Predictive Disturbance Management in Manufacturing Control Systems

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Abstract

The manufacturing systems are dynamic, non-linear and often chaotic environments, subject to the occurrence of unexpected disturbances that leads to deviations from the initial plans and usually degrades the performance of the system. The treatment of exceptions and disturbances is one major requirement to the next generation of intelligent manufacturing control systems, that should be able to treat emergency as a normal situation. In this paper, a predictive disturbance management approach that transforms the traditional "fail and recover" practices into "predict and prevent" practices, improving the control system performance, will be presented. The predictive mechanism is based in the frequency analysis of each type of disturbance to find repetitive patterns in their occurrence.

Keywords

Predictive Disturbance Management, Intelligent Manufacturing Systems, Holonic Control, Frequency Analysis.

1 Introduction

The industrial manufacturing systems are dynamic, non-linear and in some sense chaotic environments, where new jobs arrive continuously to the system, and certain resources become unavailable and additional resources are introduced at random times. The occurrence of unexpected disturbances leads to deviations from the initial, optimized plans and usually degrades the performance of the system. In these circumstances, the manufacturing control system should react quickly to the unexpected disturbances, adapting the schedule plans as fast as possible, to improve the manufacturing control system performance.

The concept of disturbance in agile, adaptive systems must take into consideration the fact that if the occurrence of certain unexpected events becomes predictable with the evolution of the system, those events are not really disturbances anymore, and may be scheduled, in the same way predictive maintenance is.

Traditionally, disturbance management mechanisms are purely reactive, i.e. the system only applies corrective procedures when the disturbances occur, Figure 1. In dynamic environments, the disturbance management systems must not only react to each disturbance but also analyze the available data to decide if it was really unpredictable or the result of some unlearned pattern. The introduction of a predictive mechanism, allowing to look for patterns upon the occurrence of disturbances, makes possible to plan in advance the occurrence of future disturbances.

As observation time become longer, it is possible to gain new insights in the stochastic industrial environment, learn and discover knowledge, and some disturbances may become normal, predictable events.

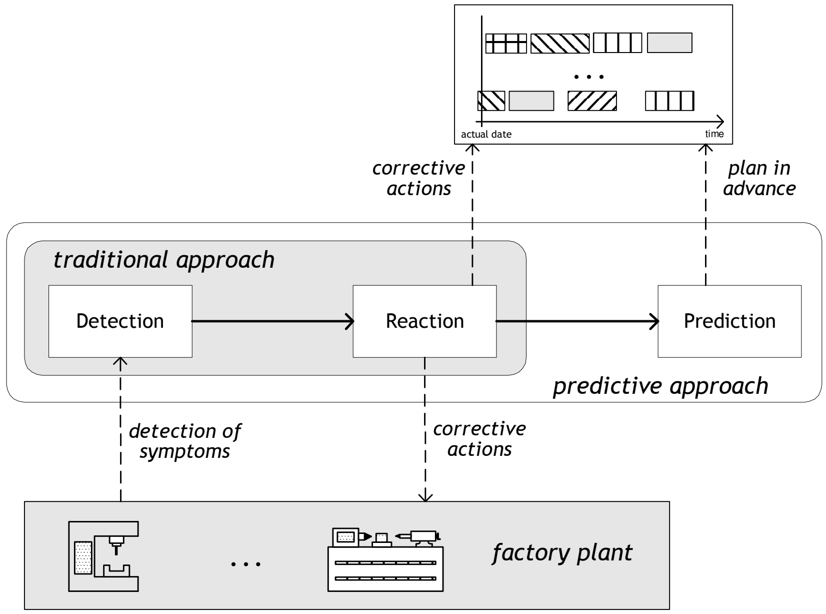

Figure 1: Traditional and Predictive Disturbance Management Approaches

The development of predictive disturbance management systems as part of manufacturing control systems is an open issue and even in the predictive maintenance a generic and scalable prognostic methodology is missing, since the developed approaches are application or equipment specific [Lee, 2004].

In this paper, it is described the predictive disturbance management approach adopted in the ADACOR holonic control architecture (see [Leitão and Restivo, 2002], [Leitão and Restivo, 2004]), based in the frequency analysis of each type of disturbance to find repetitive patterns in their occurrence.

