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# A holonic disturbance management architecture for flexible manufacturing systems

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# A holonic disturbance management architecture for flexible manufacturing systems

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Manufacturing systems are dynamic, non-linear and often chaotic environments, subjected to the occurrence of unexpected disturbances that provoke deviations from the initial plans and degrades the system's performance. Traditionally, disturbance management is performed in a centralised manner, using a fail-fix approach and considering only one type of disturbance, the machine failure. However, the new generation of intelligent manufacturing systems should be able to treat emergencies much quicker and in an effective way, to minimise its negative impact on the production performance. This paper addresses this challenge by introducing a holonic disturbance management architecture based on the ADACOR foundations. The disturbance handling functions are performed in a distributed manner, introducing a predictive dimension to the re-scheduling problem and considering the major types of shop floor disturbances. An experimental implementation was performed and the obtained results showed the applicability of the proposed approach.

**Keywords:** disturbance management; flexible manufacturing systems; holonic systems; multi-agent systems

## 1. Introduction

The manufacturing industry is one of the main wealth generators of the world economy (CMV 1998), generating approximately 22% of the European Union (EU) National Gross Product (ManuFuture 2004). Manufacturing systems are notorious for their complexity and unpredictability, due to the increasing requirements for productivity, flexibility and re-configurability. These systems exhibit complex stochastic and chaotic dynamics, often non-linear, where new tasks arrive continuously to the system, some scheduled tasks may be cancelled or modified, certain machines breakdown, some delays may occur and new products/processes may be introduced.

The occurrence of unexpected disturbances causes deviations in the established plans, and usually the schedules produced by the front office are out of date the moment they hit the (shop) floor (Parunak 1987). Possible consequences of the disturbance occurrences are the degradation of the system productivity and the losing of business opportunities, which are crucial to achieve competitiveness. Traditional manufacturing systems are not prepared to exhibit responsiveness and re-configurability capabilities, since they are

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built upon centralised and hierarchical control structures, which present good production optimisation but a weak response to change due to the rigidity of their control structures. Usually, in these approaches, the shutdown of the system is required when a failure occurs. The current challenge is to develop innovative manufacturing control systems that respond quickly to changes and production fluctuation, without stopping, re-programming or re-starting the process.

Multi-agent systems (MAS) is a suitable paradigm to develop this new class of systems, since they present decentralisation of control over distributed structures, modularity, robustness and autonomy, solving at least 25% of the manufacturing problems (Marik and McFarlane 2005). This paradigm has the capability to respond promptly and correctly to change, and differ from the conventional approaches due to its inherent capabilities to adapt to emergence without external intervention (Wooldridge 2002). Similarly, holonic manufacturing systems (HMS), that translates to the manufacturing world the concepts developed by Koestler for living organisms and social organisations (Koestler 1969), are pyramidal systems based on the concept of holon. A holon is an identifiable part of a manufacturing system, yet is made up of sub-ordinate parts and in turn is part of a larger whole. Several manufacturing control systems using MAS and HMS principles and addressing the above referred requirements were reported in the literature (see Monostori *et al.* 2006 and Leitão 2009 and the references therein).

The work on MAS and HMS is a good framework for the development of the new generation of these systems in the sense that they support re-configurability and agility quite naturally. However, even in these solutions, the disturbance management, which plays a crucial role in a manufacturing control system, is not truly handled. The disturbance management is related to the monitoring, diagnosis, error recovery and re-scheduling functions, as illustrated in Figure 1. It is traditionally performed in a centralised manner, and usually, corrective maintenance procedures are applied when a disturbance occurs, following a fail-fix approach.

Several approaches using the referred emergent paradigms were found in the literature (see Monostori *et al.* 2006 and Leitao 2009 and the references therein). Namely, AARIA (Autonomous Agents at Rock Island Arsenal) used autonomous agents to control a production system focusing on the dynamic scheduling and dynamic re-configuration (Parunak *et al.* 1998) and MASCADA (Manufacturing Control Systems Capable of Managing Production Change and Disturbances) studied how manufacturing control systems are capable of managing production disturbances focusing mainly on dynamic re-scheduling (Valckenaers *et al.* 1999). Liu *et al.* (2000) used the product-resource-order-staff architecture (PROSA) to develop a control system for an AGV system capable of being robust in the presence of disturbances and Lee *et al.* (2004) used multi-agent systems to achieve intelligent and predictive maintenance systems. Hossack *et al.* (2002) presented a multi-agent approach to power system disturbance diagnosis.

However, these attempts are mainly focused on only one disturbance management function and usually consider only one type of shop floor disturbance, the machine breakdown. A more generic and agile approach is then required, especially one that considers the detection, diagnosis, re-scheduling, recovery and prognosis for the major types of shop floor disturbances, in an integrated way. The ultimate dream is to contribute to increase the competitiveness of industrial manufacturing enterprises, especially SMEs, through responding quickly to change and being more predictable by anticipating future disturbances.

