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Workforce Assignment into Virtual Cells using Learning Vector Quantization (LVQ) Approach

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Abstract: In this study, an attempt has been made to apply Learning Vector Quantization (LVQ) approach, one of the network types of Artificial Neural Networks (ANN), into worker assignment problems for VCMS environment and analyze the network performance and effectiveness under different cell configurations and time periods. Worker assignment problems assume a crucial role in any type of manufacturing systems due to the fact that it is one of the major resource implicating factors. Its influence is much more significant in case of a dynamic production environment such as cell-based manufacturing systems. In this type production environment, product variety is changing very rapidly prompting the need to redesign the production facility quickly so as to accommodate *agility*. Virtual Cellular Manufacturing Systems (VCMS) have come into existence, replacing traditional Cellular Manufacturing Systems (CMS), to meet highly dynamic production conditions in terms of demand, production lots, processing times, product mix and production sequences. Traditional CMS involves formation of machine cells and part families based on the similarity characteristics in the product and process route. While cell formation phase has been dealt quite voluminously, researchers have started realizing, not long before, that workers' role during implementation of this cell-based manufacturing systems has been a major dimension. The problem of worker assignment and flexibility in cell based manufacturing environments has been studied and analyzed in plenty and various heuristics/mathematical models are developed to achieve reduced labor costs, improved productivity and quality, effective utilization of workforce and providing adequate levels of labor flexibility. Application of ANN, adapted from the biological neural networks, is the recent development in this field exploiting its ability to work out mathematically-difficult-to-solve problems. Previous studies of the author have prompted that ANN technique is a useful approach for solving worker assignment problems while the present study expands the previous efforts through applying a unique class of ANN i.e., LVQ into worker assignment problems for VCMS environment. The results obtained in this study affirm that LVQ based approach is useful and effective under different cell configurations and time periods.

Keywords: Artificial neural networks, Learning Vector Quantization (LVQ), virtual cellular manufacturing, worker assignment

INTRODUCTION

Group Technology (GT) has revamped the classical method of manufacturing of parts and products. GT is a manufacturing philosophy in which parts are grouped together as part families on the basis of similarity in design characteristics of parts such as dimensions, shape and type of materials and similarity in production factors such as type of operations performed, required machineries and tools and production sequence. Cellular Manufacturing Systems (CMS), a brain child of GT, refers to the physical division of the functional job shop's machineries into production cells. Each production cell is designed to produce a part family. A part family is defined as a group of parts or products requiring similar machinery, operations, tooling, jigs and fixtures. When a new product arrives or demand pattern changes, the existing cells need to be reconfigured suitably to meet the production requirements. Key advantages of CMS are reduced set up time and material movement time, reduced work-in-process inventory, simplified scheduling and enhanced product quality. On the other hand, limitations of CMS are frequent physical rearrangement of machineries, loss of robustness to product variety & product mix and loss of routing flexibility which are the key attributes of conventional functional layouts. It is indicated in literature that when demand values are highly stochastic in nature or changes in product variety are recurrent, then frequent reconfiguration of layouts in CMS may be expensive, infeasible and sometimes not viable. The concept of Virtual Cellular Manufacturing Systems (VCMS) is designed and developed to address this issue in a broad sense.

In VCMS, the machineries and facilities are not physically transferred closer to one another and hence the existing layout of the shop floor need not be reconfigured

for every time period. The machineries and facilities are logically and virtually grouped (virtual cells) for a particular production period and this grouping will be redone for subsequent production periods when a new product arrives or a demand fluctuates. In each production period under VCMS, production conditions and parameters and customer requirements are different and therefore newly formed production cells will possess different machine members, part families and worker teams. The reward of employing VCMS concept is that, in addition to benefits obtained in CMS at hand, functional layout advantages are also compounded.

Nomden *et al*. (2006), reported that during the VCMS design, all researchers have considered machine related sources and issues predominantly while a few studies considered material handling aspects but worker related aspects are almost neglected with a few exceptions (Min and Shin, 1993; Suer, 1996; Askin and Huang, 2001; Suresh and Slomp, 2005). Suresh and Gaalman (2000) have unearthed VCMS literature and pointed out the importance of considering workers as a second constraining resource in VCMS environments. Worker assignment to the virtual cells requires consideration of labor skill requirements, capacities, load balancing and cross-training needs to sustain cellular operations with adequate levels of worker flexibility (Suresh and Slomp, 2001).

