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Technical paper

Distributed adaptive control of production scheduling and machine capacity

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ABSTRACT

This paper considers modeling and simulation of a unified control system that uses a continuous control-theoretic approach for distributed production scheduling at the shop floor and machine capacity control at the CNC level. Specifically, a distributed production scheduling method is unified with a distributed machine capacity control to generate realistic schedules considering the available capacity of production resources. In this distributed control system, machine capacity is adaptively controlled based on current physical conditions of the production resources and changes in production demands at the shop-floor level as well. The proposed system considers a multi-attribute objective that consists of production rate and product quality, production cost, and mean-squared deviation of job completions about due dates. The results obtained from the computational experiments show that the proposed system can improve the system performance through fully utilizing machine capacity while reducing production costs, production delays, missed deliveries, and customer dissatisfaction.

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

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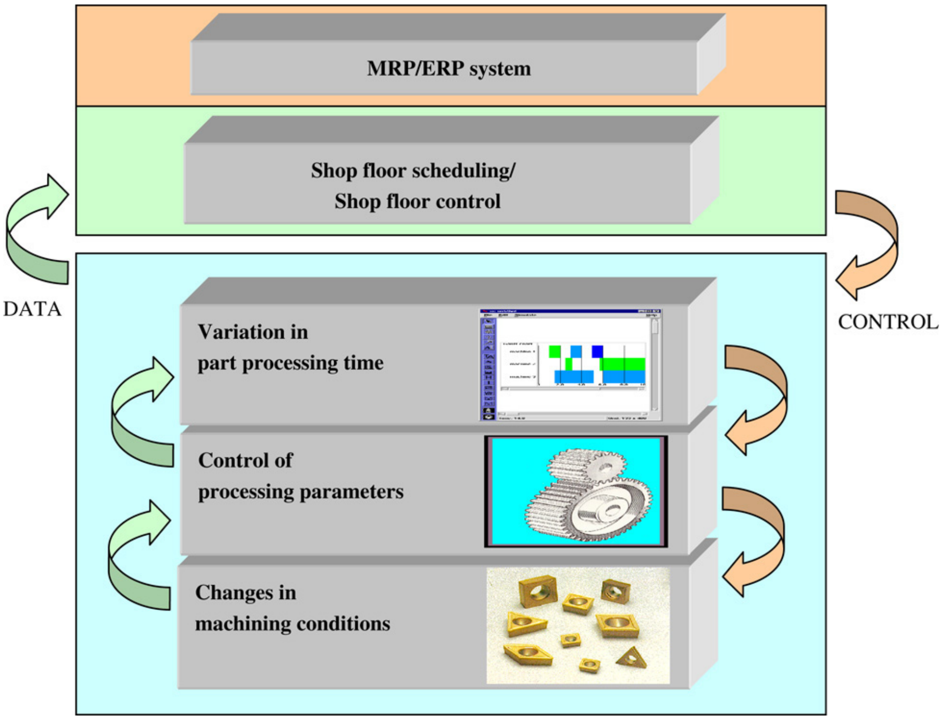

Fig. 1. Functional hierarchy in manufacturing systems.

