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Cell Production System Design: A Literature Review

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ABSTRACT

Purpose: In a cell production system, a number of machines that differ in function are housed in the same cell. The task of these cells is to complete operations on similar parts that are in the same group. Determining the family of machine parts and cells is one of the major design problems of production cells. Cell production system design methods include clustering, graph theory, artificial intelligence, meta-heuristic, simulation, mathematical programming. This article discusses the operation of methods and research in the field of cell production system design.
Methodology: To examine these methods, from 187 articles published in this field by authoritative scientific sources, based on the year of publication and the number of restrictions considered and close to reality, which are searched using the keywords of these restrictions and among them articles Various aspects of production and design problems, such as considering machine costs and cell size and process routing, have been selected simultaneously.
Findings: Finally, the distribution diagram of the use of these methods and the limitations considered by their researchers, shows the use and efficiency of each of these methods. By examining them, more efficient and efficient design fields of this type of production system can be identified.
Originality/Value: In this article, the literature on cell production system from 1972 to 2021 has been reviewed.

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1. Introduction

Increased competition between manufacturers, shortening the useful life of products, increasing diversity in customer demand, customizing products and as a result variability in many parameters such as product demand and access to production resources, have led manufacturers to reduce costs as much as possible. Increase competitiveness and flexibility in the face of constant changes in demand to use systems with high efficiency and flexibility. That's why researchers were looking to create another production system called the cell production system. In this article, 187 articles in the field of cell production system design have been reviewed and compared, in order to determine a complete reference of the methods that have been considered more and can consider more aspects of the subject of designing a cell production system. In this regard, first, the cell production system has been introduced and then the methods of designing the cell production system have been described and the literature of each of these methods has been compared based on the number of uses, the number of limitations considered and being close to the present. The use of these methods is discussed. The articles used in this article from 1972 to 2021, published by: Elsevier, Taylor & Francis and Springer, are reviewed. These articles are searched based on keywords such as: cell production system, cell production system design, production system design methods, meta-heuristic algorithms and a review of cell production system. The number of articles published in the field of cell production system design from 1972 to 2021 is several thousand, of which the articles used in this study are based on their comprehensiveness (number of limitations considered) and the year of their publication. It’s been chosen. In a way, articles that have been more comprehensive or published in recent years have been used. The meaning of comprehensiveness considering different production conditions to design the production system, so that it is closer to the real conditions. Conditions close to reality can be: market dynamics, market competitiveness, production outsourcing capacity or part of it or workshop environment conditions such as: workflow routing, system reorganization, production cell flexibility or machine problems Such as: time and cost of commissioning, machine warehouse, machine breakdown, the need for a specialized operator, multi-objective machines, personnel training costs, and so on. Articles that are more comprehensive using keywords such as:

central processing unit (CPU), work in progress (WIP), cell formation (CF), group layout (GL), Automated guided vehicle (AGV), meta-heuristic algorithms, multi-objective models, etc. were identified. From the identified articles, articles were selected that considered different restrictions simultaneously. For example, articles that simultaneously consider the problems of machinery and personnel or consider routing the process with multi-objective machines in a dynamic environment with outsourcing scores, or simultaneously considering cell workload with head costs. Internal and intercellular loads and displacements can be expressed. The more articles that cover different production problems at the same time, the more attention is paid to them.

2. Literate Review

2.1. Cell production system

Cell production is a production system that can be used to produce products with medium volume and variety, cell production to the main problems of group production, including repeated set-up, inventories under additional manufacturing, long output (production) times, complexity of tasks Control and planning, etc. prevail and provide a basis for the implementation and implementation of production techniques such as on-time production and flexible production systems [1]. A production cell consists of a set of dissimilar machines (in terms of performance) that are located at relatively close distances to produce a family of parts. CMS consist of one or more cells, each cell ideally containing all the resources necessary to produce a specific set of similar products [2]. CMS is able to implement the production system to overcome the weaknesses of the traditional production system such as workshop system and workshop flow [3]. Wu et al., discussed the random problem of customer ordering in cellular production systems with parallel machines. They minimized the waiting time for random customer orders under budget constraints. In the literature review, research has been presented to investigate the effect of demand uncertainty and production need on design and purpose [4]. Today, companies need to respond quickly to demand fluctuations and manage their capacity in the most efficient way. However, with the increasing complexity of the production organization, and the random nature of demand, reducing production has become a major challenge [5].

Cell production is an accepted organizational approach to reduce production time due to efficiency and flexibility in variable production [6]. Zhao et al., considered a system in which production is limited by inventory, and they provided maximum power through analysis and mathematical programming. For a multi-stage processing environment, most research focuses on tasks or a static environment, while random customer orders receive less attention [7]. Chen et al., considered the synchronization of order production production with the dynamic entry into a flowshop problem [8]. Alaei et al., discussed a dynamic cell production system under discrete scenarios with random product demand [9]. Xue and Offodile used a hierarchical production planning model to solve the problem of cell reconfiguration with different needs in different periods [10]. Dehnavi-Arani et al., considered the production of customer orders in which the entry, volume and type of product of customer orders is random and all products enter and exit production systems in a single order [11]. In most studies of stochastic demand in cellular production systems, minimizing costs such as machine costs, reconfiguration costs [12]. Yan et al., solve a dynamic robotic cell rescheduling problem, in which new tasks arrive at the time of stochastic cell entry and are scheduled simultaneously. In their model, existing time intervals are planned for processing new tasks and transport operations. The objective is to minimize the makespan for only one single cell [13]. The importance of problem such as customer demand, reducing production costs, is clear to industry owners. Manufacturers need to be able to produce lower cost and higher quality products in the shortest possible time to deliver products to customers on time. Also, manufacturing systems must be able to respond quickly to changes in product design and demand without significant investment. Therefore, one of the ways to increase productivity and strong presence in the competitive market is to integrate Virtual Cellular Product (VCM) in the supply chain (SC) by considering the concept of new product development. Rostami et al., presented a multi-objective mathematical model for simultaneous integration (VCM) with (SC) and new product development [14].

