Distributed Manufacturing Scheduling Based on a Dynamic Multi-criteria Decision Model

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Abstract Distributed manufacturing scheduling is increasingly necessary in nowadays global manufacturing environments and assumes primal importance to ensure enhanced solutions for such globally distributed manufacturing scheduling problems. In this chapter an approach based on a dynamic multi-criteria decision model is proposed, which enables (re)scheduling strategies and trade-offs between different performance measures. In this dynamically changing environment, real-time changes may occur in production and there is a need for a global view and manufacturing (re)scheduling to improve the globally distributed manufacturing scenario. The approach main aim is to support scheduling decision making, namely through reliable and timely deliveries, as well as improved manufacturing management of available resources. An illustrative example, integrating a set of manufacturing cells is provided to clarify the approach.

1 Introduction

In dynamic and stochastic manufacturing systems, production planners and manufacturing engineers can benefit from better understanding how (re)scheduling strategies affect system's performance. This knowledge will support them to design and operate better manufacturing scheduling systems.

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Dynamic scheduling has been solved using different approaches and techniques, as for instance [1–4]: heuristics, meta-heuristics, knowledge-based systems, fuzzy logic, neural networks, Petri nets, hybrid techniques, and multi-agent systems.

Most manufacturing systems operate in dynamic environments where usually inevitable unpredictable real-time events may cause a change in the scheduled plans, and a previously feasible schedule may turn infeasible when it is released to the shop floor. Examples of such real-time events include machine failures, arrival of urgent jobs, due date changes, etc.

In dynamic, stochastic manufacturing systems (see for example [5–9], unpredictable events like breakdowns, expedite orders, quality problems, and material shortages occur during processing. Although careful scheduling coordinates activities to maintain productivity, these disruptions can render the desired schedule infeasible. Re-scheduling attempts to diminish the loss by creating a new schedule that more accurately reflects the current state of the production system.

An approach to solve the kind of problems referred above is proposed in this chapter. This contribution relies on the use of a dynamic multi-criteria decision model (spatial-temporal) for better supporting globally distributed manufacturing scheduling.

For accomplishing a clear and structured idea about the main subjects underlying this work, this chapter is organised as follows. Section 1 defines the problem of dynamic scheduling and the categories of real-time events. Next, Sect. 2 presents some important related work regarding approaches, techniques and systems used to solve the problem of dynamic (re)scheduling. Section 3 briefly describes our proposed approach for distributed dynamic manufacturing scheduling. Section 4 introduces an illustrative example of our proposal. Finally, Sect. 5 presents a conclusion and planed future work.

2 Related Work on Manufacturing Scheduling

In most real-world environments, scheduling is an ongoing reactive process where the presence of a variety of unexpected disruptions is usually inevitable, as well as continually forces reconsideration and revision of pre-established schedules.

Many approaches to solve the problem of static scheduling are often impractical in real-world environments, and the near-optimal schedules with respect to the estimated data may become obsolete when they are released to the shop floor. Vieira et al. [8] outline the limitations of the static approaches to scheduling in the presence of real-time information and presents a number of issues that have come up in recent years on dynamic scheduling.

2.1 The Dynamic Scheduling Problem

Literature on dynamic scheduling usually addresses a significant number of real-time events and their effects in various manufacturing systems, such as: single machine systems, parallel machine systems, flow shops, job shops, and flexible manufacturing systems.

Real-time events have been classified into two categories [1, 3, 5, 6]:

- Resource-related: machine breakdown, operator illness, unavailability or tool failures, loading limits, delay in the arrival or shortage of materials, defective material (material with wrong specification), etc.
- Job-related: rush jobs, job cancellation, due date changes, early or late arrival of jobs, change in job priority, changes in job processing time, etc.

Dynamic scheduling has been defined under three categories [6–10]: completely reactive scheduling, predictive–reactive scheduling, and robust pro-active scheduling.

2.2 Completely Reactive Scheduling

In completely reactive scheduling no firm schedule is generated in advance and decisions are made locally in real-time.

