# AI-based techniques in cellular manufacturing systems: a chronological survey and analysis

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**Abstract:** This article portrays a chronological review of the influence of artificial neural network in group technology applications in the vicinity of cellular manufacturing systems. The research trend is identified and the evolvement is captured through a critical analysis of the literature accessible from the very beginning of its practice in the early 90s till the 2012. Analysis of the diverse ANN approaches, spotted research pattern, comparison of the clustering efficiencies, the solutions obtained and the tools used make this study exclusive in its class.

**Keywords:** cell formation; group technology; artificial neural network; ANN; cellular manufacturing; survey; review.

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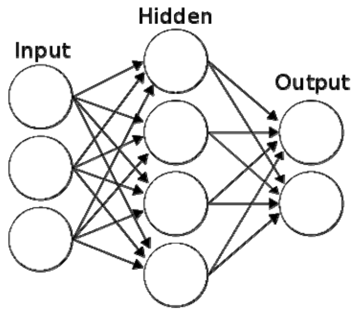
## 1 Introduction

Over the past three decades, in response to the competitive market's need for increased industrial automation, product diversification and the trend towards shorter product life cycles, new manufacturing philosophies have been adopted by many of the established manufacturing firms. Among those, group technology (GT) has been used to reduce throughput and material handling times, to decrease work-in-progress and finished goods inventories and to increase the ability to handle forecast errors (Won and Currie, 2007). GT can be defined as a manufacturing philosophy identifying similar parts and grouping them together to take advantage of their similarities in manufacturing and design (Selim et al., 1998). GT is mainly applied in flexible manufacturing systems (FMS) and cellular manufacturing systems (CMS) (Rao, 2006). Cellular manufacturing (CM) is an application of GT and has emerged as a promising alternative manufacturing system. CM could be characterised as a hybrid system linking the advantages of both the jobbing (flexibility) and mass (efficient flow and high production rate) production approaches. CM entails the creation and operation of manufacturing cells. Parts are grouped into part families and machines into cells. The aim of CM is to reduce setup and flow times and therefore to reduce inventory and market response times (Wemmerlöv and Hyer, 1989). Setup times are reduced by using part-family tooling and sequencing, whereas flow times are reduced by minimising setup and move times, wait times for moves and by using small transfer batches. GT addresses issues such as average lot size decreasing, part variety increasing, increased variety of materials with diverse properties and requirements for closer tolerances. Venugopal (1999) described the basic idea behind GT/CM is to decompose a manufacturing system into subsystems by identifying and exploiting the similarities amongst part and machines. The very first step in this process is to solve the complex part machine grouping (PMG) problem and the problem being quite challenging under real time scenario, various approaches have been developed, and among those, artificial neural network (ANN) have an eminent role in the GT/CM literature (Sofianopoulou, 2010). ANN is being used in GT/CM literature from past two decades (Rezaeian et al., 2011; Chattopadhyay et al., 2011). It is noticed that many review works have been carried out in the area of GT/CM recently but only ANN-based review work has not yet been done (Ghosh et al., 2011; Chattopadhyay et al., 2013). This paper presents a chronological quantitative review of ANN in CMS from the very beginning of its use in the early 90s till the 2012. An in depth analysis is carried out to identify the research trend, which captures the chronological progress and continuous improvement in the CMS. The study focuses on the influence of the ANN in CM, emphasising various ANN approaches applied, analytical comparison of the research patterns, and improvements achieved over the years.

## 2 Overview of ANN

ANN is also called connectionist model, neural net, or parallel distributed processor (PDP) model as reported by Odejobi and Umoru (2009). ANNs are massively parallel computer algorithms with an ability to learn from experience (Wasserman, 1989). They have the capability to generalise, adapt, approximate given new information, and provide reliable classifications of data. They basically consist of different components, e.g., processing unit (PU), connections, propagation rule, activation/transfer function and learning rule (Venugopal, 1999). The PUs are densely interconnected through directed links (connections). PUs take one or more input values, combine them into a single value using propagation rule, then transform them into an output value through an activation/transfer function. Complex networks can be constructed by connecting a number of PUs together (Sengupta et al., 2011). The simplest network is a group of PUs arranged in a single layer. Multi-layer networks may be formed by simply cascading a group of single layers as shown in Figure 1. A neural network learns from a set of training patterns by generalising the features within the training patterns. After sufficient generalisation, the network stores these features internally in its architecture. After the training, the neural network should be able to recognise and classify input patterns that it has never seen before.

**Figure 1** Basic structure of an ANN




The learning takes place mainly through the readjustment of the weights using certain learning procedures such as the delta learning rule, Hebbian learning rule and competitive learning rule. Supervised learning requires the pairing of each input value with a target value representing the desired output and a 'teacher' who provides error information. In unsupervised learning, the training set consists of input vectors only. The output is determined by the network during the course of training. The unsupervised learning procedures construct internal models that capture regularities in their input values without receiving any additional information (Potočnik et al., 2012). Neural networks are of major interest because when it is connected to computer, it mimics the brain and bombard people with much more information. ANNs are being used in production and manufacturing domain heavily (Azadeh et al., 2011a, 2011b).

## 3 ANN in GT/CM

The neural network approach in engineering field has been the subject of intensive study by interdisciplinary researchers for a long time (Paliwal and Kumar, 2009). Though neural networks have been successfully applied in a variety of fields, their use in CM problems started in the late 80s and early 90s. Recognising ANN's pattern recognition ability, several researchers began to investigate neural network methods for the part-machine grouping problem. Neural networks are of major interest because when it is simulated to computer, it mimics the brain and bombard people with much more information.

In this study, the ANN application in GT/CM has been classified in chronological order. The next subsection reviews the literature from 90s to 2000 and the other subsection portrays the articles published during 2000 to 2012.

### *3.1 ANN in GT/CM: from 1990 to 2000*

An interactive activation and competition (IAC) model based on ANN was proposed by Kao and Moon (1991) where part and machine similarities were considered to form the part families for CM, which mimics the way biological brain neurons perform to generate intelligent decisions. The procedure was described with suitable examples.

Kao and Moon (1991), Dagli and Huggahalli (1991) and Kusiak and Chung (1991) have applied ART1 to group parts or machines. Back propagation learning rule was also implemented by Kao and Moon (1991) to address the PMG problems while Malave and Ramachandran (1991) utilised competitive learning rule to the cell formation problem. The input to the ANN is the process plan of each part, which offers a mechanism to identify the ratio of the number of shared (bottleneck) machines to the total number of machines used in each cell.

