Technical paper

Distributed adaptive control of production scheduling and machine capacity

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1. Introduction

With today’s fierce global competition, companies cannot survive unless they introduce new products or services in a timely manner, meeting requirements of high quality, low costs, and short lead times. Importantly, order promises for these products must be made based on minute-to-minute reality of operations or the visibility into shop floor activities. Otherwise, the company may suffer from loss of sales and good will. Under this pressure, one of the key determinants for business enterprises to succeed is efficient control of manufacturing and associated systems because manufacturing is where value is added. Manufacturing resource planning (MRP) has been developed to provide a general control structure for manufacturing systems that breaks the manufacturing control problem into a hierarchy based on time scale and production aggregation. More recently, enterprise resource planning has integrated the hierarchical approach in MRP into a formidable management tool that can consolidate and track enormous quantities of data [11]. In these MRP/ERP systems, a gap, a so-called “information gap”, exists between the resource control and shop floor control due to the assumptions of infinite capacity and fixed lead times that are found even in some sophisticated ERP systems [33,11]. A primary reason for this gap is the heterogeneous nature of control variables: They are continuous at lower levels and discrete at higher levels. For example, control at the CNC level mostly deals with continuous variables such as spindle speed, feed rate, and temperature, while scheduling decisions at the shop-floor level are concerned with discrete sequences of production orders. Fig. 1 shows the functional hierarchy in manufacturing systems together with information flow of both control and data. At the CNC (process) level, machining conditions such as tool life and machine health change dynamically. These changes can require the adjustment of processing parameters such as cutting speed, feed rate, and depth of cut, which leads to changes in part processing times, as shown in Fig. 1.

However, at the shop-floor level, part processing times are assumed in general to be static in conventional manufacturing systems that employ static scheduling methods rather than dynamic scheduling methods, and thus plans and schedules generated with this assumption are often impractical, leading to considerable variations in planned order releases in MRP/ERP systems. Therefore, changes in processing conditions need to be considered in the scheduling or planning systems in the form of processing time changes so that the information gap can be bridged and the variations in delivery time reduced. To this end, there is a need to develop an integrated control system with low complexity of adaptive CNC control and production scheduling that can ensure real-time responsiveness to changes in resource conditions and production demands along with intelligent utilization of capacity [2]. Fig. 2 shows the concept of such an integrated control system in which distributed entities interact over the communication network to cope with changes in both resource conditions and production demand.

This paper focuses on modeling and simulation of such a unified system of distributed production scheduling at the shop-floor level...
and machine capacity control at the CNC level using a continuous control-theoretic approach. Importantly, increased adaptiveness by the unified system to the changes in both machining conditions and production demands will be discussed, and an improved fault-tolerant ability of the unified system due to underlying distributed control architecture will be studied as well.

2. Literature review

Significant developments in control of manufacturing and associated systems can be viewed from both the shop-floor level and CNC level. At the shop-floor level, MRP systems have been developed to determine the raw materials and resource requirements that satisfy production orders. Early computer-based implementations of MRP were extensions of accounting and stock control systems and were developed primarily around the needs of discrete-part manufacturing industry [21]. While such data-intensive and transaction processing systems were valuable to make-to-stock manufacturing companies with deep bills of material (BOM), one of the central drawbacks of the plans produced by MRP systems was that they are not necessarily feasible because they are based on an assumption of infinite capacity and may generate infeasible plans that result in significant delays in delivery [19,30]. To overcome this problem, finite capacity scheduling (FCS) methods have been developed, where the adjustment and control of capacity is allowed for shop-floor-level planning, resulting in improved delivery commitments. Application of the FCS method in assembly operations can be found in [31,7,5].

