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A Product-Driven System Approach for Multi-Level Decisions in Manufacturing Planning and Control

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Decision making in Manufacturing Planning and Control Systems (MPCS) use processes that consider several levels of product aggregation and different time horizons. Decisions rendered on each level do not always have similar goals. The problem is that building Intelligent Manufacturing Systems (IMS), involves coordinate decisions on different levels to achieve a common objective. There is no current research on IMS regarding coordination among decision levels in Product-Driven Control Systems (PDCS), hence simulations of the planning and control processes should be conducted to analyze the behavior of multi-level objectives. Accordingly, in this paper a simulation model gives account of different coordination issues between tactical and operational levels. At the *tactical level*, production plans are generated by an Advanced Planning and Scheduling (APS) system, whereas at the *operational level*, a distributed decision rule is used. The whole simulation makes decentralized decisions that are managed by production lots represented by *holons*. Results for our simulation indicate that coordination among active lots is capable of making effective multi-level distributed decisions when compared with conventional approaches.

Keywords: manufacturing systems; intelligent manufacturing systems; production planning and control.

1. Introduction

Holonic Manufacturing Systems (HMS) show promising results towards improving features such as flexibility and adaptability, due to the complexity and dynamism of current manufacturing systems (Valckenaers et al., 2007; Valckenaers et al., 2009). In a HMS, entities (i.e, machines, robots, AGVs or workers) are modeled as *holons*, which

consist of a physical component and an information processing component (Pannequin et al., 2007; Pannequin et al., 2009).

The majority of the manufacturing applications use different approaches to model HMS, focusing only on operational and control levels, specifically to model and implement manufacturing execution systems (MES). For instance, *ExPlanTech* is an agent-based technology for planning and production control (Pechoucek et al., 2007, Marik et al., 2000), which was developed as a multi-agent system for project-based production systems. *ExplanTech* uses a community of autonomous agents that represent entities or information production entities, in which no centralized decision mechanism is used.

On the other hand, hierarchical architectures such as *PABADIS Promise* allows for production control based on multiple levels of automation (Wunsch and Bratukhin, 2007), so that decisions centralization is avoided by locating decision levels closer to work-flow levels. Decision levels correspond to the ERP (Enterprise Resource Planning) at tactical level, MES at operational level, and control levels, and communication between ERP and MES is based on “web services” using ACL (Agent Communication Language).

While these approaches consider planning and control levels, they do not include products as central entities in the decision-making process. On the contrary, PDCS (McFarlane et al., 2002; Morel et al., 2003, 2007) transforms products into active agents in the decision-making process, in which products can be also represented as holons.

Decisions made at the planning level must include medium-term horizons to prevent “myopia”, so resources required for production (i.e., personnel, labor, raw materials, and machinery maintenance) should be planned in advance.

Conversely, operational-level decisions are concerned with short-term horizons, which are inherently “myopic”, and must respond quickly and efficiently to disturbances (i.e., production blocking, machine breakdowns, and demand changes). Thus, planning and control systems should be robust, flexible and reactive with respect to short, medium, and long term decisions.

In order to deal with these issues, an architecture to model a holarchy from products and sets of products at each level have been proposed (Herrera 2011, Herrera et al. 2012), This approach allows coordination among multiple decision levels and their associated decision horizons, while focusing on the work flow (products). Like other related manufacturing approaches (Tang et al., 2011), this architecture allows for recursion, that is, each composition level of the holarchy organization exhibits the same structure and organization on each of its levels. In addition, recursion enables the replication of the same functions at each level, by doing slight modifications to the objectives and decision methods.

Accordingly, this work aims to analyze the coordination between centralized planning and decentralized control decisions in PDCS. To achieve this objective, decentralized decisions are assumed to be performed by numerous holons, which detect disturbances in planning and trigger local changes that affect central planning. To deal with this, an agent-based simulation model is proposed. At the planning level, the goal is to preserve the stability of the plans. At the operational level, the goal is to minimize makespan (maximum completion time or C_{max}) degradation by satisfying buffer-stock constraints.

Our claim is that a product-driven system may become more effective than conventional production planning and control approaches to coordinate multiple objectives and

tactical decision levels.