Priority dispatching rules are frequently used. A dispatching rule is used to select the next job with highest priority to be processed, from a set of jobs awaiting service, at a machine that becomes free. The priority of a job is determined based on job and machine attributes. Dispatching rules are quick, usually intuitive, and easy to implement. In contrast, global scheduling has the potential to significantly improve shop performance, when compared to myopic dispatching rules, where it is hard to predict system performance, as decisions are made locally in real-time.

2.3 Predictive-Reactive Scheduling

Predictive-reactive scheduling is the most common dynamic scheduling approach used in manufacturing systems [11]. Predictive-reactive scheduling/rescheduling is a process in which schedules are revised in response to real-time events.

Most predictive-reactive scheduling strategies are based on simple schedule adjustments that consider only shop efficiency. The new schedule may deviate significantly from the original schedule, which can seriously affect other planning activities based on the original schedule and may lead to poor schedule performance [11]. It is therefore desirable to generate predictive-reactive schedules that are robust. Robust predictive-reactive scheduling focuses on building predictive-reactive schedules to minimize the effects of disruptions on the performance measure value of the realised schedule [12–14].

2.4 Robust Pro-active Scheduling

Robust pro-active scheduling approaches focus on building predictive schedules, which satisfy performance requirements predictably in a dynamic environment [6, 7]. The main difficulty of this approach is the determination of the predictability measures.

2.5 Rescheduling in the Presence of Real-Time Events

Rescheduling in the presence of real-time events needs to address two issues: how and when to react to real-time events. The first issue concerns the definition of rescheduling strategies to react to real-time events, and the second issue addresses the problem of when to reschedule.

Regarding the first issue, what strategies to use to reschedule, the literature focus on two main strategies [5, 6, 15]: schedule repair, and complete rescheduling. Schedule repair refers to some local adjustment of the current schedule and may be preferable because of the potential savings in CPU times and the stability of the system is preserved. Complete rescheduling regenerates a new schedule from scratch. Complete rescheduling might, in principle, be better in maintaining optimal solutions, but these solutions are rarely achievable in practice and require prohibitive computation time.

Regarding the second issue, when to reschedule, three policies have been proposed in the literature [6, 15]: periodic, event driven, and hybrid. The periodic and hybrid policies have received special attention under the name rolling time horizon [8, 9, 16–18].

In the periodic policy, schedules are generated at regular intervals, which gather all available information from the shop floor. The dynamic scheduling problem is decomposed into a series of static problems that can be solved by using classical scheduling algorithms. The periodic policy yields more schedule stability and less schedule nervousness. Unfortunately, following an established schedule in the face of significant changes in the shop floor status, may compromise performance since unwanted products or intermediates may be produced. Determining the rescheduling period is also a difficult task.

In event driven policy, rescheduling is triggered in response to an unexpected event that alters the current system status. Most approaches for dynamic scheduling use this policy.

A hybrid policy reschedules the system periodically and also when an exception occurs. Events usually considered are machine breakdowns, arrival of urgent jobs, cancellation of jobs, or job priority changes.

3 A Distributed Dynamic Manufacturing Scheduling Model

As exposed before, important work has already been put forward by different authors, for dealing with distributed dynamic manufacturing scheduling problems, but there is still much room for improving these complex problems. Therefore the main purpose of this work consists on providing a novel approach for better solving this kind of problems. Our contribution is a scheduling decision support system, based on a fuzzy dynamic multi-criteria decision model (DMCDM) [19–21], as well as on web services, XML modeling and related technologies [22–24]. Here we will focus on the dynamic approach, but we have in mind that the XML and other documents will be stored on a distributed data repository, spread through a set of dynamically updated collaborating businesses within a globally distributed manufacturing environment [24–26].