In production line factories, the impact of (CMS) with recent advances in (GT) and (AMS) leads to minimization of costs related to maintenance and overhead and machine operation and the cost of moving intracellular materials. Sharif et al. (2020) addressed the problem of design planning horizons (CMS) with regard to changing customer demand patterns. In the case of a dynamic cell production system, fluctuation is considered by dividing the entire planning horizon into smaller periods. Alimian et al., discussed a new integration approach for cell formation, group planning, production, and preventive maintenance (PM) planning in a dynamic cell production system. The purpose of cell formation is to minimize transport, and displacement of intracellular material. They also showed that by adding PM decisions to dynamic tactical decisions (CMS), optimal configuration and system production schedules are strongly affected [15]. The integration of cell formation problems with other aspects of production and management has been considered in recent research. These integrated problems include planning, production and planning, supply chain management [16], queue theory, layout, and facility location problems [17, 18]. Kia et al., presented cell formation and overall planning decisions in dynamic CMS and used the GA genetic algorithm to solve the model [19]. Feng et al. (2019) proposed a new integrated model that considered intermittent process routing and machine repetition. They used a large-scale improved genetic algorithm to solve the model. Wang et al., investigated the learning and forgetting factors for multi-skilled workers in cell formation and product planning and used the Improved Bacteria (IBFA) algorithm to solve the model [20]. Chen et al., discussed the problem of precise maintenance planning and production for a flexible workshop system and used the ANSGA-III algorithm to solve the multi-objective model [21]. Kataoka, et al., proposed a multi-period mixed integer programming model for solving two types of cell systems. In the first step, the traditional model is defined with new parameters. In the second step, the proposed model is solved with 2-step optimization problems [22]. Sadeghi et al., discussed the integration of design and control stages into a three-level blood sugar ribbon supply chain system. The first stage is to design the system based on a layered cell production system for which a complex integer linear programming method was used. The objective of the model is to minimize the required number of cells [23]. Hong et al., discussed the problem of energy efficient planning of a multi cellular production system with eligibility constraints. Each production cell is configured as a flexible workshop stream. The objective of the schedule is to optimize energy consumption and optimize energy consumption, total displacement distance and lifespan [24].

Tayal et al., defined the criteria for sustainability in a production plan and provided a general mathematical formula for the Sustainable Facility location (SFLP) problem. Using big data analysis, machine learning, hybrid heuristics, data envelopment analysis (DEA) and mean clustering (K), they proposed a stable optimal scheme with energy efficiency in uncertain conditions. Given the increasing complexity of planning and scheduling production processes, researchers are looking to identify near-optimal solutions to ensure quick and accurate decisions [25]. Mourtzis et al., Contributed to adaptive planning by providing an algorithm that allows for close collaboration between machines, the workforce, and the production manager [26]. Duffner et al., developed a cost model for a battery cell plant. Their proposed model relies on process-based cost modeling (PBCM). Based on this cost model, instructions are provided on how to reflect the minimum costs that reflect the current and future state of technology [27]. Salimpour et al., Examined cell formation (CF) and cell location (CL). This proposed problem is presented as a multi-objective mathematical planning model. They used a genetic algorithm (MNSGA-II) to obtain Pareto optimal solutions [28]. CMS is a new production system that is compatible with custom production. Ebrahimi et al., focused on planning CMS with the aim of maximizing total profit as a function of sales revenue as well as energy costs and order delay penalties.

Components that need to be considered in the current problem include the dependence of time on energy prices, price elasticity of demand, and power consumption based on machine speed [29]. Shorter CMS were introduced to meet production needs and provided desirable results. Design and implementation CMS includes many problems such as cell formation, machine layout, alternative process paths, and warehouse size [30]. Various innovative, meta-heuristic, hybrid and precision solving CMS algorithms were designed in medium and large dimensions. When equipment is not installed in a systematic way, it will be very difficult to produce parts using machines. The distance traveled by the parts increases, which in turn increases the production time of each product. Therefore, productivity is reduced and the flow of parts is not uniform. Adinarayanan et al., proposed the concept of cell production (CM) using batch production. The purpose of their model is to minimize the travel distance of the parts. They used the particle swarm optimization (PSO) algorithm to solve the model [31]. Saraçoğlu et al., discussed a three-level solution method for a parallel multi-stage, multi-product cell production company. The production process under study has three stages, namely persistent cells, injection molding cells, and final packaging cells. System performance is measured based on total flow time and duration. High quality products, minimum production costs and cellular production system are the objectives of central planning [32]. Weeber et al. used a multi-level simulation approach. Yang et al. examined the dynamics of a three-component model for hierarchical cell production systems. Their proposed model is based on a multi-component model [33].

2.2. Methods of Cell production system design

Cell production system design is an application of group technology that involves the process of making a set of similar parts by a group of machines that are assigned to the cell. In a cell production system, a number of machines, which are usually different in function, are grouped in a production cell called a machine cell. In fact, machines are grouped inside cells in such a way as to perform operations on a group of similar parts (Fig. 1). This cell is responsible for completing operations on similar components that are in the same group and are known as the component family.

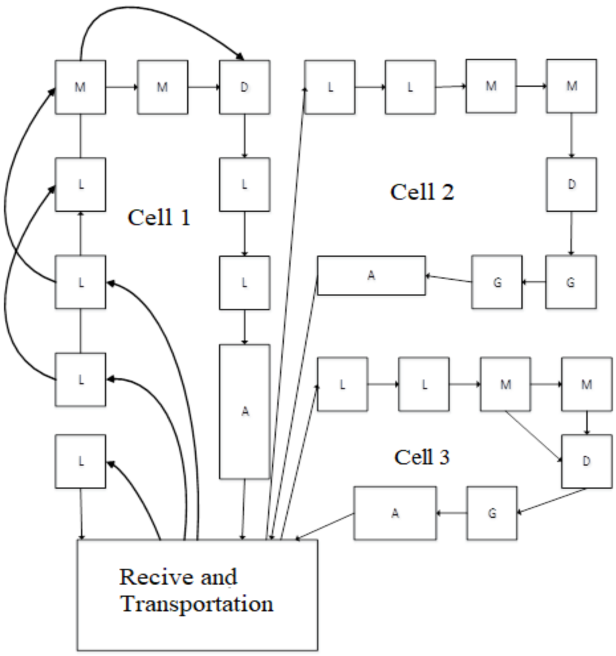

Fig. 1. Cell production system

In solving the problem of cell formation, various methods have been used, which can be divided into the following diagrams according to the literature review:

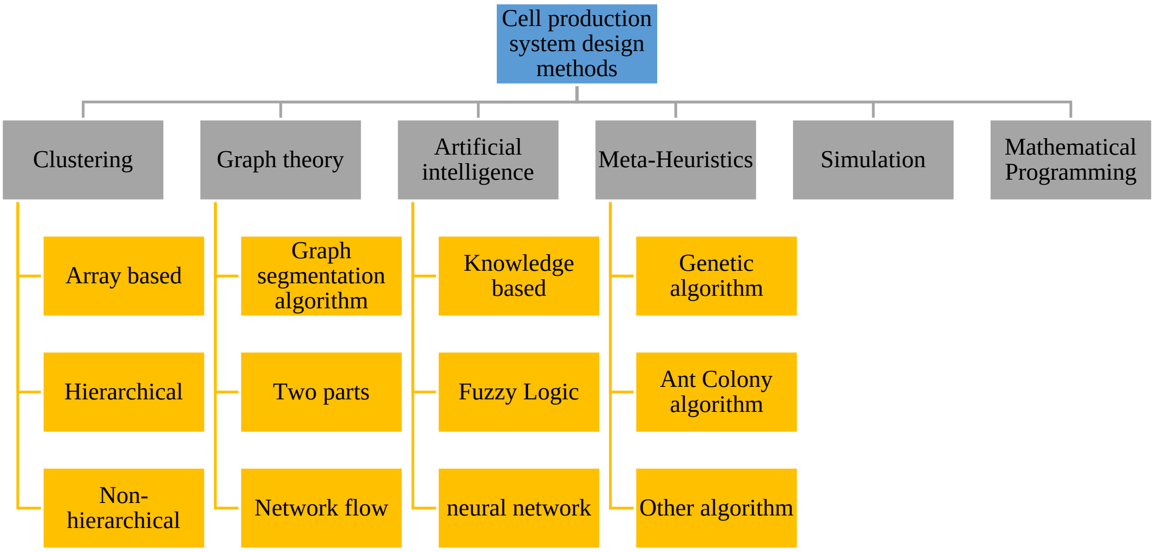

Fig. 2. Cell production system design methods

2.2.1. Clustering Methods

The main purpose of clustering methods is to group parts or entities or their properties into categories in which the elements of each category have the most relationship with each other and the least relationship with other clusters. Clustering methods are divided into the following three categories:

Array-based clustering techniques

The array-based clustering approach was first proposed by McCornick et al. In 1972 with the introduction of bond energy analysis algorithms [34]. The ranking-based clustering algorithm was proposed by King 1980 in which a binary value is set for each row and column, then the rows and columns are sorted in descending order, and then the clusters are determined [35]. This algorithm is very simple and can be easily used to determine clusters with a diagonal block shape. Each cluster identifies a group of machines and a family of corresponding parts. This approach was later used by other researchers such as Chan, Mills, and Kusiak [36]. Li et al. proposed a partition design method for an integrated load energy system. They proposed a design method based on an integrated cluster model with multiple energies. Alternative structure based on data features simplifies design [37]. Giulio et al. used the cluster analysis method for energy demand data to design the cogeneration system. This approach helps to improve the energy efficiency of the cogeneration plant [38].

Hierarchical clustering methods

These methods are divided into two categories: divider and compactor. Dividing methods start from a cluster that contains all the elements. Then, in the next steps, based on the similarity or dissimilarity between the elements of the matrix, they are divided and placed in different groups. On the other hand, condensing methods first consider each element as a separate cluster and then gradually place them in clusters based on similarity or dissimilarity, including the advantage of these methods is that there is no need to determine the number. Clusters are at the beginning [39, 41, and 41]. Erenay et al., presented a mathematical model for designing a cell production system in a high oscillation environment. Their objective was to minimize the number of working cells in a planning period using a five-step hierarchical method. These steps include: 1) product family formation 2) calculating cell productivity and demand coverage probabilities 3) allocated cells and empty cells 4) Layered systems simulation for performance evaluation 5) Statistical analysis [42]. Hierarchical clustering allows for better performance in grouping heterogeneous and non-circular data sets than centered clustering, with increasing temporal complexity. Meanwhile, the bottom-up approach to hierarchical clustering methods often tends to be sensitive to datasets containing ambiguous cluster boundaries [43]. In order to solve the problem of hierarchical classification in traditional evaluation, a hierarchical clustering method has been developed for unknown grading standards. First, the traditional evaluation is transformed into a partial evaluation using a relative relation, and the classification is performed based on the Hasse diagram, which is relatively arranged. In the next step, the information inside the layer expresses the result of clustering and the information between the layers shows the difference in scores [44].

Non-hierarchical clustering methods

Non-hierarchical clustering methods are iterative methods that begin to solve using initial segmentation. In other words, in these methods, the number of houses must be determined first. After the formation of the initial clusters, the movement of machines (or parts) according to the criterion of optimality is done regularly. Unlike hierarchical methods, in these methods the elements of each cluster can be transferred to another cluster in the next step [45]. Lemoine and mutel introduced the non-hierarchical clustering method for the automatic formation of production cells and the family of parts [46]. Rajagopalan and Chandraskaran, proposed an innovative algorithm. This technique uses evaluation criteria called group performance, which measures intercellular and intracellular displacements [47]. Algorithmography has been developed by Srinivasan and Narendran [48] to overcome some of the limitations of the zodiac method. This algorithm obtains the initial answer by solving an allocation problem. Further work in this area includes an algorithm proposed by Narendran and Nair that uses data related to the sequence of operations to form cells and family of parts [49]. Jihwan et al. used real operational data related to collection, transportation, and recycling in South Korea. The results showed that clustering accuracy is best for classification that uses the hierarchical method. Based on these results, ANOVA tests were performed. They used the four-cluster hierarchical method as an important decision tool [50].

2.2.2. Methods based on graph theory

A graph $G\ (V, E)$ consists of a set of vectors $V = [v1, v2, \dots, vm]$ and a set of edges $E = [e1, e2, \dots, em]$. In graph segmentation methods, machines (or parts) are thought of as the vertices of the graph and the process that the parts go through to produce them as edges. The purpose of these methods is to obtain non-correlation between graphs in order to identify the production cells.

Graph segmentation algorithm

In these methods, machines or parts are considered as graph vertices and component processing is considered as the connecting edges of these nodes. Rajagoplan and Batra, developed a practical pure graph method for the problem of Cell arrangementce [51]. De witte, examined the use of different similarity coefficients in a similar way [52]. Askin and Chiu, presented a cost-based mathematical formulation and a heuristic solution method for graph separation [53]. Faber and Carter, used a practical graph algorithm that divides a machine similarity matrix into a cluster grid [54]. A multi-objective segmentation method was proposed to extract the specific image regions pertaining to individual target organs in abdominal CT images. Then the images of individual target organs are extracted by minimizing the energy function [55]. Using fixed, group, state, and individual partitions to define nodes, they showed that functional connection changes in nodes significantly affect network-level findings. In some cases, changes depending on the state or group of the reported type usually do not continue, while in others, changes are observed only when node reconfiguration is considered [56]. Graph theory is an important theory in mathematics. An old style graph shows the old style connection between objects. Items are spoken with vertices and relations with edges. Chart coloring is a subject intended for combination simplification. F-diagram theory has various applications in current sciences and innovations, especially in the fields of neural networks, cluster analysis, control theory, medical diagnosis [57].

Two-part graphs

This method was proposed by King and Nakornchai [58] in which parts and machines represent two sets. In this method, the edges between two sets of nodes indicate the need for m-machine to produce the p-piece. Such a problem is formulated in graph theory as the problem of k decomposition. This is achieved by deleting locations to create k independent graphs.As data volumes increase dramatically, traditional data analytics operating systems face problems with storage, management, and analysis. Big Data Analysis (BDA) overcomes these problems by providing decentralized and distributed processing. Yıldırım et al. proposed two new models. In the first model called DPModel-1, statistical methods (logistic regression) and machine learning methods (decision tree, random forest, and slope increase) are used to predict the company's default. Based on the first model, they proposed DPModel-2 based on graph theory [59].

