CHEMICAL ENGINEERING TRANSACTIONS
VOL. 55, 2016
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet
Guest Editors: Tichun Wang, Hongyang Zhang, Lei Tian

ISBN 978-88-95608-46-4; **ISSN** 2283-9216
DOI: 10.3303/CET1655037

Flexible Manufacturing Cell Formation of Processing Workshop based on Intelligent Computing

Jurong Liu

School of Mechanical Engineering, Shaanxi University of Technology, Shaanxi, China.
124505282@qq.com

Flexible manufacturing cell model of multiple workshops is constructed, which combines the advantages of physical manufacturing cell and logical manufacturing cell. A cell formation method based on adaptive inertia weight PSO is worked out, which considers the layout of manufacturing resources, the selection of processing path and the setting of processing batches. The experiment proves that the method can effectively reduce the total manufacturing cost.

1. Introduction

Design process of unit manufacturing system (cellular Manufacturing system, CMS) is called cell formation, and based on different environment, many scholars put forward different cell formation method. Defersha and Chen analysed manufacturing resources environment of multiple cycles, multiple processing routes and multi-types, which reduced the total cost of production by optimizing the production batch, and resource quantity (Defersha and Chen, 2008). Manufacturing resources of the same unit is arranged in the same physical location to form physical manufacturing cell. Safaei and Saidi proposed a cell formation model in the similar dynamic environment, the objective function of which aimed to get the lowest cost of machine purchase cost, machine operating cost, material moving cost and cell reformation cost (Safaei and Saidi, 2008).

Wu et al. investigated the physical manufacturing cell formation method based on machine layout under the condition of considering the layout of the manufacturing resources position (Wu et al., 2007). Wang and Wang investigated logical manufacturing cell formation under the premise of analysing additional cost of cross cell manufacturing, which did not change its physical location, and divided manufacturing resources into cells logically (Wang and Wang, 2004). Most researches on cell formation considering certain types of processed products, processing requirements, product type demand and environmental issues of certain available resources, a separate physical manufacturing unit or logical manufacturing unit was used to build cells respectively. Although manufacturing cells formed by these two methods have achieved good results, in the cloud manufacturing environment, selected manufacturing resources were not limited to this manufacturing cell, this workshop or this enterprise. There are still some problems and technical difficulties which have not been satisfactorily resolved (Wang et al, 2012; Li et al, 2011; Jozef et al, 2011; Yang et al, 2011). First of all, physical manufacturing cells are used to build MC, although it is in favour of transport and management control of processed products, some cloud manufacturing resources may not be able to be moved or moving costs is very high in the actual production process, which leads to the results that cell formation cannot be practical. If logic manufacturing unit construction method is used, physical layout of manufacturing resources does not need to changed, which can form manufacturing cell promptly. But it does not change the physical location of manufacturing resources; it may cause huge transportation costs and times. Secondly, in the cell formation process, a part of manufacturing resources are moved into groups to reduce transport costs and product time. But in the cloud manufacturing environment, manufacturing resources may be distributed in several different units, workshops or enterprises, so how to consider the layout of manufacturing resources in different workshops will inevitably become a key issue in the cell formation. In addition, there are more choices for products processing methods and processing path in the cloud manufacturing environment. Therefore in the cell formation process, how to assign multiple tasks and set batches become important factors affecting cell formation flexibility. In the next section, manufacturing resource layout description and mathematical

Please cite this article as: Liu J.R., 2016, Flexible manufacturing cell formation of processing workshop based on intelligent computing, Chemical Engineering Transactions, 55, 217-222 DOI:10.3303/CET1655037

model is investigated. In Section 3, flexible manufacturing cell formation based improved PSO (Yannis and Magdalene, 2010; Lin et al, 2010; Fan et al, 2004; Erwie and Hu, 2008) is proposed. In section 4, the proposed flexible manufacturing cell formation method is used in the cloud manufacturing environment. Finally, we conclude our paper in section 5.

