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Fuzzy Inference System (FIS) Based Worker Assignment Model for Virtual Cells

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Abstract: In this attempt, the researcher aims to formulate an optimized worker assignment model for virtual cells by using Fuzzy Inference System (FIS) which is regarded as a successful programming technique using words rather than numbers. Improved productivity and superior quality in operations with maximum utilization of existing resources, i.e., physical and human resources are always the primary objective of manufacturing organizations. Many manufacturing philosophies have been developed to achieve the above objective and Virtual Cellular Manufacturing System (VCMS), a logical extension of Cellular Manufacturing System (CMS) is one of such philosophy developed quite recently. Worker assignment problems in the above VCMS context are highly non-linear and dynamic in nature because machineries and workforces in VCMS environment are virtually and logically rearranged to meet a particular production requirement. Tasks of workforce assignments into virtual manufacturing cells are very well handled by the researchers and various techniques namely mathematical programming models including Integer Programming (IP) and Goal Programming (GP) are developed for meeting the static and dynamic production conditions. Application of Artificial Neural Networks (ANN) into worker assignment shows enough potential as revealed from researcher's previous attempts recently. In the current attempt, the researcher extends his research efforts on worker assignment problems and presents a novel method of doing the above assignment using Fuzzy Inference System (FIS) which is regarded as a successful programming technique using words rather than numbers. Fuzzy logic, the core substance of FIS is a convenient way to map an input dataset to an output dataset and in this study datasets corresponding to two cell configuration problem under VCMS environment are used as input and output data. Results of worker assignments from the present attempt and the previous models proposed are then compared, analysed and discussed. The study and results obtained affirm that FIS also shows prominence and promise in solving problems related to workforce assignment into virtual cells.

Key words: Virtual cellular manufacturing, workers assignment, fuzzy inference system, fuzzy logic, ANN

INTRODUCTION

CMS, a brain child of Group Technology (GT), involve formation of production cells consisting of machineries and facilities in order to process a family of parts. Identification of specified parts and clustering of machineries and subsequent dedication of them into specified cells is carried out based on similarity attributes among the products and required machineries to process them into final products. VCMS, inherited from CMS, virtually arrange and rearrange machineries and facilities for forming production cells without moving them closer to one another physically. This is an advantage with VCMS when frequent changes to part mix and volumes are encountered. Under such circumstances, VCMS only requires logical reconfiguration within the planning and control system, instead of physical reconfiguration. Literature studies (Slomp *et al*., 2005; Suresh and Slomp, 2005; Nomden *et al*., 2006) claim that most of the VCMS design problems considered only machine-part grouping aspects while workers' role was rarely considered. However, human related aspects are a major impending factor in the manufacturing business and this factor has been largely ignored while assessing the effectiveness of the manufacturing systems particularly operating under the context of cells-based environments. Workers and assignment of workers into specified cells are traditionally done with production managers 'expertise with a help of worker skill matrices. The role of human beings and human related aspects and issues under this dynamic environment have been realized recently (Bidanda *et al*., 2005; McDonald *et al*., 2009).

Mural *et al*. (2010) previously initiated preliminary works on application of ANNs into worker assignment tasks under VCMS environment and developed subsequently (Murali, 2010) by forming worker fitness attributes from the cell formation solutions available in the literature.

Fitness attributes (Mural *et al*., 2010) are derived based on worker skills, parts and machines assigned to each cell and part sequence and they would grow in size as the cell size and configurations increase. These attributes determine the suitability of each worker as to how best he/she could contribute to a particular cell, if he/she is assigned to it. Machine coverage ratio, workers' multi-functionality and total processing time are the fitness attributes employed in this study. More information on worker fitness attributes can be found in previous publications of the same researchers.

In another study by Satoglu and Suresh (2009), a Goal Programming (GP) Model was formulated for worker assignments applicable to a hybrid cellular manufacturing system and solved by GAMS Software considering real time factory data from a glass mould manufacturer. In the present research, researchers proposes a novel method of carrying out worker assignment task using FIS with the datasets used by the researchers in the past in order to demonstrate the validity and utility of FIS approach. During this phase of work, cellular configuration data such as number of cells, parts and machines assigned and worker skill matrix, demand values corresponding to a two-cell configuration problem are considered for implementing the FIS Model using MATLAB Software. Finally, results of the FIS approach are compared with the previous results reported in the literature and relevant discussions are then presented.