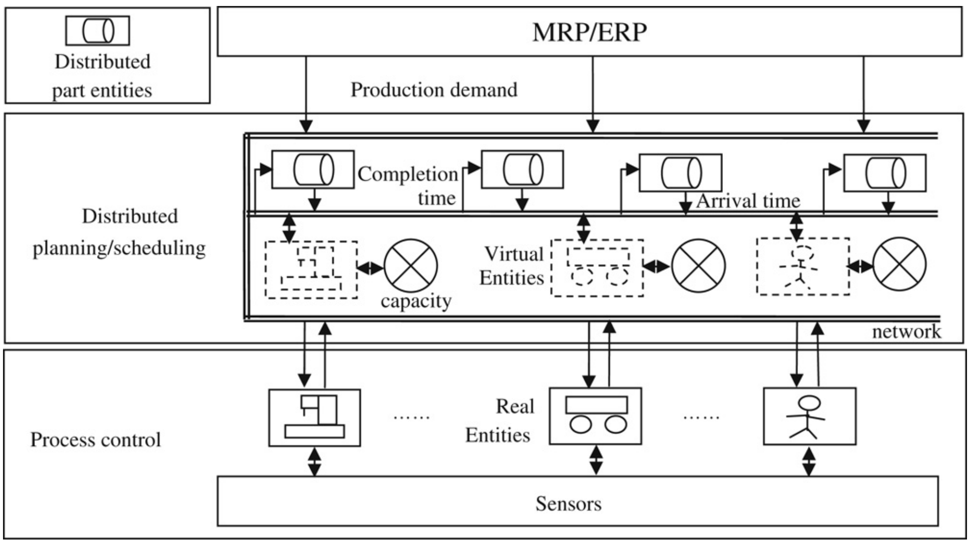

Fig. 2. Integrated system with distributed scheduling and machine capacity control.

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 computer simulation 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], linear programming and 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 volume 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 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:

$$a_i(t) = k_i \int (d_i - c_i(\tau))\mathrm{d}\tau + a_i(0) \tag{1}$$

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 ith part, respectively. The first derivative of Eq. (1) gives

$$\frac{\mathrm{d}a_i(t)}{\mathrm{d}t} = k_i(d_i - a_i(t) - q_i(t) - p_i) \tag{2}$$

where $q_i(t)$ is queuing time until processing starts and p_i is the processing time of the ith part. The DATC system transforms the combinatorial production scheduling problem into the dynamic

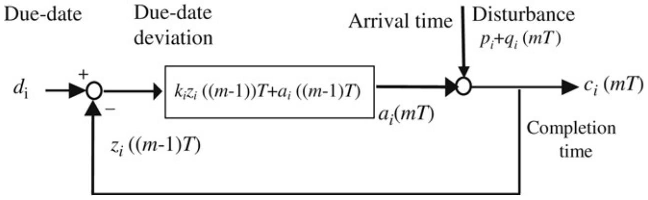

Fig. 3. Closed control loop of DATC system in discrete time.

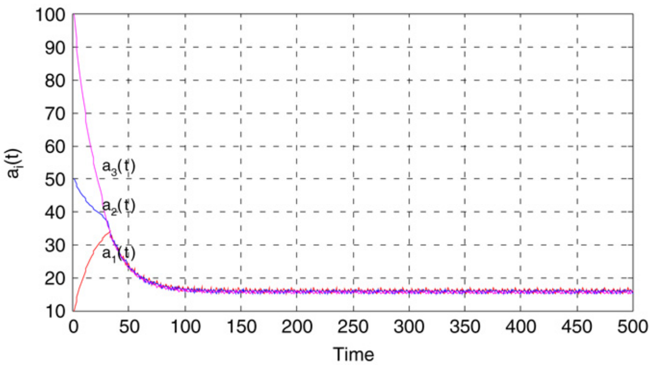

Fig. 4. Trajectory of arrival times ($k_i = k = 0.1$, $T = 0.1$).

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_c current spindle speed in revolutions per minute (rpm)
N_n nominal spindle speed in revolutions per minute (rpm)
λ_j capacity variable for a machine j
D diameter of part (mm)
L length of workpiece
TL tool life (min)
C Taylor's tool-life constant
α, β, γ 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 ($/min)
c_{ch} tool-changing cost ($/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 I).

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 $\left(x_1^2 + x_2^2 + x_3^2\right)$. 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_3 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

$$x_1 = \frac{\pi DL}{fv}$$
$$x_2 = \begin{cases} 1.22 \times 10^2 \times r^{-0.714} \times BHN^{-0.323} \times f^{1.004} \times v^{-1.52}, 25 \leq v \leq 250, f \leq 0.75 \\ 0.071057 \times r^{-0.714} \times BHN^{-0.323} \times f^{1.54}, ^{v} > 250, f \leq 0.75 \\ 0.3013 \times r^{-0.714} \times BHN^{-0.323} \times f^{4.54}, ^{v} > 250, f > 0.75 \end{cases}$$
$$x_3 = n_p n_t \left(c_c TL + c_{ch} t_r\right) + c_t TL/t_c$$
$$x_4 = \sqrt{\frac{\sum_i (d_i - c_i)^2}{n}}$$

Box I.

