Dynamic Neural Networks for Real-Time Manufacturing Cell Scheduling

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Abstract

In this paper, a control aspect of the non-acyclic FMS scheduling problem is considered. Based on a dynamic neural network model derived herein, an adaptive, continuous time neural network controller is constructed. The actual dispatching times are determined from the continuous control input discretization. The controller is capable of driving system production to the required demand and guaranteeing system stability and boundedness of all signals in the closed loop system. Modeling errors and discretization effects are taken into account thus rendering the controller robust. A case study demonstrates the efficiency of the proposed technique.

I Introduction

Production control of manufacturing systems involves decisions such as part release, routing, machine scheduling, set up times etc. with the objective of producing customers' demands in a timely and economic fashion [1]-[4]. Control theory has only recently been applied to discrete production scheduling. Gershwin [7] views scheduling as a dynamic activity. Defining release and dispatching times, setup times and maintenance as control input, and levels of inventory and machines status as system states, the scheduling problem is then to drive the state vector to some desired value (production requirement) or follow some distributed over time trajectory (varying demand).

In this work, we are interested in taking advantage of adaptive control [9]-[11] based on dynamic neural networks (DNN) [8], and apply such techniques for the job-shop scheduling of manufacturing systems consisting of flexible machines and producing a multiple of part types. Each machine is subdivided to a number of submachines equal to the number of parts it processes, fed by one or more buffers and outputting products to a single buffer, thus allowing for assembly processes. The processing times are assumed deterministic.

An alternative control input definition, based on the machine working rate (operating frequency) is employed, leading to a continuous control signal and the introduction of non-linearities as well. The model derivation of the manufacturing system is realized through the use of dynamic neural networks (DNN) [14], known of their approximation capabilities [12] on identifying complex non-linear, MIMO, continuous time non-linear dynamical systems. The model obtained is linear with respect to its parameters, which depend on machine interconnection, operations time and product routings.

Using Lyapunov stability theory [13] we construct a neural network controller for each submachine, outputting operating frequencies. The continuous-time signal obtained is translated to a dispatching times series through a sampling procedure. The controllers of all submachines belonging to the same machine may conflict due to commands that exceed machine capacity. In this case, the decision for the actual part to be processed by the flexible machine is taken using some criterion based on the several route work-in-process. Errors due to discretization of the continuous control input and the introduction of the work-in-process based criterion are addressed. We show that the regulation error can be arbitrarily small, depending on design constants, and thus the production objective is reached.

In our approach, individual decisions are not considered myopically [5],[6], since at any time-instant work-in-process along each production route and the control error of the route finished products buffer, are taken into account. The adaptivity properties, inherent in the proposed scheduler, allow for a fast reaction to a potential change in the finished product demand. The control procedure is redirected immediately to achieve the updated control objective.

II The manufacturing cell dynamic model

We consider manufacturing systems consisting of M machines and producing a multiple of P part types. Each part type requires a number of operations to be performed in a given sequence, defined by its route. Multiple routing is possible and parts may visit some machines several times.

Each machine m is assumed to consist of a number of submachines equal to the number of different part types it is able to process. Each submachine actually represents an operating mode of machine m. Only one submachine is allowed to be working at a time, processing parts of a single type. Machine operation times are supposed to be constant, where different operation times for every submachine are allowed. Set up times are assumed to be insignificant. Assembly procedures are allowed for submachines possessing more than one input buffers.

For a continuous time control signal to be obtained, the "equivalent frequency" defined as the inverse of the time between two successive machine-starts, is employed [14]. Using this definition, frequencies range between zero and u_{max}, which equals to the reciprocal of machine operation time and corresponds to a maximum working rate.