MATERIALS AND METHODS

Applicability of fis approach: Fuzzy Inference System (FIS) is gaining high momentum in solving engineering problems that operate on input-output matching methodology and show enough evidence of classifying successfully the input data of more complex and non-linear problems through learning and training. They are currently being used in a variety of engineering and non-engineering applications with satisfactory classification success rates. One of the positive points of FIS structure is that they do not require a user-specified problem solving algorithm since they operate on learning from input patterns much like human beings. Another attractive feature with them is inherent generalization ability based on what is required in real terms. This means that they can identify and respond to patterns that are similar but not identical to the ones with which they have been trained.

FIS is simple, adaptable, easily applied and yet most efficient method of interpreting the values in the input vector and assigns values to the output vector, based on some set of rules. Functional relationships are established between the input values (ranges) and the output values (ranges) available through these set of rules. These rules form the basic rationale for the solutions generated. When the mathematical constraints in a problem at hand are converted into linguistic forms (rules), then the fuzzy inference system is created. The methodology of fuzzy logic comprises of how the rules all combined in a particular fashion and how to define mathematically the anticipated output values. Fuzzy logic is conceptually easy to understand and layer it on more functionality without starting again from scratch. It is tolerant of imprecise data since, it is based on common sense statements. Whenever, changes are needed in the rules in future, it is possible to add more rules to the bottom of the list that influenced the shape of the overall output earlier without needing to undo what had already been done. In other words, making the subsequent modification on the rules is relatively easier in FIS. By using fuzzy logic rules, FIS enables the maintenance of the structure of the algorithm fairly flexible and can be customized from place to place or country to country or conditions of the problem under study (Fig. 1).

If-then rules statements are used to formulate the conditional statements that comprise fuzzy logic. A single fuzzy if-then rule assumes the form if value of a variable Q is A then another variable R is B where A and B are linguistic values defined by fuzzy sets with ranges X and Y, respectively. The if-part of the rule (Q is A) is called the antecedent while the then-part of the rule (R is B) is called the consequent. The values of each state is represented as a number with specific range (between 0 and 1, for example) and so the antecedent is an interpretation that returns a single number between 0 and 1. Conversely, average is represented as a fuzzy set and so the consequent is an assignment that assigns the entire fuzzy set B to the output variable y. In general, the input to an if-then rule is the current value for the input variable and the output is an entire fuzzy set. This set will later be defuzzified, assigning one value to the output. The conceptof defuzzification is described as a method in which firstly evaluating the antecedent and secondly applying that result to the consequent.

Figure 2 shows the flow proceeds up from the inputs in the lower left, then across each row or rule and then down the rule outputs to finish in the lower right. This compact flow shows everything at once, from linguistic variable fuzzification all the way through defuzzification of the aggregate output. Figure 3 shows the rules embedded in the membership functions based on which the output is determined.

Industrial problem description: This industrial problem is related to cellular manufacturing concept being adopted in the company in order to produce moulds for glass products. Previously, researcher has used these datasets for validating the novel approach based on ANN to solve the worker assignment problems under VCMS

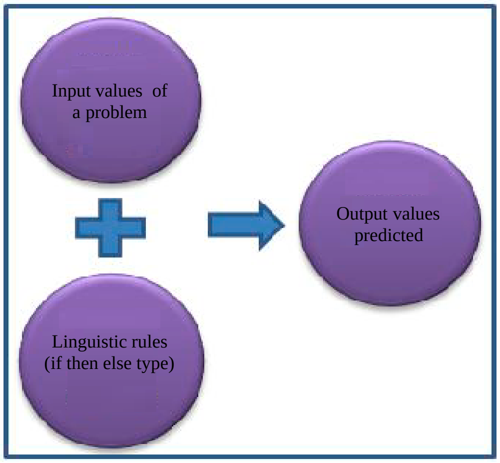

Fig. 1: Fuzzy Inference System (FIS)