2. Manufacturing resource layout description and mathematical model

Researched manufacturing environment is as follows. A certain type and number of cloud manufacturing resources (machines) are distributed in workshops of different companies. In order to meet different production tasks, physical layout can be carried out for manufacturing resources and the movement of manufacturing resources will produce re-layout costs. For a given set of tasks, processed products (artefacts) have more than one species, and at the same time, each product has more than one processing path. In the processing of the product, the product can be processed by a different path. Considering the above environment, through effective cell design, the following objectives are required to achieve. (1) For the corresponding tasks, assign optimal processing path, in order to improve the use efficiency of processing resources. (2) Layout optimization is carried out for manufacturing resources distributed in different processing workshops, consider the path of processing tasks, the number of processing cells and cell formation and adjust the machine layout to achieve the smallest manufacturing costs.
For the above requirements, physical manufacturing cell and virtual manufacturing cell are combined. The processing systems (processing equipment and auxiliary equipment, etc.) of the traditional manufacturing enterprises in different regions, logistics systems (transportation, storage and handling equipment, etc.) and control systems (planning, scheduling, process control, etc.) are effectively combined to construct a flexible manufacturing cell for cloud manufacturing. Flexible manufacturing cell construction and task assignment process is shown in figure 1.

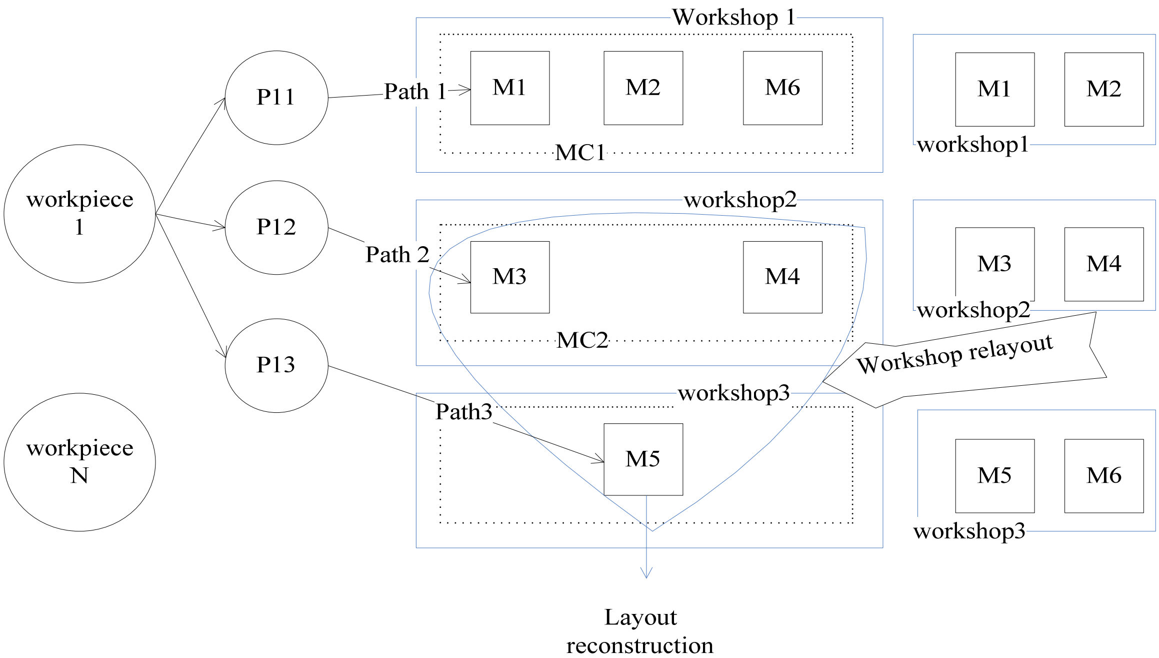

Figure 1: Flexible manufacturing cell construction and task assignment process

Flexible manufacturing cell construction and task assignment process is as follows. Specify the processing path for the processing tasks, while re-layout of manufacturing resources in different workshops is carried out. On this basis a new logic manufacturing cell is constructed. A single or multiple manufacturing resource (may belong to different processing workshop) is grouped virtually to process products with similar technology.
The proposed flexible cell construction method based on manufacturing resources dynamical layout and manufacturing resources logical grouping is actually to seek an optimal compromise between physical manufacturing cell construction and logical manufacturing cell construction, and to achieve the purpose of reducing manufacturing costs. The mathematical model is as follows. p represents type of work, p=1, 2, …, P,

