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Designing Cell Production Arrangement Scenarios with the Approach of Artificial Neural Networks

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Abstract
The arrangement of machines and how to move them is one of the most important issues in factories and production units, which always imposes a lot of costs on the collections. Although the arrangement of machines is done once over a long period of time, its effects are very widespread. Accordingly, it is necessary to pay more attention to the matter of arrangement. Today, cellular production is also one of the widespread production methods at the industrial level, which requires this precision. The current research aims to produce new arrangements by using artificial neural networks. The way of working is that by using the data related to the number of production parts, the production time of each part, and the group of parts under investigation, as well as the costs of the devices, this clustering is done in 3 modes of 4, 6, and 9. Performing this type of clustering has higher accuracy and speed than other methods, and the results may be somewhat different in each scenario and with each clustering time, which increases flexibility in selection.
Keywords: Artificial neural networks, cell production, production line arrangement, scenario analysis

Introduction

Group technology is a production philosophy based on organizing and grouping common tasks with the aim of improving the productivity of the production system (Sun et al., 2021). Cell production is one of the most important applications of group technology that forms production cells in such a way that each family of parts in a cell is processed by a specific group of machines related to that cell (machine cell) (Moscote & Tyagunov, 2022). Cellular production is an innovative production strategy that has been used in modern production systems such as flexible production systems and just-in-time production (Quintanar et al., 2022).

Cell formation, cell arrangement, and cell management are three important steps that must be considered in the successful design of a cell production system. Cell formation includes determining the family of machine parts and cells with the aim of reducing the time of moving parts between cells. The design of a cell arrangement includes two parts: 1) determining the arrangement of cells at the workshop level and 2) specifying the arrangement of machines in each cell, both of which are done with the aim of reducing the time of transfers; finally, cell management deals with planning issues such as cell

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scheduling (Clark, et al., 2022). In cell scheduling, the problem of scheduling the family of parts and each unique part is considered. Communication between these three decisions plays an important role in the design of a cellular production system (Wu et al., 2020).

In most of the studies conducted in the field of cell production systems, efforts have been made to solve only one of the three mentioned issues (CF, CL, CS), and some research has been done to solve two or all three factors consecutively. These approaches create solutions that are likely to work for one of these three problems while not being satisfactory for the overall system. This phenomenon is due to the effect of these three sub-problems on each other during the design of the cell production system. The only integrated mathematical model in which cell formation, cell arrangement, and scheduling are considered simultaneously was presented by Wu (2007), but in their model and solution algorithm, cell arrangement is not correctly specified and cells may overlap with each other. In Arkat et al.'s (2012) model, in addition to keeping all the assumptions and advantages of the previous model, the problem of overlapping cells was solved, and the position (coordinates) of the machines was accurately determined. Since in the cell production system, the intercellular movement factor is of great importance in terms of time and cost, the position of the cells relative to each other and their distance from each other is important during cell formation (Wu and colleagues, 2020). For this reason, it is necessary to pay attention to the arrangement of cells and the way they are placed when designing a cell production system so that the problem appears more realistic. Therefore, in this research, it was tried to design the cell production system in parallel with the cell formation process and do this with the approach of an artificial neural network based on the relationships of parts production. In the following, after reviewing previous studies, we will discuss how to model and use artificial neural networks.

Literature Review

For the successful design of a cell production system, three basic factors of cell formation, cell arrangement, and cell management (scheduling) should be considered (Wu et al., 2007). Most of the studies conducted in the field of designing cell production systems are related to the issue of cell formation because it is the most important issue when designing this system. This research can be divided into two categories based on the two main groups of production data used (Jabal Ameli et al., 2007); the first group is the methods that use the part-machine matrix as the only input data. The second group are methods that use other manufacturing information such as production volume, setup and processing time, sequence of operations, machine capabilities, alternative process paths, machine reliability, etc.

Many innovative and accurate solution approaches that have been developed to solve cell formation problems include the Clustering analysis approach, the Graph Partitioning approach, the Branch and Bound algorithms, and metaheuristic algorithms. Detailed reviews of cell formation problem solving approaches are available in articles (Risman et al., 1997; Hachicha et al., 1998; Mahdavi et al., 2009; and Lee et al., 2010). Cell arrangement design is the goal of some studies on the design of cell production systems. Most research has assumed that the cell is formed and then solves the problem of intracellular and intercellular arrangement. Baronti et al (2022) proposed a multi-dimensional measurement and scaling algorithm for the design of intercellular arrangements considering the preformed cell. The Computerized Layout Solutions using Simulated Annealing (CLASS) method is a method based on refrigeration simulation that was presented by Jajodia (2012) so that it determines the intercellular and intracellular arrangement simultaneously. Salum (2000) presented a two-step approach using simulation to solve the layout problem of a cell production system. Urban et al. (2000) have proposed an integrated model for formulating the machine layout problem as well as the product allocation problem in which the configuration of the production system is dictated by the manufacturing requirements.

