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Empirical study on entropy models of cellular manufacturing systems

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Abstract

From the theoretical point of view, the states of manufacturing resources can be monitored and assessed through the amount of information needed to describe their technological structure and operational state. The amount of information needed to describe cellular manufacturing systems is investigated by two measures: the structural entropy and the operational entropy. Based on the Shannon entropy, the models of the structural entropy and the operational entropy of cellular manufacturing systems are developed, and the cognizance of the states of manufacturing resources is also illustrated. Scheduling is introduced to measure the entropy models of cellular manufacturing systems, and the feasible concepts of maximum schedule horizon and schedule adherence are advanced to quantitatively evaluate the effectiveness of schedules. Finally, an example is used to demonstrate the validity of the proposed methodology.

Keywords: Cellular manufacturing systems; Structural entropy; Operational entropy; Scheduling

1. Introduction

Manufacturing systems operate a complex system within a challenging and ever-changing environment. They can be used to deal with many products that are made on many different machines, with several possible routes in the factory. However, how to cope with the increasing structural and operational complexity in manufacturing systems and respond to customer demands quickly is still a tough question for modern manufacturing organizations. Hence, executing effective measurement and assessment to the running of manufacturing systems has become one of the focuses in the manufacturing field, through describing and analyzing the information of the states of manufacturing resources [1,2].

Shannon [3] first proposed that the amount of information could be measured by entropy function in 1948. For a given manufacturing system (suppose that the nature and the meaning of the information of its states are under a known or a certain condition), the states of each resource are determined by their technological structure and operational status. Therefore, we are able to carry out the measurement and assessment to the states of manufacturing resources, if the amount of information needed to describe their technological structure and operational status is calculated [4]. As a result, the expected amount of information needed to describe the scheduled states of a manufacturing system can be defined as structural entropy, denoted by H_s, whereas the amount of information needed to describe the scheduled states of manufacturing systems that actually occur over time in operation can be defined as operational entropy, denoted by H_d. According to the Shannon entropy, the higher the uncertainty in the system is, the higher the entropy is, and the more information is required to understand what is happening in it. But for a manufacturing system itself, the values of its structural entropy and operational entropy are not absolute. On one hand, manufacturing systems with a smaller entropic value may lack

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enough flexibility; on the other hand, manufacturing systems with a larger entropic value are hard to control. Therefore, the states of manufacturing systems can be quantitatively analyzed through their entropy, and the complex traits of the structure and operation of manufacturing systems can also be understood and grasped exactly [5–7]. We can evaluate and compare the design and structure in different systems and deeply analyze the reasons that result in the uncontrolled state in the operation of these systems, and then optimize the design and improve the operational performance by using the data and results obtained.

As an advanced mode of production, cellular manufacturing has been widely used in many manufacturing organizations, and it can be introduced into the traditional manufacturing firms by means of executing technical reformations. Focusing on cellular manufacturing systems, in this study, we will describe the information of states of manufacturing resources by constructing the structural and operational entropy models, and introduce schedule adherence as a measurement for the models constructed in cellular manufacturing systems. Finally, the validity of the proposed methodology is demonstrated by an empirical study.

2. Entropy model of cellular manufacturing systems

It has been 60 years since information entropy was proposed, and recently, theoretical research on the application of information entropy of manufacturing systems has made great progress. For example, Karp and Ronen [8,9] stated that as long as different probabilities of products on the assembly line were known, the amount of information needed for that batch of products could be calculated, and entropy in systems was considered to be the function of the production scale; Frizelle [10] proposed DEM (dynamic entropy model) and divided it into structural complexity and operational complexity; Checkland [11] concluded that the meaning of information entropy calculated in manufacturing systems was different from its common one; Dretske [12] used entropy to describe the complexity of manufacturing systems, and found that the greater the amount of states in facilities was, the larger the entropic value was; Efstathiou et al. [13] proved that systematic entropy equaled the complexity and it could be used to describe and control the total amount of information of manufacturing systems.

Based on the studies mentioned above, the concrete meaning of information entropy is defined, and the entropy models are also developed by analyzing the relationships of facilities, parts, and tasks in systems so that the manufacturing systems can be described through using qualitative and quantitative ways. However, these theoretical analyses do not consider the application of information entropy in manufacturing systems. Furthermore, the models are usually developed under some ideal conditions. In this study, we will develop an entropy model that can be used in actual cellular manufacturing systems and verify it by scheduling in an empirical study.