Significant developments in controls at the CNC level, which mostly focus on the optimal processing parameters, include off-line optimization techniques and on-line adaptive control methods. The off-line optimization techniques can be categorized into
the CAD-based approach and the operations research approach. In the CAD-based approach, cutting force and tool wear are calculated through computer simulation using information in NC code for initial machining parameters. Note that the content of this article is conducted using machining process models and tool wear models within the CAD system. In this approach, optimum processing parameters are achieved by maximizing material removal rate without violating machining constraints [20]. Advantages of this approach are that it is effective in practical applications with the aid of graphical tools. However, the drawback of this approach can be its high computational complexity, which makes the approach not suitable for real-time control. Operations research (OR) approaches solve problems for either maximizing material removal rates or minimizing production cost, or both, which are subject to constraints on processing parameters, which is called the machining economics problem. Various OR techniques can be used for the machining economics problem, such as geometric programming [8], linear programming [9], branch-and-bound [28], dynamic programming [26], and numerical method [1]. Recently, nonlinear programming techniques have been proposed for economic processing of multiple flexible machines [27]. Specifically, these nonlinear programs optimize processing parameters using deterministic or probabilistic tool-life models. Malakooti and Deviprasad [18] formulated a metal-cutting operation as a discrete multiple-objective problem and provided a solution method using multiple-criterion decision making. One of the shortcomings of such OR techniques is that they are suitable for centralized and off-line computations and are difficult to scale up for real-time control of large manufacturing systems because of their inherent computational complexity [2].

On the other hand, the adaptive control approach has the capability to respond to changes in machining conditions in real time and optimally compensate for the processing variables such as speeds and feeds during the process. Spindle deflection or force, torque, cutting temperature, vibration amplitude, and horsepower are a few examples of the machining conditions considered in this approach. Although many attempts have been made to construct sophisticated adaptive control systems, the results obtained have been limited by the difficulty of measuring critical process variables accurately and the cost of such systems. Thus, the research on adaptive control has been focused on adaptive control optimization (ACO) and adaptive control constraints (ACC) [14]. ACO systems optimize a performance index, such as production rate or cost per unit of metal removed, by controlling speeds and/or feeds. ACO has been successfully employed in grinding processes where on-line tool wear measurement is not required. However, there have been no industrially acceptable methods developed for the direct measurement of tool wear in other processes, making the implementation of the ACO impractical. In ACC systems, the objective is to manipulate speeds and/or feeds to maintain the measured variables below their constraint limit values. In other words, ACC adjusts the processing parameters in real time to the maximum within the prescribed region bounded by process and system constraints. It has been pointed out that there has been some level of success in the development of ACC for various processes [29,17,15,12].

From the review of relevant research, it is observed that there is a need in finite capacity scheduling to utilize more accurate information about the capacity at the CNC level in real time to increase the responsiveness of manufacturing systems to the dynamically changing conditions at the shop-floor level. Also, it should be pointed out that adaptive control approaches can be improved by considering the changes at the shop-floor level, such as changes in production demands, not just considering the changes in machining conditions, because in some cases meeting customer demand changes may be more important than reducing the cost of a machining operation. Therefore, intelligent control systems that can respond and adapt to the changes at the CNC level and shop-floor level simultaneously are studied in this paper.

3. Distributed arrival time control system for production scheduling

The state of systems in discrete-part manufacturing moves through a set of discrete events, including productive and disruptive events. The timing of these events, which are associated with dynamically changing shop floor conditions, has a significant impact on system performance because they can determine the evolution of events in the system. Although there has been a considerable amount of effort to develop algorithms that can optimize combinations of decisions on timing, they generally require excessive computing due to the combinatorial complexity inherent in these systems. Therefore, in many practical applications, simple rules such as the shortest processing time first (SPT) and the earliest due date first (EDD) are used at the cost of poor performance.

A critical issue in dealing with discrete events for production scheduling is the ability to react to uncertainties in real time by making rapid decisions to maintain an acceptable level of performance. In response to this practical need, distributed decision making and control approaches must be developed to reduce the software complexity while maintaining high levels of fault tolerance and flexibility. Recently, production planning and control problems in manufacturing have been modeled in terms of agents, especially multi-agents that can represent physical production resources such as machines and parts. Agents have their own beliefs about and preferences over the status of their environment and have particular sets of actions to change it. As a distributed problem-solving paradigm, an agent-based approach breaks complex problems into small and manageable subproblems [13,6,32,16]. Due to these properties, an agent-based scheduling model can operate in environments that are partly unknown and unpredictable. To address the need of reduced complexity and increased fault tolerance and flexibility, a continuous feedback control system approach has been developed in distributed manufacturing applications [23]. Furthermore, the need for tractable continuous control-theoretic approaches for distributed systems has led to the development of a distributed arrival time control (DATC) system utilizing autonomous entities [22]. The DATC system utilizes local autonomous entities for shop floor control, such as part and machine entity. Since arrival times have a significant impact on system performance, due to their implicit determination of the evolution of events in the system, the DATC system continuously controls arrival time using completion time feedback to minimize due date deviation. Using virtual entities, the DATC system simulates various combinations of event timing to provide better decision making. Shop floor conditions of the physical systems are feedback to the simulation for the DATC system.

