, where $t_{max} \leq t_x$, can be extracted of a sequence using the Algorithm 2 with the following adaptations:

1. In the input of the algorithm, set as maximal gap between events $k = [t_{min}\ \ t_{max}]$ and set as expiry-time constraint $win = t_x$. If the maximal gap between events is not an interval then $t_{min} = 0$.

2. Replace the instruction $list.a_{j-1}(1) < mo(a_j) \leq list.a_{j-1}(end)+k$ with $list.a_{j-1}(1) < mo(a_j) - k(1) \leq list.a_{j-1}(end) + k(2)$ and $mo(a_j) - list.a_1(1) \leq win$ at line 7 of Algorithm 2 as:

```
7: $oc \leftarrow mo(a_j)$ such that $list.a_{j-1}(1) < mo(a_j) - k(1) \leq list.a_{j-1}(end) + k(2)$ $mo(a_j) - list.a_1(1) \leq$
   $win$ and $mo(a_j) \notin maxnO(\mathbf{S}, \alpha, k, win)$ and $mo(a_j) \notin maxnO(\mathbf{S}, \alpha, k)$
```

3. Replace the instruction $sO(1) - list.a_j(kk) \leq k$ with $k(1) < sO(1) - list.a_j(kk) \leq k(2)$ and $sO(end) - list.a_j(kk) \leq win$ at line 15 of the Algorithm 2 as:

```
15: if $k(1) < sO(1) - list.a_j(kk) \leq k(2)$ and $sO(end) - list.a_j(kk) \leq win$ then
```

With these adaptations, the output of the algorithm is the set of serial occurrences of α in $\mathbf{S}$ with both inter-event time constraint and expiry-time constraint $maxnO(\mathbf{S}, \alpha, k, win)$, where $k = (t_{min}, t_{max}]$ and $win = t_x$.

2.4.2 Time complexity of the Algorithm 2

To determine the time complexity of the proposed Algorithm 2, note that it enters the main loop $|mo(a_1)|$ times, once for each occurrence of the event a_1 in the input sequence. To count each occurrence of α, the creation and evaluation of *list* is required which in the worst-case have a time complexity of $O(m + m^2)$. Then, the time complexity of the algorithm 2 can be expressed as $O(|mo(a_1)|\, m(1 + m))$ or more simplified as $O(|mo(a_1)|\, m^2))$. In the worst-case $|mo(a_1)|$ can be expressed as $\frac{n}{m}$, hence, the time complexity of Algorithm 2 is $O(nm))$, where n is the length of the sequence and m is the size of α. This expression is similar to the worst-time complexity of the methods based on fixed-width window obtained in (Mannila et al., 1997) and non-overlapped frequency obtained in (Laxman et al., 2005). The main difference being that, in our case, the main loop is not directly conditioned by n but the number of occurrences of the event a_1 which is usually far less than n.

Other methods such as the algorithm based on maximal non-redundant sets of occurrences in (Gan and Dai, 2010) or the method based on minimal occurrences in (Mannila et al., 1997) take only $O(n)$ time to count the frequency of an episode $alpha$. These methods are time-wise efficient, due that they use the occurrences of sub-episodes.

2.4.3 Frequency of the episodes with the proposed algorithm

The main advantage of the proposed method is that all the occurrences of an episode can be counted and indexed, however the selection of a serial occurrence is limited by the location of its suffix. To ensure the anti-monotonicity property the frequency of an episode is calculated as:

$$fr(\alpha) = min(|maxnO(\mathbf{S}, \alpha, k)|, |maxnO(\mathbf{S}, prefix(\alpha, k))|) \qquad (2.10)$$

where $|maxnO(\mathbf{S}, \alpha, k)|$ and $|maxnO(\mathbf{S}, prefix(\alpha, k))|$ represent the number of occurrences of α and its prefix, respectively.

2.4.4 Considerations for candidate episodes generation

Candidate episodes are episodes for which occurrences must be found in order to establish if they are frequent or not. They are a combination of shorter frequent episodes. According to the nomenclature used in the Algorithm 1 of Section 2.3, the candidate episodes of length L, $\mathbf{C}^L$ are generated from the set of frequent episodes F^{L-1} of size $L-1$. Each candidate in $\mathbf{C}^L$ is generated by combining two suitable frequent episodes in F^{L-1}. The main steps in the candidate generation process are the following:

1. Selection suitable pairs of episodes from F^{L-1}.
2. Combining each such pair to generate new episodes of size L that are potential candidates.

3. Pruning the potential candidates to retain only those whose sub-episodes are frequent. They are the candidate episode $\mathbf{C}^L$.

The candidate generation step is the main filter to guaranty the anti-monotonicity of the frequent episodes. The pruning step is key to ensuring the validity of the candidate episodes and to increase the mining process efficiency.

Using the algorithm for frequency measure proposed in Section 2.4, the candidate generation strategy to complete the mining process of serial episodes, is describe below.

For all pairs of frequent episodes $\alpha_i, \alpha_j \in F^{L-1}$, $i, j = 1, ..., \left|F^{L-1}\right|$ a candidate episode α_c is generated as:

$$\alpha_c = \{join(\alpha_i, suffix(\alpha_j)) \mid |\alpha_i| = 1 \ \vee \ lsuffix(\alpha_i) \subseteq prefix(\alpha_j)\} \tag{2.11}$$

The *join* function adds $suffix(\alpha_j)$ to α_i as the last one element of α_c. The pruning step is included in the selection of the suitable pair of episodes. Finally, $\mathbf{C}^L$ is composed for all α_c generated iteratively.

2.4.5 Parallel occurrences with inter-event time constraint

In a parallel episode there are no constraints about the partial order of the events. Formally, a parallel episode corresponds to the set of all permutations of event types of the episode, and its frequency is always equal or greater than the corresponding frequency of any serial episode composed by the same event types.

Given a sequence of events $\mathbf{S}$, a candidate parallel episode $\alpha = \langle a_1 \cdot a_2 \cdot ... \cdot a_m \rangle$ and a maximal gap between events $max\_gap = k$, the Algorithm 3 returns the set of maximal non-redundant occurrences $maxnO$. For $m = 1$, the occurrences of the episode are the same minimal occurrences of the event a_1, $maxnO(\mathbf{S}, \alpha, k) = mo(a_1)$. For $m > 1$, the occurrences of all events in α are sorted in a structure vm where $vm.o = unique(mo(a_1), ..., mo(a_m))$ contains the occurrences and $vm.e$ contains the corresponding event types, then the set $maxnO(\mathbf{S}, \alpha, k)$ is obtained from it. For each occurrence $vm.o(i)$ the corresponding set of events located between $tm(i)$ and $tm(i + (m-1)k)$ are evaluated to search the more proper occurrence.

The structure of the algorithm is as follows (Algorithm 3). Each parallel occurrence of an episode is selected in three phases. In the first phase (line 6), for each occurrence in

Algorithm 3 Fminevent: Parallel occurrences with inter-event time constraint

```
Input: An event sequence $\mathbf{S}$, a candidate episode $\alpha = \langle a_1 \cdot a_2 \cdot ... \cdot a_m \rangle$, the maximal gap $k$, occurrences of the events in $\alpha$ i.e, $mo(a_1), ..., mo(a_m)$.
Output: The maximal non-redundant occurrences of $\alpha$, $maxnO(\mathbf{S}, \alpha, k)$.
Procedure:
 1: Initialise $maxnO(\mathbf{S}, \alpha, k) \leftarrow \{\}$
 2: $vm \leftarrow unique(mo(a_1), ..., mo(a_m))$
 3: for $i = 1$ to $|vm|$ do
 4:     if $vm(i) \notin maxnO(\mathbf{S}, \alpha, k)$ then
 5:         //Create a list of likely occurrences
 6:         $list \leftarrow vm(i)$ to $vm(i + (m-1)k)$ for all $vm.o \notin maxnO(\mathbf{S}, \alpha, k)$
 7:         //Sort the most probable serial episode
 8:         $\alpha_s \leftarrow unique(list.e)$
 9:         for $j = 1$ to $|\alpha|$ do
10:             $Oaux.\alpha_j \leftarrow list.o$ such that $list.e = \alpha_j$
11:         //Find the most properly occurrence
12:         if $\alpha \subset \alpha_s$ then
13:             $pO \leftarrow serialMethod(list, \alpha_s, Oaux, k)$
14:             if $pO = \{\}$ then
15:                 for $j = 2$ to $|\alpha| - 1$ do
16:                     $\alpha_s \leftarrow reorder(\alpha_s)$
17:                     $pO \leftarrow serialMethod(list, \alpha_s, Oaux, k)$
18:                     if $pO \neq \{\}$ then
19:                         break
20:             if $pO \neq \{\}$ then
21:                 Add $pO$ to $maxnO(\mathbf{S}, \alpha, k)$
```

$vm.o(i)$ that has not been considered in previous occurrences, a *list* with the occurrences between $vm.o(i)$ to $vm.o(i + (m-1)k)$ is created.

In the second phase (lines 8-10), the occurrences of each event are saved in an auxiliary list *Oaux*. The most probable serial episode α_s is extracted (line 8) from *list.e* using the function *unique*. This function selects the first event of each type in α that appears in *list.e*.

Finally, the most proper occurrence *pO* is extracted (lines 13-21) using the method for serial episodes with α_s, *list*, *Oaux* and k as inputs. Each parallel occurrence *pO* is added to *maxnO* (line 21) and constitutes the output of the algorithm.

As example, consider the sequence $\mathbf{S3} = \langle (a, 1), (b, 2), (b, 3), (a, 4), (c, 5), (c, 6) \rangle$. We are interested on the occurrences of the parallel episode $\alpha = \langle a \cdot b \cdot c \rangle$, assuming the maximal gap between events $k = 2$. The search can be oriented as follows:

1. From the occurrences of the individual events $mo(a) = \{1, 4\}$, $mo(b) = \{2, 3\}$, $mo(c) = \{5, 6\}$, build a single vector to guide the search, *vm=((a,1), (b,2), (b,3),(a,4),(c,5),(c,6))*.
2. For each occurrence in vm, build the temporal list of possible locations. For the first occurrence, $i = 1$, $list = ((a, 1), (b, 2), (b, 3), (a, 4), (c, 5))$.
3. Select from the *list* the serial episode that would be more likely (based on the first occurrence of each event). In this case is $\langle a, b, c\rangle$.
4. From *list* search the most proper occurrence of $\langle a, b, c\rangle$ using the serial method: $\{1, 3, 5\}$. Thus, $maxnO(\mathbf{S3}, \alpha, 2) = \{1, 3, 5\}$.
5. Return to step 2, and build the possible location, for the second occurrence, $list = ((b, 2), (a, 4), (c, 6))$.
6. Select from the *list* the serial episode that would be more likely (based on the first occurrence of each event). In this case, the only option is $\langle b, a, c\rangle$.
7. From *list*, search the more properly occurrence of $\langle b, a, c\rangle$ using the serial method, $\{2, 4, 6\}$, then $maxnO(\mathbf{S3}, \alpha, 2) = \{\langle 1, 3, 5\rangle, \langle 2, 4, 6\rangle\}$.

The set of parallel occurrences of α given by the algorithm as output is $maxnO(\mathbf{S3}, \alpha, 2)$ $= \{\langle 1, 3, 5\rangle, \langle 2, 4, 6\rangle\}$ and the parallel frequency of α in **S3** is $fr(\alpha) = |maxnO(\mathbf{S3}, \alpha, 2)| = 2$.

Algorithm 3 shows the extraction of parallel occurrences of an episode using a inter-event time constraint (t_{max}) or maximal gap (max_gap) for the duration of the episodes. However, similarly to Algorithm 2, this algorithm can also be used for parallel occurrences with a expiry-time constraint, t_x or observation window, win for parallel occurrences with inter-event time constraint defined as an interval $(t_{min}, t_{max}]$, and for parallel occurrences which duration is a combination of both, inter-event time constraint and expiry-time constraint.

2.4.5.1 Parallel occurrences with expiry-time constraint

Parallel occurrences of episodes which duration is defined by the maximal elapsed time allowable between the first and the last event, can be extracted of a sequence using the Algorithm 3 with the following adaptations:

1. Include in the input the expiry-time constraint, t_x or win defined by the user and set as maximal gap between events $k = t_x$ or $k = win$.

2. Replace the instruction $list \leftarrow vm(i)$ to $vm(i + (m - 1)k)$ with $list \leftarrow vm(i)$ to $vm(i + k)$ at line 6 of Algorithm 3.

3. Replace the function $serialMethod(list, \alpha_s, Oaux, k)$ with a function using the method of serial occurrences with expiry-time constraint of Section 2.4.1.1 at lines 13 and 17 of the Algorithm 3.

With these adaptations, the output of the algorithm is the set of parallel occurrences of α with a maximal fixed duration without inter-event time constraint.

2.4.5.2 Parallel occurrences with inter-event time constraint defined as an interval

Parallel occurrences of episodes which elapsed time between two consecutive events is defined by an interval $(t_{min}, t_{max}]$, can be extracted of a sequence using the Algorithm 3 with the following adaptations:

1. In the input of the algorithm, set as maximal gap between events $k = [t_{min} \;\; t_{max}]$. Then, $k(1) = t_{min}$ and $k(2) = t_{max}$

2. Replace the instruction $list \leftarrow vm(i)$ to $vm(i + (m - 1)k)$ with $list \leftarrow vm(i)$ to $vm(i + (m - 1)k(2))$ at line 6 of Algorithm 3.

3. Replace the function $serialMethod(list, \alpha_s, Oaux, k)$ with a function using the method of serial occurrences with inter-event time constraint defined as an interval of Section 2.4.1.2 at lines 13 and 17 of the Algorithm 3.

With these adaptations, the output of the algorithm is the set of parallel occurrences of α with inter-event time constraint defined as an interval without maximal duration constraint.

2.4.5.3 Parallel occurrences with inter-event time constraint and expiry-time constraint

Parallel occurrences of episodes which duration is a combination of both, inter-event time constraint t_{max} or an interval $(t_{min}, t_{max}]$ and expiry-time constraint t_x, where $t_{max} \leq t_x$, can be extracted of a sequence using the Algorithm 2 with the following adaptations:

1. In the input of the algorithm, set as maximal gap between events $k = [t_{min} \;\; t_{max}]$ and set as expiry-time constraint $win = t_x$. If the maximal gap between events is not an interval then $t_{min} = 0$.
2. Replace the instruction $list \leftarrow vm(i)$ to $vm(i + (m-1)k)$ with $list \leftarrow vm(i)$ to $vm(i + k)$ at line 6 of Algorithm 3.
3. Replace the function $serialMethod(list, \alpha_s, Oaux, k)$ with a function using the method of serial occurrences with inter-event time constraint and expiry-time constraint of Section 2.4.1.3 at lines 13 and 17 of the Algorithm 3.

With these adaptations, the output of the algorithm is the set of parallel occurrences of α in $\mathbf{S}$ with both inter-event time constraint and expiry-time constraint $maxnO(\mathbf{S}, \alpha, k, win)$, where $k = (t_{min}, t_{max}]$, $win = t_x$ and $t_{max} \leq t_x$.

2.4.6 Time complexity of the Algorithm 3

To count the parallel occurrences of an episode α, the proposed Algorithm 3 enters the main loop $|vm|$ times, once for each occurrence of the events a_1 to a_m in the input sequence. To count each parallel occurrence of α, the creation and evaluation of $Oaux$ is required which in the worst-case have a time complexity of $O(2m)$. Then, the time complexity of the algorithm 3 can be expressed as $O(2m\,|vm|)$. In the worst-case $|vm|$ can be expressed as n, hence, the time complexity of Algorithm 3 is $O(2mn)$, where n is the length of the sequence and m is the size of the episode α.

2.4.7 Evaluation of the proposed algorithm

Given a candidate episode, the proposed method is useful to extract and to count both serial and parallel occurrences. All occurrences are indexed adding information useful for post-processing analysis, for example the occurrences can be plotted to look the distribution along the sequences.

The results of the mining process using the proposed algorithm are compared with those obtained by the method based on maximal non-redundant sets of occurrences described in Section 2.3.2.1. This algorithm proposed by Gan and Dai (Gan and Dai, 2010) gave the best mining results in a comparison against the others described in Section 2.3.

A synthetic sequence is used for testing and demonstrative purposes. It was generated by embedding two frequent episodes $\alpha = \langle L, M, N \rangle$ and $\beta = \langle E, F, G, H \rangle$ into a random stream of events using an alphabet of 14 event types. The total sequence time is 5 s and 0.01 s is the average time between events. The detail of the sequence generator can be consulted in (Patnaik, 2006)[1]. For data generation, the simulator maintain a counter for the current time. Whenever an event is generated, it is timestamped with the current time and the counter is incremented by a small random integer. Each time, with probability ρ, the next event is generated randomly with a uniform distribution over all event types; with the remaining probability $(1 - \rho)$, it is determined by the patterns to be embedded. Whenever the next event is to be from one of the patterns to be embedded, simulator randomly decide between continuing with a pattern partially embedded or starting a new occurrence of a pattern. Thus, the synthetic data is like arbitrarily interleaving outputs of many Hidden Markov Models and an independent and identically distributed (iid) noise source (Laxman et al., 2005).

The resulting distribution of the events of the sequence generated with $\rho = 0.01$, is shown in Fig. 2.4.

From this sequence, the number, frequency and occurrences of frequent episodes extracted using both methods are compared. Shortening the proposed method as Me_1 and the method based on maximal non-redundant sets of occurrences as Me_2, the comparison is done using the following indicators which were also used in (Gan and Dai, 2010):

1. Missed frequent episodes (M): episodes missed by Me_2 but found by Me_1.

2. False frequent episodes (F): episodes found by Me_2 but no found by Me_1.

[1] Software is available at address http://minchu.ee.iisc.ernet.in/new/people/faculty/pss/TDMiner.html or https://code.google.com/p/tdminer/

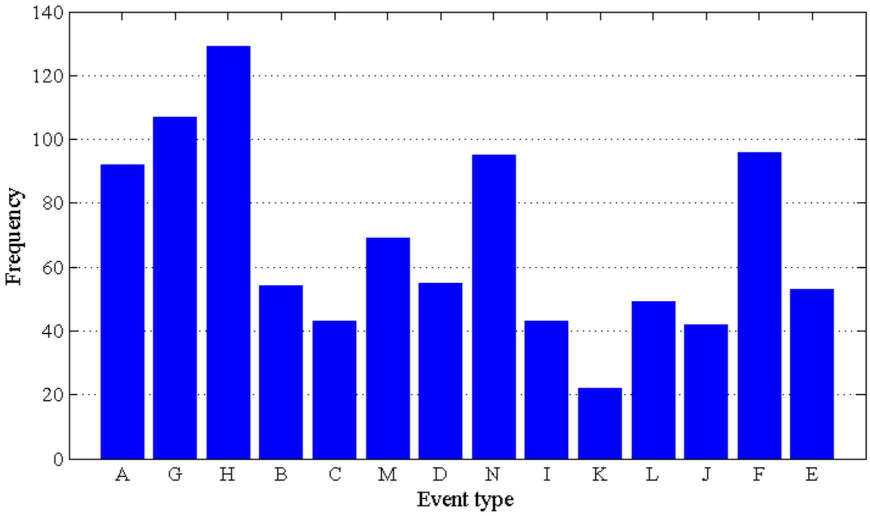


Figure 2.4: Distribution of the events of the synthetic sequence.

3. Positive Inaccurate frequency (PI): episodes found by the two methods with more occurrences by Me_1.

4. Negative Inaccurate frequency (NI): episodes found by the two methods with more occurrences by Me_2.

The corresponding ratios are calculated as follow:

$$\text{RM} = \frac{\text{M}}{|Me_1|} \tag{2.12}$$

$$\text{RF} = \frac{\text{F}}{|Me_1|} \tag{2.13}$$

$$\text{RPI} = \frac{|\{\alpha \text{ such that } \alpha \in Me_1 \cap Me_2, fr(\alpha) \in Me_1 > fr(\alpha) \in Me_2\}|}{|Me_1 \cap Me_2|} \tag{2.14}$$

$$\text{RNI} = \frac{|\{\alpha \text{ such that } \alpha \in Me_1 \cap Me_2, fr(\alpha) \in Me_2 > fr(\alpha) \in Me_1\}|}{|Me_1 \cap Me_2|} \tag{2.15}$$

Frequent episodes were found using as minimum threshold $min\_fr = 20$ *occurrences* (2% of the total length of the sequence)and several maximal gaps *max_gap* between events. Table 2.4 summarises the results according to the previous indices.

Table 2.4: Evaluation of results in the synthetic sequence.

max_gap in s	$\lvert Me_1 \rvert$	$\lvert Me_2 \rvert$	$\lvert Me_1 \cap Me_2 \rvert$	M	F	PI	NI	RM	RPI
0.01	28	28	28	0	0	0	0	0.00	0.00
0.02	132	119	119	13	0	22	0	0.10	0.18
0.03	389	330	330	59	0	119	0	0.15	0.36
0.04	1149	775	775	374	0	437	0	0.33	0.56
0.05	4354	2074	2074	2280	0	1424	0	0.52	0.69

According to column F in Table 2.4, all episodes found by the method Me_2 based on maximal non-redundant sets of occurrences are also found by the proposed algorithm Me_1 while, according to column M ($k \geq 0.02s$), the proposed method found additional frequent episodes not discovered by Me_2. Columns PI and NI show that the number of occurrences found by the proposed method are not lower than those found by Me_2.

In summary, columns RM and RPI shows that the total number of frequent episodes and their number of occurrences found by the proposed method Me_1 are not lower than those found by the method Me_2, becoming the differences larger as the value of *max_gap* increases (increasing the overlap of the occurrences).

The frequent episodes are only constrained by a minimum threshold and a maximal inter-event time, and a large number of them is discovered in the sequence by the two methods. However, only two episodes are embedded in the sequence. This means that the majority of frequent episodes are random connections between events. Then, a post processing of frequent episodes is required to recognize the most significant frequent episodes. This step of the mining process will be explained in Chapter 3.

Next, some simulation results are presented to show the behaviour of the two analysed methods in the extraction of the patterns embedded in the sequence with different level of noise. The two patterns embedded were: $\alpha = \langle L, M, N \rangle$ and $\beta = \langle E, F, G, H \rangle$. Data sequences were generated for different values of ρ. The respective number of occurrences discovered for each method is shown in Table 2.5. According to this table, Fminevent is as effective as the method based on maximal non-redundant sets of occurrences in discovering hidden temporal patterns.

Table 2.5: Frequency of the patterns α and β obtained by the two methods using a *max_gap*=0.03 s.

ρ	Me_1		Me_2	
	α	β	α	β
0.01	36	39	36	39
0.2	16	19	16	17
0.3	14	12	14	12
0.4	9	5	9	5
0.5	8	< 5	7	<5

2.5 Conclusions

The main techniques to discovery patterns in data set of events are described. Extensions to deal with time constraints among events have been motivated by the definition of power events. Frequent episodes can be extracted of these data sets if they are organised as sequences of events. Frequent episodes are ordered set of events that reveal the existence of regularities in the data as well as causal relations between events.

For different application domains, there exist several methods to find and to count the occurrences of an episode. Serial episodes are the most used because they allow representing causal and order relationships between elements in the episode. Strategies used to select the occurrences and the constraints applied for their duration, characterise the episodes. For the reviewed algorithms the characteristics of the episodes obtained are different for each one. However, over-counted or missed of occurrences are common weaknesses of them. While methods based on minimal occurrences tend to miss occurrences, methods based on occurrences tend to over-count occurrences when they are based on fixed-width windows or to miss occurrences otherwise. A new method to deal with sequences of events registered in power distribution networks is proposed. The method is able to extract both serial and parallel occurrences. The occurrences extracted with this method have an inter-event time constraint and they can be overlapped and non-minimal.

Under the point of view of number of non-redundant occurrences found and flexible duration of the episodes, the proposed algorithm has better performance than other methods reviewed in this research. A possible weakness of the method is that the running time would be greater than methods using sub-episodes occurrences.

3

Significant episodes in sequences of events

In the previous chapter, frequency of occurrences has been considered a discriminant criterion to select relevant episodes from a sequence of events. However, this criterion is independent of the source where these events have been generated and consequently does not not take into consideration possible requirements, derived form the context, related with the order or position of events in an episode in order to be considered significant. For example, events generated in an industrial context, as is the case of power networks, are constrained to physical laws that define the process dynamics and consequently some order relations, as causality or cause-effect relations, exist. From that perspective, frequency can not be the only criterion to discover significant episodes and other order relations as precedence, causality or existence in an episode have to be considered during the discovery process.

In this chapter, we explore how these constraints can be incorporated in the pattern discovery procedure to find frequent and significant episodes. Descriptive indices and methods used to assess the quality of the episodes in terms of their significance are revised and two new indices, based on the analysis of serial and parallel frequency of episodes, are proposed and illustrated with application examples.

3.1 Introduction

In this thesis, sequence pattern discovery approach through frequent episodes is divided in two main steps. Frequent episode discovery discussed in Chapter 2 is the first one and the second one is the identification of significant episodes which is presented in this chapter.