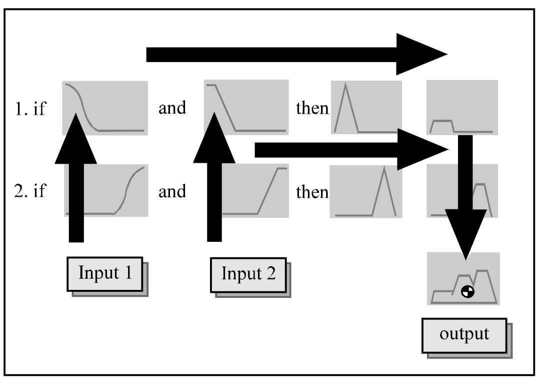

Fig. 2: FIS-interpretation flow (Fuzzy Logic Toolbox™ User's Guide, 2015)

environment (Murali, 2010). Presently, the same datasets are being reused here in this study to test the validity of FIS based model which is the crux of this study. Real factory data such as number of cells, parts and machines assigned and worker skill matrix, demand values are taken from a glass mould manufacturing company as reported by Satoglu and Suresh (2009). There are totally thirty five types of parts, twenty eight machine tools and the factory works 7 h/day, 26 days/month and 12 months a year which results in 131,040 min/year as available capacity. It is also reported that all machines are considered to have the same capacity, i.e., 131,040 min of annual capacity. The problem described by Satoglu and Suresh (2009) is a hybrid in nature, i.e., having manufacturing cells along with functional layout arrangements as well. Therefore, sixteen parts should be produced in manufacturing cells and the rest should be produced in the functional layout. This problem configuration is formulated as Goal Programming (GP) Model with conflicting multi-objective function and is solved using GAMS Software. However, in the current research, the researchers have abstracted various data related to only manufacturing cells for worker assignment under dual resource constrained contexts and the resources allotted for functional layout are not considered. Therefore, the part types and workers to be dedicated to functional layouts are ignored in this study. In summary, there are 16 parts to be produced in the manufacturing cells with 7 machine types and 21 workers available. From annual demand and machine loading for each part, processing times are calculated and presented in Table 1 and 2 illustrates the worker skill matrix as given

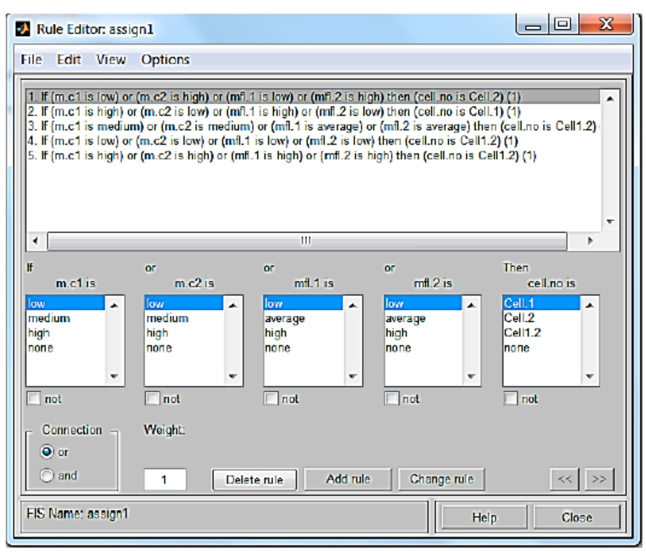

Fig. 3: If-then rules for membership function in FIS

Table 1: Part processing times and annual demand

	Machine type							
Parts	M1	M2	M3	M4	M5	M6	M7	Annual demand
1	1.050	0.440	0.300	0.300	0.000	0.000	0.076	2337
2	0.189	0.058	0.000	0.000	0.000	0.000	0.000	2303
3	0.626	1.332	0.240	0.000	0.000	0.000	0.000	2480
4	0.430	1.780	0.359	0.000	0.000	0.000	0.344	1730
5	0.259	0.373	0.000	0.071	0.000	0.071	0.086	1525
6	1.137	2.872	0.350	0.000	0.218	0.000	0.510	1501
7	0.460	0.400	0.000	0.071	0.087	0.000	0.114	1442
8	0.071	0.114	0.000	0.000	0.000	0.000	0.000	937
10	0.502	0.071	0.000	0.000	0.000	0.000	0.000	907
11	0.165	0.000	0.000	0.035	0.000	0.000	0.000	811
12	0.800	0.000	0.000	0.000	0.000	0.000	0.287	789
13	0.359	0.043	0.000	0.000	8.613	0.000	0.000	774
14	1.430	1.000	0.271	0.225	0.000	0.150	0.000	684
15	0.277	0.000	0.110	0.000	0.000	0.070	0.000	718
16	0.185	0.340	0.000	0.000	0.000	0.000	0.000	691
17	0.401	0.373	0.000	0.000	0.000	0.057	0.000	615

