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Dynamic Models for Production Control and Scheduling

A Brief Review

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***Abstract*—Agility may be an important competitive advantage in many markets. In order to achieve it, the dynamics of the manufacturing systems must be considered. Control theory supports the development of dynamic models for production and inventory control. This paper discusses some dynamic models of production control specifically applied to scheduling and shop floor control. A comparative and critical analysis of the models is presented and directions for future works are provided.**

Control theory; scheduling algorithms; shop-floor oriented systems; production control

I. Introduction

In most manufacturing environments, the production system is always subjected to disturbances of several sources, such as changes of demand and customer requirements, machine breakdowns, urgent jobs, absenteeism, financial fluctuations, and so on. In order to be competitive, the companies must be able to quickly respond to these uncertainties without a large penalty in cost. In other words, "Agile companies [...] are strong in their adaptability to changing conditions in the production environment" [1].

System Dynamics & Control Theory, originally come from Mechanics and Electronics, provide a range of tools for modeling and analyzing dynamic systems that can be suitably applied to production planning and control of manufacturing systems. As known, some of the first works in this field was developed by [2]. Since then, several other models have been developed to approach different levels of the production planning hierarchy or the analysis of supply chain dynamics. After a broad literature scanning, few models were found focusing on scheduling and shop floor control, that is, the lower levels in the planning hierarchy. Thus, the aim of this paper is to present a short review of these works, i.e., to discuss some dynamic models of production control applied to scheduling and shop floor control. The scope of the review mainly includes publications of the last fifteen years. A comparative analysis of the models is carried out and some directions for future work are provided.

II. Literature Review and Presentation of the Models

As already mentioned, a reasonable number of models to control the dynamics of production systems have been developed. A comprehensive review is presented in [3]. These authors have identified two areas of application of control theory to production-inventory systems.

The first one approaches the supply chain dynamics and related topics, such as the bullwhip effect. The developments in this area were labeled as "horizontal extensions" of the deterministic models of production-inventory systems [3]. One of the first works in this area was developed by [4]. In this, an inventory order based production control system was considered to have three fundamental system parameters: production delay time (i.e. production lead time), the time-to-adjust inventory, and demand averaging time. Similarly, [5] considered three main elements while modeling manufacturing systems: forecasting, lead times and replenishment rules (or order policies). In the mentioned work, expressions in the frequency domain to represent manufacturing lead times and replenishment rules are presented. In general, demand forecast represents the feedforward path of these systems, while work-in-process and inventory level are usually transmitted as feedback information. In some systems, the order policy is the control element. Following this line of reasoning, several models are developed and improvements were proposed to the existing models [6-8]. Most of these models aimed at finding an optimum order policy to reduce the bullwhip effect, i.e., the variations in the inventory levels.

The second area of application focuses on "hierarchical approaches" or "vertical extensions" [3] of the models. This area comprises multi-echelon models where the product structure tree or bill of materials (BOM) is used as an input matrix for the production-inventory system. As known, the bill of materials is a hierarchical representation of the assemblies, subassemblies, components and parts that form a product. Some authors that worked on this vertical approach are [9-12], among others. In the dynamic models, besides the BOM, these authors also employed the input-output analysis. According to [3], "input–output analysis models present the opportunity to transform one set of resources into another set using efficient mathematical language". The main objective

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of these models is lot sizing optimization, i.e., defining batch sizes and the optimum moments to start their production in time.

In the literature review presented by [3], there are only a couple works approaching Operations Scheduling and shop floor control [1], [13]. Lately, a few more models have been developed for these applications. These models are the focus of this paper and will be discussed with some detail in the following subsections. The model presented by [1] will be also included in the discussion, since it was considered relevant in this subarea.

A. The Lever Heuristic for Adaptive Production Scheduling (Model 1)

A computer-aided production scheduling and control system is proposed by [14]. In this system, an average processing time and lever heuristic (APT-LVR) is integrated with a closed-loop feedback control scheme, as shown in Fig. 1. The jobs are rescheduled based on simulation and reapplication of the heuristics to the updated boundary conditions of the problem. The simulation module employed by the mentioned authors is named THOCPN-CS and was developed using Petri nets.