Next, recall from [14] the non-linear high order DNN [12] dynamic model describing the evolution of the level x_i of buffer i

$$\dot{x}_i = {W^\star_{0i}}^T S_{0i}(\bar{x}_i, u_i)u_i + {W^\star_{1i}}^T S_{1i}(\bar{u}_i) + \varepsilon_i(\bar{x}_i, \bar{u}_i, u_i) \tag{2.1}$$

where $\bar{x}_i$ is the vector containing the levels of all directly connected preceding buffers, $\bar{u}_i$ is the vector containing the frequencies of all submachines collecting products from x_i, u_i is the frequency of the submachine feeding buffer i and $\varepsilon_i(.)$ is a modelling error term. We assume that the modelling error term is bounded, that is

$$\|\varepsilon_i(.)\| \leq \epsilon_i$$

III The control law

III.1 The ideal case

Let us consider the ideal case in which $\varepsilon_i(.) = 0$ and derive a basic control law. After adding and subtracting the terms $W_{0i}^T S_{0i}(\bar{x}_i, u_i)u_i$ and $W_{1i}^T S_{1i}(\bar{u}_i)$, (3.1) becomes

$$\dot{x}_i = -\tilde{W}_{0i}^T S_{0i}(\bar{x}_i, u_i)u_i - \tilde{W}_{1i}^T S_{1i}(\bar{u}_i) +$$

$$+ W_{0i}^T S_{0i}(\bar{x}_i, u_i)u_i + W_{1i}^T S_{1i}(\bar{u}_i) \tag{3.1}$$

where $\tilde{W}_{0i} \triangleq W_{0i} - W_{0i}^\star$, $\tilde{W}_{1i} \triangleq W_{1i} - W_{1i}^\star$ and W_{0i}, W_{1i} are weight estimates of the unknown weight values $W_{0i}^\star, W_{1i}^\star$ respectively. Let by x_{i_t} denote the target value for each buffer and define the control error e_{c_i} as

$$e_{c_i} \triangleq x_i - x_{it}$$

To derive stable control and update laws take the following Lyapunov function candidate

$$\mathcal{L} = \frac{1}{2}\sum_{i=1}^{B} e_{c_i}^2 + \frac{1}{2}\sum_{i=1}^{B} \tilde{W}_{0i}^T \tilde{W}_{0i} + \frac{1}{2}\sum_{i=1}^{B} \tilde{W}_{1i}^T \tilde{W}_{1i} \tag{3.2}$$

Differentiating (3.2) along the solution of (2.1) and choosing

$$\sum_{i=1}^{B} \dot{\tilde{W}}_{0i}^T \tilde{W}_{0i} = \sum_{i=1}^{B} e_{c_i} \tilde{W}_{0i}^T S_{0i}(\bar{x}_i, u_i)u_i \tag{3.3}$$

$$\sum_{i=1}^{B} \dot{\tilde{W}}_{1i}^T \tilde{W}_{1i} = \sum_{i=1}^{B} e_{c_i} \tilde{W}_{1i}^T S_{1i}(\bar{u}_i) \tag{3.4}$$

then $\dot{\mathcal{L}}$ becomes

$$\dot{\mathcal{L}} = \sum_{i=1}^{B} e_{c_i} \left[W_{0i}^T S_{0i}(\bar{x}_i, u_i)u_i + W_{1i}^T S_{1i}(\bar{u}_i)\right] \tag{3.5}$$

From (3.3), (3.4) we obtain

$$\dot{W}_{0i} = e_{c_i} S_{0i}(\bar{x}, u_i)u_i \tag{3.6}$$

$$\dot{W}_{1i} = e_{c_i} S_{1i}(\bar{u}_i) \tag{3.7}$$

Consider the continuous time control law

$$u_i = -q_i \operatorname{sgn}\left(W_{0i}^T S_{0i}(\bar{x}_i, u_i)\right) \operatorname{sgn}(e_{c_i}) \tag{3.8}$$

$$q_i = \frac{1}{w_i^-}\left[|W_{1i}^T||S_{1i}(\bar{u}_i)| + \gamma|e_i|\right] \tag{3.9}$$