It is rather important to consider well-organized manufacturing systems, which include appropriate requirements for enabling collaborative management, in terms of intra and inter factories manufacturing scheduling. Figure 1 illustrates this kind of scenario, which integrates four manufacturing cells, each one including two similar machine-centers, for jobs processing. The manufacturing cells perform their work integrated in a network, in the scope of a distributed manufacturing system (DMS), where a brokering service plays an important role in several distinct aspects, namely assignment of orders received from clients to the distributed working cells.

In the DMS context, integration or collaboration of humans and technology - in a versatile environment - play fundamental roles to obtain suitable and efficient decisions about manufacturing scheduling solutions, for the global integrated manufacturing system. Another important aspect is to ensure user-friendly interfaces to facilitate sharing information among the manufacturing cells, occurring inside the DMS, to support enlightened decisions in a widened and integrated manufacturing management context.

In this context, reconfigurability dynamics and business alignment are important requirements for considering using a dynamic multi-criteria decision support model [19–21] for dealing with responsiveness of market demands that require increasingly shorter product life cycles and shorter time to market. Furthermore, these problems are constantly forcing product life cycles to suffer frequent redesigns, which imply requirements for increased dynamics to ensure accurate and timely responses to problems arising dynamically, in a real-time basis. These dynamic reconfiguration requisites are the motivation for the multi-criteria decision-making model, within the DMS dynamic reconfiguration support, which we are going to describe next.

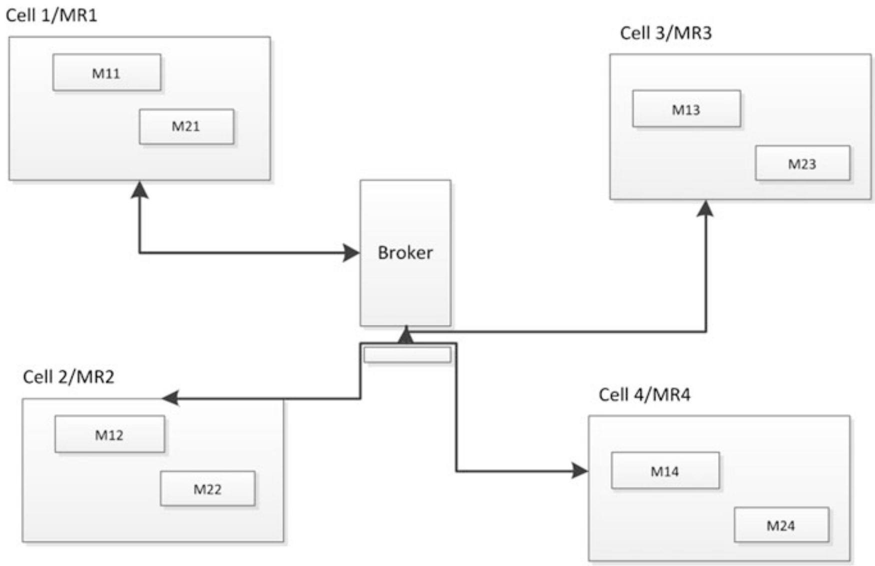

Fig. 1 Inter and intra manufacturing scheduling scenario within a DMS

In general, the aim of multiple-criteria decision-making is to find the best compromise solution from a set of feasible alternatives assessed with respect to a predefined set of criteria [21, 27, 28]. This type of decision problems is widespread in real-life situations, and many approaches have been proposed in the literature to deal with the static decision process, from utility methods to scoring and ranking ones [21, 27, 28]. However, when facing dynamic decision-making problems, where feedback from step to step is essential (e.g. any periodical evaluation of collaborating businesses), very few contributions can be found in the literature (see, for example [20, 25, 29]). Usually, dynamic multi-criteria decision-making (DMCM) belongs to spatial-temporal contexts, in that exploration of the problem might result in new alternatives being considered, others being discarded, and a set of criteria to be similarly altered [19].

In distributed manufacturing contexts, the problem of multiple resources manufacturing scheduling can be easily understood as a temporal multi-criteria decision-making problem: periodically and dynamically, businesses express their preferences with respect to manufacturing resources, for instance, manufacturing cells, which can then be ranked and selected to improve the complete manufacturing scheduling.