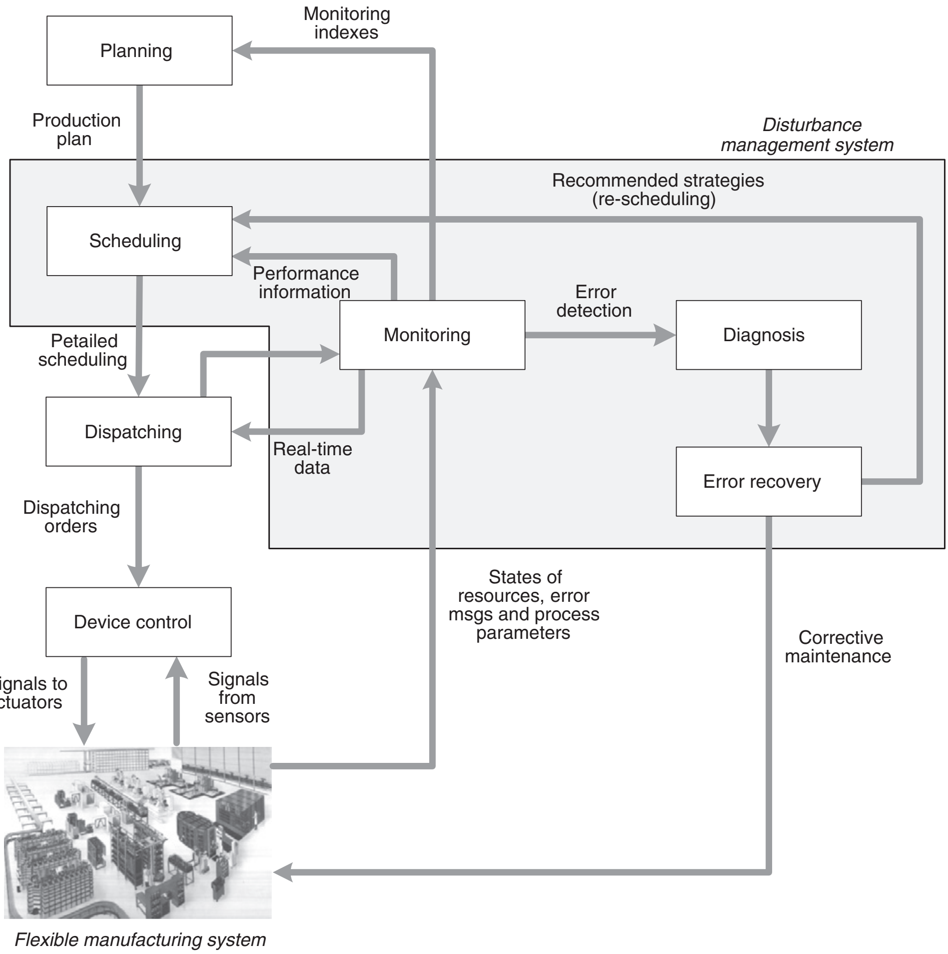


Figure 1. Traditional approach to manufacturing control systems.



Having in mind this challenge, this paper introduces a new disturbance management system approach, as part of a manufacturing control system, based on the ADACOR holonic control architecture (Leitão and Restivo 2006), enriched with mechanisms to accommodate the desired requirements of this particular domain. Basically, the proposed approach is built upon the following main foundations:

- Instead of a centralised approach, it considers decentralisation over distributed structures based on autonomous entities.
- It considers pluggable mechanisms embedded in distributed entities that offer services to support the effective execution of detection, diagnosis, recovery and re-scheduling functions.
- Rather than considering only the machine failure, it also considers other shop floor disturbances, such as delays and rush orders, that can have an impact at the planning and control level.

- Rather than the traditional detection-recover mechanisms it also considers a predict–prevent approach.

The rest of the paper is organised as follows. Section 2 introduces the ADACOR-based disturbance management architecture and Section 3 describes how the disturbance detection and diagnosis are performed. Section 4 presents a dynamic scheduling approach that considers different scheduling strategies to combine optimisation with agile response to disturbances and Section 5 describes the experimental validation of the proposed concepts. Finally, Section 6 rounds up the paper with the conclusions.

## 2. ADACOR-based disturbance management architecture

The proposed disturbance management system explores the distributed nature offered by multi-agent and holonic systems to address the challenge of dealing with unexpected behaviour, namely the frequent product changes, internal disturbances and customer demand fluctuations.

### 2.1 *Architectural elements*

The disturbance handling functions, i.e. the detection, diagnosis, recovery and re-scheduling, are distributed by a community of autonomous and co-operative holons, representing the manufacturing components, e.g. robots and pallets. In such distributed environment, and following the ADACOR guidelines, the proposed architecture identifies several types of holons according to their specialisation (Figure 2): product holons, task holons, operational holons and supervisor holons.