$$\mathrm{sgn}(W_{0i}^T S_{0i}(\bar{x}_i, u_i)) = \begin{cases} 1 & \text{if } W_{0i}^T S_{0i}(\bar{x}_i, u_i) \geq 0 \\ -1 & \text{otherwise} \end{cases} \tag{3.10}$$

$$\mathrm{sgn}(e_{c_i}) = \begin{cases} -1 & \text{if } e_i < 0 \\ 0 & \text{if } e_i = 0 \\ 1 & \text{otherwise} \end{cases} \tag{3.11}$$

with γ a strictly positive constant and w_i^- as defined in (3.13). Then (3.5) becomes

$$\dot{\mathcal{L}} = -\sum_{i=1}^{B} \gamma e_{c_i}^2 \leq 0 \tag{3.12}$$

However, in order for (3.9) to be valid the following must hold

$$w_i^- \leq |W_{0i}^T S_{0i}(\bar{x}_i, u_i)| \leq w_i^+ \tag{3.13}$$

By the definition of $S_{0i}(\bar{x}_i, u_i)$ it can be bounded from bellow by a positive constant. Furthermore, since the actual weight values W_{0i}^* are positive, a projection modification is employed to guarantee that the weight estimates W_{0i} remain positive also $\forall t \geq 0$. After these changes are made, condition (3.13) is guaranteed.

Thus the update law (3.6) is modified to

$$\dot{W}_{0i} = \begin{cases} D_1 & \text{if } W_{0i} \in \mathcal{W}_{0i} \text{ or} \\ & W_{0i} \in \partial \mathcal{W}_{0i} \text{ and } Cr \geq 0 \\ D_1 + D_2 & \text{if } W_{0i} \in \partial \mathcal{W}_{0i} \\ & \text{and } Cr < 0 \end{cases} \tag{3.14}$$

where $\mathcal{W}_{0i}$ is a set that guarantees the positiveness of the entries of W_{0i} and $\partial \mathcal{W}_{0i}$ is its boundary, $D_1 = e_{c_i} S_{0i}(\bar{x}_i, u_i) u_i$, $D_2 = D_1^T W_{0i} \left(\frac{1+\|W_{0i}\|}{w_{0i}}\right)^2 W_{0i}$ and $Cr = e_i S_{0i}^T(\bar{x}_i, u_i) u_i W_{0i}$. Using standard adaptive control arguments based on the boundedness and positiveness of the Lyapunov function and its derivative respectively, we find that :

- $e_{c_i}, W_{0i}, W_{1i}, x_i, \dot{e}_{c_i} \in L_\infty$
- $\lim_{t\to\infty} e_{c_i}(t) = 0, \lim_{t\to\infty} \dot{W}_{0i}(t) = 0$
- $\lim_{t\to\infty} \dot{W}_{1i}(t) = 0$

III.2 The modeling error case

Here we investigate the more general case in which modeling errors are incorporated. Hence now (3.8) becomes:

$$\dot{\mathcal{L}} = \sum_{i=1}^{B} e_{c_i} \left[W_{0i}^T S_{0i}(\bar{x}_i, u_i) u_i + W_{1i}^T S_{1i}(\bar{u}_i) + \varepsilon_i(\bar{x}_i, \bar{u}_i, u_i) \right] \tag{3.15}$$

If we choose (3.7), (3.8)-(3.11) and (3.14), by reinforcing $\dot{\mathcal{L}}$ we finally obtain that $\dot{\mathcal{L}} \leq 0$ provided that

$$|e_{c_i}| > \frac{\epsilon_i}{\gamma} \tag{3.16}$$

Inequality (3.16) implies that the control error e_{c_i} possesses a uniform ultimate boundedness property with respect to the arbitrary small set

$$\mathcal{E}_{c_i} = \left\{ e_{c_i}(t) : |e_{c_i}| \leq \frac{\epsilon_i}{\gamma}, \gamma > 0 \right\}$$