Carpenter Grossberg network is used by Kaparthi and Suresh (1992) for the identification of clusters with fast execution time. It is a heuristic clustering method to support procedures such as PFA. The network could also be trained without supervision. Moon (1992) presented a neuro-computing model for part/machine grouping. The spontaneous generalisation capability of ANN models is exploited by Moon and Chi (1992) for solving the part family formation problem. The approach combined the useful capacities of the ANN technique with the flexibility of the similarity coefficient method, which proved to be highly flexible in satisfying various requirements and efficient for integration with other manufacturing functions. The study of Burke and Kamal (1992) introduced fuzzy ART neural network for CM. Whereas Moon and Roy (1992) presented a new approach to part classification in GT, which advocated the introduction of a feature-based solid-modelling scheme for part representation which, in turn, helped in identifying features of interest. In this article a back-propagation learning rule was implemented. ART1 neural network approach is used by Dagli and Sen (1992) to large scale GT problems. However, Lee et al. (1992) presented an improved method for cell formation, bottleneck machine detection and the natural cluster generation using a self-organising neural network. In addition, the generalisation ability of the neural network made it possible to assign the new parts to the existing machine cells without repeating the entire computational process.

Chu (1993) presented a procedure which was based upon competitive learning paradigm to form cells. The proposed algorithm was better than optimal algorithms or other conventional heuristics as it took less time to obtain optimal or near optimal solutions compared to other methods. Besides Liao and Chen (1993) used ART1 neural network model and Chakraborty and Roy (1993) used Kohonen's self-organising feature maps for part family and machine cell formation. Lozano et al. (1993) also addressed cell formation problem using neural network. Kaparthi et al. (1993) proposed a robust neural network-based leader algorithm for the part-machine grouping problem. The clustering method involved is a modification to the normal use of Carpenter and Grossberg's ART1 neural network. The robustness of the modified algorithm to random ordering of the input data was tested with the datasets including an industry-size problem consisting of 1,000 parts and 100 machine types.

Venugopal and Narendran (1994) made a comparative study based on competitive learning model, SOFM and ART1 to suggest a cell that minimises within cell dissimilarities and balances the number of machines assigned to each cell. The individual performances of each network were compared to Zodiac, while Suresh and Kaparthi (1994) investigated the performance of fuzzy ART in CF problem which outperformed ART1 in terms of bond energy recovery. The proposed model clearly represented a viable alternative for PMG problem. Rao and Gu (1994) presented a multilayered constraint-bound neural network, which was structured to include practical limitations such as duplicate machine availability and machine capacity during the cell design process. The interactive expert system took its input from the neural network and used alternate process plans to reassign any exceptional parts that could occur as a result of the constraint imposition during the initial cell design. Thus the hybrid neural net-expert system technique gave an added flexibility to the design approach.

Dagli and Huggahalli (1995) used ART1 for automatic generation of an optimal family formation solution promising both speed and functionality, while Chen and Cheng (1995) improved the quality of grouping by the introduction of set of supplementary procedure especially in the presence of bottleneck machines/bottleneck parts using the ART1. Arizono et al. (1995) used stochastic neural network model to overcome the defects of deterministic neural network problems which often stuck at local optimal solutions. Burke and Kamal (1995) applied fuzzy ART neural network technique to the part family formation problem in CM. This approach to GT solved to varying degrees, the problems of speed and flexibility. Kulkarni and Kiang (1995) used a self-organising neural network for dynamic grouping of parts in FMS. Malakooti and Yang (1995) proposed an unsupervised clustering neural network method for solving machine part group formation problem, which depicted a moderately good final grouping result in terms of percentage of exceptional elements (EE), machine utilisation, and grouping efficiency. Kiang et al. (1995) used SOFM as a clustering tool in GT problem, where the part groupings were based on operations and not on machines. A multi-constraint neural network was proposed by Rao and Gu (1995) for the pragmatic design of CMS. The proposed multilayered neural network was capable of incorporating multiple constraints and objectives during the cell design process.

Chen et al. (1996) proposed an improved ART neural net for machine cell formation. To reduce the disadvantages of ART1 they proposed modified algorithm to improve the learning rule of the standard ART1 and the representation of input vectors. Kamal and Burke (1996) proposed a clustering algorithm fuzzy ART with add clustering technique (FACT) for GT. It could be trained to cluster machines and parts for CM under a multiple objective environment. Kusiak and Lee (1996) proposed a neural computing-based component design for CM.

Chu (1997) proposed an unsupervised network model, based upon the IAC learning paradigm which was easy to use, fairly efficient and robust and could simultaneously form part families and machine cells. The computational results showed that the proposed procedure was more efficient and effective than a similar IAC model. Inho and Jongtae (1997) used SOFM for generalised CF problems considering material flow and plant layout. The proposed method considered factors such as the operational sequences and lot sizes and proved to be a flexible solving tool to GT. Kao and Moon (1997) presented a new approach namely feature-based memory association network (FBMAN) using the memory association of neural networks to identify naturally existing families, operates by the exhaustive association approach which dealt with the difficult problem of exceptional parts. FBMAN system with the exhaustive association approach was a robust part clustering system. The evaluation criteria considered are the total bond energy, the percentage of EE, the machine utilisation and the grouping efficiency. Lee et al. (1997) proposed a new machine cell formation method based on the adaptive hamming net which could produce good cells for the machine cell formation problem. The proposed method was compared with other existing methods successfully. Zolfaghari and Liang (1997) proposed a new structure of Hopfield neural network, OSHN, for the machine grouping problems which was designed in conjunction with an objective-guided search and could effectively handle bottleneck machines.

Enke et al. (1998) presented a new ARTI paradigm which involved reordering of the input vectors with a modified procedure for storing a group's representation vectors. It proved successful in both speed and functionality compared to previous techniques. The techniques proved to be efficient and practical when implemented on a serial computer that could be incorporated into a parallel environment with relative ease. Pilot and Knosala (1998) presented a classification method based on the Kohonen network and its modifications. Parallel, 2-layers net which allowed joining of both geometrical technological features was used in the application. Input patterns were written in the form of a raster grid, in which every raster had a defined number code. Kao and Moon (1998) proposed a new approach for multiple-application set formation using feature-based memory association performed by networks which demonstrated that feature-based memory association is an effective way of forming cells.