The necessary steps to run the system, as presented in [14], are reproduced as follows.

1. Manually assign possible manufacturing resources (e.g. operators/machines) to each stage, and hence form a task-resource matrix (TRM).

2. Schedule the jobs by the APT-LVR heuristic.

3. The simulation module will simulate the execution of the jobs, and the bottleneck stages will be identified. Human schedulers may reallocate operators/machines in stages accordingly, to smooth production flow.

4. Reschedule the jobs by the APT-LVR heuristic.

5. Repeat steps 3 and 4 in the offline production scheduling phase until a satisfactory production schedule is obtained.

6. Deliver the production schedule to the shop floor and switch the control loop from the simulation model to the shop floor.

7. If any disturbance occurs on the shop floor, switch the control loop back to the simulation model, and go back to step 3 if operators/machines reallocation is necessary, or go back to step 4.

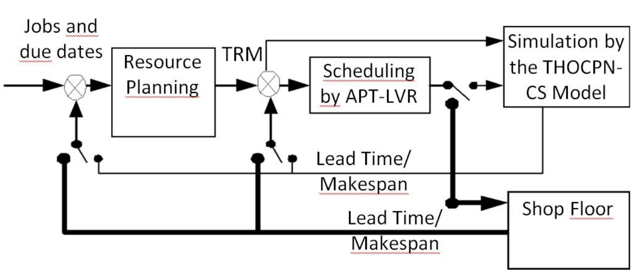

Figure 1. A computer-aided production scheduling and control system [14].

The heuristic developed by the authors is an extension of Johnson's algorithm. Basically, m machines are grouped into two virtual machines several times, and Johnson's algorithm is applied to obtain a set of sequences. The lever concept comes from an analogy with the moment of punctual forces applied on a beam. A flow line with *m* machines is modeled as a lever, as shown in Fig. 2. On this lever, the counter, *Ctr*, is regarded as a fulcrum. Each machine acts as a force with magnitude of d_{ij}, where d_{ij} is an array with the differences between the processing times of the jobs on machine j and the average of all processing times (APT). The distance between machines is of one unit. The counter is used as an auxiliary variable to split up the machines into two groups. As it moves along the beam, the sum of the moments in each side of the counter is calculated. Each of these sums correspond to an arrays associated to each virtual machine. Johnson's algorithm is thus applied to these arrays to generate a sequence. The sequence with best performance is chosen.

The proposed heuristic was applied to benchmark data for performance assessment. In addition, a case study was carried out in a company that manufactures windows and doors. In this company, 1396 jobs should be processed on a five-stage flow shop in one day. The researchers claimed that an improvement in productivity of 1,49% was obtained, which corresponds to processing 20 additional products daily [14].

B. A Scheduling Heuristic Based on the Distributed Arrival Time Controller (Model 2)

The Distributed Arrival Time Controller, DATC [15-16] is a scheduling model where an integral controller is used to determine the arrival times of parts. In this model, shown in Fig. 3, the scheduling is processed according to the just-in-time logic, where both earliness and tardiness from due date are penalized. The closed loop system iteratively adjusts the arrival time of a given part *i* so that it may be completed as close as possible from its due date. The completion time of the parts is calculated by a shop floor simulation module based on the arrival times of each iteration and the given processing times of the parts.

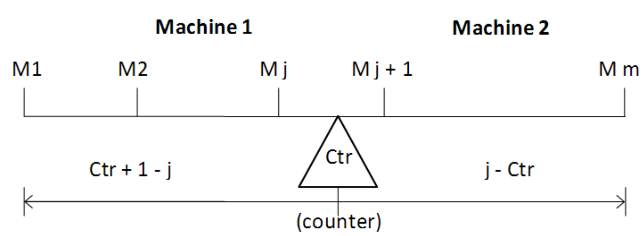

Figure 2. The lever concept for an m-machine flow line [14].

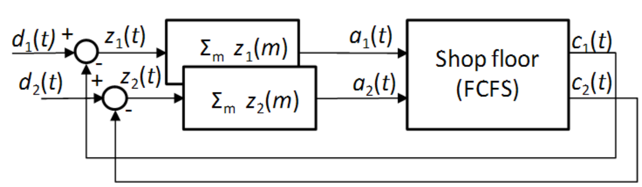

Figure 3. Structure of the Distributed Arrival Time Controller [16].