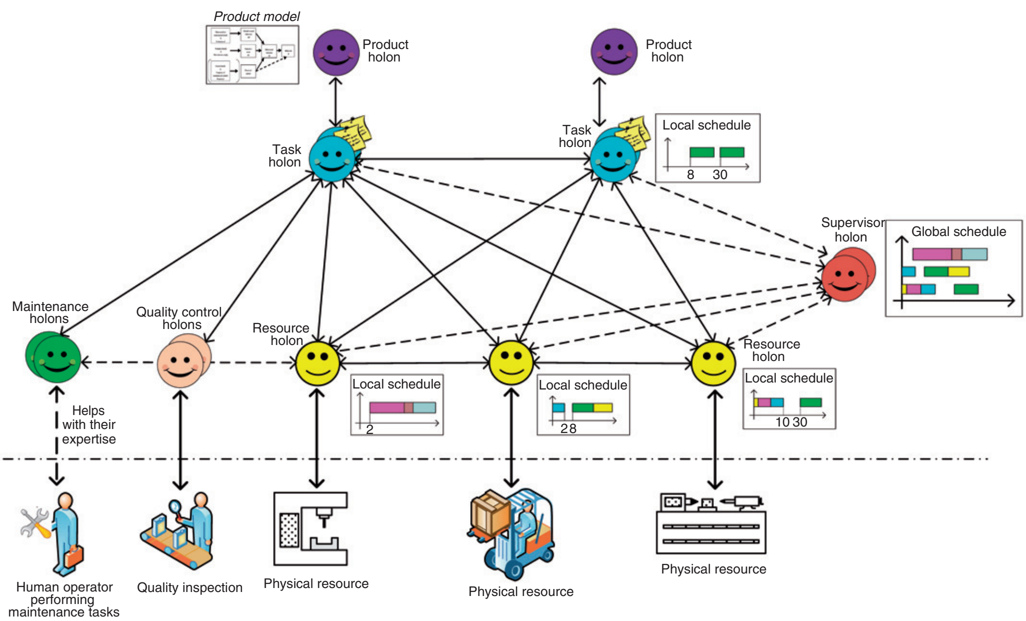


Figure 2. Disturbance management architecture.

The product holons represent the products available in the factory catalogue, containing the knowledge related to produce the products and the task holons represent the production orders launched to execute the requested products. The operational holons represent the resources available at shop floor. The proposed architecture refines the concept of operational holons, introduced by ADACOR, considering three specialisations, the resource, maintenance and quality control holons. The resource holons represent the physical devices, such as robots and conveyors, and the quality control holons represent quality control stations or operators that are responsible to perform quality control operations. The maintenance holons represent human operators responsible for performing the corrective and preventive maintenance operations, which are usually complex and require expertise skills to be executed shortly and effectively.

The supervisor holons provide co-ordination and optimisation services to the group of holons under their supervision, and thus introducing hierarchy in a decentralised system. Additionally, supervisor holons provide aggregated manufacturing control functions as services; for example, they may act as global observers of the system, monitoring the production process to detect the occurrence of disturbances.

In this community of holons, each individual has a proper role, objectives, skills and knowledge, and behaves according to a small number of simple rules, which constitutes its behavioural repertoire. In spite of their particularities, a generic structure is established, comprising three main components: communication, decision and physical interface (Leitão and Restivo 2006), as illustrated in Figure 3.

The communication component is responsible for the inter-holon interaction, supporting the sharing of knowledge by distributed holons during the co-operation processes. In the interaction processes, the involved holons (and also the users) should understand themselves, using a proper agent communication language, ontologies and interaction protocols. Particularly, it is important to consider the use of ontologies to guarantee the unambiguous interpretation and standardisation of the content of the exchanged messages.

The decision component is responsible for regulating the holon's behaviour, performing the manufacturing control functions and, in particular, the disturbance handling functions. Each holon is able to perform these functions using appropriate and pluggable algorithms and techniques, which are embedded according to the type and particularities

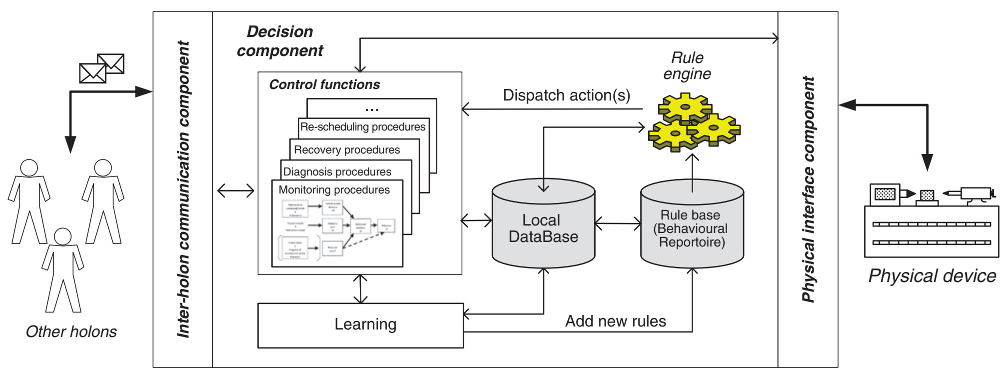


Figure 3. Architecture of a generic ADACOR holon.

of each holon. A rule-based system may be used for this purpose, applying declarative knowledge, expressed in a set of few and simple rules that reflects the holon's behaviour.

The physical interface component is responsible for the intra-holon interaction, providing mechanisms that make transparent the access to the physical resources. As local resource controllers usually have closed architectures, this component provides a virtual resource that abstracts the functionalities of the real resource by supplying primitives to be invoked by the client part, i.e. the decision component.

The individual holons have the capability to self-organise, adapting to unexpected disturbances. For this purpose, the learning capabilities, embedded in ADACOR holons, provide the ability to improve dynamically the disturbance handling function in the future, namely deciding to classify some disturbance occurrences as normal behaviour.