Liang and Zolfaghari (1999) presented a neural network approach considering processing time, lot size, machine capacity, and machine duplication. The computational results obtained were compared against those obtained via an SA approach. Suresh et al. (1999) identified families of parts having a similar sequence of operations using fuzzy ART neural network. The experimental factors included size of the part machine matrix, proportion of voids, proportion of EE, and vigilance threshold. Lee and Fischer (1999) proposed a new part family classification system (IPFACS: image processing and fuzzy ART-based clustering system), which incorporated image processing techniques and a modified fuzzy ART. IPFACS could classify parts based on geometrical shape and manufacturing attributes, simultaneously. Besides Lozano et al. (1999) also used a fuzzy neural network (FNN) for part family formation.

Rao et al. (2000) applied SOFM utilising a syntactic pattern recognition approach. The selection of an appropriate cell for a new part is based on the operational information of the part. Enke et al. (2000) modified ART1 paradigm which reordered the input vectors, along with a modified procedure for storing a group's representation vectors. The parallel implementation resulted in tremendous speed.

## *3.2 ANN in GT/CM: from 2001 to 2012*

Lozano et al. (2001) considered a more comprehensive CF problem where the sequence of operations on part types was also included. The authors proposed two sequence-based neural network approaches, namely Hopfield model and Potts mean field annealing, with the objective of minimising overall transportation costs and the latter proved to give better and faster solutions, while Kuo et al. (2001) used fuzzy SOFM for clustering the parts into several families based on the image captured from the vision sensor. Mahdavi et al. (2001) develop an algorithm using graph neural approach with fast computation and the ability to handle large scale industrial problems without the assumption of any parameter and the least EE in the presence of bottleneck machines-parts. Kiang (2001) extended the KSOM networks for clustering analysis. The combination of SOM and the contiguity-constrained clustering method produced comparative clustering results.

Soleymanpour et al. (2002) addressed a number of drawbacks of previous neural network-based approaches for the CF problem and proposed a transiently chaotic ANN algorithm with supplementary procedures to overcome a number of deficiencies. Dobado et al. (2002) applied fuzzy min-max ANN for part family formation problem and a minimum cost flow model to form the corresponding machine cells minimising intracell voids and intercell moves. Chen et al. (2002) presented integrated approach of ART1 and tabu search (TS) to solve cell formation problems. The number of EE and group efficiency (GE) were considered as the objectives for the problems under the constraints of the number of cells and cell size. Guerrero et al. (2002) applied a new SOM approach to form cells in two steps: first, part families were formed and then machines were assigned. In phase one, weighted similarity coefficients were computed and parts were clustered. In phase two, a linear network flow model was used to assign machines to families.

Park and Suresh (2003) identified families of parts having a similar sequence of operations. Based on promising new developments about the use of the fuzzy ART neural network for sequence-based clustering, the objective here was to develop this methodology further by introducing additional improvements.

Peker and Kara (2004) used both binary and non-binary part–machine incidence matrices effectively using fuzzy ART network, applied to 26 test problems. Results showed that the fuzzy ART network could solve both binary and non-binary problems effectively, also showed that parameter combinations for binary and non-binary problems differ. Intervals for parameter values for optimal solutions were. Solimanpur et al. (2004) used transiently chaotic neural network (TCNN) that had the advantages of both the chaotic and the Hopfield network and investigated the dynamics of the network and studied the feasibility and robustness of final solutions.

Venkumar and Haq (2005) proposed a modified binary adaptive ART1 algorithm for the binary machine/part matrix. The generated output was the list of the part families, machine cells and number of EE. The results obtained, were superior and computationally efficient. Miljkovic and Babic (2005) used ART1 simulator and FLEXY in machine-part family formation problem. For a realistic size problem such as 1,500 parts and 110 machines, ART1 Simulator and FLEXY could be used successfully.

Venkumar and Haq (2006a) further applied modified ART1 in fractional cell formation. The input is binary machine-part incidence matrix. Further they used Kohonen SOM networks to measure the effectiveness with number of EE (Venkumar and Haq, 2006b), bottleneck parts and grouping efficiency of complete and fractional cell formation. The computational effort was very low in the KSOM. Kuo et al. (2006) presented a fuzzy ART2 neural network approach. The novel FNN, integrated both the fuzzy set theory and ART 2 neural network for grouping the parts into several families based on the image captured from the vision sensor. Even under the shift and noise conditions, fuzzy ART2 had very promising results. In addition, the fuzzy ART2 neural network, which was a kind of unsupervised network, did not need a very long training time. Ozturk et al. (2006) made a comparative study on competitive neural network (CNN) with Other AI Techniques. In this study, a CNN was presented to group parts and machines into cells simultaneously. To test the success of this CNN in CF problems, its performance was compared with those of other AI techniques such as genetic algorithms (GA), simulated annealing (SA), TS and ant systems (AS). CNN outperformed all except the AS technique.

Won and Currie (2007) used fuzzy ART neural network/RRR-RSS: a two-phase neural network algorithm to solve the comprehensive PMG considering operation sequences with multiple visits to the same machine, production volumes and multiple identical machines. Experimental results from the modified replicated clustering showed that the proposed fuzzy ART/RRR-RSS algorithm had robustness and recoverability to large-size ill-structured datasets. This could be applied as a useful alternative for comparing and evaluating the robustness of PMG algorithms. Mehrabad and Safaei (2007) proposed a new model of dynamic cell formation by a neural approach. Ozdemir et al. (2007) introduced a two-stage clustering approach to cell design using modified fuzzy ART neural network. The proposed algorithm involved modifications of the learning procedure and resonance test of the fuzzy ART neural network. The two-stage clustering approach had succeeded in grouping parts and machines with better degree of perfection.

Yang and Yang (2008) proposed a modified ART1 neural learning algorithm with a more efficient vigilance parameter than the traditional ART1 network. The method was vigilance parameter-free and also more efficient in CF. It tried to overcome the limitations of the previously addressed ART1 models. Ponnambalam et al. (2008) proposed another modified ART1 neural network model for cell formation using production data. An attempt was made to form disjoint machine cells using modified ART1 (adaptive resonance theory) to handle the real valued workload matrix. The proposed algorithm used a supplementary procedure to effectively take care of the problem of generating cells with single machine that could be encountered at times.

