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# ENHANCED PRODUCTION THROUGH NOVEL SWARM-INTELLIGENT ENABLED VIRTUAL CELL FORMATION: MULTIFACETED APPROACH

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A B S T R A C T

*In the dynamic realm of manufacturing, it is essential to optimize production processes to attain efficiency and competitiveness. This study presents an innovative enhanced dragonfly optimization (EDFO) method to improve production by utilizing a diverse strategy that combines swarm intelligence and virtual cell development. The suggested methodology includes the parallel EDFO algorithm, which is a cutting-edge variety of swarm intelligence, to address the intricate optimization difficulties related to virtual cell creation. The virtual cell construction process entails the consolidation of machines into cells to optimize output and reduce manufacturing lead times. The benchmark test results offer valuable insights into the algorithm's capabilities and effectively demonstrate its effectiveness in optimizing virtual cell generation for various manufacturing conditions. The proposed approach, which simultaneously takes numerous essential characteristics, is a comprehensive solution for improving production efficiency in virtual cellular manufacturing systems due to its multifunctional nature.*



## 1. INTRODUCTION

The implementation of enabled Virtual Cell Formation (CF) represents an advanced manufacturing concept that is transforming conventional production methods. By integrating cutting-edge technologies such as Artificial Intelligence (AI), the Industrial Internet of Things (IIoT) and data analytics, it revolutionizes traditional manufacturing facilities into dynamic and flexible ecosystems (Forghani and FatemiGhomi (2019)). They enable the flexible arrangement of assembly lines, thereby enhancing production efficiency and optimizing resource allocation. Enabled Virtual CF utilizes real-time data and predictive algorithms to facilitate efficient coordination between interconnected machines, thereby improving overall operational performance (Cheng et al., (2022)). This shift in paradigm enables manufacturers to rapidly adapt to market requirements, decrease operational interruptions and mitigate expenses. The incorporation of virtual cells facilitates the establishment of a flexible and

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reactive manufacturing setting, thereby promoting competitiveness in the swiftly changing industrial domain. Enabled Virtual CF is a prime example of Industry 4.0, showcasing the integration of digital technologies with conventional manufacturing (Abid et al., (2022)). This paves the way for a revolutionary era of intelligent and interconnected production systems (Yu et al., (2022)).

Enhanced Production through Enabled Virtual CF is a strategy that utilizes the concept of virtual CF in manufacturing to optimize and improve production processes. This entails generating digital models of manufacturing cells to simulate and analyze different production scenarios (Chiapponi (2021). Potential strategies for enhancing production encompass optimizing resource allocation, minimizing cycle durations and augmenting overall operational efficiency. Virtual CF utilizes computer simulations to identify bottlenecks and optimize processes without the need for physical implementation, resulting in time and resource savings (Priyadarshini and Gupta (2023)). The incorporation of cutting-edge technologies such as AI and IoT can augment the capabilities of real-time monitoring and decision-making processes. They enable the implementation of adaptable production systems that can respond to changing market demands. By adopting virtual CF, industries can leverage advanced methodologies to optimize production processes, reduce operational interruptions and establish a highly adaptable as well as streamlined manufacturing ecosystem, resulting in enhanced market competitiveness (Chien et al., (2022)).

The incorporation of swarm intelligence techniques into the virtual CF methodology aims to enhance the efficiency and effectiveness of manufacturing processes. They utilize the aggregated decision-making capabilities of a group, imitating the innate behavior observed in social insects. By implementing these principles in the context of virtual CF, the system is able to dynamically adjust and optimize production configurations based on fluctuating demands and operational conditions (Guo et al., (2023) and Kumar et al., (2022)). This technology optimizes operational effectiveness, minimizes periods of inactivity and enhances overall output in the manufacturing industry. The combination of swarm intelligence and virtual CF facilitates a dynamic and responsive production environment, resulting in efficient operations and optimal resource allocation (Feng et al., (2021), (Sibalija (2019) and Lan and Chen (2023)).

### 1.1 Contribution

- The study provides a novel approach by integrating swarm intelligence principles with virtual cell development tactics.
- The development of the parallel EDFO algorithm represents cutting-edge progress in swarm intelligence. This approach has been customized to address complex optimization difficulties that appear during the formation of virtual cells.
- The study focuses on the process of constructing virtual cells, with a specific focus on combining machines into cells to accomplish maximum output and minimize manufacturing lead times.