2.1. Characteristic of cellular manufacturing systems

Cellular manufacturing, based on the theory of group technology, is the mode of production used in manufacturing single or variable products through arranging the manufacturing equipment in the shape of the letter "U" within a work cell. It is an efficient way to cut down the costs, improve the quality of the products and strengthen the manufacturing flexibility. Cellular manufacturing has been widely used in many leading countries in manufacturing. For example, 40% of manufacturing enterprises in Germany have successfully introduced cellular manufacturing into production [14].

The work cell is the basic unit of cellular manufacturing [15]. It is composed of the manufacturing equipment, operators and equipment for transfer. Usually, the manufacturing equipment in the work cell is arranged in the shape of the letter "U". The operators can operate flexibly and efficiently in this U-workshop. Cellular manufacturing systems are different from the traditional manufacturing systems which are progressive in their management structure, and are fixed and meticulous in their production structure. Every relatively independent work cell can be a unit of the relatively independent manufacturing systems, and several units are managed and coordinated together via the network.

2.2. Structural entropy model

In order to deduce the structural entropic model of cellular manufacturing systems, we firstly introduce the definition of information entropy.

Suppose that there is a discrete stochastic variable X, whose n possible outcomes are $x_1, x_2, \ldots, x_n$, each with a probability of occurrence of p_i. Let p $(p = p_1, p_2, \ldots, p_n)$ be the probability distribution. The measure of entropy for this distribution is given by

$$E(X) = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{1}$$

where $p_i \geqslant 0$, $\sum_{i=1}^{n} p_i = 1$. If X denotes a system, x_i and p_i $(i = 1, 2, \ldots, n)$ are its n possible states and their probabilities in the system, then $E(X)$ is the information entropy of X, i.e. the amount of information needed to describe X. $E(X)$ also shows the uncertainty of X. The larger $E(X)$ is, the more uncertain X is. The information entropy described in Eq. (1) has the following characteristics:

(i) When the value of the only one p_i equals 1, the others equal 0, the information entropy is the smallest, i.e. $E(X) = 0$. And so X is under the state of full certainty.
(ii) The maximum value of $E(X)$ occurs when all the outcomes have an equal probability of occurring. This maximum value can be shown to be equal to $\ln n$.

(iii) Any change that leads to the equalization of p_i will increase the uncertainty of the system, so will the information entropy.

According to the definition above, suppose that a cellular manufacturing system has n manufacturing units, the Kth unit has m ($m \geqslant 1$) resources, the ith resource has S_i expected states, and the different states of every resource are independent of each other. When one part is manufactured solely by one machine, the states of the machine can be defined by the products being processed or its idle time. From Eq. (1), the structural entropy of resource i can be deduced by

$$H_{\mathrm{s}} = -\sum_{j=1}^{S_i} p_{ij}\log_2 p_{ij} \tag{2}$$

where p_{ij} represents the probability of state j of resource i, with $1 \leqslant j \leqslant S_i$, and $\sum_{j=1}^{S_i} p_{ij} = 1$.

According to the information entropy, the structural entropic model that consists of m resources in a manufacturing unit is

$$H_s = -\sum_{i=1}^{m}\sum_{j=1}^{S_i} p_{ij}\log_2 p_{ij} \tag{3}$$

From the above model, we are able to measure the states of resources in the whole system by measuring the amount of information of the states of every manufacturing cell instead, and so the difficulty of measuring the states of the whole system is reduced. If a manufacturing cell is treated as a whole, we can define its states as follows: the whole manufacturing cell will be in an operational state provided that one machine in this cell is working continually; the manufacturing cell will be in an idle state provided that one machine in this cell is in malfunction.

The key point to calculate the structural entropy is to confirm the states of resources in the system. Taking a discrete manufacturing system as an example, if we only pay attention to the facilities' load, then the facilities' states can be defined as "producing," "technological equipment adjustment," "machine maintenances," and "idle." But if we care more about the specific production, we can further define each facility's states as "Process product A," "Process product B," "Technological equipment adjustment for product A," "Technological equipment adjustment for product B," etc. Because the technological structure of cellular manufacturing systems essentially determines possible states of the resources in manufacturing systems, it also determines the structural entropy of the systems.

2.3. Operational entropy model

The structural entropy only emphasizes the expected states of manufacturing systems, but the operational entropy describes the actual states of the systems in processing. The actual states of cellular manufacturing systems can be divided into two parts: one is the normal expected states (in-control) according to the predetermined scheduling; the other is the abnormal states deviating from scheduling (out-of-control), such as equipment breakdown and operation delay. The actual states can be monitored directly from cellular manufacturing systems in processing.