Ateme-Nguema and Dao (2009) minimised the sum of dissimilarities between machines using a hybrid algorithm of quantised and fluctuated Hopfield neural networks and TS which proved to be effective in cell formation for big size industrial dataset in a fast and effective manner. It is also illustrated that the fluctuation associated with this quantisation enabled the network to escape from local minima, to converge to global minima, and consequently to obtain optimal solutions very frequently and much more quickly than pure quantised Hopfield networks (QHN). To improve the performance, a local optimisation method (TS algorithm) is combined to form a global hybrid heuristic. Pandian and Mahapatra (2009) applied modified ART1 in cell formation addressing production factors like operation time and sequence of operations.

Xing et al. (2010) made a comparison between ART and ACO system in part-machine clustering. Benchmark problems were chosen from literature and the performance measure GE was selected to evaluate the results.

Rezaeian et al. (2011) solved a new non-linear programming model using a novel hybrid approach based on the GA and ANN. From the computational analyses, the proposed algorithm is found to be efficient than other published techniques. Chattopadhyay et al. (2011) dealt with the self-organising map (SOM) method used as a visually decipherable clustering tool to CMS. The objective is to cluster the binary machine-part matrix through visually decipherable cluster of SOM colour-coding and labelling via the SOM map nodes. The proposed SOM approach produced solutions with a grouping efficacy that is at least as good as any results earlier reported in the literature and improved the grouping efficacy for 70%. Sengupta et al. (2011) demonstrated a new hybrid neural network approach, fuzzy ART K-means clustering technique (FAKMCT), to solve the PMG problem considering operation time. The performance of the proposed technique is compared to the existing clustering models such as simple K-means algorithm and modified ART1 algorithm as found in the recent literature.

Potočnik et al. (2012) presented an approach to organise the production cells by means of clustering-manufactured products into groups with similar product properties. Several clustering methods are compared, including the hierarchical clustering, k-means and SOM clustering. Obtained results optimise the production resources and minimise the work and material flow transfer between the production cells.

## 4 Analysis and discussion

Based on the above discussion, the different ANN approaches are identified and the literature available is classified and presented in Table 1.

**Table 1** Various ANN approaches in CF are categorised

| | |
|---|---|
| IAC model | Moon (1990, 1992), Moon and Chi (1992) and Chu (1997) |
| Stochastic neural network/modifications | Arizono et al. (1996) |
| Carpenter Grossberg network | Shashidhar et al. (1992) |
| Competitive learning/modifications | Chu (1993), Malve and Ramachandran (1991), Venugopal and Narendran (1992, 1994) and Malakooti and Yang (1995) |
| Graph neural approach | Mahdavi et al. (2001) |
| Self-organising feature map/modifications | Venugopal and Narendran (1992, 1994), Lee et al. (1992), Rao and Gu (1994), Kiang et al. (1995), Rao and Gu (1995), Kulkarni and Kiang (1995), Jang and Rhee (1997), Onwubolu (1999), Rao et al. (2000), Kuo et al. (2001), Guerrero et al. (2002), Chattopadhyay et al. (2011) and Potočnik et al. (2012) |
| Adaptive resonance theory/modifications/fuzzy ART/ART2 | Kusiak and Chung (1991), Dagli and Huggahali (1991), Kao and Moon (1991), Burke and Kamal (1992), Dagli and Sen (1992), Liao and Chen (1993), Kaparthi et al. (1993), Liao and Lee (1994), Suresh and Kaparthi (1994), Dagli and Huggahalli (1995), Chen and Cheng (1995), Burke and Kamal (1995), Suresh et al. (1995), Chen et al. (1996, 2002), Kamal and Burke (1996), Enke et al. (1998), Lee and Fischer (1999), Suresh et al. (1999), Enke et al. (2000), Ming-Laing et al. (2002), Park and Suresh (2003), Peker and Kara (2004), Venkumar and Haq (2005, 2006a, 2006b), Kuo et al. (2006), Won and Currie (2007), Ozdemir et al. (2007), Yang and Yang (2008), Ponnambalam et al. (2008), Pandian and Mahapatra (2009) and Sengupta et al. (2011) |
| Fuzzy min-max | Dobado et al. (2002) |
| Transiently chaotic neural network | Soleymanpour et al. (2002) and Solimanpur et al. (2004) |
| Hopfield neural network/modifications | Ateme-Nguema and Dao (2009) and Zolfaghari and Liang (1997) |
| Kohonen self-organising map networks | Chakraborty and Roy (1993), Pilot and Knosala (1998), Kiang (2001) and Venkumar and Haq (2006) |
| Adaptive hamming net | Lee et al. (1997) |
| Back propagation (BP) models | Kao and Moon (1991), Moon and Roy (1992), Kao and Moon (1998) and Onwubolu (1999) |

Further Figure 2 highlights the major ANN approaches in CMS and demonstrates the usage percentage of the various neural network models as found in the literature. Table 1 states that the SOM and fuzzy ART-based methods are highly practiced as cell formation methodologies due to the various advantages and disadvantages of both of the techniques.

**Table 2** Discussion on the major ANN approaches in CMS

| | | *SOM* | | *ART* |
|---|---|---|---|---|
| Advantage | 1 | SOM networks are good at accepting such multi-dimensional input and transforming it into a visual map of fewer dimensions which provides an easy-to-use graphical UI to visualise the similarities between parts. This map is then used to cluster parts into families (Kulkarni and Kiang, 1995). | 1 | With the similarity co-efficient method, ART could create a number of alternative solutions by simply adjusting the vigilance parameter which increases the flexibility of problem (Chen and Cheng, 1995). |
| | 2 | SOM does not actually group the parts but offers an easy way to visualise a picture of the parts to be grouped together. Thus SOM can not only allow control over the number of cells but it also suggests alternative groups (Chattopadhyay et al., 2011). | 2 | Uses simple network architecture to reduce computational burden. |
| | 3 | It accepts different types of input data (Kulkarni and Kiang, 1995). | 3 | ART networks can continue to learn (without ignoring past learning) incorporating new information (Burke and Kamal, 1995). |
| | 4 | A powerful clustering tool with improved results (Kiang, 2001). | 4 | It supports on-line learning which allows new parts and machines to be immediately classified and scheduled on the shop floor and results in an intelligent manufacturing system (Enke et al., 2000). |
| | | | 5 | Ability to provide efficient clustering solutions at a very high computational speed and capability to handle large datasets. |