A general schema for sequence pattern discovery approach including the main elements involved in it, is shown in Fig. 3.1. The sequence of events and the pattern specifications, defined by the user according to the problem, are the inputs of the problem. The outputs are the frequent episodes as first step. Then, in a second step, only the significant ones are selected as possible patterns.

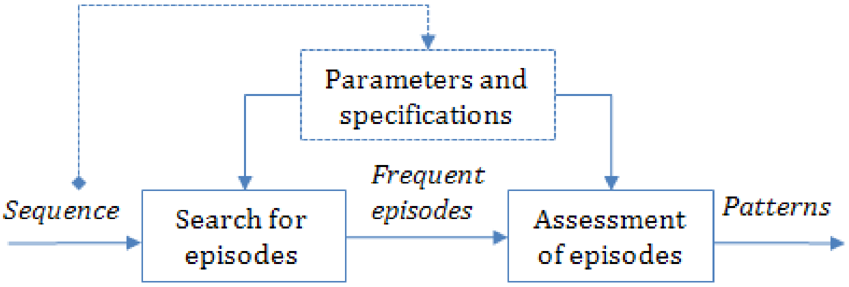


Figure 3.1: General schematic of the pattern discovery approach through frequent episodes.

Frequent episodes are those that have a number of occurrences greater than a fixed threshold (min_fr), predefined by the user; but only some of them are really significant for knowledge discovery purposes. Other relevant criteria consist in exploring connections between events inside those frequent episodes that are consistent with the physical constraints of the event source. According to these relations different type of rules can be used to infer knowledge from the exploitation of episodes. These rules describe connections between events more clearly than frequent episodes alone (Agrawal and Srikant, 1994; Mannila et al., 1997).

A rule assesses the link among the prefix and the suffix of an episode as the fraction between the frequency of the episode and the frequency of its prefix. From the property of anti-monotonicity, this value is equal or less than one, and it is named as confidence of the episode (see Definition 3.4). The idea is that episodes with high confidence are significant.

Consider as example the frequent episodes obtained from the synthetic sequence in Section 2.4.7 using the method Fminevent (described in Section 2.4), which are summarised in Table 3.1. Cumulated distribution of these episodes according with their confidence is shown in Fig. 3.2. According with this figure, for *max_gap* of 0.02s and 0.03 s, about 40% of the episodes have a confidence greather than 0.5 and about 25% have a confidence greather than 0.8. For *max_gap* of 0.04s and 0.05 s confidence and number of episodes increase, about 25% of then have a confidence greater than 0.9.

Table 3.1: Number of frequent episodes found in the synthetic sequence by the method Fminevent (Algorithm 2).

max_gap= 0.02 s	*max_gap* = 0.03 s	*max_gap* =0.04 s	*max_gap*= 0.05 s
132	389	1149	4354

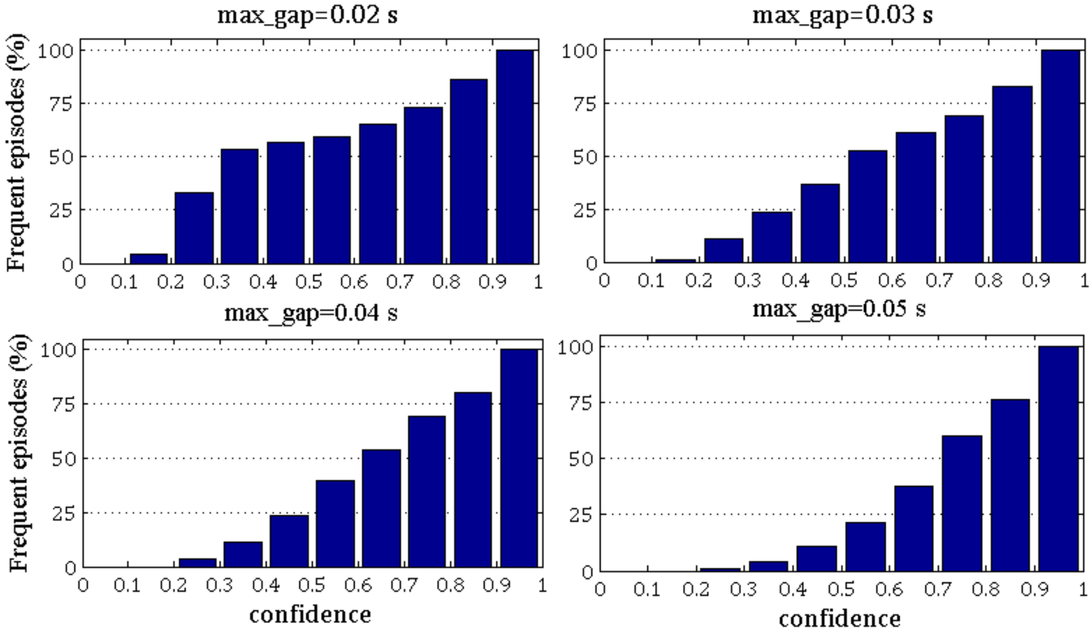


Figure 3.2: Cumulated distribution of frequent episodes in Table 3.1 according with their confidence values.

Results show that with a simple search usually a huge number of frequent episodes and rules are found. Therefore, to extract more relevant information, formulation of auxiliary criteria is required.

3.2 Significant episodes in event sequences

Significant episodes are those that address meaningful relationships between events and are not formed simply because the events inside the episode are the most frequent.

Definition 3.1. Significant episode. An episode α is significant if it reveals information of probable associations between its events, which are not product of randomness.

Two main strategies have been proposed to recognise the significant episodes in an event sequence. The first one is based on the statistical behavior of length and frequency of frequent episodes (Gwadera et al., 2003; Laxman et al., 2005; Tatti, 2009), and the second one aims to avoid redundant information (Gan and Dai, 2011; Zhou et al., 2010).

The main weakness of these two strategies is that they do not take advantage of the general knowledge that can exist about the system where the sequence has been generated and its operation. As a contribution of this research, we propose a new approach based on an event directed search over frequent episodes. This strategy consists in filtering frequent episodes to select only those that include sets of events that follow meaningful order relations.

3.2.1 Statistical methods for significant episodes recognition

These strategies take advantage of the central limit theorem to bound the probability that the frequency of an episode is above or below some threshold given a generative model for the data.

According to (Tatti, 2009) an episode is significant if the average length of its minimal window deviates greatly when compared to the expected length obtained when independence model. Given a sequence of events, they first split the sequence in two parts. The first sequence is used for discovering the episodes with a large number of minimal windows (candidate episodes) and to compute the distribution of the minimal windows and the probabilities of occurrence of each event type in the sequence. From the second sequence, the expected length of a minimal window against the average length of the observed minimal windows are compared using a Z-test. A Z-test is any statistical test for which the distribution of the test statistic under the null hypothesis can be approximated by a normal distribution. Episodes that obey the independence model (normally distributed) are pruned and consequently the number of output episodes is reduced. In summary, given a sequence and a candidate episode they first discover the set of all minimal windows in which the given episode occurs. Then, the length of these minimal windows is analysed. If their distribution is abnormal, the episode is considered as significant episode.

Gwadera et al., considers significant an episode when it occurs too often or not often enough in a fixed window (Gwadera et al., 2003, 2005). The problem is formulated to answer the following question: When the frequency of occurrences of a certain type of episodes is indicative of suspicious activity? The solution simply consists in fixing a threshold based on the quantitative analysis to deal with the trade off between false alarms and missed detections. The method assumes that the sequences are generated by a memoryless source such as a Bernoulli or a Markov model. Thus, given a candidate episode, the first step is finding the number of windows containing at least one occurrence of the candidate episode. This number constitutes the observed value of the frequency of the episode. Next, a probabilistic model is created taking into account attributes as the length of the sequence, the size of the episode and the cardinality of the set of event types. Finally, a threshold is fixed based on the expected value and the variance of the probabilistic model. Observed frequency is compared with this threshold to decide whether a suspicious activity took place or not.

Laxman et al., uses the connection between non-overlapped episodes and Hidden Markov Models (HMM) to assess the significance of the episodes without using training data to estimate a model for the data generation process (Laxman et al., 2005). They test the null hypothesis that the data is generated by an independent and identically distributed (iid) model against the alternative hypothesis that the data comes from an HMM model. According to this framework, a good frequency threshold for non-overlapped episodes can be formulated as a function of the length of the sequence, the size of the episode and the size of the set of events type as follows:

$$\Gamma = \frac{T}{M} + \sqrt{\frac{T}{M}\left(1 - \frac{1}{M}\right)}\Phi^{-1}\left(1 - \epsilon\right) \tag{3.1}$$

where ϵ is the probability of false rejection of the null hypothesis, T is the length of the event sequence, M is the cardinality of the symbol set (event types) and Φ is the distribution function of a standard normal random variable. Given an episode α, the null hypothesis is rejected if:

$$Nfr(\alpha) > \Gamma \tag{3.2}$$

where N is the size of α, $N = |\alpha|$, and $fr(\alpha)$ is its number of non-overlapped occurrences. From Equation 3.1, since T is usually much larger than M, $\frac{T}{M}$ is the dominant factor in the value of Γ. Then, from Equation 3.2, $\frac{T}{NM}$ is the significant initial frequency threshold for the episodes.

3.2.2 Avoiding redundant episodes

These strategies seek to compress the information provided by all frequent episodes, delivering only the most representative episodes.

Zhou et al. (2010) proposes mining closed episodes because they provide the lossless compression of frequent episodes and consequently improve efficiency during the mining process.

Definition 3.2. Closed episodes. Given an event sequence **S**, an episode α is closed if α is frequent and there not exist a super episode β such that $\beta \supset \alpha$ with the same frequency.

The mining process follows a breadth-first search strategy, i.e., the candidate episodes of length *k+1* are generated from frequent episodes of length k adding one event. The minimal occurrence of this new episode is computed from the minimal occurrence of its sub-episode.

Gan and Dai (2011) use the maximal frequent episodes as basis to obtain the representative patterns in a sequence.

Definition 3.3. Maximal frequent episode. An episode α is a maximal frequent episode with respect to min_fr in a sequence **S** if there not exists any episode β in **S** such that α is a sub-episode of β and β is frequent in **S**. I.e., for any $\beta \supseteq \alpha$, $fr(\beta) < min\_fr$ Doucet and Ahonen-Myka (2006).

These strategies are useful to compress the number of frequent episodes obtained in the mining process. The idea is to retain only super episodes since they store information of their sub-episodes. Through the maximal frequent episodes a greatest compression of the data is obtained but information about the frequency of sub-episodes is missed, while with the closed episodes, this information is retained. However, using these strategies, the quality of the relationships between events in frequent episodes can not be evaluated.

3.2.3 Directed search of episodes

In the process of significant episode discovery, usually there exists a domain knowledge that can be exploited during the analysis of event sequences. This includes aspects such as common behaviours that generate large number of events, or knowledge about abnormal situations that can evolve to failures and the identification of specific symptoms can alert them. Usually these interesting situations are reflected in the sequence with the presence of specific events, or ordered sets of them.

In this thesis, we propose a simple strategy to guide the search of episodes focusing on events predefined by the user. A heuristic search, based on the principle of existence of events in the episode, is proposed to avoid the exhaustive exploration any combination of events.

With this aim, three especial cases are addressed in this section: filtering events, forward-association of an event and backward-association of an event. The first case, *filtering events*, prevents that certain types of events (usually very frequent events) could mask significant episodes. The second case, *forward-association of an event*, aims finding the existence of episodes triggered by a specific event whereas the third case, *backward-association of an event*, focuses on discovering antecedents of the specific event. These approaches are of interest for finding cause-effect relationships among events, for prognosis and diagnosis purposes, respectively.

3.2.3.1 Filtering events

The problem consists in finding all the frequent episodes in a sequence, regardless some types of unwanted events. The general method exposed in Section 2.3 can be adapted for this problem, adding a constraint on the generation of the first set of candidate episodes (Algorithm 1, line 2), as follows. If A is the set of event types in the sequence and A_u is the set of unwanted events, then:

$$C^1 = \{all\ a_i \in A \text{ such that } a_i \notin A_u\} \tag{3.3}$$

This simple adaptation on the step of candidate generation, allows all frequent episodes found not include unwanted events, preventing episodes of interest to be hidden.

3.2.3.2 Forward associations of an event

Given a specific event type a_x, we fix the objective of finding events a_j that frequently occur after the occurrence of a_x. So, the frequent pattern discovery problem is constrained to episodes that always start with the predefined event. This set of episodes with the forward associations (FA) of an event can be extracted from the frequent episodes in a post processing step as:

$$FA(a_x) = \{ \text{ all } \alpha \in F \text{ such that } a_1 \subseteq a_x \} \tag{3.4}$$

where F is the set of frequent episodes (output of the Algorithm 1) and a_1 is the first event of α.

The strategy proposed in Equation 3.4 is a post-processing step of frequent episodes. It can be applied regardless of the algorithm for frequent episode discovery.

The candidate generation procedure presented in Section 2.4.4 can be adapted to focus search on a specific type of event, improving the general performance of the method without violating the principle of anti-monotonicity.

Given the specific event a_x defined by the user and the set of frequent episodes of size $(L = 1)$, F^1, the generation of the candidate episodes of size $L + 1$, C^{L+1} is shown in Algorithm 4.

The candidate episodes of size $L + 1$ are generated from the frequent episodes of size L, F^L, and the frequent events F^1 which include the event a_x. If $L = 1$, C^{L+1} is constructed adding a_x to the each frequent event in F^1 (line 4). If $L > 1$, each episode in C^{L+1} is constructed joining frequent episodes with frequent events (line 11). The anti-monotonicity of the episodes is preserved since the frequency of episodes is regulated by their prefix when the proposed algorithm (Section 2.4) is used for frequent episode discovery.

Algorithm 4 Candidate episode generation focused on the forward associations of an event

Input: The set of frequent events F^1, the set of frequent episodes F^L, the event a_x to focus the search.
Output: The set of candidate episode of size $L+1$, C^{L+1} with the forward associations of a_x.
Procedure:

```
Initialize $C^{L+1}$ as null
if $L = 1$ then
    for $k = 1$ to $|F^1|$ do
        $C^{L+1}.k \leftarrow [a_x \;\; F^1.k]$
else
    $j \leftarrow 1$
    for $k = 1$ to $|F^L|$ do
        for $m = 1$ to $|F^1|$ do
            $C^{L+1}.j \leftarrow [F^L.k \;\; F^1.m]$
            $j \leftarrow j + 1$
```

3.2.3.3 Backward associations of an event

It consists in searching episodes containing a_x as the last element. That is, the antecedents of event a_x are contained in frequent episodes. In other words, the set of episodes that contains the backward association of a specific event a_x.

The set of episodes that contain the backward associations (BA) of an event a_x can be expressed as:

$$BA(a_x) = \{ \text{ all } \alpha \in F \text{ such that } a_x \subseteq a_m \ \} \tag{3.5}$$

where F is the set of frequent episodes of a sequence (output of the Algorithm 1) and a_m is the last event of α.

This information can be extracted in a post processing step from the frequent episodes as shown in Equation 3.5 or directing the search for episodes through candidates generation step, as long as it meets the principle of anti-monotonicity. The results could be useful in diagnosis and prognosis tasks, since the events that usually precede an event of interest can be identified.

As with the forward association of an event, using the proposed mining algorithm, the procedure for the candidate episodes generation is simply the concatenation of frequent events with frequent episodes as shows the Algorithm 5.

The candidate episodes of size $L+1$ are generated from the frequent episodes of size L and the frequent events (episodes of size 1, F^1). The set of frequent episodes

Algorithm 5 Candidate episode generation focused on the backward associations of an event

Input: The set of frequent episodes F^L, the set of frequent episodes F^1, the event E_i to focus the search.

Output: The set of candidate episode of size $L+1$, C^{L+1}.

Procedure:

```
 1: Initialize $C^{L+1}$ as null
 2: if $L = 1$ then
 3:     for $k = 1$ to $|F^1|$ do
 4:         $C^{L+1}.k \leftarrow [F^1.k \;\; E_i]$
 5: else
 6:     $j \leftarrow 1$
 7:     for $k = 1$ to $|F^L|$ do
 8:         for $m = 1$ to $|F^1|$ do
 9:             $C^{L+1}.j \leftarrow [F^1.m \;\; F^L.k]$
10:             $j \leftarrow j + 1$
```

are frequent events, including the event a_x. If $L = 1$, C^{L+1} is constructed joining a_x as the first event to each frequent episode in F^1 (line 4). If $L > 1$, each episode in C^{L+1} is constructed joining frequent episodes with frequent events (line 11) using a similar concept as used for the forward associations.

3.3 Meaningful patterns from frequent episodes

Association rules describing relationships between events are commonly used to assess the patterns obtained through frequent episodes. Such associations describe the strength of the link, sometimes causal, between events or sets of events, contained in the episode.

Consider the episode α, described by the pattern $\boldsymbol{p}$, as a sequence of two episodes α_1 and α_2 ($\alpha = \langle \alpha_1, \alpha_2 \rangle$) associated also with respective patterns $\boldsymbol{p}_1$ and $\boldsymbol{p}_2$ and with known supports s, s_1 and s_2, respectively. It can be interpreted as an association rule of the form $\boldsymbol{p}_1 \rightarrow \boldsymbol{p}_2$ or the equivalent in term of episodes $\alpha_1 \rightarrow \alpha_2$, where $\boldsymbol{p}_1$ is the antecedent and $\boldsymbol{p}_2$ is the consequent of the rule. The support of the rule coincides with the support of $\boldsymbol{p}$ and its confidence is given by the relation $c(\boldsymbol{p}_1 \rightarrow \boldsymbol{p}_2) = s(\boldsymbol{p}_1 \rightarrow \boldsymbol{p}_2)/s(\boldsymbol{p}_1) = s/s_1$, and can be seen as an estimator of the conditional probability of $P\left(\alpha_2 | \alpha_1\right)$ useful for reasoning and on-line inference tasks.

Two new indexes to assess the significance of frequent episodes are suggested in this thesis. They are proposed as complementary criteria to the confidence of the episode rules. The first one, named *cohesion of the episode*, is based on the comparison of the number of serial and parallel occurrences, whereas the second, named *backward-confidence of the episode*, is analogous to the confidence of an episode rule but it focuses on the beginning of the episode instead of the end (Quiroga et al., 2012a).

3.3.1 Confidence of an episode

It is a common criterion used to evaluate the association between an episode and its extensions.

Definition 3.4. Confidence of an episode. The confidence of an episode α, $conf(\alpha)$, is the fraction between the frequency of the episode and the frequency of its prefix (Mannila et al., 1997).

$$conf(\alpha) = \frac{fr(\alpha)}{fr(prefix(\alpha))} \tag{3.6}$$

The episodes whose confidence is greater than a threshold, min_conf, are called episode rules and can be considered relevant for reasoning tasks. These rules can be interpreted as the probability of occurrence of a new episode once its prefix has occurred.

3.3.2 Cohesion of an episode

This index measures the strength of order relation expressed by the serial episode with respect to other episodes in the sequence containing the same events in different order (parallel episodes).

Definition 3.5. Cohesion of an episode. The cohesion of an episode α, $coh(\alpha)$, is defined as the fraction between the number of occurrences of a serial episode, α, an the number of occurrences of a parallel episode, α_p, containing the same events as α which are abbreviated in Equation 3.7 as fr and fr_p , respectively.

$$coh(\alpha) = \frac{fr(\alpha)}{fr(\alpha_p)} = \frac{fr}{fr_p} \tag{3.7}$$

The cohesion can be useful to discover significance of order of events in an episode. Events that mainly appear in a given order (serial episode) can help to explain causal relationships.

3.3.3 Backward-confidence of an episode

Backward-confidence concept is analogous to the confidence (Definition 3.4) but focused on triggering events. It evaluates the importance of the first event, with respect to the episode allowing to discover possible triggering events. The concept is based on the fact that an episode is the backward-extension super episode of its large suffix (Definition 2.15).

Definition 3.6. Backward-confidence of an episode. The backward-confidence of an episode α, $conf_B(\alpha)$, is the fraction between the frequency of the episode, $fr(\alpha)$, and the frequency of its large suffix, $fr(lsuffix(\alpha))$ as shown in Equation 3.8.

$$conf_B(\alpha) = \frac{fr(\alpha)}{fr(lsuffix(\alpha))} \tag{3.8}$$

This index measures the probability of occurrence of an episode given the frequency of its large suffix. It reveals information about the origin of the episode.

3.3.4 Evaluation of frequent episodes

The significance of frequent episodes can be evaluated from their corresponding levels of confidence, cohesion and backward-confidence as a quality factor Q_f defined as:

$$Q_f(\alpha) = f\left(conf(\alpha), coh(\alpha), conf_B(\alpha)\right) \tag{3.9}$$

Restrictions of this quality factor will be set by the user according to discovery goals. The criterion can include one or several indexes combined in different ways. As example, a possible index could be defined by $Q_{f\_min} \Leftrightarrow \{conf \geq min\_conf\}$ or $Q_{f\_min} \Leftrightarrow \{conf \geq min\_conf \wedge coh \geq min\_coh \wedge conf_B \geq min\_conf_B\}$.

Frequent episodes (fE) that meet the minimum quality requirement are classified as significant frequent episodes, sfE.

$$sfE = \{\alpha \mid Q_f(\alpha) \geq Q_{f\_min} \ \forall \ \alpha \in fE\} \tag{3.10}$$

Finally, to avoid redundant information, significant patterns are obtained compressing the significant episode information through strategy or maximal or closed episodes

(Definitions 3.3 and 3.2, respectively), i.e., meaninful patterns are the set of significant maximal or closed frequent episodes $sMfE$, classified according to the Equation 3.11.

$$sMfE = \{\alpha \mid \neg\exists\beta \neq \alpha \text{ such that } \beta \supseteq \alpha \ \forall \ \alpha, \beta \in sfE\} \tag{3.11}$$

The process of extraction of significant episodes and meaningful patterns can be summarised by Algorithm 6.

Algorithm 6 Evaluation of frequent episodes

```
Input: The set of frequent episodes $fE$, the minimum quality factor $Q_{f\_min}$.
Output: The set of significant maximal frequent episodes $sMfE$.
Procedure:
1: Initialize $sfE$ and $sMfE$ as null
2: for all $\alpha \in fE$ such that $|\alpha| > 1$ do
3:     $Q_f(\alpha) \leftarrow f((conf(\alpha), coh(\alpha), conf_B(\alpha))$
4:     if $Q_f(\alpha) \Leftrightarrow Q_{f\_min}$ then
5:         Add $\alpha$ to $sfE$
6: for all $\alpha \in sfE$ do
7:     if $\neg\exists\beta \neq \alpha$ such that $\beta \supseteq \alpha$ then
8:         Add $\alpha$ to $sMfE$
```

The minimum quality factor Q_{f_min} for the meaningful patterns defined by the user and all frequent episodes fE found in the sequence, where each frequent episode must contain information related with the serial and parallel frequency, are the inputs. The algorithm has two main phases. In the first phase (lines 2-5), the quality factor Q_f of each frequent episode is found (line 3) and the episodes with minimum quality are stored in a set of significant episodes sfE (lines 4-5). In the second phase (lines 6-8), only the closed or maximal episodes found in sfE are retained as patterns. This set is called $sMfE$ and constitutes the output of the algorithm. Through the maximal frequent episodes a greatest compression of the significant episode information is obtained but information about the frequency of sub-episodes is missed.

3.4 Experimental evaluation of the proposed strategies

In this section, frequent episodes discovered by the method Fminevent (Algorithm 2 and 3) are evaluated. The same synthetic sequence described in Chapter 2, Section 2.4.7 and generated with $\rho = 0.01$ is used. The frequent serial episodes are evaluated by the proposed criteria of cohesion, backward-confidence and confidence looking for the two episodes $\langle L, M, N\rangle$ and $\langle E, F, G, H\rangle$ embedded in the random sequence. Although these two episodes have a serial order, both serial and parallel frequencies are required to measure the strength of their order relation, according with the indexes presented in Section 3.3.

According to the results reported in Section 2.4.7 a huge number of frequent episodes are obtained, then to select the significant ones it is necessary the implementation of the second step of the sequent pattern discovery approach, i.e., the assessment of episodes (Fig. 3.1). In this sequence, compression of the frequent episodes information retaining only the maximal episodes, is not sufficient to properly reduce the search space of the most significant episodes as it is shown in Table 3.2.

Table 3.2: Number of frequent and maximal episodes found in the synthetic sequence for several values of maximal gap.

Description	Maximal gap values in seconds			
	0.02	0.03	0.04	0.05
Frequent episodes	132	389	1149	4354
Maximal frequent episodes	35	103	252	902

Following, as part of the process for the assessment of episodes, the behavior of the episodes according to their values of cohesion, confidence and backward-confidence indexes is analyzed, and then a quality factor is defined to extract the most relevant episodes.