Some researchers have studied the two issues of cell formation and cell arrangement together. Arvindh and Irani (2014) have investigated the effects of four problems (cell formation, machine duplication, intracellular and intercellular arrangement) in the design of the cell production system and also their effects on each other, and to solve these sub-problems simultaneously, they have proposed an iterative solution approach. Akturk et al. (2016) presented a mathematical model to determine the intracellular arrangement and cell formation with the aim of minimizing the cost of moving materials. He has also proposed values as dissimilarity values between pieces based on the sequence of operations. Chiang and Lee et al. (2014) have investigated the two problems of cell formation and intercellular arrangement in terms of linear arrangement for machine cells with the aim of minimizing the cost of intercellular flow. To solve this problem, they have used a combined approach of refrigeration simulation with a dynamic programming algorithm.

Mahdavi et al. (2008) have proposed an innovative algorithm based on the flow matrix for the formation of cells and the arrangement of machines inside each cell simultaneously. Ahi et al. (2009) developed a two-stage solution approach for simultaneously solving cell formation and cell arrangement problems, in which, in the first stage, an initial solution is obtained using a technique for ranking criteria by the ideal solution, and then, in the second step, this solution is improved. Wu et al. (2006 and 2007) proposed a mathematical model and developed a genetic algorithm to solve the problem of cell formation and cell arrangement simultaneously.

In an article, Mohammadi and Farqani (2016) discussed the design of an S-shaped cell production system. In this research, the main goal is to present a dual-purpose model of the formation and arrangement of cells based on the S-shaped arrangement for a cell production system. The outputs of the model include the dimensions of the machines, the length and width of the corridors, as well as the number and optimal arrangement of the machines in the cells. In this research, in order to solve the problem, they used a combined approach of simulated annealing and dynamic systems, and the presented results indicate the efficiency of the solution method compared to other solution methods presented in similar articles.

Murugan et al (2016) in an article addressed the simultaneous optimization of the problem of arrangement and scheduling of activities for a robotic cell production system. In this article, a model was presented that simultaneously performs layout design and activity scheduling for several discussion machines. They used a multi-objective genetic algorithm to solve the above problem.

Al-Badi et al (2022) in an article with title:" Artificial Neural Network Modelling and Experimental Evaluation of Dust and Thermal Energy Impact on Monocrystalline and Polycrystalline Photovoltaic Modules" argued that the accuracy of the predicting power of the six PV modules was considerable, at 97.5%, 97.4%, 97.6%, 96.7%, 96.5%, and 95.5%, respectively. The dust negatively reduces the PV modules' power production performance by about 1% in PV modules four and six. Furthermore, the results were evident that the negative effect of the dust on the PV module production based on the values of RMSE, which measures the square root of the average of the square's errors. The average errors in predicting the power production of the six PV modules are 0.36406, 0.38912, 0.34964, 0.49769, 0.46486, and 0.68238.

Webber et al (2022) in research with title: "Application of Artificial Neural Networks in Construction Management: A Scientometric Review" conclued that there is still a lack of systematic research and sufficient attention to the application of ANNs in CM. Furthermore, ANN applications still face many challenges such as data collection, cleaning and storage, the collaboration of different stakeholders, researchers and countries/regions, as well as the systematic design for the needed platforms. The findings are valuable to both the researchers and industry practitioners who are committed to ANNs in CM.

Martin et al (2022) in article with title: "Artificial neural networks: a practical review of applications involving fractional calculus" argued that Regarding the parameters training using optimization algorithms issue, in this manuscript, the systems types, the fractional derivatives involved, and the optimization algorithm employed to train the ANN parameters are also presented. In most of the works found in the literature where ANNs and FC are involved, the authors focused on controlling the systems using synchronization and stabilization. Furthermore, recent applications of ANNs with FC in several fields such as medicine, cryptographic, image processing, robotic are reviewed in detail in this manuscript. Works with applications, such as chaos analysis, functions approximation, heat transfer process, periodicity, and dissipativity, also were included. Almost to the end of the paper, several future research topics arising on ANNs involved with FC are recommended to the researcher's community. From the bibliographic review, we concluded that the Caputo derivative is the most utilized derivative for solving problems with ANNs because its initial values take the same form as the differential equations of integer-order.

Despite the research done in the literature of the research subject, the gaps in the past research can be mentioned in the following cases: a separate and isolated look at the topics of production planning, operator allocation, and facility layout; In addition, the innovation of the plan is to design an integrated model to consider the connection of parts production with facility layout simultaneously.

Research Methodology

According to the nature of the problem, the main question that must be answered is how the system is arranged. Arrangement means the arrangement of cells next to each other, which defines the neighborhoods. It is also necessary to determine how many members each cell has and how much they move.Finally, based on the optimal state of the problem, the allocation of manpower will be done. For the aforementioned analysis, the model designed in this research is to use an artificial neural network to suggest the layout and then model and solve the problem based on a non-linear mathematical model using a genetic algorithm. In the following, these two stages of the model will be explained.

