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OPTIMIZING PRODUCTION SCHEDULING THROUGH HYBRID DYNAMIC GENETIC-ADAPTIVE IMPROVED GRAVITATIONAL OPTIMIZATION ALGORITHM

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A B S T R A C T

Mass customization is becoming the more and more of emphasis on the production optimization. In many manufacturing and service organizations, production planning and scheduling are characterized as the daily decision-making procedures. The significance of the choices made is therefore to shown in the areas of work orders, manufacturing, transportation, and distribution of the finished goods. Production scheduling is the process of regulating, determining, and maximizing the restricted resources of the production system. In this study, a novel Hybrid Dynamic Genetic-Adaptive Improved Gravitational Optimization Algorithm (HDG-AIGOA) approach is introduced to optimize the production schedule. In this case, the AIGOA classification effectiveness is increased by using the HDG method. The small and benchmark iMOPSE dataset has been used to assess the success of suggested approach. The noisy data from raw data samples are removed using the Adaptive Median Filter (AMF) filter. To extract the properties from the segmented data, a Kernel Principal Component Analysis (KPCA) is performed. The results of the research show that the recommended methodology beats earlier approaches in terms of the accuracy, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Square Error (MSE). Our proposed method might consider to improve the production scheduling in an dynamic environment.

1. INTRODUCTION

In manufacturing and production operations, optimizing production scheduling is a crucial responsibility. It entails effectively allocating resources, such as tools, supplies, and people, to carry out production orders while lowering costs, fulfilling delivery dates, and increasing general productivity. Planning strategically, using resources effectively, and using cutting-edge tools and algorithms are all necessary components of the continual process of optimizing production scheduling (Negri et al., 2021). The study may enhance manufacturing operations' efficiency, save costs, and increase customer happiness by using the tactics. To handle optimization issues in dynamic

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contexts, the Dynamic Genetic Adaptive Optimization Algorithm (DGAOA) combines the concepts of genetic algorithms (GA) with adaptive processes. GA is made to deal with circumstances where the issue or its restrictions change over time, necessitating continual search strategy adaptation on the part of the algorithm. The Dynamic Genetic Adaptive Optimization Algorithm's primary features are as follows: To create and grow a population of potential solutions, DGAOA uses the fundamental framework of genetic algorithms, which makes use of genetic operators such as selection, crossover, and mutation. The architecture enables DGAOA to investigate the search space and take advantage of attractive areas to discover ideal or nearly ideal answers (Choueiri and Portela Santos 2021).

DGAOA stands out for its flexibility in responding to changes in the issue domain. DGAOA includes systems for keeping an eye on and spotting changes in the problematic environment. adjustments to the goal function, restrictions, or problem structure are examples of the adjustments. The algorithm constantly modifies its parameters or operators as a change is recognized to better fit the new issue circumstances. DGAOA often uses systems for fitness monitoring to keep track of the historically most effective solutions (Babor et al., 2021). The algorithm may modify its search strategy by taking into account the most successful people from earlier generations by keeping track of the fitness levels of prior solutions. The aids in the preservation of valuable genetic material and offers a framework for adaptability when an issue changes. DGAOA often uses methods to modify the algorithm's settings while it is running (Xu et al., 2022).

DGAOA can swiftly adapt to changing situations and enhance its performance over time by continually monitoring the issue landscape and modifying its settings and operators. It is crucial to remember that the kind of dynamic issue being handled and the caliber of the utilized adaption mechanisms are what determine how successful DGAOA will be. Achieving the best outcomes requires careful evaluation of problem-specific traits, appropriate parameter adjustment, and selection of appropriate adaptation approaches (Manríquez et al., 2023). To address optimization issues in dynamic contexts, the Dynamic Genetic Adaptive Optimization Algorithm is a potent tool. It enables the flexibility to adapt to shifting issue circumstances and enhances the efficiency and efficiency of the optimization process by integrating genetic algorithms with adaptive mechanisms. Its performance across many problem domains must be investigated, and it must be compared with other dynamic optimization methods, via ongoing study and testing. The Gravitational Optimization Algorithm's central tenet is that each potential solution in the search space should be seen as a celestial body (Yang et al., 2022). The interaction is comparable to the gravitational force in physics. According to their fitness scores, each solution's mass is assumed to either attract or repel other solutions by the algorithm. The larger a solution's mass and gravitational force, the more optimum it is. The Gravitational Optimization Algorithm's principal elements and actions are as follows: The program first creates a population of initial potential solutions. The answers, which stand in for celestial bodies, are generated at random inside the search area. Based on the optimization problem's objective function, each solution's fitness value is assessed. The mass of the solution is determined by the fitness value (Ajagekar et al., 2022). The fitness value of each solution to the other solutions in the population is often taken into account when calculating the mass of each solution using a mass calculation algorithm. Larger masses are a consequence of higher fitness values. Based on the masses and separations between the solutions, the gravitational force is determined. Nearby solutions are gravitationally pulled away more strongly by solutions with bigger masses. Each solution moves according to the gravitational force that pulls on it. Higher mass solutions are subject to larger forces and gravitate toward better solutions (Togo et al., 2022).

The action enables the algorithm to investigate several areas of the search space. Numerous optimization issues, such as feature selection, data clustering, scheduling, and function optimization, have been addressed using the gravitational optimization algorithm. Its advantages are in being straightforward, effective, and capable of escaping local optima by scouring new parts of the search area. It's crucial to remember that the Gravitational Optimization Algorithm's performance might change based on the issue at hand and the parameter values used (Avval et al., 2022). The study may benefit from proper parameter tweaking and adaption strategies to speed up convergence and balance exploration and exploitation. By mimicking the behavior of celestial entities, the Gravitational Optimization Algorithm provides a novel and efficient method for resolving optimization issues. It is an effective tool for many optimization fields since it may use gravity to direct the search process. Continuous investigation and testing are required to fully understand its potential, evaluate it against competing algorithms, and create improvements to address increasingly challenging issues (Bao et al., 2022).