A closed-loop arrival time controller can be constructed for each part entity in which tentative arrival time is iteratively adjusted to improve system performance. For a multi-variable closed-loop feedback control system, adjustment of arrival times for a single machine can be expressed as a function of continuous time as follows:

\[ a_i(t) = k_i \int (d_i - c_i(t)) \, dt + a_i(0) \]  

where \( a_i(t) \), \( k_i \), \( d_i \), and \( c_i(t) \) denote the arrival time, control system gain, due date, and completion time of the \( i \)th part, respectively. The first derivative of Eq. (1) gives

\[ \frac{da_i(t)}{dt} = k_i(d_i - a_i(t) - q_i(t) - p_i) \]  

where \( q_i(t) \) is queuing time until processing starts and \( p_i \) is the processing time of the \( i \)th part. The DATC system transforms the combinatorial production scheduling problem into the dynamic
problem of continuous control for arrival times, which can be expressed as Eq. (2). This continuous control nature offers an opportunity to the DATC system to be suitably unified with adaptive machine control systems, which deal with optimal control of processing parameters in response to dynamically changing machining conditions. Eq. (1) can be rewritten in the discrete time domain for computer-based implementation, as follows:

\[ a_i(mT) = k_i(d_i - c_i((m - 1)T)) + a_i((m - 1)T) \tag{3} \]

where \( T \) is the discrete time step. Fig. 3 illustrates the closed-loop control of the DATC system in discrete time.

It should be emphasized that even though each controller manipulates its arrival time autonomously, the global effects of all the arrival time controllers are included in the global simulation and therefore in the completion time feedback. The completion time feedback in real time plays an important role in unifying the DATC system with an adaptive machine control system because it takes account of the changes in part processing times. Note that information on the CNC level is transmitted to the higher-level production scheduling system due to the real-time feedback.

Fig. 4 depicts that the arrival times modeled using Eq. (1) exponentially converge to a single steady-state value when the production demand in the manufacturing shop floor exceeds the available resource capacity. It has been shown that the single steady-state value of arrival times can be analytically predicted [22]. After the arrival times converge to the steady-state value, the relative order of arrival times continues to change, generating various part processing sequences. The DATC system keeps searching various schedules based on part processing sequence change. Thus, the DATC system can be viewed as “search heuristic based on feedback control”. Recent work has focused on developing techniques to design control system parameters such as gains in order to improve scheduling performance and predictability [3,4].

4. Unified control system

- \( N_m \): current spindle speed in revolutions per minute (rpm)
- \( N_{nm} \): nominal spindle speed in revolutions per minute (rpm)
- \( \lambda_j \): capacity variable for a machine \( j \)
- \( D \): diameter of part (mm)
- \( L \): length of workpiece

\[ \text{TL tool life (min)} \]
\[ C \]: Taylor's tool-life constant
\[ \alpha, \beta, \gamma \]: speed, feed, and depth of cut exponents in tool-life equation, respectively
\[ v \]: cutting speed (mm/min)
\[ f \]: feed rate (mm/rev)
\[ d \]: depth of cut (mm)
\[ dc \]: total depth of material removed (mm)
\[ n_p \]: number of tool paths per part
\[ n_t \]: number of tool changes per pass
\[ t_p \]: time per pass (min)
\[ t_c \]: cutting time (min)
\[ BHN \]: material hardness (Brinell Hardness Number)
\[ c_c \]: cutting cost ($/min)
\[ c_{ch} \]: tool-changer cost ($/min)
\[ c_t \]: tooling cost ($).

This paper considers a problem to minimize a multiple-criterion objective function of

\[ U = U_1 + U_2 = \frac{\left( x_1^2 + x_2^2 + x_3^2 \right)}{n} + \frac{x_4^2}{n}. \tag{4} \]

Here \( x_1, x_2, x_3, \) and \( x_4 \) denote processing speed (time/part), surface finish (height of roughness), production cost, and mean-squared deviation of job completions about due dates to address the customer satisfaction and work-in-process together, respectively, and \( n \) is number of parts to be processed (see the equations in Box 1).