Network flow

Vohra et al., developed a network-based algorithm that reduces intracellular currents [60]. Lee and Diaz, proposed the problem of clustering as a network considering capacity, which measures functional similarity between machines [61]. Bainy et al. showed the measurement and movement areas diagrammatically, which facilitates the implementation of the method and the expansion of the logic of selecting the dynamic area in the arrangement of the passage. They introduced a low impedance differential protection scheme based on graph theory [62].

2.2.3. Artificial intelligence methods

In recent years, a growing number of studies have focused on the use of artificial intelligence techniques to solve the problem of cell production. Techniques developed include expert / knowledge-based policies, fuzzy logic, and neural networks. These methods are relatively new methods in the design of cell production systems.

Knowledge-based expert systems

Expert systems are computer programs that contain specific artificial knowledge of one or more human experts. The most common type of expert system is a program that consists of a series of rules that analyze information (usually provided by the system user) that is about a specific class of problems. The program also creates a mathematical analysis of the problem and can suggest a set of steps for the user to make corrections. Knowledge-based expert technique has been used by [63, 64] for the problem of cell makeup. Leung et al., provided a knowledge-based system that made suggestions during the conceptual phase of production cell design. These suggestions sought to preserve system responses and provide information about cell types [65].

Fuzzy Logic

Xu and Wang, applied fuzzy mathematics to the problem of cellular arrangement, in which the properties of parts are converted to fuzzy numbers using membership functions. In this method, the obtained fuzzy numbers enable each piece to be differentiated according to the process requirements; then a matrix of similarity coefficients is formed using fuzzy numbers and a piece is placed in a family provided that the value of its similarity coefficient is greater than a certain value [65]. In connection with the fuzzy logic method; Chu and Hayya, used a non-hierarchical fuzzy clustering algorithm to generate data. This algorithm had the limitations of other non-hierarchical clustering algorithms [66]. Gungor and Arikan, used fuzzy set theory to design production cells through an algorithm that considers production, design, and sequencing features as input parameters in the formulation of a cellular arrangement problem [67]. The use of fuzzy mathematics in CMS design has been done by [68, 69].

Neural Networks

Neural network models are used to mimic the way in which biological intelligence neurons make intelligent decisions. Neural networks have been widely used in cell formation due to their versatility and ability to solve problems. Also among the researchers who used the neural network method can be mentioned Zolfaghari and Liang, who introduced a new structure of Hopfield neural networks (HN) for grouping machines [70]. Soleymanpour et al., with reference to some of the weaknesses of the previous methods, for the problem of cell production, they presented the algorithm of transient disordered neural networks. The proposed algorithm was tested on a number of existing problems and compared with existing methods. The computational results showed the superiority of the proposed method over the previous methods [71]. Guerreroet al., developed a two-level strategy to group parts and machines within cells. In the first stage, the problem of forming a family of parts is modeled as an exponential planning problem. Then, in the second step, a linear network flow model is used to allocate the machines [72]. Saidi Mehrabad and Safaei, proposed a nonlinear integer programming model to solve the problem of cell formation in dynamic conditions by considering alternative production routes and operations sequences. The proposed model is linearized using linearization methods and the optimal solution for a number of problems is calculated. Because the problem is NP-hard, a neural network approach is proposed to solve the problem in large dimensions [73]. Delgoshaei and Gomez, used artificial neural networks to program cell layout. They presented their proposed model while considering preventive maintenance and periodic services [74].

2.2.4. Meta-heuristics Method

Designing a cell production system is a complex, multi-criteria, multi-level process. The complexity of the NMS design problem has been widely reported in the literature [75]. The meta- heuristic methods used in CMS include the following:

Genetic algorithm

Genetic algorithms have been developed since 1975 as artificial adaptation systems to simulate natural evolution. In fact, genetic algorithms use Darwinian principles to find the optimal formula for predicting or matching patterns. Many researchers used genetic algorithm to identify and form cells in the cell production system. Due to the combined nature of the problem, it is very easy and good to provide a solution to this algorithm [76-83]. Solimanpour et al., proposed a multi-objective integer programming model with independent cells to design the cell production system. They also used a genetic algorithm to solve the problem [84]. Iranmanesh et al., proposed a method of genetic algorithm to solve the problem of multi-objective cell formation, so that this method provides a set of ideal solutions for decision makers to make the best decision. The objectives are to minimize intracellular and intercellular displacements and change the workload of the cell [85]. Neto and Filho, used a multi-purpose model using GA for CFP, in which fitness assessment was performed by simulating cell production systems in which the effect of congestion was incorporated and a dynamic routing policy was performed. The presented computational result shows the improvement in WIP level conditions, intracellular movement with reduced investment and machinery [86]. Kia et al., presents an integer mixed programming model for a multi-floor design of cellular production systems (CMS) in a dynamic environment. One of the new aspects of this model is the simultaneous determination of cell formation (CF) and group design (GL) as related decisions involved in CMS design in order to achieve the optimal (or near-optimal) system design solution for a multi-level one-horizon factory [19]. An efficient genetic algorithm (GA) with a matrix-based chromosome structure is also used to achieve the optimal solution. In addition, the structure of the solution is presented as a matrix with five elements to meet the constraints in the hierarchy. Computational results showed that GA development has a more satisfactory performance in achieving good solutions compared to CPLEX software based on objective function value and computational load. Chandrasekar & Kumar, used a hierarchical genetic algorithm to design both intracellular and intercellular arrangement. Their input data was a component-machine matrix in which the component operation sequence was also considered. They compared the performance and effectiveness of the proposed algorithm with previous work done. They also showed that the proposed new algorithm offers better results than previous approaches [87]. Information such as production volume and production costs are among the other things that can be added to their model. Wicks, presented a mathematical model for designing dynamic cell production systems based on the family of parts and grouping machines. The objective function of his model is to minimize the total cost of intercellular mobility, the fixed cost of purchasing machines, and the cost of cellular restructuring with machine capacity constraints and low cell capacity. He solved the proposed model using a genetic algorithm [88]. Izui et al., presented a multi-objective mathematical model for the design of cellular production systems and used robots in its design. This means that one or more flexible robots are used that can perform a number of operations such as assembly and the like. They used a genetic algorithm for a multi-objective problem to find the optimal solution for the fragment [89]. Khaksar et al., by developing a genetic algorithm using a linear programming model to design a multi-floor cell production system with simultaneous consideration of cell formation (CF), and group layout (GL), for Achieving an optimal solution is used in a multi-storey factory. They also considered some layout features such as process routing, production volume, sequence of operations, material flow between machines, and flexible configuration [90]. Lokesh and Jain, presented a nonlinear mixed integer model for cell formation. Their model has some important production features such as: machine failure effects (maintenance and cost loss time), production planning (inventory maintenance cost, internal production cost and outsourcing cost), cell size and in-house transportation Cell, machine capacity, cell reconfiguration were considered. They proposed a hybrid hierarchical algorithm (HHGA) to solve the model, which showed that the proposed algorithm requires less time than solving with Lingo [91]. Sakhaei et al., presented an integrated linear integer model for designing a cell production system in a dynamic environment. In their model, they considered the problem of unreliable machines and production planning for a dynamic environment [92]. Among the things they considered in their model include: 1) dynamic cell formation 2) machine reliability 3) machine failure cost 4) displacement cost 5) process routing 6) operator 7) operator training 8) minimum inventory 9) Hires an operator. They solved the proposed model with a few numerical examples in CPLEX. (Rena and Ambrico, 2015) presented a new approach to designing a cellular validation system. They presented a mathematical model for the design of a cellular production system considering multi-objective machines in a dynamic environment with production planning, in a way that is consistent with the conditions of supply and demand market uncertainty. Suemitsu et al., proposed a new multi-objective optimization scheme for the design of a robotic cell production system that can simultaneously determine the position of parts manufacturing as well as work planning. They solved their proposed model with a multi-objective genetic algorithm [93]. Mohammadi and Forghani, presented a new framework called S for the design of cell production system. They expressed their model by considering parameters such as segment requirements, operation sequence, device dimensions and corridor width in two objectives. The first objective is to minimize the total cost of moving in and out of the cell. Also, the second objective is maximum similarity between machines. They solved the proposed model with the Annealing simulation algorithm [94]. Bootaki et al., presented a two-objective model for cell production with the objectives of increasing cell productivity and using skilled labor. They solved the proposed model with the (NSGAII) genetic algorithm and presented the results [95]. Delgshaei et al., expressed the variability of cell workload as an important problem. Which can lead to long queues in front of machines and impose redesigning costs. In their paper, they considered the effect of inflation on cell workload. That's why they came up with a new way to program a dynamic cellular production system with bottlenecks and parallel machines. They used a combined genetic and simulated annealing algorithm to solve their model [96]. Deep and Singh, presented a mathematical model for designing a cell production system in a dynamic environment. The proposed model included the problem of rescheduling, machine allocation, dynamic production, and process routing. In their model, they considered outsourcing for work balance [97]. Azadeh et al., proposed a new mathematical programming model for the formation of production cells in which the personality of operators, decision-making style, skill in working with machines, as well as job security are simultaneously incorporated. They solved their model with the NSGA-II metaheuristic algorithm and used the MOPSO multi-objective particle multi-objective algorithm to validate their solution method [98]. Shirzadi et al., provide an integer bi-objective model for designing a cellular production system by minimizing total costs (intracellular and intercellular transport, overhead costs, and restarting) and maximizing the reliability of processing paths. They gave. They used the algorithm of colonial competition and compared it with the NSGA-II algorithm [99]. Rostami et al., presented a multi-objective mathematical model for simultaneous integration (VCM) with (SC) and new product development. They used genetic algorithms to solve the model [14]. Chen et al., discussed the problem of precise maintenance planning and production for a flexible workshop system and used the ANSGA-III algorithm to solve the multi-objective model [21].

Ant Colony Algorithm

A method inspired by the behavior of ants in finding the path between the nest and food; It was first proposed in 1992 by Marco Dorigo in his doctoral dissertation. Soleimanpour et al., proposed an ant algorithm (ACO) to solve CFP by considering the yield sequence and production volume with the aim of reducing cell motility and the number of cavities [71]. Megala et al., proposed an ACO-modified ant colony optimization algorithm to solve CFP. With the available data set and the results showed that the ability of the algorithm to maximize the effectiveness of grouping is very high [100]. Li et al., proposed an integrated system of low and high ants (MAX-MIN) based on the local search method for the ACO-CF model implemented in a multi-dimensional cube framework. The result is not only better than previous techniques. You can also increase the effectiveness by allowing the cells left in the oblique blocks [101]. Xing et al., proposed two machine segmentation techniques, one with the ART1 neural network-based approach and the other with the ant colony-based approach (ACS). The computational results showed that ACS was better than the ART1 method [102]. Bajestani et al., presented a multi-objective dynamic cell formation problem that simultaneously trades the total cell load and the sum of different costs (machine cost, intercellular material handling cost, machine handling cost) using the scatter search method. At least it does [103]. Slomp et al., considered a new type of virtual cell manufacturing system (VCMS) and developed a multi-objective design method for designing such cells in real time. Jazz cells are shown as a temporary grouping of machines, jobs, and workers to identify the benefits of CM [104]. Dehnavi Arani, presented a two-stage model for the problem of cell formation in which AGV is used to move parts between cells. In the first level, the basic problem of cell formation, and in the second level, the problem of AGV routing at the job shop level is investigated. Finally, the model is solved by a heuristic algorithm and the performance of the proposed algorithm is investigated by solving a small sample [105]. Delgoshaei et al., proposed a new method for dynamic CMS programming using a combination of ant algorithm optimization and annealing simulation [106].