In the past, virtual cell formation phase of VCMS has been solved using a range of techniques right from the conventional approach Rank Order Clustering (ROC) method to the recent method of using ANN concept. Similarly, worker assignment problems are previously dealt with various heuristics/mathematical and goal programming models in order to achieve reduced production costs, improved productivity and quality, effective utilisation of workforce. Use of ANN for manufacturing cell formation has been an excellent domain for ANNs to show its strength and there are a number of neural network approaches experimented for cell formation (Kaparthi and Suresh, 1992; Dagli and Huggahalli, 1993). While application of ANN based approaches for virtual production cell formation is reported in plenty, its use to worker assignment tasks is recently explored and reported by Murali *et al*. (2010). ANN is a massively parallel distributed computing processor widely used to solve non-linear and mathematically difficult-to-solve problems operating on the basis of matching input and output patterns. In this study, an attempt has been made to apply LVQ approach into worker assignment problems for VCMS environment and analyze the network performance and effectiveness under different cell configurations and time periods.

LITERATURE REVIEW

Irrespective of the type of manufacturing systems being adopted for production, worker assignment has positioned itself strongly due to a fact that work force is a major constraining resource in a manufacturing organization. However, workforce issue is traditionally addressed on the basis of matching technical skills of the workers with production requirements. Most labor assignments are made based on the experience of the personnel involved with the cells. Many times, particularly at the cell implementation level, labor decisions involve a lot of trial and error and therefore, companies do not make the best use of their labor and machine resources. Viviana and Steude (2005). It is also indicated (Suresh and Slomp, 2005) that in cell based manufacturing, many of the perceived advantages are derived from holding sufficient levels of worker flexibility within each cell.

In line with the above, a multi-objective mathematical model was framed by Min and Shin (1993) in an effort to perform simultaneous formation of machine and human manufacturing cells. Again, the worker assignment was on the basis of skill match. One of the shortcomings of this approach was that the data analyzed are hypothetical and skill levels were static.

Süer (1996) proposed a two-phase hierarchical methodology in order to achieve an optimal manpower assignment. In this study, mixed integer and integer programming formulations are proposed to generate alternative operator levels and to achieve the optimal operator and product assignment to the cells. Eventually as an extension of this study, mathematical models are developed (Süer and Sánchez-Bera, 1997) to generate alternative operator levels and to obtain the optimal common operator and product assignment to the cells. This was further modified for analyzing the impact of lot-splitting in terms of setup times (Süer and Sánchez-Bera, 1998).

Askin and Huang (1997) developed two integer programming models for assigning workers to cells and determining an appropriate training programme schedule for employees. A major assumption made in this model was that each different skill has only one level rather than multiple levels for each skill. They later extended their study (Askin and Huang, 2001) to examine not only the formation of worker teams, also the specification of cross-training plans for workers in cellular design. The objective was to minimize multi-objective cost model consisting of training costs, misfit costs and costs associated with cognitive abilities. However, the worker skill level was considered to be a binary variable: 1 if the worker possesses the skill and 0 otherwise.

Bryan, A. Norman *et al*. (2002) indicated that the worker assignments have been traditionally based on only the technical skills of the workers, not other abilities. Subsequently, they proposed a mixed integer programming model that considers human skills and permits the ability to change the skill levels of workers by providing them with additional training. This study showed that there was a significant improvement in cell

performance if human skills were explicitly considered in the worker training plan and assignment strategies.

Bopaya *et al*. (2005) have indicated that although cell based manufacturing results in productive benefits and forms the central theme of research for researchers, yet, the importance of human issues is never dealt in full and further there is a singular absence of articles in relation to human element in cellular manufacturing. It is also emphasized that the lack of understanding of the human side of cellular manufacturing could significantly reduce the benefits associated with this mode of manufacturing. Slomp *et al*. (2005) presented a virtual cellular design framework employing goal programming model to form virtual cells initially and then to assign workers to these virtual cells. Two main objectives were dealt in this study namely

- Efficient use of the capacity
- Formation of independent virtual cells

McDonald *et al*. (2009) presented a mathematical worker assignment model to assign cross-trained workers to tasks within a manufacturing cell in order to minimize the net present cost and to ensure job rotation while meeting customer demand. This model also determines the training necessary for workers to meet skill requirements for tasks and customer demand.