Detailed information on the objective functions, \( x_1, x_2, \) and \( x_3, \) can be found in [18], where they investigated interactive and paired comparisons of alternatives for minimizing the utility function of \( (x_1^2 + x_2^2 + x_3^2) \). It should be pointed out that minimizing \( x_4 \) is equivalent to the objective in just-in-time (JIT) production and is important because it simultaneously lowers work-in-process inventory and improves production timeliness. In addition, from a scheduling perspective, \( x_4 \) is a non-regular performance measure, which implies that decreasing completion times by decreasing \( x_4 \) does not guarantee that \( x_4 \) will be decreased [3]. Here, the following assumptions are made:
- all parts are available for processing at time zero
- setup times are sequence independent and may be included in the processing times
- there is no machine idle time or downtime during processing of any part
- no preemption is allowed.

The need for adaptation to changes requires the Distributed Machine Capacity Controller (DMCC) to use the output of higher-level scheduling systems, such as production demand, and to receive feedback of machine conditions from the lower level. This leads to the unification of the DMCC and DATC, as shown in Fig. 5. In Fig. 5, integral controller adjusts arrival times to minimize deviations between projected completion times and given due dates, a virtual plant floor computes projected completion times using simulation, and a capacity controller adjusts operating capacity of machines using information on health from sensory and arrival times from the DATC. Fig. 5 illustrates shop floor conditions, including machine deterioration feedback to the DMCC. It also shows that the processing time in the simulation using the virtual system will change based on the output of the DATC system in the form of demand. Machine condition feedback is obtained in real time from physical measurements. This implies that the DMCC will try to increase its capacity to meet the production demand, while satisfying constraints imposed by real-time machine conditions. It should be emphasized that the proposed approach allows intelligent machines to fully utilize their local intelligence and sensing capabilities to evaluate their
An extended form of Taylor's tool-life equation is:

\[ x_1 = \frac{\pi DL}{f v} \]

\[ x_2 = \begin{cases} 
1.22 \times 10^2 \times r^{-0.714} \times BHN^{-0.323} \times f^{1.004} \times v^{-1.52}, & 25 \leq v \leq 250, f \leq 0.75 \\
0.071057 \times r^{-0.714} \times BHN^{-0.323} \times f^{1.54} \times v^{-0.75}, & v > 250, f \leq 0.75 \\
0.3013 \times r^{-0.714} \times BHN^{-0.323} \times f^{4.54}, & v > 250, f > 0.75 
\end{cases} \]

\[ x_3 = \pi TL/\alpha \]

\[ x_4 = \frac{\sum (d_i - c_i)^2}{n} \]

**Box I.**

**Scheduling (DATC)**

Due date Deviation Arrival time Completion time

**Integral Controller**

**Virtual Plant Floor**

**Capacity Controller**

Machine Health

**Machine Capacity Control (DMCC)**

Fig. 5. Unified system for manufacturing systems control.

By substituting (7) and (8) into \( TL = t_p/n_p \), and rearranging,

\[ TL = \left( \frac{\pi DL}{\pi^2} \left( \frac{d}{C (n_p)} \right)^{\frac{1}{n_p}} \right) \cdot \frac{r}{\alpha} \]  \tag{9} \]

Using (9), feed rate \( f \) can be expressed as a function of tool life \( (TL) \) as follows:

\[ f = \left( \frac{TL}{\pi^2} \right)^{\frac{1}{n_p}} \left( \frac{d}{C (n_p)} \right)^{\frac{1}{n_p}} \pi DL \]  \tag{10} \]

Depth of cut \( (d) \) can be obtained from the following relationship:

\[ d = \frac{dc}{n_p} \]  \tag{11} \]

Therefore, processing parameters can be expressed as a function of capacity variable.