Table 2: Worker skill matrix

	Machines						
Workers	M1	M2	M3	M4	M5	M6	M7
1	1	1	0	0	1	0	1
2	0	1	0	0	0	1	1
3	0	1	0	0	1	0	1
4	1	0	0	0	1	1	1
5	0	0	1	0	1	1	1
7	0	1	0	0	1	1	1
8	1	1	1	0	1	1	1
9	1	1	1	0	1	1	1
10	0	1	1	1	1	0	1
12	0	1	0	1	1	1	1
13	1	1	1	1	1	1	1
14	1	1	1	1	1	0	1
15	0	1	1	1	0	1	1
17	0	1	1	1	0	1	1
18	0	1	1	1	1	0	1
19	1	0	0	1	1	1	1
20	0	0	1	1	1	1	1
22	0	1	0	1	1	1	1
23	1	1	1	1	1	1	1
24	1	1	1	1	1	1	1
25	0	1	1	1	1	0	1

Table 3: Results of GP approach

	Manufacturing cells	
GP approach	Cell 1	Cell 2
Machines	M1, M1, M1, M2, M2, M3, M4, M6, M7	M1, M2, M2, M3, M5, M5, M5, M5, M7
Parts	P1, P2, P3, P5, P7, P8, P10, P12, P14, P15, P16, P17	P4, P6, P7, P9, P13
Workers	W2, W4, W5, W8, W9, W13, W15, W17, W20, W23, W24	W1, W3, W7, W9, W10, W12, W14, W18, W19, W22, W25

in the original work. However, costs projected towards cross training, hiring and firing costs are not accounted while deriving the worker skill matrix.

Table 3 presents the original results (such as parts, machines and workers assigned to each cell) of the GP Model solved by GAMS Software. From these product data and information, processing times for each part on a specific machine is calculated and shown in Table 1 which is referred to as Part Machine Incidence Matrix (PMIM). The production data of this problem are considered to be the relevant data for a particular production period under VCMS environments.

RESULTS AND DISCUSSION

A Mamdani FIS three inputs, one-output and five-rule classification problem-structure is designed in MATLAB Software for two cell configuration problems and is tested and validated with literature datasets as generated in the previous attempt. The 3 inputs (machine coverage ratio, multi-functionality and total processing load) have been designed with Gaussian membership function with specific value of ranges. The output is designed with triangular membership function with values ranging from 1-3. There are totally 150 datasets derived from literature used for testing the FIS Model while industrial data are considered for validation of the model. Industrial data reported by Satoglu and Suresh (2009) are suitably preprocessed, transformed into worker fitness attributes and then fed into FIS Model for testing. Table 4 reproduces the same sample datasets used previously from the literature while Table 5 shows the preprocessed testing data inputs transformed from the industrial data. After carefully structuring the FIS architectural parameters and membership functions, the model is executed in Mathworks (2011). Results of the FIS Model prediction and key membership function and rules are shown in Table 6 and 7. These results show close agreement with the results generated by ANN or GP approach and Fig. 4 illustrates the comparative results of prediction results of FIS with that of ANNs and GP approaches. It is observed from this figure that most of assignment prediction matches with that of GP results while few assignments deviated from the results of ANN/GP approaches. As stated earlier, the basic concept in IFS is the membership function and

