ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) BASED WORKER ASSIGNMENT MODEL FOR LARGE SIZED VIRTUAL CELLS

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Abstract- In this paper, the author aims at developing an optimized worker assignment model for large sized virtual manufacturing cells by using adaptive neuro-fuzzy inference system (ANFIS). Improved productivity and superior quality in operations with maximum utilization of existing resources are always the primary objectives of any manufacturing organization. Many manufacturing philosophies have been developed to achieve the above objectives and Virtual Cellular Manufacturing System (VCMS), a logical extension of Cellular Manufacturing System (CMS), is one of such philosophy developed quite recently. Worker assignments are invariably a challenging task under any manufacturing environments. Though there are many techniques and algorithms developed, tested for worker assignment tasks, application of ANFIS into this task is an innovation and novel which has enough potential to be used as a tool. ANFIS, functionally equivalent to fuzzy inference system, is a convenient way to map an input dataset to an output dataset. In this paper, datasets corresponding to three cell configuration problems under VCMS environment from literature are implemented in the ANFIS model as input and output datasets. Results of worker assignments obtained from the present ANFIS model and the previous published models are then compared, analysed and discussed. The study and results obtained affirm that ANFIS also shows prominence and promise in solving problems related to workforce assignment into virtual cells of higher configurations.

Index Terms- worker assignment, adaptive neuro-fuzzy inference system, worker fitness attributes, fuzzy logic.

I. INTRODUCTION

Many manufacturing philosophies have been developed, in the past, to achieve improved productivity and superior quality in operations with maximum utilization of existing resources. 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 & 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 has been realized recently (Bopaya et al, 2005; Thomas et al, 2009). 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.

Murali et al (2010-a) previously initiated preliminary works on application of ANNs into worker assignment tasks under VCMS environment and developed subsequently (Murali et al, 2010-b; Murali et al, 2010-c) by forming worker fitness attributes from the cell formation solutions available in the literature. Fitness attributes (Murali et al, 2010-a) 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. In another study by Satoglu & 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 work, author proposes to apply ANFIS, an extension of fuzzy logic, to carry out worker assignment task for higher order virtual cells using the datasets previously used by the same author. During this study, cellular configuration data such as number of cells, parts and machines assigned and worker skill matrix, demand values corresponding to a three-cell configuration problem are considered for implementing the ANFIS model using MATLAB software. Finally, results of the ANFIS approach are compared with the previous results reported in the literature and relevant discussions are then presented.

II. APPLICABILITY OF ANFIS APPROACH

A. ANFIS redefined

ANFIS 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. Figure 1 illustrates the basic structure of a fuzzy logic system in which the input values are subject to certain set of rules as appropriate to the conditions of the problem stated therein and results are generated eventually.

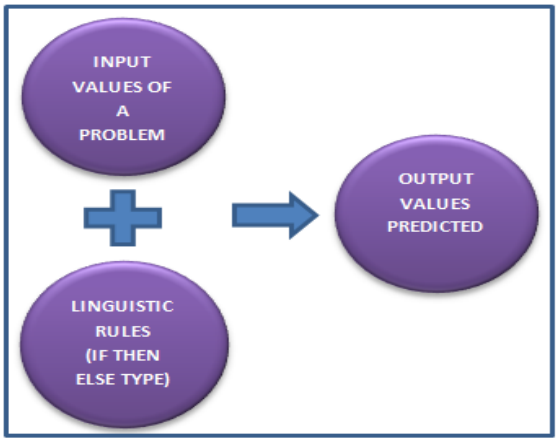

Figure 1 Fuzzy Inference System Elements

ANFIS are a class of adaptive networks that are functionally equivalent to fuzzy inference systems. Using a given input/output dataset related to the worker assignment problems, the toolbox function ANFIS in MATLAB constructs a model operating on a membership function whose parameters are readjusted following a specific algorithm such as back propagation or least squares or combination of both. This adjustment allows the fuzzy systems to learn from the data they are modeling. ANFIS uses a hybrid learning algorithm, which is a combination of the gradient rule and the least squares estimate. The difference between a fuzzy logic and an ANFIS is as follows: when a fuzzy system's membership function parameters are set using neuro-adaptive learning methods similar to those used in training neural networks, it becomes an ANFIS. Some of the advatages of ANFIS include (i) easy to implement (ii) fast and accurate learning (iii) strong generalization abilities, (iv) excellent explanation facilities through fuzzy rules, and (iv) easy to incorporate both linguistic and numeric knowledge for problem solving (Jang & Sun, 1995; Jang et al., 1997).