Employing ANNs into worker assignment problems of cellular manufacturing has been quite recently carried out (Murali *et al*., 2010) and it is documented that ANNs have adequate potential to successfully predict worker assignments under varying inputs and conditions manufacturing cells. The above approach has been applied to two cell configuration cells initially and later extended to higher cell configuration i.e., three-cell configuration and the results of this study demonstrate that application of ANNs into worker assignment tasks has huge prominence and potential. It is then advocated that workers assignments depend on to what extent a worker adds value to a particular cell in terms of fitness attributes such as machine coverage ratio, multi-functionality and total processing time. Fitness attributes for each worker are determined and fed into ANNs framework as training/validating/testing inputs.

From literature, it is clear that various heuristics, mathematical and simulation models were developed for solving worker assignment problems as applied to cell-based manufacturing environments. It is brought forward that a very recent and rapidly growing technique i.e., ANN method is found to have huge prominence and potential for solving worker assignment problems cellular manufacturing environments. In this attempt, an important and widely used class of neural network called LVQ has been modeled for workforce assignment problems under VCMS environment and the results are analysed.

NEURAL NETWORK CLASSIFIER SCHEME

Artificial Neural Networks strive to behave in a much similar way as the brain of human beings and it is deemed to perform tasks through gaining knowledge obtained by learning or training process. More precisely, ANNs have the ability to learn from experience, adapt to new situations and provide reliable classifications and approximations of data. It consists of processing units called artificial neurons (interconnection of simple computing cells) to achieve desired performance in the chosen task. Each neuron or node receives an input data, processes it and produces an output that acts as an input to other nodes in the network. The connections among the nodes and various learning algorithms to alter the weight factors between the connecting nodes are the strength and flexibility of neural networks. Neural networks are capable of achieving optimal and near-optimal solutions of nonlinear problems through input-output mapping and adaptive characteristics.

Supervised or unsupervised are the two major types of neural networks that find wider acceptance among the researchers. Supervised networks will essentially function based on the training sets i.e., valid and relevant input/output values to train the network and adjust the connection weights between the individual nodes. In recent times, unsupervised neural networks are preferred owing to a fact that it has the ability to adapt and classify the input data without needing input/output values for training. In this attempt, LVQ class of neural network is employed to carry out the classification task of workers into different virtual cells.

Learning Vector Quantization (LVQ) network: Learning Vector Quantization is another important class of neural network which is operating on a principle of assigning a vector representation of the given multi-dimensional training datasets and then transforming them to one of the target classes which are predefined in the problem. As found in other types of neural networks types, LVQ network structure consists of two computational layers namely competitive layer, to learn similar patterns of training data and their correlations in the input vectors and assigns them to as many subclasses as the number of neurons that the layer contains and an output layer, to transform the competitive layer's output results into target classes defined previously from the training datasets. The primary factors on which the performance of an LVQ structure depends are the number of hidden units in the competitive layer, learning rate and training time adopted.

Figure 1 depicts the general structure of the LVQ neural network where the input vectors are assigned to one of target classes. The equivalent MATLAB© code for creating a new LVQ network is *newlvq()*. One of the

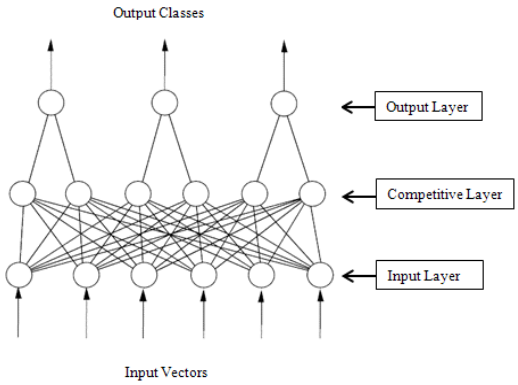


Fig. 1: General structure of an LVQ network

arguments for this MATLAB© function is the number of neurons (hidden units) in the competitive layer determining the accuracy of the classification process. The main logic behind the working of every LVQ is the choice of an appropriate measure of distance (*Euclidean*) or similarity among the training datasets and their appropriate target classes. The distance of a training vector from each neuron is determined and the nearest hidden unit is declared to be the winner class. *Euclidean* distance between a training vector, x and each hidden unit's weight vector, wi, can be calculated using the following equation:

$$D_i = \|w_i - x\| = \left\{ \sum_{j=1}^{N} (w_{ij} - x_j)^2 \right\}^{\frac{1}{2}} \quad (1)$$

where, N is the number of elements in the input vector, x. LVQ learning process adopts two progression criteria as explained below. If the winning neuron is in the same class as the training vector, it is then moved towards the training vector according to:

$$w' = w - \propto (x - w) \quad (2)$$

where, α is called the attraction coefficient and its values range (0<α<1). On the other hand, if the winning neuron is not in the same class as the training vector, it is moved away from the training vector as in equation 3:

$$w' = w - \gamma(x - w)$$

where, γ is called the repulsion coefficient and its values range (0<γ<1).

One of the major and distinct features of LVQ as compared to other classes of ANN is that LVQ networks can classify any set of input vectors, not just linearly separable sets of input vectors. The decision boundaries may form shapes in multidimensional space, which are more complex than ordinary hyper planes. However, only one constraint in this type of networks is that the competitive layer should be loaded with adequate number of hidden units and so each target class.

From literature it is found that LVQ network type is the most widely used because of its high flexibility and robustness to classify non-parametric statistical datasets although other classes of ANN such as Multilayer Perceptrons (MLP) and Radial Basis Function (RBF) networks prove worthy for accurate classification. However, in the LVQ network each hidden unit can be considered as representing a point in *N*-dimensional space. It retains the principle of operation of other types i.e., based on the proximity of the input vector to determine the winning neuron and therefore target classes.

PROBLEM SETTING and PARAMETERS FOR THE ANN-LVQ FRAMEWORK

The key difference between cellular and virtual cellular manufacturing systems is the need of reconfiguration of the machines and layouts. In cellular manufacturing, machines are brought closer to form cells while VCMS does not impose upon this. Mere dedication of identified machines across various departments in the form of logical groups will suffice for creating virtual cells. For every time period, member machines of this logical group will change based on the demand, products, product mix and production sequence. Therefore, in this study, the results of traditional cell formation problems adapted from literature are treated as applicable to virtual cells and for each period different datasets with different production time and sequence are considered which is equivalent to working on virtual cell formation problems and data. For detailed information on problem setting and parameters, please refer to author's study (Murali *et al*., 2010).

The conceptual diagram of the proposed study (2-phase worker assignment methodology plus ANN framework) is illustrated in Fig. 2. Initially, from open literature (Table 1) on traditional cell formation problems, salient result features such as number of cells formed, jobs and machines allotted to each cell, processing time, number of exceptional elements with production details and sequence for each part being processed are extracted. In the present context, only 2-cell configurations are considered and later this approach will be extended to multiple cell configurations.

In phase 1, these details are preprocessed and transformed into worker fitness attributes namely machine coverage ratio, multi-functionality and total processing load for each worker in each cell. Author strongly advocates that worker assignment into cells will be based on to what extent a particular worker adds value to a