The remaining part of this article is categorized into the subsequent sections: Part 2-Literature review, Part 3-Methodology, Part 4-Result coupled with Discussion and Part 5- Conclusion.

## 2. LITERATURE REVIEW

Zandieh (2019) demonstrated optimal and productive schedules for the VCF concerns using the biogeography-based optimization (BBO) algorithm. The VCF structure involved combining machines with varying processing capabilities in nearby ranges to boost the overall system's resilience against various changes. The arrangement provided multiple alternate paths for job execution. The existing methods are used to assess the efficiency of the best algorithm. Mehdizadeh et al., (2020) presented a comprehensive "integer nonlinear programming (INLP)" framework for the "dynamic cell manufacturing system (DCMS)," which takes the constrained resources required for setting up cells as well as procuring production machinery for the CF and production planning (PP). The suggested model aimed to reduce the expenses related to the PP, cell creation and formation, specifically the related costs to cell preparation that setup in a system. Furthermore, the Taguchi method was employed to fine-tune the variables of the meta-heuristics with the goal of obtaining superior-quality answers. The numerical results have verified the effectiveness of the suggested techniques. Al-Zuheri et al., (2022) created a novel strategy that utilized many flexibility factors to direct the formation of cells. The recommended methodology was developed to address the challenges of optimizing the architecture of CM that involve large-scale and multi-objective optimization challenges. The outcomes were achieved when the suggested method was implemented in a specific instance. They offered practical consequences and advice that decision-makers can utilize when designing CMs. Mansour et al., (2022) introduced an innovative two-stage technique that uses heuristics to address challenges linked to CMS. By giving each cost component the proper weight, the technique attempted to reduce the total expenses related to inter or intra-cell motions, execution, along with faults. The outcomes demonstrated that the suggested strategy addressed the CMS-related issues in a respectable period.

Shunmugasundaram et al., (2019) presented a novel CF approach that integrates agglomerative clustering with array-based clustering. The technique was implemented in the real-time issue. The response acquired from the suggested method was compared to the answer derived from the existing research. Subhaa et al., (2019) presented a framework for CM that addresses the architectural layout concerns of CF as well as the functional challenges of optimal schedules. The method validation demonstrated that the suggested CM framework optimized CF while minimizing operational costs. Aghajani-Delavar et al., (2022) proposed a method for machine cell generation depending on real-life manufacturing parameters, utilizing a fuzzy c-mean clustering technique. The technique employed a membership function to quantify the degree of connection with each machine cell. The efficacy of the suggested methodology was evaluated by using "group technology efficiency (GTE) and exceptional elements (EE)" on different problem-solving situations of varying sizes sourced from existing fields. The obtained outcomes were evaluated with the most optimal results.

Bhowmik et al., (2020) introduced a "bi-objective dynamic CF Problem (CFP)" in a dynamic atmosphere. The objective of the concept was to decrease overall expenses while maximizing the performance of operators. The analytical tests conducted to evaluate the efficiency of the generated techniques indicated that the suggested algorithm outperformed the others. Zhao et al., (2020) presented a novel approach for designing the layout of a "multi-floor linear cellular manufacturing" facility. The suggested machinery layout technique not only deviated from the traditional single-floor CM but also satisfied the layout criteria of the intelligent production workshop for "the stereoscopic aisle manufacturing cell."The simulation scenarios indicated that the adaptive "multi-objective fruit fly optimization algorithm" outperformed other current techniques in solving linear cellular industrial challenges. Chu et al., (2019) provided a novel quantitative program model called "workload imbalance in the worker assignment problem (WAP-CLF)," which aims to solve the issue of labor allocation in CM. The framework takes into account cross-training, as well as the processes of learning and forgetting, the suggested model aimed to reduce the expenses associated with training.