As it can be seen, each part has an embedded controller that computes the deviations of the expected completion time from the due date and adjusts the arrival times based on the accumulated deviations. For this reason, the controller of DATC is classified as an integral one. The completion times are calculated by the simulation module according to a first-come-first-served (FCFS) dispatching policy, which is applied in each iteration based on the current arrival times. The arrival time of *i*-th part in discrete time domain can be written as in

$$a_i(t) = k_i \sum_{m=0}^{t-1} [d_i(m) - c_i(m)] + a_i(0) = k_i \sum_{m=0}^{t-1} z_i(m) + a_i(0), \qquad (1)$$

where $a_i(t)$, $p_i(t)$, $c_i(t)$, $d_i(t)$ and $z_i(t)$ refer to arrival time, processing time, completion time, due date and deviation from completion time about due date of *i*-th part, respectively, and k_i is the control gain for *i*-th part.

In the proposed model, the scheduling objective is to minimize the Mean Squared Deviations of completion times from due dates (MSD), as follows:

$$MSD = \sum_i (d_i - c_i)^2 / n. \qquad (2)$$

According to [16], the integral controller of DATC works as a search engine that replaces the heuristics used in the traditional models. However, it is important to highlight that the controllers are distributed on part entities and computation of deviations and adjustment of arrival times in part entities takes place with limited global information, since each controller is independent of the other ones, as can be seen in (1).

The response of the model depends on the relationship between processing times and due dates. If the due dates are infeasible, that is, if they are too close to each other and cannot be simultaneously met due to insufficient resource capacity, then the trajectory of arrival times converges to a steady-state value, regardless of the initial values of arrival times. On the other hand, the trajectory converges to distinct values of $d_i - p_i$ when due dates are feasible.

The DATC was applied to static single machine scheduling problems with known optima, in order to evaluate its performance in this context. The biggest values for the average percentage deviation from the optimum solution were around 5%.

C. An Automatic Production Control System Based on a Continuous Flow Model (Model 3)

An Automatic Production Control (APC) system based on flow models in continuous time is presented by [1], [17]. According to them, a flow model is advantageous since control theory offers many more methods for continuous models than for discrete ones. The mentioned authors propose a flow-oriented stochastic job shop model based on the funnel model and the theory of logistic operating curves. They represent the work-in-process (WIP) of a work centre within a flow network in continuous time as in (3).

$$\begin{aligned} mwip_{order,k}(t) &= mwip_{order,k}(0) + extin_{order,k}(t) \\ &+ \sum_{j=1}^{k} [out_{order,\max,j}(t) - out_{order,loss,j}(t)]\, p_{j,k} \\ &- [out_{order,\max,k}(t) - out_{order,loss,k}(t)], \end{aligned} \qquad (3)$$

where $mwip_{order,k}$ (t) = mean work-in-process of centre k at time t, $mwip_{order,k}(0)$ = initial mean work-in-process of centre k, $extin_{order,k}(t)$ = cumulative external input of centre k until time t, $out_{order,max,j}(t)$ = cumulative potential outflow of upstream centre j until time t, $out_{order,loss,j}(t)$ = cumulative potential lost of outflow due to empty upstream centre j until time t, $out_{order,max,k}(t)$ = cumulative potential outflow of centre k until time t; $out_{order,loss,k}(t)$ = cumulative potential loss of outflow due to empty centre k until time t, and $p_{j,k}$ = fraction of total output from centre flowing directly to centre k. All these variables (except $p_{j,k}$, which is dimensionless) are expressed in number of orders.

As it can be seen in the right side of (3), the momentary work-in-process of work centre k depends on its initial inventory, its cumulated external input, the actual cumulative input of its upstream work centers flowing to k and its own actual cumulative output until time t. In simple terms, the work-in-process of each work centre on time t is a result of the difference between the input flow and the output flow, summed to the initial WIP. Thus, the second term and the summation in the right side of (3) represent the input flow, while last term in brackets refers to the output flow of work centre k.

