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A multi agent method for cell formation with uncertain situation, based on information theory

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Abstract: This paper assumes the cell formation problem as a distributed decision network. It proposes an approach based on application and extension of information theory concepts, in order to analyze informational complexity in an agent- based system, due to interdependence between agents. Based on this approach, new quantitative concepts and definitions are proposed in order to measure the amount of the information in an agent, based on Shannon entropy and its complement in possibility theory, U uncertainty. The paper presents an agent-based model of production system as a graph composed of decision centers. The application of the proposed approach is in analyzing and assessing a measure to the production system structure efficiency, based on informational communication view. Information flow in cells and grouping algorithm are investigated in this paper.

Keywords: *Cell formation problem; Informational complexity; Agent based system; Shannon entropy; U uncertainty; Possibility theory*

1. Introduction

The conditions governed on 21st Century manufacturing systems necessitate decentralized manufacturing facilities whose design and manufacture-ability allows the integration of production stages in a dynamic, collaborative network. Such facilities can be constructed through agent-oriented approaches (Wooldridge and Jennings, 1995).

Especially the self-organization property requires new and improved approaches to distributed intelligence and knowledge management. The idea of researches in this domain are encapsulated in the development of a Metamorphic, self-organizing architecture which comprises planning, control and application agents that collaborate to satisfy both local and global objectives (Norrie and Gaines, 1996). The self-organization property is implemented through virtual clusters of agents dynamically created, modified, and destroyed as needed for collaborative planning and action on tasks. Mediator agents coordinate activities both within clusters and across clusters.

Cell formation problem is defined as grouping the parts into part families and the machines into machine cells and then to assign the part families into corresponding machine cells (Ahi *et al.*, 2009). Cellular manufacturing is an application of group technology that is based on manufacturing similarity of group technology. Two very important stages in designing a cellular manufacturing system are the identification of part families and machine groups. The methods for solving cell formation problems are classified to six methods (Yu *et al.*, 2010; Dixit and Mishra, 2010): array-based method, heuristic methods, hierarchical methods, graph partition methods, artificial intelligence methods, and mathematical programming methods. A number of papers have been published as review studies for existing cell formation literature (Joines *et al.*, 1996; Selim *et al.*, 1998).

In this paper a new concept and method is developed to design CM based on information theory. In this approach, the cell formation problem is viewed as a multi agent that its behavior is like a decision network. The base of the cell formation process in this approach is the information flow between the parts and machines that are the agents. Any agent is responsible for a different decision and so must be grouped with suitable other agents. Because this new concept introduced in this paper, we must have a discussion on information theory concepts, related to topic, and also on Shannon entropy. First it must be given some explanations about using multi agent concept in our study. The main motivations for tendency to decentralized architecture in huge systems and organizations can be listed as follows:

- Incompleteness, dispersion and uncertainty in information sources.

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- Limits in complete and on time access to these sources due to limited capacity of communication channels and communication costs.
- Limitation of receiving and processing the information in decision centers.
- Low reliability and fault possibility of central decision making.

In these architectures, receiving, gathering and processing the information and also decision making functions are distributed between agents or intelligent active sensors that can be interpreted as machines. There must be a mechanism to define the quality of communication between agents and their environment and also to determine the decision rules and patterns.

Therefore the distributed decision network models, information flow models and information spread patterns, are the subject of many researches in many science and engineering branches. For example in neurobiology (Golomb and Hansel, 2000), in artificial intelligence (Fazlolahhi *et al.*, 2000), in ecology (Ulanuwicz, 2004), in control engineering (Schaeffer *et al.*, 2004), in economics (Marschak and Reichelstein, 1998), in organization and management (Pete *et al.*, 1998), and so on.