Again a projection modification can be used to satisfy that W_{1i}'s are confined into a set $\mathcal{W}_{1i} = \{W_{1i} : \|W_{1i}\| < w_{1i}\}$. Hence, (3.6) is modified to :

$$\dot{W}_{1i} = \begin{cases} D_1 & \text{if } W_{1i} \in \mathcal{W}_{1i} \\ & \text{or } W_{1i} \in \partial \mathcal{W}_{1i} \text{ and } Cr \geq 0 \\ D_1 + D_2 & \text{if } W_{1i} \in \mathcal{W}_{1i} \\ & \text{and } Cr < 0 \end{cases} \tag{3.17}$$

where $D_1 = e_i S_{1i}(\bar{u}_i)$, $D_2 = D_1^T W_{1i} \left(\frac{1+\|W_{1i}\|}{w_{1i}}\right)^2 W_{1i}$ and $Cr = e_i S_{1i}^T(u) W_{1i}$.

The result above practically states that if we start from inside the set $\mathcal{E}_{c_i}$ then e_{c_i} is uniformly bounded by $\frac{\epsilon_i}{\gamma}$. Otherwise, there exist a finite time in which e_{c_i} reaches the boundary of $\mathcal{E}_{c_i}$ and remains there in for all time thereafter. It is obvious that the performance of the continuous time control law is controlled by ϵ_i and γ. The first term ϵ_i is strongly related to the continuous time model developed in section II, while the second one, γ is a design constant which can be chosen arbitrary.

IV Real-time scheduling

IV.1 Actual dispatching decisions

The control input signal obtained by the control law is a continuous frequency signal. Therefore, some dispatching policy has to be employed to determine the actual parts dispatching times as follows : The controller output is sampled at a certain time instant, and the control input frequency is transformed to a time interval by taking its reciprocal. At the same time instant a new command is sent to the specific submachine. The controller equations (3.8)-(3.11) are allowed to evolve in time, while the submachine state is left untouched until the precalculated time interval is completed. Afterwards, a new sample of the control input is taken and the process is repeated. The proposed policy is demonstrated in figure 1.

For the case of FMS systems containing multiproduct machines, in order to determine which buffer is to be served, we propose the use of some criterion representing a measure of the priority to be given. The criterion is calculated on each route and based on the semifinished product availability (work-in-process, WIP) as well as the control error of the route output buffer. According to the proposed policy, the route to be served is the one with the largest criterion value.

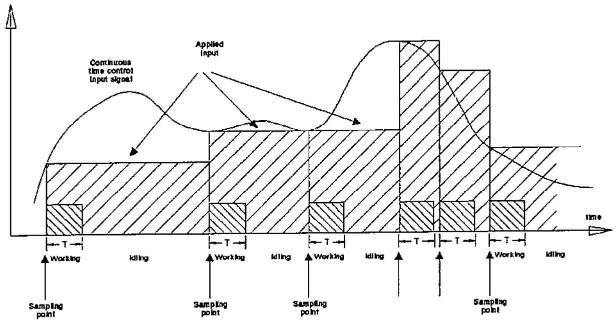

Figure 1: Continuous control input discretization

The proposed criterion value for submachine s is given by

$$J_s = \frac{\lambda_0 f(x_0) + \lambda_1 g(x_1) + \lambda_2 g(x_2) + \ldots + \lambda_N \frac{e_i^2}{1+e_i^2}}{\mu_0 + \mu_1 + \mu_2 + \ldots + \mu_N} \tag{4.1}$$

where x_0 is submachine s preceding buffer level, while x_j, $j = 1 \ldots N$ are the following buffer levels on the same route and λ's are weighting factors. The dependence of x_j, λ_j and N on s has been omitted for the sake of simplicity.