Fig. 3.3 shows the cumulated distribution of the frequent episodes according to its values of *conf*, *coh* and $conf_B$ for values of maximal gap of 0.02 s, 0.03 s 0.04 s and 0.05 s. This figure indicates that the larger the value of *max_gap*, the lower cohesion of the episodes is, while the higher confidence or backward-confidence is. For example, for *max_gap*=0.02 s around 80% of frequent episodes have a cohesion lower than 0.8, while for *max_gap*=0.05 s this percentage increases above the 95%. In turn, for *max_gap*=0.02 s, around 75% of frequent episodes have a confidence lower than 0.8, while for *max_gap*=0.05 s this percentage decreases to 60%. A similar trend is observed for the backward-confidence.

Fig. 3.4, Fig. 3.5 and Fig. 3.6 show the dependencies between $conf$ versus coh, $conf$ versus $conf_B$ and coh versus $conf_B$, respectively. These dispersion diagrams indicate

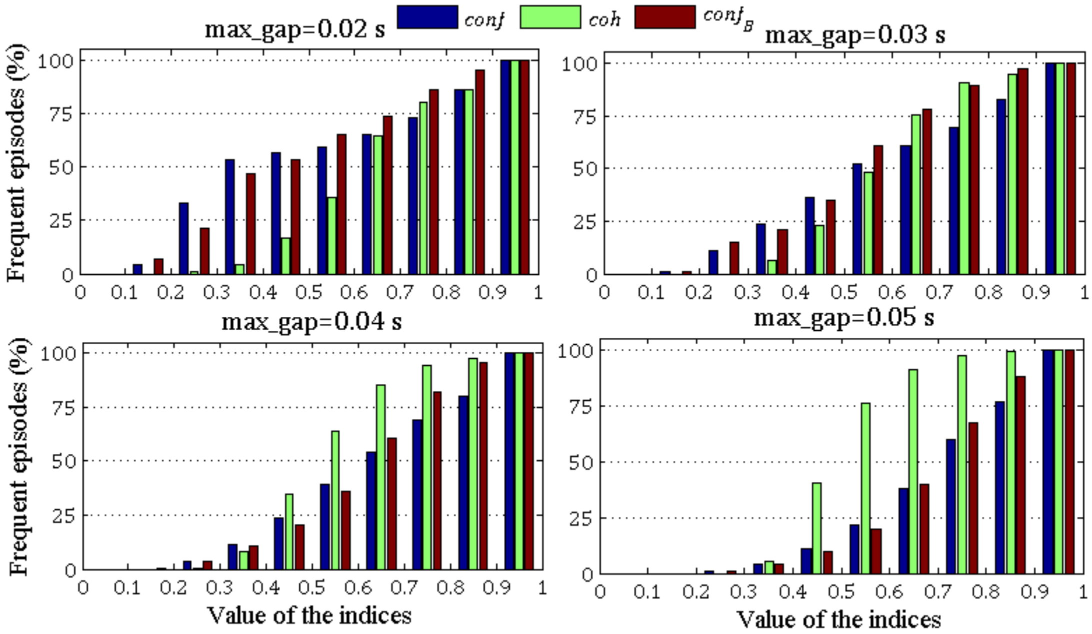


Figure 3.3: Cumulated distribution of frequent episodes in Table 3.1 according with their values of $conf$, coh and $conf_B$.

that the indexes are independent. This means that if an episode reaches the minimum confidence requirement does not imply that also reach the minimum requirements of cohesion and/or backward-confidence. As the constraint of maximal gap (max_gap) increases, figures show that most episodes tend to have low values of coh and high values of $conf$ and $conf_B$.

By the Algorithm 6 in Section 3.3.4, the most significant episodes are identified. According with this algorithm a minimum quality factor Qf_{min} must be specified by the user. We have fixed several Qf_{min} combining the criteria of $conf$, coh and $conf_B$ as follows:

$$\begin{aligned} Q_{f\_min} &\Leftrightarrow \{conf \geq min\_conf\} \\ &\Leftrightarrow \{conf_B \geq min\_conf_B\} \\ &\Leftrightarrow \{coh \geq min\_coh\} \\ &\Leftrightarrow \{conf \geq min\_conf \wedge conf_B \geq min\_conf_B\} \\ &\Leftrightarrow \{conf \geq min\_conf \wedge coh \geq min\_coh\} \\ &\Leftrightarrow \{conf \geq min\_conf \wedge coh \geq min\_coh \wedge conf_B \geq min\_conf_B\} \end{aligned} \tag{3.12}$$

where min_conf, min_coh and min_conf_B are the minimum required values for the

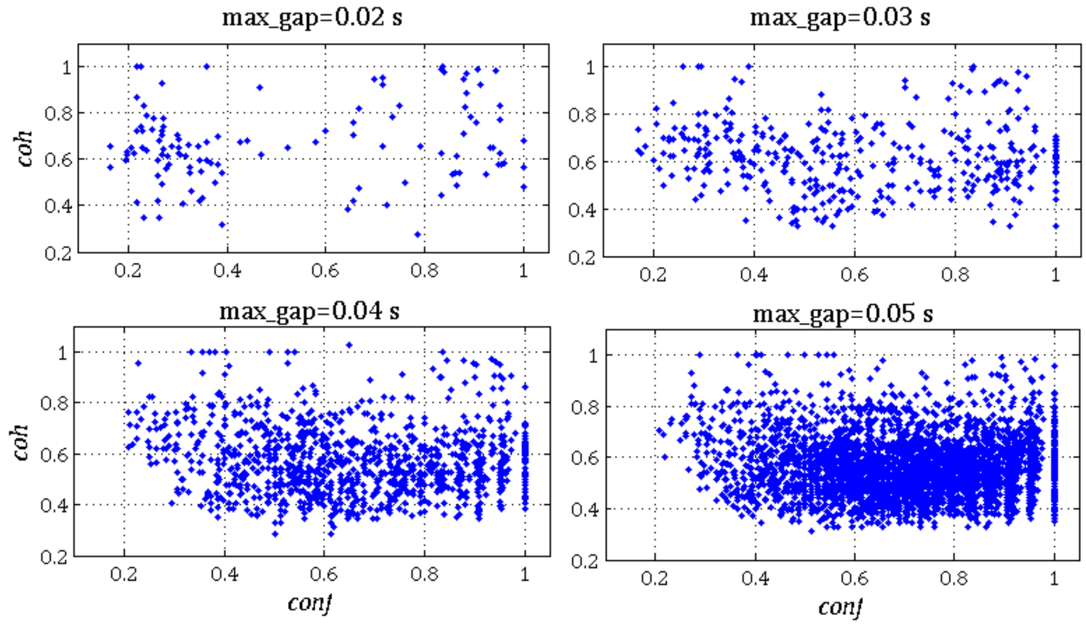


Figure 3.4: *conf* vs *coh* for different values of *max_gap*.

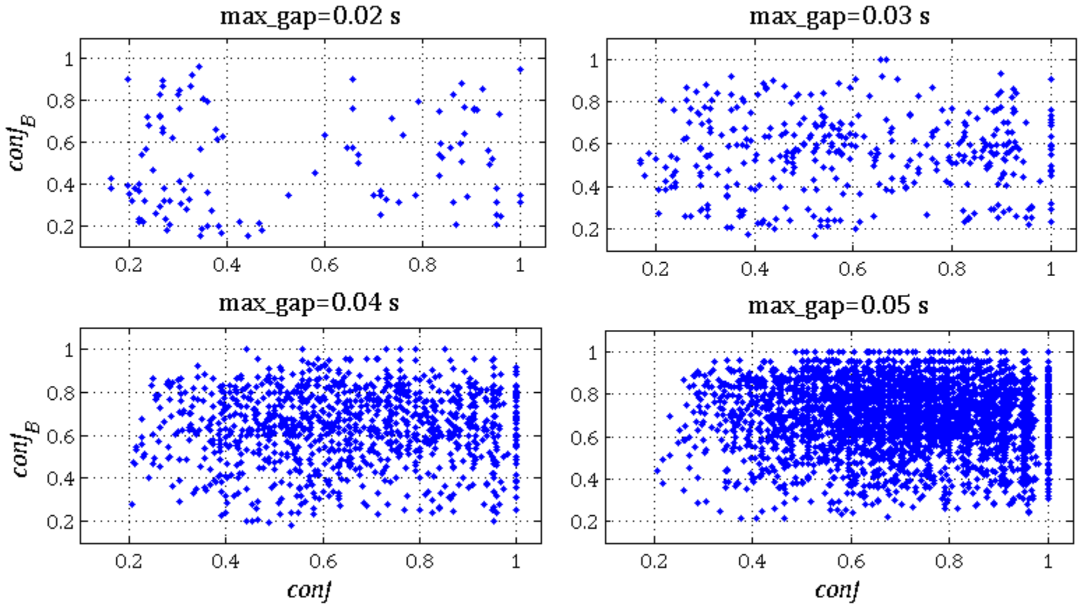


Figure 3.5: *conf* vs $conf_B$ for different values of *max_gap*.

recognition of the two embedding patterns, which are $min\_conf = 0.8$, $min\_coh = 0.8$ and $min\_conf_B = 0.5$.

Table 3.3 shows the number of significant episodes identified from the different min-

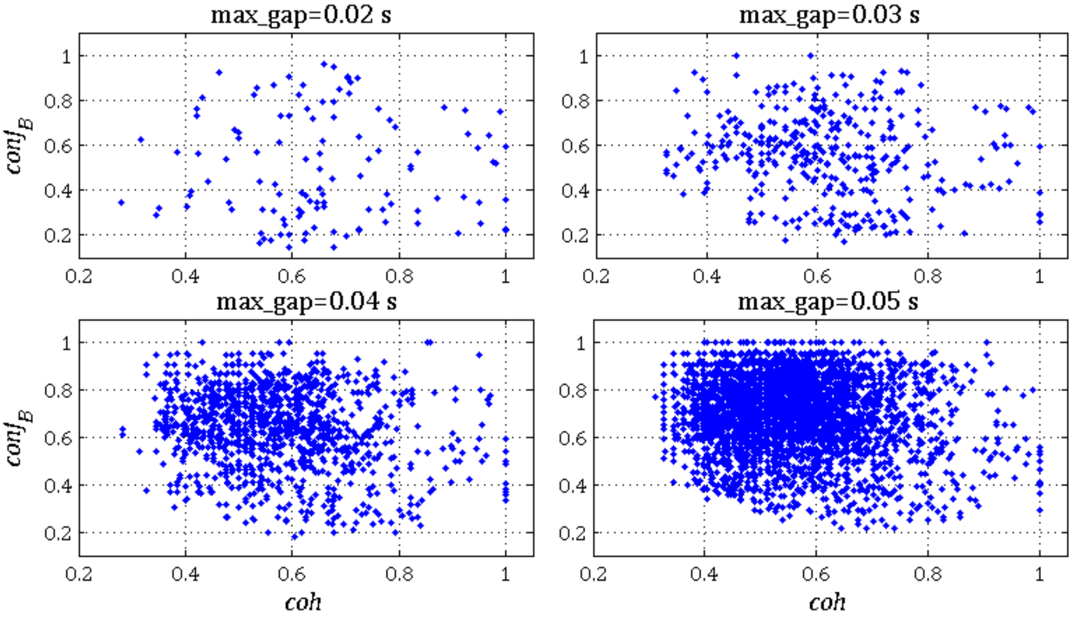


Figure 3.6: *coh* vs $conf_B$ for different values of *max_gap*.

imum quality factor Qf_{min} used. These significant episodes are the maximal frequent episodes that reach the minimum quality factor.

Table 3.3: Number of frequent and maximal episodes and patterns found in the synthetic sequence for several values of maximal gap.

Description	Maximal gap values in seconds			
	0.02	0.03	0.04	0.05
Frequent episodes	132	389	1149	4354
Maximal frequent episodes	35	103	252	902
Patterns:				
$Q_f \Leftrightarrow \{conf \geq 0.8\}$	12	32	89	456
$Q_f \Leftrightarrow \{conf_B \geq 0.5\}$	16	67	208	824
$Q_f \Leftrightarrow \{coh \geq 0.8\}$	9	17	24	46
$Q_f \Leftrightarrow \{conf \geq 0.8 \wedge conf_B \geq 0.5\}$	5	20	77	413
$Q_f \Leftrightarrow \{coh \geq 0.8 \wedge conf_B \geq 0.5\}$	4	6	13	32
$Q_f \Leftrightarrow \{conf \geq 0.8 \wedge coh \geq 0.8\}$	4	5	6	14
$Q_f \Leftrightarrow \{conf \geq 0.8 \wedge coh \geq 0.8 \wedge conf_B \geq 0.5\}$	3	4	5	11

The first row of Table 3.3 shows the total number of frequent episodes for different values of maximal gap. It is observed that their number increases rapidly as the maximal gap is relaxed. The corresponding number of maximal episodes is show in the second row of the table. Their number is still significantly high, since the number of embedded episodes is only two.

From row three, the number of meaningful patterns extracted using one or several of the proposed criteria are shown. For *max_gap* not equal to 0.01 s the number of patterns using the criteria of *min_coh* is smaller than those extracted using criteria of *min_conf* or min_conf_B, respectively. With combination of two criteria, the best result (smaller number of patterns) is obtained using *min_conf* and *min_coh*. However, the combination of the three criteria delivers much better results.

Table 3.4: Patterns extracted using $Q_f \Leftrightarrow \{conf \geq 0.8 \wedge coh \geq 0.8 \wedge conf_B \geq 0.5\}$ as selection criteria.

Maximal Episode	fr	fr_p	*coh*	$conf_B$	*conf*
max_gap=0.02s					
$\langle L, M, N\rangle$	36	38	0.95	0.59	0.88
$\langle G, H, G, H\rangle$	23	26	0.88	0.77	0.88
$\langle E, F, G, H\rangle$	37	45	0.82	0.51	0.88
max_gap=0.03s					
$\langle L, M, N\rangle$	36	39	0.92	0.59	0.88
$\langle G, H, G, H\rangle$	32	34	0.94	0.76	0.89
$\langle F, G, F, G\rangle$	27	29	0.93	0.77	0.90
$\langle E, F, G, H\rangle$	39	48	0.81	0.53	0.91
max_gap=0.04s					
$\langle L, M, N\rangle$	37	39	0.95	0.60	0.90
$\langle M, N, M, N\rangle$	20	24	0.83	0.65	0.91
$\langle E, F, G, H\rangle$	43	48	0.90	0.57	0.96
$\langle E, F, G, F, G\rangle$	22	27	0.81	0.76	0.85
$\langle G, H, G, H, G, H\rangle$	19	20	0.95	0.95	0.95
max_gap=0.05s					
$\langle N, N, G\rangle$	34	40	0.85	0.59	0.89
$\langle L, M, N\rangle$	37	41	0.90	0.60	0.90
$\langle M, N, M, G\rangle$	22	27	0.81	0.71	0.92
$\langle M, N, M, N\rangle$	21	25	0.84	0.66	0.88
$\langle F, G, F, H\rangle$	34	41	0.83	0.58	0.92
$\langle F, F, F, H\rangle$	19	23	0.83	0.56	1.00
$\langle E, F, H, G, H\rangle$	32	39	0.82	0.80	0.89
$\langle F, G, H, G, F, G\rangle$	21	26	0.81	0.84	0.84
$\langle G, H, G, H, F, G, H\rangle$	23	27	0.85	0.88	1.00
$\langle F, G, H, N, F, G, F\rangle$	19	21	0.90	0.95	0.83
$\langle E, F, G, G, H, F, G\rangle$	19	23	0.83	0.90	0.86

Table 3.4 shows the meaningful patterns extracted with the combination of the three criteria ($conf \wedge coh \wedge conf_B$) for *max_gap=0.02 s* to *max_gap=0.05 s.* The two patterns $\langle L, M, N\rangle$ and $\langle E, F, G, H\rangle$ embedded in the sequence were extracted satisfactorily. As the constrain of maximal gap is relaxed (*max_gap* increases), other frequent episodes involving mainly the frequent events F, G, and H begins to be significant.

This example shows that the proposed indexes of cohesion (coh) and backward-confidence ($conf_B$) may be helpful in the selection of the most significant patterns, improving the results obtained by the simple extraction of maximal episodes or episode rules.

3.5 Conclusions

In this Chapter a new strategy to recognize significant episodes in event sequences is proposed. The idea is to take advantage of the domain knowledge that can exist about interesting events in the sequence. This strategy can be implemented as a post processing step of the frequent episodes or directly by modifying the candidate generation step in the mining process. Three cases were addressed: filtering events, forward-association of an event and backward-association of an event. The first case, filtering events prevents that certain types of events (usually very frequent events) could mask significant episodes. The second case, forward-association of an event, aims finding the existence of episodes triggered by a specific event whereas the third case, backward-association of an event, focuses on discovering antecedents of the specific event.

The analysis of the frequent episodes concludes with the evaluation of strength of associations described by them. The usually criteria is the use of the confidence of the episode that describe the causal relation between its prefix and suffix. This simple criteria is insufficient to reduce the search space of the most relevant patterns. In this order, two new auxiliary criteria called cohesion and backward-confidence of the episodes are proposed. The proposed criteria are also based on frequencies. While the cohesion measures the strength of order relation expressed by the serial episode with respect to other episodes in the sequence containing the same events in different order, the backward-confidence evaluates the importance of the first event, with respect to the episode allowing to discover possible triggering events.

The useful of the findings described in the present chapter were shown by experimental results. They were developed for the analysis of frequent episodes discovered in event sequences recorded in power distribution networks but they are also applicable to other application domains.

4

Mining voltage dip sequences recorded in power distribution substations

This chapter adapts previous strategies for discovering significant frequent patterns to deal with sequences of events collected in distribution networks. A dataset of voltage dip events recorded in power distribution networks is analysed. From this data set, two different types of associations between events are discovered using the mining algorithm proposed in Section 2.4. The first association describes regularities in the elapsed times between successive voltage dips, while the second one is associated with possible regularities in the network locations where the events occur. Finally, the most significant relationships are obtained and analysed using the indexes developed in Chapter 3 and their physical meaning are discussed.

4.1 Introduction

As it was explained in Chapter 1, voltage dips are the most frequent events in power distribution networks. They are the main type of event associated with faults (short-circuits) occurring in the power network, and they also are related with others sudden increases of current due to operations of the network such as motor starting, transformer energising or load commutation.

Usually, the occurrence of a fault in an electrical network over time is considered an isolated and independent phenomenon and their apparition is modeled in terms of probabilities. Such approach is useful to model the network performance from the power quality point of view. However, the independence assumption is not always true and sets of events appear following specific order relations describing patterns. Automatic discovering of such episodes is the challenging task addressed in this chapter. A tool to discover the existence of such patterns can be exploited for predicting faults and to assist maintenance and operation task contributing to reduce the time response to failures and consequently resulting in better power quality indices.

Relations between events in a sequence can be constructed through the study of frequent episodes. These dependencies are causal relationships between events. Consider as an example the sequence shown in Fig. 4.1, where the algorithm of fixed-width window (Section 2.3.2.1) is used to illustrate the search for frequent episodes. In the example, the sliding window has a width of 4 units and moves along the sequence linking the events in a total of six windows.

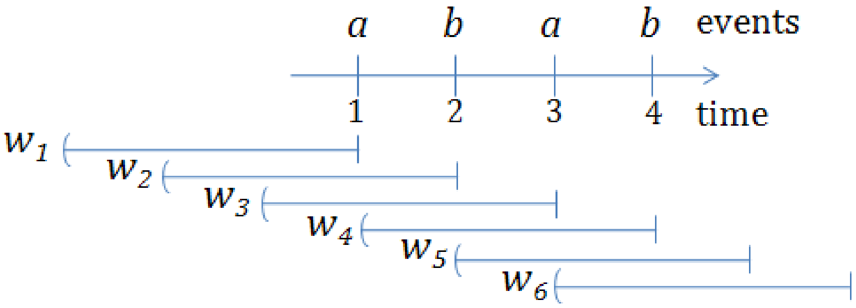


Figure 4.1: Construction of dependencies between events in a sequence using fixed-width windows.

The following sets of events can be found in the sequence of Fig. 4.1 using the sliding window paradigm:

- Set of windows containing episode $\langle a \rangle$, $M = \{w_1, w_2, w_3, w_4, w_5\}$.
- Set of windows containing episode $\langle b \rangle$, $N = \{w_2, w_3, w_4, w_5, w_6\}$.
- Set of windows containing serial episodes $\langle a, b \rangle$, $O = \{w_2, w_3, w_4, w_5\}$.
- Set of windows containing serial episodes $\langle b, a \rangle$, $P = \{w_3, w_4\}$.

- Set of windows containing parallel episodes $\langle a \cdot b \rangle$, $Q = \{w_2, w_3, w_4, w_5\}$. This set can be derived as $Q = M \cap N = O \cup P$.
- Set of windows containing episodes both serial episodes $\langle a, b \rangle$ and $\langle b, a \rangle$, $R = \{w_3, w_4\}$. This set can be derived as $R = O \cap P$.

The cardinality –the number of elements– of each set equals to the frequency (support) of the episodes classified by each set.

- Frequency of the episode $\langle a \rangle$, $fr(\langle a \rangle) = |M| = 5$
- Frequency of the episode $\langle b \rangle$, $fr(\langle b \rangle) = |N| = 5$
- Frequency of the serial episode $\langle a, b \rangle$, $fr(\langle a, b \rangle) = |O| = 4$
- Frequency of the serial episode $\langle b, a \rangle$, $fr(\langle b, a \rangle) = |P| = 2$
- Frequency of the parallel episode $\langle a \cdot b \rangle$, $fr(\langle a \cdot b \rangle) = |Q| = |O| + |P| - |O \cap P| = 4$
- The cardinality of R can be obtained from the frequency of the serial and parallel episodes, $|R| = |O \cap P| = |O| + |P| - |Q| = 2$

Likewise, if the total number of windows is considered, the frequency of each episode can be interpreted in terms of probabilities as shown in Fig. 4.2.

Through the conditional probability –although causal or temporal relationships are notions that do not belong to the realm of probability– an interpretation of the link between an episode and their sub-episodes can be established.

As example, consider that we are interested in the link between the episode $\langle a, b \rangle$ and its sub-episode $\langle a \rangle$. Through the conditional probability, this link can be expressed as $p(\langle a, b \rangle | \langle a \rangle)$. Then, by the relations mentioned above:

$$p(\langle a, b \rangle | \langle a \rangle) = \frac{p(O \cap M)}{p(M)} = \frac{p(O)}{p(M)} = 0.8 \tag{4.1}$$

This relation between an episode and its sub-episode –as shown in Section 3.3– is called an association rule and it expresses the level of confidence that an episode occurs because the causal sub-episode occurred.

The objectives elucidated in Section 1.2 suggested at least two cases where frequent episodes can be extracted from data sets of voltage dip collected in power networks.

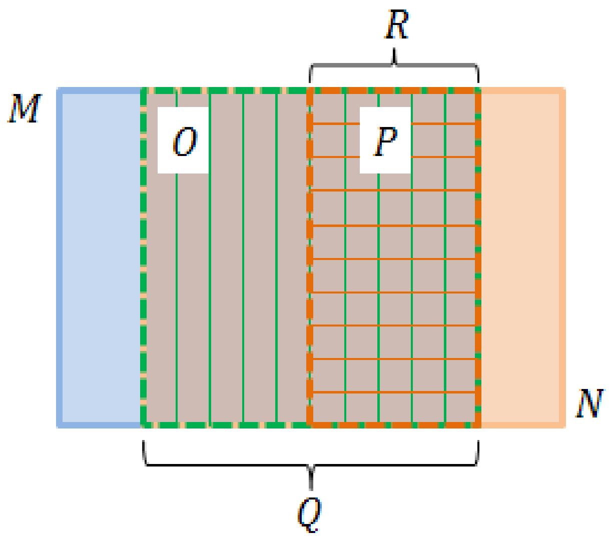


Figure 4.2: Representation of the relation between the six sets of windows

The first case mentioned that permanent faults usually cause multiples events on the network due to the actuation of the protective systems. The elapsed times between these events correspond to the reclosing settings of the protection relays. If multiples permanent faults occur in the network, then frequent episodes related with the settings of the protective system should appear in a sequence of voltage dips. The second case refers to the fact that voltage dips that occurred in nearby region of the network probably have similarities in magnitude and duration. If there exist recurrent problems in the network linked to the same or different regions of it, then these problems should appear as frequent episodes of voltages dips which are characterized by their magnitudes and durations.

In this chapter, two types of frequent episodes (different characteristics) are found using the mining algorithm proposed in Section 2.4, taking advantage of its flexibility:

1. Frequent episodes that describe regularities in the time intervals of the voltage dips occurrences. Given that the maximal duration of these episodes should not be limited, a maximal gap or inter-event time constraint is used in the search.

2. Frequent episodes associated with possible regularities between points of occurrence of events in the network. In this case the episodes should be limited in both inter-event and maximal duration.