According to [1], although the parameters of initial work-in-process, external input and potential cumulative output of each work centre are relatively easy to determine, the relation between losses in utilization ($out_{loss,k}$) and the momentary WIP level cannot be easily defined. In order to overcome this issue, the funnel model and the derived theory of logistic operating curves are applied.

The funnel model states the relationship among the work in process of a system, its performance (in terms of production rate or throughput rate) and its mean range (or lead time). The mean range is related to the mean runout time of the work centre. "The incoming orders, measured in hours of work content, form a stock of pending lots, which have to flow through de funnel outlet. The diameter of the outlet can be described as the capacity of the work system, which is adjustable within limits" and determines the actual performance of the system [1].

According to the theory of the logistic operating curves [18], the output of a work centre is independent of the mean work-in-process as long as every work system has a buffer of pending orders at all times. If so, the performance of the system is equal to its capacity. Losses in production will occur only if the buffer is further reduced, due to interruptions in material flow. Also, the range decreases in proportion to the WIP until the physical minimum is reached. Beyond this point the range cannot be further reduced because it is limited by the sum of the operation time and the transport time, which is the minimum range. The ideal WIP minimum represents the WIP level necessary to run the system, considering that the arriving orders do not have to wait and the material flow is not interrupted. Considering (3) and both the aforementioned theories, the flow of work in a work centre may be represented as in (4).

$$
\begin{aligned}
&mwip_{order,k}(t) = mwip_{order,k}(0) + \\
&\int_0^t \left(extin_{order,k}(t) + \sum_{j=1}^{k} per_j(mwip_j(t)) \frac{1}{mot_j} p_{j,k} \right) mot_j dt \\
&- \int_0^t per_k(mwip_k(t)),
\end{aligned} \tag{4}
$$

where $per_j(mwip_j(t))$ is the output performance of a center j for a given level of mean work-in-process. The performance is measured in terms of throughput rate, and its value is taken from the logistic curve. Actually, the term $per_j(mwip_j(t))$ represents a specific operating point of the work centre j in relation to its characteristic logistic curve of performance.

In order to adapt (3) to the continuous time domain and use control-theory elements, the dimensions of the variables must be converted from number of orders into work content (e.g. hours). This conversion is done by means of the mean order time of the work centers (*mot*), which appears in (4).

The transition probabilities are used since (4) represents a job shop configuration. These probabilities can be easily calculated with the aid of a common material flow matrix (MFM) obtained by using real data from the job shop. As known, this matrix shows the quantities of the material or the number of orders that flow from a work centre to another. To obtain the transition probabilities, the matrix must be normalized.

Based on the presented equations, a job shop model with two controllers was developed: a backlog controller and a WIP controller [1], [17], as shown in Fig. 4 and Fig. 5. The backlog of a system may be defined as the difference between the planned sum of work and the actual output. Thus, in this case, the planned performance is the reference variable whereas the capacity is used as a correcting variable. "The essential task of a work system is to allocate the required performance to process the system load" [1]. In the proposed system, the difference between the actual and the planned performance is integrated over a time interval, resulting in the above-mentioned backlog.

In most production systems, capacity can be increased or decreased in different size steps and a reaction time is required. This reaction time was included in [19]. Thus, the capacity installation and de-installation is represented in the model by envelope curves, as seen in Fig. 4.

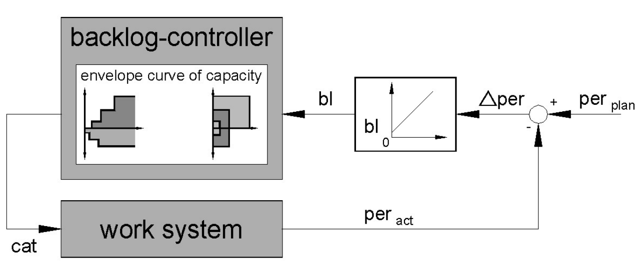

Figure 4. Concept of the automatic backlog controller [1], [17].