The Hungarian author and philosopher Arthur Koestler proposed the word "holon" to describe a basic unit of organization in biological and social systems (Koestler, 1967). A holon, as Koestler devised the term, is an identifiable part of a system that has a unique identity, yet is made up of sub-ordinate parts and in turn is part of a larger whole. The word "holonic" is used to characterize the relationships between elements of a system. Autonomy and cooperativeness characterize these relationships. Holons are more structured agents which act synergistically with other holon-type agents, as they behave simultaneously as autonomous (sub) wholes and as dependable parts. Referring to Intelligent Manufacturing Systems (IMS) Steering Committee (Parker, 1997), the Holonic Manufacturing Systems (HMS) aims to translate the concepts that Koestler developed for social organizations and living organisms into a set of appropriate concepts for manufacturing industries, e.g., stability in the face of disturbances, adaptability and flexibility in the face of change, and efficient use of available resources (Christensen, 1994; Norrie and Gaines, 1996). The concept of holonic self-organization combines the best features of hierarchical ("top down") and heterarchical ("bottom up", "cooperative") organizational structures by clustering the entities of the system into nested hierarchies (Dilts, 1991).

The holonic multi agent systems can be viewed as decision making networks.

A study of numerous articles in different fields about the mentioned subject, clarifies that the investigations are performed in divergent branches and so do not converge in many cases. However the main subjects in the related researches can be divided into three main topics:

- Detecting, modelling and improving the decision methods in a unique decision maker.
- Detecting, modelling and improving the decision aggregation and fusion in the decision network.
- Information and uncertainty modelling in different conditions and determining uncertainty and information flow patterns.

In fact in order to explain specifications of organic social systems such as intelligence, self organization, order, chaos, complexity, and evolvement and so on, mathematical concepts and theories must be extended and new rules and patterns by new organization theories must be explored. In classical cell formation methodologies, in simple and stable conditions, information received and processed by agents are usually performed by predetermined channels and in a constant amount. But in a complex and dynamic condition such as knowledge–based or organic organization, centralized decision architecture does not work efficiently.

Therefore in agent-based approach in organization theories, organization is not considered as a unique identity with a unique willing and wisdom, but also it is a combination of different agents with different goals, interacting together based on accessible information and limited processing capabilities. So the organization corresponds to an information transaction pattern. Following this introduction, this paper extends information theories concepts in decision networks in the cell formation problem, tries to explain and defines some specifications of these networks and applies them in order to analyze the informational complexity of the manufacturing system, to propose methods to improve cell formation efficiency. The proposed model and its definitions and basic concepts are presented in Section 2, then in Section 3 their applications are investigated, Section 4 contains some examples, at the end conclusion and guidelines for the model extension and the complementary researches will be given.

2. Decision network

In the proposed model, it is assumed that the manufacturing system is composed of a number of distinct agents, so called machines and parts, with the interactions between them. In this definition, any agent is responsible for a different decision.

In this paper, the words: agent, DM and node have equal meanings and mean decision making center. Decision is defined as selecting a choice among some alternatives. So every agent corresponds to a set of decision alternatives, $D_i = \{d_{i1}, d_{i2}, ..., d_{ik}\}$. Figure 1 is an example of a decision network that the agent is its node.

2.1. Measuring the amount of the decision information

It is possible to assign a grade of possibility of selection or probability of occurrence to each decision alternative. Abstract information of a decision center can be defined, when the agent is considered independently from the other agent's information. However the possibility and utility grade of any choice is modified according to other agent's decisions and also environmental information (conditional decision information). So this paper tries to propose some quantitative definitions for decision information and conditional decision information for different situations that can be occurred in a cell formation problem.

We assume D_i the set of decision alternatives of agent i. The probability of selection of m th alternative is p_{im}. The number of agents is n.

$$D_i = \{d_{i1}, d_{i2}, ..., d_{ik}\} \tag{1}$$

$$p(d_{im}) = p_{im}, i = 1,...,n$$

So decision entropy of node i that present the average decision information according to Shannon formulas is as follows:

$$H_i = -\sum_m p_{im} \log_2 p_{im} \tag{2}$$

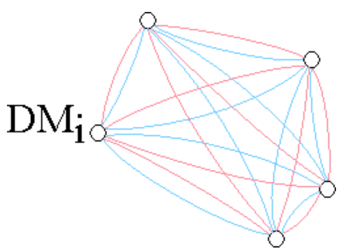

Figure 1. Decision network.