Other Meta heuristics algorithm

Wu et al., proposed a hybrid TS to solve CFP and stated that the use of this hybrid algorithm in this scheme could be more convenient than other meta-heuristic methods, such as SA, GA modified, based on problem characteristics or User settings [107]. Safaei et al., presented a model of Dynamic Cell Production System (DCMS) with different objectives of minimizing the total cost of the device, and the cost of material transportation, reconfiguration cost, and solved their model using the SA algorithm. It turned out that the proposed model is very optimal in minimizing costs [108]. Defersha and Chen, developed a mathematical planning model of production forms over different time periods to minimize various costs such as investment costs, intercellular transfer costs, operating costs, contracting costs, tool consumption costs, the cost of setting up and the cost of reconfiguring the system. They also used a hybrid parallel SA [109]. Tavakkoli Moghadam et al., introduced an integer programming model for dynamic CFP. They envisioned a multi-period planning horizon in which product mix and demand are different but definite for each period. They developed an SA algorithm and compared the results with the desired results obtained through the mathematical model, which has an efficiency with an average deviation of less than 4% [110]. Tavakkoli Moghadam et al., presented a model of common and specific cells and families that the demand for components in each period can be in a form of a certain size. In the proposed model, there are two types of capital constraints: 1) capital constraints on cell setup and 2) capital constraints in order to provide the equipment needed to produce parts. They also used SA for the proposed model in which there are three objectives: 1) to minimize the total cost of delaying delivery of a portion to customers by shared and dedicated cells in each period; 2) Minimize the cost of idle cell time for each period; And 3) solving the problem of unused capital costs. They compared their results with LINGO software, and the proposed solution was faster and more efficient [111]. Delfard, proposed a new mathematical model based on the average number of intracellular and intercellular movements for a planning period. He solved the proposed SA and the branch and bound method and showed that on a large scale the metaheuristic algorithm shows better results than the branch and bound method [112]. Kia et al., used an efficient SA algorithm to solve their model. The proposed Kia model is a nonlinear mixed integer model for designing a group layout (GL) in a cellular production system in a dynamic environment [113]. Liu and Wang, provided a nonlinear integer model for the cellular production system, considering multi-purpose machines, multi-skilled workers with different processing times. They used a hybrid simulation algorithm (HSA) to solve the proposed model [114]. Logendran and Karim, presented a nonlinear model that examines two important problems in the design of the cell production system: 1) the availability of alternative locations for a cell, 2) the use of alternative pathways for Moving component packages between cells, depending on the capacity of the transmitters. The objective function of the proposed model focuses exclusively on minimizing the total service time to meet production demands in cellular production systems [115]. Mahdavia et al., formulated a two-level mathematical planning model integrates three topics of cell formation, cell designs, and sequencing of intracellular devices considering process routing, operation sequence, and production volume. Due to the combined nature of the above model, an efficient tabu search algorithm based on the overall similarity coefficient is proposed. The computational results of the test problems show that the proposed model and solution approach is effective and efficient [116]. Foulds et al., designed a mixed integer programming model with the allocation of spare machines to individual, grouping of individual machines to cell, and individual modification of machines to increase processing per share, called the Sustainable Cell Formation Problem (SCFP) And used an heuristic algorithm called tabu Search (TS) to achieve better results [117]. Lei and Wu, for the multi-objective CF problem, proposed an optimal Pareto based on the Multi-Objective Tabu Search (MOTS) with the objectives of: minimizing the total weight of cell movements and minimizing changes in total cell load. The computational results showed that the proposed MOTS is more desirable than TS to find the Pareto solution [118]. Caprihan et al., proposed a quantum PSO (QPSO) method for designing a virtual cell production system (VCM) and tested the proposed method with GA and ideal planning in which the QPSO approach consumes less CPU time [119]. A similar study was conducted by Anvari et al., [120]. Where a hybrid (PSO) technique for CFP was reported. The initial solution was generated randomly using a diverse generation method as well as the mutation operator method embedded in the update speed equation to prevent local optimal solutions. It was then effectively solved by this method due to the wide range of machine-piece matrices. Duran et al., proposed a modified PSO algorithm to solve the problem of cell formation. The most important change in this algorithm is that unlike the original PSO method, the proposed method does not use the velocity vector. The criterion used to group the machines in this paper is also to minimize intercellular displacements. The results are presented and compared in the form of simulation studies. The computational results show the ability of the PSO algorithm to find the optimal or near-optimal answer [121]. Ghahremani et al. Presented a robust fuzzy model for controlling uncertain parameters. They used the Wall optimization algorithm to solve the model [122].

2.2.5. Simulation Method

Simulation is defined as mimicking the performance of a real system process and performing experiments with this model in order to understand system behavior or evaluate different strategies for system operation [123]. Reeb et al., used discrete event simulation to develop and select a family of components for cell production in a wood production company [124]. Durmusoglu and Satoglu, designed methods based on obvious principles for the cell production system. In the proposed method, simulation is used to identify and eliminate bottlenecks [125]. Siemiatkowski et al., highlighted problems related to multi-level process planning in flexible cell manufacturing systems, multiple process routing options. In their proposed framework, they examined the trend of alternating current through simulation [126]. Azadeh et al., in CMS presented an integrated method for optimizing operator allocation. They developed a simulation model to evaluate different layouts and use fuzzy data envelopment analysis to evaluate the simulation results. They applied the proposed method to a real case study [127]. In a similar study, Azadeh et al., used computer simulations and genetic algorithms to find the optimal operator according to the cellular conditions in the content management system [128]. Ranaeifar et al., presented the material flow study in a CMS and the use of simulation to determine the appropriate material flow in order to achieve the company's development plan and also increase production capacity [129]. Pitchika et al., Investigated the transition from an application system to a cellular system by obtaining queue loads for both systems through queue theory, for single-level, and simulation, for multi-level generation under the same time settings They performed the process, start-up time, batch size and login section. They also identified conditions in which a cellular system is better than a functional system [130]. Chtourou et al., performed a system layout focusing on the objectives of the comparison method and the classification of key factors and performance measurements by comparing CL and FL simulation studies. They mostly used simulation to show some shortcomings [131].

2.2.6. Mathematical Programming

Mathematical programming has been widely used in CMS design. Methods based on mathematical programming methods have the ability to consider many production factors with different purposes. However, these methods are usually used for relatively small problems. And they cannot be used to solve problems on a real scale. Mathematical programming methods for cell formation include linear or nonlinear formulation of integer programming problems. The advantage of mathematical programming methods is that different objective functions and many limitations in cell design can be considered. Minimizing intercellular mobility, cost and preparation time, production costs, number of exception parts, machine idle time, investment in equipment purchase and maximizing machine utilization are among the most important objective functions used in these techniques [132]. Vakharia et al., examined the three problems of determining the family of parts, determining the cell of machines, and intracellular arrangement linearly [133]. Alfs et al., examined the problem of grouping machines and determining the arrangement in cellular production systems and presented this problem as a mathematical model in which different dimensions were considered for machines [134]. Balakrishnam and Cheng, presented a flexible two-level method for solving the problem of cell formation by considering changes in demand with the help of dynamic planning and the problem of machine allocation [135].

The first phase of the method involves solving any allocation of machines to the machines in each of the periods. The second phase of the method is the use of dynamic planning for design during planning periods. Their objective function is to minimize the total cost of moving materials and relocating machinery. Kia et al., presented a nonlinear complex integer programming model for designing a cell production system [136]. Multiple operational paths, the amount of intracellular and intercellular transport costs per unit of movement, the costs of cellular restructuring, the minimum and maximum number of machines per cell are among the assumptions included in their model. Paydar et al., expressed a fuzzy ideal programming approach to solve the problem of cell formation and layout design. In the proposed model, they considered assumptions such as operation time, batch size, and component demand, minimum and maximum number of machines per cell [137]. Ahi et al., examined three problems of cell formation, intracellular arrangement and cellular arrangement with multi-criteria decision approach (MCDM) in two level. In the first level, first by TOPSIS problem Cell formation is solved and improved by other techniques, and in the second level, cellular and intracellular arrangements are identified [138].