Mei et al., (2023) developed "a weighted allocation" framework for a joint selection issue, including formation scheduling the waiting time in the process. An approach called "adaptive differential evolution-simulated annealing (ADE-SA)" was presented to address the "nondeterministic polynomial (NP) problem."The empirical findings from a range of arbitrary instances demonstrated that the proposed algorithm outperformed other established approaches in terms of overall performance. Mohtashami et al., (2020) introduced an innovative and valuable "fuzzy multi-objective mathematical" framework for CM that the dynamic machines flexibly, the suggested technique aimed to determine the optimal design for each manufacturing phase. To evaluate and assess the effectiveness of the methods, they examined the solutions to the standard issues, which were generated based on the critical metrics in that domain. Behnia et al., (2019) developed a bi-objective, bi-level framework for CM. The mathematical outcomes of all three objectives showed that while selections were produced simultaneously regarding "inter-and intra-cell layouts" and CF to balance designated workloads by examining gaps and employees' interests, the outcomes varied from the suitable scenario, making the issue more realistic.

Goli et al., (2021) focused on the issues of cell creation and intercellular timing in a CM setting and combined them into a single concern. A "fuzzy Mixed Integer Linear Programming (MILP)" model was formulated to design CM that utilizes Automated Guided Vehicles (AGV) to navigate among cells and identify pathways that avoid conflicts. The outcomes demonstrated that the suggested techniques outperformed others in solving small and medium-sized issues. It indicates that the methods are dependable and suitable for more significant problems, delivering quality approaches in a reasonable computational timeframe. Deliktaş et al., (2021) focused on the issue of planning in a flexible workshop cell with several objectives. They consider the challenges posed by extraordinary and sequence-dependent household installation durations. The experimental findings demonstrated the effectiveness of a revolutionary transgenerational memetic algorithm that incorporates a newly developed hill-climbing algorithm. Hashemi et al., (2022) addressed CF issues by employing alternate routings, with a specific focus on reducing inter-cell movements. The utilization of the particle swarm optimization (PSO) meta-heuristic method achieved it. They demonstrated that utilizing PSO with an individual count closely matching the number of parts scaled in relation to the highest, optimal solutions can be produced in a shorter amount of time using a standard set of instructional variables and a restricted number of possible pathways.

Rabbani et al., (2019) presented a novel multi-objective statistical framework for a dynamic CM, considering machinery reliability and alternate process pathways. In the framework, they aimed to address the issue of coordinated family development and the allocation of workers to the cells. Multiple test instances were performed to demonstrate the efficacy of the suggested algorithm and the outcomes were evaluated based on comparison criteria. A revolutionary intelligent PSO technique was designed by (Mahmoodian et al., (2019)), for the discrete problem of CF and it can be utilized for such purpose. The proposed approach integrated artificial human intelligence and swarm intelligence by employing Kohonen's learning rules. The quantitative analysis demonstrated the higher performance of the presented method compared to others in terms of both effectiveness and efficacy metrics. This study provides a novel parallel enhanced dragonfly optimization (PEDFO) method for increasing production by combining swarm intelligence with virtual cell development.

## 3. MATERIALS AND METHODOLOGY

This article proposes a multi-step approach for virtual cell creation. The physical aspects that affect production in real-world scenarios include possibilities for different routes along with the time it takes to process parts, the capacity, flexibility of machines, as well as the volume of manufacturing and demands. The incidence matrix, which includes both engine and non-machine components, contains this information. The next stage involves calculating the similarity index between all machines using the information provided in the part-machine incidence matrix. Cluster representation is identified based on the required amount of cells using the similarity index. The next phase utilizes a parallel EDFO technique to assign machines to different partitions. The objective is to minimize the similarity between cells while maximizing the similarity inside each cell. Finally, the components are distributed across various machine cells using a part allocation method. After identifying the machine cells and their related part families, performance measurements are assessed on the virtual cells that have been created. Figure 1 displays an outline of the proposed methodology.