N_P represents processing number of work p. r_p represents processing path serial number of work p, r_p=1, 2, …, R_P. J represents the number of workshops. m represents serial number of the manufacturing resources, which represents processing equipment used to complete processing tasks of work, m=1, 2, …, M. $K_{r\sigma}(p)$ represents the number of operation when work p adopting processing path r_p. MD_{mj} represents the initial position of the manufacturing resources in the system. If resource m locates at processing workshop j, MD_{mj}=1. On the contrary, MD_{mj}=0. CC_p represents additional cell processing cost when work p circulates among manufacturing cells. CR_m represents movement cost of the manufacturing resource m. c represents serial number of the constructed manufacturing cell, c=1, 2, …, C, and C represents the maximum number of permitted cell. $W_{rp}(p)$ represents resource sequence when adopting the r_p-thtype of processing path to process work p. $W_{rp}(p)=(W^1_{rp}(p), W^2_{rp}(p), …, W^k_{rp}(p))$, $W^k_p(p)\in(1, 2, …, M)$. E_m represents processing ability of resource m within completion date. NC represents the maximum number of resources in the cell. NJ represents the maximum number of resources in the processing workshop. $MC^k_{rp}(p)$ represents unit processing cost, when work p adopts the r_p type of processing path to deal with the k-th procedure. $MT^k_{rp}(p)$ represents processing time, when work p adopts the r_p type of processing path to deal with the k-th procedure. CI_p represents unit cost of transportation, when work p is moved in the same processing workshop. $CO_p(i, j)$ represents the unit cost of transportation, when work p is moved between workshop i and workshop j, with $CO_p(i, j)$=0. $X_{rp}(p)$ represents processed batches, when work p adopts path r_p. Y_{mc} represents whether resource m locates in the processing cell c. If it is in the cell, Y_{mc}=1. Otherwise Y_{mc}=0. Z_{mj} represents whether resource m locates in the processing cell j. If it is in the cell, Z_{mj}=1. Otherwise Z_{mj}=0.
The objective functions are shown from (1) to (6).

$$C_{job}=\sum_{p=1}^{P}\sum_{r_p=1}^{R_p}(X_{r_p}(p)\cdot\sum_{k=1}^{K_{r_p}(p)}MC^k_{r_p}(p)\cdot MT^k_{r_p}(p)) \tag{1}$$

$$C_{lo}=\sum_{p=1}^{P}\sum_{r_p=1}^{R_p}(X_{r_p}(p)\cdot\sum_{k=1}^{K_{r_p}(p)-1}\sum_{i=1}^{J}\sum_{j=1}^{J}CO_p(i,j)\cdot Z_{w^k_{r_p}(p)j}\cdot Z_{w^{k+1}_{r_p}(p)j}) \tag{2}$$

$$C_{li}=\sum_{p=1}^{P}\sum_{r_p=1}^{R_p}(X_{r_p}(p)\cdot\sum_{k=1}^{K_{r_p}(p)-1}\sum_{j=1}^{J}CI_P\cdot Z_{w^k_{r_p}(p)j}\cdot Z_{w^{k+1}_{r_p}(p)j}) \tag{3}$$

$$C_m=\frac{1}{2}\sum_{m=1}^{M}(CR_m\cdot\sum_{j=1}^{J}\left|MD_{mj}-Z_{mj}\right|) \tag{4}$$

$$C_e=\frac{1}{2}\sum_{p=1}^{P}\sum_{r_p=1}^{R_p}(X_{r_p}(p)\cdot\sum_{k=1}^{K_{r_p}(p)-1}\sum_{c=1}^{J}CC_P\cdot|Y_{w^k_{r_p}(p)c}-Y_{w^{k+1}_{r_p}(p)c}|) \tag{5}$$

$$C=C_{job}+C_{lo}+C_{li}+C_m+C_e \tag{6}$$

The constraint is as follows:

$$\sum\nolimits_{\forall(p,r,k)|w^k_{r_p}(p)=m}MT^k_{r_p}(p)\cdot X_{r_p}(p)\le E_m, m=1,2,\ldots,M \tag{7}$$