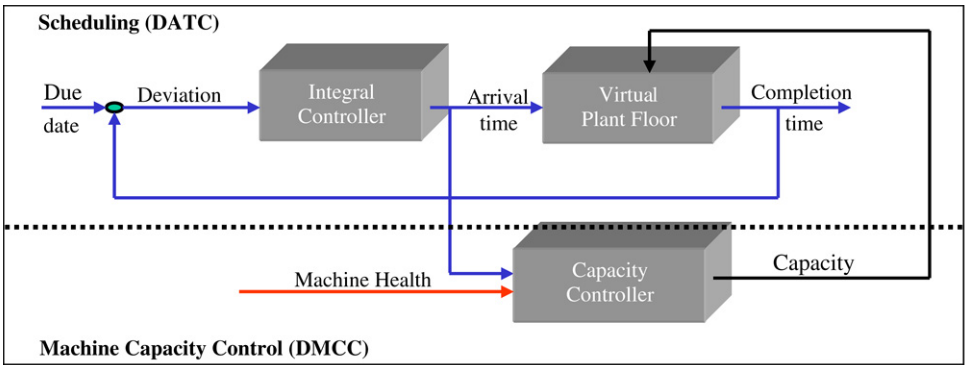

Fig. 5. Unified system for manufacturing systems control.

individual failure and utilization characteristics and integrate real-time machinery conditions with production scheduling [25]. In addition, the unified system of the DATC and DMCC can be successfully used for Finite Capacity Scheduling (FCS) because it provides the information at the CNC level to the shop-floor level scheduling system in real time.

In the unified control system, the capacity variable is introduced and adjusted in real time during the control of the manufacturing system. The actual machining conditions can be imposed as

$$\lambda_{j,\min}(t) \leq \lambda_j(t) \leq \lambda_{j,\max}(t) \tag{5}$$

where $\lambda_{j,\min}(t)$, $\lambda_{j,\max}(t)$ are the minimum and the maximum allowable capacity under the current machine condition, respectively. Since, in general, computer-controlled machines have nominal and maximum values in machining parameters such as feed rate and operational speed, the capacity variable can be interpreted as the ratio between current operating spindle speed (rpm) and nominal spindle speed (rpm). For example, if $\text{RPM}_{\text{nominal}}$ is 3000 (rpm) and the capacity variable of the jth machine, $\lambda_j(t)$, is 1.67, the current spindle speed is determined as $\text{RPM}_{\text{current}} = 5000$ rpm.

To unify the DATC and DMCC, that is, to continuously control the processing times as a function of the machine capacity variable, machining parameters must be expressed using the capacity variable because the processing times are determined by the machining parameters. First, cutting speed (v) is expressed as a function of capacity, nominal spindle speed, and diameter of the part for a turning process. Thus,

$$v = \pi \cdot N_n \cdot D \cdot \lambda_j. \tag{6}$$

An extended form of Taylor's tool-life equation is,

$$TL = \frac{C}{v^{\alpha} f^{\beta} d^{\gamma}}. \tag{7}$$

Using $v = \pi DN$, time per pass is

$$t_p = \frac{\pi DL}{1000 f v}. \tag{8}$$

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

$$TL = \left(\frac{\pi DL v^{\frac{\alpha-\beta}{\beta}} (dc)^{\frac{\gamma}{\beta}}}{C^{\frac{1}{\beta}} (n_t) (n_p)^{\frac{\gamma}{\beta}}} \right)^{\frac{\beta}{\beta-1}}. \tag{9}$$

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

$$f = \left(\frac{TL^{\frac{\alpha-1}{\alpha}} C^{\frac{1}{\alpha}} (n_t) (n_p)^{\frac{\gamma}{\alpha}}}{\pi DL (dc)^{\frac{\gamma}{\alpha}}} \right)^{\frac{\alpha}{\beta-\alpha}}. \tag{10}$$

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:

$$\lambda(t) = \frac{\sum_q p_q}{p_p} \tag{12}$$

where p_p denotes processing time of the part in machining and p_q 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:

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

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
    Select first arrival part based on FIFO dispatching policy
Step 3: Computing processing parameters using Eqs. (6), (10) and (11)
    Computing processing times using processing parameters
    Adjusting capacity variable using processing time information
    Computing completion times
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.