In this research, first a matrix is formed based on 8 criteria and 25 machines. The first 6 criteria are related to the total operation time by each machine, and the last 2 criteria are related to the depreciation cost and moving cost of each machine. The reason for considering these criteria is that the amount of activity, displacement, and high cost should be reduced as much as possible within the clusters, and as a result, human resources should be used accordingly. Calculation of manpower based on the results of two mathematical models and a neural network is done at the end of the work.

A Clustering Model Based On an Artificial Neural Network

A cluster is a series of similar data points that behave as a single group. It should be mentioned that clustering is somewhat similar to classification, with the difference that the classes are not predefined and specific, and the act of grouping data is done without supervision (Uzsoy et al. 2018).

Unlike classification, which analyzes data based on classes, in clustering, data is analyzed without considering the class labels, and usually the class labels are not clear in the training data. Clustering is sometimes used to determine and generate labels for data (Tashtosh et al., 2020). Clustered data are arranged in such a way that the objects within each cluster have the greatest similarity to each other (Haraguchi, 2019). Each cluster is a class. The rules of each class are derived from its corresponding cluster.

Implementation of Artificial Neural Networks

Many methods and algorithms have been presented for clustering. One of these methods is self-organized mapping. Self-organizing mapping is a type of artificial neural network that is trained in an unsupervised manner and whose purpose is to create a representation of the input data space into a space with lower dimensions (usually two), which is called a map (Yari et al., 2021). A self-organizing map is different from other artificial neural networks because it uses a neighborhood function to preserve the topological properties of the input space. This model was presented for the first time by a Finnish professor named Kohonen. That's why it is known as the Kohonen map.

Like most artificial neural networks, SOM is implemented in two phases of training and mapping. In the training phase, the map is made using the input samples. Education is a competitive process, which is also known as vector progression. In the mapping phase, new input vectors are automatically classified.

The self-organizing map consists of components called neurons. Each neuron is characterized by a weight vector with dimensions equal to the dimensions of the input data and its position in the mapping space. Neurons are usually arranged in a regular space in the form of a hexagonal or rectangular grid. As mentioned before, the self-organizing map is a description of the input space with high dimensions transformed into a map with low dimensions. To place a vector from the input data space in the map, SOM finds the neuron that has the closest weight vector to the input data space. Then, after the closest neuron is determined, the weight vector value of the neuron is updated according to the input data. In this method, it is very conventional to use the U matrix. The value of a neuron in the U matrix is the average distance between the neuron and its nearest neighbors. In a square network, four or eight neighbors are considered, and in a hexagonal network, six neighbors are considered. Among the useful developments that have been made in this type of network, we can mention torus networks. In these networks, the opposite edges are connected to each other and use a large number of neurons.

It has been shown that self-organizing maps with a small number of neurons behave like the k-means method, while large self-organizing networks sort the data in a way that preserves the original topological features. This feature led to the emergence of ESOM networks. The difference between ESOM and traditional SOM is that ESOM uses a very large number (at least several thousand) of neurons. Therefore, ESOM is more suitable for creating an overview of the structure of scattered and high-dimensional data. In ESOMs, the characteristics of the data are better defined, so ESOMs, which have thousands of neurons, can be used for more appropriate clustering of data.

Research Findings

At this stage, it is necessary to prepare the tables related to the artificial neural network using the available data. For this purpose, using the number of parts and the operation time of each part obtained from the average table, six parts-time columns were calculated, which show the importance of each machine and its relationship with the parts. Accordingly, two other criteria, such as depreciation cost and relocation cost, have been included as auxiliary and required criteria for clustering.

Table 1.
Input of artificial neural network including cost criteria and part-time relation of machines

	piece of time 1	piece of time 2	piece of time 3	piece of time 4	piece of time 5	piece of time 6	Depreciation cost	Moving cost
Machine 1	0	34565.7	0	0	0	0	1442.5	820
Machine 2	73348	55836.9	0	0	14239	0	1767.5	810.5
Machine 3	44008.8	0	0	0	21358.5	0	1942.5	817.5
Machine 4	0	0	0	75222	0	93600	1762.5	564
Machine 5	0	0	66851.8	0	0	104000	1590	827.5
Machine 6	0	50519.1	0	0	0	0	2965	350
Machine 7	42175.1	0	0	0	41293.1	0	3350	170
Machine 8	34840.3	0	0	0	0	0	2237.5	870
Machine 9	0	0	40692.4	0	0	20800	2950	847.5
Machine 10	0	0	72665	85968	39869.2	0	1605	265
Machine 11	45842.5	0	0	0	0	47840	1597.5	497.5
Machine 12	0	0	0	32238	0	0	2127.5	557.5
Machine 13	0	82425.9	0	0	0	0	1845	265
Machine 14	38507.7	0	0	64476	0	0	2245	482.5
Machine 15	0	0	58132	0	0	0	2267.5	540
Machine 16	0	53178	0	0	28478	62400	1672.5	225
Machine 17	27505.5	0	0	0	0	41600	2010	527.5
Machine 18	0	53178	95917.8	0	0	62400	2620	280
Machine 19	0	0	0	42984	28478	0	2985	222.5
Machine 20	0	0	0	64476	0	41600	1565	592.5
Machine 21	0	53178	0	0	42717	62400	1330	505
Machine 22	45842.5	85084.8	66851.8	0	0	0	2670	412.5
Machine 23	64179.5	0	0	42984	0	62400	2945	855
Machine 24	0	0	0	0	42717	22880	1872.5	715
Machine 25	73348	0	58132	0	0	74880	2740	267.5