For each case, frequent episodes are evaluated using the criteria of cohesion, backward-confidence and confidence, and concepts of directed search of episodes proposed in Chapter 3. The most relevant patterns are analysed and discussed.

4.1.1 Dataset description

The dataset of events that have been used for the analysis consists in voltage dips produced by single-phase-to-ground faults, which were recorded over several years in a power distribution network by the utility[1]. They were collected by power quality monitors (PQM) located in the secondary of power distribution transformers (25kV) as shown in Fig. 4.3.

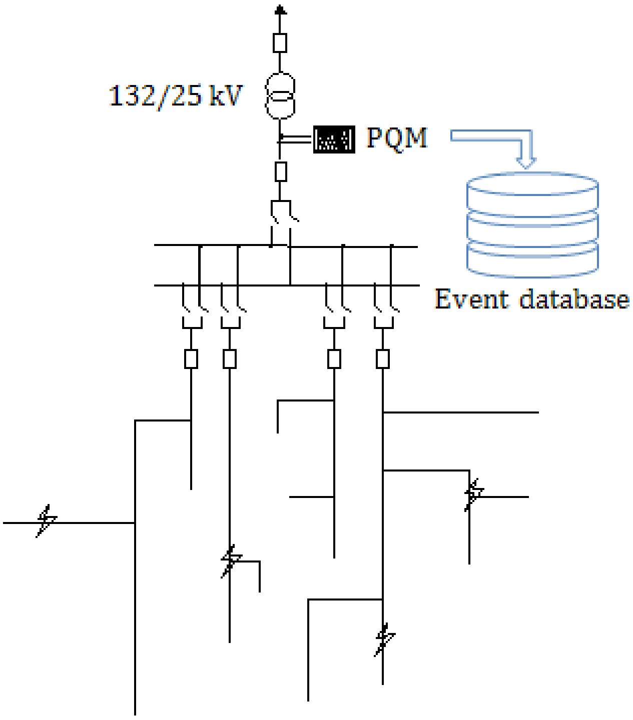


Figure 4.3: Schematic for the registration of voltage dip events.

Each logged voltage dip in the database has three main attributes: the time stamp of the event, the duration, in milliseconds, is the time for which the *rms* voltage stays below of 0.9 in p.u., and the magnitude, in percentage, is the value of the residual

[1] ENDESA DISTRIBUCION.

voltage during the event. Table 4.1 exemplifies the representation of successive events recorded in the database for a measurement point.

Table 4.1: Set of events registered in a measurement point

time stamp	duration(ms)	magnitude (%)
07-09-22 12:28:11.145	1081	38
07-09-22 12:31:57.231	501	39
07-09-22 14:30:02.287	1001	43
07-10-21 06:07:36.491	881	30
07-10-22 14:57:10.262	760	25
07-12-25 21:44:24.553	862	39
08-01-20 18:05:02.142	1100	36

A sequence of events consists of registers of voltage dips, monitored at the same point of the distribution network, during a period of time and sorted by their dates of occurrence. The sequences of voltage dips collected in five monitored points are selected as case study. Information related to the origin, cause and actuation of protective systems for most of the events has been provided by the utility and used for validation.

Table 4.2 summarises for each substation the number of feeders, the number and types of faults (transient, permanent and undocumented), the number of voltage dips that constitutes the sequence of events and the monitoring period for each sequence.

Table 4.2: Description of the sequences of the case study.

Description	Substation				
	S1	S2	S3	S4	S5
Number of feeders	4	8	12	10	6
Permanent faults (*)	6(6)	6(4)	18(17)	15(14)	19(14)
Transient faults	22	33	78	52	15
Permanent fault events	29	33	96	97	80
Transient fault events	22	39	79	59	18
No documented events	0	18	33	21	9
Total number of events	51	90	208	177	107
Monitoring period (years)	1.02	2.36	4.80	4.78	4.66

(*) In brackets: number of permanent faults causing three or more voltage dips.

For example, distribution substation S1 feeds four lines. A total number of 51 voltage dips were recorded over a period of 1.02 years by the monitor installed in this substation. These voltage dips reflect the occurrences of six and 22 permanent and transient faults, respectively. The six permanent faults are reflected in 29 events, each one of them with more than three events associated while only one event was recorded by each transient fault.

As example, Table 4.3 shows in detail the information related with the faults (permanent/transient, causes and affected line) associated with the voltage dips in the sequence S1. The nomenclature $\langle e_i, ..., e_{i+k}\rangle$ is used to represent a set of consecutive $k+1$ events (episode) associated with a single permanent fault.

Table 4.3: Faulty situations and events related for each line in the S1 sequence.

Transient faults[1]	Permanent faults
L1: $e_1, e_2, e_4, e_7, e_8, e_9, e_{42}, e_{50}$	L2[2]: $\langle e_{14}, .., e_{20}\rangle$, $\langle e_{38}, .., e_{41}\rangle$, $\langle e_{44}, .., e_{48}\rangle$
L2: $e_3, e_5, e_6, e_{10}, e_{11}, e_{12}, e_{26}, e_{34}$	L2[3]: $\langle e_{22}, .., e_{24}\rangle$
L3: $e_{13}, e_{21}, e_{25}, e_{51}$	L2[4]: $\langle e_{27}, .., e_{33}\rangle$
L4: e_{43}, e_{49}	L3[5]: $\langle e_{35}, .., e_{37}\rangle$

[1] Events occurred by unknown causes.

[2] Cable degradation.

[3] Contact between cable and overhead structure due to wind.

[4] Degradation of insulators in an overhead line.

[5] Accidental cable break.

4.2 Analysis of the elapsed times between successive events

Elapsed times between successive events can give information about permanent faults episodes occurred in the power network. Such elapsed times between successive events are related with settings of protective system if they are caused by the same fault situation. Table 4.4 shows the settings of the protective system when the data were recorded. They show typical time intervals between protection tripping and re-energisation of faulted feeders. The first two steps correspond to automatic reclosings. If they fail –i.e., the supply can not be restored– and no breakdown has been located then manual steps are executed to locate the fault and restore the service. The times in Table 4.4 are the reference values for the settings of the main protection of the lines (feeders), but the exact times may vary from one feeder to another.

Table 4.4: Typical reclosing settings of the protective system in distribution networks.

Step	Time settings
1. Automatic reclosing	0.5s - 1s
2. Slow automatic reclosing	40s or 60s
3. Manual reclosing	1min or 3min
4. Maneuver by telecontrol	8min
5. Maneuver on-site	25min

Each event $e_i(t_i)$ of the sequence of voltage dips **S** is described by their magnitude M_i and duration Δt_i. Elapsed times between successive events are calculated in order to create a new sequence **S'** consisting of the elapsed times between successive events. Likewise, each t_i in **S** is replaced by values $j = 1, 2, ...n - 1$ in **S'**. Then, $t_i = j$ means that the i-th data element occurs at the j-th timestamp.

$$\mathbf{S'} = \langle (t_2 - t_1 - \Delta t_1)(1), (t_3 - t_2 - \Delta t_2)(2), ..., (t_n - t_{n-1} - \Delta t_{n-1})(n-1) \rangle \qquad (4.2)$$

where n is the length of **S**.

Next, the values of the sequence of elapsed times between events are discretized to form a sequence of labeled categories. Then, frequent episodes describing sets of intervals within events that usually occur, are obtained by the mining algorithm.

Ten intervals are used to discretize the elapsed times between events, based on settings of the protective system (Table 4.4) and other relevant time intervals where high occurrence of events were observed. Table 4.5 shows the intervals used, where A, B, E, F and G correspond to the different reclosing steps of the protective system.

Distribution of the elapsed times between events for all sequences in accordance with the assigned categories is shown in Table 4.6. According to this table, for sequences S1' and S2', about 40% of elapsed times between events are under 30 min (within the settings of the protective system mentioned in Table 4.4), while for the other sequences this percentage is about 50%.

Fig. 4.4 shows the global distribution of the elapsed times between events according to the information in Table 4.4. For the intervals under 30 min, A, C and E are the most frequent categories. The first two intervals (A and C) include automated reclosing settings and the third (E) includes manual reclosing settings. For the intervals above

Table 4.5: Intervals for characterization of elapsed times between events.

Interval	Description
A	**t ≤ 3 s**
B	3 s<t≤20 s
C	**20 s < t ≤ 2 min**
D	**2 min< t ≤5 min**
E	**5 min< t ≤ 30 min**
F	30 min< t ≤2 h
G	2 h< t ≤1 day
H	1 day< t ≤ 7 day
I	7 day < t ≤ 30 day
J	t >30 day

Table 4.6: Distribution of the intervals for the sequences of the case study.

Event type	S1’		S2’		S3’		S4’		S5’	
	Number	%	Number	%	Number	%	Number	%	Number	%
A	6	12.0	13	14.6	22	10.6	29	16.5	13	12.3
B	0	0.0	1	1.1	8	3.9	2	1.1	3	2.8
C	7	14.0	10	11.2	31	15.0	33	18.8	24	22.6
D	3	6.0	3	3.4	11	5.3	9	5.1	9	8.5
E	4	8.0	11	12.4	32	15.5	15	8.5	13	12.3
F	6	12.0	10	11.2	26	12.6	16	9.1	12	11.3
G	4	8.0	14	15.7	16	7.7	12	6.8	9	8.5
H	6	12.0	8	9.0	14	6.8	19	10.8	4	3.8
I	12	24.0	12	13.5	30	14.5	22	12.5	4	3.8
J	2	4.0	7	7.9	17	8.2	19	10.8	15	14.2

30 min, *F* and *I* are the most frequent categories. While *F* would be related with maneuvers to locate a permanent fault in the process of service restoration, *I* involves two different faults.

4.2.1 Extraction of regularities in the elapsed time between events

For each sequence of discretized elapsed times between events, regularities are extracted through frequent episodes. According with the reclosing settings, in permanent fault situations such regularities can associate two or more successive events, then maximum duration of the episodes should not be limited. With this purpose, episodes with inter-

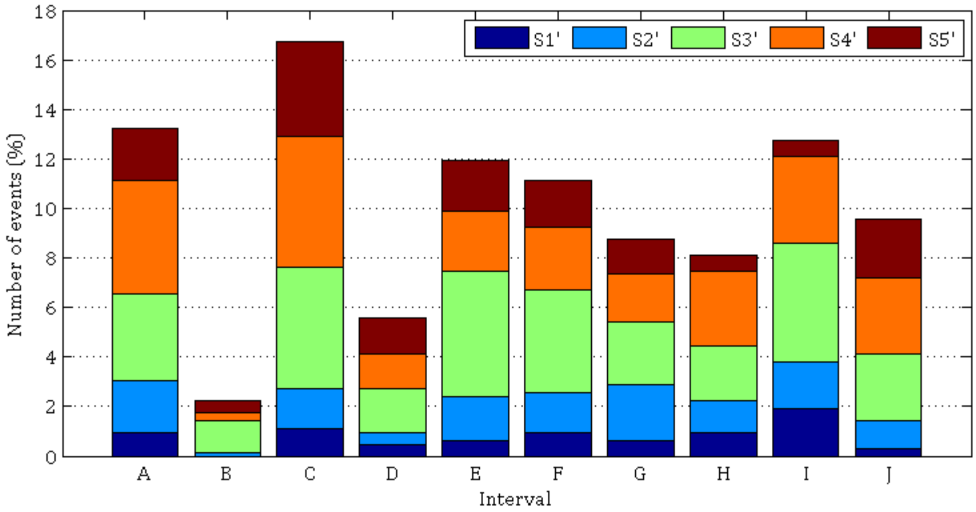


Figure 4.4: Histogram of elapsed time between consecutive events.

event time constraint (Definition 2.12) are extracted using the algorithm proposed in Section 2.4.

Given that each element in the sequence S' was obtained from timestamps of consecutive events, a maximal gap of 1 and 2 elements is used in the search. Likewise, several minimum frequency (min_fr) values were tested. Episodes related with settings of the protective system were obtained using min_fr values no greater than 4, 5, 10, 9 and 7 for the sequences S1' to S5', respectively. The frequency of relevant intervals of each sequence (see Table 4.6) can be used as a guide for setting the threshold frequency of frequent episodes. So, for example in the sequence S1', interval A or C have frequencies of 6 and 7 occurrences, respectively, then episodes –with length greater than one event– that involve any of these two intervals must have min_fr values less than 6 or 7, respectively.

Table 4.7 shows the frequent episodes (length greater than 1) for each sequence and the two values of maximal gap (1 and 2 elements) are used. In this table, it can be observed that episode $\langle A, C \rangle$ is frequent in all sequences analysed. This episode involves the two intervals containing the automatic reclosing settings of the protective system. Its frequency is about the number of permanent faults (permanent faults causing three or more voltage dips) when a maximal gap of two elements is used.

Using maximal gap of two elements, episodes $\langle A, C, C \rangle$ for sequence S4', $\langle A, C, F \rangle$

Table 4.7: Frequent episodes and number of occurrences in the sequences for two values of maximal gap.

Episode	Maximal gap=1					Maximal gap=2				
	S1’	S2’	S3’	S4’	S5’	S1’	S2’	S3’	S4’	S5’
$\langle A, C\rangle$	5	7	14	15	9	5	8	15	18	18
$\langle C, C\rangle$									10	10
$\langle C, E\rangle$							5	10		
$\langle C, F\rangle$								15	9	9
$\langle C, G\rangle$							5			
$\langle E, E\rangle$								10		
$\langle E, I\rangle$								10		
$\langle E, J\rangle$										7
$\langle F, E\rangle$								11		
$\langle F, G\rangle$							5			
$\langle G, A\rangle$							6			
$\langle H, I\rangle$						4	5			
$\langle I, A\rangle$		5					5	10	10	10
$\langle I, I\rangle$						4				
$\langle J, A\rangle$								10	9	9
$\langle J, C\rangle$										9
$\langle A, C, C\rangle$									9	
$\langle A, C, E\rangle$							5			
$\langle A, C, F\rangle$								10		
$\langle J, A, C\rangle$										7

for sequences S3’ and $\langle A, C, E\rangle$ for sequence S2’, are frequents. These episodes include manual reclosing times and suggest that correspond to permanent faults causing at least four voltages dips. Episodes such as $\langle C, F\rangle$, $\langle C, G\rangle$, $\langle E, E\rangle$, $\langle E, I\rangle$ and $\langle E, J\rangle$, include manual reclosing times and suggest that these manoeuvres are frequent in these substations but with different operating times. Episodes such as $\langle I, A\rangle$ are frequent in sequences S2’ to S5’ or $\langle J, A\rangle$ are frequent in sequences S3’ to S5’, which show that after several days (more than 30 days) of the occurrence of an event, new faults (causing at least two voltage dips) usually occur. Episode $\langle J, A, C\rangle$ frequent in S5’ shows that after several days without events (more than 30 days), new faults causing at least three voltage dips usually occur. Finally, episodes such as $\langle H, I\rangle$ or $\langle I, I\rangle$ which are frequent in sequence S4’, show the occurrences of several successive events associated to different fault situations.

4.2.2 Significant regularities in the elapsed time between events

Frequent episodes found in the previous section (Table 4.7) are evaluated using definitions and indexes described in Section 3.3. So, the strength of the link between the different elapsed times contained in each episode is evaluated from their cohesion, confidence and backward-confidence values, and the most significant associations are identified.

Using a maximal gap of two elements, Table 4.8 contains for each episode, the corresponding serial and parallel frequencies and the values of cohesion, confidence and backward-confidence indexes.

According to Table 4.8 all frequent episode have a cohesion greater than 0.7, i.e., the order relation expressed by the serial episodes is strong. Episode $\langle A, C\rangle$ occurs with a confidence greater than 0.6 in all sequences. This episode shows that if two successive voltage dips have a elapsed time less than 3 s, one may expect with a confidence greater than 0.6 (0.83, 0.62, 0.68, 0.62 and 0.77 for S1' to S5', respectively) that there will be a third event within 20 s to 120 s of the second one.

Episodes $\langle A, C, C\rangle$ (for S4'), $\langle A, C, E\rangle$ (for S2') and $\langle A, C, F\rangle$ (for S3'), which are forward-extensions (see Section 2.3.1.3) of the episode $\langle A, C\rangle$, have confidences greater than 0.5. These episodes show that at least half of the occurrences of an episode $\langle A, C\rangle$ (described above) are followed by a fourth event within 20 s to 120 s and 5 min to 30 min of the third one, respectively.

Finally, episodes $\langle A, C\rangle$ for S1', $\langle A, C, E\rangle$ for S2', $\langle A, C, F\rangle$ for S3', $\langle A, C, C\rangle$ for S4' and $\langle J, A, C\rangle$ for S5', are the maximal episodes with higher values (> 0.5) of cohesion, confidence and backward-confidence. They are the most relevant pattern in these sequences. However, the pattern $\langle A, C\rangle$ have significant vales of cohesion and confidence in all sequences analysed. This pattern involves the two intervals containing the automatic reclosing settings of the protective system, therefore it may identified permanent faults that cause at least three successive voltage dips.

Figures 4.5 to 4.9 show for each sequence, the episodes selected as patterns. They are marked by a dashed line between circular marks (green circular marks for episode $\langle A, C\rangle$ and red circular marks for their extensions). At the top of the figures, the sequences of elapsed times between events and the corresponding patterns are shown, while in the bottom of the figures, it adds information about the events in the sequence.

Table 4.8: Frequent episodes and their corresponding values of of cohesion (*coh*), confidence (*conf*) and backward-confidence ($conf_B$).

Sequence	Episode	$fr(\alpha)$	$fr(\alpha_p)$	*coh*	$conf_B$	*conf*
S1'	$\langle A, C\rangle$	5	5	1.00	0.71	0.83
	$\langle H, I\rangle$	4	4	1.00	0.33	0.67
	$\langle I, I\rangle$	4	4	1.00	0.33	0.33
S2'	$\langle A, C\rangle$	8	8	1.00	0.80	0.62
	$\langle C, E\rangle$	5	6	0.83	0.45	0.50
	$\langle C, G\rangle$	5	5	1.00	0.36	0.50
	$\langle F, G\rangle$	5	5	1.00	0.36	0.50
	$\langle G, A\rangle$	6	6	1.00	0.46	0.43
	$\langle H, I\rangle$	5	6	0.83	0.42	0.63
	$\langle I, A\rangle$	5	7	0.71	0.38	0.42
	$\langle A, C, E\rangle$	5	6	0.83	1.00	0.63
S3'	$\langle A, C\rangle$	15	15	1.00	0.48	0.68
	$\langle C, E\rangle$	10	12	0.83	0.31	0.32
	$\langle C, F\rangle$	15	17	0.88	0.58	0.48
	$\langle E, E\rangle$	10	10	1.00	0.31	0.31
	$\langle E, I\rangle$	10	13	0.77	0.33	0.31
	$\langle F, E\rangle$	11	14	0.79	0.34	0.42
	$\langle I, A\rangle$	10	12	0.83	0.45	0.33
	$\langle J, A\rangle$	10	10	1.00	0.45	0.59
	$\langle A, C, F\rangle$	10	11	0.91	0.67	0.67
S4'	$\langle A, C\rangle$	18	19	0.95	0.55	0.62
	$\langle C, C\rangle$	10	10	1.00	0.30	0.30
	$\langle C, F\rangle$	9	9	1.00	0.56	0.27
	$\langle I, A\rangle$	10	11	0.91	0.34	0.45
	$\langle J, A\rangle$	9	10	0.90	0.31	0.47
	$\langle A, C, C\rangle$	9	11	0.82	0.90	0.50
S5'	$\langle A, C\rangle$	10	10	1.00	0.42	0.77
	$\langle C, F\rangle$	9	11	0.82	0.75	0.38
	$\langle E, J\rangle$	7	8	0.88	0.47	0.54
	$\langle J, A\rangle$	9	9	1.00	0.69	0.60
	$\langle J, C\rangle$	9	10	0.90	0.38	0.60
	$\langle J, A, C\rangle$	7	7	1.00	0.70	0.78

This information indicates which events are caused by permanent or transient faults and which of them are no documented events.

A comparison of the results in Fig. 4.5 with the information in Table 4.3 confirms that acting times during manual operation are not performed strictly in this sequence.

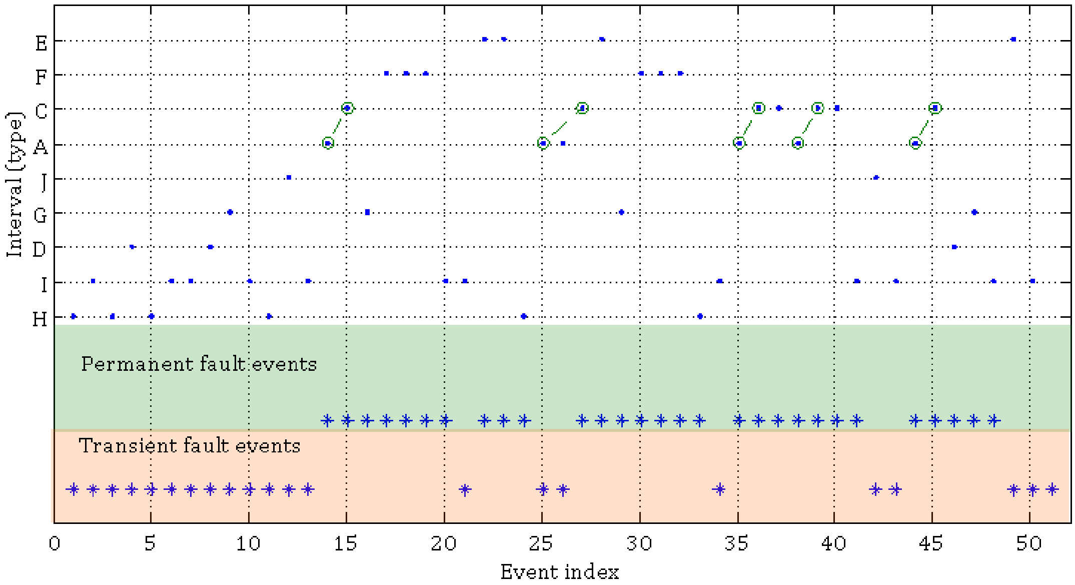


Figure 4.5: Sequence S1' and occurrences of the episode $\langle A, C \rangle$.

This is probably because manual actuations are related to fault location strategies followed in each situation. Moreover, there is a permanent fault ($\langle e_{22}, e_{23}, e_{24} \rangle$) that does not follow the pattern. A possible interpretation is the involvement of secondary protections such as fuses, or that the fault was caused by another abnormal situation, not considered in the studied pattern.

Finally, in order to assess the identification of permanent fault situations by the episode $\langle A, C \rangle$ shown in Figures 4.5 to 4.9 the following parameters are used: number of permanent faults correctly identified or true detection (TD), permanent faults not detected or missed by detection (MD) and, number of non permanent faults identified as permanent or false alarms (FA). The corresponding ratios also included in Table 4.9 are useful to evaluate the accuracy of the search: true detection rate (TDR = TD/(TD+MD)), missed detection rate (MDR = MD/(TD+MD)) and false alarm rate (FAR = FA/(TD+FA)). The results are summarised in Table 4.9.

For sequences S1' to S5', TDR values indicate that 83%, 100%, 76%, 86% and 80% of permanent faults with more than three events follow the automatic reclosing pattern of the protective system, respectively. However, the pattern can not be found in some situations, for example, when a single event is enough to detect or locate the failure or when a secondary protection acts. An accurate analysis discovered that the high value

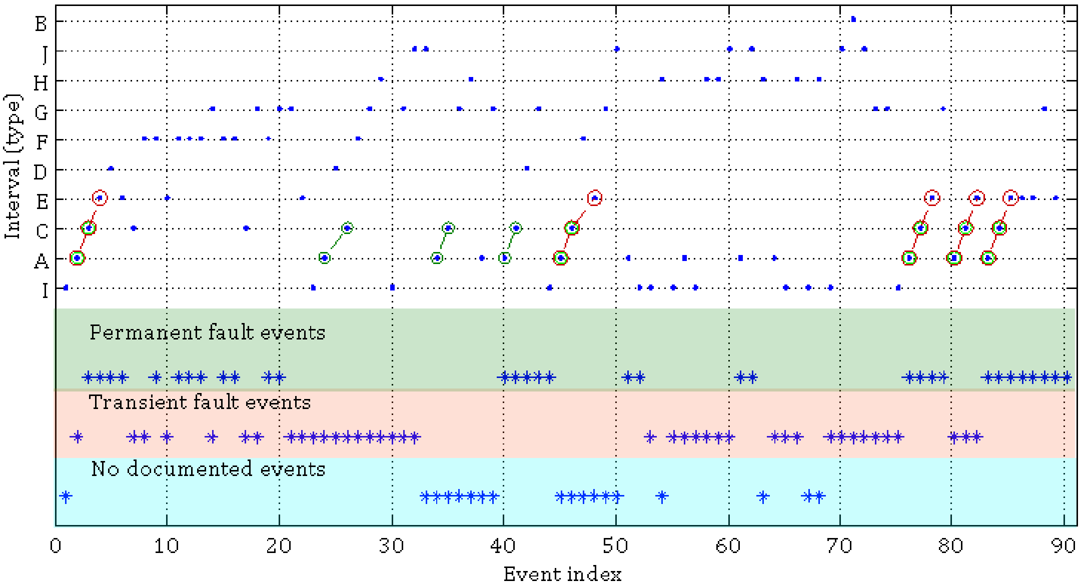


Figure 4.6: Sequence S2' and occurrences of episodes $\langle A, C\rangle$ and $\langle A, C, E\rangle$.