To define the conditional decision information, the conditional probabilities are defined as follows:

$$p(d_{in} | d_{jm}) \underline{\underline{\Delta}} p(^{in}|_{jm}) \tag{3}$$

So the conditional decision entropy is defined according to its formula:

$$H(^i|_j) = -\sum_m p_{jm} \sum_n p(^{in}|_{jm}) \log_2 p(^{in}|_{jm})$$

$$= -\sum_m \sum_n p_{jm} p(^{in}|_{jm}) \log_2 p(^{in}|_{jm})$$

$$= -\sum_m \sum_n p(in, jm) \log_2 p(^{in}|_{jm}) \tag{4}$$

It can be observed that the above definitions arise from a probabilistic view. In this view, the phenomenon relation's can be studied only by statistical correlation approach. But the causality concept is different from probability concept and can not be explained by it. For example a positive statistical correlation between two variables is not a reason for causality relation between them.

So if considering the causality and freedom degree in decision alternatives selection, the application of weighted Shannon entropy will be useful. Therefore assume that the node i in selecting the alternative d_{in} is affected by the selection of d_{jm} by the node j with weight coefficient $w(in, jm)$. We have:

$$H(^i|_j) =$$

$$-\sum_m p_{jm} \sum_n w(in, jm)\, p(^{in}|_{jm})\, Log_2\, p(^{in}|_{jm})$$

$$= -\sum_m \sum_n w(in, jm)\, p(in, jm) \log_2 p(^{in}|_{jm}) \tag{5}$$

In the simplest form the causality coefficients can be considered equal to 1 for a complete independence and 0 for a total causal dependence.

As mentioned before, the above definitions are resulted from the assumption that choosing options follows from a probabilistic nature. This assumption arises some problems in different cases. So applying it is restricted to the conditions that are explainable only by probabilistic models. Here the use of utility function in defining decision information will be investigated. One may propose the use of normalized utility function instead of probability functions. (Normalized utility function is derived by modifying utility values in such a way that the sum of the utility values is 1 and satisfies the conditions of a probability function).

Assume A and B are two independent alternatives. By the probability theory, the probability value assigned to the set of (A U B) will be:

$$P(A \cup B) = P(A) + P(B) \quad (6)$$

But it can be observed that the maximum utility resulted by selection the one of them is equal to the maximum utility of them. The correspondence of this concept to the possibility value of union of two sets in possibility theory, guides to applying the possibility distribution function in defining decision information.

$$\prod(A \cup B) = \max\{\prod(A), \prod(B)\} \quad (7)$$

So we can use the Shannon entropy in fuzzy possibility theory, U, and try to present the information decision definition.

Assume that we have the possibility distribution for decision alternatives of node i, as a descending sequence, $r = (r_{i1}, r_{i2}, \ldots, r_{ik})$.

Decision uncertainty and so decision information in this condition isn't due to probabilistic nature of alternative selection but is due to no specificity in decision process. No choice has a certain possibility for selection and the selection possibility is distributed between different alternatives.

So a measure of uncertainty is defined for this distribution as a critique for measuring the information decision of node i, according to U function (Klir and Yuan, 1995).

$$U_i = \sum_j (r_{ij} - r_{i,(j+1)} \log_2 j \quad (8)$$

Also the base assignment function on the D_i can be presented by m_i and the set of focal elements by F_i. Then we'll have:

$$U_i = \sum_{A \in F_i} m_i(A) \log_2 |A| \quad (9)$$

Now the conditional decision information, based on conditional possibility distribution function can be defined. It is clear that the possibility values of an alternative selection can be modified due to other agents' decisions. Assume the set of focal elements of the base assignment function on the Cartesian product of sets d_i and d_j is F_{ij} and the base assignment function on this set is m_{ij}. We will have:

$$U({}^i\big|_j) = \sum_{A \times B \in F_{ij}} m_{ij}(A \times B) \log_2 \frac{|A \times B|}{|B|} \quad (10)$$