$c_c = 0.3$ \$/min.
$c_{ch} = 0.5$ \$/min.
$c_t = 0.5$ \$
$D = 100$ mm
$C = 6.0 \times 10^{26}$
$\alpha = 5.0$
$\beta = 1.75$
$\gamma = 0.75$
BHN = 195 BHN
$dc = 5.0$ mm
$L_1 = 1000$ mm
$L_2 = 1300$ mm
$L_3 = 1800$ mm.

Table 1
Comparison of objective functions of DATC and unified system

	Objective function		
	U	U_1	U_2
DATC	870.2	651.3	218.9
Unified system	857.1	669.3	187.8
Unified/DATC (%)	98.2	102.8	85.8

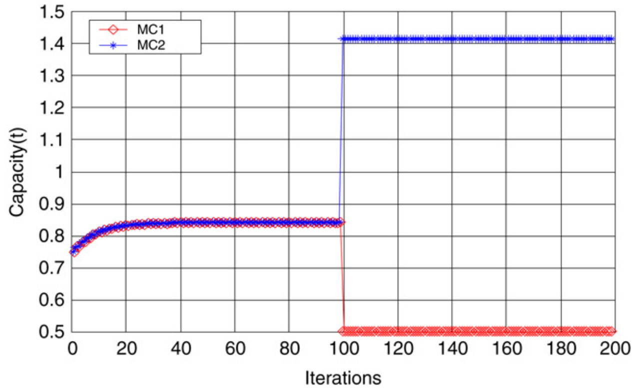

Fig. 6. Autonomous capacity control.

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 2
Machine capacity and processing parameters

	Sequence	Capacity	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)
DATC	3	1.00	157.08	0.30	1.67
	1	1.00	157.08	0.30	1.67
	2	1.00	157.08	0.30	1.67
Unified system	2	1.00	157.08	0.30	1.67
	1	1.00	157.08	0.30	1.67
	3	1.35	211.67	0.43	1.67

Table 3
Parameters for flow shop problem

Parts	Part type	Routing	Due date
Part 1	1	1, 2	3000
Part 2	2	1, 2	3000
Part 3	1	1, 2	3000
Part 4	1	1, 2	3000
Part 5	2	1, 2	3000

Table 4
Parameters for job shop problem

Parts	Part type	Routing	Due date
Part 1	1	1, 2	3000
Part 2	2	2, 1	3000
Part 3	1	1, 2	3000

Table 5
Computational result for flow shop problem

	U	U_1	U_2
DATC	2035	1059	976
Unified	2159	1515	643
Unified/DATC (%)	106	143	66

Table 6
Computational result for job shop problem

	U	U_1	U_2
DATC	1004	162	842
Unified	1006	910	96
Unified/DATC (%)	100	561	11

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.

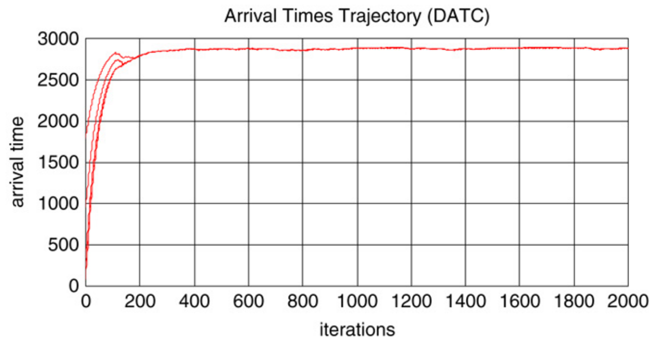

Fig. 7. Arrival-time trajectory for a flow shop problem ($n = 5, m = 2$).

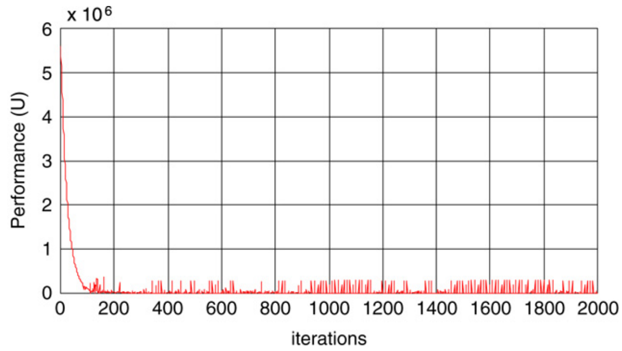

Fig. 8. Total cost for a flow shop problem ($n = 5, m = 2$).