**Table 2** Discussion on the major ANN approaches in CMS (continued)

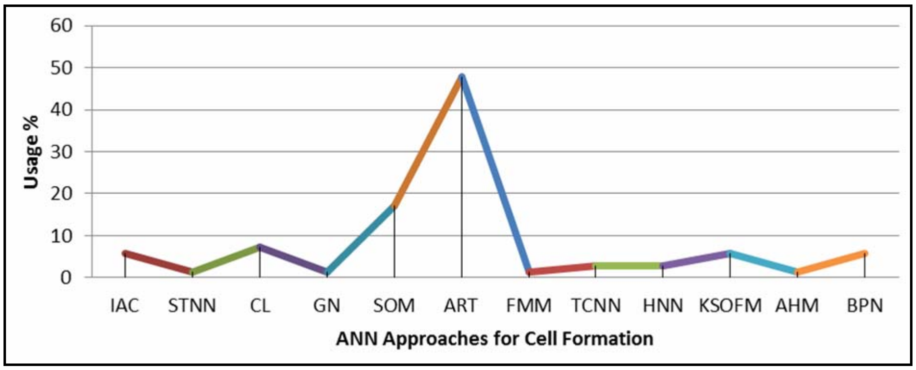
| | | *SOM* | | *ART* |
|---|---|---|---|---|
| Limitation | 1 | Usually requires a large number of experiments and long training cycles to decide appropriate network configuration (Kulkarni and Kiang, 1995). | 1 | The stored patterns grow sparser as more input vectors are applied (Dagli and Huggahalli, 1995). |
| | 2 | No direct procedure for duplicating bottleneck machines (Chattopadhyay et al., 2011). | 2 | The classification process is dependent on the order in which the input vectors are applied (Enke et al., 2000). |
| | 3 | Output of an SOM network does not automatically provide groupings of the points on the map (Kiang, 2001). | 3 | The performance of the ART1 is very sensitive to the values given to the threshold and heuristic (Enke et al., 2000). |
| | | | 4 | Determining the proper vigilance value can be problematic. |
| | | | 5 | Requires a completely binary representation of the parts to be grouped. |
| | | | 6 | A cluster exemplar is degraded (or decayed) during the learning phase which may lead to an improper classification in future iterations (Chen et al., 1996). |
| | | | 7 | The problems of bottleneck machines, or dealing with exceptional elements are not addressed (Enke et al., 1998). |

**Table 2** Discussion on the major ANN approaches in CMS (continued)

| | *SOM* | *ART* |
|---|---|---|
| Progress | Lee et al. (1992), Rao and Gu (1994) and Kulkarni and Kiang (1995) popularised SOM in cell formation problem. Inho and Jongtae (1997) proposed SOFM network where the manufacturing environment factors such as the operational sequences and lot sizes were considered and good solution in the sense of the total inter-cell movement, was obtained. Kiang (2001) explored the capability of KSOM in cluster analysis. Venkumar and Haq (2006) and Chattopadhyay et al. (2011) modified SOM for better results. | In an attempt to improve performance, Dagli and Huggahalli (1995) proposed modifications to the basic ART1 algorithm while Chen and Cheng (1995) proposed a set of supplementary procedures to handle the ill structured data. Further incorporation of the fuzzy ART overcame some limitations of binary representation of parts and Burke and Kamal (1995) made modifications where inputs could take on continuous values straightforward. Many more hybrid and modified works came up exploring the capability of ART. Modification made by Venkumar and Haq (2005) showed improved results. Yang and Yang (2008) identified the existing limitations of the modified ART approach (Dagli and Huggahalli, 1995) and tried to correct them. Pandian and Mahapatra (2009) also proposed some modifications considering production sequence data and operation time of the parts. |

These are demonstrated in Table 2. Furthermore the progress report is also provided in Table 2 for both of the methodologies. From the Figure 2, it could clearly be seen that among the major ANN approaches, ART and SOM (including modifications) are the most common approaches with significant results which supports the discussion of Table 2.

**Figure 2** Usage percentage of various neural network models in CM (see online version for colours)




### 4.1 A quantitative analysis of the neural approaches in CMS

Some detailed analysis are presented in Tables 4.1 and 4.2 to analyse the solution trend in the cell formation problem using neural network from its very beginning in the early 90s till date. As presented earlier, numerous ANN-based models have been proposed in the last two decades and provided some effective solutions in the CM domain. The survey highlights the major contributions, ANN models used, their clustering efficiencies based on GE, group efficacy, group technology efficiency (GTE), computational time and weighted group capability index (WGCI) to calculate the solution's performance.

In most cases the largest dataset used to demonstrate the performance is figured out, compared and finally, each of the solutions capability discussed. The number of clusters formed in each approach is noted. The programming language used and the computers configurations are also enlisted for a better comparison. Table 3 shows the list of references. Table 4.1 projects the solution approaches, experimented datasets and compared algorithms, while in Table 4.2 the clustering efficiency, tool used, machine configuration and overall improvements of the resulting solutions are analysed.

### 4.2 Observations

From Tables 4.1 and 4.2,

- It could clearly be seen that hybrid approaches provides good solutions and fuzzy neural approaches are the most common which covers around 25% of the literary observations, and has frequent successful results.

- Grouping efficiency and efficacy are the common performance measures used in the literature (around 53%) while computational time clearly demonstrates the efficiency of the algorithm to handle large complex datasets.
- Among the datasets used in the literature, dataset presented by Chandrasekharan and Rajagopalan (1987) proved to be a common participant with 40 machines and 100 parts. With the progress of neural network in cell formation the solution time of the dataset kept reducing from 2 minutes and 36 EE to 0.05 seconds with just 2 EE remaining.
- The programming language used and the computer configuration gives a better understanding of the solutions capability and its dependence on the PC and individual programming skills. Pentium Processors are used often while C and C++ are the most frequent programming languages (around 37%).
- Figure 3 demonstrates the approximate quantum of research carried out based on neural network approaches in CMS since the last two decades while Figure 4 traces the progress of the various ANN approaches in the domain by analysing the time taken (in seconds) to cluster an incidence matrix of 40 × 100 [dataset given by Chandrasekharan and Rajagopalan (1987)] by the different ANN models. The results show a clear improvement in the speed of execution over the years.

So finally from these observations a holistic view and the success factors are conveyed and the analysed research trend of neural networks in cell formation problem is identified.