B. ANFIS Structure

ANFIS is gaining high popularity 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 nonlinear 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 ANFIS 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. The neuro-fuzzy method is rather a way to create a fuzzy model from data by some kind of learning method that is motivated by learning procedures used in neural networks. This substantially reduces development time and cost while improving the accuracy of the resulting fuzzy model (Fuzzy Logic Toolbox™ User's Guide, 2015).

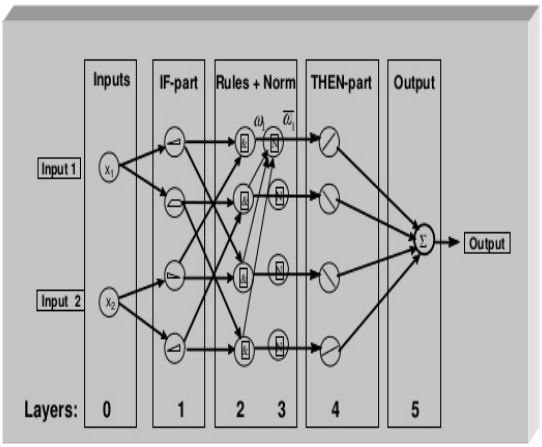

Figure 2 ANFIS Structure

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 as illustrated in figure 2

Table 1 Training parameters of ANFIS prediction model

ANFIS Parameter	Value
Numbers of Rules	20
Number of Training Epochs	50
Number of nodes	40
Number of Membership functions	2
Defuzzification Method	Weighted average

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. Table 1 presents the training parameters used for ANFIS architecture to solve the worker assignment tasks.

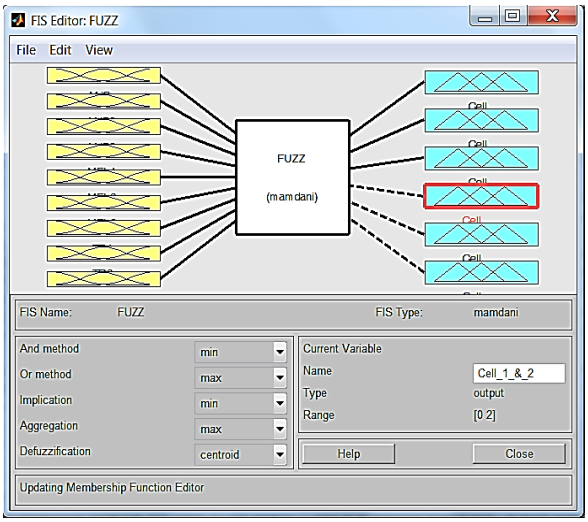

Figure 3 Inputs and Output Variable of a mamdani FIS

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 concept of defuzzification is described as a method in which firstly evaluating the antecedent and secondly applying that result to the consequent. Figure 3 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 represents the inputs and outputs for the problem under study and Figure 4 portrays the rules being formulated using the 'edit rules' option of the FIS and the rules embedded in the membership functions based on which the output is determined.