Table 4: Sample training data

Workers	Workers fitness attributes (6 input variables): Machine coverage ratio of each worker, Cell 1	Machine coverage ratio of each worker, Cell 2	Multi-functionality of each worker, Cell 1	Multi-functionality of each worker, Cell 2	Total processing (h) load, Cell 1	Total processing (h) load, Cell 2	Desired output variables (3 output variables)		
W1	0.667	0.500	4	4	3.38	2.92	0	0	1
W2	0.333	1.000	3	7	1.37	4.12	0	1	0
W3	1.000	0.000	7	0	4.75	0.00	1	0	0
W4	0.667	0.500	4	3	3.38	1.20	1	0	0
W1	0.500	0.667	2	7	1.53	3.54	0	1	0
W2	1.000	0.333	3	4	2.03	1.31	1	0	0
W3	0.000	1.000	0	11	0.00	4.85	0	1	0
W4	0.500	0.667	1	7	0.50	3.54	0	1	0
W1	0.667	0.500	10	12	5.73	7.64	0	1	0
W2	0.333	1.000	5	24	2.40	14.93	0	1	0
W3	1.000	0.000	15	0	8.13	0.00	1	0	0
W4	0.667	0.500	10	12	5.73	7.29	0	0	1
W1	0.333	0.400	6	14	2.86	9.18	0	1	0
W2	0.333	0.400	9	16	5.41	8.70	0	1	0
W3	0.667	0.400	18	14	8.90	7.18	1	0	0
W4	0.333	0.400	6	16	2.86	7.67	0	1	0
W5	0.000	0.400	0	16	0.00	8.70	0	1	0
W6	0.333	0.400	9	14	3.49	8.15	0	1	0
W7	0.667	0.200	15	8	8.27	4.25	1	0	0

Table 5: Data inputs for validation 2 cells

Workers	Worker fitness attributes: Machine coverage ratio of each worker, Cell 1	Machine coverage ratio of each worker, Cell 2	Multi-functionality of each worker, Cell 1	Multi-functionality of each worker, Cell 2	Total processing (h) load, Cell 1	Total processing (h) load, Cell 2
W1	0.833	1.0	17	7	8.285	0.789
W2	0.833	0.6	18	2	11.506	0.185
W3	0.667	0.8	13	5	6.419	0.413
W4	0.667	0.6	17	7	10.927	0.789
W5	0.667	0.6	16	5	11.259	0.413
W7	0.667	0.6	15	5	9.308	0.413
W8	1.000	1.0	22	7	13.372	0.789
W9	1.000	1.0	22	7	13.372	0.789
W10	0.667	0.8	13	5	6.419	0.413
W12	0.833	0.8	18	4	10.459	0.561
W13	1.000	1.0	22	7	13.372	0.789
W14	0.833	1.0	17	7	8.285	0.789
W15	0.833	0.6	18	2	11.506	0.185
W17	0.833	1.0	17	7	8.285	0.789
W18	0.833	0.6	18	2	11.506	0.185
W19	0.667	0.6	17	7	10.927	0.789
W20	0.667	0.6	16	5	11.259	0.413
W22	0.833	0.8	18	4	10.459	0.561
W23	0.667	0.6	15	5	9.308	0.413
W24	1.000	1.0	22	7	13.372	0.789
W25	0.667	0.8	13	5	6.419	0.413

relevant rules (fuzzy rule). Although, rule-based systems have a long history of use in Artificial Intelligence (AI), what is missing in such systems is a mechanism for dealing with fuzzy consequents and fuzzy antecedents. In fuzzy logic, this mechanism is provided by the calculus of fuzzy rules. The calculus of fuzzy rules serves as a basis for what might be called the Fuzzy Dependency and Command Language (FDCL). Although, FDCL is not used explicitly in the toolbox, it is effectively one of its principal constituents. In most of the applications of fuzzy logic, a fuzzy logic solution is in reality, a translation of a human solution into FDCL.

A trend that is growing in visibility relates to the use of fuzzy logic in combination with neurocomputing and genetic algorithms. More generally, fuzzy logic, neurocomputing and genetic algorithms may be viewed as the principal constituents of what might be called soft computing. Unlike the traditional, hard computing, soft computing accommodates the imprecision of the real world. The guiding principle of soft computing is: exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost.