### 2.2 *Emergent disturbance management architecture*

Individual holons are able to perform the disturbance handling functions locally using proper embedded algorithms. However, they have a partial knowledge of the problem and need to interact with each other when they do not have enough knowledge or skills to perform these functions alone. The overall disturbance handling is achieved in a distributed manner, emerging from the behaviour of individual entities and their coupled non-linear interactions with each other and the environment, replacing a pre-programmed and centralised control by an autonomous and distributing functioning (Bonabeau *et al.* 1999) (note that the emergent behaviour is more complex than the simple sum of individual behaviours (Holland 1998)).

Figure 4 illustrates the sequence of interactions among the distributed holons to achieve the disturbance handling functions from the contribution of individual holons.

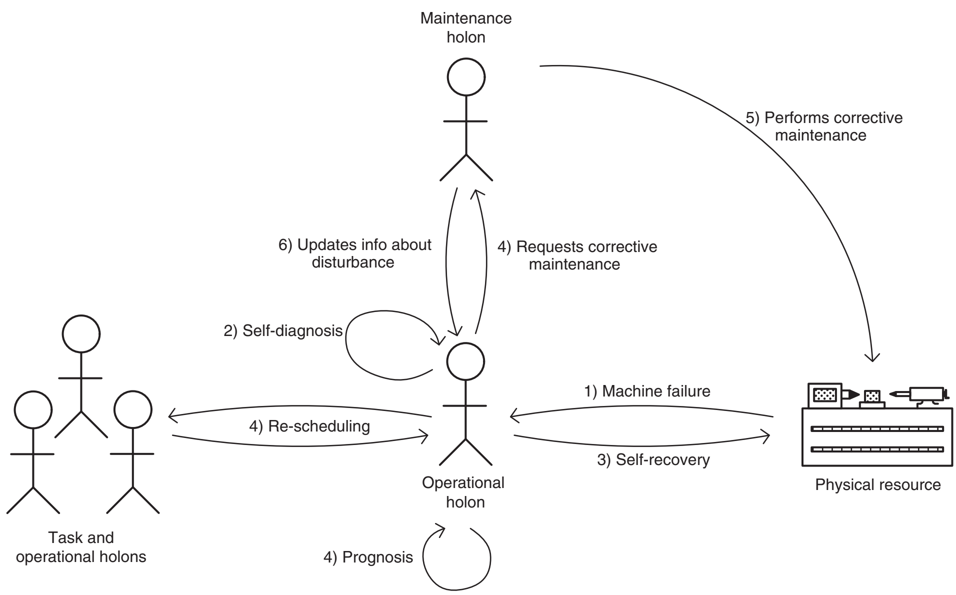


Figure 4. Interaction among holons to achieve the disturbance handling functions.

Briefly, each holon is continuously monitoring the execution of the operation, performing a comparison with the existing plans to verify if a deviation occurs. In case of detection of a deviation, a diagnostic is elaborated, identifying the causes for the disturbance and pointing out the possible actions to be executed to recover from the disturbance. If the holon cannot reach a diagnostic by itself it will ask for support from the other holons.

Having a diagnostic, the holon proceeds with a self-repair procedure; if it is not possible, the holon requests a corrective maintenance intervention to the available maintenance holons. In parallel, the holon executes a prediction of future similar disturbance occurrences, using the historic data and a proper forecasting algorithm. It also starts a re-scheduling procedure trying to adjust the production plan according to the new conditions, considering the forecasted information about future occurrences.

The achievement of this disturbance handling system encompasses a strong effort in designing co-operation mechanisms to combine the local disturbance handling behaviours. The next two chapters will detail the mechanisms to achieve some disturbance handling functions, namely the disturbance detection and diagnosis, and the dynamic (re-)scheduling.

## 3. Disturbance detection and diagnosis

A manufacturing disturbance can be defined as an unexpected deviation from the established plan that causes a negative effect in the production. A typical example of a manufacturing disturbance is a machine breakdown, but others should also be considered, such as rush orders, operator absenteeism and delays, since they have an impact at the planning and control levels.

The capability of shop floor devices to detect and tolerate internal failures, in order to continue performing their operations without the need for an immediate intervention, can save time and costs involved in their reparation (i.e. the device can continue operating, waiting for a realistically scheduled repair operation, and in this way does not stop the system). Being more tolerant, the downtime is reduced, and being able to detect and diagnosis, the repair process is speeded up, increasing the robustness and productivity of manufacturing systems.

### 3.1 *Foundations of detection and diagnosis systems*

The fault detection and diagnosis problem is widely researched in the research community. Usually these systems implement the following tasks (Gertler 1998):

- *Detection*, i.e. the indication that something is not going as expected.
- *Isolation*, i.e. the determination of the exact disturbance location.
- *Identification*, i.e. the determination of the magnitude and impact of the disturbance.

The detection of disturbances is related to discovering symptoms that can lead to an unexpected disturbance. Diagnosis is the process of identifying the nature or cause of some phenomenon (e.g. a bad functioning of a device or system) by its signs, symptoms, and from the results of various diagnostic procedures. Usually, diagnosis considers the problem of isolating and identifying a disturbance, but in certain cases, when identification is not implemented, diagnosis is only referred to in isolation.

The detection and diagnosis tasks are running in real time, and can be performed in parallel or sequentially (i.e. diagnosing at the same time as detecting or triggering the diagnosis only when a disturbance is detected). The methods for detection and diagnosis may be classified into two groups: model-free and model-based methods (Gertler 1998). The model-free methods do not use the mathematical model of the plant, and can range from physical redundancy to limit checking (methods that compare the observed value with a pre-defined value), passing by logic reasoning (that may use logical rules to evaluate the symptoms). The model-based methods use an explicit mathematical model of the production plant, represented in the form of differential equations.