2.2. Informational dependence coefficients

According to the above explanation, $H_i - H_{(i|j)}$ clears how information of node i is modified with respect to node j. So we propose this difference as a critique to measure the dependence node i to node j. Proportional dependence coefficient (node i to node j) is defined:

$$r_{ij} = \frac{(H_i - H(i|j)}{H_i} \quad (11)$$

$r_{ij} \neq r_{ji}$ in the general case or by considering U_i and $U_{(i|j)}$, then:

$$r_{ij} = \frac{(U_i - U_{(i|j)})}{U_i} \quad (12)$$

According to this definition, when node i is not dependent to node j at all, it means that ($H_i = H_{(i/j)}$), then $r_{ij} = 0$ and if node i is completely dependent to node j, it means that ($H_{(i|j)} = 0$), then $r_{ij} = 1$.

2.3. Informational dependence coefficients matrix

The dependence coefficients matrix can be defined as follows:

$$r_{ij} \in [0,1] \qquad R = \lfloor r_{ij} \rfloor \quad (13)$$

3. Grouping

Now the application of the mentioned definitions and concepts in finding an effective grouping algorithm in a cell formation problem is studied. As mentioned before, two main informational limitations are communication links limitations and information processing capability of agents. One way for increasing the processing capability and then the number of links to other agents effectively, is using the group making concept. We propose that agents (machines), who have more informational dependence to each other, be included in one cell. In fact, the maximization of informational dependency in a cell is the objective of the group formation. Here one of the limitations is the number of a cell.

Again, consider R, informational dependency coefficients matrix. It can be considered as a fuzzy relation on D^2, ($D = \{D_1,\ldots,D_n\}$). So we can use fuzzy clustering methods for equivalent relations in order to classify agents in such a way that agents with maximum informational dependence be arranged in the same class. The number of each member in class does not exceed a predetermined upper limit. A fuzzy relation on the set X is the equivalence relation if and only if it has the following conditions:

- Reflexive: $\mu_R(x_i, x_j) = 1$
- Symmetric: $\mu_R(x_i, x_j) = \mu_R(x_j, x_i)$
- Transitive: $\mu_R(x_i, x_j) = \mu_1$ and $\mu_R(x_j, x_k) = \mu_2$ then $\mu_R(x_i, x_k) = \mu$, $\mu \geq \min(\mu_1, \mu_2)$

It can be shown that any fuzzy tolerance relation (that is reflexive and symmetric) can be reformed into a fuzzy equivalence relation by at most (n-1) composition with itself (Ross, 1997). So we derive matrix R' symmetrically from R:

$$\forall (r_{ij}, r_{ji}) \rightarrow r'_{ij} = r'_{ji} = \min(r_{ij}, r_{ji}) \qquad (14)$$

As it is mentioned, R' can be transferred to an equivalence relation by combination by itself, so called the matrix R_e. The derived equivalence relation produces equivalence classes by defining adequate λ-cut in such a way that the number of each class doesn't exceed a defined limitation.

3.1. Numerical example

An example for cell formation according to informational dependence coefficients between agents is shown in this section. Assume a manufacturing system with 12 parts and 4 machines. The matrix R for 16 agents is given in Table 1 (Ross, 1997).

The goal is to determine the cells in such a way that agents, who have higher informational dependence, compose the same cell. As it is mentioned, R can show a fuzzy relation on the set of agents. This relation is not necessarily symmetric and according to Relation (14) can be transformed to symmetrical form. So the relation is a tolerance relation and can be transformed to an equivalence relation R'. M_1 to M_4 are assumed to be the machines and P_1 to P_{12} are the parts. The rows and the columns 1 to 4 are assigned to machines and the rows and columns 5 to 16 are assigned to the parts.)