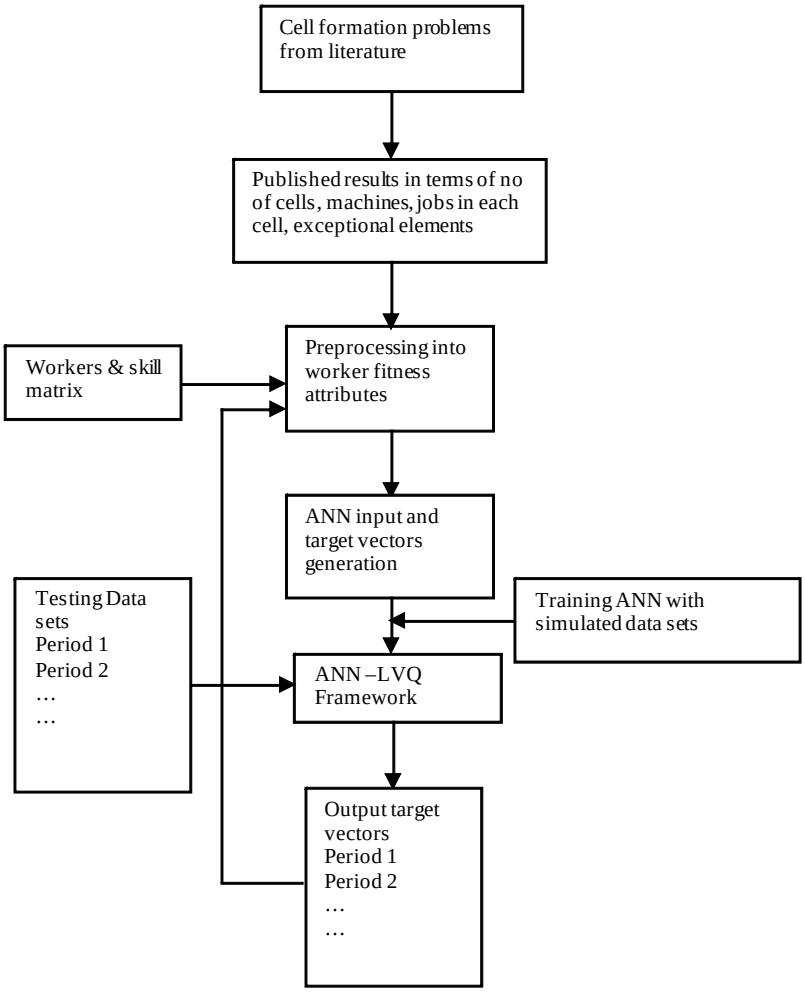


Fig. 2: Conceptual illustration of the proposed framework

particular cell in terms of number of operations, total processing time and number of machines he is capable of operating within a cell. If he/she does not contribute value to a particular cell, his fitness for this cell would be lower and hence not preferred to be assigned into this cell. The fitness attributes are explained as follows.

Machine coverage ratio: In literature (Slomp *et al*., 2005) machine coverage of machines is defined as the number of operators capable of operating each machine. In this context machine coverage ratio of operators is referred to be a ratio of the number of machines he/she is eligible to operate to the total number of machines assigned to the particular cell. Higher values of this parameter imply that he/she is qualified to process more jobs in that particular cell. Therefore, it is contended that the more the machine coverage ratio of a worker in a virtual cell, more the chances of the worker getting assigned to that particular virtual cell.

Table 1: Literature problems, sizes and sources (for training and testing ANN-LVQ)

	Data set No	Literature source	Problem size (MxP)
For training ANN	1	King and Nakornchai (1982)	5×7
	2	Waghodekar and sahu (1984)	5×7
	3	Seiffodini (1989)	5×18
	4	Chandrasekaran *et al*. (1986b)	8×20
	5	Generated set 1	-
	6	Generated set 2	-
For testing ANN	7	Kusiak (1992)	6×8
	8	Sudhakara and Mahapatra (2008)	5×7
	9	Sudhakara and Mahapatra (2008)	6×8

Table 2: Cell configuration details for data set 1

Machines in	Cell 1	M1, M3, M4, M6
	Cell	2M2, M5
Parts in	Cell	2P3, P4, P7, P8
	Cell	2P1, P2, P5, P6
No of workers	4	