Based on Eqs. (1) and (3), the operational entropy of cellular manufacturing systems can be expressed as

$$H'_{\mathrm{d}} = -\sum_{j=1}^{S'_i} p'_{ij}\log_2 p'_{ij} \tag{4}$$

where S'_i denotes the actual number of states of resource i in the processing, and p_{ij} denotes the probability of state j of resource i in the operational, with $1 \leqslant j \leqslant S'_i$, and $\sum_{j=1}^{S'_i} p'_{ij} = 1$.

If we suppose the in-control state of resource i in processing is the first state of S'_i (its probability is P_i), and the other states of S'_i are treated as the out-of-control states, from the characteristics of information entropy, and from Eq. (4), we can obtain

$$H'_{\mathrm{d}} = -p_i\log_2 p_i - \sum_{j=2}^{S'_i} p'_{ij}\log_2 p'_{ij} \tag{5}$$

where p'_{ij} refers to the probability of state j of resource i in the out-of-control states, with $\sum_{j=2}^{S'_i} p'_{ij} = 1 - p_i$.

Suppose the probability of all the in-control states is P, the amount of out-of-control states of resource i is n_i, so the operational entropy model of cell manufacturing systems is

$$H_{\mathrm{d}} = -p\log_2 p - \sum_{i=1}^{m}\sum_{j=1}^{n_i} p'_{ij}\log_2 p'_{ij} \tag{6}$$

The second part of Eq. (6) is the occurring operational entropy because manufacturing systems deviate from the expected scheduling in processing, and it denotes the uncertainty of manufacturing systems in processing.

3. Entropic measures to cellular manufacturing systems

In Section 2, according to the information entropy, we have developed the structural entropy and the operational entropy models to describe cellular manufacturing systems, but the models are only used to describe the maximum value of the amount of information of the states of manufacturing resources. (However, as the probability in the operating process is not totally stochastic, the actual value of entropy is smaller than this maximum value.) How to use the entropy models to measure information of the resources during the actual operating process, and then to assess the systems states? This is a problem on which we should do further research. In this section, the method of scheduling will be used to measure entropy models in the actual manufacturing systems.

3.1. Feasibility of measure in scheduling

In a cellular manufacturing system, the actual productions sometimes more or less deviates from the original plan of production due to the outer or inner interruptions. If the artificial interference is not conducted in time, this deviation will become more and more serious [16]. The nature of this deviation is that a part of the static amount of information is transformed into the dynamic one in the process of operating. Then, scheduling is used to adjust the original plan and makes the production as smooth as possible. According to Eq. (6) in Section 2.3, the second item is the entropic increase because of the deviation from the expected state in the process of operating, which indicates the degree of the uncertainty. Therefore, if we can measure the structural entropy in the scheduling and the transferring rate from the structural entropy to the operational entropy, the entropy models will be measured in the actual manufacturing systems.

During the process of scheduling, it is necessary to set a time limit for the scheduling, such as schedule horizon [17], only in this way can the scheduling be executed effectively. If this time horizon is overmuch and exceeds a certain amount of time, the actual production situation will be totally different from the original scheduling plan, and there will be no significance for scheduling. But if this time horizon is not enough, the execution of the original plan will be interrupted, and the costs of management will be increased. To measure the structural entropy, Eq. (3) can be used, but the value obtained is the structural entropy at any time in the system. Because the data monitored in scheduling are obtained within every time interval Δt (the time interval for monitoring the states of scheduling), for the scheduling plan with the schedule horizon T, we can calculate its structural entropy by

$$H_{\mathrm{ss}} = -\frac{T}{\Delta t}\sum_{i=1}^{m}\sum_{j=1}^{S_i} p_{ij}\log_2 p_{ij} \tag{7}$$

where p_{ij} represents the probability of resource i being in the expected state j, S_i represents the expected number of the states of resource i. Eq. (7) denotes that the structural entropy of the amount of T/t time interval in a schedule horizon T is added up.

According to Eq. (6), the operational entropy produced because of the deviation from the expected state at any time in the actual operation is

$$H_{\mathrm{dd}} = -\sum_{i=1}^{m}\sum_{j=1}^{n_i} p'_{ij}\log_2 p'_{ij} \tag{8}$$

where p'_{ij} represents the probability of resource i being in the deviating state j and n_i represents the number of deviation states of resource i.