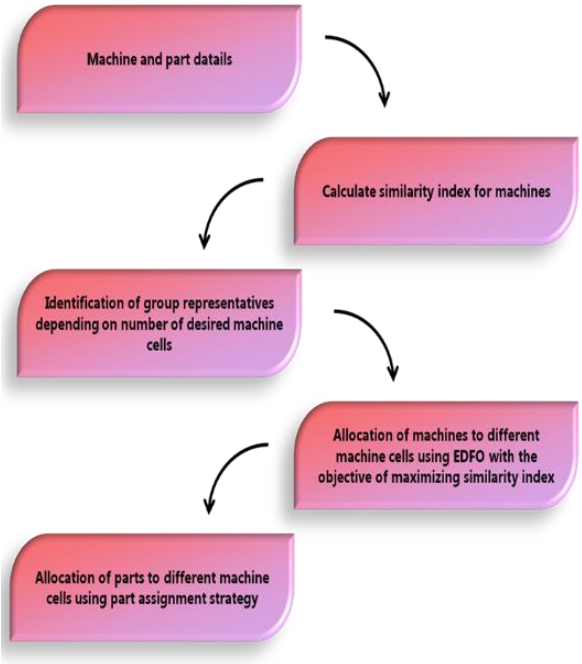


**Figure 1.** The overall methodology of Swarm-intelligent Enabled Virtual CF.

### 3.1 Virtual CF

In this study, we utilize a novel similarity coefficient to calculate the similarity measures between machinery. This coefficient considers various production factors that are relevant to real-life scenarios, such as product demand, etc in Equations (1-2).

$$\frac{\sum_{l=1}^{m_{wjilq}} \sum_{q\in lj \text{ and } q\in li}^{Q} \left[max\left(\frac{s_{ljq}}{D_j} \times \frac{m_{pj}}{M_{pj\,max}}, \frac{s_{liq}}{D_i} \times \frac{m_{pi}}{M_{pi\,max}}\right) W_{jilq}\right] \frac{U_l}{C_l}}{\sum_{l=1}^{m_{wjilq}} \sum_{q\in lj \text{ and } q\in li}^{Q} \left[max\left(\frac{s_{ljq}}{D_j} \times \frac{m_{pj}}{M_{pj\,max}}, \frac{s_{liq}}{D_i} \times \frac{m_{pi}}{M_{pi\,max}}\right) W_{jilq}\right] \frac{U_l}{C_l} +} \quad (1)$$

$$\sum_{l=1+m_{wjilq}}^{m-m_{wjilq}} \sum_{q\in lj \text{ and } q\in li}^{Q''} \left[max\left(\frac{s_{ljq}}{D_j} \times \frac{m_{pj}}{M_{pj\,max}}, \frac{s_{liq}}{D_i} \times \frac{m_{pi}}{M_{pi\,max}}\right) Z_{jilq}\right] \frac{U_l}{C_l} \quad (2)$$

#### 3.1.1 Head for the machine group

The model is a valuable tool for clustering scenarios, with the goal of aggregating m objects into n groups. The target functions in p-median frameworks are dependent upon the selection of group medians and the assigned values of similarity coefficients. The target value could be described as the sum of resemblance coefficients among every pair of components in all clusters, expressed using a "quadratic allocation framework”. The clustering aims to classify elements with unique attributes into separate clusters. Therefore, it is reasonable to deduce that the n most miniature comparable objects are allocated to n distinct groups. Instead of using group averages or medians, one can select the m least significant outliers to represent each group, with each item representing a particular group. The similarity coefficient matrix, denoted as$\forall_{ji}, t_{ji} = t_{ij}$, typically exhibits symmetry. The cluster participants could be identified using the subsequent recursive approach in Equations (3-4).

$$q_1, q_2 = arg_{(j,i)}\, min\, t_{ji} \quad (3)$$

$$q_h = arg_{j\in\{1,2,\ldots,h-1\}} min \sum_{i=1}^{h-1} T_{jq_i}, \quad h = 3,4,\ldots,n \quad (4)$$

$q_h$Represents the group h head. Eq (2) identifies the combination of components that have the smallest coefficient of similarity. Eq (3) iteratively computes the residuals of the m-2 group members that exhibit the highest degree of contrast, one at a time, based on those that have been identified. Linear allocation framework by utilizing m preselected cluster heads in Equations (5-7).

$$\sum_{i=1}^{n} \sum_{h=1}^{m} T_{iq_h} w_{ih} \quad (5)$$

$$\sum_{h=1}^{m} w_{ih} = 1, \quad i = 1,2,\ldots,n \quad (6)$$

$$w_{ih} \geq 0 \quad (7)$$

$w_{ih}$Is a “binary decision variable” that is denoted as $w_{ih} = 1$the item was allocated to cluster$w_{ih} = 0$. Equ (5) guarantees that each item is assigned to approximately one cluster. Table 1 contains the machine matrix, Table 2 contains part details and Table 3 contains machine data. The highest amount of machine cells varies between four and seven or five and eight to enhance management.