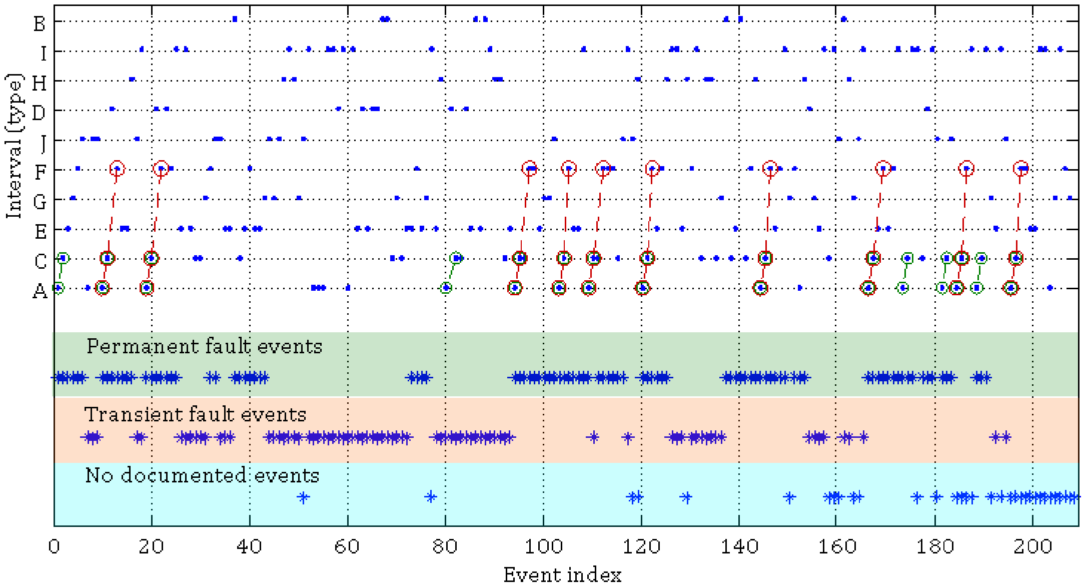


Figure 4.7: Sequence S3' and occurrences of episodes $\langle A, C\rangle$ and $\langle A, C, F\rangle$.

of FAR in S2', S3' and S5 was due to the fact that the episode $\langle A, C\rangle$ was detected in no documented events. Also, the high value MDR in S3' and S4' was due to the fact that the first automatic reclosing was not recorded for several permanent faults.

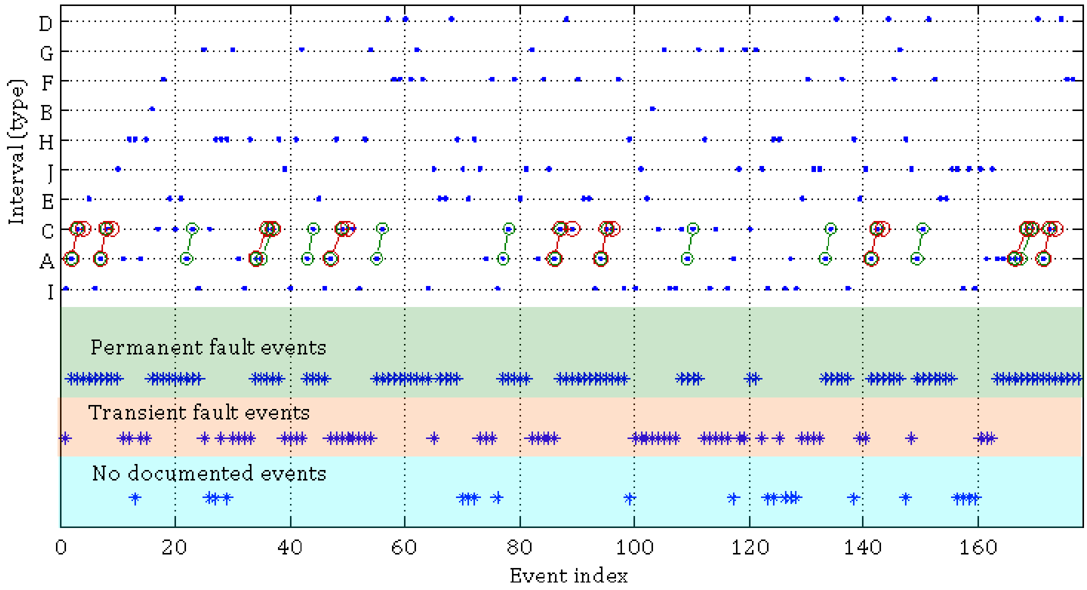


Figure 4.8: Sequence S4’ and occurrences of episodes $\langle A, C\rangle$ and $\langle A, C, C\rangle$.

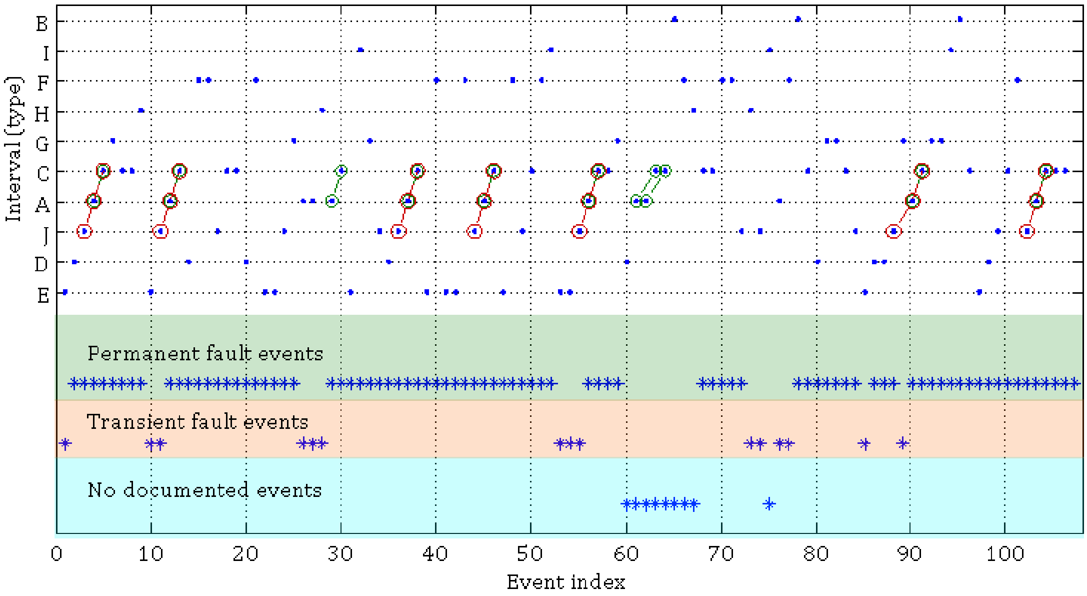


Figure 4.9: Sequence S5’ and occurrences of episodes $\langle A, C\rangle$ and $\langle J, A, C\rangle$.

Table 4.9: Results of the identification of permanent fault situations by the episode $\langle A, C \rangle$.

Sequence	Parameters					
	TD	MD	FA	TDR	MDR	FAR
S1'	5	1	0	0.83	0.17	0.00
S2'	4	0	4	1.00	0.00	0.50
S3'	13	4	2	0.76	0.24	0.13
S4'	12	2	1	0.86	0.14	0.08
S5'	8	1	2	0.89	0.11	0.20

4.3 Analysis of the magnitude and duration of voltage dips in a sequence of events

In distribution radial networks, voltage dips are related with fault locations. Similar voltage dips in magnitude and duration probably occur in nearby locations or at similar distances from the distribution substation on the network (Bollen, 1999). As it shows in Fig. 4.10, faults occurred within a specific area of the network, enclosed by a dotted line in the figure, probably cause voltage dips of similar magnitudes. Faults located in areas near to the main bus cause more severe voltage dips (low magnitude) than those located in more distant areas of the network.

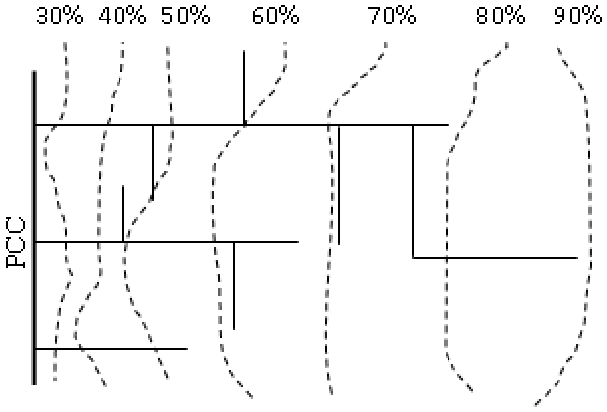


Figure 4.10: Magnitude of voltage dips in a radial network according to fault locations.

In this section, the mining goal is to discover possible regularities between point locations of events in the network, in terms of frequent episodes. These frequent episodes can show relationships between a fault and other faults occurred at the same or another location on the network. Two different interpretations can be derived from such episodes:

1. Frequent episodes composed by multiple and similar (magnitude an duration) events will represent areas of the network susceptible to the occurrence of successive faults.

2. Frequent episodes composed by events of different magnitudes could show interactions between faults located in different regions of the network.

4.3.1 Dataset description

A set of voltage dips caused by single-phase faults are analysed. Events, recorded as shown in Section 4.1.1, correspond to a substation with a high rate of events.

Voltage dip density tables is a common method for presenting large repositories (or surveys) of dips gathered during long periods of time (more than one year). There are several proposed tables (Yuan et al., 2009). We use the table recommended by the standard IEC61000-2-8 (2002). In this table, magnitude of dips is split in 9 categories defined by the following intervals: 80%–90%, 70%–80%, 60%–70%, 50%–60%, 40%–50%, 30%–40%, 20%–30%, 10%–20% and <10%. For the dips duration, 8 intervals are used: <0.1s, 0.1s–0.25s, 0.25s–0.5s, 0.5s–1s, 1s–3s, 3s–20s, 20s–60s and 60s–180s.

The analyzed data set is represented in Table 4.10. It contains a total of 527 voltage dips recorded during a monitored period of three years.

Duration intervals are represented by a 8-letter alphabet (A to F), while numbers 1 to 9 are used to represent the magnitude intervals. Each voltage dip in the sequence is represented by their corresponding identifier of row and column in Table 4.10. For example, the voltage dip type $B6$ represents dips with duration between $0.1s$ to $0.25s$ and magnitude between 50% to 60% while the voltage dip type $D3$ represents dips with duration between $0.5s$ to $1s$ and magnitude between 20% to 30%. So, the sequence can have 72 different types of events. Likewise, $H1$ will be the most severe voltage dips, while $A9$ will be the less severe.

Fig. 4.11 shows the distribution of the cumulated number of voltage dips according with the classification of Table 4.10. This figure shows that the sequence has only 36 of 72 possible voltage dip types. $B6$ with around of 10% of the events is the most

Table 4.10: Cumulative voltage dip table.

Magnitude		Duration							
		A	**B**	**C**	**D**	**E**	**F**	**G**	**H**
		<0.1 s	0.1–0.25 s	0.25–0.5 s	0.5–1 s	1–3 s	3–20 s	20–60 s	60–180 s
9	80%–90%	4	3	1	2	4	0	0	0
8	70%–80%	4	6	11	2	4	0	0	0
7	60%–70%	1	42	28	4	15	1	0	0
6	50%–60%	0	55	39	8	9	0	0	0
5	40%–50%	0	28	13	10	17	0	0	0
4	30%–40%	1	21	20	32	25	4	0	0
3	20%–30%	0	5	5	39	13	0	0	0
2	10%–20%	0	0	38	14	0	0	0	0
1	<10%	0	0	0	0	0	0	0	0

frequent voltage dip type in the sequence, followed by $B7$ with around of 8% of the events. Likewise, $C2$, $C6$ and $D3$, each one with around of 7% of the events, have similar frequencies in the sequence.

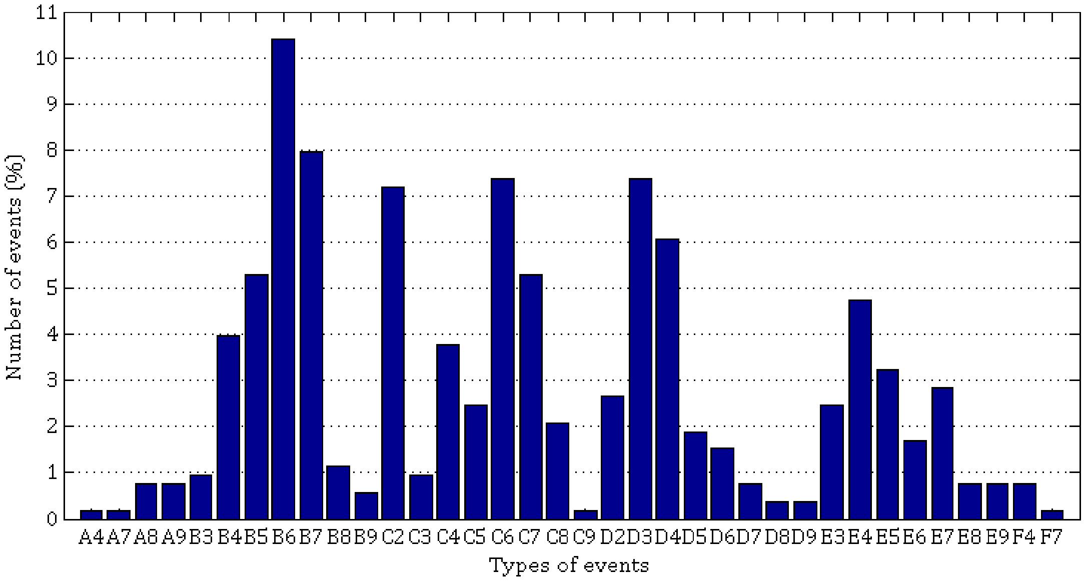


Figure 4.11: Distribution of the voltage dips according to magnitude and duration.

4.3.2 Frequent regularities between points of occurrence of events in the network

As it was introduced in this section, the main interest for the extraction of frequent episodes in sequences of voltage dips is to find relations between fault location areas. So, in the mining process, it is only necessary to consider one voltage dip for each fault occurred in the network. However, as shown in Section 4.2 several events close in time can be generated for the same fault. This problem can be partially solved using *temporal aggregation* (Bollen, 1999). If several voltage dips occur within a time interval less than a predefined time of aggregation, then the aggregated event could be defined by one of the following options:

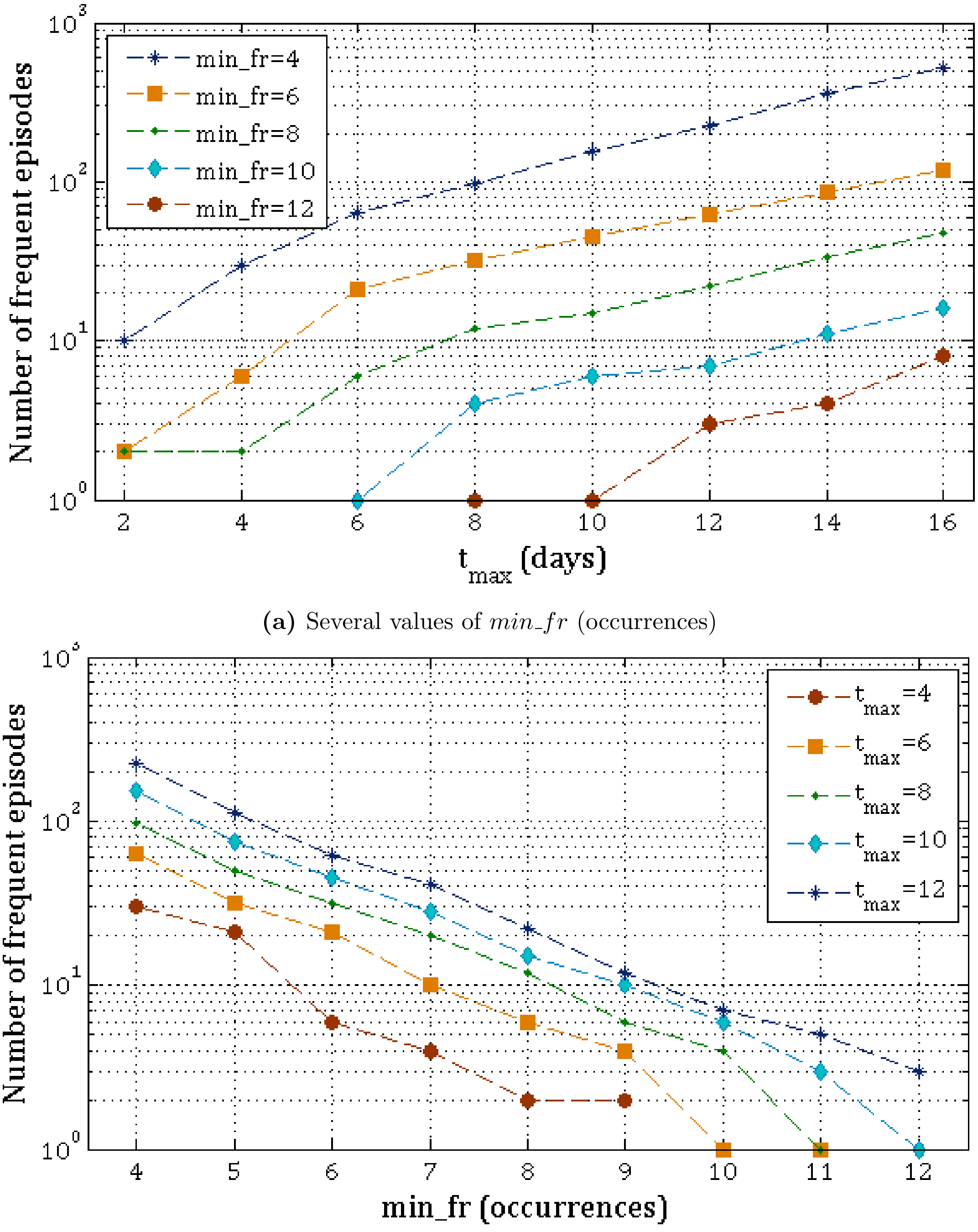
1. The time between the start of the first event and the end of the last event, and the residual voltage of the first event.
2. The sum of the individual durations and the minimal residual voltage of the events.
3. The duration and the residual voltage of the first event.
4. The maximal duration and the minimal residual voltage of the events.

Option 3 is the most appropriate to include the behavior of all events in the analysis of the sequence without changing the information contained in the event. Likewise, considering observations in Section 4.2, 2 hours can be used as time of aggregation.

Algorithm Fminevent proposed in Section 2.4 is used for the search of frequent episodes. With this algorithm, temporal aggregation can be included by using a time interval, $(t_{min} \;\; t_{max}]$ for the inter-event time constraint between events of the episodes as shown in Section 2.4.1.2. For a candidate episode, successive events with elapsed times less than t_{min}, are not considered for their occurrences. So, t_{min} serves as aggregation time, reducing the effects of multiples events of the same fault.

Fig 4.12 shows the number of frequent episodes discovered in the sequence for several values of minimum frequency threshold (min_fr) and for several values of maximal gap between events (t_{max}). This results are obtained using a t_{min} value of 2 hours.

Fig. 4.12a shows wide differences between the number of episodes obtained with $min\_fr = 4$ (occurrences) and $min\_fr = 6$ (occurrences) for the same value of t_{max}.



(a) Several values of *min_fr* (occurrences)

(b) Several values of t_{max} (days)

Figure 4.12: Number of frequent episodes for several values of *min_fr* and maximal gap between events (t_{max})

For example, for t_{max} = 8 days, the number of frequent episodes is reduced from 100 to 30 for $min\_fr = 4$ and $min\_fr = 6$, respectively. For min_fr values greater than 6 occurrences, there are minor differences in the number of frequent episodes. Likewise, for different values of t_{max}, Fig. 4.12b show that few frequent episodes are obtained for min_fr values greater than 8 occurrences.

Fig. 4.13 shows a schema of frequent episodes with $min\_fr = 6$ occurrences and t_{max} = 8 days. Two-event and three-event episodes are linked by thin and thick arrows, respectively. For this sequence, these frequent episodes suggest the presence of regularities between events of the same region (episodes with two or more events of the same type) and between events of different regions (episodes with events of different types). Most of them are episodes of two-event length and only 4 episodes have three-event length. They are: $\langle B4, B4, D3\rangle$, $\langle B5, B4, D3\rangle$, $\langle B4, C4, D3\rangle$ and $\langle C2, C2, C2\rangle$ which are highlighted in the figure. Several episodes are composed of events $C6$ and $D3$ (linked by a thin orange and black arrow in the figure, respectively)and many of them end with event $D3$. In these episodes, the most severe voltage dips (lowest magnitude) correspond to events $C2$ and $D3$ while the less severe are $B7$ and $C7$.

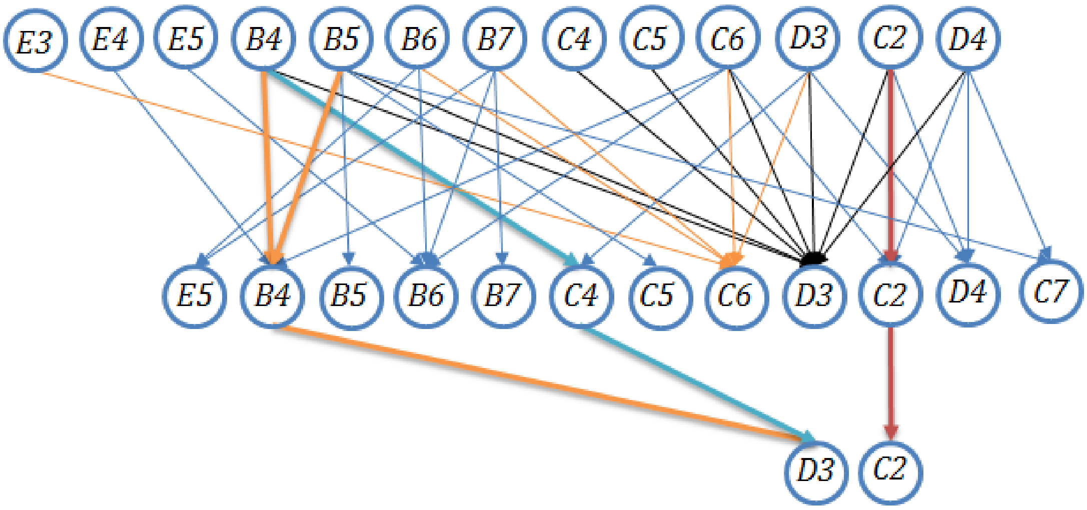


Figure 4.13: Representation of frequent episodes with $min\_fr = 6$ occurrences and t_{max} = 8 days.

Most frequent episodes in Fig. 4.13, show that the first event is greater in magnitude than later events or they are associated to voltage dips similar in magnitude. Table

4.11 contain the list of frequent episodes grouped by their frequency which are between 6 to 13 occurrences.

Table 4.11: List of frequent episodes with $min\_fr = 6$ (occurrences) and $t_{max} = 8$ (days).

Episodes	Frequency
$\langle B4, B4, D3 \rangle$; $\langle B4, C4, D3 \rangle$, $\langle B5, B4 \rangle$, $\langle B5, B4, D3 \rangle$, $\langle B5, B5 \rangle$, $\langle B5, C7 \rangle$, $\langle B7, E5 \rangle$, $\langle C2, C2, C2 \rangle$, $\langle C5, D3 \rangle$, $\langle C6, B4 \rangle$, $\langle C6, D4 \rangle$, $\langle D3, B4 \rangle$, $\langle D3, B7 \rangle$, $\langle D4, C7 \rangle$, $\langle D4, D3 \rangle$, $\langle E3, C6 \rangle$, $\langle E5, B6 \rangle$	6
$\langle B4, B4 \rangle$, $\langle B5, C5 \rangle$, $\langle B5, C6 \rangle$, $\langle B5, D3 \rangle$, $\langle B6, B7 \rangle$, $\langle B6, E5 \rangle$, $\langle B7, C6 \rangle$, $\langle C2, D4 \rangle$, $\langle C6, C2 \rangle$, $\langle D3, D3 \rangle$, $\langle D4, C2 \rangle$, $\langle D4, D4 \rangle$, $\langle E4, B4 \rangle$	7
$\langle B4, C4 \rangle$, $\langle C2, D3 \rangle$, $\langle C4, D3 \rangle$, $\langle C6, B6 \rangle$, $\langle D3, C4 \rangle$	8
$\langle B4, D3 \rangle$, $\langle B7, B7 \rangle$, $\langle C6, C6 \rangle$, $\langle D3, C6 \rangle$	9
$\langle B6, B6 \rangle$, $\langle B6, C6 \rangle$, $\langle C6, D3 \rangle$	10
$\langle B7, B6 \rangle$, $\langle D3, D4 \rangle$	11
$\langle C2, C2 \rangle$	13

$\langle C2, C2 \rangle$ is the most frequent event with 13 occurrences while the 4 episodes with three-event length have 6 occurrences.