In order to run the software, first the neural network was evaluated and cleaned based on the prepared table. The data was entered into the software line by line and saved in the workspace environment. The codes related to neural networks have been prepared and are in the Dimension section. They have been prepared in 2x2 and 3x3 modes. Because the output of these data gives 4 and 9 clusters, respectively, the experts determined that this difference in the number of clusters is irrational. Therefore, an intermediate mode was made for the number of clusters in the form of 6 in 2x3 dimensions. The view of the 9-cluster network is shown in the figure below.

The results of the analysis in this section are divided into two general parts: the results of the neural network and the model. The results of running the neural network in three modes of 4 clusters, 6 clusters, and 9 clusters show how many machines and which machines should be placed in each cell.

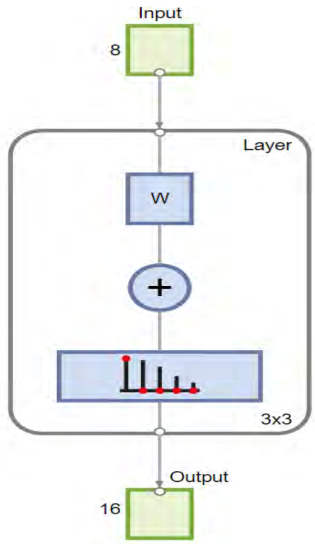


Fig 1: Sketched network map of the artificial neural network for the 9-cluster mode

The Results of Artificial Neural Network Implementation

4-Cluster Mode

After analyzing the neural network in 2x2 mode, the maps obtained from the analysis have been determined, which show the neighborhood of the clusters, the cluster distribution based on each criterion, and finally the number of members in each cluster. The neighborhood diagram of the clusters generally shows that the cluster with coordinates (0.5,1) in the upper left and the cluster with coordinates (1,0) in the lower right have the closest neighborhood (light yellow color) to each other. In addition, the cluster (0,0) has the greatest distance with the cluster (1,0), which indicates the farthest neighborhood (black color).

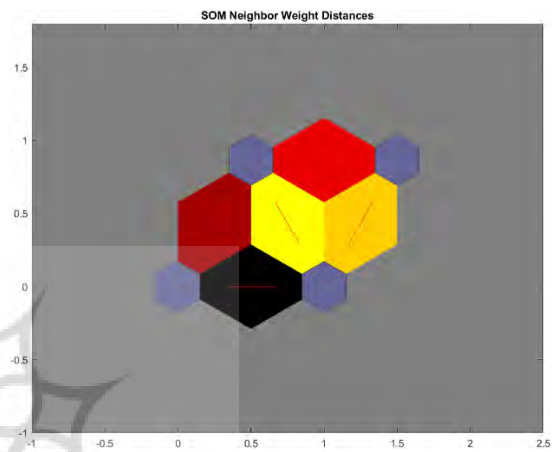


Fig 2. Inter-cluster communication map in 4-cluster mode

In the scatter plot based on each attribute, lighter colors indicate low membership and dark colors indicate high cluster membership.

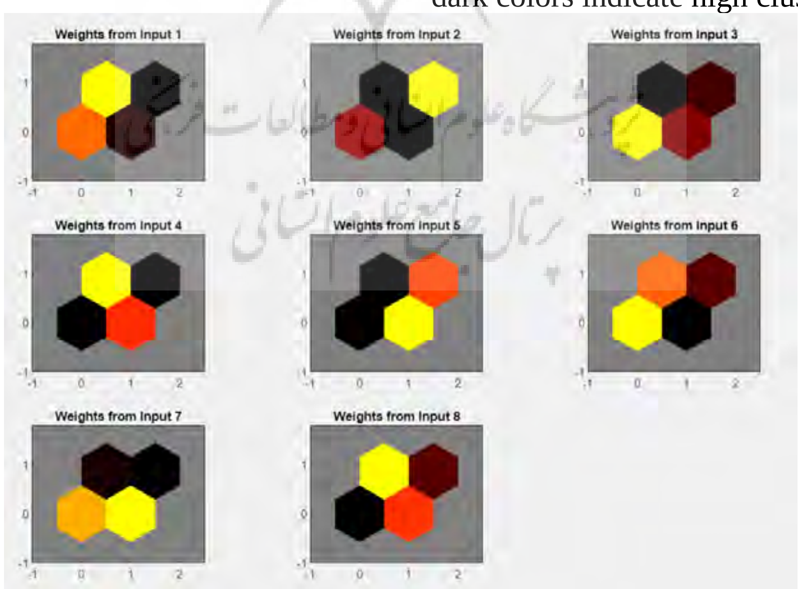


Figure 3. The map of the number of intra-cluster membership in the 4-cluster state by each index

In the diagram of the number of members in the cluster, it is shown that the cluster (1,0) contains the most members (10) and the cluster adjacent to it is on the left side, with the largest distance and the least number of members.