**Table 3** List of references

| *Solution no.* | *Reference* | *Solution no.* | *Reference* |
|---|---|---|---|
| 1 | Shashidhar and Suresh (1992) | 17 | Enke et al. (2000) |
| 2 | Chao-Hsien Chu (1993) | 18 | Lozano et al. (2001) |
| 3 | Suresh and Kaparthi (1994) | 19 | Kiang (2001) |
| 4 | Dagli and Huggahalli (1995) | 20 | Chen et al. (2002) |
| 5 | Chen and Cheng (1995) | 21 | Guerrero et al. (2002) |
| 6 | Burke and Kamal (1995) | 22 | Dobado et al. (2002) |
| 7 | Kulkarni and Kiang (1995) | 23 | Soleymanpour et al. (2002) |
| 8 | Chen et al. (1996) | 24 | Peker and Kara (2004) |
| 9 | Kamal and burke (1996) | 25 | Venkumar and Haq (2005) |
| 10 | Chao-Hsien Chu (1997) | 26 | Venkumar and Haq (2006a) |
| 11 | Inho and Jongtae (1997) | 27 | Venkumar and Haq (2006b) |
| 12 | Kao and Moon (1997) | 28 | Won and Currie (2007) |
| 13 | Zolfaghari and Liang (1997) | 29 | Ozdemir et al. (2007) |
| 14 | Enke et al. (1998) | 30 | Yang and Yang (2008) |
| 15 | Liang and Zolfaghari (1999) | 31 | Pandian and Mahapatra (2009) |
| 16 | Suresh et al. (1999) | 32 | Ateme-Nguema and Dao (2009) |

**Table 4.1** Solution methods, datasets used and compared algorithms

| *Solution no.* | *Year* | *Author* | *HB* | *Approach* | *Dataset used* | *DS* | *Compared to* |
|---|---|---|---|---|---|---|---|
| 1 | 1992 | Shashidhar and Suresh | | CGNN | Kumar and Vennelli (1987) | 30 × 41 | Linear clustering algorithm |
| 2 | 1993 | Chao-Hsien Chu | | CL | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | Zodiac |
| 3 | 1994 | Suresh and Kaparthi | Y | FART | Generated | 2,800 × 70 | DCA, ROC2 |
| 4 | 1995 | Dagli and Huggahalli | | ART1 | Dagli and Huggahalli (1991) | 90 × 36 | ROC2 |
| 5 | 1995 | Chen and Cheng | | Extended ART1 | Boe and Cheng (1991) | 20 × 35 | Boe and Cheng's algorithm |
| 6 | 1995 | Burke and Kamal, | Y | Fuzzy ART | Burbidge (1971) | 16 × 43 | PFA and ART1 |
| 7 | 1995 | Kulkarni and Kiang | | SOM | Burbidge (1971) | 16 × 43 | PFA, ROC, DCA |
| 8 | 1996 | Chen et al. | | Modified ART1 | Boe and Cheng (1991) | 20 × 35 | Boe and Cheng's algorithm |
| 9 | 1996 | Kamal and burke | Y | FACT | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | Zodiac |
| 10 | 1997 | Chao-Hsien Chu | | IAC | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | CL and ART1 |
| 11 | 1997 | Inho and Jongtae | | SOFM | Industry-size examples | 80 × 92 | ROC and SCM |
| 12 | 1997 | Kao and Moon | | FBMAN | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | Zodiac |
| 13 | 1997 | Zolfaghari and Liang | Y | OSHN | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | ART1 |
| 14 | 1998 | Enke et al. | | ART1 | Industry-size examples | 256 × 256 | Serial ART1 |
| 15 | 1999 | Liang and Zolfaghari | | OSHN | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | Simulated annealing |
| 16 | 1999 | Suresh et al. | Y | FART | Generated | 1,400 × 70 | CASE |

Notes: HB: Hybrid, DS: dataset

**Table 4.1** Solution methods, datasets used and compared algorithms (continued)

| *Solution no.* | *Year* | *Author* | *HB* | *Approach* | *Dataset used* | *DS* | *Compared to* |
|---|---|---|---|---|---|---|---|
| 17 | 2000 | Enke et al. | | Parallel ART1 | Industry size | 3,500 × 500 | Serial ART1 |
| 18 | 2001 | Lozano et al. | | Hopfield | Generated | 50 × 100 | TS and PFMA |
| 19 | 2001 | Kiang | | KSOM | Burbidge (1971) | 16 × 43 | PFA |
| 20 | 2002 | Chen et al. | Y | ART1 and TS | Burbidge (1975) excluding machine 6 and 8 | 14 × 43 | RAN and TS |
| 21 | 2002 | Guerrero et al. | | SONN | Chandrasekharan and Rajagopalan (1989) | 24 × 40 | Maximum spanning tree (MST) |
| 22 | 2002 | DOBADO et al. | Y | FMM | Chandrasekharan and Rajagopalan (1989) | 24 × 40 | FART |
| 23 | 2002 | SOLEYMANPOUR et al. | | TCNN | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | ART1, extended-ARTl, OSHN |
| 24 | 2004 | PEKER and KARA | Y | Fuzzy ART | Boctor (1991) | 16 × 30 | Simulated annealing (SA) |
| 25 | 2005 | Venkumar and Haq | | Modified ART1 | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | Zodiac |
| 26 | 2006 | Venkumar and Haq | | Modified KSOM | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | HA and SAA |
| 27 | 2006 | Venkumar and Haq | | Modified ART1 | Chandrasekharan and Rajagopalan (1987) | 40 × 100 | HA and SA |
| 28 | 2007 | WON and CURRIE | Y | Fuzzy ART/RRR-RSS | Wu (1998) | 13 × 13 | Wu's algorithm |
| 29 | 2007 | Ozdemir et al. | Y | Modified fuzzy ART | King and Nakornchai (1982) | 16 × 43 | Fuzzy ART, fuzzy ART/FCSR algorithms, TSCA |
| 30 | 2008 | Yang and Yang | | Modified ART1 | Dagli and Huggahalli (1995) | 28 × 35 | Dagli and Huggahalli algorithm |
| 31 | 2009 | Pandian and Mahapatra | | Modified ART1 | trial dataset | 90 × 35 | |
| 32 | 2009 | Ateme-Nguema and Dao | Y | QFHN and TS | Chandrasekharan and Rajagopalan (1989) | 24 × 40 | Pure Hopfield net and pure QFHN net |