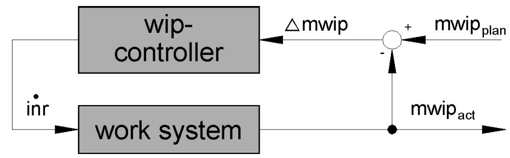

Figure 5. Concept of the automatic WIP controller [1],[17].

The main task of the WIP controller is "to set the system to an operating point on the operating characteristic curve that was defined within the scope of production planning" [1]. The reference variable is the planned WIP, and the controller adjusts the input rate of the production system based on the difference between the actual and the planned WIP, as shown in Fig 5.

In the model presented in [1], the backlog and the WIP controller were combined, as can be seen in Fig. 6. This combination is more effective to control the system since the backlog controller only acts when the planned utilization of the system is reached, otherwise, backlog does not arise. In this case, the WIP controller assumes the control task. The authors of the aforementioned work compare the two controllers to the conventional production control methods: capacity is usually increased when backlog increases in a production system; if the range keeps growing, the queue in front of the work system can be reduced by reducing the input rate of the system.

The functioning of the combined system is outlined as follows. First, in order to run the model, it is necessary to decide to which operating state on the characteristic curve the system should be driven. For this purpose, a value of utilization of the system must be set. Then, the necessary capacity is derived from the planned output and the planned utilization. In the other branch of the system shown in Fig. 6, the relative planned WIP ($mwip_{rel,plan}$) is multiplied by the mean WIP minimum resulting in the planned mean WIP. The backlog of the system is calculated by means of the integration of the deviations between the planned and realized performance over a time interval. The backlog controller then calculates the planned performance for the next period, which will lead to the corrected capacity of the system. The actual mean WIP of the system is also compared to the planned mean WIP. Based on the deviations, the WIP controller corrects the input rate of the system [1], [17].

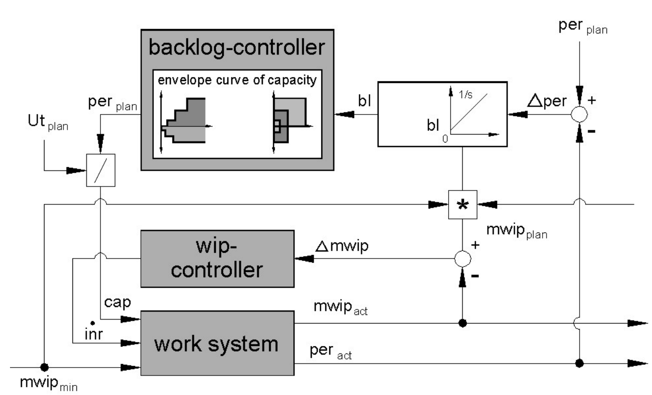

Figure 6. Concept of the combined WIP and backlog controller [1], [17].

In order to evaluate the proposed system, the aforementioned authors carried out simulations where an urgent order is introduced when the system is balanced. They compared the performance of the system without control and with control, observing the behavior of the mean WIP and the backlog over time in both cases. As expected, in the controlled system, work-in-process and backlog were reduced to the initial level much faster than in the uncontrolled system.

D. A dynamic single-product manufacturing system modeled with bond-graphs (Model 4)

The dynamics of the manufacturing systems is modeled using the bond-graph methodology in [20]. The bond graphs express general class physical systems through power interactions between the components. The methodology is based upon an analogy with the ideal properties of basic electronic components, such as resistors, capacitors and transformers. Each of these components have a correspondent graphical representation. From the graphical model, the mathematical structure of the system, i.e., the state representation, can be deducted.

Four types of generalized variables are considered in this technique, as known: stress (e), flow (f), moment (q) and displacement (p). In the model developed by [20], the flow variable f represents the evolution of the material flow over a given section of the manufacturing system, while the moment q is the production volume, which corresponds to the integral of the production flow. The variable stress e is used to represent the coupling phenomenon between a machine and its precedent stock, in the case when its production capacity is impeded by the entity located upstream for missing available material. The displacement variable is not used.