Fardis et al., presented a mathematical model to solve the problem of cell formation in the cell production system. They defined the parameters of cell entry rate and machine service rate through exponential distribution. In addition, they defined the average waiting time of components behind each device as a solution to overcome the problem of programming disruption that may occur in the system. They presented the proposed model with CPLEX and its solution with GAMS [139]. Safaei et al., presented a nonlinear integrated correct planning model that tries to integrate the concepts of production planning and cell production. This model tries to minimize fixed and variable machine costs, intracellular and intercellular relocation costs, cell rearrangement costs that include car relocation costs, and outsourcing costs that include inventory management costs, pre-order, has a different time period. In this model, it is assumed that AGV is used to move parts between cells and robots are used to move parts between cells, although the impact of using AGV and how to allocate material management operations to it has not been studied in the proposed model. The main finding of this study indicates the significant effect of outsourcing on cell configuration, which is evident in the relocation / removal or addition of machines in each cell [140].

Eski and Ozkarahan, considered the design of production cells with production requirements in conditions of uncertainty. They showed the random nature of the production system with a simulation model. The processing times of the part, the intercellular movement times of the part and the time of presence of the part are considered randomly. The objectives are to maximize system utilization and minimize the average latency in the model [141]. Tavakkoli Moghadam et al., presented a mathematical model to solve the problem of arrangement of facilities in the cellular production system in conditions of random demand with the aim of minimizing the total cost of intracellular movements [142]. Ghazavati et al., developed a correct stochastic model for designing cell production systems with stochastic parameters. They assumed that the processing time of the parts on the machines and the arrival time of the parts into the cells were random, which is described by the continuous distribution. They considered each machine as a server and each piece as a client that the server should serve. Therefore, the arranged cells of a queuing system are defined, which are optimized through queuing theory [143]. Torabi and Shamekhi, desighned a cell production system in which the demand for parts and costs under the behavior of fuzzy numbers to be possible in the form of distribution. They proposed an adaptive fuzzy ranking method to identify low-demand, non-repetitive components assigned to a functional cell. Then, they use an interactive programming model for the Cell arrangement problem to allocate the remaining components [144]. Arikan et al., presented a new satisfactory multi-objective fuzzy model for designing a cell production system. In the proposed model, they considered two important problems in the design of a cell production system called cell formation and exceptional elements simultaneously in a fuzzy environment. Part demand, machine capacity and cost of removing exceptional elements were considered as fuzzy parameters and the model was solved using their proposed method [145]. Arikan et al., presented a two-level method for solving multi-objective fuzzy linear programming problems. This method is a fuzzy parametric and linear programming to solve real life problems with all fuzzy coefficients [146]. Mahdavi et al., proposed a new satisfied model for cell formation in the cell production system based on the concept of cell utilization, which aims to minimize exceptional elements [147]. Tavakkoli Moghadam et al., presented a new mixed integer mathematical model for CFP developed with dynamic and uncertain conditions [148]. Eguia et al., presented a linear integer model for designing a cell production system by considering machine grouping and routing determination while using CNC numerical control tools [149].

3. Conclusion

Manufacturing industries are under severe pressure from the global competitive market. Shortening the life cycle of goods has forced the time required for marketing and different needs of manufacturers to improve the efficiency and productivity of their production activities. Production systems must be able to produce a product with low production cost and high quality in the shortest possible time to deliver products to customers on time. In addition, production systems must be able to adapt or respond quickly to changes in product design and demand without the need for major investment. Cell production system design methods include clustering methods, graph theory, neural network, meta-heuristic methods, simulation and mathematical programming. The following diagram tries to determine the use of each of these methods.

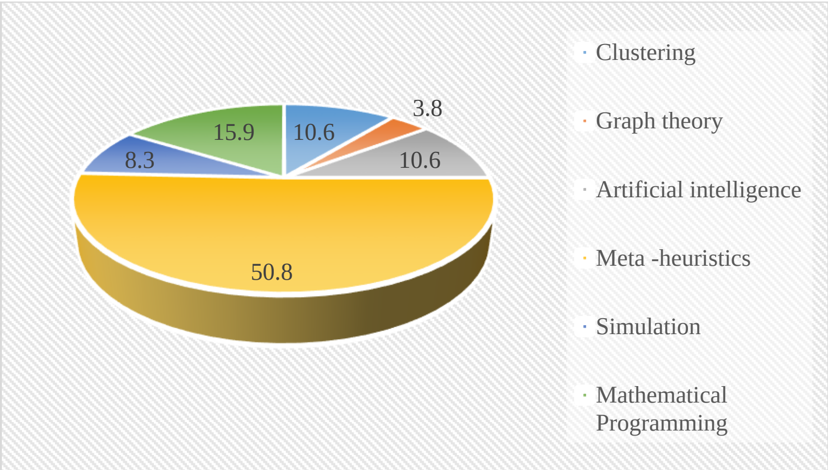

Fig. 3. Cell production system design methods

As shown in the diagram above, the most common use is meta-heuristic methods. Due to the complexity and NP-Hard of cell design system design, the use of sophisticated and modern methods is inevitable. As mentioned, a comprehensive design is a design that can take into account the constraints of a production system that are closer to the real environment. This complicates the design of the production system. Meta-heuristic methods are one of the good methods in the field of production system design. These methods have been considered by researchers due to their breadth and dynamism in the face of various factors and the low amount of calculations. As can be seen in the diagram above, the rate of application of meta-heuristic methods is above 50%, which indicates the importance and scope of their performance. After meta-heuristic methods, mathematical programming has been used more. Mathematical programming methods can take into account many limitations, which is why they are very suitable for problems with many limitations but small in size. After mathematical programming, the order of use of other methods includes neural network, simulation, and clustering and graph theory, respectively. Its meta-heuristic methods include many algorithms such as genetics, annealing simulation, Tabu search, Particle swarm optimization, and ant colony. Due to the importance of meta-heuristic methods, the amount of application of each of the stated algorithms is also important, which is shown in the following diagram of the dispersion of the use of each of them.