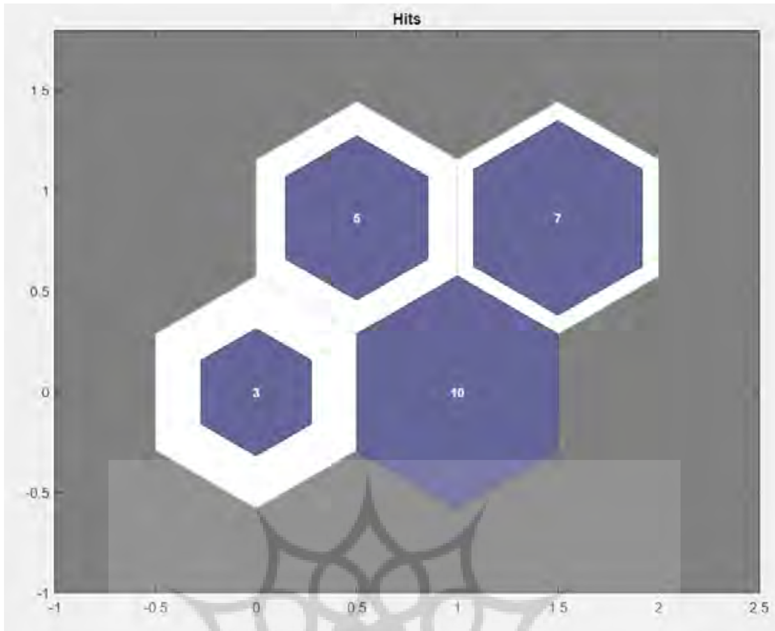


Fig 4. Location map of clusters (cells) and the number of members in the cluster in the 4-cluster state

The following table shows which machines each cluster (cell) has assigned to itself. This table will be considered as the basis of celling in the mathematical model.

Table 2.
Allocation of machines and cells in 4-cluster mode

	Cell 1	Cell 2	Cell 3	Cell 4
Machine 1	0	0	0	1
Machine 2	0	0	0	1
Machine 3	0	0	0	1
Machine 4	0	0	1	0
Machine 5	1	0	0	0
Machine 6	0	0	0	1
Machine 7	0	0	0	1
Machine 8	0	0	0	1
Machine 9	0	1	0	0
Machine 10	0	1	0	0
Machine 11	0	0	1	0
Machine 12	0	1	0	0
Machine 13	0	0	0	1
Machine 14	0	1	0	0
Machine 15	0	1	0	0
Machine 16	0	0	1	0
Machine 17	0	0	1	0
Machine 18	1	0	0	0

	Cell 1	Cell 2	Cell 3	Cell 4
Machine 19	0	0	0	1
Machine 20	0	0	0	1
Machine 21	0	0	1	0
Machine 22	0	0	0	1
Machine 23	0	0	1	0
Machine 24	0	0	1	0
Machine 25	1	0	0	0
Sum of members	3	5	7	10

Cluster Mode

After analyzing the neural network in 3x2 mode and 6-cluster mode, the maps obtained from the analysis have been determined, which respectively show the neighborhood of the clusters, the cluster distribution based on each criterion, and finally the number of members in each cluster. The cluster neighborhood diagram generally shows that the cluster with coordinates (1.5,1) and the cluster with coordinates (2,0) have the closest neighborhood (light yellow color) to each other. In addition, the cluster (1,0) has the greatest distance from the cluster (2,0), which indicates the farthest neighborhood (black color).