4.3.3 Significant regularities between points of occurrence of events in the network

Frequent episodes in Table 4.11 are evaluated starting from their corresponding values of cohesion, confidence and backward-confidence. For these indexes, Fig. 4.14 shows the distribution of the number of frequent episodes. Only two episodes have cohesion values lower than 0.5, i.e, most of them follow a serial order in the sequence. In contrast, for confidence and backward-confidence, only 7 and 5 episodes have values grater than 0.4, respectively. Then, only few episodes have relevant probabilities of apparition in the sequence.

Table 4.12 shows frequent episodes which values of cohesion (coh), confidence ($conf$) and backward-confidence ($conf_B$) are greater than 0.4.

Episode $\langle B4, B4, D3 \rangle$ shown in Table 4.12, relates two type of events. $B4$ represents voltage dips with magnitude of 30%–40% and 0.1–0.25 s of duration, and $D3$ represents voltage dips with 20%–30% in magnitude and 0.5–1 s of duration. According to their

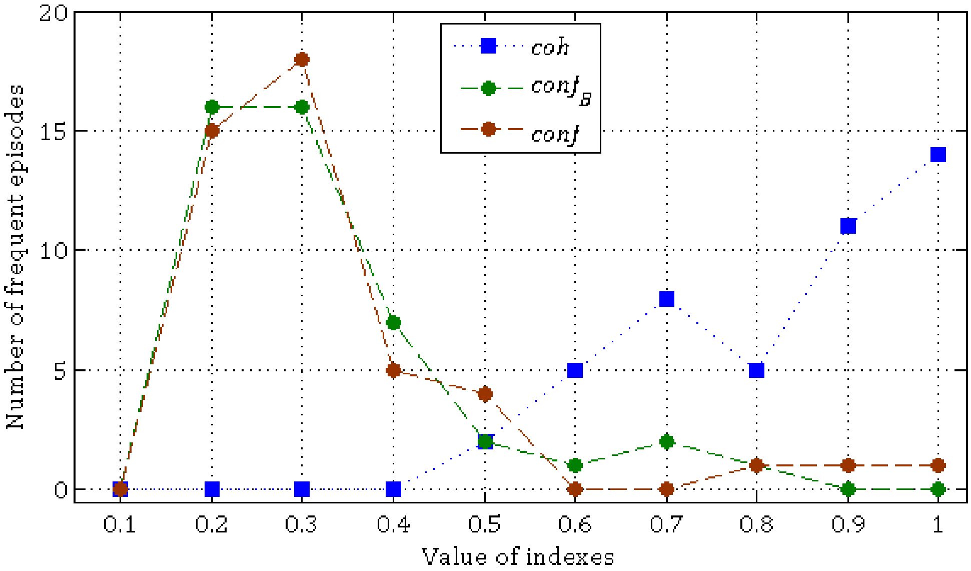


Figure 4.14: Number of frequent episodes according to their values of cohesion (coh), confidence ($conf$) and backward-confidence ($conf_B$).

Table 4.12: Significant episodes and their corresponding values of of cohesion (coh), confidence ($conf$) and backward-confidence ($conf_B$).

Episode	$fr(\alpha)$	$fr(\alpha_p)$	coh	$conf_B$	$conf$
$\langle B4, B4, D3\rangle$	6	6	1.00	0.67	0.86
$\langle B4, C4, D3\rangle$	6	8	0.75	0.75	0.75
$\langle B5, B4, D3\rangle$	6	7	0.86	0.67	1.00
$\langle C2, C2, C2\rangle$	6	6	1.00	0.46	0.46

magnitudes, $D3$ is more severe than $B4$, which suggests that $D3$ represents voltage dips located closer to the main bus of the distribution network (substation), than those represented by $B4$. Fig. 4.15 shows occurences of episode $\langle B4, B4, D3\rangle$ along the sequence, marked by a dashed line between red circular marks. Occurrences of their prefix (episode $\langle B4, B4\rangle$) are also highlighted in the figure by blue circular marks. According to this figure, 6 of 7 occurrences of $\langle B4, B4\rangle$ also comprise occurrences of $\langle B4, B4, D3\rangle$. Two of these occurrences appear at the beginning of the sequence, two at the center and two at the end.

Episode $\langle B4, C4, D3\rangle$ shown in Table 4.12, combines three type of events. $B4$ rep-

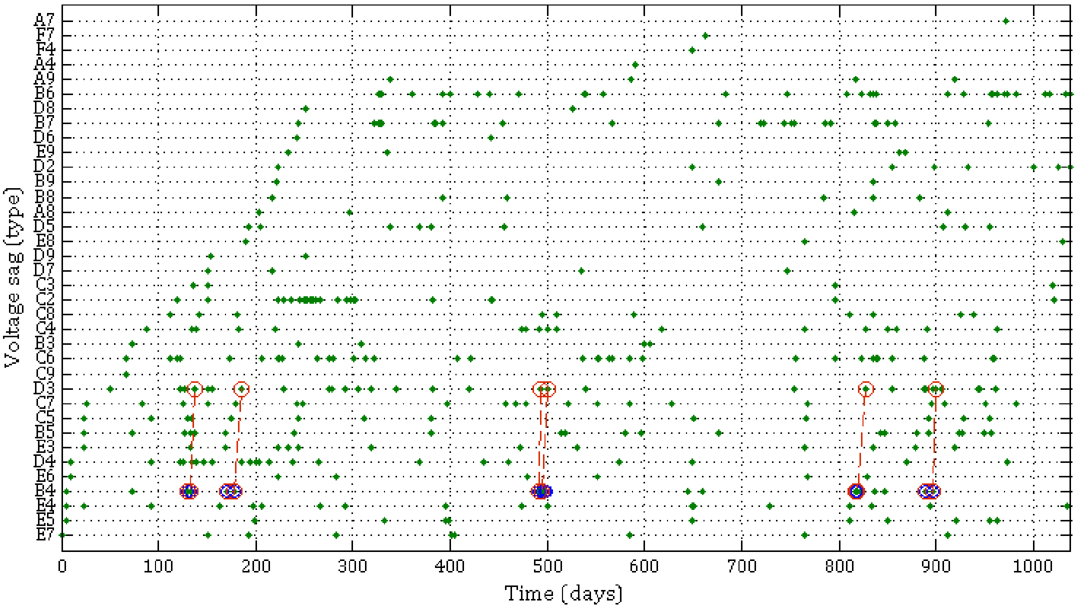


Figure 4.15: Sequence of voltage dips and occurrences of episodes $\langle B4, B4\rangle$ and $\langle B4, B4, D3\rangle$.

resents voltage dips with magnitude of 30%–40% and 0.1–0.25 s of duration, $C4$ are voltage dips with same magnitude of $B4$ and 0.25–0.5 s of duration and $D3$ represents voltage dips with 20%–30% in magnitude and 0.5–1 s of duration. According to their magnitudes and durations, $D3$ is more severe than $C4$ and $C4$ is more severe than $B4$, which suggest that $D3$ represent voltage dips located closer to the main bus of the distribution substation, than those represented by $C4$, while $B4$ represent voltage dips located in similar areas than $C4$. Occurences of this episode along the sequence are shown in Fig. 4.16, marked by a dashed line between red circular marks. Figure also shows occurrences of their prefix (episode $\langle B4, C4\rangle$) by blue circular marks. According to this figure, occurrences of $\langle B4, C4, D3\rangle$ are derived from 6 of 8 occurrences of $\langle B4, C4\rangle$. Two of these occurrences appear at the beginning of the sequence, one at the center and three at the end. Occurrences of $B4$ and $D3$ of this episode are also involved in episode $\langle B4, B4, D3\rangle$ shown in Fig. 4.15.

Episode $\langle B5, B4, D3\rangle$ shown in Table 4.12, combines three type of events. $B5$ represents voltage dips with magnitude of 40%–50% and 0.1–0.25 s of duration, $B4$ are voltage dips with 30%–40% of magnitude and the same duration as $B5$, and $D3$ represents voltage dips with 20%–30% in magnitude and 0.5–1 s of duration. According

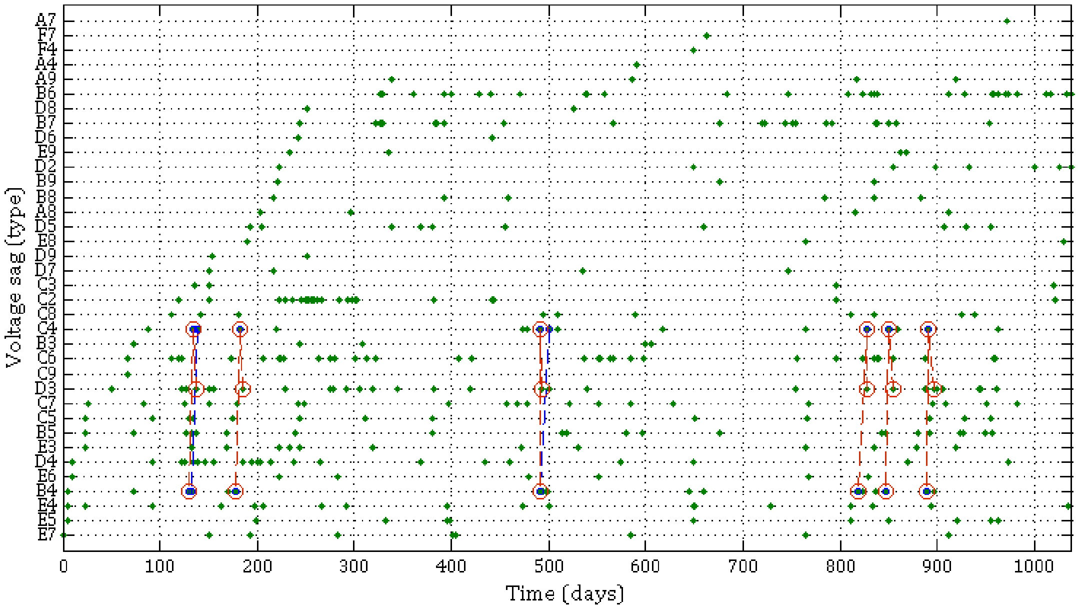


Figure 4.16: Sequence of voltage dips and occurrences of episodes $\langle B4, C4\rangle$ and $\langle B4, C4, D3\rangle$.

to their magnitudes and durations, $D3$ is more severe than $B4$ and $B4$ is more severe than $B5$, which suggests that $D3$ represents voltage dips located closer to the main bus of the distribution network, than those represented by $B4$, while $B5$ represents voltage dips located further than the $B4$. Occurences of this episode along the sequence are shown in Fig. 4.17, marked by a dashed line between red circular marks. Figure also shows occurrences of their prefix (episode $\langle B5, B4\rangle$) by blue circular marks. According to this figure, occurrences of $\langle B5, B4, D3\rangle$ are derived from the same occurrences of $\langle B5, B4\rangle$. Three of these occurrences appear at the beginning of the sequence, and the remaining three at the end. Occurrences of $B4$ and $D3$ of this episode are also involved in episodes $\langle B4, B4, D3\rangle$ (Fig. 4.15) and $\langle B4, C4, D3\rangle$ (Fig. 4.16).

Episode $\langle C2, C2, C2\rangle$ relates voltage dips with 10%–20% in magnitude and duration of 0.25–0.5 s. This episode suggests the recurrence of fault close in time, located on the same network zone. Occurences of this episode along the sequence are shown in Fig. 4.18, marked by a dashed line between red circular marks. Figure also shows occurrences of their prefix (episode $\langle C2, C2\rangle$) by blue circular marks. occurrences of $\langle C2, C2, C2\rangle$ appear only at the beginning of the sequence.

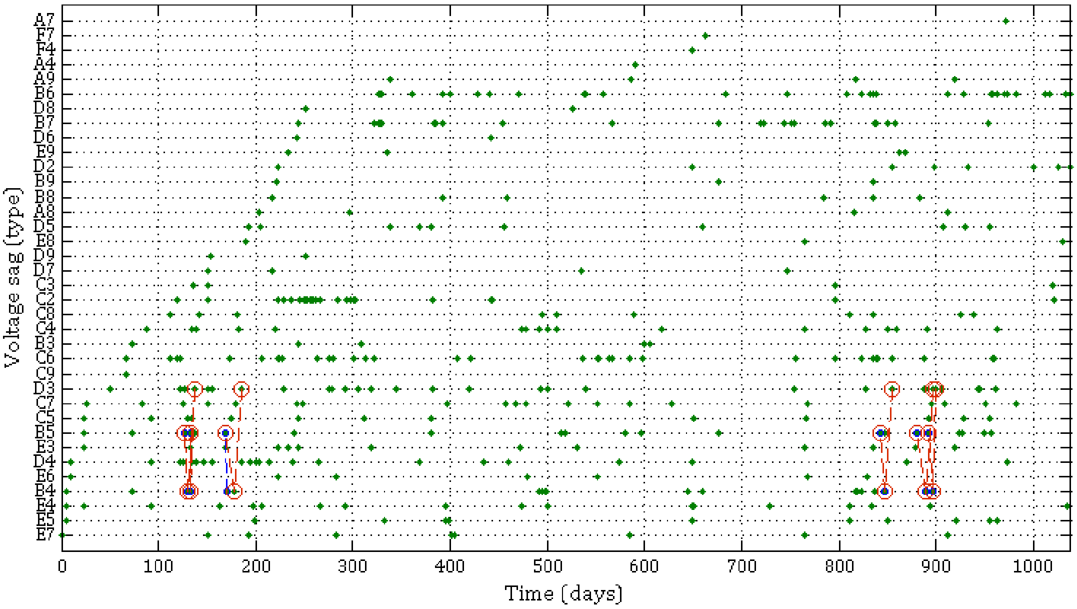


Figure 4.17: Sequence of voltage dips and occurrences of episodes $\langle B5, B4 \rangle$ and $\langle B5, B4, D3 \rangle$.

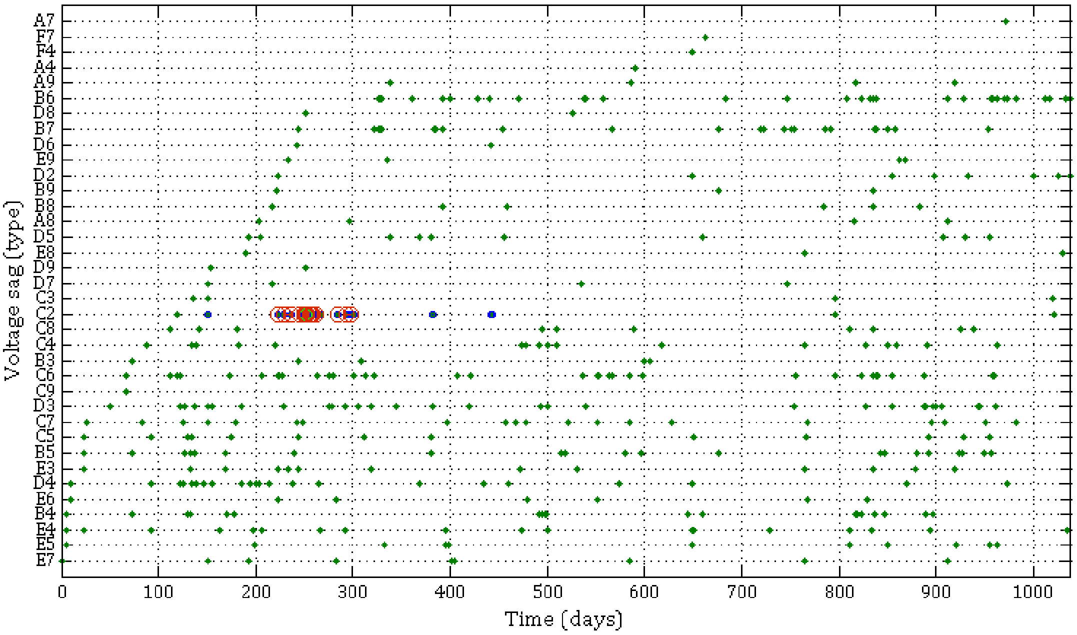


Figure 4.18: Sequence of voltage dips and occurrences of episodes $\langle C2, C2 \rangle$ and $\langle C2, C2, C2 \rangle$.

4.4 Conclusions

Sequences of voltage dips recorded in a power distribution network were analysed in order to find causal associations between events. Two types of regularities were discovered in this sequences. The first one involves the elapsed time between voltage dip events, while the second associates voltage dips starting from their magnitudes and durations.

Elapsed times between voltage dip events can show reclosing settings of the protective system. In power distribution networks, protective system usually have scheduled two automatic reclosing for clearing a fault. For the sequences studied in this work, results show that over 60% of the occurrences of the first automatic reclosing are followed by a second automatic attemp. Likewise, for over 80% of permanent faults (single-phase faults), the two automatic reclosing attempts are performed.

Magnitude and duration of voltage dips reflect the fault location in the network. Network areas prone to fault occurrences can be found from frequent episodes composed by similar voltage dips closed in time. Also, possible causal interactions between faults of the network could be found from frequent episodes composed by several events. These two situations were observed in the analysed sequence. Most frequent episodes found are associated to voltage dips similar in magnitude or they indicate that early events are larger in magnitude than subsequent events. These frequent episodes may show that early events influence the occurrences of subsequent events.

The mining algorithm –Fminevent– developed in Section 2.4, is suitable for the analysis of these sequences of voltage dips. It is able to determine the frequency of episodes without missing or over-counting occurrences. According to the criteria developed in the Section 3.3, serial and parallel frequency values of an episode are key to assess its significance. Nevertheless, each sequence must be analyzed individually to establish the most appropriate parameters related to the threshold frequency and duration of episodes.

5

Pattern discovery in sequences of incidents collected in power distribution networks

Incidents registered in power distribution networks are analysed in this chapter. Utilities use the term incident to indicate the existence of faults or situations that affect the continuity of supply. They are recorded from customer service centers or incidents management systems. Each incident is documented with different attributes such as the occurring date, its cause and its duration. Mining algorithm proposed in Section 2.4 is adapted for the discovery of order relations between main causes of incidents on the network. Methods developed in Chapter 3 are used to identify significant associations between these incidents cause and their physical meaning is discussed.

5.1 Introduction

Environmental conditions, external agents (animals, vegetation, vehicles, etc.) or aging of components are factors that affect the frequency of occurrence of faults and failures in the network. Moreover, depending on the severity of faults, protective systems are automatically fired, affecting continuity and quality of supply in different manner. Utilities usually use the term *incident* to indicate the existence of such misbehaviours (faults and failures) that affect the continuity of supply and are systematically reported together with the activity performed to restore the normal operation of the system (reparation, material substitution, fuse replacement, etc.) (ECO/797/2002, 2002). Examples of incidents are failures in cables produced by moisture or aging and its corresponding reparation, the actuation of protective system in the head of a feeder in presence of lightning followed by a restoration sequence or the automatic reclosing after a branch tree contact in a windy day.

If incidents recorded in a feeder or sector of the distribution network are sorted as a sequence of incidents then the existence of order relations between them can be discovered. The analysis involves the application of frequent episode discovery algorithms as well as the evaluation of the relevance of episodes found. We focus the search on short-term episodes that is set of incidents occurring with a time difference less than a fixed expiry-time, while their inter-event time is not constrained. Episodes that contain representative types of incidents can be identified and the analysis of the occurrence causes can be performed.

5.2 Dataset description

The dataset of incidents available in this research were collected over three years in a real power system by the utility from customer service centers or incidents management systems. Each incident was documented with the occurring date, the main cause (storm, tree, component failure, etc.) and the voltage level where it was originated (medium voltage MV, low voltage LV, etc). Table 5.1 shows a short description of each cause and an alphabet of 15 letters is used to typify each one of them.

Five feeders with large number of incidents were selected for the case study. The incidents occurred in each one of the feeders were analyzed as single sequences and each incident is represented with two attributes: its cause and its corresponding time of occurrence. In case of an incident does not correspond to an interruption of the supply, the corresponding lowercase letter is used. The distribution of the incidents in the five feeders is shown in Table 5.2.

Table 5.2 shows that more than 50% of incidents were caused by unknown causes (f) and they did not originate interruptions in the power supply. For the feeder 1, vandalism (Q) was the second most common cause of fault. In feeder 2 and feeder 5 around 1% of the incidents correspond to component breakdown (H) while in the other feeders, this incident type represents more than 5% of the incidents. Also, feeder

Table 5.1: Types of causes and short description.

Type	Description	Type	Description
A	animals	J	cable falls to ground
B	trees	K	fuse
C	storm/lightning	L	live-line work
D	wind	M	contractor personnel
E	rain	N	individuals
F	unknown	O	excavations
G	overload	P	vehicles
H	component breakdown	Q	vandalism
I	handling to restore supply	R	private facilities
		T	customer connection

Lowercase letters are used when the incident did not cause interruptions (punishable) of supply.

2 and feeder 5 are the most afected by incidents originated in private facilities (R) and incidents with unkown cause (f and F). Feeder 1, feeder 3 and feeder 5 are the most afected by incidents related with supply restoration (i), while feeder 4 is the most afected by melted fuse (K).

5.3 Order relations between main causes of network incidents

For each sequence described in Table 5.2 the frequent episodes are extracted. We focus the search on short-term episodes that are composed by incidents that occurred with a time difference less than the expiry-time, then their inter-event time is not constrained. Frequent episodes are obtained using the mining algorithm Fminevent proposed in Sections 2.4 and 2.4.1.1.

Fig. 5.1 shows for each feeder the number of frequent episodes for several values of expiry-time T_x (between 1 and 20 days) using a $min\_fr = 4$ occurrences. An inter-event time constraint equal to the expiry-time $T_{max} = T_x$ is used for each case.

According to these results, although the sequences of the case study are short sequences, a huge number of frequent episodes are found. This number increases as the time-expiry constraint increases. The number of frequent episodes in feeder 1 and feeder 2 show a similar trend until $T_x = 15$ days, and then both grow exponentially. Feeder 3, 4 and 5 show a similar linear trend for all T_x.

Table 5.2: Types and number of incidents for each feeder in the case study.

Type	Feeder 1		Feeder 2		Feeder 3		Feeder 4		Feeder 5	
	Number	%	Number	%	Number	%	Number	%	Number	%
A					3	1.36	1	0.52		
B	1	0.36	1	0.36						
C			3	1.09	2	0.90	3	1.55	3	1.59
c	1	0.36	3	1.09	1	0.45	2	1.03	1	0.53
D					1	0.45	2	1.03	1	0.53
d			1	0.36	1	0.45	3	1.55	3	1.59
E			2	0.73	2	0.90				
e					2	0.90				
F	12	4.35	28	10.22	11	4.98	12	6.19	4	2.12
f	150	54.35	198	72.26	155	70.14	117	60.31	151	79.89
g	1	0.36								
H	14	5.07	3	1.09	16	7.24	11	5.67	2	1.06
h	5	1.81			2	0.90	1	0.52		
I	5	1.81	3	1.09	6	2.71	3	1.55	1	0.53
i	24	8.70	3	1.09	9	4.07	4	2.06	8	4.23
J					1	0.45				
K			3	1.09	1	0.45	10	5.15	3	1.59
k	1	0.36					1	0.52		
L							4	2.06		
l			3	1.09			6	3.09		
M	2	0.72								
N	1	0.36								
n	1	0.36								
P	1	0.36					3	1.55	1	0.53
Q	49	17.75	1	0.36						
q	6	2.17								
R	2	0.72	19	6.93	8	3.62	8	4.12	11	5.82
r			2	0.73			2	1.03		
t			1	0.36			1	0.52		
Total	276		274		221		194		189	
λ^1	0.25		0.25		0.20		0.18		0.17	

[1] Average rate of incidents per day.

