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ABSTRACT.

The scheduling of parts in a production system is an NP-complete problem. To search an optimal solution is incompatible with the "real time" constraint. The usual procedures (clusters-job, introduction of constraints on the fabrication starting time, hierarchical schedulind) all contribute to vanish the combinatorial aspect of the problem.

We propose to memorize some behaviour-classes and to use them in order to choose the management rule in relation with the aimed targets. A numerical example will describe this approach.

RESUME.

L'ordonnancement dans un système de production est NP-complet. La recherche d'une solution optimale est incompatible avec la contrainte "temps réel". Les procédures usuelles (familles de produits, introduction de contraintes sur le temps de début de fabrication, ordonnancement hiérarchisé) contribuent à diminuer l'aspect combinatoire du problème.

Nous proposons de mémoriser des classes de comportement et de les utiliser pour choisir les règles de gestion qui conduiront au but visé. Cette approche sera décrite par un exemple numérique.

ARTIFICIAL MEMORY IN PRODUCTION MANAGEMENT

I INTRODUCTION.

We call "management rule" any algorithm that, starting from the initial state of the system, leads to the decisions.

For example we may wish to manage a machine, that is, we have to take a decision as soon as this machine becomes free.

We can choose the following rule :

1) If no product is waiting in front of the machine, then wait for the arrival of the first product.
   When a product is present, go to 2.

2) Choice of the product :

> 2.1 if only one product is waiting, the machine takes it on.
> 2.2 if several products are waiting :
>
>> 2.2.1 look for the maximal waiting time of the products in front of the machine
>> 2.2.2 if only one product is related to this time, the machine takes it on ; if not, one product is chosen randomly among those having the maximal waiting time.

It is possible to substitute the maximal waiting time for the minimal delay, or for the shortest working process, or for the maximal time of remaining inside the system, so that various rules are defined. It is to notice that in practise a management rule can be applied only if the firm is prepared for it : men must be trained up and decisional structures have to fit to its implementation. A consequence of this remark is that the set of the management rules which are applicable to a firm can be considered as well-known ; so that a procedure consisting of searching an optimal working, even supposing that a criterion could be defined,

would lead to non-applicable decisions. Our procedure is based on this remark. Moreover we know that the management rule to apply must be chosen in "real time", that means in a delay which does not retard the course of operations.

The problem can then be presented as follows : the state of the system is known at time t as well as the target to reach at time (t+T) ; it is then the matter to choose in "real time" among a known set of management rules the one wich leads "as close as possible" to the aimed target, this target beeing often qualitatively defined.

The solution of this problem needs the definition of a set of parameters which enables to characterize the state of the system and the possible targets. We suppose that these parameters are known and we are satisfied with showing, in this paper, how the artificial memory is elaborated and used in real time.

II FORMULATION OF THE PROBLEM.

Let us denote $\{R_1, R_2, \ldots, R_k\}$ the set of available management rules. The system state E is defined by parameters and we note by E(t) the set of their values at the time t :

$$E(t) = \{I_1(t), I_2(t), \ldots, I_n(t)\}$$

The choice of the parameters is very significant and it can be carried out with some techniques of data analysis.

Let us suppose that the set of these parameters is known.

We also define a set of parameters which characterize the target to reach at the end of the period T.

This target is denoted $O = \{S_1, S_2, \ldots, S_p\}$. These are two-types parameters :

1) those which describe the evolution of the system along the period T, that means the variations of $\{I_1, I_2, \ldots, I_n\}$.

They generally are quantitative parameters, but estimated as qualitative ones. As example we will say that the use of machines is regular or not, that the in-process inventories increase more or less, and this is obtained from observed numerical values.

2) those which characterize the state of the system at the end of the period T ; it is the set E(t+T).

If t is the beginning of the considered working period, the target O at the time t+T depends on :

$$\blacktriangle\ E(t)\ \Big\} \text{ given values}$$
$$\blacktriangle\ T$$

$\blacktriangle\ R_i \in \{R_1, \ldots, R_k\}$, chosen by the user.

Because T remains constant, we will use the notation A(t,E) to design the concatenation of the values of the parameters of O at the time t+T when we successively apply $R_1, \ldots, R_k$ to E. To make it more simple we will from now on speak of targets set to design A(t,E).