Therefore, the average operational entropy (the speed of the structural entropy transformed into the operational entropy) produced for deviation from scheduling in the system is

$$H_{\mathrm{da}} = -\frac{1}{\Delta t}\sum_{i=1}^{m}\sum_{j=1}^{n_i} p'_{ij}\log_2 p'_{ij} \tag{9}$$

That is to say, in schedule horizon T, for the interruptions of environment, H_{ss}, the structural entropy contained in scheduling, is transforming into the operational entropy at the average speed of H_{da}. The maximum feasible schedule horizon can be calculated by

$$T_{\max} = \frac{H_{\mathrm{ss}}}{H_{\mathrm{da}}} = T\frac{\sum_{i=1}^{m}\sum_{j=1}^{S_i} p_{ij}\log_2 p_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n_i} p'_{ij}\log_2 p'_{ij}} \tag{10}$$

The numerator in Eq. (10) expresses the structural entropy in the whole schedule horizon T with t as the time interval for monitoring of the state, and the denominator of the equation expresses the average speed of the structural entropy transformed into the operational entropy. So $T_{\max}$ denotes the time needed to totally transform the structural entropy contained in scheduling into the operational entropy. The scheduling plan will never be coincident with the actual situation after $T_{\max}$. Thus, the re-scheduling must be conducted.

3.2. Schedule adherence

In order to denote the degree of the accordance between the actual execution and the original scheduling plan, we first introduce the concept of scheduling adherence. As mentioned above, the nature of the deviation in the operating systems is that part of the structural entropy contained in scheduling is transformed into the operational entropy. The degree of deviation can be described by Eq. (8). Similarly, the degree of accordance in the scheduling can be described by the structural entropy left in scheduling. We may use the relative value to indicate

$$C = \frac{H_{\mathrm{ss}} - H_{\mathrm{da}}T}{H_{\mathrm{ss}}} \times 100\% \tag{11}$$

i.e.

$$C = \frac{\sum_{i=1}^{m}\sum_{j=1}^{S_i} p_{ij}\log_2 p_{ij} - \sum_{i=1}^{m}\sum_{j=1}^{n_i} p'_{ij}\log_2 p'_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{S_i} p_{ij}\log_2 p_{ij}} \times 100\% \tag{12}$$

Therefore, by adopting schedule horizon and schedule adherence, we can measure the entropy models developed and make a corresponding improvement plan to increase the efficiency in scheduling according to the result of measure.

4. An empirical study

Cellular manufacturing was implemented in a mechanical job shop. The unit of cellular manufacturing included the equipment of generating milling machine, spline milling machine, keyway milling machine and internal grinder. Five kinds of products in the unit of cellular manufacturing were selected, and they were annular gear A_1, angle gear A_2, conical gear A_3, brake spindle A_4, and milled spindle A_5. According to the weekly processing plan, the daily (12 h) scheduling program was arranged, and the precision

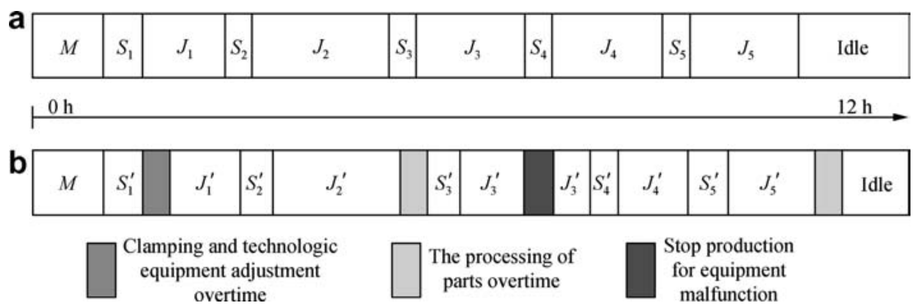

Fig. 1. Daily scheduling and actual operational status. (a) Daily scheduling program; where M denotes the amount of time in equipment maintenance, J_1–J_5, respectively, denote the amount of time in job of parts A_1–A_5, S_1–S_5, respectively, denote the amount of time in clamping and technologic equipment adjustment and idle denotes the amount of time in idling equipment; (b) actual implementation of the corresponding scheduling; where J'_1–J'_5, respectively, denote actual amount of time of the job of parts A_1–A_5. S'_1–S_5, respectively, denote actual amount of time of clamp and technologic equipment adjustment of the parts.

of scheduling was 0.5 h. The daily scheduling program is expressed by Fig. 1(a). Scheduling often deviated from the original scheme in the actual implementation process owing to the change of manufacturing environments. The actual implementation of the corresponding scheduling is expressed by Fig. 1(b).