**Table 1.** Matrix of parts.

| Parts | Routes | Machine | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| 1 | 1 | 5 | - | - | - | 1 | 1 | - | - |
| | 2 | 3 | - | 3 | 3 | - | - | - | 1 |
| 2 | 1 | - | 4 | 4 | - | - | 1 | 1 | 3 |
| 3 | 1 | 4 | - | 3 | 4 | - | - | 1 | 1 |
| | 2 | - | - | - | 3 | - | 3 | 1 | 1 |
| | 3 | - | - | 1 | - | 4 | 3 | - | 1 |
| 4 | 1 | 1 | 3 | 4 | - | 4 | 5 | 1 | 1 |
| | 2 | 3 | 4 | - | - | 1 | 3 | - | 4 |
| 5 | 1 | 1 | 3 | 5 | 1 | - | 4 | - | 3 |
| | 2 | - | - | - | - | - | - | 1 | - |
| 6 | 1 | 3 | 3 | - | 4 | - | - | 3 | - |
| 7 | 1 | 5 | 3 | 1 | - | 3 | - | 4 | 1 |
| | 2 | - | - | 1 | - | - | - | - | - |
| 8 | 1 | 3 | - | 3 | - | - | 4 | - | - |
| | 2 | - | - | - | - | - | - | 4 | - |
| 9 | 1 | - | 1 | 3 | 5 | 4 | - | 3 | 5 |
| | 2 | 5 | - | - | 3 | 1 | - | - | 4 |
| 10 | 1 | 3 | 3 | - | 1 | 1 | - | - | 3 |

**Table 2.** Description of parts.

| Part | Routes | Machine | | | | | | | | Manufacture volume | Demand |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | | |
| 1 | 3 | 3.15 | - | - | - | 3.03 | 3.15 | - | - | 2,650 | 2,350 |
| | 2 | 3.59 | - | 2.19 | 3.07 | - | - | - | 3.00 | 2,650 | 2,350 |
| 2 | 3 | - | 2.23 | 1.53 | - | - | 1.39 | 0.15 | 0.96 | 3,350 | 2,550 |
| | 2 | 1.76 | 3.96 | 2.32 | 3.67 | - | 1.73 | - | - | 3,350 | 2,550 |
| 3 | 3 | 3.52 | - | 3.91 | 3.36 | - | - | 2.01 | 1.51 | 2,650 | 2,350 |
| | 2 | - | - | - | 1.39 | - | 1.31 | 3.37 | 2.95 | 2,650 | 2,350 |
| | 3 | - | - | 1.36 | - | 2.75 | 1.06 | - | 3.01 | 2,650 | 2,350 |
| 4 | 3 | 3.33 | 1.11 | 3.92 | - | 3.15 | 2.16 | 1.51 | 1.23 | 2,950 | 2,350 |
| | 2 | 3.27 | 3.11 | - | - | 3.31 | 3.31 | - | 2.09 | 2,950 | 2,350 |
| 5 | 3 | 2.51 | 3.23 | 3.55 | 1.13 | - | 2.35 | - | 3.19 | 3,350 | 2,550 |
| | 2 | - | - | - | - | - | - | 1.63 | - | 3,350 | 2,550 |
| 6 | 3 | 3.53 | 3.03 | - | 1.96 | - | - | 3.06 | - | 3,950 | 3,650 |
| 7 | 3 | 3.99 | 2.93 | 2.01 | - | 0.79 | - | 3.11 | 0.13 | 2,650 | 2,350 |
| | 2 | - | - | 3.55 | - | - | - | - | - | 2,650 | 2,350 |
| 8 | 3 | 3.53 | - | 2.53 | - | - | 3.90 | - | - | 3,350 | 2,550 |
| | 2 | - | - | - | - | - | - | 3.13 | - | 3,350 | 2,550 |
| 9 | 3 | - | 2.33 | 3.91 | 2.79 | 3.66 | - | 3.23 | 3.13 | 2,750 | 2,350 |
| | 2 | 1.26 | - | - | 1.56 | 2.10 | - | - | 3.73 | 2,750 | 2,350 |
| 10 | 3 | 3.73 | 3.16 | - | 3.33 | 2.96 | - | - | 1.01 | 2,350 | 3,950 |

**Table 3.** Description of machine.

| Machine | Machine capacity in hours | Amount of functions accomplished | The machine's highest amount of functions |
|---|---|---|---|
| 1 | 2,150 | 31 | 31 |
| 2 | 2,650 | 26 | 28 |
| 3 | 2,550 | 28 | 28 |
| 4 | 2,850 | 22 | 24 |
| 5 | 2,950 | 26 | 26 |
| 6 | 2,450 | 23 | 23 |
| 7 | 3,150 | 28 | 28 |
| 8 | 2,650 | 30 | 32 |

In the illustration given, there are a total of seven machines, resulting in a count of four cells. The coefficient matrix (Table 4) is examined to identify cluster heads utilizing Equations (2-3).