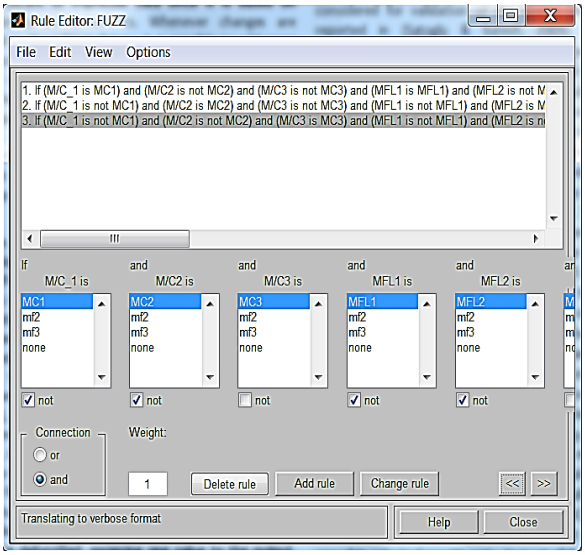

Figure 4 IF-THEN rules (sample) for membership function

III. RESULTS AND DISCUSSION

A mamdani FIS – nine inputs, six outputs and twenty rules classification problem is designed in MATLAB software for three cell configuration problems and is tested and validated with literature datasets as generated in the previous attempt. 9 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 to 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 in (Satoglu & Suresh, 2009) are suitably preprocessed, transformed into worker fitness attributes and then fed into FIS model for testing. Table 2 presents the sources abstracted from on training and testing datasets for the problem under study. Table 3 reproduces the same sample datasets processed from the inputs taken various sources as seen in Table 2. These are the processed testing / training datasets transformed from the industrial data. After carefully structuring the FIS architectural parameters and membership functions, the model is executed in MATLAB. Results of the FIS model prediction a are shown in Table 4 with comparative results from other approaches. These results show close agreement with the results generated by ANN ML-FF model and Figures 5 (a) and (b) illustrate the comparative results of prediction results of ANFIS with that of ANN approach.

It is observed from figures 5 (a) and (b) that most of assignment prediction matches with that of ANN

ML-FF results. As stated earlier, the basic concept in ANFIS is the membership function and relevant rules (fuzzy rule).

Table 2 Sources for Training and Testing Datasets

	Dataset No	Literature Source	Problem Size (Machine x Parts)
training ANN	1	Kusiak and Chow (1987)	7 x 11
	2	Seiffodini and Wolfe (1986)	8 x 12
	3	Mosier and Taube (1985) a	10 x 10
	4	Chan and Milner (1982)	10 x 15
	5	Generated Set 1	--
	6	Generated Set 2	--
Testing ANN	7	Chandrasekaran et al (1986) a	8 x 20
	8	Boctor (1991)	7 x 11

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

Table 3 Sample training datasets

Datasets*	Workers	Workers Fitness Attributes (9 input variables)									Desired cell number for assignment					
		Machine coverage ratio of each worker in			Multi-functionality of each worker in			Total processing (hr) load in						Cells		
		Cell 1	Cell 2	Cell 3	Cell 1	Cell 2	Cell 3	Cell 1	Cell 2	Cell 3	1	2	3	1,2	2,3	1,3
1	W1	0.500	0.500	0.333	3	1	3	2.560	0.880	2.350	1	0	0	0	0	0
	W2	0.500	0.500	0.333	2	3	3	1.830	2.320	2.350	0	0	0	0	1	0
	W3	1.000	0.500	0.333	5	3	3	4.390	2.320	1.860	1	0	0	0	0	0
	W4	0.000	1.000	0.667	0	4	5	0.000	3.200	3.620	0	0	1	0	0	0
	W5	0.500	0.000	0.333	2	0	3	1.830	0.000	2.350	0	0	1	0	0	0
	W6	0.000	0.500	0.667	0	1	5	0.000	0.880	3.620	0	0	1	0	0	0
2	W1	0.500	0.250	1.000	2	4	8	1.430	1.640	4.310	0	0	1	0	0	0
	W2	0.000	0.500	0.500	0	7	4	0.000	3.930	2.640	0	1	0	0	0	0
	W3	0.500	0.500	0.500	2	7	4	1.430	3.930	1.670	0	1	0	0	0	0
	W4	0.500	0.750	0.000	2	12	0	1.040	6.540	0.000	0	1	0	0	0	0
	W5	0.000	0.250	0.500	0	4	4	0.000	1.640	2.640	0	0	1	0	0	0
	W6	1.000	0.500	0.000	4	9	0	2.470	4.250	0.000	0	1	0	0	0	0
	W7	0.000	0.500	0.500	0	8	4	0.000	4.900	2.640	0	1	0	0	0	0
3	W1	0.500	0.500	0.500	4	2	7	2.410	1.330	2.190	0	0	0	0	0	1
	W2	0.500	0.500	0.250	5	2	3	3.500	1.320	1.890	1	0	0	0	0	0
	W3	0.250	1.000	0.250	3	4	3	1.690	2.650	0.650	0	1	0	0	0	0
	W4	0.750	0.000	0.500	6	0	6	2.590	0.000	2.480	1	0	0	0	0	0
	W5	0.250	0.500	0.000	2	2	0	1.810	1.320	0.000	0	0	0	1	0	0
	W6	0.500	0.500	0.500	3	2	5	0.900	1.330	2.830	0	0	1	0	0	0
	W7	0.750	0.000	0.250	6	0	4	3.800	0.000	1.540	1	0	0	0	0	0
	W8	0.250	0.500	0.000	2	2	0	1.810	1.320	0.000	0	0	0	1	0	0
	W9	0.500	0.000	0.500	3	0	6	0.900	0.000	2.480	0	0	1	0	0	0