Table 3: Sample training data for ANN-LVQ framework

		Worker fitness attributes								
		Machine coverage ratio of each worker in		Multi-functionality of each worker in		Total processing (min) load in				
Dataset No.	Workers	Cell 1	Cell2	Cell1	Cell 2	Cell 1	Cell 2	Target	vectors	
1	W1	0.667	0.50	4	4	3.38	2.92	0	0	1
	W2	0.330	1.00	3	7	1.37	4.12	0	1	0
	W3	1.00	0.00	7	0	4.75	0.00	1	0	0
	W4	0.66	0.50	4	3	3.38	1.20	1	0	0
2	W1	0.50	0.66	2	7	1.53	3.54	0	1	0
	W2	1.00	0.33	3	4	2.03	1.31	1	0	0
	W3	0.00	1.00	0	11	0.00	4.85	0	1	0
	W4	0.50	0.66	1	7	0.50	3.54	0	1	0
3	W1	0.66	0.50	10	12	5.73	7.64	0	1	0
	W2	0.33	1.00	5	24	2.40	14.9	0	1	0
	W3	1.00	0.00	15	0	8.13	0.00	1	0	0
	W4	0.66	0.50	10	12	5.73	7.29	0	0	1
4	W1	0.33	0.40	6	14	2.86	9.18	0	1	0
	W2	0.33	0.40	9	16	5.41	8.70	0	1	0
	W3	0.66	0.40	18	14	8.90	7.18	1	0	0
	W4	0.33	0.40	6	16	2.86	7.67	0	1	0
	W5	0.00	0.40	0	16	0.00	8.70	0	1	0
	W6	0.33	0.40	9	14	3.49	8.15	0	1	0
	W7	0.66	0.20	15	8	8.27	4.25	1	0	0

Multi-functionality: Multi-functionality of a worker is defined (Slomp *et al*., 2005) as number of machine types that each worker can operate. Author proposes to consider, in this attempt, multi-functionality as an index referring to the total number of operations he/she is eligible to perform on different machines in a particular cell, he is likely to be assigned. This index is deemed to measure the ability of a worker to process a number of operations in a virtual cell. When a worker is able to perform more number of operations on different parts in a particular cell, then he/she will secure higher fitness values for assignment into this virtual cell.

Total processing time: In addition to the number of machines and number of operations a worker is eligible to process in a cell, total processing time for all operations a worker is eligible to process would also have to be accounted for exercising the assignment task. Therefore, it is proposed to include this factor as one of the fitness attributes in this study. It is contended that when values of fitness attributes for the virtual cells under question tie or match or run closer, it leads to a condition that this particular worker is fit to be allotted to both cells. This may perhaps result in bottleneck worker which is taken care of by second phase of study assignment methodology.

Upon completion of this procedure, the total study load of each worker in each cell, machine utilization for each cell, total cell load of each cell are calculated and a deep look at the study load data is given in order to confront (phase 2) the exceptional elements ie., the parts requiring operations in cells other than they are allotted.

In phase 2, the number of exceptional elements and their processing sequence are considered. At first look, these jobs are assigned to workers with low or medium work load values and suitability of this worker to process them wherever possible and appropriate. Otherwise, production manager and his team would resort to cross training and/or overtime to process certain number of exceptional elements. The logic employed in this methodology and thereafter the results obtained are strengthened by examining the work load distribution of each individual worker, cell load values and machine utilization in each cell.

Table 1 lists various referred literature problems (2-cell configuration) with sizes to be adapted in this study for generating training data sets to the ANN-LVQ framework. Table 2 gives the published cell configuration details for dataset 1 adapted from King and Nakornchai (1982).

The values of fitness variables for each worker for various time periods are calculated through production data, worker skill matrix and machineries/jobs available in each cell. These are the training datasets for LVQ-ANN framework and presented in Table 3. The output target nodes are denoted as 3 digit numbers which reflect the classification scheme of various cells. Cell 1 and Cell 2 are indicated by [1 0 0] and [0 1 0] respectively while worker assignments to both cells are mapped into representation scheme [0 0 1]. Demand for each part has been uniformly distributed and workers skill matrix is retained for all the time periods. The number of workers is so chosen considering the Dual Resource Constrained contexts in which the number of workers available is less than the number of machines.