Notes: HB: Hybrid, DS: dataset

**Table 4.2** Clustering results and tools used

| *No.* | *Clustering efficiency* | | | | *Comments* | *Tool* | *Computer configuration* |
|---|---|---|---|---|---|---|---|
| | *Metric* | *Value in %* | *Comp time* | *No. of cells* | | | |
| 1 | | | 41 s | | Computational time was much less compared to 5 min. taken by the LCA. | PASCAL | |
| 2 | G-EFI | 82.3 | <2 min. | 10 | Inefficient in case of bottleneck machines. | BASIC and CLGS | IBM PC/AT 8 MHz |
| 3 | | | 29.25 s | | Outperformed DCA and ROC2 yet ART1 was faster. | FORTRAN 77 | IBM 4381 mainframe |
| 4 | | | 36 s | | Comparable to ROC2 and can handle bottle necks. | UNIX | HP-Apollo workstation |
| 5 | GE | 80.38 | | 4 | Average grouping efficiency is 2.02% higher. More reliable and efficient in case of ill structured data. | | |
| 6 | | | > 10 s | 5 | Fast computation yet result same as Burbidge and better than ART1. | | 486-based PC |
| 7 | G-EFI | 60.9 | <1 s | 5 | Outperformed ROC and PFA and got same result as DCA. | C++ | IBM RS/6000 |
| 8 | G-EFI | 77.36 | | 4 | Reduce dependence of result on incidence matrix with same or better results from literature. | | |
| 9 | GE | 95.09 | 15–20 s | 10 | Overcomes fuzzy ART limitations and had a good clustering result. | | IBM RISC/6000 |
| 10 | G-EFI | 82.32 | 53.3 s | 10 | Faster than CL and ART1 with grouping efficacy more than ART1 and same as CL. | BASIC and Turbo-C | 586 PC |
| 11 | G-EFI | 61.4 | 374 s | | Result outperformed ROC and SCM considering material flow and plant layout in cell formation. | | |
| 12 | GE | 95 | | 10 | Outperformed Zodiac and capable to deal with the difficult problems of exceptional parts. | | |

Notes: GE: grouping efficiency, GTE: group technology efficiency, EFI: grouping efficiency, WGCI: weighted group capability index

**Table 4.2** Clustering results and tools used (continued)

| *No.* | *Clustering efficiency* | | | | *Comments* | *Tool* | *Computer configuration* |
|---|---|---|---|---|---|---|---|
| | *Metric* | *Value in %* | *Comp time* | *No. of cells* | | | |
| 13 | GE | 95.1 | 4.18 s | 10 | Under restricted no of cells its computational time is very small and outperforms ART1. | C | 486 PC 33 MHz |
| 14 | | | 2.95 s | | Parallel ART1 shows a 95.1% decrease in time compared to serial ART.its speed is way ahead. | UNIX and CNAPS-C | CNAPS neuro-computer |
| 15 | GE | 94.81 | 4.67 s | 10 | SA method took 67.71 s while OSHN only 4.67 s hence it is much faster and the solution quality is also reasonably good. | C | 486-33 MHz PC. 486-33 MHz |
| 16 | | | 107 s | 7 | Viable approach for sequence-based clustering of parts and machines and has fast execution times for large datasets. | FORTRAN 77 | 233 MHz Pentium processor (laptop computer) |
| 17 | | | 141.18 s | | Capable t handle very large dataset with a very fast execution time though processing time is a bit high. | UNIX and CNAPS-C | CNAPS neuro-computer |
| 18 | | | 11.649 s | 10 | Its execution time is the lowest. | | Intel P II 450 MHz |
| 19 | G-EFI | 60.9 | | 5 | Flexibility in determining the number of clusters needed and provides a visual map that can be used as a decision-support tool. | C++ | IBM RS = 6,000 mini-computers |
| 20 | GE | 83 | 1.08 s | 5 | The computational results showed that it generated the best solutions in most of the examples. | | |
| 21 | | | 6.92 s | | While MST is faster than SONN, SONN always gives a better solution. | | Intel Pentium 166 MHZ |
| 22 | | | 0.2 s | 10 | Computational time was more than FART in most of the cases but FMM provided better solutions. | | Intel Pentium 133 MHz |

Notes: GE: grouping efficiency, GTE: group technology efficiency, EFI: grouping efficiency, WGCI: weighted group capability index

**Table 4.2** Clustering results and tools used (continued)

| *No.* | *Clustering efficiency* | | | | *Comments* | *Tool* | *Computer configuration* |
|---|---|---|---|---|---|---|---|
| | *Metric* | *Value in %* | *Comp time* | *No. of cells* | | | |
| 23 | GE | 95.1 | 3.37 s | 10 | Grouping Efficiency though is almost similar to the three compared, computational time taken was less. | Borland C++ | 550 MHz Pentium III PC |
| 24 | G-EFI | 62.1 | | | For both small- and large-scale problems, the fuzzy ART neural network was fast, effective and easy to implement. solved both binary and non-binary problems effectively. | PASCAL | |
| 25 | | | 0.05 s | 6 | Outperformed Zodiac with a very efficient CPU time and less no of cells, suitable for any size of machine-part incidence matrix. | C++ | Pentium III, 700 MHz system |
| 26 | | | 0.05 s | 6 | Fractional cell formation reduced the no of exceptional elements to great extent while time taken was reasonable | MATLAB 6.5 | Pentium IV 900 MHz systems |
| 27 | | | | 6 | Fractional cell formation reduced the no of exceptional elements to 2 which outperformed all other algorithm. | | |
| 28 | WGCI | 97.71 | | 3 | The proposed algorithm is robust and recoverable to large-sized ill-structured datasets, producing highly independent block diagonal solution close to the near-best one. | C++ | IBM compatible Pentium III PC with 1 GHz |
| 29 | GE | 78.98 | | 7 | Modified fuzzy ART outperformed all others except TSCA. | C | P 4 CPU 3 GHz PC with 512 MB RAM |
| 30 | GE | 90.68 | | 6 | Outperformed the existing results, analysed the drawbacks of ART1 and propose a modified ART1 to fit the application to GT. | | |
| 31 | GTE | 77.69 | 1.85 s | | Can deal with combination of operation sequence and operation time of the parts to address CF problem and outperforms others in most cases. | C++ | IBM Pentium IV PC with 2.4 GHz processor |
| 32 | GE | 86.4 | 72 s | 7 | Could escape from local minima, to converge to global minima, and outperformed pure Hopfield net and pure QFHN net. | | |