Therefore, each candidate manufacturing resource, at each decision moment (t) is assessed by collaborating businesses according to some set of decision criteria (such as lack of reliability, or speed, time and costs) that may also change over time. These assessments are then distilled down (aggregated) to a single (static) rating using some aggregation operator. After, in dynamic contexts, this rating

Fig. 2 Dynamic decision making model

value has to be joined (aggregated) with historical information to produce dynamic ratings that take in consideration past behaviors (historic rating). Finally a linear programming model can be used to cover processes that include collaboration of many-to-many business. This process goes on (feedback process) and in any new iteration both the alternatives and criteria may change, new ones can be added and/or others can be deleted, according to the real-time events. Figure 2 (based on [20, 21]) displays the general dynamic process.

With this dynamic model in mind we can now generalize the scheduling scenario, depicted in Fig. 1. Let us consider a time instant t and m collaborating businesses (CB_j), which are planning their orders on a set of n manufacturing resources (MR_i). Each collaborating business CB_j is assumed to be evaluated by the behavior regarding breakdowns on orders satisfaction, i.e. the value represents a penalty, where the lower the better ("good behavior"). At each time instant t an evaluation, regarding penalties for breakdowns, is produced for each CB_j (e.g. monthly periodicity) and this value is combined with the corresponding historical information from the previous period, t-1, to obtain Pi (details about this aggregation process are presented in [19, 21, 29]). Furthermore, each collaborating business has a certain production demand D_j and each manufacturing resource has a maximum production capacity, C_i. Moreover, the variables of the network of collaborating businesses and manufacturing resources includes the quantities x_{ij} that collaborating business, CB_j order from manufacturing resources, MR_i.

Another important aspect of the proposed model is related to the requisite of a satisfaction level imposed for each candidate manufacturing resource; in our case it consists on pre-defined values for penalties to express that if the penalty is higher than a certain threshold, M_i, the MR_i is eliminated as an alternative manufacturing resource candidate on that iteration.

Hence, the total lack or un-satisfaction levels of all collaborating businesses (L), in terms of the breakdowns related to deficiency or nonexistence of orders satisfactions is minimized.

4 Illustrative Example

Let us consider a manufacturing context that includes four different manufacturing resources, for short (MR_1–MR_4), distributed worldwide, each one being able to process a set of four distinct jobs (J_1–J_4), with a same processing time of 1 time unit. Moreover, we will consider four distinct scenarios (R_1–R_4) where each MR_i will produce either 1 or 2 or 3 or 4 jobs (i.e. all possible combinations can be distributed by the businesses MR_i).

We will also consider that each job requires a setup cost/time for being processed on a manufacturing resource, which varies according to the number of jobs to be processed on that manufacturing resource, as follows: 0.8 time units if the whole set of four jobs is processed on one of the four manufacturing resources available; 1.5 time units if three of them are processed on a given manufacturing resource; 2 time units if 2 of the jobs are processed on the same manufacturing resource; and 3 time units if only one job is processed on a manufacturing resource. Moreover, the jobs also have to be delivered to the final clients and this final transportation cost/time will be 0 time units if the job is processed next to the corresponding client location (i), assuming that MR_1 is located in the same location as Client 1 (C_1) and so forth (e.g. MR_2 is located next to Client 2, C_2). Otherwise, if a job has to be delivered to some other location, the corresponding transportation time of job j to location i follows the rule of time = |i-j| time units, for example, the time for transportation of job 2 to manufacturing resource 3 is equal to 1 (|2–3|) time units, and so one.