The production entities used are: sources, stocks, machines, convergent and divergent junctions and wells. The sources provide the material flow to the system, while the wells are similar to stocks with infinite capacity, used to represent the system outputs. The machines are represented by resistors, while the stocks are modeled, by analogy, as capacitors. Each machine is preceded by a correspondent stock; they are connected by means of a coupling structure, forming a production station. The convergent and divergent junctions enable the representation of the topology of the manufacturing system, i.e., they aggregate the different paths of flow that must go through an specific station or they distribute the material flow into the different stations of the system. The bond-graph representation of a station, that is, a stock-machine entity is shown in Fig. 7.

In order to illustrate the bond graph application to manufacturing systems, [20] modeled the single-product manufacturing system presented in Fig. 8.

The state representation of the manufacturing system is derived from the constitutive equations of each element, i.e., resistor, capacitor, junction, etc., which are well known among the bond graph users.

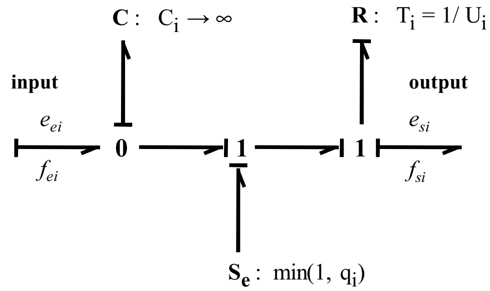

Figure 7. Bond graph model of a station [20].

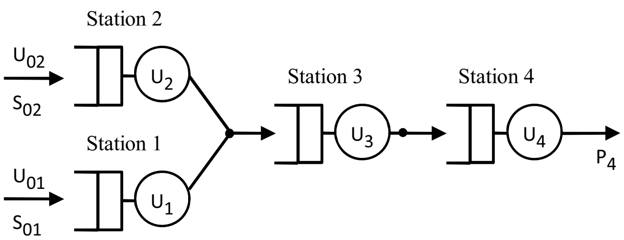

Figure 8. Elementary single-product manufacturing system modeled and simulated in [20].

The control objective is to adjust the level of the output flow of the system to attend the demand of the considered product, while, at the same time, keeping the work in process (WIP) at the desired levels. This objective must be achieved by controlling the production frequencies of the machines and the flow sources, represented by the variable U in Fig. 8. In [20], the control of the system was simulated for the following conditions: null initial stock levels for all the intermediate stocks; reference levels of 15, 10, 20 and 22 material units for the stocks 1 to 4, respectively; reference production frequency of the machines derived from the solution of the state model of the system for the permanent regime.

This presented system is dynamic in the sense that it can respond to some unexpected events, such as machine breakdowns. In order to test this feature of the system, the breakdown of machine 3 at the time t = 45s was simulated. The machine remained broken for 3s. After machine 3 stops, the production frequencies of the machines 1 and 2 are temporally reduced to avoid an excessive WIP accumulation at station 3. Also, the supply flow of the sources 01 and 02 is reduced. The quantity of material accumulated in the stock of station 4 enables it to continue production normally. After approximately 120s, all the reference levels for the stocks are achieved and the system becomes stable, operating at its permanent regime. Therefore, the results showed that the system was able to dynamically respond to the machine breakdown.

III. COMPARATIVE AND CRITICAL ANALYSIS

A comparative analysis among the three discussed models is summarized in Table 1. As it can be seen, models 1 and 2 are similar regarding their application and time domain. These models work with detailed and discrete production orders, whilst model 3 uses weighted averages calculated from discrete orders data. Also, model 3 is suitable for a more complex production configuration. Thus, the use of average values may be advantageous to simplify the solution of the problem, since job shop scheduling problems are *NP*-complete.

TABLE I. COMPARISON BETWEEN THE PRESENTED MODELS

	Modelo 1	***Modelo 2***	***Modelo 3***	***Modelo 4***
Domain	discrete	discrete	continuous	continuous
Application	scheduling	scheduling	shop floor control	shop floor control
Nature of the problems	dynamic, not automatic	static	dynamic, automatic	dynamic, automatic
Production configuration	flow shop	single machine	job shop	not applicable (single product)
Number of products/ jobs	multiple	multiple	multiple	single
Main variables and parameters	processing times, makespan	processing times, due dates, controller gains, lateness	work content, WIP, range, backlog, utilization, performance	WIP, inventory reference levels, frequency of operation of the machines
Theoretical background for modeling	extension of Johnson's algorithm	expressions of PI and PID controllers (not used in the dynamic sense)	analogy with fluid systems, funnel model, logistic curves	analogy with electrical systems, bond graph technique