### 3.2 *Disturbance detection and diagnosis approach*

The proposed detection and diagnostic mechanisms will follow the holonic principles in the sense that the system exhibits self-monitoring/diagnosis in its parts as well as in the whole. This multilevel analysis (i.e. device and cluster) not only enhances the accuracy and performance of the detection and diagnosis processes but also extends its application domain to heterogeneous systems.

#### 3.2.1 *Detection of disturbances*

The detection of disturbances is mainly performed by individual entities, both representing manufacturing resources (i.e. resource, maintenance and quality control holons) and production functions (i.e. task and supervisor holons). Each holon is continuously monitoring the progress of the production plan exhibiting different roles in the monitoring process:

- *Resource holons* perform the detection by verifying that the operation execution is going as expected. Additionally, they can monitor the device's status by implementing predictive maintenance systems, which are usually designed case-by-case. A resource holon can manage more than one predictive system, e.g. a system predicting the wearing of cutting tools and also another system predicting excessive vibration in the rotational motor.
- *Quality control holons* perform detection through verifying the quality of the produced items, using quality control stations or human operators. The detection of non-conformant quality items is seen as a disturbance and implies the need to determine responsibilities.
- *Task holons* perform the monitoring of the production orders they represent, by observing the progress execution of the operations that constitutes the order.
- *Supervisor holons* perform meta-monitoring, aggregating the information provided by the holons under their cluster.

The detection mechanism requires the design of monitoring patterns exploring the distributed nature of the system. At the device level, the monitoring is related to the acquisition of information from the physical process, with resource holons accessing the resource to know their status or the state of their sensors (e.g. to know if the machine door is open or if the water cooling system is activated). The values from multiple sensors are evaluated by (i) comparing with pre-defined threshold values and (ii) monitoring long-term trends, e.g. seasonal trends. The detection of symptoms, based on the monitoring information, is normally strongly dependent on the type of disturbance, requiring a customised and case-by-case implementation. At the cluster level, the distributed holons interact with each other to get a wider view of the system, supporting the detection of other types of disturbances besides the machine failures, as delays, rush orders and quality problems in manufactured products. The query of information between distributed holons can be performed in passive or active forms.

The active monitoring involves an event-driven mechanism. In this schema, when an event occurs, the holon notifies all other holons that had subscribed the service related to the occurrence of that event. These mechanisms can be used to detect failure symptoms in the physical devices, delays inside the factory and problems with production quality parameters. In certain situations, the implementation of active notification is not possible, being used as passive monitoring of an alternative solution, which involves a continuous polling of the required information. In this monitoring mechanism the initiative to request information (e.g. read the value of a sensor or asking about the progress execution) is from the entity that needs to know or acquire knowledge.

In spite of the particular differences in terms of scope, all holons provide the monitored information in a meaningful form to the user and store the acquired knowledge in their internal knowledge base. The different actors in the system (i.e. devices, human operators and logical entities) collaboratively provide input in this process.

#### 3.2.2 *Diagnosis of disturbances*

When symptoms are detected it is necessary to isolate them, making a clear diagnosis of the detected symptoms to identify the disturbance. The observed symptoms are matched with the symptoms associated to each disturbance type, defined in the knowledge base, ensuring the ability of performing self-diagnosis in each holon.

In the proposed approach, each holon representing manufacturing resources or production functions have the ability to make diagnoses, which require the need to reason about its state. The reasoning capability can be implemented using algorithms that can range from artificial neural networks and genetic algorithms to machine learning, rule-based systems and data mining. These algorithms are selected according to the particularities of the holon and the characteristics of the disturbance to be diagnosed, and usually implemented in a case-by-case manner. For example, Qu and Shen (1993) used a holospectrum technique to diagnose large scale centrifugal compressors, Shen *et al*. (2000) used rough sets theory to analyse the vibrations of a diesel engine and Anand *et al*. (2008) used artificial neural networks to diagnose faults in industrial manipulator robots.

The set of symptoms for each disturbance is continuously updated according to the knowledge acquired when a disturbance occurs. When the detected symptoms do not allow one to reach a conclusion, the learning mechanisms embedded in individuals may lead to the discovery of the type of disturbance in similar cases. Even if, after using analogous cases to diagnose, the holon cannot reach a diagnostic, it should interact with the other holons (namely other resources, maintenance and supervisor holons) or request external intervention from the users to teach the system. At this stage, the concept of collective learning, as a result of the contribution of individual holons, is crucial to generate new knowledge that will support the treatment of future disturbance occurrences. The propagation and the discovery of sensor failures are examples of occurrences that can hardly be tracked at the device level but can be easily handled at the cluster level.

## 4. Dynamic holonic re-scheduling

The occurrence of disturbances leads to the implementation of different recovery actions, such as corrective maintenance operations and the re-scheduling of the production plan.

The maintenance holons act as expert advisors of human operators during the execution of corrective maintenance operations aimed at reducing the equipment downtime. For this purpose, they combine the diagnostic report with their previous experience in analogous situations, to determine an action plan to be carried out during the recovery and preventive maintenance operations, using artificial intelligence techniques and virtual reality tools. Human operators, using for example PDAs or head mounted displays, can see, among others, the steps to be followed during the operation and the estimated time to perform the task.