Under a collaborative context let us now consider the set of all alternative scenarios for jobs allocation for being processed and delivered to the corresponding four clients—placed next to each of the four manufacturing resource available—as follows:

- Scenarios considering only 1 job per manufacturing resource include 24 situations (R_1^1 to R_1^{24});
- Scenarios considering 2 jobs per manufacturing resource include 36 situations (R_2^1 to R_2^{36}). These occur when two of the 4 jobs will be processed on one of the four manufacturing resources available and the remaining two jobs on another available manufacturing resource;
- Scenarios considering 3 jobs include 48 situations (R_3^1 to R_3^{48}) that arise from the context of processing three of the set of the four jobs on one of the four manufacturing resources available and the remaining job being processed on another manufacturing resource of the four available;
- Scenarios considering 4 jobs include 4 different situations (R_4^1 to R_4^4) correspond to processing each set of four jobs on one of the four manufacturing resources available.

After establishing the possible scenarios we can calculate the best inter-scheduling, expressed on time units, for the example, which totals nine alternative solutions.

From the obtained results, we select the best solutions (minimums) for each manufacturing resource:

(1) Scenario $R_4^2 = \{(MR_2, J_1, J_2, J_3, J_4)\} = 9$
(2) Scenario $R_4^3 = \{(MR_3, J_1, J_2, J_3, J_4)\} = 9$
(3) Scenario $R_2^2 = \{(MR_1, J_1, J_2); (MR_3, J_3, J_4)\} = 10$

(4) Scenario $R_2^3 = \{(MR_1, J_{1,} J_2); (MR_4, J_{3,} J_4)\} = 10$
(5) Scenario $R_2^{19} = \{(MR_2, J_{1,} J_2); (MR_3, J_{3,} J_4)\} = 10$
(6) Scenario $R_2^{20} = \{(MR_2, J_{1,} J_2); (MR_4, J_{3,} J_4)\} = 10$
(7) Scenario $R_3^{15} = \{(MR_2, J_{1,} J_{2,} J_3); (MR_4, J_4)\} = 11$
(8) Scenario $R_3^{28} = \{(MR_1, J_1); (MR_3, J_{2,} J_{3,} J_4)\} = 11$
(9) Scenario $R_1^1 = \{(MR_1, J_1); (MR_2, J_2); (MR_3, J_3); (MR_4, J_4)\} = 16$

It is obvious that the best solutions are the ones from scenario R_4^2 and R_4^3 with either MR_2 or MR_3 (total time = 9) producing all the jobs. The worst scenario is R_1^1 (total time 16) where each job is divided per manufacturing resource (mainly due to the set-up times involved).

Now, if we are in a collaborative environment we could expect some negotiation to take place to ensure selection of the best option in terms of members of the "social network" established by the four manufacturing resources. Notice that this negotiation will correspond to a second iteration in our dynamic model. Since the 2 best scenarios for R_3 (total costs 11) R_1^1 present the worst results for the second round of negotiation we will only consider the 6 best candidate alternatives, independent of the manufacturing resources used. Furthermore, let us now consider that we have information about the historic timely deliveries (mean lateness) from each manufacturing resource, hence, this allow us to run a second round of negotiations/re-scheduling to decide which MR_{i} will win the contract.

Table 1 depicts the results for the candidate scenarios of using this criterion to decide between the six best candidates. Table 1 also depicts the total times to produce the combination of jobs in each resource. Observing this table the results are inconclusive since R_4^2 and R_2^{20} obtained the same global result of 12 time units. Using this simple re-scheduling does not bring much added value to decision makers and a third round of negotiation would have to take place to select between the best two scenarios.

Now, we will consider the influence of historical information (dynamical aspect of the MCDM model) to close the loop of information, based on previous behaviour/performance and un-satisfaction levels of the manufacturing resources being analysed. For the second phase of the dynamic MCDM, where we want to include an additional performance measure, regarding past experience related with lateness of orders, more specifically, the mean lateness of the manufacturing resources, regarding the execution of a similar set of jobs. Furthermore we will also discard the worst 3 scenarios from the first phase of our DMCDM, and only keep the 6 best candidate solutions for the second iteration.