The machine capacity variable can be characterized in a number of ways, and this is investigated in two ways in this paper. One way can be expressed as follows:

\[ \lambda(t) = \sum_{q} p_q \]  \tag{12} \]

where \( p_q \) denotes processing time of the part in machining and \( p_p \) presents processing time of a part in the machine queue. In this way, the machine capacity at any given time is characterized as the amount of work at the queue for the machine at that time. The other way investigated in this paper is presented as

\[ \lambda(t) = \frac{q_p}{p_p} \]  \tag{13} \]

In this way, the machine capacity variable increases as the queuing time becomes greater than the processing time of the part. These two ways will be evaluated in another section.
Eq. (2) of the dynamic model for the DATC can be modified with a capacity variable as follows:

$$\frac{da_i(t)}{dt} = k_i \left( d_i - \left( a_i(t) + q_i(t) + \frac{p_i}{\lambda_j(t)} \right) \right).$$ (14)

When the jth machine operates at its nominal capacity, machine capacity $\lambda_j(t)$ is denoted as unity. When the machine operates at higher capacity than nominal capacity, then $\lambda_j(t) > 1$ and thus the actual processing time for the part will be less than its nominal processing time. In this unified system, the DATC tries to meet its due date by continuously adjusting its arrival time by considering the actual processing time, $p_i/\lambda_j(t)$, which changes corresponding to the machine capacity. The algorithm for this unified system can be outlined as follows:

Step 1: Initialize arrival times
Step 2: Computing completion times
  - Computing local performance ($z_i = (d_i - c_i)$)
  - Adjusting arrival times by integral control law
Step 3: Computing processing parameters using Eqs. (6), (10) and (11)
  - Computing processing times using processing parameters
  - Adjusting capacity variable using processing time information
Step 4: Compute objective function using Eq. (4)
Step 5: Go to Step 2

5. Numerical examples

To illustrate the working of the unified control system, an example problem with three parts on a single machine is presented first in this section. The unified control system is then applied for general manufacturing systems such as parallel machine, flow shop, and job shop problems where multiple parts are processed through multiple stages.

5.1. Single-machine example

In the single-machine example, all three parts have identical material property and geometry except their lengths ($L_1, L_2, L_3$). The machining data for this example are based on a turning process where a carbide cutting tool works on a mild steel workpiece, which can be obtained from the literature [10]. This example is also used in [18], where they proposed a heuristic, gradient-based multiple-criterion decision-making approach for efficient processing parameter selection in metal cutting. It has been found that their algorithm could not be used for minimizing multiple criteria for multiple parts and multiple machines, including objective functions associated with customer satisfaction [18].

The reason for this restriction is that there is no parameter in their algorithm to account for customer satisfaction based on the earliness/tardiness of job completions.

$\gamma = 0.9$
$\beta = 1.75$
$BHN = 195$ BHN
$d$ = 5.0 mm
$L_1 = 1000$ mm
$L_2 = 1300$ mm
$L_3 = 1800$ mm.

For this example, the unified system has been simulated with the number of iterations as 1000 and the control system gain as 0.1. Tables 1 and 2 show the results obtained from this simulation, such as the objective function and corresponding sequences, machine capacity variables, and processing parameters. From these tables, it can be observed that by increasing the machine capacity the objective function for due date deviations ($U_2$) decreases by 85.8%, while the objective function for production ($U_1$) increases by 102.8%. Here, the deviation is defined as the ratio (%) of the performance of the unified system to that of the DATC:

$$\frac{U_{2_u}}{U_{2_d}} \times 100$$

where $U_{2_u}$ is $U_2$ of the DATC and $U_{2_d}$ is $U_2$ of unified system. The unified system outperforms the DATC in terms of overall objective function, as shown in Table 1. In the next section, the unified system and DATC will be tested for large size problems ($n = 20, 40$).

5.2. Multiple machine example

The unified control system has also been applied for general manufacturing systems such as parallel machine, flow shop, and job shop. First, a system with 10 parts and two parallel machines has been tested to explore the relationship between the machine capacity and the demands in that machine. Two parallel machines (MC1 and MC2) are initially identical with common nominal capacity. Fig. 6 illustrates that when MC1 becomes degraded such that the capacity decreases by approximately 50%, DMCC autonomously adjusts the capacity of MC2 by approximately 150% without explicit notification.