It is worth mentioning that model 2 is, in fact, an iterative method to obtain a near optimal schedule, replacing conventional heuristics. Therefore, it is not a dynamic model in the strict perspective of System Dynamics and Control Theory. The feedback loop present in this model is an internal element that is part of the algorithm for scheduling optimization; it does not work as a controller itself. The discrete variable t that appears in this model represents the iterations executed to reach the solution. There is no direct relation between this variable and the real time of shop floor events. Although some disturbances may be presented to the model, such as the inclusion of an extra job to be scheduled, it deals in essence with a static problem, where there is a fixed number of parts to be scheduled and, after a given number of iterations, the best schedule is found.

The model 1, on its turn, has a valid feedback system. From the design perspective, however, it does not fit into the conventional parameters of control theory, since the compensation action of the system is not automatic and it is not mathematically represented. The compensation, in this case, is done by an action of the user, which reapplies the proposed heuristics to a different set of initial conditions. On the other hand, this practical feedback of the scheduling execution status is of much interest for managers, even if it is not automatic. Thus, this feature is an advantage of model 1.

In the sense of automatic feedback, the models 3 and 4 are the most aligned to control theory principles. The controllers of these models automatically respond to an input disturbance, aiming to minimize the effect of this disturbance and bring the system back to a stable point. The disturbance corresponds to the arrival of an urgent job, in the case of model 3 and a machine breakdown, in the case of model 4. The variable time (t) considered in model 3 corresponds to real shop calendar days. Thus, it is possible to obtain an accurate estimative of how much time the system would need to stabilize and how much capacity increment would be necessary. On the other hand, model 3 is much more complex than the others not only regarding mathematics, but also in terms of practical application. It requires the continuous measurement of several variables related to the schedule execution in the shop floor and the estimation of various parameters of the system. In summary, this model encompasses more variables and requires higher data acquisition and pre-processing efforts.

The common element of the models are the application for which they are designed. As previously said, all the models are developed for production scheduling or production control in the short term. On the other hand, it can be seen that the methodologies employed for modeling and the variables used are pretty diverse. The production configuration for which the models are applicable also differs.

IV. CONCLUSIONS AND DIRECTIONS FOR FUTURE WORKS

This paper presented and discussed three recent models for Scheduling and Shop Floor Control based on control theory elements. The presented comparative analysis highlighted some advantages and disadvantages of each model, being also useful to help practitioners when choosing the most suitable model for specific contexts.

This short review showed that there is a lot of room for the development of dynamic models for Scheduling and Shop Floor Control. In comparison to the other applications of control in production and inventory systems, this body of knowledge is still incipient. One relevant branch would be using control theory in the development of models for dynamic scheduling, since the vast majority of works approaches static problems, using a variety of heuristics. Other direction could be the extension of some models, which were applied to a single machine configuration, for instance, to more complex configurations such as flow shop or job shop systems. An additional contribution would be the application of the presented models in real systems, in order to define more realistic parameters and evaluate system performance.

Many dynamic and control models rely on several parameters, i.e. time constants, and values for the controller gains. Usually, for electrical or mechanical applications, there is a systematic procedure for determining these parameters, which does not exist for most of the manufacturing applications. A methodology that focuses on this point can be also a subject for future research. The Artificial Intelligence tools could be applied in the System Identification field, in order to help to define the parameters of the modeled manufacturing systems. The pattern recognition capabilities of the Artificial Neural Networks are often applied to that aim, such as in [21-25]. In some of these works, fuzzy logic is also applied [21] [25]. Once again, most of the existing applications are devoted to mechanical, electrical or chemical systems. The literature lacks applications of AI tools to System Identification of manufacturing systems. Also, the design and optimization of the controller for the dynamic manufacturing systems may be certainly improved with the aid of AI methods, such as fuzzy logic and genetic algorithms, which are usually applied to the control of mechanical and electrical systems.

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