Now, we will compare these results with the ones obtained in a second iteration with our dynamic MCDM model. In this second iteration the same new criteria is used, but the main difference is that the approach takes in consideration past information from the previous iteration. The additional criterion (mean lateness) is included in the second phase of the DMCDM by aggregating it with the historic results (obtained through the application of the first phase). Here we selected the simple weighted sum, as aggregation operator, with a relative importance of 40 %

Table. 1 New performance measure with historical information about mean lateness of resources for each scenario

Scenario	R_4^2	R_4^3	R_2^2	R_2^3	R_2^{19}	R_2^{20}
New criteria: mean lateness	3	6	3	4	3	2
Total times	12	15	13	14	13	12

for the historic information and 60 % for the current new criteria. In the general dynamic MCDM any other suitable aggregation operator could have been used both for combining criteria as well as we for combining historic information with current one [19]. The updated final results (second iteration) obtained for this example are the following:

(1) Scenario $R_4^2 = 9*0.4 + 3*0.6 = 5.4$
(2) Scenario $R_4^3 = 9*0.4 + 6*0.6 = 7.2$
(3) Scenario $R_2^2 = 10*0.4 + 3*0.6 = 5.8$
(4) Scenario $R_2^3 = 10*0.4 + 4*0.6 = 6.4$
(5) Scenario $R_2^{19} = 10*0.4 + 3*0.6 = 5.8$
(6) Scenario $R_2^{20} = 10*0.4 + 2*0.6 = 5.2$

Observing the results, we see that the best solution obtained is now R_2^{20} and this scenario consists on producing jobs 1 and 2 on manufacturing resource 2 and jobs 3 and 4 on manufacturing resource 4, with a global time unit of 12 and an evaluation value of 5.2.

Notice that all solutions vary not only according the additional performance measure of mean lateness, but also consider the total time (historic information), regarding jobs processing, setup times and transportation times. Furthermore, this model spatial-temporal characteristic allows (along re-scheduling steps) including new criteria, changing input values and so forth, without forgetting past behaviours.

This model allows that sometimes we may make a decision based on a trade-off situation in terms of lowest total time, if we are considering time based performance measures for our decision making or other kind of performance measures. For instance, cost or resources utilization or combined situations, according to each preferred situation occurring on each decision scenario, and even considering adding other criteria related to promoting collaboration between businesses or any other constraints.

Moreover, when execution times approximate—more or less equally—preferable situations tend to occur, as we enter on a collaborative environment. Therefore, it may be wise to highlight that, in a globally distributed market of resources it is relevant to pay attention not only to local production scheduling approaches but also to global ones, considering the diverse situations related to inter manufacturing environments planning and scheduling alternative scenarios, besides the intra manufacturing scenario. Concluding, our dynamic re-scheduling approach allows historical information to play an important role in supporting decision makers, by providing enriched information about previous behaviour of alternative solutions.

5 Conclusion

In this chapter we showed the importance, as a competitive strategy, to explore and use a dynamic multi-criteria decision model to better support collaborative manufacturing scheduling systems, particularly in today's Internet and Intranets, for solving distributed dynamic manufacturing scheduling problems. A simple illustrative example was presented, which highlighted how the decision making process could be supported within globally distributed manufacturing scenarios, for instance, based on a set of distributed manufacturing cells, each one integrating a set of manufacturing resources available for producing a set of jobs. Although the main goal was to highlight decision support in manufacturing scheduling resolution, the collaborative decision support system could also play other important roles. For instance, for enabling an easy and user friendly interface for problem data introduction and processing as well as easy access to solving methods and its implementation(s), for further intra manufacturing system (e.g. cell, or manufacturing resource scheduling, occurring in the context of the whole distributed manufacturing system scenario).

As future work, we plan to develop a platform for solving distributed manufacturing scheduling problems occurring in real-time distributed manufacturing environments, for instance, either for intra or inter cellular manufacturing scheduling scenarios. Concepts, related to problems and alternative solving methods will be modelled through XML and put available through a globally distributed network, where a set of collaborating business are dynamically integrated.

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