**Table 4.** Matrix of co-efficient similarity.

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 |
|---|---|---|---|---|---|---|---|---|
| *M1* | 1.002 | 0.573 | 0.380 | 0.333 | 0.460 | 0.294 | 0.344 | 0.408 |
| *M2* | 0.573 | 1.002 | 0.303 | 0.367 | 0.442 | 0.416 | 0.367 | 0.477 |
| *M3* | 0.380 | 0.303 | 1.002 | 0.342 | 0.313 | 0.397 | 0.496 | 0.491 |
| *M4* | 0.333 | 0.367 | 0.342 | 1.002 | 0.190 | 0.334 | 0.294 | 0.468 |
| *M5* | 0.460 | 0.442 | 0.313 | 0.190 | 1.002 | 0.276 | 0.385 | 0.454 |
| *M6* | 0.294 | 0.416 | 0.397 | 0.334 | 0.276 | 1.002 | 0.289 | 0.505 |
| *M7* | 0.344 | 0.367 | 0.496 | 0.294 | 0.385 | 0.289 | 1.002 | 0.447 |
| *M8* | 0.408 | 0.477 | 0.491 | 0.468 | 0.454 | 0.505 | 0.447 | 1.002 |

## 3.2 Proposed methodology

### 3.2.1 Parallel Enhanced dragonfly optimization (EDFO)

A dragonfly's best fitness value to date is denoted by pbest and the best fitness value achieved by all dragonflies in the immediate area is represented by gbest. In addition, EDFO incorporates principles of quantum physics to calculate the drag force acting on flies and update their position accordingly. During every repetition, the fitness value of a DF is contrasted with the best value in the current population. The improved fitness value is stored in the best variable. The highest fitness value achieved thus far by the DF is stored as the best value. A dragonfly changes its position according to the Equations (8-11).

$$\Delta W_j^{s+1} = \left(tT_j^s + bB_j^s + dD_j^s + eE_j^s + fF_j^s\right) + xW_j^s + D_1 q_1\left(NO_j^s - W_j^s\right) * \ln\left(\frac{1}{u}\right) + D_2(1-q_1)\left(O_H - W_j^s\right) \quad (8)$$

$$NO_j^s = \frac{1}{M}\sum_{j=1}^{M} o_j^s \quad (9)$$

$$q_1, v \sim (0,1) \quad (10)$$

The variables $D_1$ and $D_2$ represent the cognitive and social factors, respectively. Both $D_1$ and $D_2$ are set to 2. The variables $o_j^s$ and $O_H$ reflects the best fitness of the $i^{th}$ DF and "the best fitness of the swarm up" to the $s^{th}$ iteration, respectively. N represents the total amount of occurrences or examples.

EDFO analyzes an extensive range of possibilities to prevent reaching a suboptimal solution too early. During the later stage of optimization, EDFO utilizes small regions to enhance the accuracy of the final answers. In order to simplify the adjustment process of EDFO, the parameters that exhibit the same change trend are assigned to the identical curve distribution. Initially, the weights are initialized to an appropriately high and gradually decrease to avoid excessive influence on subsequent steps yet to avoid getting stuck in a suboptimal solution. Finally, the settings gradually decrease to strengthen the capacity to exploit.

$$e(s) = Init\left(1 - \frac{1}{1+f^{-0.1\,(s-50)}}\right) \quad (11)$$

T represents the number of iterations, while $Init$ denotes the initial values. To improve operating efficiency, the EDFO employs parallel computing techniques. The system mimics dragon collective behavior and adaptive nature as they negotiate difficult problem areas in search of optimal solutions. The method maintains a population of prospective solutions that communicate and share information to alter their positions in the solution space. Parallelization allows for the concurrent evolution of several subpopulations, allowing for faster convergence and the evaluation of a wide variety of solution sectors.