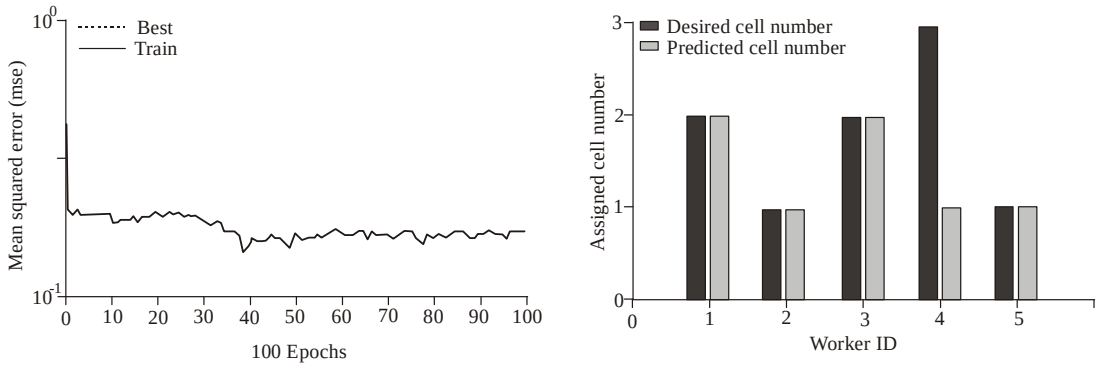
RESULTS AND DISCUSSION

Figure 3 to 5 illustrate the variation of Mean Squared Error (MSE) with the number of epochs ANN has taken after reaching the goal and the regression analysis between the desired target and actual output for different periods under consideration. These curves illustrate the closeness of the predicted results and desired targets and it is getting closer and closer as the number of epochs progresses for each time period. These graphs are produced by MATLAB© software. For testing process, the number of maximum epochs is specified as 100 and it is observed that for all periods, the iteration process is stopped after reaching 100 epochs. The proposed ANN-LVQ scheme is catagorised under *supervised neural network* class since it needs training data to perform the classification data. Although, the accuracy and performance can be improved by altering the process parameters such as training algorithm, learning rate and mean square error values, the major factor that dictates its performance is the validity and accuracy of the training data which will play a crucial role in applying neural network techniques. In this attempt, 2-cell configuration problems are analyzed and results are presented. The effectiveness of ANN-LVQ techniques will be completely realized when worker assignments to multi-cell problems with larger number of machines and jobs are done which is identified as future study.

Table 4: Classifications success rates %

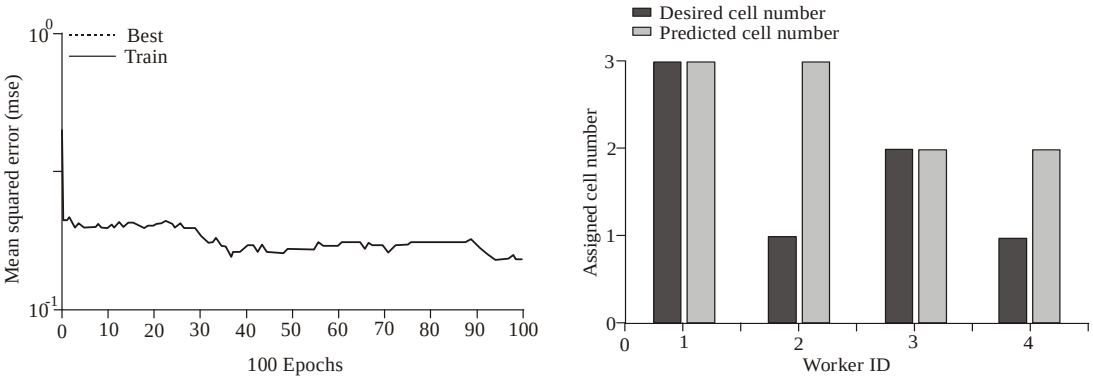
Periods	Success rate (%)	Simulation time taken (min)
1	80	1.18
2	50	1.26
3	80	1.35

The LVQ-ANN network performance is measured through the ability of the framework to closely predict the worker assignments into various manufacturing cells i.e., *classification success rates* and the time taken for the simulation run to complete. Table 4 illustrates the values obtained in the simulation run and the success rates are very much satisfactory for period 1 and 3 while for period 2, its performance shows 50% due to the smaller size of workers involved in testing data. However, the network