This paper is organized as follows: Section 2 describes the main components and methods of our HMS-based simulation approach, Section 3 discusses the results of the simulation experiment, Section 4 analyses the main results, and Section 5 highlights the conclusions and further work.

2. Materials and Methods

2.1 Centralized and distributed decisions

At different levels of MPCS, decisions are made by considering a rolling horizon, and the levels of the architecture are associated with different degrees of aggregation for products (i.e., product families, production orders, lots, finished products, etc.).

A major challenge for these systems is to preserve the coherence of decisions among the levels. However, whenever disturbances occur, the objectives for each level are not easily achieved, and disturbances may cause major planning changes. Note that frequent changes can be the source of considerable instability. In addition, these effects often cause reduced efficiency and poor productivity. Short-term changes are more frequent and can significantly reduce system performance. Thus, MPCS should provide sufficient flexibility at the operational levels and ensure consistency with objectives at the upper levels.

Accordingly, our approach considers two decision levels: tactical and operational. At the tactical level, a decision concerns the production quantities for every item within a product family and for each period on a planning time horizon. This problem is generally associated with the Master Production Schedule (MPS) and is usually represented using a *lot-sizing model* (Pochet and Wolsey, 2006). This model aims to

minimize production costs by defining a set of parameters such as marginal costs and system capacity. During the first period of this planning horizon and once each quantity has been obtained, these quantities must be divided and sequenced to be incorporated into the manufacturing system. This problem has been called the lot-streaming problem, (Sarin and Jaiprakash, 2007) whose objectives are to reduce the total production time (C_{max}). This model is usually applied to manufacturing systems that contain parallel manufacturing processes. The decision at this level is comprised of a sequence of sub-lots that correspond to the weekly planning, which considers the production start time and the quantity of each product to be manufactured.

Since lot-streaming assumes constant production rates, various disturbances (i.e., machine blocking, machine breakdowns, accidents) may affect the rates. Thus, changes of the parameters of the model may affect planning efficiency, by reducing production capacity and increasing the gap between planning and the launched production (system nervousness).

In our approach, products or sub-lots are modeled as *holons* which can modify their environment. Holons are assumed capable of making a single distributed decision that is stopping its production at a certain stage and heuristically reassigning the remaining quantity. Re-assignment consists of assigning the quantity that has not been manufactured to another scheduled lot (one or many), which modifies the planning. Until the new assignment is completed, a part of the sub-lot remains in an intermediate stock (buffer). Splitting decision is then dependent on the remaining production and stock capacities, and the existence of similar types of sub-lots that were previously planned.

Once divisions have been made, a *holon sub-lot* evaluates the variation in planning by

using a re-planning linear programming model. The model seeks to replace the partitioned lots and assess different choices that will minimize the increase of C_{max} , which correspond to different sub-sets of the same reference that will increase their size, to be placed in the queue sub-module.

2.2 Study Case

In order to perform our simulation, a company was selected as a case study. It manufactures turbochargers for the automotive industry, and produces a maximum of ten thousand products per day with hundreds of references. The plant is divided into production cells, which encompass all stages of production that are required to produce a finished product. Some production cells are dedicated to a specific customer.

The production cell includes storage of raw materials, semi-finished (buffer), and finished products. In addition, the cell-based production process is divided into two stages. An initial set of operations are performed in the first line (module A), generating semi-finished products. These products are then assembled into three independent assembly sub-modules (module B).

Figure 1 About Here

2.3 Distributed Decision Rule

The decision rule is based on a Linear Programming (LP) model that allows to evaluate the global effects on the C_{max} with respect to the changes in the size of the sub-lots.

Since that at each time, the holon sub-lot detects a change in processing times, the rule is used to approximate the overall effect of the change in the planned quantities.

Rules using LP are specified as follows:

Indexes

$l = 1, 2, \dots, L$: lots,

$i \in \Omega_l$: sub-lots in lot l ,

$j = 1, 2, \dots, J$: sequence positions,

$k = 1, 2, \dots, K$: cells at B.