The use of this parallel technique enables EDFO to address optimization difficulties of substantial size while capitalizing on the benefits of distributed computing. In summary, PEDFO is a trailblazer in optimization, effectively combining swarm intelligence and parallelization approaches to improve scalability and solution quality. The parallel computing EDFO is depicted in Figure 2.

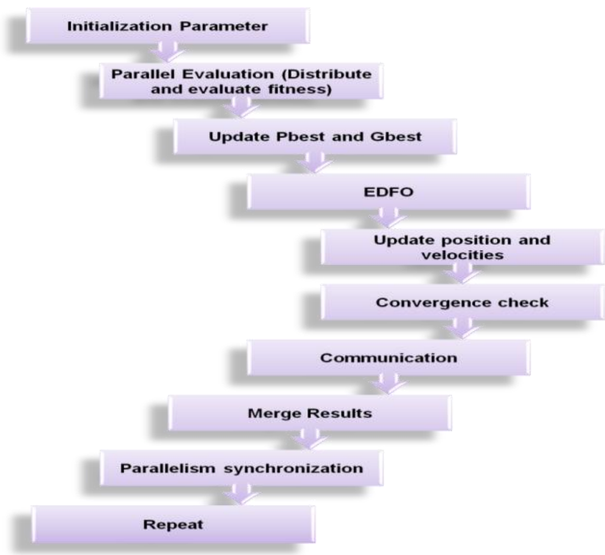


**Figure 2.** The flow of parallel EDFO

### 3.2.2 Machine distribution to cells using P-EDFO

The primary distinction between the typical DFO method and the P-EDFO consists of the absence of a velocity vector, which is a characteristic feature of the standard DFO algorithm. Each element of the individual (vector) is provided a value from 1 to the number of clusters (n) to indicate the group to which the machinery belongs. The swarm of individuals represents a possible collection of alternatives to the optimization problem. The swarm consists of m individuals. Wj maintains a log of its highest achieved position. The data is carried in a distinct individual identified as Aj. The data is carried in a particular individual denoted as G. The beginning population of individuals is formed by generating a sequence of unpredictable integers that determine the placements of the group representatives. The amounts are created uniformly from a range of one to n, including both endpoints. The objective problem can be addressed by representing alternative solutions as discrete strings of defined length.

As an example, let's consider the following numerical scenario: there are two possible clusters and eight machines. An individual $W_j$= {1; 2; 2; 1} indicates a potential solution. Once the original population of individuals is produced, the value is calculated using Equ (4). Within the realm of multimodal optimization, the speed of an individual is defined as a sequential series of modifications that act upon a response. The conversion of a solution is denoted by a word that signifies the disparity between two points. The discrepancy between $W_j$and $A_j$represents the alterations required to transition individual i from W to A. The symbol μ indicates the number of elements that are different by 0 after subtracting A from W. If the variance between a specific component $W_j$ and $A_j$ is non-zero, it means the potential for a modification in that place. If the conflict is not equal to 0, that location can be changed using the actions outlined below. A unique vector V is created to record the areas of the items that are similar to zero. A stochastic number is made and allocated to β. The value β represents the number of modifications that will be applied to $W_j$, depending on the discrepancy between $W_j$ and $A_j$. Thus, β falls in the range of values between 0 and μ. Next, a set ψ consisting of randomly established β numbers is formed.

## 4. RESULT

### 4.1 Part formation

The allocation of parts to machinery cells is determined using the membership index. The membership index quantifies the level of affiliation between a component and a machinery cell yet it is calculated using Equations (12-13),

$$J_{ld} = \frac{n_{ld}}{N_d} \times \frac{n_{ld}}{n_l} \times \frac{s_{ld}}{S_l} \tag{12}$$

The allocation of part l is determined by calculating its level of identity to cells and assigning part l to cell d based on its highest level of uniqueness to cell d. The maximum sense of identity can be determined by,

$$J_{ld} = \max\{J_{ld}\} ford = 1, \dots, d \tag{13}$$

The range of $J_{ld}$ is from zero to one, $J_{ld} = 1$ indicates complete affiliation of parts l in cell d and $J_{ld} = 0$ means that zero action of part l is carried out in cell d.