The problem of achieving a fast alternative plan by implementing a dynamic re-scheduling is a major task in disturbance handling to minimise the impacts of the disturbance occurrence. Manufacturing scheduling is traditionally elaborated in a centralised manner using an optimisation method, often calculated off-line and considering a static and deterministic problem. Examples of such methods are constraint satisfaction techniques, heuristics, meta-heuristics (e.g. simulation annealing or taboo search) and population-based methods (e.g. genetic algorithms or particle swarm optimisation). However, in industrial environments things rarely go as expected and the optimised schedule can quickly become unacceptable, requiring dynamic re-scheduling, as fast as possible. The traditional methods do not fulfil these real dynamic re-scheduling needs, mainly because they are inflexible and slow to achieve a solution.

The challenge is to design a dynamic re-scheduling approach that fulfils the industrial requirements; in case of reaction to disturbances, in spite of losing some optimisation, it is preferable to achieve a non-optimal but fast solution than to wait a significant amount of time for an optimised schedule, which is likely to be not optimised again soon.

### 4.1 *ADACOR-based approach to re-scheduling*

In this context, ADACOR introduces a dynamic scheduling mechanism that combines a centralised, optimised scheduling strategy provided by the supervisor holons and a distributed scheduling strategy based on the interaction of distributed holons, each one embedding simple scheduling algorithms (Leitão and Restivo 2008a), as illustrated in Figure 5. The achievement of this adaptive mechanism, allowing combining centralised and distributed scheduling strategies, is not the focus of this paper and is described in Leitão and Restivo (2006, 2008a). Instead, the focus is related to how centralised and distributed strategies are achieved by ADACOR holons.

In normal operation, i.e. when the objective is the production optimisation, the holons are running in a hierarchical structure, with supervisor holons acting as co-ordinators. They generate, periodically, optimised scheduling plans that are proposed to the holons under their cluster, as illustrated in Figure 6 (a). These holons, in spite of having autonomy to reject the proposals, follow the pre-defined plans since they are optimised.

In case of occurrence of disturbances, the system self-organises to achieve a distributed re-scheduling. The idea is not to achieve an optimised solution but a fast solution in order to maintain the production performance; as an example, in case of a machine breakdown it is necessary to re-allocate the operations to alternative machines. For this purpose, a direct negotiation between task and operational holons is performed using a resource allocation

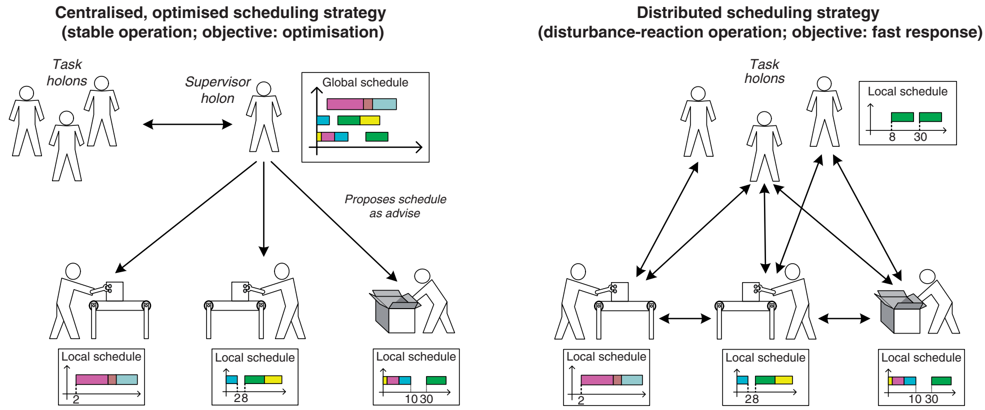


Figure 5. Dynamic re-scheduling considering the optimised and distributed strategies.