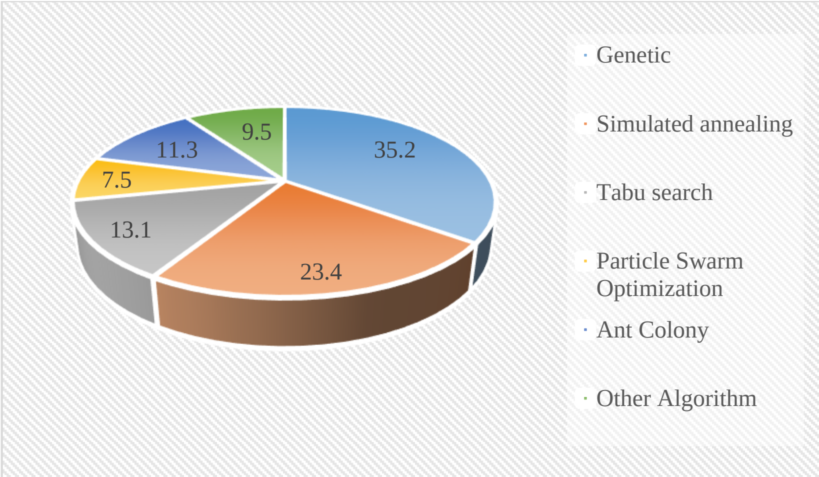

Fig. 4. Percentage of using ultra-heuristics algorithms

As can be seen in the diagram above, the use of algorithms is genetic algorithm, annealing simulation, Tabu search, ant colony, Tabu search and particle optimization, respectively. Genetic algorithms are among the oldest algorithms. It has also received more attention due to its simplicity of learning and coding. There are several types of limitations that can be considered to make it easier to examine cellular constraints (cell formation, intracellular motions, intercellular motions, cell design, location, cell heterogeneity, cell charge transaction, cell reconfiguration, cell capacity and. ..), capital constraints (initial capital, delay cost, cell start-up capital, staff recruitment capital, etc.), machine constraints (machine purchase, machine efficiency, machine unemployment, machine relocation , Grouping of machines, capacity of machines, etc.) and operational constraints (sequence of operations, family of parts, alternative production routes, process routing, intermittent demand, etc.) can be divided. The more sophisticated the solution methods used, the more the limitations considered by the researchers increase. In real-world operating conditions, a wide variety of problems and constraints can occur for a production system, which a production system designer must be able to take into account in his model in order for his design to conform to the actual conditions. To create a comprehensive system with high productivity rates in different work environment conditions.

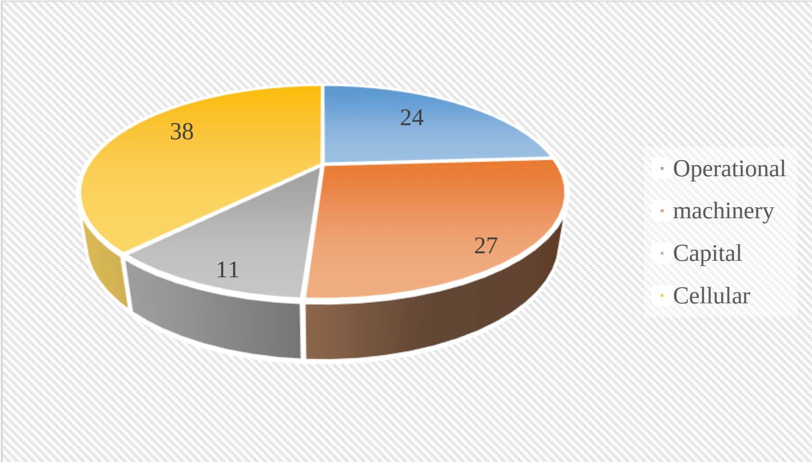

Fig. 5. Limitations in cell production

As shown in Figure (5), most attention is initially paid to cellular limitations. When forming a cell, many problems must be considered, such as the location of the machines, the number of cells required, how the cells are placed next to each other with the least cost of movement, preventing reconfiguration, etc. Another basis is restrictions. By forming the right cell, the costs of machines such as purchasing, moving, etc., and operating costs can be reduced. Therefore, the reason why cellular limitations are taken into account is that it covers other limitations. After cellular constraints, respectively, machine constraints, operational constraints and then capital constraints have been more considered by researchers. Of course, in many articles these limitations are considered simultaneously, which leads to better use in the real production environment.

Also, the journals that have published various articles in the field of cell production system can be shown in the table below. Table (1), can be used as a good reference for searching in the field of cell production system

Table 1. Active journals in the field of cell production

Rank	Journal Name	Number of articles	publisher
1	International Journal of Production Research	42	Taylor and Francis
2	Computers and Industrial Engineering	23	Elsevier
3	Manufacturing International Journal of Advanced Technology	18	Springer
4	Journal of Manufacturing Systems	10	Elsevier
5	Applied Mathematics Modelling	9	Elsevier
6	Computers & Operations Research	8	Elsevier
7	European Journal of Operation Research	6	Elsevier
8	International Journal of Production Economics	6	Elsevier
9	IIE Transactions	5	Taylor and Francis
10	Expert Systems with Applications	5	Elsevier
11	IEEE	5	IEEE
12	Fuzzy set and system	3	Elsevier
13	Robotics and computer integrated manufacturing	2	Elsevier
14	Journal of the Operational Research Society	2	Springer
15	Applied soft computing	2	Elsevier
16	International Journal of computing integrated management	2	Taylor and Francis
17	Journal of Manufacturing technology management	2	Emerald
18	Operation research	2	Elsevier
19	Other Journal	35	

The chart shows 6% of the journals used. This chart shows the extent to which various journals pay attention to the subject of the cellular production system and the extent to which articles in this field are published by these journals.

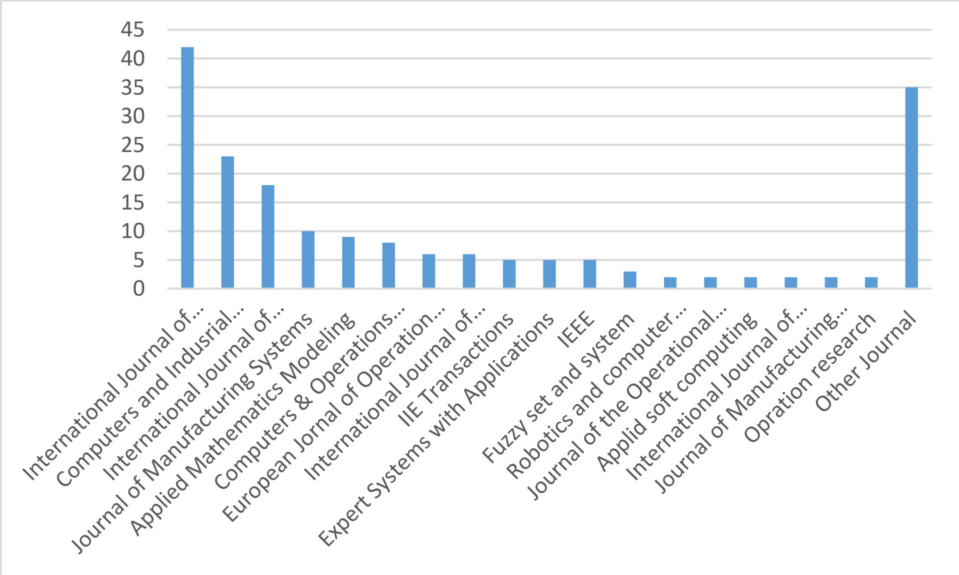

Fig. 6. Active journals in the field of cell production

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