### 4.2 Group technology efficiency (GTE)

GTE is a measure that quantifies the ratio between the most outstanding amount of feasible “inter-cell travels” and the absolute amount of cell trips performed by the framework. The GTE is computed using an Equations (14-17),

$$GTE = \frac{s_o - s_q}{s_o} \tag{14}$$

The system can accommodate a maximal amount of inter-cell excursions.

$$s_o = \sum_{l=1}^{m} (M_p - 1) \tag{15}$$

The system requires a certain number of inter-cell excursions.

$$s_q = \sum_{l=1}^{m} \sum_{x=1}^{(M_p - 1)} y_{nkw} \tag{16}$$

System utilization refers to the ratio of the operating time to the overall time necessary to perform actions.

$$TV = \frac{F_s}{(F_s + J_s)} \tag{17}$$

The repetitive approach is utilized to determine the group head, ensuring that the most excellent dissimilar machinery is placed into distinct and non-overlapping groups. Out of the eight machines along with ten pieces, three cluster heads have been identified as M3, M6 and M8. The arrangement of cells for CM is presented in Table 5. The layout indicates the presence of machinery cells and two parts. Due to the absence of a factor for machinery cell 2 and considering that machines M6 and M8 in machine cell 2 have additional functions to be carried out on part 1, it has been decided to assign machines M6 and M8 to machinery cell for improved manufacture planning and control (Table 6). This could lead to a reduction in the quantity of cells as well as the occurrence of machinery overlap, hence leading to a decrease in conveyance and handling expenses. The chance of a mutation ranges from 7% to 60%, while the individual size ranges from 8 to 65 to achieve the optimum level of fitness function. The virtual cell's ideal structure was performed with a population size of 15, a mutation rate of 18 and a maximum of 280 iterations. The optimum value of the goal function is 7.12. The combined effectiveness and system utilization were determined to be 65.36 and 43.55, respectively. The outcomes of these experiments are presented in Table 7. The virtual effectiveness for the evaluated situations was determined to be promising.

**Table 5.** Cell setup.

| No. | Cells | Part |
|---|---|---|
| **1** | (M3, M7) | (P3, P5, P7, P8) |
| **2** | (M8) | ------- |
| **3** | (M1, M4, M6,) | (P2, P6, P10) |

**Table 6.** Enhanced cell setup.

| No. | Part | Cells |
|---|---|---|
| 1 | (P2, P4, P6, P9, P10) | (M1, M4, M6, M8,) |
| 2 | (P3, P5, P7, P8) | (M3, M7) |

**Table 7.** Efficiency metrics.

| No. | Problem | Grouping technology | Frame work utilization | GTE |
|---|---|---|---|---|
| 1 | 5 × 7 | 73.33 | 5 × 7 | 38.10 |
| 2 | 5 × 5 | 85.71 | 5 × 5 | 52.80 |
| 3 | 10 × 15 | 69.84 | 10 × 15 | 40.82 |
| 4 | 40 × 25 | 58.81 | 40 × 25 | 41.16 |
| 5 | 10 × 7 | 60.00 | 10 × 7 | 37.71 |
| 6 | 5 × 4 | 71.43 | 5 × 4 | 34.43 |
| 7 | 20 × 12 | 72.22 | 20 × 12 | 50.55 |
| 8 | 12 × 10 | 72.00 | 12 × 10 | 33.66 |
| 9 | 10 × 10 | 75.51 | 10 × 10 | 34.57 |
| 10 | 20 × 20 | 65.39 | 20 × 20 | 39.55 |

## 5. CONCLUSION

The virtual CF test entails establishing an ideal arrangement of parts and machines by assigning parts to machines in a way that enhances performance metrics without requiring any resource reconfiguration. The virtual CF issue is classified as NP-hard, which means that it is challenging to find optimal or nearly optimum solutions using traditional optimization algorithms. This work introduces a novel Parallel EDFO method that utilizes the proportion of probabilities. The technique is employed to solve the virtual CF issue. The machines are organized into cells by maximizing the matrix coefficient in each cell and reducing the matrix coefficient between various cells. The proposed methodology is applied to evaluate its efficacy in terms of GTE and system utilization. The proposed strategy is considered adequate based on its capacity to address issues of different sizes. Therefore, the supervisor can utilize the proposed methodology as a preliminary tool to evaluate the effectiveness of virtual cells in relation to system utilization and GTE without requiring any alterations. Moreover, it is possible to design as well as to implement dispatched algorithms with the aim of improving manufacturing, scheduling and control.

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