III ARTIFICIAL MEMORY (A.M.).

We need a simulation software which reproduces as perfectly as possible the behaviour of a production system. Some states of the system are generated at random. Starting from each of them, a simulation is done during a period T by appling each of the possible management rules. Thus, at each initial state E_i, defined with n numerical values, corresponds a set of k realizations of the target (one realization for each rule), every of them being defined by p numerical values.

A distance d_0 is chosen for the set of the initial states E_i and another distance d_1 is defined for the set of the targets denoted X^{k*p}. We then make a classification of the initial states starting from d_0 and we also classify the results of the simulation using the distance d_1 ; these classifications are based on the "nuées dynamiques" method. We choose the same number of classes in $\mathbb{R}^n$ and in X^{k*p}.

The clusters obtained are denoted C_i (i=1,..., r), E_i^* being the moste representative element of C_i.

$A_i^* = A(t, E_i^*)$ is the set of targets wich are reached starting from E_i^* at time t. W_i is the class of X^{k*p} defined using d_1 and which includes A_i^*.

W_i^1 is the subset of X^{k*p} defined by the following relation :

$$W_i^1 = W_i \cap \{A(t,E) \ / \ E \in C_i\} \tag{1}$$

The elements of W_i^1 belong to W_i and are the concatenation of targets obtained starting from elements of C_i (see fig.1).

The most favourable situation that we can find is the following :

$$\begin{cases} W_i^1 = W_i \\ A_i^* \text{ is the most representative element of } W_i \end{cases} \quad \forall \ i \in \{1,\dots, r\}$$

We call Artificial Memory of the system, the set :

$$\{C_1,\dots, C_r, W_1^1,\dots, W_r^1\}$$

Let us define $\quad \varepsilon_i = \underset{E \in D_i}{\text{Max}} \ \{d(E,E_i^*)\}$ (2)

where $\quad D_i = \{E \ / \ A(t,E) \in W_i^1\}$ (see figure 2)

IV THE USE OF THE A.M.

Let E^0 be a state at time t and $\lambda \in [0,1]$ a real number chosen by the user in relation with the accuracy that he wants.

We search Min $\quad \dfrac{d_0 \ (E^0, E_i^*)}{\varepsilon_i} \quad$ for $i = 1,\dots, r$. Let be i_1 the index giving this minimum value.

We have to consider two cases :

1) $d_0 \ (E^0, E_{i_1}^*) > \lambda \ \varepsilon_{i_1}$.

In that case we consider that the state E^0 does not belong to any of the defined classes C_i. So that the artificial memory does not yield a management rule and some classical procedures must be used.

2) $d_0 \ (E^0, E_{i_1}^*) \leq \lambda \ \varepsilon_{i_1}$.

Here we consider that the production system has the same behaviour regarding the management rules if the state at the time t is E^0 or $E_{i_1}^*$.

These behaviours could be characterized when the artificial memory has been created. For example, the rule R_1 applied on $E_{i_1}^*$ leads to a decrease of the in-process inventories and to a non-respect of the prescribed times ; R_2 leads to a satisfying use of the machines, and so on.

When the computer will have recognized in real time that E^0 and E_i^* have the same behaviour regarding the management rules, it will be enough to look at the targets obtained with each rule. The user is then able to choose the target which is as close as possible to the aimed target.

V AN EXAMPLE.

The principle we have just explained will be applied to a job-shop.

A) Description of the system.

1) Characterization of the state of the system (initial state).

There are ten machines in the job-shop and they are denoted by $M_1, \ldots, M_{10}$. A state is defined using 20 independent parameters.

- 10 parameters correspond to the quantity of each product i which is inside the system at the considered time. There are 10 different products.

- 10 parameters correspond to the working time of each machine j and are denoted tc(j). These times are calculated from two data :

    * the ratios mq (i) of product i which has to be obtained.
    * the working time tp (i,j) of the machine j for the product i.

We then can write :

$$tc\ (j) = \sum_{i=1}^{10} tp\ (i,j) \times mq\ (i)$$

We give the production process of each of the ten products. The quantities in brackets are the production times.