This paper is organized as follows. First, Section 2 analyses the possible types of disturbances that exist at the shop floor and that have impact at the scheduling and planning level. Section 3 introduces the main components of predictive disturbance management systems, discussing mainly the mechanisms for the detection of symptoms and identification of the disturbances and the need for the prediction of occurrence of future unforeseen disturbances, to minimize their effects. Section 4 describes the proposed approach to predictive disturbance management using the frequency analysis concepts. Finally, Section 5 rounds up the paper with the conclusions.

2 Disturbances at Shop Floor Level

A manufacturing disturbance can be defined as an unexpected disruption that affects the production. A typical example of a manufacturing disturbance is a machine breakdown.

The analysis of the main possible types of disturbances that exist in industrial manufacturing environments at the shop floor, particularly those that may cause impact at the scheduling and planning level, is required before a strategy for their handling is developed.

2.1 Classification of Disturbances

In literature the disturbances at shop floor level are classified in different ways, such as described in [Frizelle et al., 1998] that considers upstream, internal and downstream disturbances. In this document the disturbances are grouped in two classes: internal and external.

Internal Disturbances

At the internal level, the disturbances are related to computational failures, operator errors, machine breakdowns, variability in machine performance (quality and production rate), unavailability of labour, layout re-configuration and delays in the material and information flow during the production. The computational failures, such as the failure to access to a database, the failure to open a file or a failure in the network, are not considered in this study, since in principle it would be possible to recover automatically from the errors and they should not cause large impact in the system.

The **machine breakdown** and **unavailability of labour** cause the unavailability of the resources to execute work orders, leading to the decrease of production capacity and normally to the decrease of throughput. A machine failure can occur due a tool collision, a broken tool or a mistake in the machine program, leading to a temporary out of service status of the machine, which becomes unable to accomplish the allocated work orders during the downtime.

The reaction to a failure in a physical resource is dependent of the capability of repairing the failure. The non-repairable components, such as electric bulbs or PC memories, are replaced in the minimum amount of time. In this class are included expensive parts that are replaced and subsequently repaired. The repairable components are those that it is economically satisfactory to repair after the occurrence of a failure, such as a robot or a machine-tool, being economically not feasible to keep in stock for immediate replacement. In the context of this work, only repairable components will be considered.

The effects of a machine failure may be reflected in the part, which can be destroyed or not, and in the machine itself, which can be physically damaged or ready to continue the service. The state of the part and of the machine will determine the type of reaction to the failure. In general, the failure leads to problems at the scheduling and planning level, with secondary disturbances related to the work order delay and layout re-configuration. The action plan in this case is to repair the machine, if necessary, and in parallel to find out alternative solutions to reduce the deviation from the initial plan, while the machine is out of service.

The **quality inspection** can lead to the detection of parts that not respect the quality requirements of the product, due to operator errors or the variability of machine performance, requiring the need to execute a corrective maintenance intervention in the defective machine. Additionally, the parts that do not obey to the quality requirements may be rejected, being necessary to execute other parts.

The **layout re-configuration** is the re-organization of the manufacturing resources available in the factory plant, due to the addition of a new resource or the removal of a resource. The addition of a resource causes small impact in the system, because it increases the number of alternative solutions for the execution of production orders. The removal of a resource leads to a more complex problem, since it may introduce conflicts in the system. In this case, the work orders allocated to the unavailable resource should be re-allocated to other available resources.

External Disturbances

At the external level, the disturbances are usually related to delays by suppliers in the delivery of raw materials or semi-finished parts, rush orders, cancellation or changes in existing orders, forecasting errors and demand variations.

The **delay** causes the need to re-schedule, delaying all production orders related to the delayed purchased order, and allowing the re-scheduling of all other production orders, trying to use the gaps open by the delayed orders.

The **cancellation** of a production order or work order may be due for example to a cancellation from the customer or to a failure that provoked the destruction of the part. This disturbance causes small impact in the system, because it is only necessary to release the work orders already allocated and to re-schedule the other work orders in order to optimize the local schedule, respecting the constraints related to the earliest and due dates.

The modification of the order attributes, such as the change of temporal window to produce (earliest and due dates), may lead to a more complex problem, requiring the need to re-schedule all work orders.

The **introduction of rush orders** implies re-scheduling, to insert the production order in the schedule, attending to earliest and due dates. This type of disturbance is a problem when it leads to temporal conflicts with other already allocated work orders or when it is a high priority work order.

2.2 Impact of Disturbances in the System

An important issue when analyzing a disturbance is the assessment of its potential impact on production performance indicators. The impact of the disturbance is related to the propagation of the disturbance in the system and the associated consequences. Measuring the appropriate performance parameters (according to the production goals), it is possible to obtain an indicator about the impact of the disturbance in the system, and also to compare the impact provoked by different types of disturbances.