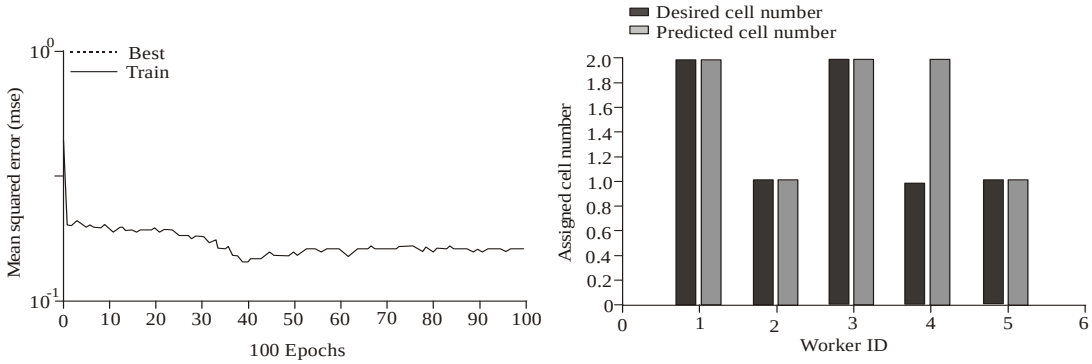
(a) (b)

Fig. 3: ANN-LVQ testing results for period 1



(a) (b)

Fig. 4: ANN-LVQ testing results for period 2



(a) (b)

Fig. 5: ANN-LVQ testing results for period 3

Table 5: ANN-LVQ testing results

			Worker fitness attributes								
			Machine coverage ratio of each worker in		Multi-functionality of each worker in		Total processing (min) load in				
Data set	Time period	Workers	Cell 1	Cell 2	Cell 1	Cell 2	Cell 1	Cell 2	Target vectors predicted		
7	Period1	W1	0.25	1	2	7	1.83	6.71	0	1	0
		W2	0.75	0	6	0	5.24	0	1	0	0
		W3	0.5	0.5	4	4	3.41	3.73	0	1	0
		W4	0.5	0.5	4	3	3.25	2.98	0	0	1
		W5	0.5	0	4	0	3.57	0	1	0	0
8	Period 2	W1	1	0.66	7	5	3.99	3.79	0	0	1
		W2	0.5	0.33	3	2	1.14	1.57	1	0	0
		W3	0.5	0.33	3	3	31.14	2.22	0	1	0
		W4	0.5	0.33	3	3	2.85	1.99	1	0	0
9	Period3	W1	0.33	0.66	2	11	1.83	9.88	0	1	0
		W2	0.66	0.33	4	3	3.57	2.67	1	0	0
		W3	0.33	0.66	2	9	1.74	8.2	0	1	0
		W4	0.66	0.33	4	5	3.25	4.35	1	0	0
		W5	0.66	0	0	0	3.57	0	1	0	0

performance can be enhanced through judicious selection of network parameters such as number of neurons, network weights and number of epochs. The ANN-LVQ model is designed, developed and tested with MATLAB© tool in Pentium 4 CPU, 3 MHz speed system.

Table 5 presents the predicted results for testing datasets that are used for validation of the network output. The predicted vectors are rounded off to a nearer value and represented as 3 digit numbers. The target Cell 1 and Cell 2 are indicated by [1 0 0] and [0 1 0] respectively while worker assignments to both cells are mapped into representation scheme [0 0 1].

CONCLUSION RECOMMENDATION

In the earlier studies of the author, the concept of ANN was introduced and applied to the problems of worker assignment of two cell and three cell configurations under VCMS environment. The types of ANN used were MLP and RBF. The results of the above study showed that ANN proved to be a potential tool to be applied to worker assignment problems. In similar line, the present study is centered on another type of ANN class called LVQ which is implemented on the worker assignment problems. The classification rates and the time taken for the simulation elucidate the acceptability of the model. The results of this study also reaffirm the prominence of ANN and its types into worker assignment problems. The proposed ANN LVQ model, with relevant testing information as input vectors, would be able to assign workers into virtual cells for any number of time periods or whenever a new product arrives and demand changes. On the other hand, the above developed model can be further expanded by integrating it with a Genetic Algorithm (GA) in order to optimize its architectural parameters for obtaining the best classification performance of LVQ model.

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