G_1 : M1 (.7801) M10 (.7971)

G_2 : M2 (.2235) M5 (.3240) M7 (.4316) M9 (.5711)

G_3 : M6 (.8648) M3 (.6899) M8 (.0817) M4 (.9419)

G_4 : M4 (.9954) M1 (.9709) M9 (.0517) M8 (.8084) M2 (.321) M3 (.9083)
M5 (.8940)

G_5 : M10 (.1027) M3 (.1905) M7 (.1109) M1 (.6905) M6 (.4979)

G_6 : M1 (.3353) M2 (.3821) M3 (.8974) M4 (.8716) M5 (.4638) M6 (.7079)
M7 (.6616) M8 (.7630) M9 (.5783) M10 (.8930)

G_7 : M8 (.0767) M3 (.2803) M1 (.1793) M9 (.2795)

G_8 : M5 (.2613) M10 (.0817) M3 (.0261) M8 (.9680)

G_9 : M9 (.8162) M6 (.6247) M2 (.2474) M3 (.5591)

G_{10} : M10 (.8337) M1 (.1165) M3 (.9252)

2) The simulation.

Starting from each initial state we make out a simulation during a period T. The machines breakdowns are also simulated.

The nine management rules applied are the following ones :

R1 : Priority to the product which has the shortest working process

R2 : Priority to the product which has the largest working process

R3 : Priority to the product which remaining working time is the lowest

R4 : Priority to the product which remaining working time is the greatest

R5 : FIFO (First in, First out)

R6 : Priority to the product which has the smallest beginning time

R7 : Priority to the product which has the greatest delay regarding the ratio
to be produced

R8 : Priority to the product which has the lowest next working time.

R9 : Priority to the product which have afterwards to get through the machine
in front of which there are the least products waiting.

With each machine, we generate at random the succession of working periods and breakdowns ones according to the rules given be the cumulative distribution function of type :

$$F(t) = 1 - e^{-qt}$$ where $q \in \mathbb{R}$ (t is either the breakdown time or the working time, but the values of q are different in the two cases).

The values which define the behaviour of the machines are given below.

	Mean value of the breakdown ratios	Mean value of the duration of the breakdowns.
M_1	12	2.4
M_2	13	3.2
M_3	14.2	2.09
M_4	16.8	2.4
M_5	8	3.098
M_6	17.04	2.45
M_7	12	2.78
M_8	4.5	3.78
M_9	11	2.456
M_{10}	13.42	4

The length of a simulation has been fixed to T = 627 time units, and 62 simulations have been done.

3) Characterization of the targets.

The parameters which define a target O are the following ones :

- the number S_1 of parts obtained during the period T.
- the number S_2 of carts which have been used during the period T.
- the number S_3 of carts which remain inside the system at the end of the period T.

$$O = \left\{ S_1, S_2, S_3 \right\}.$$

We applied the nine management rules to each initial state ; is then characterized by $3 \times 9 = 27$ variables.

We notice that the parameters S_1 and S_2 belong to the history of the system while S_3 is a feature of the system state at the end of the period T.

B. The classification.

All the parameters which characterize the system at times t_0 and t_0+T are quantitative ones. In applying the "nuées dynamiques" method we realize a classification of these variables. For this, we use the automatic classification software SICLA asking for an analysis into five classes.

Each initial state so corresponds to 20 parameters and the 5 classes obtained from the set of the 62 initial states are the following ones :

$C_1 = \{7,7,11,17,18,30,33,34,42,44,45,47,56,58,61\}$. The most representative element is $E_1^* = 42$

$C_2 = \{4,8,9,20,25,29,31,36,38,62\}$, $E_2^* = 25$

$C_3 = \{3,10,14,19,21,27,37,40,41,43,46,55,59,60\}$, $E_3^* = 41$

$C_4 = \{1,5,22,26,28,39,48,51,57\}$, $E_4^* = 5$

$C_5 = \{2,12,15,16,24,32,35,49,50,52,53,54\}$, $E_5^* = 24$

A set of targets O_i is defined by 27 variables (3 parameters, 9 rules) and the 5 classes W_i are (d_1 is also the euclidian distance) :

$W_1 = \{6,7,9,11,13,17,18,30,33,34,36,38,42,44,45,47,48,49,52,58\}$
$W_2 = \{4,20,25,29,61\}$
$W_3 = \{3,8,10,14,15,19,21,27,31,37,40,41,43,46,59,60\}$
$W_4 = \{1,5,22,26,28,39,51,53,56,57\}$
$W_5 = \{2,12,16,24,32,35,50,62\}$

The set of the targets reached starting from a given state is designed with the same integer as the state.