The level of impact is dependent of the type of disturbance and the physical and temporal conditions.

In terms of the disturbance type, each event will lead to specific consequences in the system, requiring different actions to be executed. As an example, the addition of a resource has lower impact in the system than the occurrence of a failure in a machine.

The physical location of the disturbance is critical in the definition of the impact, since a disturbance occurred in a critical path (bottleneck) has higher impact than a disturbance occurred in a machine with alternative paths.

At last, the level of the impact of the disturbance is also dependent of the moment in time when a disturbance occurs. As an example, the impact of a failure in a machine is higher when the agendas are full or alternative resources are out-of-service.

3 Predictive Disturbance Management

Traditionally, the disturbance management mechanisms are purely reactive, i.e. the system only applies corrective procedures when the disturbance occurs. The improvement of the disturbance management, by planning the production in advance, requires the existence of a predictive mechanism that estimates the occurrence of disturbances.

In these circumstances, the predictive disturbance management comprises the detection of disturbances, the reaction to the disturbance and the prediction of future disturbances.

In the following sections, each component of the predictive disturbance management will be briefly described.

3.1 Detection and Identification of Disturbances

The detection of disturbances is based in the discovery of symptoms that reveal the presence of a disturbance. A symptom can be a work order delay, a rush order, a quality problem, but also an unexpected value in a sensor, such as high temperature in a component or high wear in a cutting tool. The detection of symptoms can be done using passive monitoring and/or active notification mechanisms.

The active notification is a rule-base mechanism implemented in each intelligent component, that notifies the entities that have subscribed to a specific event when the event occurs. These mechanisms can be used to detect failure symptoms in the physical manufacturing machines (which requires the implementation of event notification features in the virtual resource that represents the real manufacturing resource), work order delays inside the factory and in deliver of materials by suppliers (which requires the subscription of active notification in an inter-enterprise platform) and problems with production quality parameters (which requires active notification by the quality management system).

The detection of symptoms using active notification is not possible if the available platforms do not provide active notification mechanisms. Passive monitoring can be used as an alternative to active monitoring, to overcome this problem. In this case, critical performance parameters are continuously monitored using sensors. The unit processing the collected data will trigger the detection of a disturbance when a performance parameter drops below or goes above a certain threshold value.

The detection of symptoms does not lead directly to the occurrence of a disturbance, but it is necessary to isolate the symptoms and to make a clear diagnosis to identify its presence.

Once the disturbance is detected and identified, the control system may react properly by taking corrective actions, according the type of disturbance.

3.2 Why to Predict Future Disturbances?

The estimation of the expected time for the occurrence of the next disturbance allows to plan in advance the occurrence of the disturbance, for example by planning predictive maintenance operations according to the production convenience, or by reserving empty capacity according to the expected time to recover from the disturbance.

A pertinent question related to the disturbances is if they are really disturbances or just normal situations in the system, which have not been previously envisaged. Real disturbances are those that result from unpredictable events. Additionally, an event can be a disturbance at one moment, but in the future may become a normal event. As an example, illustrated in Figure 2 where each one of lines is a unit impulse that represents the occurrence of a disturbance, the events of type e_1 seem to be disturbances, since they are not predictable in the analyzed time window, but the events of type e_2 are considered disturbances only at the beginning of the period, since with the increase of the number of occurrences it is possible to recognize a pattern and to extract the frequency of occurrence, allowing to predict future occurrences.

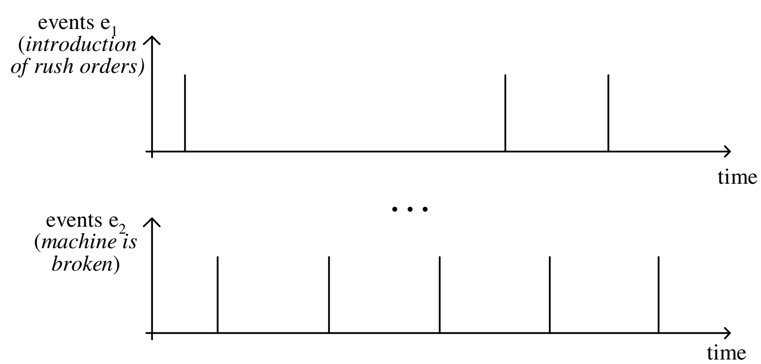

Figure 2: Example of a Range of Unexpected Events

The control system should be able to analyze the events and decide when an event is a real disturbance or a normal situation, using appropriated learning mechanisms. The objective is to find patterns in the occurrence of disturbances hidden under the stochastic behaviour of an industrial environment, so that the occurrence of future disturbances becomes predictable and may be planned in advance, instead of reacting to their occurrence.