$$\sum_{c=1}^{C}Y_{mc}=1, m=1,2,\ldots,M \tag{8}$$

$$\sum_{j=1}^{J}Z_{mj}=1, m=1,2,\ldots,M \tag{9}$$

$$\sum_{m=1}^{M} Y_{mc} \le N_c, c = 1, 2, \ldots, C \,. \tag{10}$$

$$\sum_{m=1}^{M} Z_{mj} \le N_j, \, j = 1, 2, \ldots, J \,. \tag{11}$$

$$\sum_{r_p=1}^{R_p} X_{r_p}(p) \le N_p, \, p = 1, 2, \ldots, P \,. \tag{12}$$

3. Flexible manufacturing cellformation based improved PSO

PSO algorithm has many advantages, but also has disadvantage of precocity (Hu and Eberhart, 2002).In order to avoid falling into local optimum, adaptive inertia weight method is used to get rid of attract of local optimum point. Adaptive particle swarm optimization algorithmmakes a balance between global search and local search capability by means of adaptive inertia weight factor w, and determinesmutation probability based on convergence degree to escape from local optimum. A periodical attenuation adaptive strategy is proposed based on damping motion.

$$w(t) = \left| w_{\max} e^{\frac{1}{T_{\max}} \ln \frac{A}{w_{\max}} t} \cos(\frac{\pi}{T} t) \right| + w_{\min} \tag{13}$$

w_{max} is the maximum value of w and w_{min} is the minimum value of w. Usually w_{min}=0.1, w_{max}=0.9. T_{max} represents the maximum iteration number. A represents amplitude of w, when t=T_{max}. T represents amplitude change cycle of inertia weight factor. A and T are determined according to test. Particle swarm optimization algorithm is always chasing individual extreme value pbest and global extreme value gbest in the iteration process and is easy to fall into local optimal solution. The proposed adaptive mutation is based on population average fitness variance, when the algorithm meeting the case of premature convergence, it can jump out of local optimum. Population average fitness variance is

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{f_i - f_{avg}}{\max\left| f_i - f_{avg} \right|} \right)^2 \tag{14}$$

$$f_{avg} = \frac{1}{n} \sum_{i=1}^{n} f_i \tag{15}$$

σ^2represents population average fitness variance, n represents the number of particles in the particle swarm, f_i represents fitness of particle i, and f_{avg} represents average fitness of particle swarm at present. σ^2reflect the convergence degree of particle swarm. The small σ^2 means that particle swarm tends to converge. On the contrary, the particle swarm is in a random
Search phase. The mutation probability is shown in (16), where k∈[0.3, 0.6], σ^2_d=0.05..

$$p_m = \begin{cases} \dfrac{k}{\sigma}, & \sigma^2 < \sigma_d^2 \\ 0, & otherwise \end{cases} \tag{16}$$

The particle encoding is divided into three parts. Four works are processed by six of equipment. Work 1 has one processing path, and work 2, 3, 4 has two processing paths respectively. Decoding formula is

$$N_{rp} = ROUND\left(N_p \cdot \frac{w_{r_p}}{\sum_{r_p=1}^{R_p} w_{r_p}} \right), \forall p = 1, 2, \ldots, P, r_p = 1, 2, \ldots, R_p$$

Prepresents the serial number of work; R_p represents the number of processing path of work p. $w_{r\sigma}$ represents the proportion of processing number at path r_p to the total number of works.

The process of improved particle swarm optimization is as follows.

Step 1. Generate particle swarm randomly, the initial speed of particle is 0, the local optimum is equal to the value of variable and calculate value of objective function according to variable value.

Step 2. Calculate inertia weight factor and calculate fitness of all particles. If the current fitness value of particle is better than individual extreme, pbest is set as position of current particle. Set gbest according to global optimal value update strategy.

Step 3. Determine whether $\sigma^2 < \sigma^2_d$ is set up. If $\sigma^2 < \sigma^2_d$ is not set up, turn to step 4. Otherwise calculate mutation probability p_m and carry out mutation operation for the particle.

Step 4. Determine whether it achieves the maximum iteration number and output external swarm. Otherwise the maximum iteration number is increased by 1 and the algorithm turns to step 2.