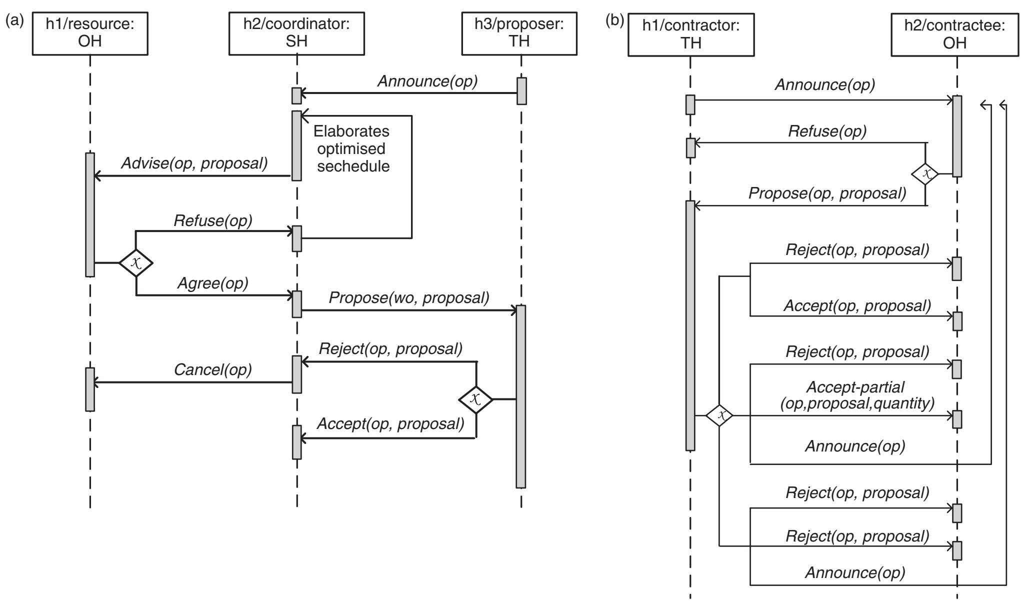


Figure 6. Dynamic scheduling using (a) a centralised strategy and (b) a distributed strategy.

mechanism based on a multi-round contract net protocol (CNP) (Smith 1980), as illustrated in Figure 6 (b).

In this negotiation mechanism, where task holons try to allocate operations at the cheapest price and operational holons try to get as many operations as possible, each operational holon

- decides, based on its skills and capacity, its availability to execute the operation,
- proposes the price to execute the operation, using formulas that model the market laws, e.g. considering its current load and bid acceptance rate.

The task holon decides the best proposal by using simple heuristic evaluation functions that may take into account the price, the location and the reputation of the resource. The reputation parameter reflects the trust that the task holon has in the proponent holon and is calculated based on the knowledge acquired in the previous interactions. The decision can be one of the following:

- Accept one proposal and reject the others.
- Award a partial quantity and start another iterative negotiation in order to allocate the remaining quantity.
- Reject all proposals and start another iterative negotiation, which requires the specification of new bid parameters.

A key issue in the proposed re-scheduling mechanism is the possibility to embed different and pluggable scheduling engines in distributed holons. Namely:

- The scheduling mechanism embedded in supervisor holons deals with the multiple machines and multiple jobs scheduling problem. In this case, the scheduling algorithms may be based on population meta-heuristics, such as genetic algorithms and particle swarm optimisation, which allows achieving optimised plans.
- The scheduling algorithm embedded in resource holons deal with multiple jobs for one machine scheduling problem, since each one is only responsible for one physical resource. In this case, simple heuristics are used such as the minimisation of the earliest due date (EDD) or the shortest processing time (SPT).

The choice of the scheduling algorithm to embed in each holon depends on the required response time and the desired level of optimisation.

### 4.2 *Predicting the future*

Traditionally, the disturbance management mechanisms are purely reactive, i.e. the system only applies corrective procedures when the disturbance occurs. The proposed approach introduces a predictive dimension to the disturbance management with the objective to determine when a disturbance is imminent, by finding patterns in the past disturbance occurrences. With the increase of predictability, the disturbances tend to became normal situations, since it is possible to plan their occurrence. For example, besides the use of corrective maintenance to recover the equipment as soon as possible, it is important to plan in advance preventive maintenance operations according to the production convenience.

The prediction of future disturbances, which is an important input in the re-scheduling algorithm, is based on understanding the historic disturbance data to find possible patterns. This is not a simple job, since some disturbances are not purely random processes, but they obey some hidden patterns that may be difficult to identify. The forecasting method ranges from simple mathematical calculations to those requiring advanced and complex mathematical skills; namely, exponential smoothing techniques, frequency analysis, Bayesian probability theory and neural networks.

In manufacturing systems, the forecasting of future disturbances normally considers only one type of disturbance, the machine failure. In this case, it is calculated that the mean time between failures (MTBF) provides the indication of the mean time a machine is operational between two consecutive failures. However, two additional issues should be considered:

- Other disturbances that can cause significant impact at planning and control level, namely delays and rush orders.
- Other forecasting techniques that can better extract the patterns of the disturbance occurrence.

For this purpose, the proposed architecture considers the use of different forecasting techniques to be embedded in distributed holons, according to the characteristics of each identified disturbance. The selection of the technique(s) that better fits the characteristics of each shop floor disturbance is dependent on several factors but important constraints are related to the error and the time to forecast future occurrences.

Having forecasted the occurrence of future disturbances, proper actions, dependent on the type of shop floor disturbance, should be taken to minimise their effects. Namely:

- In case of machine failures, the system should plan in advance preventive maintenance operations.
- In case of delays, the system should consider the relaxation of the time execution of the scheduled operations.
- In case of rush orders, the system should schedule virtual production orders.

Since the prediction can fail, it is also necessary to consider mechanisms that evaluate the prediction decision, adjusting the prediction parameters based on the knowledge learned from previous experience. This issue is very important since a bad prediction normally leads to a new disturbance occurrence (note that if the disturbance occurrence was planned and it did not occur, a deviation from the initial plan appears).

## 5. Experimental results

A preliminary implementation of the proposed concepts was performed to verify their applicability. The holonic system was implemented using the multi-agent systems technology, and particularly the JADE (Java Agent Development) framework (Bellifemine *et al.* 2007), which is compliant with the Foundation of Intelligent Physical Agents (FIPA) specifications. Each holon is basically implemented by a Java class that extends the 'Agent' class provided by JADE, inheriting basic functionalities (e.g. registration services), and extending them with features that represent its specific behaviour. The communication between the distributed holons is done by message passing, being the messages encoded using the FIPA-ACL communication language, their content formatted according to the FIPA-SL0 language and the meaning of the message content standardised according to the ADACOR proprietary ontology. The decision component was implemented using a rule-based system using the JESS (Java Expert System Shell) tool.