Then, a flow shop where five parts are processed through two machines and a job shop, where three parts are processed through two machines have been tested to show that the unified control system can be scaled up to general manufacturing systems, minimizing production costs and MSD simultaneously. Tables 3 and 4 summarize problem parameters in detail. Machines used in this problem are turning machines. Material properties are identical to the single-machine example. Note that due dates are given as common for both examples, and machines 1 and 2

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Comparison of objective functions of DATC and unified system</th>
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<tbody>
<tr>
<td></td>
<td>Objective function</td>
</tr>
<tr>
<td></td>
<td>DATC</td>
</tr>
<tr>
<td>Unified system</td>
<td>857.1</td>
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<tr>
<td>Unified/DATC (%)</td>
<td>98.2</td>
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![Fig. 6. Autonomous capacity control.](image-url)
Table 2
Machine capacity and processing parameters

<table>
<thead>
<tr>
<th>Sequence</th>
<th>Capacity</th>
<th>Cutting speed (m/min)</th>
<th>Feed rate (mm/rev)</th>
<th>Depth of cut (mm)</th>
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<tr>
<td>DATC</td>
<td>3</td>
<td>1.00</td>
<td>157.08</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1.00</td>
<td>157.08</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.00</td>
<td>157.08</td>
<td>0.30</td>
</tr>
<tr>
<td>Unified system</td>
<td>2</td>
<td>1.35</td>
<td>211.67</td>
<td>0.43</td>
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<td></td>
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<td>1.00</td>
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<tr>
<td></td>
<td>3</td>
<td>1.00</td>
<td>157.08</td>
<td>0.30</td>
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Table 3
Parameters for flow shop problem

<table>
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<tr>
<th>Parts</th>
<th>Part type</th>
<th>Routing</th>
<th>Due date</th>
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<tbody>
<tr>
<td>Part 1</td>
<td>1</td>
<td>1, 2</td>
<td>3000</td>
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<tr>
<td>Part 2</td>
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<td>1, 2</td>
<td>3000</td>
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<tr>
<td>Part 3</td>
<td>1</td>
<td>1, 2</td>
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<td>Part 4</td>
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<tr>
<td>Part 5</td>
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<td>3000</td>
</tr>
</tbody>
</table>

Table 4
Parameters for job shop problem

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<th>Parts</th>
<th>Part type</th>
<th>Routing</th>
<th>Due date</th>
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<td>3000</td>
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<tr>
<td>Part 3</td>
<td>1</td>
<td>1, 2</td>
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Table 5
Computational result for flow shop problem

<table>
<thead>
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<th></th>
<th>U</th>
<th>$U_1$</th>
<th>$U_2$</th>
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</thead>
<tbody>
<tr>
<td>DATC</td>
<td>2035</td>
<td>1059</td>
<td>976</td>
</tr>
<tr>
<td>Unified</td>
<td>2159</td>
<td>1515</td>
<td>643</td>
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<tr>
<td>Unified/DATC (%)</td>
<td>106</td>
<td>143</td>
<td>66</td>
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Table 6
Computational result for job shop problem

<table>
<thead>
<tr>
<th></th>
<th>U</th>
<th>$U_1$</th>
<th>$U_2$</th>
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</thead>
<tbody>
<tr>
<td>DATC</td>
<td>1004</td>
<td>162</td>
<td>842</td>
</tr>
<tr>
<td>Unified</td>
<td>1006</td>
<td>910</td>
<td>96</td>
</tr>
<tr>
<td>Unified/DATC (%)</td>
<td>100</td>
<td>561</td>
<td>11</td>
</tr>
</tbody>
</table>

are used for processing of parts with lengths of 1000 mm and 1500 mm, respectively. Tables 5 and 6 present the computational results for flow shop and job shop examples, respectively. The main design parameter to “tune” the DATC feedback controller is the controller gain. A higher gain can result in faster convergence but potentially lead to poorer schedule performance. Prior work analyzing the nonlinear switching dynamics in the DATC has shown that as the problem size increases, smaller control gain (about 0.02) serves as a good trade-off between convergence rate and schedule performance [4]. For simpler configurations, such as a single-machine system, a gain of 0.1 provides fast convergence without any significant loss in scheduling performance. Control system gains of 0.02 have been used for these examples, and the results in the tables are the average values of 10 replications. As in the example of the single machine, the unified system has reduced $U_2$ by 66% and 11% for flow shop and job shop, respectively, by changing machine capacity. Figs. 7 and 8 show the arrival-time trajectory and total cost for the flow shop example. Fig. 9 shows that the scheduling performance has been improved in the unification of the DATC and DMCC by 12.74%.