Variables

C_{\max} : makespan,

xb_{ijk} : re-planned sub-lot quantity of item I in sequence position j assigned to module k of stage B,

STA_j : start time at stage A of sub-lot in position j ,

STB_{jk} : start time at module k of sub-lot in position j

Parameters

x_{cut} : quantity to be re-planned,

q_i : minimum sub-lot size of item i ,

TPA_i : marginal production time at A of item i ,

TPB_i : marginal production time at B of item i ,

SA_i : setup time at A of item i ,

SB_i : setup time at B of item i ,

$I = \sum_{l=1}^L |\Omega_l|$: number of sub-lots,

L : number of items,

K : number of sub-modules,

$n_l = \lfloor Q_l/q_l \rfloor$: maximum number of sub-lots

in lot l ,

$\Omega_l = \{1, 2, \dots, n_l\}$: set of sub-lots in lot l

xf_{ijk} : fixed sub-lot quantities.

yf_{ijk} : fixed sequence.

t_{new} : new start time at A for the first sub-lot in the planning after disturbance detection.

$$(P_0) \min C_{max} \quad (1)$$

$$\sum_{i \in \Omega_w} \sum_{j=1}^J \sum_{k=1}^K xb_{ijk} = x_{cut} \quad (2)$$

$$xb_{ijk} = 0, i \in \Omega_l, \forall l : l \neq w, \forall j, \forall k \quad (3)$$

$$STA_1 = t_{new} \quad (4)$$

$$STA_j = STA_{j-1} + \sum_{i \in \Omega_w} \sum_{j=1}^J \sum_{k=1}^K TPA_1 \cdot xf_{i(j-1)k} + SA_1 \cdot yf_{i(j-1)k}, \forall j: j > 1 \quad (5)$$

$$STB_{jk} \geq STA_j + \sum_{l=1}^L \sum_{i \in \Omega_l} TPA_l \cdot yf_{ijk}, \forall j, \forall k \quad (6)$$

$$STB_{jk} \geq STB_{(j-1)k} + \sum_{l=1}^L \sum_{i \in \Omega_l} TPB_l \cdot (xf_{i(j-1)k} + xb_{i(j-1)k}) + SB_l \cdot yf_{i(j-1)k}, \forall j: j > 1, \forall k \quad (7)$$

$$C_{max} \geq STB_{jk} + \sum_{l=1}^L \sum_{i \in \Omega_l} TPB_l \cdot (xf_{ijk} + xb_{ijk}) + SB_l \cdot yf_{ijk}, \forall k \quad (8)$$

$$xb_{ijk} \in \mathbb{Z}^+; STA, STB, C_{max} \geq 0 \quad (9)$$

In our decision model, the *objective function* (1) minimizes the C_{max} represented by the end date of the last piece in the sequence. Constraint (2) ensures that the sum of the re-assignments (xb_{ijk}) will be equal to the remaining quantity in the intermediate stock (x_{cut}). Constraint (3) establishes that the re-assignment can only be performed for the planned sub-lots that belong to the same lot that was previously divided. The start time of the sub-lot in position j is set to t_{new} by constraint (4).

Constant t_{new} represents the new start time of the first sub-lot after disturbance detection. This sub-lot corresponds to the first sub-lot in the planned sequence (not yet in production). The recursive relationship in constraint (5) expresses that the start time of module A for the sub-lot in the j -th position must be equal to the start time of the previous sub-lot (sub-lot in position $j - 1$) plus its setup and production time, which is determined by considering a fixed sequence ($x_{f_{ijk}}$ and $y_{f_{ijk}}$). Constraint (6) ensures that the start time of module B will always be greater than the start time of module A plus the production time for module A corresponding product). Constraint (7) considers that the production time for module B must be increased proportionally by the re-assigned quantities. The makespan is defined by constraint (8).

2.4 Simulation Settings

In order to simulate of distributed decision model, two decision levels have been defined for our system:

- 1) *Tactical Level*: it uses an integer programming model that defines quantities as produced by item and period in a rolling horizon (Herrera and Thomas 2009). Quantities are divided into sub-lots during the first period, and the sequence to be used in the manufacturing process must be defined using an integer programming model that solves the lot-streaming problem. Unlike P_0 models, the quantities and sequences are variable, which increases the execution time. However, this is only performed only at the beginning of the operation period.
- 2) *Operational Level*: during the production period (week), variations in the production times are simulated for different modules (i.e., disturbances are

simulated as blocking and breakdowns). In order to react to perturbations, (P_0) is solved to determine if a certain quantity of items is placed into stock so as to determine whether this decision improves the planning with respect to the initial situation. This distributed decision process depends on the variation between the planned waiting time and the real waiting time of a product in the queue of module B. Table 1 shows the main parameters considered on the simulation.