4. Model testing

Some company needs to make six kinds of work, P_1, P_2, P_3, P_4, P_5, P_6. The number of work is N_1=30, N_2=40, N_3=30, N_4=60, N_5=50, N_6=40. There are ten machine tools, which are divided into three sets {M_1, M_2, M_3}, {M_4, M_5, M_6, M_7}, {M_8, M_9, M_{10}}. These machine tools are distributed in three workshops, J_1, J_2, J_3. Processing ability E_m is {2000, 2500, 4000, 3000, 2000, 4500, 3500, 4500, 3000, 5000}.

CC_p={30, 40, 50, 40, 30, 40}, CR_m={2000, 2500, 1500, 2000, 1000, 1500, 2000, 2500, 1000, 2000}, NJ=4, C=3, NC=4. Cost comparison of three algorithms is shown in table 1. Total cost of proposed algorithm is 272650, which is less than the other two algorithms.

Table 1: Cost comparison of three algorithms

	Flexible cell	Physical cell	Logic cell
Processing cost	258150	258150	258150
Cross workshop transportation cost	8100	8200	10800
Transportation cost within the workshop	750	786	656
Movement cost of the resources	1200	1500	0
Cross cell processing cost	4450	5410	4450
Total cost	272650	274046	274056

5. Conclusions

On the basis of physical manufacturing cell and logical manufacturing cell, the flexible manufacturing cell formation of cloud manufacturing resources is investigated. A method based on improved PSO is used to construct flexible manufacturing cell and the experiment proves that the method can effectively reduce the total manufacturing cost.

Acknowledgements

This work is supported by Shaanxi Provincial Education Department Key Scientific Research Project of Key Laboratory (12JS033), Shaanxi University of Technology Fund Project (SLGKY14-02).

References

Defersha M.F., Chen M.Y, 2008, A linear programming embedded genetic algorithm for an integrated cell formation and lot sizing considering product quality, European Journal of Operational Research, 187, 46-49, DOI: 10.1016/j.ejor.2007.02.040.

Erwie Z., Hu C.H., 2008, Solving constrained optimization problems with hybrid particle swarm optimization, Engineering Optimization, 40(11), 1031-1049.

Fan S.K., Liang Y.C., Zahara E., 2004, Hybrid simplex search and particle swarm optimization for the global optimization of multimodal functions, Engineering Optimization, 36, 401-418.

Hu X., Eberhart R.C, 2002, Multi-objective Optimization Using Dynamic Neighborhood Particle Swarm Optimization, Proceedings of the IEEE Congress on Evolutionary Computation, 1677-1681.

Jozef B., Lewoc A.I., Slawomir S., Antonina K., Peter K., 2011, An Integrated Manufacturing and Management System for Manufacturing Enterprises, Journal of Computational Information Systems, 1, 1, 1-10.

Li C.Q., Shang Y.L., Hu C.Y., Zhu P.F., 2011, Research on Cloud Manufacturing Multi-granular Resource Access Control based on Capacity Constraint, Advances in Information Sciences and Service Sciences, 3, 5, 79-86.

Lin T.L., Horng S.J., Kao T.W., 2010, An efficient job-shop scheduling algorithm based on particle swarm optimization, Expert Systems with Applications, 37, 3, 2629-2636.

Safaei N.M., Saidi M.S., Jabal M.A., 2008, A hybrid simulated annealing for solving an extended model of dynamic cellular manufacturing system, European Journal of Operational Research, 185, 563-592, DOI: 10.1016/j.ejor.2006.12.058.

Wang S.L., Chen G.S., Kang L., Li Q., 2012, Information Model of Cloud Manufacturing Resource Based on Semantic Web, International Journal of Digital Content Technology and its Applications, 6, 19, 339-346.

Wang Z.L., Wang H.F., 2004, Manufacturing cell reconstruction technology research under agile manufacturing mode, Journal of computer integrated manufacturing system, 10, 7, 727-731.

Wu X.D., Chu C.H., Wang Y.F., 2007, A genetic algorithm for cellular manufacturing design and lay put, European Journal of Operational Research, 181, 156-167.

Yang Q., Li L., He G.Z., 2011, An Improved Particle Swarm Optimization for Constrained Optimization Problems, International Journal of Advancements in Computing Technology, 3, 10, 216-223.

Yannis M., Magdalene M., 2010, A Hybrid Multi-Swarm Particle Swarm Optimization algorithm for the Probabilistic Traveling Salesman Problem, Computers and Operations Research, 37, 3, 432-442.