6. Computational experiment

The performance of the unified control system can be evaluated empirically using a well-designed computational experiment.

In this paper, the designed computational experiment for the proposed system is shown in Table 7.

Two levels have been tested for each parameter, which in turn leads to a $2^5$ factorial design. Due dates ($d_j$) can be generated as follows, considering the tardiness factor and spread factor [24]:

$$d_j = U \left( \sum_k p_k \times (1 - \tau) \left( 1 - \sigma / 2 \right) \right) + \sum_k p_k \times (1 - \tau) \left( 1 + \sigma / 2 \right)$$.

Fig. 7. Arrival-time trajectory for a flow shop problem ($n = 5, m = 2$).

Fig. 8. Total cost for a flow shop problem ($n = 5, m = 2$).

Fig. 9. Total cost for a job shop problem ($n = 50, m = 4$).
Tardiness and spread factor can control tightness and variance of due dates, respectively. The levels of spread factor have been set to 0.1 and 0.5 to ensure that due dates are infeasible. The levels of the number of parts were chosen as \( n = 20 \) and \( n = 40 \) to ensure reasonably large problem sizes. Also, significant variability in processing times was tested as given in the workpiece length information in Table 7. The effect of the number of iterations is investigated using two levels, as given in the table. Algorithms tested in this computational experiment include the DATC, the unified control system of the DATC and DMCC with a method of capacity control using Eq. (12), and the unified control system of the DATC and DMCC with another method of capacity control using Eq. (13). In all \((2^2) \times (10 \text{ replications}) = 320 \text{ instances}\)

were solved by each of the three algorithms (DATC, Unified DATC #1, Unified DATC #2). Table 8 shows the results obtained from the computational experiment. Each cell of Table 8 is the best value over the 10 instances tested. Tables 8 and 9 present the performance of two unified control systems, including the effect of each objective such as plant floor \((U_1)\) and shop floor \((U_2)\) together. From Tables 8 and 9, it can be observed that there is no significant difference between the two unified systems in terms of overall system performance \((U)\). However, unified system #1 outperforms unified system #2 in terms of the first objective of plant floor \((U_1)\), while unified system #2 outperforms unified system #1 in case the second objective of shop floor \((U_2)\) is more critical. Fig. 10 graphically shows the performance comparison of the two unified control systems to the DATC system, which is summarized in Table 9.

7. Conclusion

In this paper, a unified control system has been developed to address the need for systems that can adapt to changes both on the shop floor and on the plant floor in real time using a continuous control-theoretic approach. Particularly, a distributed scheduling method (DATC) and a distributed machine capacity control (DMCC) have been unified and tested, which can generate a realistic schedule based on the available capacity of production resources at the CNC level. In this unified system, DMCC uses measured consumption of production resources, such as machine degradation, and the part processing times dynamically change corresponding to variation in the production demand that is obtained from the DATC. The objective of the proposed system has been set to minimize overall cost.

Table 7

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of parts ( N )</td>
<td>20, 40</td>
</tr>
<tr>
<td>Lower and upper limits on workpiece length ( l_1, l_2 )</td>
<td>[1,1000], [1,2000]</td>
</tr>
<tr>
<td>Tardiness factor on due dates ( \tau )</td>
<td>0.5, 1.0</td>
</tr>
<tr>
<td>Spread factor on due dates ( \sigma )</td>
<td>0.1, 0.5</td>
</tr>
<tr>
<td>Number of iterations ( I )</td>
<td>2000, 4000</td>
</tr>
</tbody>
</table>