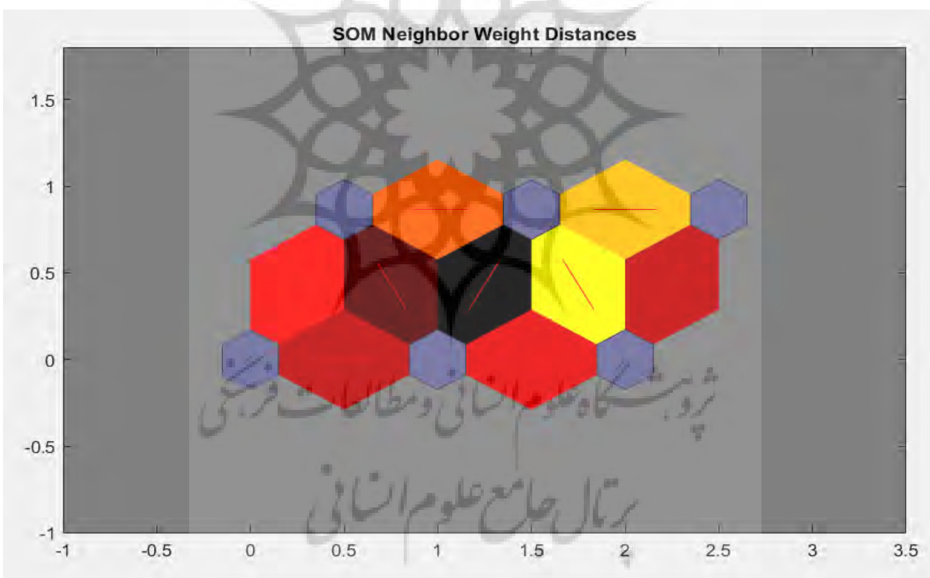


Fig 5. Inter-cluster communication map in 6-cluster mode

In the scatter plot based on each attribute, lighter colors indicate low membership and dark colors indicate high cluster membership. In most cases, the lower-middle cluster shows the largest number of members.

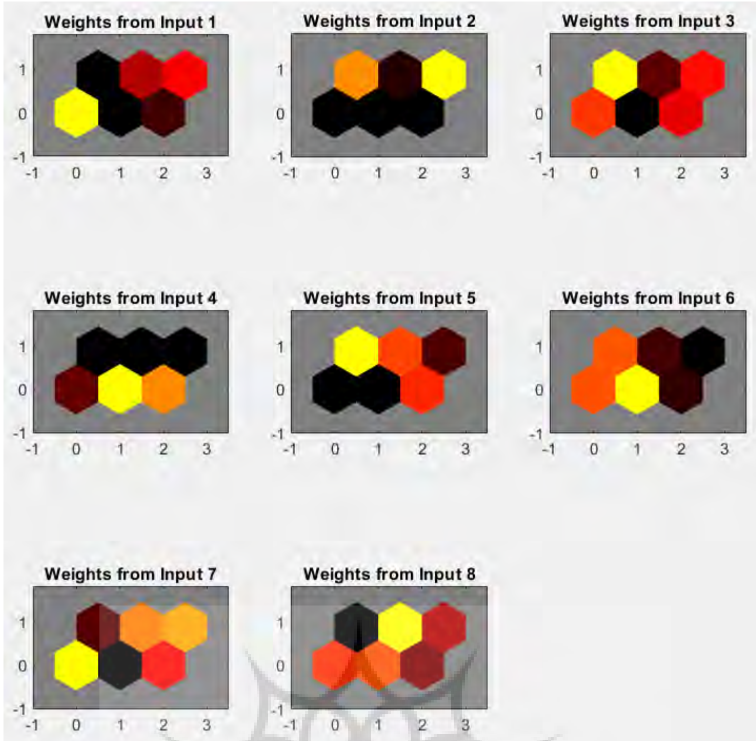


Fig 6. The map of the number of intra-cluster membership in the 6-cluster state by each index

In the diagram of the number of members in the cluster, it is shown that the cluster (1.5, 1) contains the most members (8) and the cluster adjacent to it is on the left-bottom side, with the largest distance between neighbors and the least number of members.

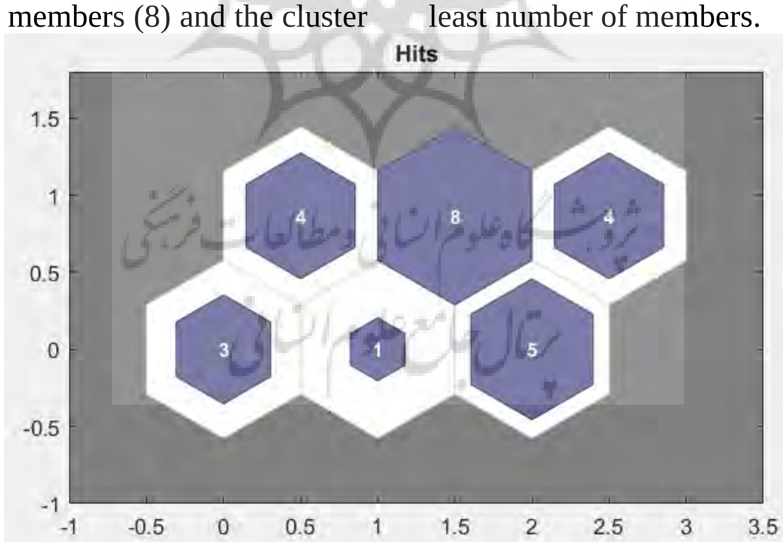


Figure 7.Location map of clusters (cells) and the number of members in the cluster in the 9-cluster state

The following table shows which machines each cluster (cell) has assigned to itself. This table will be considered as the basis of celling in the mathematical model.