Setting

$$\mu_0 = \mu_1 = \ldots = \mu_N = \frac{1}{N+1}, \quad f(w) = g(w) = w$$

taking λ_i's, $i = 0, 1, 2, \ldots, N-1$ to stand for WIP cost per stored part in the corresponding buffer and $\lambda_N = 0$, giving priority to route possessing the largest value of J_s reduces the WIP cost of the most burdened route.

An alternative formulation, including non-linear functions $f(.)$ and $g(.)$ approximates better real situations. In this case we take $f(.)$ to be a positive, monotonically increasing non-linear function, with $f(0) \approx 0$ and $f(c) \approx 1$, where c stands for the buffer capacity. Similarly, $g(.)$ is a mirrored version of $f(.)$, with $g(0) \approx 1$ and $g(c) \approx 0$. Both functions $f(.)$ and $g(.)$ can be closely approximated by shifted sigmoids.

By this formulation, criterion J_s gives a measure of the current route necessity for priority to be given. The weights λ_i can all be selected to be equal to the unity, thus allowing all WIP to be equally taken into account. A series of decreasing weights, leads to a criterion with a local scope, taking into account the buffers in a small neighborhood near the current machine.

IV.2 Discretization effects

From the discretization procedure, an additional error is introduced in the control input signal. More precisely, the continuous time controller developed in section III, contains the actual scheduling as follows

$$u_i = u_{d_i} + \omega_i(\bar{x}_i, \bar{u}_i, u_i) \tag{4.2}$$

where u_i is the continuous time control law, u_{d_i} is the actual scheduling and $\omega_i(.)$ is the difference between the above mentioned signals.

Obviously $\omega_i(.)$ is bounded. Since the actual control law implemented is u_{d_i}, we substitute u_i in (3.5) by u_{d_i}. Hence, $\dot{\mathcal{L}}$ becomes

$$\dot{\mathcal{L}} = \sum_{i=1}^{B} e_{c_i} \left[W_{0i}^T S_{0i}(\bar{x}_i, u_i) u_{d_i} + W_{1i}^T S_{1i}(\bar{u}_i) + \varepsilon_i(\bar{x}_i, \bar{u}_i, u_i) \right] \tag{4.3}$$

Employing (4.3), choosing (3.8)-(3.11), (3.14) and (3.17), and reinforcing $\dot{\mathcal{L}}$, we finally obtain that $\dot{\mathcal{L}} \leq 0$ provided that

$$|e_{c_i}| > \frac{w_{0i}^{+} |\omega_i(\bar{x}_i, \bar{u}_i, u_i)| + \epsilon_i}{\gamma} \tag{4.4}$$

Again (4.4) implies that the control error e_{c_i} possesses a uniform ultimate boundedness property with respect to the arbitrary small set

$$\mathcal{E}_{c_i} = \left\{ e_{c_i}(t) : |e_{c_i}| \leq \frac{w_{0i}^{+} |\omega_i(\bar{x}_i, \bar{u}_i, u_i)| + \epsilon_i}{\gamma}, \ \gamma > 0 \right\} \tag{4.5}$$

The term

$$\frac{w_{0i}^{+} |\omega_i(\bar{x}_i, \bar{u}_i, u_i)| + \epsilon_i}{\gamma}$$

serves as a performance index which can be improved mostly by allowing the design constant γ to admit larger values. Moreover, better approximation of the continuous control law by the actual scheduling will lead to smaller values of $\omega_i(\bar{x}_i, \bar{u}_i, u_i)$ which in turn will improve further the overall performance.

V Simulation results

In this section the design methodology developed herein, is illustrated through simulations performed on a realistic example which consists of five machines m_i, $i = 1, 2, \ldots, 5$ and produces five different part types. Due to one assembly process, six routes are defined, given in the following table. Of them, routes 2, 3, 4, and 5 lead to finished products. Routes 1 and 6 lead to part types which are assembled into a new product. The assembly operation is performed on machine 5. The table elements show the order in which every product visits the machines.