3.3 How to Predict Disturbances?

The prediction of occurrence of future disturbances involves complex analysis tools since some disturbances are not purely random processes, but obey to some hidden patterns that may be difficult to identify.

In manufacturing systems it is normally possible to define the Mean Time Between Failures (MTBF) that provides the indication of the mean time a machine is operational between two consecutive failures, and allows forecasting the occurrence of the next disturbance.

However, the use of this simple average to forecast the future occurrence of disturbances can lead to unsatisfactory results, since it is possible to have complex patterns in the historic events that are not characterized by a simple average. Additionally, in the manufacturing domain different types of disturbances are handled, besides machine failures, requiring different models to represent the disturbance sequence. This implies the use of more complex processing that does not simply memorize the incoming information but understands and interprets the information supplied by the environment.

The recognition of patterns in historical disturbance data can be supported by several other available approaches, and some of them has been applied to predict or make prognostics about the failures in mechanical machines, such as time-frequency analysis [Cohen, 1995], Bayesian probability theory, neural networks [Pham and Pham, 2001], [Liang et al., 1988], and unsupervised learning methods [Leitão and Restivo, 2003]. When the manufacturing systems present non-linear and possibly chaotic characteristics, proper analysis tools for dynamic, non-linear systems must be used. As an example, [Leitão and Restivo, 2003] describes an approach for foreseeing the occurrence of future disturbances using an unsupervised learning mechanism based in the statistical clustering technique that predicts the time interval between consecutive disturbances.

4 A Predictive Disturbance Mechanism

In some cases, disturbances are not purely random processes, but they obey to some hidden patterns that may be identified. The prediction of future disturbances is based in understanding the gathered data to find those patterns in the historic disturbance data.

4.1 Prediction using Frequency Analysis

As part of the ADACOR holonic control architecture, the authors suggested a simple mechanism to predict future disturbances based in the frequency analysis of each type of disturbance. Repetitive patterns are revealed by peaks in the Fourier spectrum, which become narrower and more identifiable when the number of events increases. Each peak corresponds to a certain frequency (number of events per time unit), which can be used by the control system to plan in advance their occurrence.

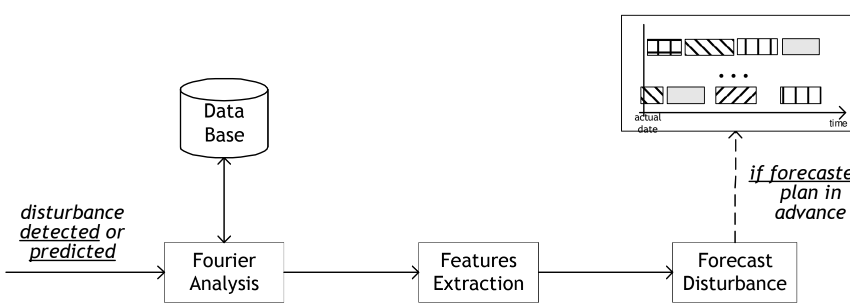

Figure 3: Predictive Disturbance Mechanism

The predictive mechanism is triggered when a disturbance is detected (a predicted disturbance that does not occur is also a disturbance), and the proposed mechanism is applied distinctly for each type of disturbance. The initial step is to store the disturbance information in the data base and to compute the Fourier transform of the historical disturbance information, to extract some features, such as the number of peaks, the intensity of each peak, the peak-to-peak value, the RMS value, etc.

The forecast of future disturbances requires the analysis of the features provided by the Fourier analysis. The disturbance is forecasted by a peak preponderant in relation to the others. When a disturbance is forecasted, a set of actions is triggered aiming to plan in advance the occurrence of the disturbance using the knowledge about the actual status of the production and the normal impact of the disturbance occurrence (known from the historical data).

A complementary learning mechanism learning new knowledge from the past occurrence of disturbances, supporting the tuning of predictive parameters or even deciding to classify some disturbance occurrence patterns as normal behaviour in future production plans, allows improving the performance of the predictive disturbance management.

Figure 4 illustrates the continuously application of the predictive mechanism when an unexpected disturbance occurs.