The current experimental prototype only considers simple but effective algorithms embedded in the distributed holons to implement the disturbance handling functions. For example, the system only considers the prediction of machine breakdowns and delays, using an exponential smoothing technique that considers the historical time series and makes a weighted average, giving bigger weights to the last values. The forecasted values are used by the scheduling algorithm embedded in individual holons to plan in advance preventive maintenance operations and to adjust the time duration of the

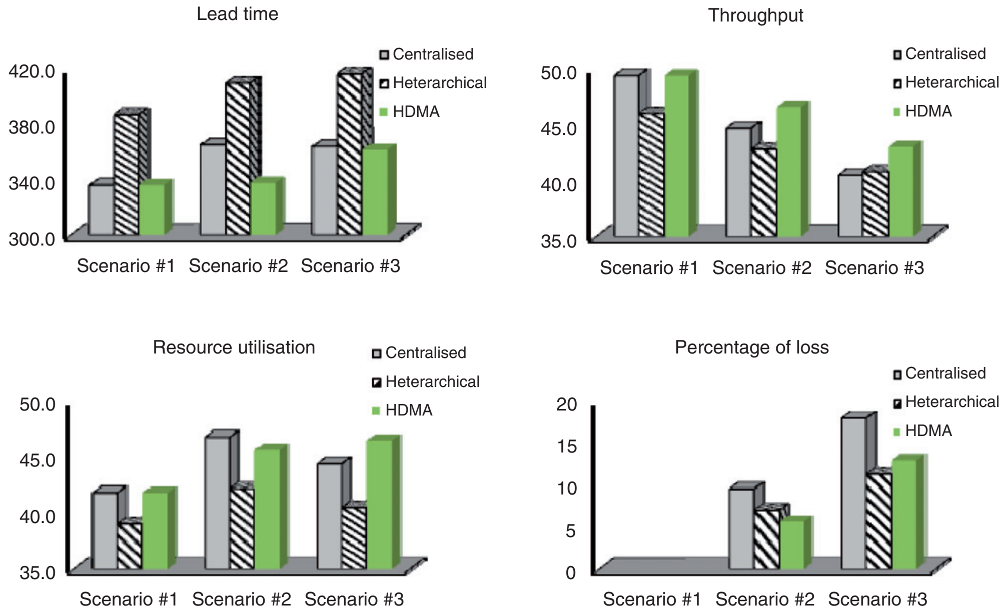


Figure 7. Summary of the experimental results.

scheduled operations. The scheduling algorithms embedded in resource holons are based on simple heuristics that minimise the EDD and the algorithms embedded in supervisor holons considers a simple algorithm that guarantees rapid, optimised scheduling.

The developed holonic disturbance management system was tested using a flexible manufacturing system, which provides the flexibility in accommodating alternative solutions at the production control level. It allows the production of several products, each one of them comprising several operations (see Leitão and Restivo 2008b for more details).

Three experimental scenarios were considered to test the system behaviour in presence of disturbances:

(1) No unexpected disturbance will occur.
(2) Failures in one turning machine will occur with a probability of 25%.
(3) Failures in two turning machines will occur with a probability of 25%.

The two approaches used in this experimental study to serve as comparison for the proposed approach are (i) a traditional centralised control approach with a central scheduling mechanism and without forecasting mechanisms, and (ii) a heterarchical-like control approach with a completely de-centralised scheduling mechanism and without forecasting mechanisms.

The preliminary experimental results are summarised in Figure 7. The quantitative production performance is illustrated by the lead time, throughput and resource utilisation parameters, and the analysis of the responsiveness and agility in the presence of disturbances is illustrated by the percentage of the loss of productivity (it reflects indirectly how agile the system is).

The experimental results show that the proposed holonic disturbance management architecture (represented by HDMA) responds better than the traditional ones to the occurrence of disturbances, being agile and responsive in the presence of disturbance without losing productivity (illustrated by the lead time and throughput parameters but also by the percentage of loss).

## 6. Conclusions

This paper introduces disturbance management architecture, part of a manufacturing control system, based on ADACOR holonic control principles and bringing the following main innovations:

- It is based on the distributed nature suggested by the multi-agent systems and holonic systems paradigms, being the disturbance management functions distributed by the control entities.
- Considers other kinds of shop floor disturbances besides the machine failures, such as delays and rush orders, that can also cause significant impact at planning and control level.
- Rather than the traditional detection-recover mechanisms, it considers a prediction component.

The focus of this architecture is centred on designing mechanisms at device and cluster levels that allows the achievement of more agile and responsiveness disturbance handling systems facing the occurrence of unexpected disturbances. Since the architecture is based on modular functional blocks, like LEGO™ components, it is easy to plug-in more adequate and powerful algorithms for each disturbance function on the fly, i.e. without the need to stop, re-program and re-initialise the other components.

The experimental results were very promising, mainly in terms of system's structure and dynamics, showing the validity of the proposed concepts. Future research work will focus on the use of more powerful algorithms and techniques in distributed holons, combined with more learning capabilities (at individual and collective levels), aiming to achieve even more robust and responsive systems.

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