Table 8

<table>
<thead>
<tr>
<th>Workpiece length</th>
<th>Tardiness factor</th>
<th>Spread factor</th>
<th>Iteration</th>
<th>Objective function</th>
</tr>
</thead>
<tbody>
<tr>
<td>( U_1 ) (1, 1000)</td>
<td>1.0</td>
<td>0.1</td>
<td>1000</td>
<td>22247 3713 18349</td>
</tr>
<tr>
<td>( U_2 ) (1, 1000)</td>
<td>1.0</td>
<td>0.1</td>
<td>3000</td>
<td>22662 4257 18386</td>
</tr>
<tr>
<td>( U_1 ) (1, 2000)</td>
<td>0.5</td>
<td>0.1</td>
<td>1000</td>
<td>15784 3304 12479</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
<td>0.5</td>
<td>0.1</td>
<td>3000</td>
<td>15915 3268 12647</td>
</tr>
<tr>
<td>( U_1 ) (1, 1000)</td>
<td>0.5</td>
<td>0.1</td>
<td>5000</td>
<td>17925 2048 15877</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
<td>0.5</td>
<td>0.1</td>
<td>10000</td>
<td>15625 3743 11881</td>
</tr>
<tr>
<td>( U_1 ) (1, 1000)</td>
<td>1.0</td>
<td>0.5</td>
<td>1000</td>
<td>36364 7692 28671</td>
</tr>
<tr>
<td>( U_2 ) (1, 1000)</td>
<td>1.0</td>
<td>0.5</td>
<td>3000</td>
<td>34112 7445 26666</td>
</tr>
<tr>
<td>( U_1 ) (1, 2000)</td>
<td>0.5</td>
<td>0.5</td>
<td>1000</td>
<td>39452 5427 34024</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
<td>0.5</td>
<td>0.5</td>
<td>3000</td>
<td>39239 7057 32181</td>
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<tr>
<td>( U_1 ) (1, 1000)</td>
<td>1.0</td>
<td>1.0</td>
<td>1000</td>
<td>38391 8271 30120</td>
</tr>
<tr>
<td>( U_2 ) (1, 1000)</td>
<td>1.0</td>
<td>1.0</td>
<td>3000</td>
<td>36213 5837 30376</td>
</tr>
<tr>
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<td>0.5</td>
<td>1000</td>
<td>37405 5205 32200</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
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<td>0.5</td>
<td>3000</td>
<td>67126 4709 62417</td>
</tr>
<tr>
<td>( U_1 ) (1, 1000)</td>
<td>0.5</td>
<td>0.5</td>
<td>1000</td>
<td>76937 5443 71494</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
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<td>0.5</td>
<td>3000</td>
<td>75691 4408 71283</td>
</tr>
<tr>
<td>( U_1 ) (1, 2000)</td>
<td>0.5</td>
<td>0.5</td>
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<td>55125 3351 51774</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
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<td>0.5</td>
<td>3000</td>
<td>52804 5125 47679</td>
</tr>
<tr>
<td>( U_1 ) (1, 2000)</td>
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<td>0.0</td>
<td>1000</td>
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</tr>
<tr>
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<td>0.0</td>
<td>3000</td>
<td>144267 11444 132823</td>
</tr>
<tr>
<td>( U_1 ) (1, 2000)</td>
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<td>0.0</td>
<td>1000</td>
<td>113571 9928 105442</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
<td>0.0</td>
<td>0.0</td>
<td>3000</td>
<td>119550 15059 104491</td>
</tr>
<tr>
<td>( U_1 ) (1, 2000)</td>
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<td>0.0</td>
<td>1000</td>
<td>128847 9079 119767</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
<td>0.0</td>
<td>0.0</td>
<td>3000</td>
<td>132338 9231 123106</td>
</tr>
<tr>
<td>( U_1 ) (1, 2000)</td>
<td>0.0</td>
<td>0.0</td>
<td>1000</td>
<td>100500 9871 90178</td>
</tr>
<tr>
<td>( U_2 ) (1, 2000)</td>
<td>0.0</td>
<td>0.0</td>
<td>3000</td>
<td>94336 4829 89506</td>
</tr>
</tbody>
</table>
Table 9
Overall performance of the unified system over DATC

<table>
<thead>
<tr>
<th></th>
<th>U1 (%)</th>
<th>U2 (%)</th>
<th>U1 in DATC #1</th>
<th>U2 in DATC #1</th>
<th>U1 in DATC #2</th>
<th>U2 in DATC #2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall (%)</td>
<td>82.0</td>
<td>80.5</td>
<td>502.6</td>
<td>653.4</td>
<td>73.0</td>
<td>66.1</td>
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</tbody>
</table>

Fig. 10. Performance of unified system over DATC.

Acknowledgments

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References


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