We then define the subsets W_i^1 according to (1) :

$E_1^* = 42$	$42 \in W_1$	$W_1^1 = \{6,7,11,17,18,30,33,34,42,44,45,47,58\}$
$E_2^* = 25$	$25 \in W_2$	$W_2^1 = \{4,20,25,29\}$
$E_3^* = 41$	$41 \in W_3$	$W_3^1 = \{3,10,14,19,21,27,37,40,41,43,46,59,60\}$
$E_4^* = 5$	$5 \in W_4$	$W_4^1 = \{1,5,22,26,28,39,51,57\}$
$E_5^* = 24$	$24 \in W_5$	$W_5^1 = \{2,12,16,24,32,35,50\}$

According to (2) we obtain :

$$\varepsilon_1 = 39$$
$$\varepsilon_2 = 27.5$$
$$\varepsilon_3 = 35$$
$$\varepsilon_4 = 27$$
$$\varepsilon_5 = 46$$

Table 1 shows the results of the simulation in the case of the 5 most representative experiences.

	Exp. 42			Exp. 25			Exp. 41			Exp. 5			Exp. 24		
	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
Rule Num. 1	3452	135	134	4411	126	119	47.63	216	208	39.6	48	40	48.12	86	86
Rule Num. 2	37.5	138	131	466	185	180	44.24	206	205	36	45	37	47.183	105	101
Rule Num. 3	50	125	88	45	175	175	50	171	169	47.2	46	21	50	80	39
Rule Num. 4	48.8	153	82	37.55	192	190	23.22	208	207	36.8	65	58	29.34	127	126
Rule Num. 5	44.34	145	89	46.83	168	167	38.97	245	229	38.8	58	49	37.08	153	127
Rule Num. 6	42.56	128	101	42.3	184	184	40.55	211	211	45.2	47	28	40.37	97	91
Rule Num. 7	46.13	137	88	50	168	166	33.18	228	222	34.4	48	47	43.19	120	119
Rule Num. 8	44.34	140	94	42.76	186	181	41.92	214	210	42	49	34	24.41	146	146
Rule Num. 9	44.34	123	78	48.86	169	165	41.33	197	189	50	48	23	48.12	104	91

Table I

S_1 Number of manufactured parts (normalized)

S_2 Number of carts used during the simulation

S_3 Number of carts which remain inside the system at the end of the simulation.

How to use the artificial memory.

Let us consider an initial state E^0 named "63".

The distances d_0 (E^0, E_i^*) obtained are the following :

d_0 (42,63) = 75.57

d_0 (25,63) = 49

d_0 (41,63) = 24.09

d_0 (5,63) = 88.66

d_0 (24,63) = 62.03

For i = 1,2,3,4,5, $\left\{ \dfrac{d_0(63, E_i^*)}{\varepsilon_i} \right\} = \{1.93,\ 1.78,\ 0.69,\ 3.28,\ 1.35\}$

Therefore $i_1 = 3$ and $\varepsilon_{i_1} = 0.69$.

So, if we choose $\lambda \in [0.69,1]$, we will be able to conclude that E^0 has a similar behaviour as E_3^* in regard of the nine management rules.

This has been verified by a simulation (compare table II with exp.41 of table I).

	S_1	S_2	S_3
Rule 1	50	230	225
Rule 2	48.26	223	208
Rule 3	46.74	197	171
Rule 4	31.08	217	215
Rule 5	42.6	200	192
Rule 6	44.13	209	208
Rule 7	39.13	230	213
Rule 8	35.87	220	214
Rule 9	44.78	223	209

Tableau II.

IV CONCLUSION.

The procedures we have just proposed, and that we have only outlined, is a way to bypass the NP- complete property of the production management problems, which is incompatible with the "real time" constraint.