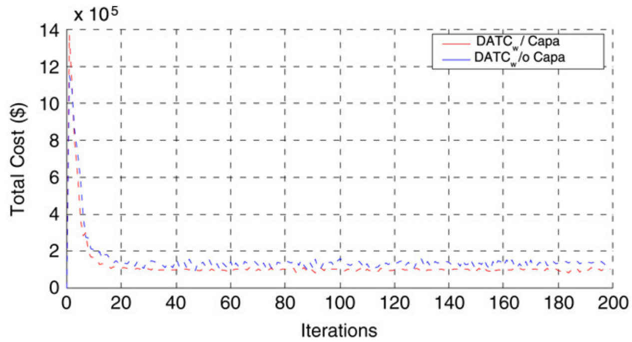

Fig. 9. Total cost for a job shop problem ($n = 50, m = 4$).

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]:

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

Table 7
Parameters for computational experiment

	Parameter	Level
N	Number of parts	20, 40
L_l, L_u	Lower and upper limits on workpiece length	[1,1000], [1,2000]
τ	Tardiness factor on due dates	0.5, 1.0
ϖ	Spread factor on due dates	0.1, 0.5
I	Number of iterations	2000, 4000

Table 8
Performance comparisons of the unified system and DATC

n	Workpiece length	Tardiness factor	Spread factor	Iteration	Objective function								
					Unified DATC #1			Unified DATC #2			DATC		
					U	U_1	U_2	U	U_1	U_2	U	U_1	U_2
20	$U(1, 1000)$	1.0	0.1	1000	22 087	3 738	18 349	22 560	3 488	19 072	28 356	792	27 564
				3000	22 661	4 275	18 386	21 563	4 385	17 177	28 156	795	27 361
			0.5	1000	15 784	3 304	12 479	15 957	2 967	12 989	19 824	679	19 145
				3000	15 915	3 268	12 647	16 286	2 137	14 148	19 911	698	19 212
		0.5	0.1	1000	22 533	4 459	18 073	21 429	4 998	16 430	24 217	758	23 458
				3000	21 801	3 492	18 309	20 645	3 512	17 132	24 743	764	23 979
			0.5	1000	17 925	2 048	15 877	12 945	2 938	1 007	18 562	746	17 816
				3000	15 625	3 743	11 881	13 172	4 523	8 649	16 504	742	15 761
	$U(1, 2000)$	1.0	0.1	1000	36 364	7 692	28 671	36 118	8 857	27 260	44 093	1515	42 577
				3000	34 112	7 445	26 666	35 936	5 976	29 960	43 969	1512	42 456
			0.5	1000	39 452	5 427	34 024	38 767	10 347	28 419	46 963	1761	45 202
				3000	39 238	7 057	32 181	39 640	8 879	30 761	46 725	1761	44 964
		0.5	0.1	1000	37 621	5 964	31 657	37 924	8 832	29 092	41 575	1875	39 700
				3000	38 391	8 271	30 120	38 549	11 928	26 620	40 439	1877	38 562
			0.5	1000	36 213	5 837	30 376	36 185	8 094	28 091	37 157	1885	35 272
				3000	37 405	5 205	32 200	36 462	14 394	22 068	37 181	1883	35 298
40	$U(1, 1000)$	1.0	0.1	1000	61 474	5 074	56 399	62 894	4 311	58 583	84 955	690	84 264
				3000	60 797	4 120	56 676	61 961	3 324	58 637	82 306	700	81 606
			0.5	1000	67 126	4 709	62 417	68 109	4 090	64 018	87 729	718	87 010
				3000	62 181	4 297	57 883	64 635	3 437	61 197	87 391	726	86 664
		0.5	0.1	1000	76 937	5 443	71 494	78 627	5 435	73 192	109 391	752	108 639
				3000	75 691	4 408	71 283	75 918	5 161	70 756	106 711	753	105 958
			0.5	1000	551 25	3 351	51 774	52 772	6 090	46 681	71 137	773	70 364
				3000	52 804	5 125	47 679	49 745	6 255	43 490	70 667	789	69 877
	$U(1, 2000)$	1.0	0.1	1000	144 690	11 290	133 400	142 414	15 455	126 958	186 881	2076	184 804
				3000	144 267	11 444	132 823	136 334	16 983	119 351	186 215	2072	184 142
			0.5	1000	115 371	9 928	105 442	122 614	20 015	102 599	150 127	1830	148 296
				3000	119 550	15 059	104 491	126 139	12 806	113 332	149 613	1830	147 782
		0.5	0.1	1000	128 847	9 079	119 767	132 401	12 651	119 749	173 252	1669	171 583
				3000	132 338	9 231	123 106	127 632	17 653	109 978	171 310	1679	169 631
			0.5	1000	100 050	9 871	90 178	95 124	21 473	73 651	116 672	2040	114 631
				3000	94 336	4 829	89 506	95 485	27 093	68 391	108 720	2038	106 682