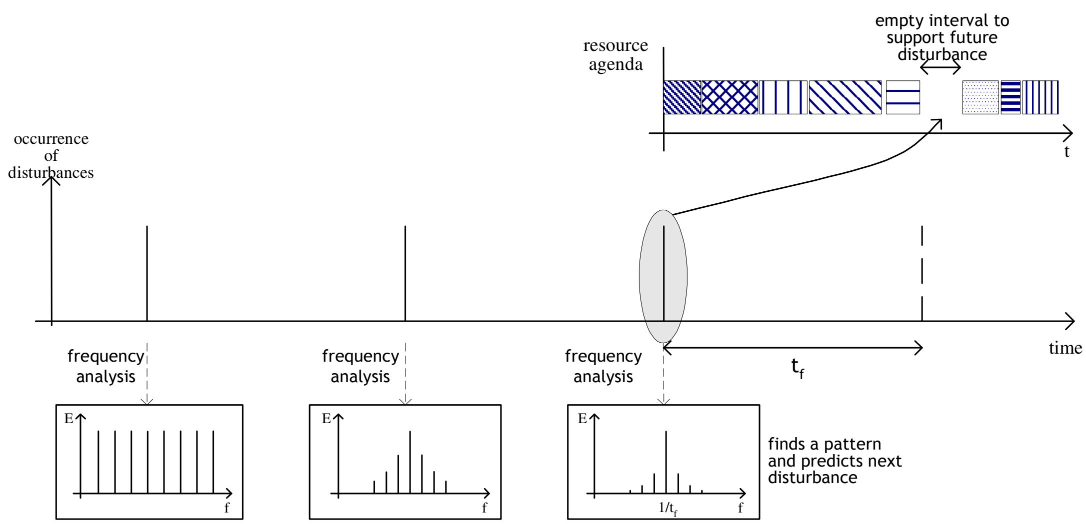

Figure 4: Determination of Disturbance Patterns

The first time a disturbance occurs the Fourier spectrum shows an infinite number of peaks with the same amplitude, which do not allow any conclusion regarding the predictability of the disturbance. If it occurs a second time, the frequency spectrum reveals a central peak but it is not sufficient to make any conclusion. At the third occurrence of the disturbance the Fourier analysis gives a central peak and some other peaks with small amplitude, which reveals the predictability of the disturbance. Using this central peak it is possible to determine t_f, which is the time to the next disturbance, and to plan in advance the production, in this case by leaving an empty space in the resource agenda.

4.2 Planning the Future using Prediction

In planning and scheduling, it is considered that t_f time after the last occurrence of the disturbance, a similar disturbance will happen.

If the disturbance is a machine failure, the control system may plan preventive maintenance operations and (re-)schedule production to minimize its effects. The planning of preventive maintenance operations is done according to the production convenience and based in the historic data. The preventive maintenance operations allows to minimize the occurrence of machine failures and thus avoid the need to use corrective maintenance, which implies to stop the machine and in certain situations to stop the whole production system.

For other types of disturbance, the control system may introduce adequate empty intervals in the schedule, allowing an agile and more effective reaction to the disturbance. The length of those intervals is estimated taking into consideration the average value of previous recovery times for the same disturbance type.

During plan execution two different scenarios can occur: the disturbance occurs and small modifications are required in the scheduling, since the disturbance was already predicted, or the disturbance does not occur, and the prediction mechanism parameters need to be adjusted and the schedule slightly modified, moving work orders backwards to the empty spaces.

5 Conclusions

In industrial manufacturing systems, characterised by stochastic and volatile demand, the occurrence of unexpected disturbances implies the degradation of optimised plans, leading to a decrease of the system performance parameters. In these circumstances, the response to change is a major aspect to consider.

The ADACOR holonic control architecture introduces a predictive mechanism as an extension of the traditional reactive disturbance management approaches, allowing to look for patterns in the occurrence of disturbances, making possible to plan in advance the occurrence of future disturbances.

The use of simple mathematical treatments to analyse the historical disturbance data may lead to unsatisfactory results, since

- the objective is to find patterns in the historic events and not only simple averages,
- in the manufacturing domain the different types of disturbances may have different behaviours,

requiring the use of more complex analysis that do not simply memorise the incoming information but understand and interpret the information supplied by the environment.

In this paper it was discussed the analysis of the system behaviour trying to predict the occurrence of future disturbances using frequency analysis, which could be applicable when there are some underlying periodic phenomena.

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