There remain numerous problems. The choice of the number of classes, notably, requires a deepened study. We remark that this number must be all the more high since the accuracy of the memory is large. But an increase of the number of classes goes hand in hand with a slowing up of the access time and a heaviness of the process which put in the memory (because of the increase of the number of parameters to take into account) ; moreover it is necessary for the user to accuratly define its targets, that is not always easy to do. Besides, the choice of the parameters remains an open problem. The techniques of data analysis (principal components analysis) should allowed an efficient approach. At last, ergonomy has to intervene in the characterization of the targets.
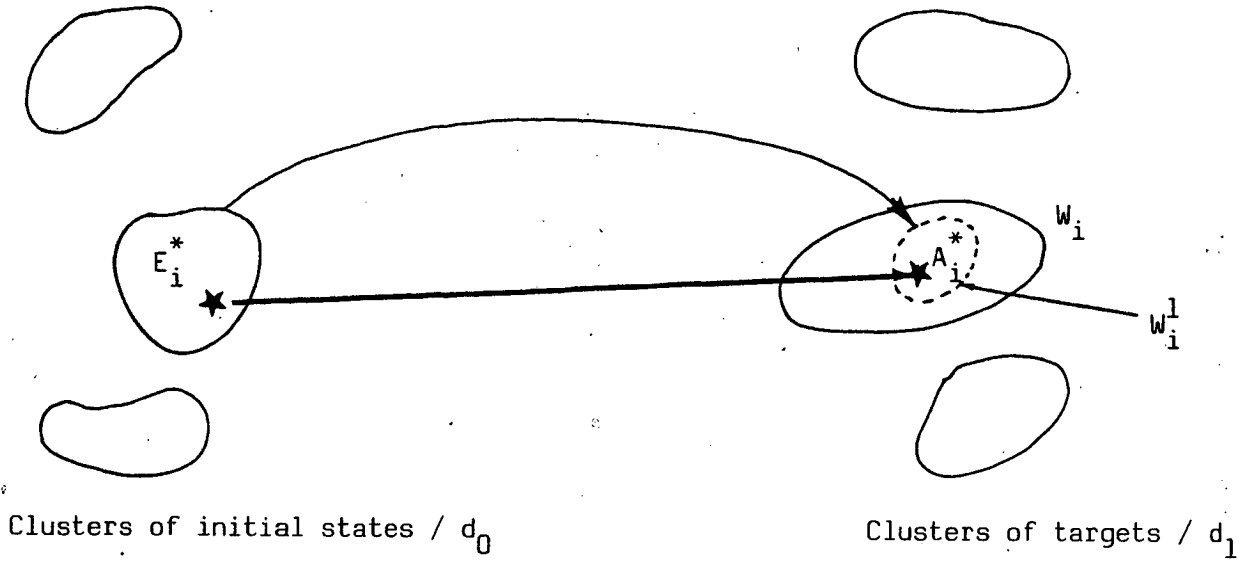
- 14 -

Clusters of initial states / d_0
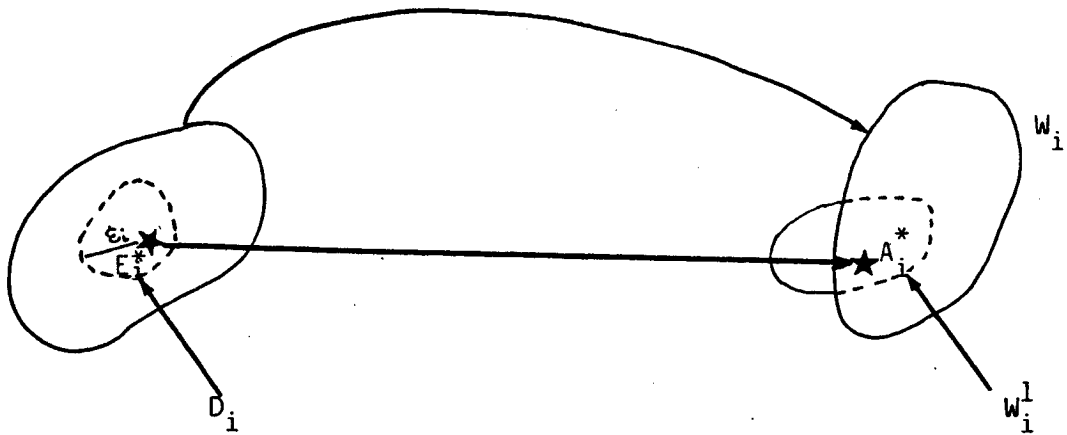
Clusters of targets / d_1

Figure 1.

Figure 2.

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