4.1. Calculation of the structural entropy in scheduling

To calculate the value of the structural entropy in scheduling, all of the expected discrete events were taken as the states of manufacturing systems in this example. The description of these states is denoted in Table 1. (We only choose one adjustment state of technologic equipment because the adjustment of technologic equipment is similar in all products.) To obtain the statistical probability of these states, a weekly (5 days) scheduling data are used as the statistical data. According to the expected average duration of each state, the probability of each state can be obtained ($p_i = t_i/5/12$). Because $T = 12$ h, $\Delta t = 0.5$ h, according to Eq. (7), the average structural entropy in the Scheduling is 68.118168 bits.

Table 1
Calculation of the structural entropy in scheduling.[a]

No.	States	The amount of time	Probabilities	$p_i \log_2 p_i$
1	The processing of A_1	6.0	0.100000	−0.332193
2	The processing of A_2	12.5	0.208333	−0.471466
3	The processing of A_3	9.0	0.150000	−0.410545
4	The processing of A_4	8.0	0.133333	−0.387585
5	The processing of A_5	7.5	0.125000	−0.375000
6	Technologic equipment adjustment	10.0	0.166666	−0.430827
7	Idle	6.0	0.100000	−0.332192
8	Equipment maintenances	1.0	0.016666	−0.098448
	Total	60.0	1.000000	−2.838257

[a] The average structural entropy $H_{ss} = (12/0.5) \times 2.838257 = 68.118168$ bits.

4.2. Calculation of the operational entropy in scheduling

For the contrastive analysis with the structural entropy, all the deviation states corresponding with the calculation of the structural entropy in scheduling were taken as the abnormal states of the operational entropy in cell manufacturing systems. The description of the states is given in Table 2. In contrast to the structural entropic calculation, the appearance probability of each abnormal state can be obtained ($p_i = t_i/5/12$) through the state statistics in the same monitoring period. According to Eq. (8), the value of the operational entropy for deviating the expected scheduling in any movement time (time-gap $\Delta t = 0.5$ h) is 0.992802 bits, and the average operational entropy is 1.985604 bits/h in a schedule period.

4.3. Validity of scheduling

According to Eq. (10), the maximum feasible schedule horizon can be calculated as follows:

$$T_{\max} = \frac{H_{ss}}{H_{da}} = \frac{68.118168}{1.985604} = 34.3 \text{ h}$$

That is to say, the maximum time of scheduling is 34.4 h (about 3 days) every time. Therefore, based on Eq. (11), schedule adherence can be calculated as follows:

$$C = \frac{H_{ss} - H_{da}T}{H_{ss}} \times 100\% = \frac{(68.118168 - 1.985604 \times 12)}{68.118168} = 65.02\%$$

As shown above, only 65.02% scheduling information (the structural entropy) is implemented in the course of actual operation and 34.98% scheduling information is transformed into the operational entropy as a result of the disordering condition. From Table 2, we can further analyze that the dominant causes that lead to the decline of schedule adherence are the 6th abnormal state, the 7th abnormal state and the 9th abnormal state, and their proportions are 19.24%, 21.77% and 21.77% in the operational entropy, respectively.

Table 2
Calculation of the operational entropy in scheduling.[a]

No.	States	The amount of time	Probabilities	$p_i' \log_2 p_i'$
1	The processing of A_1 overtime	0.5	0.008333	−0.057557
2	The processing of A_2 overtime	0.0	0.000000	0.000000
3	The processing of A_3 overtime	1.0	0.0166667	−0.098448
4	The processing of A_4 overtime	0.5	0.008333	−0.057557
5	The processing of A_5 overtime	0.0	0.000000	0.000000
6	Technologic equipment adjustment overtime	2.5	0.041667	−0.191010
7	Non-planning processing	3.0	0.050000	−0.216096
8	Non-planning technologic equipment adjustment	0.5	0.008333	−0.057557
9	Stop production for equipment malfunction	3.0	0.050000	−0.216096
10	Stop production for exterior reasons	1.0	0.016667	−0.098448
11	Total	12.0	0.200000	−0.992802

[a] The operational entropy $H_{\rm dd} = 0.992802$ bits; the average operational entropy $H_{\rm da} = 1.985604$ bits/h.