	Machine				
Route	m_1	m_2	m_3	m_4	m_5
1		2,4	3	1	5
2	1	2			
3		1	2		3
4	2	5	1,4	3	
5	3	2		4	
6		2	1	3	4

All buffers are assumed to be initially empty, with the exception of the raw material buffers, which are for simplicity assumed to have a sufficient number of resources. A production demand of 20 parts of all 5 part types, has to be achieved. A total of 21 submachines and an equal number of controllers is required. The operation times for all submachines of the same main machine are assumed here for simplicity to be equal. The machine operation times are taken equal to 5,6,5,4 and 3 time units respectively.

As indicated in section III.2, due to the flexibility of system machines, the submachine that will recieve a dispatching command in case of a conflict, will be selected with respect to the criterion defined in (4.1). In this case study we use the sigmoidal definition of $f(.)$ and $g(.)$, while all λ_i weighting factors have been taken equal to unity. Hence, all buffers along a route are equally taken into account.

It can be easily verified that machine 2 is the bottleneck of the system, due to the largest work it has to produce. More precisely, the time required by each admissible part type is equal to 12 for route 1, (where a multiple visit exists), and 6 for the others. For a total of 20 parts to be produced, a total work of $(12+5\times6)\times20 = 840$ time units is required. This represents a lower bound of the time required for the whole job to be completed, and serves well for comparison purposes.

In figure 2 we present the evolution of some output buffers as a function of time. The total time required to complete the task is 900 time units, representing a very efficient schedule with respect to the lower bound calculated. The utilization rate of the bottleneck machine is approximately 93%. Moreover, the intermediate buffer level, did not exceed two parts in any case. As a consequence, the required buffer capacity for the schedule obtained is extremely low, compared to the usual circumstances.

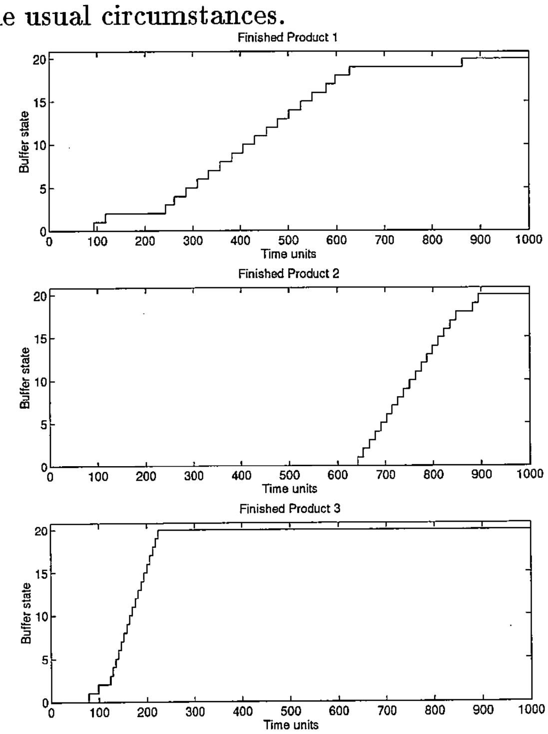

Figure 2: Output buffers evolution

VI Conclusions

In this work, the manufacturing cell scheduling problem is considered to be a control regulation problem, where system states, (buffer levels), have to be driven to some predefined values, (production requirements), by means of control input commands. A non-linear neural network controller for on-line scheduling of small manufacturing cell processes is developed. Stable adaptive laws are derived, guaranteeing convergence of the control error to an arbitrarily small ball, as well as stability and boundedness properties.

The results shown in the simulations section show that the proposed model displays a satisfactory performance. No matter the presence of modeling errors (model inaccuracy, control input truncation), the system is capable of completing its task, due to the robustness properties. Furthermore, the control procedure is on-line redirected by the time the production demand is altered and the control policy proposed is in general non-myopical but rather distributed, thus allowing for decisions based on the whole plant state vector.

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