In the future, soft computing could play an increasingly important role in the conception and design

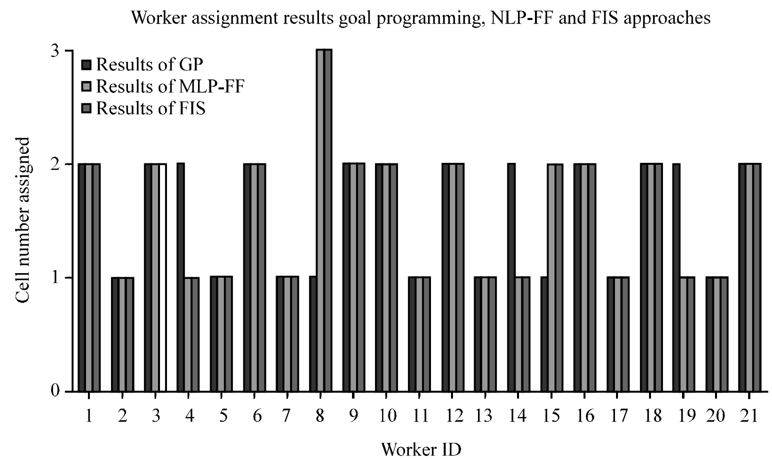

Fig. 4: FIS-GP-ANN approach for two cell problems

Table 6: FIS results comparison

	Cell assignment		
Worker ID	ANN approach	GP	FIS approach
W1	2	2	2
W2	1	1	1
W3	2	2	2
W4	2	1	1
W5	1	1	1
W7	2	2	2
W8	1	1	1
W9	1	3	3
W10	2	2	2
W12	2	2	2
W13	1	1	1
W14	2	2	2
W15	1	1	1
W17	2	1	1
W18	1	2	2
W19	2	2	2
W20	1	1	1
W22	2	2	2
W23	2	1	1
W24	1	1	1
W25	2	2	2

Table 7: FIS parameters settings

ANN training parameters		
Variables	Membership function	Values (range)
Machine coverage	Gaussian	0-1
Multi-functionality	Gaussian	0-30
Processing load	Gaussian	0-20 h
Cell assignment	Triangular	1-3

of systems whose MIQ (Machine IQ) is much higher than that of systems designed by conventional methods. Among various combinations of methodologies in soft computing, the one that has highest visibility at this juncture is that of fuzzy logic and neurocomputing, leading to neuro-fuzzy systems. Within fuzzy logic such systems play a particularly important role in the induction of rules from observations. An effective method developed by Dr. Roger Jang for thispurpose is called ANFIS (Adaptive Neuro-Fuzzy Inference System). This method is an important component of the toolbox.

There are two types of fuzzy inference systems that could be designed using MATLAB Software namely Mamdani-type and Sugeno-type. The type used in this study is of Mamdani-type where the output membership functions are to be fuzzy sets. After the validating process of the inputs and outputs, there is a fuzzy set for each output variable needing defuzzification. In Sugeno-type, there will be only one single spike as the output membership function rather than a distributed fuzzy set. This has enhanced defuzzification efficiency in the process because it greatly simplifies the computation required by the more general Mamdani method which finds the centroid of a two-dimensional function.

CONCLUSION

In this study, a Fuzzy Inference System (FIS) based model for worker assignment into virtual cells has been developed and implemented with an example. The results of the aforementioned approach are presented and compared with those of already validated models (GP and ANN-MLP-FF Models). The results show FIS based model has equal scope and competence in comparison and could be used as a potential tool for worker assignment under VCMS environment. In fact, FIS approach is relatively easier to structure and has the capability to add more constraints and conditions to the problem under study.

Since, FIS integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. In their earlier researches, researchers of this study have proposed a new approach based on ANNs in order to assign workers into manufacturing cells under virtual manufacturing environments. The proposed model is then trained, validated and tested with datasets abstracted from VCMS literature. The present study considers another different approach based on the fuzzy logic concepts integrated with ANN framework so that the architecture of the model can be made better and more beneficial in terms of parameters and computational complexities. Future phases of the above work could be to apply Adaptive Neuro Fuzzy Inference System (ANFIS) which could prove to be more efficient and optimal with precise set of parameters. In order to obtain the precise set of parameters, Genetic Algorithm (GA) tool can be developed and implemented.

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