CONCLUSION

In this study, an adaptive neuro-fuzzy inference system (ANFIS) based model for worker assignment into virtual cells of higher configurations has been developed and implemented with an example. The results of the aforementioned approach are presented and compared with those of already validated models (ANN ML-FF model). The results show ANFIS 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, ANFIS approach is relatively easier to structure and has the capability to add more constraints and conditions to the problem under study.

Table 4 Cell Assignment Results – Comparison

Worker ID	CELL ASSIGNMENT (Cell No)		
	Desired Assignment	ML-FF ANN Prediction	ANFIS Approach
PERIOD 1			
W1	2	3	3
W2	3	3	3
W3	2	2	2
W4	2	2	1
W5	3	3	3
W7	1	1	1
W8	3	3	3
PERIOD 2			
W1	2	1	1
W2	2	2	2
W3	1	1	2
W4	3	3	3
W5	1	1	1
W6	3	3	3

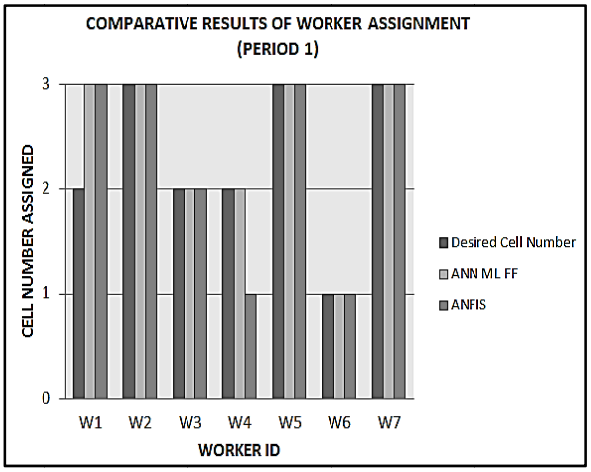

Figure 5(a)

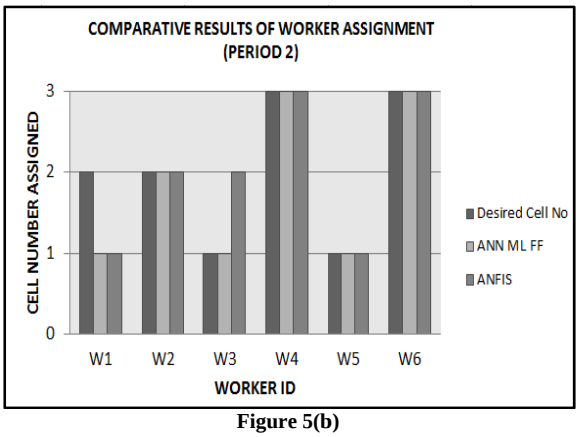

Figure 5(b)

Figure 5 Comparative Results for Period 1 & 2

Since ANFIS integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. In their earlier works, authors of this paper 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 ANFIS models to much larger sized virtual cells which could provide an insight into the applicability of ANFIS with an optimal with precise set of parameters in the structure. In order to obtain the precise set of parameters of ANFIS structure, a genetic algorithm (GA) tool can be developed and implemented.

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