Table 3.
Allocation of machines and cells in 6-cluster mode

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6
Machine 1	0	0	0	0	1	0
Machine 2	0	0	0	0	0	1
Machine 3	0	0	0	0	1	0
Machine 4	0	1	0	0	0	0
Machine 5	0	0	0	1	0	0
Machine 6	0	0	0	0	0	1
Machine 7	0	0	0	0	1	0
Machine 8	0	0	0	0	1	0
Machine 9	0	0	0	0	1	0
Machine 10	0	0	1	0	0	0
Machine 11	1	0	0	0	0	0
Machine 12	0	0	1	0	0	0
Machine 13	0	0	0	0	0	1
Machine 14	0	0	1	0	0	0
Machine 15	0	0	0	0	1	0
Machine 16	0	0	0	1	0	0
Machine 17	0	0	0	0	1	0
Machine 18	0	0	0	1	0	0
Machine 19	0	0	1	0	0	0
Machine 20	0	0	1	0	0	0
Machine 21	0	0	0	1	0	0
Machine 22	0	0	0	0	0	1
Machine 23	1	0	0	0	0	0
Machine 24	0	0	0	0	1	0
Machine 25	1	0	0	0	0	0
Sum of members	3	1	5	4	8	4

Cluster Mode

The latest implementation of the neural network in 3x3 mode is the 9-cluster mode, and in the maps obtained from the analysis, the neighborhood of the clusters, the cluster distribution based on each criterion, and finally the number of members in each cluster and the state of them are determined.

The cluster neighborhood diagram generally shows that the cluster with coordinates (1.5, 1) and the cluster with coordinates (2, 0) have the closest neighborhood (light yellow color) to each other. Furthermore, the cluster (1.5, 1) has the greatest distance with the cluster (2.5,1), indicating the most distant neighbor (black color).

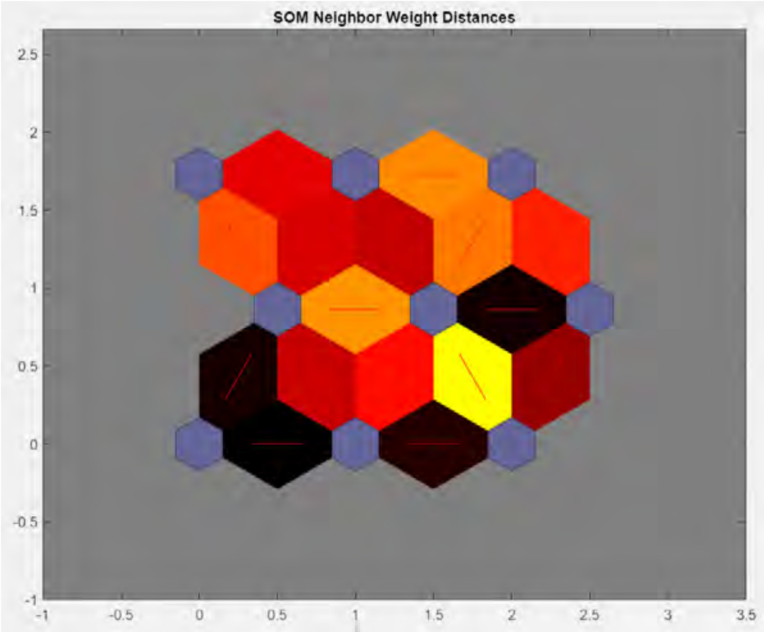
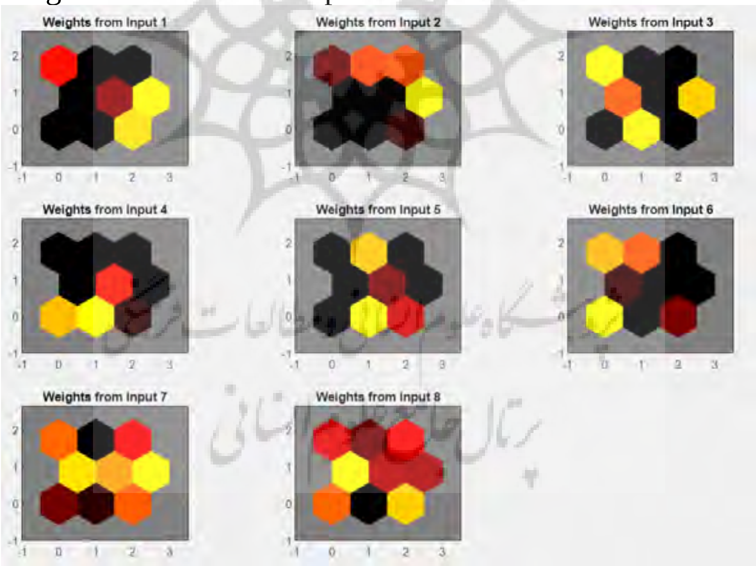


Figure 8. Inter-cluster communication map in 9-cluster mode

In the scatter plot based on each attribute, lighter colors indicate low membership and dark colors indicate high cluster membership. The top-right cluster shows the largest number of members in most cases.