Likewise, Fig. 5.2 shows the number of frequent episodes varying the minimum frequency threshold for a fixed time-expiry of 15 days. Selection of this time-expiry is reinforced by the behaviours of feeders 1 and 2 observed in Fig. 5.1. The exponential grow in the number of frequent episodes seems to be given by the random combination

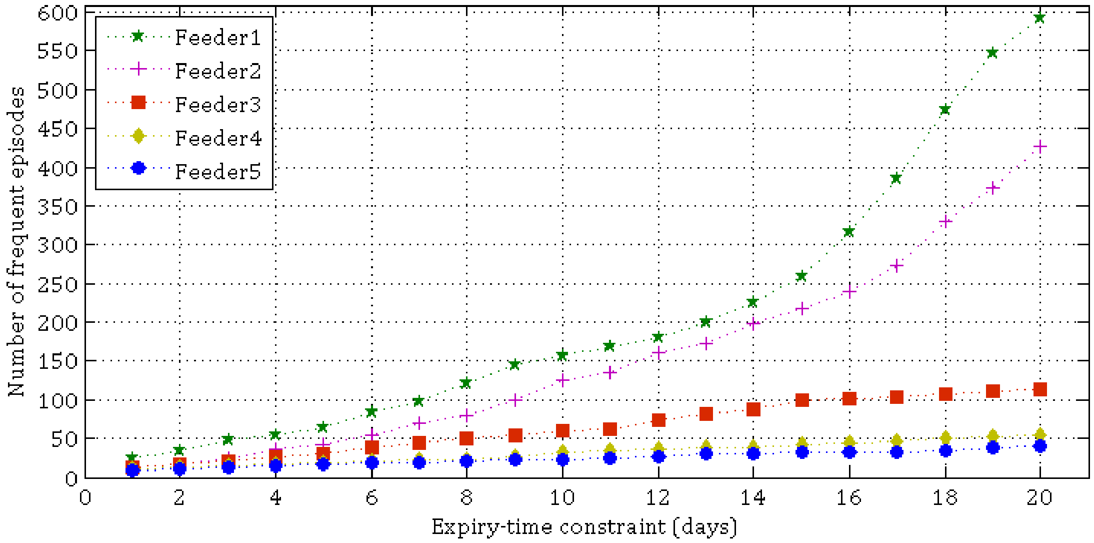


Figure 5.1: Number of frequent episodes found in each feeder for several values of expiry-time, $min\_fr = 4$ occurrences.

of independent and frequent causes of incidents. The objective is to identify frequent episodes that are not given by random combination of frequent causes of incidents, but specific situations linked to the ordered occurrence of the incidents in the episode. Fig. 5.2 shows, for each feeder, that the number of frequent episodes decreases exponentially as the threshold (min_fr) increases. The plot suggests a threshold for feeder 1 and 2 around $min\_fr = 4$ while for feeder 3, 4 and 5 is around $min\_fr = 3$. From these values further, the number of frequent episodes that are found stabilizes with independence of the threshold.

As it occurs with the time-expiry constraint, the maximal gap between events (inter-event time constraint) influences on the number of occurrences found for each episode and also on the total number of frequent episodes. So, if the maximal gap between incidents increases also the number of frequent episodes increases. Table 5.3 shows the total number of frequent episodes discovered in the sequences for several values of maximal gap using a time-expiry constraint of 15 days. In the table these maximal gaps are expressed as fractions of time-expiry, 0.2, 0.4, 0.6, 0.8 and 1, which are equals to 3, 6, 9, 12 and 15 days, respectively. According to the observations in Fig. 5.2, two minimum threshold were used: $min\_fr = 4$ for feeder 1 and 2 and $min\_fr = 3$ for feeder 3, 4 and 5.

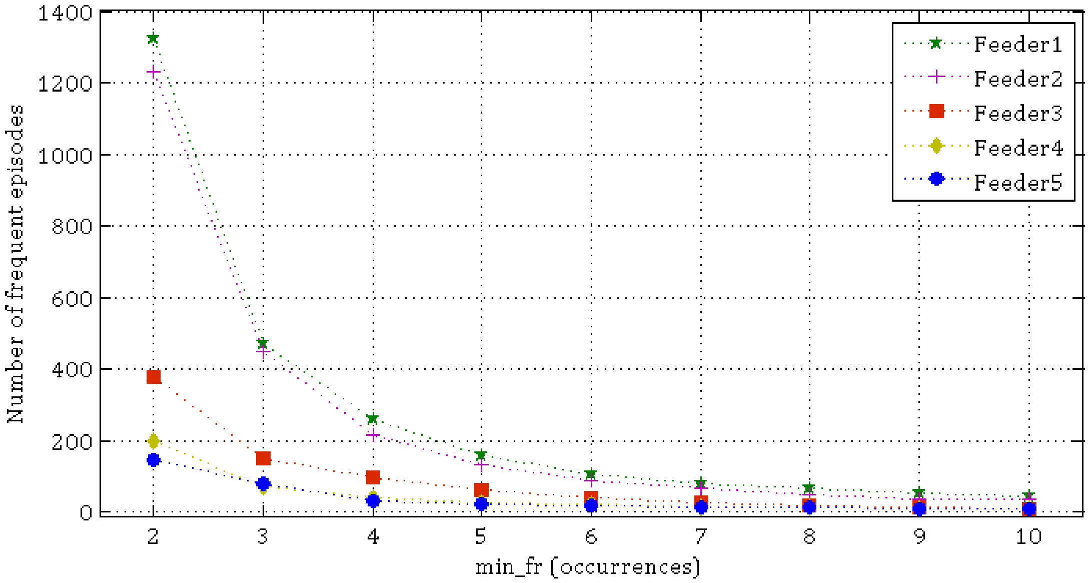


Figure 5.2: Number of frequent episodes found in each feeder for several values of min_fr and $T_x = 15$ days.

Table 5.3: Number of frequent episodes found in the sequences for several values of maximal gap.

Sequence	Maximal gap as fraction of the expiry-time $T_x = 15$ days				
	0.2	0.4	0.6	0.8	1
Feeder1 [1]	60	143	209	235	260
Feeder2 [1]	67	151	201	212	217
Feeder3 [2]	34	116	138	152	152
Feeder4 [2]	30	53	61	70	73
Feeder5 [2]	27	34	66	75	79

[1] With 4 occurrences as minimum threshold.

[2] With 3 occurrences as minimum threshold.

5.4 Significant order relations between main causes of network incidents

According to the distribution of the incidents in the different feeders shown in Table 5.2, the most frequent incidents are associated to unknown causes (type f), which means that the majority of frequent episodes that are mined probably involve this type of incident. However, this is an incident type that has not significant information. This fact can mask other relevant episodes, less frequent but related with known causes. So, excluding the incident type f in the candidate generation step (see Section 3.2.3.1) and using $min\_fr = 4$ for feeder 1 and 2 and $min\_fr = 3$ for feeder 3, 4 and 5, the number of frequent episodes (last column of Table 5.3) are reduced to 31, 6, 10, 13 and 7 for each feeder, respectively. This number represent less than 10% of the total frequent episodes found when the incident f was included in the search. Table 5.4 shows the maximal frequent episodes (Definition 3.3) for each feeder avoiding the influence of the incident type f.

Table 5.4 contains for each episode the corresponding values of cohesion, confidence and backward-confidence indexes, which are calculated from the definitions in Chapter 3. If the episodes with higher value indexes (> 0.5) in this cited parameters are considered as patterns, then only the episodes $\langle i, H, i\rangle$ for feeder 1 and $\langle F, F, F\rangle$ for feeder 2 could be extracted. The pattern $\langle i, H, i\rangle$ shows that handling to restore the supply i usually involves the breakdown of components H. The pattern $\langle F, F, F\rangle$ shows that successive incidents of unknown cause F (interruption of the supply of unknown cause) are frequent. The plot of the occurrences of these patterns for each sequence is shown in Fig. 5.3 and Fig. 5.4.

Likewise, it can be observed that in three feeders (1, 3 and 4) where incidents caused by components breakdown H were frequent, the episode $\langle F, H\rangle$ also was frequent. This relation shows that incidents caused by component breakdown usually are preceded by an interruption of the supply of unknown cause.

5.5 Relative location of the incidents within the frequent episodes

An analysis of the relative location of the incidents within the frequent episodes is presented in this section as a validation of the patterns found. The aim is to know if a preferred location of certain types of incidents within the episodes exists. For example, if the component breakdown usually is the *final event* of an episode or if unknown incidents are the start events of the episodes. This analysis could help to establish the most probably association that can perform an incident, i.e., if an incident has a

Table 5.4: Maximal frequent episodes (excluding the incident type f) and their corresponding values of of cohesion (coh), confidence ($conf$) and backward-confidence ($conf_B$).

Feeder	Episode	fr	fr_p	coh	$conf_B$	$conf$
1	$\langle i, I\rangle$	4	4	1.00	0.80	0.17
	$\langle i, F\rangle$	5	5	1.00	0.42	0.21
	$\langle H, I\rangle$	4	5	0.80	0.80	0.29
	$\langle H, Q\rangle$	6	9	0.67	0.12	0.43
	$\langle h, i\rangle$	4	5	0.80	0.17	0.80
	$\langle Q, H\rangle$	7	9	0.78	0.50	0.14
	$\langle Q, F\rangle$	6	10	0.60	0.50	0.12
	$\langle Q, q\rangle$	4	5	0.80	0.67	0.08
	$\langle F, H\rangle$	4	4	1.00	0.29	0.33
	$\langle F, Q\rangle$	7	10	0.70	0.14	0.58
	$\langle i, i, i\rangle$	4	4	1.00	0.40	0.40
	$\langle i, i, H\rangle$	4	7	0.57	0.67	0.40
	$\langle i, i, Q\rangle$	5	8	0.63	0.45	0.50
	$\langle i, H, i\rangle$	4	7	0.57	0.80	0.67
	$\langle i, Q, i\rangle$	4	8	0.50	0.31	0.36
	$\langle Q, i, i\rangle$	5	8	0.63	0.50	0.38
	$\langle Q, Q, i\rangle$	4	7	0.57	0.31	0.24
	$\langle Q, Q, Q\rangle$	8	8	1.00	0.47	0.47
2	$\langle F, R\rangle$	8	12	0.67	0.42	0.29
	$\langle R, F\rangle$	6	12	0.50	0.21	0.32
	$\langle F, F, F\rangle$	6	6	1.00	0.60	0.60
3	$\langle H, i\rangle$	6	6	1.00	0.67	0.38
	$\langle H, H\rangle$	5	5	1.00	0.31	0.31
	$\langle H, I\rangle$	5	5	1.00	0.83	0.31
	$\langle F, H\rangle$	3	4	0.75	0.19	0.27
4	$\langle K, K\rangle$	3	3	1.00	0.30	0.30
	$\langle F, H\rangle$	3	3	1.00	0.27	0.25
5	$\langle R, R\rangle$	3	3	1.00	0.27	0.27

forward or backward association with other frequent incidents in a sequence as it was discussed in Section 3.2.3.

Whit this aim, for each incident type, the corresponding number of occurrences and location within the episodes are counted and classified. Two main categories are used to classify the location of each incident type: *start* or *final event*, percentage of total occurrences where the incident is located at the beginning or end of the episodes and

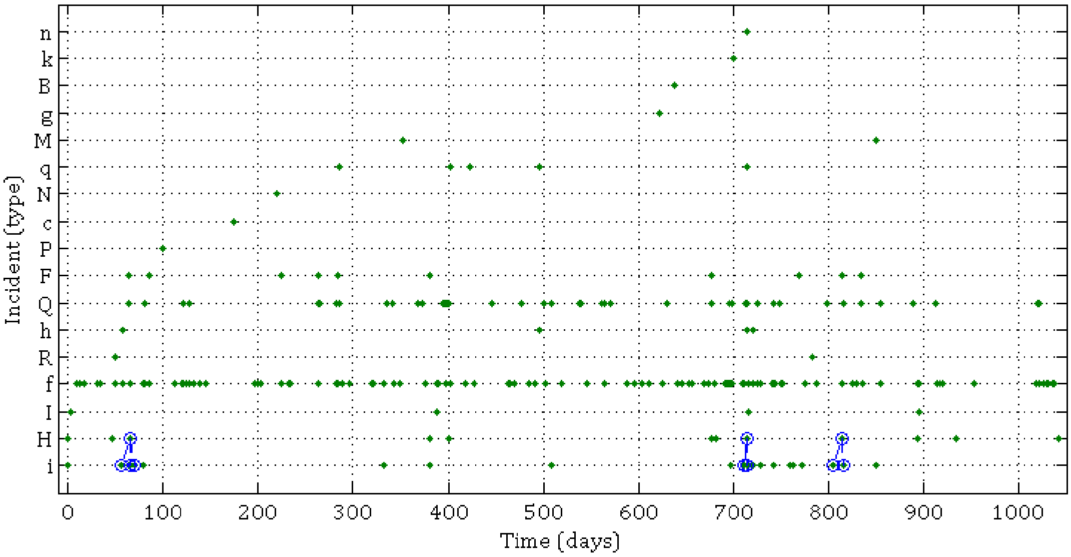


Figure 5.3: Sequence of incidents of feeder 1 and occurrences of pattern $\langle i, H, i \rangle$.

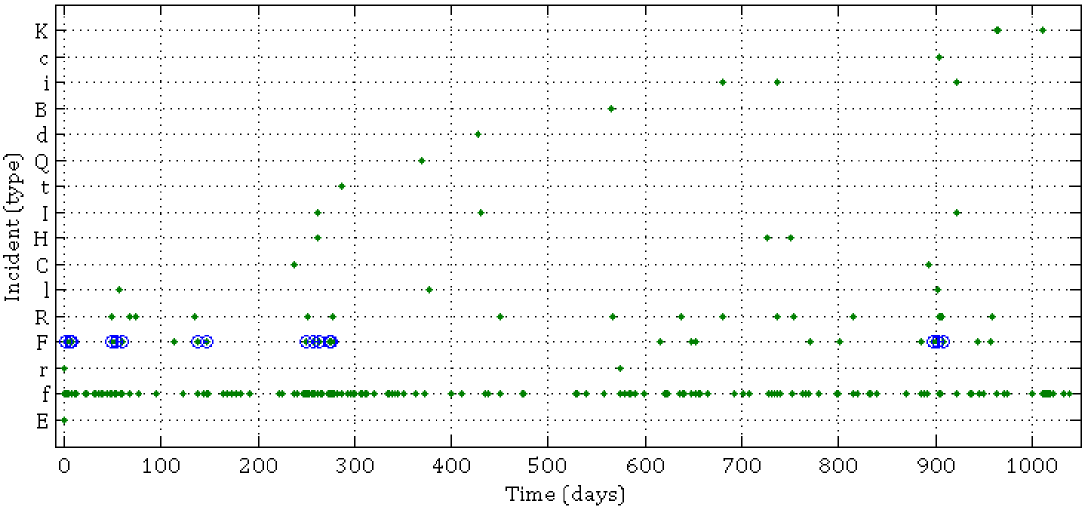


Figure 5.4: Sequence of incidents of feeder 2 and occurrences of pattern $\langle F, F, F \rangle$.

intermediate event, percentage of occurrences where the incident is located only in the middle of the episode. Table 5.5 shows the evaluation of the relative position of the incidents between the maximal frequent episodes, shown in Table 5.4. For example, the incident by vandalism (Q) in the feeder 1, have 56 serial occurrences considering the 10 maximal episodes where it appears. 92.9% of this ocurrences have Q as the first or the *final event*, being the 60.7% the number of occurrences where it appears as the *first event*, 7.1% of the occurrences it has a intermediate location, while 46.4% times the incident appear as the last event of maximal episodes. The result would show that incidents by vandalism Q could mainly trigger new incidents (the same or different type).

In contrast, the incident type F (interruption of the supply of unknown cause) is located at the beginning or at the end of the occurrences in similar proportion (50%). Then, a role of this incident in the beginning or conclusion of episodes can not be identified.

Table 5.5: Relative location of the incidents within the maximal frequent episodes.

Feeder	Frequent incidents	Maximal Occurrences	*Start* or *Final event* %	*Start event* %	*Final event* %	Only *intermediate event* %
1	Q	56	92.9	60.7	46.4	7.1
	i	43	100.0	69.8	58.1	0.0
	h	4	100.0	100.0	0.0	0.0
	H	29	86.2	34.5	51.7	13.8
	F	22	100.0	50.0	50.0	0.0
	I	8	100.0	0.0	100.0	0.0
	q	4	100.0	0.0	100.0	0.0
2	F	20	100.0	70.0	60.0	0.0
	R	14	100.0	42.9	57.1	0.0
3	F	3	100.0	100.0	0.0	0.0
	H	19	100.0	84.2	42.1	0.0
	i	6	100.0	0.0	100.0	0.0
	I	5	100.0	0.0	100.0	0.0
4	K	3	100.0	100.0	100.0	0.0
	F	3	100.0	100.0	0.0	0.0
	H	3	100.0	0.0	100.0	0.0
5	R	3	100.0	100.0	100.0	0.0

The main results of the role of the incidents in the episodes, according to the Table 5.5 are: for feeder 1, the incidents types Q (vandalism) and h (component breakdown without interruption of the supply) are related with the beginning of episodes, while incidents type H (component breakdown), I (handling to restore the supply) and q (vandalism without interruption of the supply) are related with the termination or completion of episodes. For feeder 2, none of the two types of incidents show a preferred location within the maximal serial episodes. For feeder 3, F (unknown) and H (component breakdown) are related with the start of episodes while i and I (handling to restore the supply) are related with the termination of episodes. For feeder 4, F (unknown) is probably related with the beginning of episodes, while H (component breakdown) show the termination of episodes. Finally, for feeder 5, only a maximal serial episode with two incidents of the same type was found and conclusions about its preferred location can not be extracted.

5.5.1 Backward association of the incident by component breakdown

The incident type *component breakdown* (H) is a frequent cause of incidents in feeders 1, 3 and 4 while in feeders 2 and 5 is infrequent. The results of Table 5.4 and according to Table 5.5, show that this incident type usually is located as *final event* of frequent episodes. Then, a search for incidents that usually precede the occurrence of a component breakdown can be performed in feeders 1, 3 and 4, in order to diagnose the probable causes of their occurrence.

Table 5.6 contains the set of episodes with the backward associations (BA) of H, obtained from the frequent episodes as exposed in Section 3.2.3.3. Each frequent episode contains the information about their serial and parallel frequency, and their corresponding cohesion (coh), confidence ($conf$) and backward-confidence ($conf_B$).

Table 5.6: Frequent episodes that end in component breakdown (H) for the Feeders 1, 3 and 4.

Feeder	Episode	fr	fr_p	coh	$conf_B$	$conf$
1	$\langle H\rangle$	14				
	$\langle i,H\rangle$	6	7	0.86	0.43	0.25
	$\langle Q,H\rangle$	7	9	0.78	0.50	0.14
	$\langle F,H\rangle$	4	4	1.00	0.29	0.33
	$\langle i,i,H\rangle$	4	7	0.57	0.67	0.40
3	$\langle H\rangle$	16				
	$\langle H,H\rangle$	5	5	1.00	0.31	0.31
	$\langle F,H\rangle$	3	4	0.75	0.19	0.27
4	$\langle H\rangle$	11				
	$\langle F,H\rangle$	3	3	1.00	0.27	0.25

For feeder 1, only three types of incidents i (handling to restore the supply), Q (vandalism) and F (unknown cause) precedes the apparition of component breakdown H. The value of $conf_B$ of the episode $\langle Q, H\rangle$ indicates that H is preceded by a Q the 50% of the time ($conf_B = 0.5$). The 43% of the time H is preceded by i and only the 29% ot the time it is preceded by F.

For the other feeders 3 and 4 again the incident type F(unknown cause) precedes the apparition of component breakdown H, in both cases with low backward-confidence, 0.19 and 0.27 for each feeder, respectively.

This information can be useful to support diagnostic decisions because once an incident has occurred then the previous incidents occurred can be estimated and verified.

5.6 Frequent episodes obtained by the algorithm of total frequency measure

Frequent episodes were also obtained using the total frequency measure described in Section 2.3.2.1 (Iwanuma et al., 2005). However, the number of parallel occurrences of each episode is required in order to calculate its cohesion (Equation 3.7). Since, the cited algorithm was formulated only for serial episodes, the adaptation proposed in this thesis (see Section 2.3.2.1) to count parallel occurrences, is used.

Analogously to the experimentation with the method based on individual occurrences of the events (Fminevent), results were obtained for several values of window length win (between 1 and 20 days) with a fixed minimum threshold ($min\_fr = 4$ occurrences) and for several values of the min_fr (2 to 10 occurrences) and a fixed window length ($win = 15$ days) as shown in Fig. 5.5 and Fig. 5.6, respectively.

In both cases Fig. 5.1 vs. Fig. 5.5 and Fig. 5.2 vs. Fig. 5.6, the number of frequent episodes obtained by the method of total frequency measure is greater than those obtained by the proposed method Fminevent. This is due to the fact that the method of total frequency measure counts redundant occurrences. However, the general trend in the number of frequent episodes found is similar for both algorithms.

Frequent episodes with $min\_fr = 4$ for feeder 1 and 2 and $min\_fr = 3$ for feeder 3, 4 and 5, within a observation window of 15 days, are evaluated. The parameter values of min_fr and observation window length are the same used in Section 5.4. So, excluding the incident type f in the candidate generation step (see Section 3.2.3.1) and

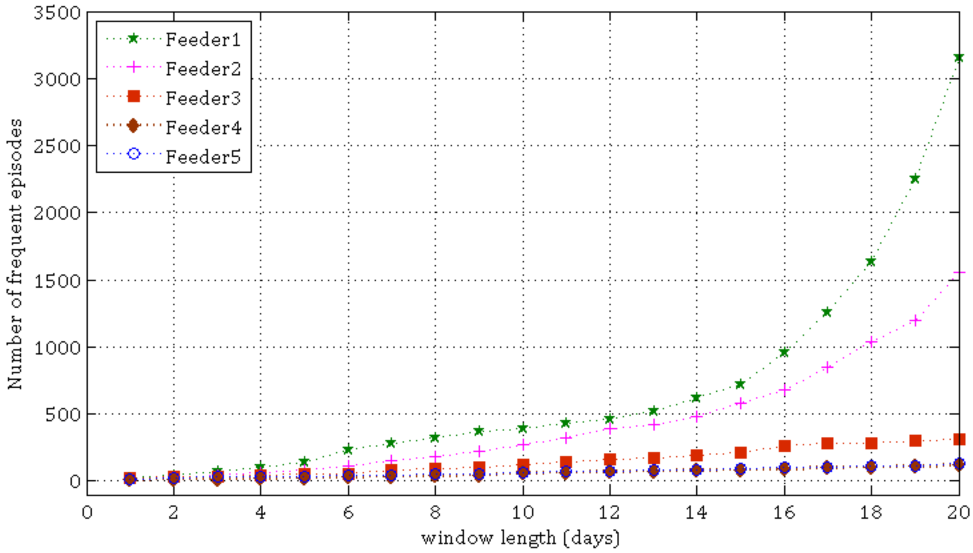


Figure 5.5: Number of frequent episodes found in each feeder for several values of the window length and a fixed $min\_fr = 4$ occurrences.

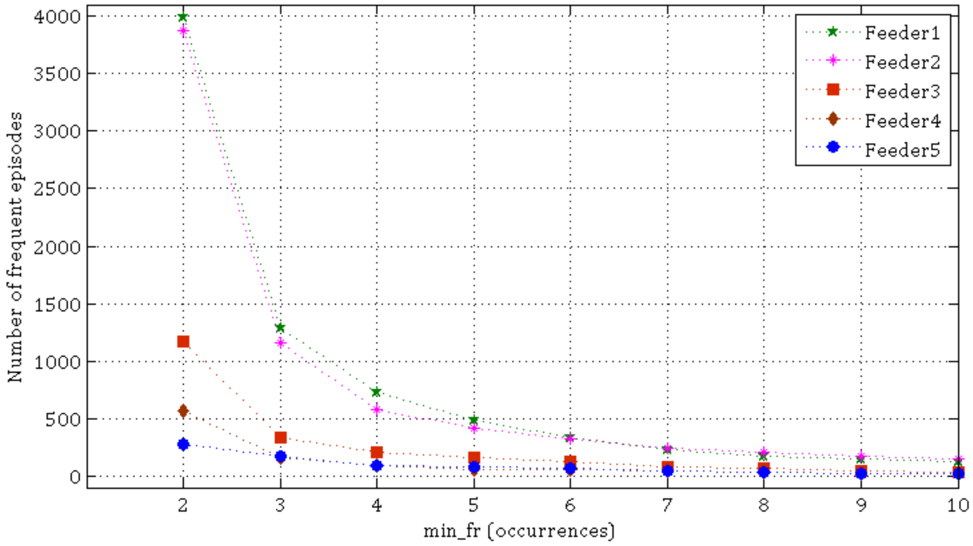


Figure 5.6: Number of frequent episodes found in each feeder for several values of the min_fr and a fixed window length $win = 15$ days.

using the cited parameters, the number of frequent episode are reduced to 52, 10, 14, 15 and 7 for each feeder, respectively. This number of frequent episodes is similar to that found in Section 5.4 except for feeder 1 where 31 frequent episodes were found using the method of Fminevent.

Table 5.7 shows the maximal frequent episodes (Definition 3.3) for each feeder excluding the incident type f. Likewise, for each episode, the corresponding values of cohesion, confidence and backward-confidence are shown.

Table 5.7: Maximal frequent episodes found excluding the incident type f.