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

$$(2^5) \times (10 \text{ replications}) = 320 \text{ instances}$$

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 9
Overall performance of the unified system over DATC

	$\frac{U(\#1)}{U(\text{DATC})}$	$\frac{U(\#2)}{U(\text{DATC})}$	$\frac{U_1(\#1)}{U_1(\text{DATC})}$	$\frac{U_1(\#2)}{U_1(\text{DATC})}$	$\frac{U_2(\#1)}{U_2(\text{DATC})}$	$\frac{U_2(\#2)}{U_2(\text{DATC})}$
Overall (%)	82.0	80.5	502.6	653.4	73.0	66.1

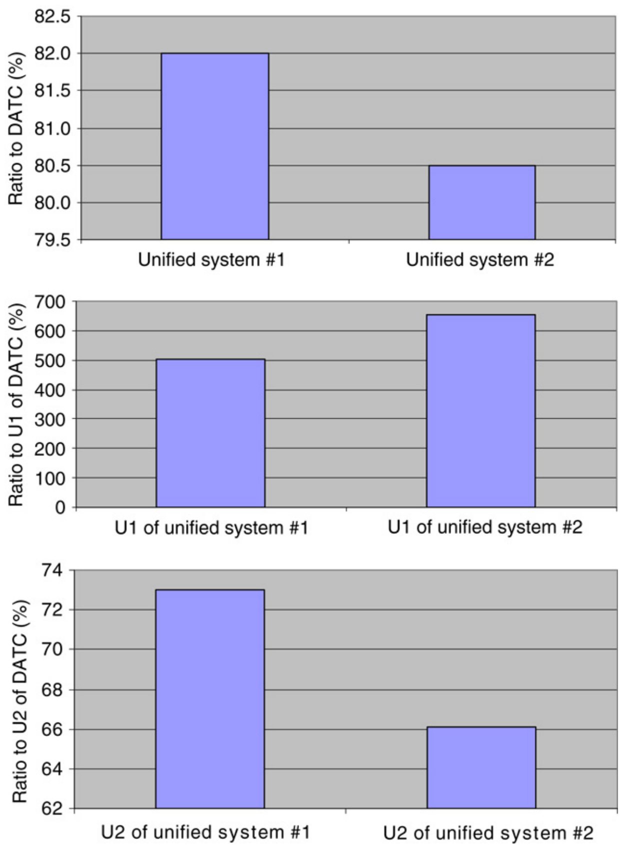

Fig. 10. Performance of unified system over DATC.

consisting of production rate, product quality, production cost, and mean-squared deviation of job completions about due dates. A computational experiment to process multiple parts on a single machine has shown that the unified system can reduce the overall costs by 20%. With distributed scheduling and machine capacity control, manufacturing control systems can improve their competitiveness by fully utilizing capacity while reducing costs, production delays, missed deliveries, and customer dissatisfaction. The method presented in this paper can be applied to general shops consisting of different kinds of equipment, such as robots, CMMs (coordinated measuring machines), and AGVs (automated guided vehicles), because these resources can be operating at different capacity levels. Note that similarly to the way the capacity variable of machine tools is defined and controlled, operating capacity of various resources can be determined by the ratio of average service time for jobs waiting in their queues to service time of jobs currently being serviced and controlled by the proposed unified system. It is expected that future research will focus on the performance evaluation of the unified system in general manufacturing systems where multiple machines are used to process multiple parts.

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