Table 1 about here

3. Results

The simulation is performed considering a horizon of one year, obtaining weekly operational results. Some results consider the distributed decision and others disregard the distributed decision. Stability is achieved at the tactical level using a *nervousness* measure (Herrera and Thomas, 2009) which quantifies the variation in the planned quantities on a weekly basis. At the operational level, the obtained C_{max} and Work-In-Process (WIP) are compared.

3.1 Nervousness

The results of the decision processes are shown in Figure 2, considering nervousness, and comparing centralized and hybrid decision approaches. The cases represent situations in which the product is active (hybrid) and situations in which the product is inactive (centralized). The complete experiment is discussed in Herrera (2011). The centralized case considers a model that reduces the nervousness of the plan,

thus, its shape in Figure 2 represents a “stable plan”. These results show the difference between the launched production and the weekly planned production for a one-year operational horizon (60 periods are covered according to a transient period of 8 weeks).

Figure 2 about here

Figure 3 about here

Table 2 about here

In order to capture major differences between the two decision systems, Figure 3 shows the same results by applying a *Savitzky-Golay* filter, which preserves the features of the initial distribution and the width of the peaks.

Table 2 displays the results of a statistical hypothesis test that was employed to verify if differences exist between the series. The H_0 hypothesis was described as “significant differences exist between both cases with respect to the nervousness results”, and the H_1 hypothesis was described as “significant differences do not exist between both cases respect to the nervousness results”. The results reveal no changes in stability for the plans in which the products are active.

3.2 C_{max}

Figure 4 displays the results comparing C_{max} by using centralized and hybrid approaches. Figure 5 shows the same result applying a *Savitzky-Golay* filter. Table 3 displays the results of a statistical hypothesis test that was employed to verify if differences exist between the series. The H_0 hypothesis was described as “significant differences exist between both cases with respect to the C_{max} results”, and the H_1 hypothesis was described as “significant differences do not exist between both cases

respect to C_{max} results”. The results reveal a statically significant difference between centralized and the proposed approach reducing C_{max} deterioration.

Figure 4 about here

Figure 5 about here

Table 3 about here

3.3 *WIP*

Figure 6 displays the results showing the work-in-process (WIP) for both approaches.

This measure represents the average stock of all references at the end of the week.

Figure 7 shows the same result that Figure 6 applying a filter. The H_0 hypothesis was described as “significant differences exist between both cases with respect to the *WIP* results”, and the H_1 hypothesis was described as “significant differences do not exist between both cases respect to *WIP* results”. These results show that the intermediate stock level is used more frequently when the products are active.

Figure 6 about here

Figure 7 about here

Table 4 about here

4. Conclusion and future work

In this paper, a multiple decision levels simulation MPCs approach is proposed which aimed at coordinating decisions at different levels using centralized and distributed methods. Here, local decisions represent decisions made by a “holons sub-lots” in the context of PDCS.

Experiments show our coordination between central and local decisions for a PDCS based approach is efficient. Stable planning at the tactical level in the middle-term is assessed indicating a significant performance in reactivity at the operation level in the short term (operational level).

The results of C_{max} are particularly interesting as they reveal a net gain with no drop in stability, and show that “robustness” can be achieved in different types of decisions. On the other hand, results show that for stock costs are paid for gain in *nervousness* and C_{max} . In addition, C_{max} efficiency is directly related to the increase and even saturation of the intermediate stock. Thus, the proposed model shows promise to enable efficient use of stock. Also, mathematical programming based models and methods are proved to enable acceptable approximations to our optimization problem when comparing with collaborative strategies.

As a further work, our system should be assessed in large-production environments or for situations in which centralized decisions are not feasible at all. For this, new formulations are needed to capture the global effects of local decisions in terms of computational efficiency. Furthermore, the adaptation of the adaptation of the proposed system should be investigated in order to be applied to Chilean industrial areas.

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