Table 3
Calculation of the operational entropy after adjusting the major abnormal states.

No.	States	The amount of time	Probabilities	$p_i' \log_2 p_i'$
1	The processing of A_1 overtime	0.5	0.008333	−0.057557
2	The processing of A_2 overtime	0.0	0.000000	0.000000
3	The processing of A_3 overtime	1.0	0.0166667	−0.098448
4	The processing of A_4 overtime	0.5	0.008333	−0.057557
5	The processing of A_5 overtime	0.0	0.000000	0.000000
6	Technologic equipment adjustment overtime	2.0	0.033333	−0.163610
7	Non-planning processing	2.5	0.041667	−0.191010
8	Non-planning technologic equipment adjustment	0.5	0.008333	−0.057557
9	Stop production for equipment malfunction	1.0	0.016667	−0.098448
10	Stop production for exterior reasons	1.0	0.016667	−0.098448
11	Total	9.0	0.150000	−0.822802

According to the above calculation and analysis, the managers in job shop have adjusted the amount of time of the three dominant abnormal states that result in the decline of schedule adherence. These measures include strategies such as quickening the adjustment of technologic equipment of conical gear A_3 and angle gear A_2, decreasing the non-planning processing and examining and repairing equipment. The amount of time of the three abnormal states is, respectively, cut down to 2 h, 2.5 h, and 1 h at last. The calculation of the operational entropy after adjusting the abnormal states is given in Table 3.

From Eq. (11), schedule adherence can be calculated after adjusting the major abnormal states as follows:

$$C = \frac{H_{\rm ss} - H_{\rm da}T}{H_{\rm ss}} \times 100\% = \frac{(68.118168 - 1.645604 \times 12)}{68.118168} = 71.01\%$$

Based on the above result, we can conclude that the amount of scheduling information (the structural entropy) implemented in the course of actual operation increases to 71.01%. That means the amount of scheduling information transformed into the operational entropy as a result of disordering condition decreases to 28.99%. Therefore, the degree of deviation in scheduling is availably controlled via adjusting those major abnormal states. Thus, the validity of the proposed methodology is demonstrated by an empirical study.

5. Analysis and discussion

From the empirical study in Section 4, we can see that the structural entropy model and the operational entropy model have been applied in the measurement of the information of the states of the manufacturing resources, which combine theory with the actual product. Furthermore, the result of measurement can be analyzed and then a more pertinent suggestion can be given to the manufacturing systems.

From Eq. (11), we can conclude that the operational entropy transformed from the structural entropy, i.e. the second part of the numerator in the equation should be decreased in order to improve the schedule adherence in the condition of a certain value of the structure entropy in manufacturing systems. On one hand, the degree of deviation in scheduling may be controlled through setting up a reasonable schedule horizon; on the other hand, the causes of the decline of scheduling adherence can be further analyzed, and finally the operating states of the manufacturing systems are improved.

According to the results of the example in Section 4, some measures should be taken as follows in order to enhance the validity of scheduling. Firstly, the reasonable schedule horizon can be reset. For example, in an empirical study, the 12 h schedule horizon should be divided into two parts: the former part is supposed to be the precise schedule horizon and the latter one is arranged for duty tabulation and not for the concrete time. As a result, the re-scheduling may be reduced on a big scale, and the scheduling efficiency can be enhanced. Secondly, the management of primary factors which lead to the decline of schedule adherence should be strengthened, especially to the non-profiting abnormal state, such as the 6th state and the 9th state in the empirical study, by which it will be more advantageous to improve the validity of scheduling.

6. Conclusion

Taking a cellular manufacturing system as a research example, information needed to describe its states has been classified into two parts: the structural entropy and the operational entropy. Based on the analysis of the recent progress of information entropy applied in manufacturing systems, we have developed the structural entropy model and the operational entropy model of cellular manufacturing systems. As a tool of measure, the schedule was introduced into the research of entropy models applied in cellular manufacturing systems. Using the maximum feasible schedule horizon and schedule adherence as two indexes, we have calculated and analyzed the values of the structure entropy and the operational entropy, and finally given suggestions on how to improve the efficiency of scheduling according to the results of calculation. Thus, the validity of the proposed methodology is demonstrated.

Entropy is suitable for continuously monitoring the state of a machine, group of machines or a complete process. The measure of entropy is based on the typical data from production or activity logs, which are readily available in any production environment. Thus, a system can be easily designed to calculate entropy.

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