Notes: GE: grouping efficiency, GTE: group technology efficiency, EFI: grouping efficiency, WGCI: weighted group capability index

**Figure 3** Variation in number of articles published over the years

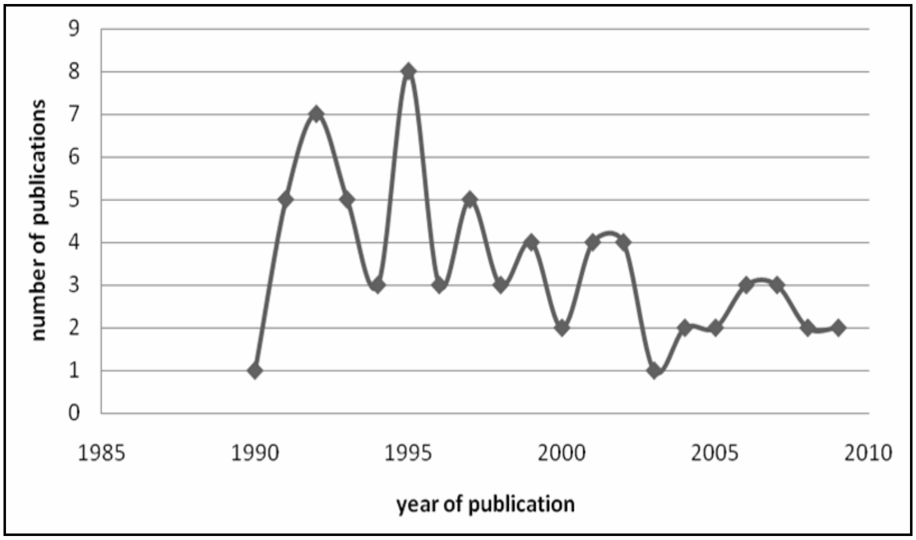
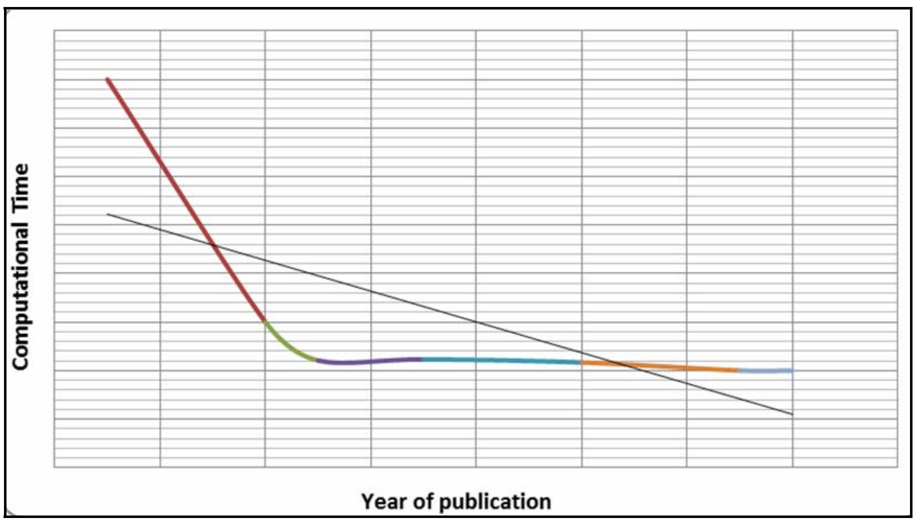



**Figure 4** Improvement over the years on a 40 × 100 dataset (see online version for colours)




## 5 Conclusions

This paper renders an analytical study of the ANN-based approaches in CF problem in CM since the last two decades. A significant list of research papers were identified, analysed and classified henceforth. The literature review part is distinctly separated in two decades to reflect the grown up complexities in the applied ANN-based methodologies. The study helped recognise the influence of ANN approaches in cell formation problem by incorporating the in-depth chronological analysis which further helped to identify the trend of research, improvements over the years and the capability of ANN approaches to handle complex data-sets in real-time industry scenario. The comparative study of the computational time, number of cells formed and the clustering efficiency obtained, helped to figure out the success rates of each approach and the progress achieved since early 90s till the recent era. The study also portrays that the future research could be carried out with the applications of SOM and ART with proper hybridisation of heuristics or clustering approaches. Hybrid methods are more complex but improved in terms of solution quality while dealing with CF problems. It is further demonstrated, how the proposed ANN-based methodologies are being improved on the largest dataset along with the period of time. The managerial implication is that increasing complexities in terms of hybridisation in methodologies will improve the solution to the CF problems when the problem is large and well balanced. Without the good blend of justified solution searching techniques with the ANN approaches, unnecessary complexities will make the cumbersome. It is also critical to utilise proper industry data to achieve more realistic solutions in CM which is scarcely available in published literature. This article could be immensely helpful for the researchers working in the above mentioned area.

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## Nomenclatures

| | |
|---|---|
| ANN | Artificial neural network |
| FACT | fuzzy ART with add clustering technique |
| ART | Adaptive resonance theory |
| IAC | Interactive activation and competition |
| SOFM | Self-organising feature map |
| SOM | Self-organising map |
| SONN | Self-organising neural network |
| KSOM | Kohonen self-organising map |
| PMIM | Part machine incidence matrix |
| FNN | Fuzzy neural network |
| GT | Group technology |
| FBMAN | Feature-based memory association network |
| OSHN | Ortho-synapse Hopfield network |
| SA | Simulated annealing |
| GA | Genetic algorithms |
| WGCI | Weighted group capability index |
| HNN | Hopfield neural network |
| CL | Competitive learning |
| IPFACS | Image processing and fuzzy ART-based clustering system |
| EE | Exceptional elements |
| TCNN | Transiently chaotic neural network |
| FMM | Fuzzy min-max |
| fuzzy ART/RRR-RSS | fuzzy ART/re-arrangement re-assignment |
| QHN | Quantised Hopfield networks |
| QFHN | Quantised and fluctuated Hopfield networks |
| TS | Tabu search |

| | |
|---|---|
| ACS | Ant colony system |
| CNN | Competitive neural network |
| AI | Artificial intelligence |
| AHM | Adaptive hamming net |
| STNN | Stochastic neural network |
| GN | Graph neural |
| BPN | Back propagation network |
| PMG | Part machine grouping |
| UI | User interface |