The elements of the following matrix, R, are r_{ij} that represents the informational dependency between the parts and machines on Table 1. Using the Relation (14), the matrix R' can be formed as follows on Table 2. For example, the element in row 4 and column 3, r'_{43} is the min{ r_{43}, r_{34} } = min{ 0.4,0.5 }= 0.4. The equivalence relation R_e can be derived by combination of R' with itself by max-min rule (Table 3). For example, the element in row 2 and column 1 is obtained as follows:

Min {r_{21}, r_{11}}={0,1}=0
Min {r_{22}, r_{21}}={1,0}=0
Min {r_{23}, r_{31}}={0,0}=0
Min {r_{24}, r_{41}}={0,0}=0
Min {r_{25}, r_{51}}={0.8,0}=0
Min {r_{26}, r_{61}}={0,0.5}=0
Min {r_{27}, r_{71}}={0.8,0}=0
Min {r_{28}, r_{81}}={0.2,0.4}=0.2
Min {r_{29}, r_{91}}={0.4,0}=0
Min {$r_{2,10}, r_{10,1}$}={0,0}=0
Min {$r_{2,11}, r_{11,1}$}={0.5,0}=0
Min {$r_{2,12}, r_{12,1}$}={0.2,0}=0
Min {$r_{2,13}, r_{13,1}$}={0,0.8}=0
Min {$r_{2,14}, r_{14,1}$}={0.8,0}=0
Min {$r_{2,15}, r_{15,1}$}={0,0}=0
Min {$r_{2,16}, r_{16,1}$}={0.6,0}=0
Max{0,0,0,0,0,0,0,0.2.0,0,0,0,0,0,0,0}=0.2

By assuming λ=0.5, the following matrix can be obtained as follows on Table 4.

Four cells are determined:

Cell 1= {M_1, P_2, P_4. P_9, P_{12}}

Cell 2= {M_2, P_1, P_3, P_7, P_{10}}

Cell 3= {M_4, P_5, P_6, P_8, P_{11}}

Cell 4= {M_3}

Table 1: Matrix R, informational dependency coefficients matrix for the numerical example.

	M1	M2	M3	M4	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
M1	1	0	0.1	0	0	0.5	0	0.5	0	0	0.1	0	0.9	0	0.1	0.6
M2	0	1	0	0	0.9	0.1	0.9	0.2	0.5	0	0.6	0	0.1	0.8	0.1	0
M3	0	0	1	0.5	0	0.2	0.1	0.3	0	0.2	0.3	0.4	0.2	0	0.3	0
M4	0.5	0.2	0.4	1	0	0.3	0	0.6	0.4	0.2	0.2	0.9	0.4	0.2	0.9	0.4
P1	0.2	0.8	0	0	1	0	0.5	0.1	0.5	0	0	0.1	0	0.5	0.1	0.2
P2	0.5	0	0.3	0.2	0	1	0	0.9	0	0.1	0.1	0	0.5	0.1	0.3	0.1
P3	0	0.8	0	0.1	0.4	0	1	0	0.5	0.2	0.8	0	0.1	0.8	0	0
P4	0.4	0.3	0.2	0.5	0	0.8	0	1	0.1	0.2	0	0	0.5	0.1	0	0.5
P5	0.1	0.4	0	0.8	0.4	0.3	0.4	0	1	0.2	0.5	0.4	0	0.3	0.3	0
P6	0	0.1	0.3	0.3	0.2	0	0.3	0	0.2	1	0.3	0.8	0.1	0.3	0	0.2
P7	0	0.5	0.2	0.2	0.3	0	0.9	0.1	0.4	0.2	1	0	0	0.7	0	0.1
P8	0.2	0.1	0.2	0.8	0	0.1	0.1	0.1	0.5	0.9	0.1	1	0.1	0.1	0.2	0
P9	0.8	0	0.4	0.5	0.1	0.4	0	0.4	0	0	0.2	0	1	0.1	0.3	0.4
P10	0	0.9	0	0.3	0.4	0	0.8	0	0.2	0.2	0.6	0.1	0	1	0.1	0.3
P11	0	0	0.4	0.8	0	0.2	0.1	0.2	0.2	0.1	0	0.2	0.2	0	1	0.5
P12	0.7	0.1	0.1	0.2	0.4	0.9	0.2	0.4	0.1	0	0	0	0.5	0.2	0.4	1

Table 2: Matrix R'.