Figu 9. Map of the number of intra-cluster memberships in the 9-cluster state by each index

In the diagram of the number of members in the cluster, it is shown that the cluster (2,0) contains the most members (8) and three single-member clusters are located in its vicinity.

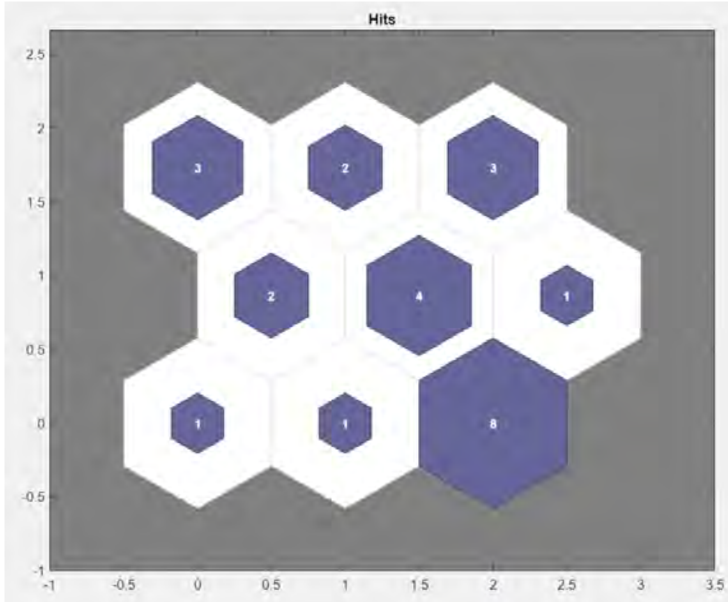


Fig 10. Location map of clusters (cells) and the number of members in the cluster in the 9-cluster state

The following table shows which machines each cluster (cell) has assigned to itself. This table will be considered as the basis of celling in the mathematical model.

Table 4.
Allocation of machines and cells in 9-cluster mode

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6	Cell 7	Cell 8	Cell 9
Machine 1	0	0	0	0	0	1	0	0	0
Machine 2	0	0	1	0	0	0	0	0	0
Machine 3	0	0	1	0	0	0	0	0	0
Machine 4	1	0	0	0	0	0	0	0	0
Machine 5	0	0	0	0	0	0	1	0	0
Machine 6	0	0	0	0	0	1	0	0	0
Machine 7	0	0	1	0	0	0	0	0	0
Machine 8	0	0	1	0	0	0	0	0	0
Machine 9	0	0	0	0	1	0	0	0	0
Machine 10	0	1	0	0	0	0	0	0	0
Machine 11	0	0	1	0	0	0	0	0	0
Machine 12	0	1	0	0	0	0	0	0	0
Machine 13	0	0	0	0	0	1	0	0	0
Machine 14	0	1	0	0	0	0	0	0	0
Machine 15	0	0	0	0	1	0	0	0	0
Machine 16	0	0	0	0	0	0	0	1	0
Machine 17	0	0	1	0	0	0	0	0	0
Machine 18	0	0	0	0	0	0	1	0	0
Machine 19	0	1	0	0	0	0	0	0	0
Machine 20	1	0	0	0	0	0	0	0	0
Machine 21	0	0	0	0	0	0	0	1	0
Machine 22	0	0	0	0	0	0	0	0	1
Machine 23	0	0	1	0	0	0	0	0	0
Machine 24	0	0	1	0	0	0	0	0	0
Machine 25	0	0	0	1	0	0	0	0	0
Sum of members	2	4	8	1	2	3	2	2	1

Conclusion

Artificial neural networks (ANNs), usually simply called neural networks (NNs) or, more simply yet, neural nets, are computing systems inspired by the biological neural networks that constitute animal brains. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives signals then processes them and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

This research has been done in order to create a structured model based on artificial intelligence, taking into account the uncertainty in determining the demand and determining the movement of machines and parts in cellular production, and finally, it has ended with results based on operator allocation. The most important point that was noticed at the beginning of the work is the lack of attention of previous modelers and researchers to the problem of determining the arrangement of cell production based on clustering.

The clustering in this research was based on artificial neural networks, which were investigated and studied in 3 different modes of 4 cells, 6 cells, and 9 cells. The important point in this clustering is that the input data to the algorithm should be carefully selected, and in this research, referring to the importance of the scheduling issue and the communication and movement between parts, it was decided that this movement and scheduled operations would be determined on a per-part basis, and would determine how much time each group of parts would spend in relation to which machines.

Along with these criteria, the factors of moving cost and depreciation were considered as two important parameters for machines in the layout problem and were included in the clustering. The clustering output in all 3 investigated cases did not have clusters without members, but in terms of proximity and neighborhood, some clusters were close to each other and could be merged. In some cases, the clusters were very far from each other, and this shows that the machines assigned to the cluster in question have a lower degree of operation than the others in terms of the amount of operations and the level of communication with other cells.

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