Feeder	Episode	fr	fr_p	coh	$conf_B$	$conf$
1	$\langle F, Q \rangle$	8	12	0.67	0.16	0.67
	$\langle i, i, Q \rangle$	5	15	0.33	0.33	0.33
	$\langle i, i, F \rangle$	4	8	0.50	0.44	0.27
	$\langle i, H, I \rangle$	4	5	0.80	1.00	0.40
	$\langle i, H, Q \rangle$	4	14	0.29	0.67	0.40
	$\langle i, h, i \rangle$	4	5	0.80	0.80	1.00
	$\langle i, Q, i \rangle$	8	15	0.53	0.50	0.53
	$\langle h, i, i \rangle$	4	5	0.80	0.27	0.80
	$\langle h, Q, i \rangle$	5	5	1.00	0.31	1.00
	$\langle Q, i, Q \rangle$	6	12	0.50	0.40	0.38
	$\langle Q, Q, i \rangle$	7	12	0.58	0.44	0.28
	$\langle i, H, i, i \rangle$	4	6	0.67	1.00	0.80
	$\langle Q, i, i, H \rangle$	4	12	0.33	0.80	0.50
	$\langle Q, i, F, H \rangle$	4	5	0.80	1.00	0.80
	$\langle Q, Q, Q, H \rangle$	5	6	0.83	0.71	0.50
	$\langle Q, Q, Q, q \rangle$	5	6	0.83	0.83	0.50
2	$\langle F, F, F \rangle$	8	8	1.00	0.47	0.47
	$\langle F, F, R \rangle$	5	11	0.45	0.45	0.29
	$\langle F, R, F \rangle$	6	11	0.55	0.60	0.55
	$\langle R, R, F \rangle$	4	5	0.80	0.40	0.80
3	$\langle H, I \rangle$	6	6	1.00	1.00	0.38
	$\langle H, H, i \rangle$	3	5	0.60	0.38	0.50
	$\langle F, H, i \rangle$	3	3	1.00	0.38	0.75
	$\langle F, H, H \rangle$	4	4	1.00	0.67	1.00
4	$\langle K, K \rangle$	3	3	1.00	0.30	0.30
	$\langle K, R \rangle$	3	3	1.00	0.38	0.30
	$\langle F, H \rangle$	3	3	1.00	0.27	0.25
	$\langle L, L \rangle$	3	3	1.00	0.50	0.50
5	$\langle R, R \rangle$	3	3	1.00	0.27	0.27

For feeders 1, 2, 3 and 4, Table 5.7 shows several maximal frequent episodes that are different from those shown in Table 5.4. These additional episodes result from over-counting occurrences with the total frequency method, when windows with the same occurrence are overlapped. Also, this over-count of both series and parallel occurrences, affects the values of cohesion, confidence an backward-confidence of the episodes, which are used to evaluate its significance. For episodes which occurrences are within non-overlapped windows, the same result of Table 5.4 is obtained, for example, episodes $\langle R, R\rangle$ (incidents caused by private facilites) of feeder 5 or $\langle F, H\rangle$ of feeder 4 (incidents by unknown causes precedes the apparition of components breakdown).

If the episodes of Table 5.7 with higher values (> 0.5) in their parameters of cohesion, confidence and backward-confidence are considered as patterns, then the following episodes could be extracted as the most relevant pattern: $\langle i, h, i\rangle$, $\langle i, H, i, i\rangle$ and $\langle Q, i, F, H\rangle$ for feeder 1, $\langle F, R, F\rangle$ for feeder 2, and $\langle F, H, H\rangle$ for feeder 3. Results differ from those obtained in Section 5.4 due to the overestimation in the frequency of episodes.

5.7 Conclusions

Sequences of incidents registered in five feeders of a power distribution network were analysed and order relations between their causes were discovered. More of $> 50\%$ of the incidents reported are of unknown cause without long supply interruptions, which adds difficulty to the sequence analysis because the majority of frequent episodes that are mined involve this type of incident. Then relevant episodes, less frequent but related with known causes are masked. Therefore, the influence in the mining process of this type of incident was avoided by applying the concepts of directed search of episodes developed in Section 3.2.3.1.

Episodes involving breakdown of components were frequent in three of the five feeders analysed. These incidents caused by breakdown of components usually occur after long supply interruptions of unknown cause.

About the role of each type of incident in the episodes, it was found that incidents involving component breakdown and handling to restore the supply are related with the termination or completion of episodes, while incidents caused by unknown cause (interruptions of unknown cause) and vandalism are related with the start of episodes.

The algorithm for frequent episode discovery proposed in Section 2.4 was used in the mining process, but using a maximal expiry-time constraint to adjust the duration of the episodes, instead of the maximal gap between events or inter-event time constraint usual. Results were compared with those obtained by the method of total frequency measure which also uses a maximal expiry-time in the episodes search. Occurrences of the episodes under the proposed method are not over-counted, then a lower number of frequent episodes is obtained and the results are more accurate.

6

Conclusions and future work

This chapter summarises the conclusions obtained as a result of this research. The relevant conclusions are highlighted and discussed, as well as several ideas for future work are proposed.

6.1 Conclusions

The recognising of the existence of faulty behaviours in a power network from the automatic analysis of sequences of events collected in the system is the main objective of this thesis. A data mining approach and knowledge discovery was followed and four subgoals were established to achieve the proposed objective. An analysis of these objectives and the work developed for each of them is presented in this section, as well as the conclusion that can be derived.

The adaptation of existing formalisms to describe sequences of events occurring in power system was the first subgoal. Section 1.5.6 proposes that the condition of each component in a power distribution network is linked –to a greater or lower extent– to the state of other components. This suggested, for example, the use of elapsed time between events as an attribute to describe power events. Then, relationships among faults or events would be found from the analysis of the set of faults monitored in an individual point of the power network. This implies the extraction and selection of adequate features from existing recorders and the use of appropriate mining algorithms and processing techniques capable of identifying useful patterns. The conclusion is that faulty behaviours of a power distribution system can be described from subsets of events that appear as regularities in a sequence of events and can be discovered by the approach of frequent episodes.

The second subgoal was to analyse existing frequent pattern discovery algorithms and propose improvements to focus in power events. In Chapter 2, several methods for frequent episode discovery were reviewed and were classified into two groups: methods based on occurrences and methods based on minimal occurrences. While methods based on minimal occurrences tend to miss occurrences, methods based on occurrences tend to over-count occurrences if they are based on fixed-width windows or to miss occurrences otherwise. In this order, a new algorithm named *Fminevent* to deal with sequences of events recorded in power distribution networks was proposed. This algorithm prevents missed or over-counted occurrences and the anti-monotonicity property of the episodes is fulfilled. Likewise, the method is able to locate and to extract both serial and parallel occurrences with several options to constrain their duration such as inter-event time constraint, expiry-time constraint or a combination of both. The occurrence of faults in a power distribution network has high randomness therefore, flexible algorithms to explore episodes with different characteristics are required in order to find useful patterns.

The third subgoal was to propose new strategies to discriminate significant episodes that are consistent with faulty behaviours in the power system. Frequent sequence pattern discovery approach has been extended towards significant pattern discovery in Chapter 3 from the perspective that frequency can not be the only criterion to discover significant episodes and other order relations among events, as for example precedence, causality or location in an episode have to be considered during the discovery process. In Section 3.2.3, three especial cases were addressed to search episodes focused on specific events: filtering events, forward-association of an event and backward-association of an event. These are useful strategies when dealing with specific objectives mining problems as it happens in power monitoring systems. The first case, filtering events prevents that certain types of events (usually very frequent events) could mask significant episodes. The second case, forward-association of an event, aims finding the existence of episodes triggered by a specific event whereas the third case, backward-association of an event, focuses on discovering antecedents of the specific event. These approaches are of interest for considering the existence of cause-effect relationships among events in an episode.

Likewise, two new indexes named cohesion and backward-confidence to facilitate the evaluation of significant episodes were proposed (Section 3.3). From these two proposed indexes and the confidence of the episodes, a quality factor to assess the significance of frequent episodes was defined in Section 3.2.3. While confidence assess the probability of occurrence of a new episode once its prefix has occurred, the cohesion measures the strength of order relation expressed by the serial episode with respect to other episodes in the sequence containing the same events in different order. Finally, backward-confidence concept is analogous to the confidence but focused on triggering events. It evaluates the importance of the first event with respect to the episode, allowing to discover possible triggering events. Once defined the minimum quality factor that significant episodes must reach, the most important patterns are obtained compressing the significant episode information through strategy of maximal or closed episodes.

Aforementioned contributions have been motivated by the problem of mining sequences of voltage dips and incidents reported by utilities, but they are also applicable to other application domains. So, voltage dips associated to single-phase faults and incidents associated with abnormal operating conditions and collected in different substations and feeders of real power system were used to validate the consistency and benefits of the proposed algorithms and strategies, which was the fourth subgoal of the thesis.

In Chapter 4, from the data set of voltage dips, two types of regularities were discovered. The first one involves the elapsed time between voltage dip events, and the second one associates voltage dips from its magnitude and duration. Elapsed time between voltage dip events reflects reclosing settings of the protective system. In power distribution networks, protective system usually have scheduled two automatic reclosing for clearing the fault. For the sequences studied in this chapter, results show that usually when a first automatic reclosing occurs, a second automatic attempt is also fired. Likewise, during most of permanent faults (single-phase faults), the two automatic reclosing attempts are performed. Moreover, since magnitude and duration of voltage dips reflect the fault location on the network, network areas prone to fault can be found from frequent episodes composed by similar voltage dips closed in time. Also, possible causal interactions between faults located in different regions of the network could be found from frequent episodes composed by events with different magnitude and duration. These two situations were observed in the analysed sequence. Most frequent episodes found are associated to voltage dips similar in magnitude or they show that early events in the episode are less severe than subsequent events. These last episodes may show that early events influence the occurrences of subsequent events.

Likewise, datasets of incidents collected in power distribution networks are analysed and order relations between main causes of incidents in the network were discovered in Chapter 5. Incidents are also a type of dataset usually collected in power distribution networks. The term *incident* is used to indicate the existence of situations that affect the continuity of supply. Such abnormal situations are registered from customer service centers or incidents management systems. They are documented with different attributes such as the occurring date, its probable cause and its duration. For the analysed sequences, most of incidents reported are of "unknown cause" without long supply interruptions, which adds difficulty to the mining process because the majority of frequent episodes that are mined involve this type of incident and relevant episodes, less frequent but related with known causes, are masked. Filtering this type of incident by applying the directed search of episodes developed in Section 3.2.3, episodes involving "breakdown of components" were discovered. These episodes show that "breakdown of components" usually occur after long supply interruptions of "unknown cause", i.e, usually firstly an interruption of "unknown cause" is reported and shortly after (few days) another incident by "component failure" is reported. Moreover, the role of each type of incident in the episodes was analised. Incidents involving "component breakdown" and "handling to restore the supply" were related with the termination or completion of episodes, while incidents caused by "unknown cause" (interruptions of unknown cause) and "vandalism" were related with the start of episodes.

The performed study shows that useful patterns that reveal cause-effect relationships in faulty behaviours can be discovered from sequences of events recorded in power networks. Such knowledge can be exploited to support the power network maintenance through the diagnosis and prognosis of faults, which has benefits to the distribution companies (utilities).

6.2 Future work

Although the initial objectives of these thesis have been accomplished, from the achieved results new research challenges are elucidated in various directions. This section shows several topics that could be extended.

Future research will address the problem of fault prediction using longer sequences of events, developing suitable strategies to define and discover patterns for other faulty situations described in the thesis, such as faults caused by cumulative stress on components or by abnormal operation of equipment. These new strategies will consider, for example, the extraction of patterns from events defined by continuous attributes, such as overvoltage values, overcurrent values, duration or phase angle. Likewise, for implementing the formalism presented in this thesis as part of the tools for event analysis in power distribution networks, strategies are required to properly define the thresholds for both frequent episodes discovery and meaningful patterns recognition.

Moreover, frequent episode discovery constitutes only a small part in the field of mining sequences. Then, sequences of events registered in power distribution networks can be analysed under other topics of the mining sequences such as sequential patterns or correlation mining.

Another challenge arises from the streaming nature of the datasets recorded in power distribution networks, since knowledge discovery techniques described in this thesis assume that the input data are available at invocation. However, in a streaming environment, inputs arrive periodically continuously and newer events may change the results based on older events substantially (Gaber et al., 2010; Gama and Gaber, 2007). Hence, frequent episode discovery algorithms able to work with data streams are required, which must be efficient in space and execution time.

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Appendices

Appendix A

Identification of transient faults in sequences of voltage dips

Identification of a particular type of disturbance in the network via a relay or other monitoring equipment, is mainly based on a predefined pattern. Evaluation of a set of samples of voltage and/or current taken at a certain sampling rate allows to deduce the existence of a particular disturbance. At a different time scale, as was mentioned in Section 1.4.2, known patterns can be used to identify faulty components in high-voltage transmission lines, based on real-time alarms provided during accidents (Liao et al., 2003). The idea is to build a set of patterns based on sequences of alarms fixed during representative incidents and failures. Then, when a new fault occurs, the sequence of alarms generated during the fault is compared with the set of patterns to identify the probable source of the problem.

A similar case is formulated in this appendix to distinguish transient faults from the characteristics of various individual events monitored in the network. As it was introduced in Section 1.5.2, transient faults (temporary and self-clearing faults) can be considered as faults occurred due to independent causes or distinct phenomena, so two or more events (voltage dips) recorded in a short period of time are expected to be different one from each other if they are caused by transient faults.

Given a sequence of voltage dips events $\mathbf{S} = \langle (e_1, t_1), (e_2, t_2), ..., (e_n, t_n) \rangle$, the search strategy proposed for identification of transient fault events consists of comparing each event (e_i, t_i) of the sequence $\mathbf{S}$ with other events (e_j, t_j) within a observation window to verify if similarities with a minimum quantity of them exist or not. So, given an event e_i and an observation window W, the procedure for identification of transient fault events have two main steps:

1. In the first step, the number of similar events of e_i, N_{sim} within W is found:

$$N_{sim}(e_i, W, t_{max}) = \sum_{j=i-k}^{i+k} \delta(dist((e_i, t_i), (e_j, t_j))) \tag{A.1}$$

   where k is half the width of the observation window (in number of events) which is centered in the event e_i as $W(t_{i-k}, t_{i+k})$ with $i - k \geq 0$ and $i + k \leq n$, and t_{max} is a restriction on the maximal elapsed time between e_i and e_j as shown in Equation A.2. The auxiliary function δ in Equation A.1 is defined as:

$$\begin{aligned} &\delta(dist((e_i, t_i), (e_j, t_j))) = \\ &\quad \begin{cases} 1 & \text{if } dist((e_i, t_i), (e_j, t_j)) \leq Th \ \wedge \ |t_i - t_j| \leq t_{max}, \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \tag{A.2}$$

   where Th is the minimum similarity threshold.

   Function $dist()$ in Equation A.2 assess the similarity among two events (e_i, t_i) and (e_j, t_j) from their attributes. Usually, each voltage dip event (e_i, t_i) is described by its magnitude M_i and duration Δt_i. From these two attributes, a Manhattan distance is proposed as similarity measure as it is stated in Equation A.3.

$$dist(e_i(t_i), e_j(t_j)) = \frac{(|M_i - M_j| + |\Delta t_i - \Delta t_j|/max(\Delta t_i, \Delta t_j))}{2} \tag{A.3}$$

   where $dist(e_i(t_i), e_j(t_j)) = 0$ indicates that these two events have the same magnitude and duration that is, the maximum similarity, and $dist(e_i(t_i), e_j(t_j)) = 1$ represent the maximum dissimilarity.

2. In the second step, from result of Equation A.1, the event e_i is labeled as transient fault event E_{Trans}, according to Equation A.4:

$$e_i \rightarrow E_{Trans} \leftrightarrow N_{sim}(e_i, W) \leq N_{max} \tag{A.4}$$

   where N_{max} is the maximum number of similar events for a transient fault within W. For example, if $N_{max} = 0$ means that (e_i, t_i) is a transient fault event if and only if does not exist any similar event within the observation window W, while if $N_{max} = 1$, (e_i, t_i) it is labeled as transient fault event, even if other similar event is found within W.

A.1 Experimental results

The data set of voltage dip events described in Table 4.2 of Section 4.1.1 is analysed as case study. The number of transient and permanent fault events for each sequence, is summarised in Table A.1.

Table A.1: Number and types of events in the sequences of the case study.

Description	Substation				
	S1	S2	S3	S4	S5
Permanent fault events	29	33	96	97	80
Transient fault events	22	39	79	59	18
No documented events	0	18	33	21	9
Total number of events	51	90	208	177	107

For each sequence, the strategy proposed above is used for the identification of transient fault events and results are evaluated by the following parameters: number of transient fault events correctly identified or true detection (TD), transient fault events not detected or missed by detection (MD) and, number of non transient fault events identified as transient or false alarms (FA). The corresponding ratios also computed: true detection rate (TDR = TD/(TD+MD)), missed detection rate (MDR = MD/(TD+MD)) and false alarm rate (FAR = FA/(TD+FA)). This ratios are useful to evaluate the accuracy of the identification. Likewise, several values for the input parameters are tested: $N_{max} = 0, 1, 2, 3$; $k = 1, 2, ..., 4$; $Th = 0, 0.05, ..., 1$ and $t_{max} = 0.01, 0.06, ..., 1.01$ (days).

Table A.2 summarises results obtained for sequence S1. According to this table, using as input parameters $N_{max} = 1$, $k = 1$, Th between 0.2 to 0.5 and t_{max} between 0.16 to 1 days, all transient fault events are identified (TDR=1) but this involves a high rate of false alarms (FAR=0.35). Identification results improve if the following parameters are used: N_{max} equal to 0 or 1, k between 1 to 4, Th between 0.2 to 0.25 and t_{max} between 0.16 to 1 days. In this case, 95.5% of transient event are

Table A.2: Results of the detection of transient faults for sequence S1

N_{max}	k	Th	t_{max}	TD	MD	FA	TDR	MDR	FAR
1	1	0.2 to 0.25	0.16 to 1	22	0	12	1.00	0.00	0.353
0	1	0.2 to 0.25	0.16 to 1	21	1	1	0.955	0.045	0.045
1	2								
	3								
	4								
1	2	0.35 to 1	0.06	20	2	3	0.909	0.091	0.13
	3								
	4								
2	3	0.4 to 1	0.16 to 1						
	4								

correctly identified, only one transient fault event is missed and only one event is wrongly identified as transient.

The best results retrieved for sequence S1 are shown in Fig. A.1. Magnitude and duration of each event is plotted in the top of this figure, and transient fault events are marked with a circle. Information about the type of fault associated with each event is added in the bottom of the figure. It can be observed that events associated with multiple reclosing actions and subsequent manual actuations (permanent faults) have been skipped. Only the event, e_{38}, have been wrongly marked as transient fault event because it is different in duration from their neighbours, while only one transient fault event, e_{26}, was not detected because it is very similar to their neighbours events.

Identification results for sequence S2 are summarised in Table A.3. According to this table, using a similarity threshold of 0.3, 0.15 and 0.1, 79%, 87% and 92% of the transient fault events can be correctly identified with a false alarm rate of 16%, 22.7% and 23%, respectively. A MDR of 0% involves a FAR of 45%.

For sequence S3, identification results of transient fault events are summarised in Table A.4. According to this table, a complete identification of transient events, implies a false alarm rate of 48%. However, this false alarm rate can decrease under 30% with a correct identification of 77% of transient fault events.

Table A.5 summarises the identification results for sequence S4. According to this table, a complete identification of transient events implies a false alarm rate of 30%.

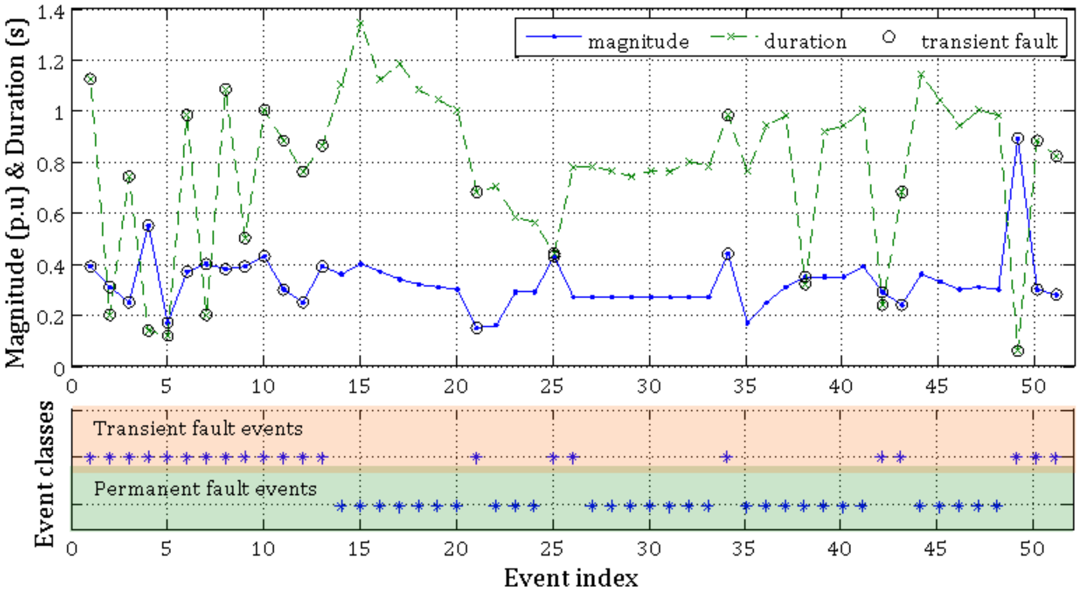

Figure A.1: Transient fault events in the sequence S1.

Table A.3: Results of the detection of transient faults for sequence S2

N_{max}	k	Th	t_{max}	TD	MD	FA	TDR	MDR	FAR
0	1 to 2	0	0 to 1	39	0	33	1.000	0.000	0.458
1	1 to 4								
2	1	0 to 1							
	2 to 4	0							
1	4	0.1	0.26 to 0.71	36	3	11	0.923	0.077	0.234
1	4	0.15	0.26 to 0.71	34	5	10	0.872	0.128	0.227
2	4	0.3	0.41 to 0.71	31	8	6	0.795	0.205	0.162

However, this false alarm rate can decrease under 12% with a correct identification over 84% of transient fault events.

Finally, Table A.6 summarises the identification results for sequence S5. The majority of events in this sequence are due to permanent faults. According to this table, 14 of 18 transient fault events (78%) can be correctly identified but this implies that 17 events are are wrongly identified (FAR=0.55) as transient. These false alarm rate (FAR) can be reduced under 20% with a TDR over 50%.

For all sequences the best identification results are obtained using a similarity threshold between 0.2 to 0.35. The high values of TDR in S1 to S4 show that most

Table A.4: Results of the detection of transient faults for sequence S3

N_{max}	k	Th	t_{max}	TD	MD	FA	TDR	MDR	FAR
2	2	0.05	0.11	79	0	73	1	0	0.480
2	4	0.05	0.11	78	1	59	0.987	0.013	0.431
1	4	0.05	0.11	74	5	48	0.937	0.063	0.393
1	3	0.1	0.11	71	8	39	0.899	0.101	0.355
1	4	0.1	0.11	70	9	36	0.89	0.11	0.34
1	2	0.25	0.11	61	18	24	0.77	0.23	0.28
1	3	0.25	0.06	58	21	24	0.73	0.27	0.29
2	3	0.3	0.16 to 0.46						
1	3	0.25	0.11	57	22	21	0.72	0.28	0.27

Table A.5: Results of the detection of transient faults for sequence S4

N_{max}	k	Th	t_{max}	TD	MD	FA	TDR	MDR	FAR
2	4	0.2	0.06	59	0	26	1	0	0.306
1		0.15		56	3	21	0.949	0.051	0.273
2		0.2	0.31 to 0.46	55	4	16	0.932	0.068	0.225
		0.3		53	6	9	0.898	0.102	0.145
		0.35		52	7	7	0.881	0.119	0.119
	3 to 4	0.4		50	9	2	0.847	0.153	0.038

Table A.6: Results of the detection of transient faults for sequence S5

N_{max}	k	Th	t_{max}	TD	MD	FA	TDR	MDR	FAR
1	2 to 4	0	0.06 to 1	18	0	77	1.00	0.00	0.81
2	2	0.35	0.61 to 1	16	2	38	0.89	0.11	0.70
0	1 to 4	0.3 to 0.35	0.01	14	4	17	0.78	0.22	0.55
	2	0.05	0.76 to 1	10	8	12	0.556	0.444	0.545
	4	0.05	0.36 to 0.56						
	1	0.3	0.46 to 1	9	9	2	0.50	0.50	0.18
		0.35	0.46 to 0.56						

of the transient faults are identified. The identification strategy fails (MD) especially when similar events appear in a short period of time (for example when several transient faults occur during storms). On the other hand, small values of FAR (for example in S1, S2 and S4) show that identification strategy does discriminate well between the events associated with transient and permanent faults. False alarms can occur, especially when the events of a permanent fault do not have similarities in their attributes. This occurs, for example, when fault impedance values change during the fault as in the case of tree contacts.