	M1	M2	M3	M4	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
M1	1															
M2	0	1														
M3	0	0	1													
M4	0	0	0.4	1												
P1	0	0.8	0	0	1											
P2	0.5	0	0.2	0.2	0	1										
P3	0	0.8	0	0	0.4	0	1									
P4	0.4	0.2	0.2	0.5	0	0.8	0	1								
P5	0	0.4	0	0.8	0.4	0.2	0.4	0	1							
P6	0	0	0.2	.0.2	0	0	0.2	0	0.2	1						
P7	0	0.5	0.2	0.2	0	0	0.8	0	0.4	0.2	1					
P8	0	0.2	0.2	0.8	0	0	0	0	0.4	0.8	0	1				
P9	0.8	0	0.2	0.4	0	0.4	0	0.4	0	0	0	0	1			
P10	0	0.8	0	0.2	0.4	0	0.8	0	0.2	0.2	0.6	0	0	1		
P11	0	0	0.4	0.8	0	0.2	0	0	0.2	0	0	0.2	0.2	0	1	
P12	0.6	0	0	0.2	0.2	0.8	0	0.4	0	0	0	0	0.4	0.2	0.4	1

Table 3: Matrix R_e.

	M1	M2	M3	M4	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
M1	1															
M2	0.2	1														
M3	0.2	0.2	1													
M4	0.4	0.4	0.4	1												
P1	0.2	0.8	0	0.4	1											
P2	0.6	0.2	0.2	0.5	0.2	1										
P3	0	0.8	0.2	0.4	0.8	0.2	1									
P4	0.5	0.2	0.4	0.5	0.2	0.8	0.2	1								
P5	0.2	0.4	0.4	0.8	0.4	0.2	0.4	0.5	1							
P6	0	0.2	0.2	0.8	0.2	0.2	0.2	0.2	0.4	1						
P7	0	0.8	0.2	0.4	0.5	0.2	0.8	0.2	0.4	0.2	1					
P8	0	0.4	0.4	0.8	0.4	0.2	0.4	0.5	0.8	0.8	0.4	1				
P9	0.8	0.2	0.4	0.4	0.2	0.5	0	0.4	0.4	0.2	0.2	0.4	1			
P10	0.2	0.8	0.2	0.2	0.8	0.2	0.8	0.2	0.4	0.2	0.8	0.2	0.2	1		
P11	0.4	0.2	0.4	0.8	0.2	0.4	0.2	0.5	0.8	0.2	0.2	0.8	0.4	0.2	1	
P12	0.6	0.2	0.4	0.4	0.2	0.8	0.2	0.8	0.2	0.2	0.2	0.2	0.6	0.2	0.4	1

Table 4: The modified matrix R_e by λ=0.5.

	M1	M2	M3	M4	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
M1	1															
M2	0	1														
M3	0	0	1													
M4	0	0	0	1												
P1	0	1	0	0	1											
P2	1	0	0	1	0	1										
P3	0	1	0	0	1	0	1									
P4	1	0	0	1	0	1	0	1								
P5	0	0	0	1	0	0	0	1	1							
P6	0	0	0	1	0	0	0	0	0	1						
P7	0	1	0	0	1	0	1	0	0	0	1					
P8	0	0	0	1	0	0	0	1	1	1	0	1				
P9	1	0	0	0	0	1	0	0	0	0	0	0	1			
P10	0	1	0	0	1	0	1	0	0	0	1	0	0	1		
P11	0	0	0	1	0	0	0	1	1	0	0	1	0	0	1	
P12	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	1

As it can be seen, M_3 Doesn't belong to any cell, considering a less number for λ-cut, the number of cells may decreases and M_3 belongs to one of them.

4. Conclusion

This paper, introducing manufacturing system as a distributed decision network, proposes the concepts such as decision information and informational dependence of agents to handle the cell formation problem. The agents (machines), who have more informational dependence to each other, are included in one cell. In fact, the maximization of informational dependency in a cell is the objective of the group formation. Here one of the limitations is the number of a cell. The base of the cell formation process in our approach is the information flow between the parts and machines that are assumed to be the agents. Any agent is responsible for a different decision and they are grouped with suitable other agents. This new concept introduced in this paper, needs a discussion on information theory concepts, related to topic, and on Shannon entropy.

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