Key Contributions:

- To prefer the hybrid strategy, which combines the Genetic Algorithm (GA) with the Improved Gravitational Optimization Algorithm (IGOA), two optimization methods? By combining the best features of the two methods, production scheduling optimization is intended to be more effective and efficient.
- To addresses the suggested method which contains adaptive mechanisms to dynamically change and optimize the production plan depending on changing circumstances, addressing the difficulty of dynamic production scheduling.

The remainder of the document is structured as follows: Segment 2 talks about the preliminary research in connection to the aims or goals of the investigation and identifies any gaps or inconsistencies. The research technique and strategies are covered in Section 3. We proceed through the data and analysis in Segment 4 before succinctly and methodically summarizing the conclusions, assessing the goals or objectives of the research, and offering reasons. In Segment 5, a summary of the Study's main parts is provided.

2. RELATED WORKS

(Waschneck et al., 2018) determined to realize the. Deep Neural Network (DNN) agents are trained with user-defined goals to improve scheduling in an RL environment. Using a tiny factory simulation that models an abstracted front end of the semiconductor manufacturing facility, the study validates the system. (Wang et al., 2018) suggested the precast component delivery on time while maintaining a low production cost may be compromised, and the production resource configuration can be modified to reduce resource waste. The created model closes the gap between precast production scheduling methodologies and simulation system design, making it more applicable to actual building projects. (Xu et al., 2018) presented a strategy for planning open pit operations that incorporates environmental expenses as internal cost elements. Inside the ultimate pit, a succession of geologically ideal (maximum-metal) push-backs is initially produced. The ideal production schedule is then obtained by sequencing the push-backs using a Dynamic Programming (DP) model, which incorporates environmental costs into economic assessment formulas. (Liu et al., 2019) presented an integrated decision model that combines single-machine scheduling choices with predictive maintenance decisions based on prognostic information to reduce the overall projected cost. The health condition and dummy age that were susceptible to machine deterioration are taken into account in the integrated model. (Qin et al., 2019) introduced a multi-objective casting production scheduling approach that aims to cut down on overall production costs, delivery delays, and makespan. To solve the model, a hybrid discrete multi-objective grey wolf optimizer is created. To increase the quality of the initial population, an initialization method focused on decreasing work transit and processing times is intended. Grey wolf optimizer (GWO) incorporates an enhanced method to prevent the GWO from becoming convergent too soon. (Both and Dimitrakopoulos 2020) preferred in addition to uncertainty relating to equipment performance and truck cycle durations, geological uncertainty is taken into account by the stochastic optimization approach. (Chen et al., 2020) suggested an Accurate Maintenance (AM) model based on reliability intervals that address the shortcomings of the previous single reliability threshold maintenance model by having varied maintenance actions at various intervals. (Zonta et al., 2022) examines estimating whether the machines will be used in the production schedule while taking into account the resources at hand. A paradigm for data engineering, validation, and normalization was put out by the study. Additionally, it demonstrates how to combine deterioration indices utilizing similarity patterns to extract time-based failures from noisy data. The method enables the application of the kind of prediction to scheduling issues. A study compares several DNN-based models. (Liu et al., 2022) improved the deep reinforcement learning algorithm's four main parts are aspect distance, action distance, incentive performance, and network architecture and organization based on Convolution Neural Networks (CNNs). (Manríquez et al., 2020) suggested building short-term production schedules utilizing the general simulation-optimization framework to increase schedule adherence via an iterative process.

3. EXPERIMENTAL PROCEDURE

This section outlined the process for creating the model, covered its essential elements, and offered a detailed description of how the steps of the recommended model in (Figure 1) were created. There are five parts to this analysis: The fundamental objective of the first phase is information collecting. The study's following portion included data pre-processing methods. The third part contains the methods for feature extraction and selection. The fourth part, which details the work done to create the recommended model and gather the crucial experiences, contains the most important information. The performance of each existing and new model is evaluated in the fifth stage by comparing the relevant parameters.

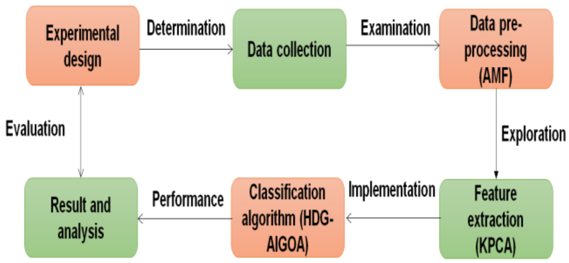

Figure 1. Experimental Procedure of Optimizing Production Scheduling

3.1 Data Collection

Two intelligent Multi-Objective Project Scheduling Environment (iMOPSE) datasets were created using the Generator application: simple for Education (EDU) (national) use, which consists of 6 instances, and benchmark dataset d36, which consists of 36 instances for research trials (Myszkowski et al., 2019). The EDU dataset is helpful for instructional purposes and only includes a handful of the activities listed in (Table 1). It may be solved to demonstrate if the approach under examination is effective and if the answer is simple for students to study, validate, and illustrate using tools. But the straightforward EDU dataset poses no problem for study. As a consequence, the research published and offered a benchmark dataset of 36 instances for comparing the outcomes of the various techniques. It varies not just in the quantity of work but also the quantity of resources, connections, and abilities needed. Although more appropriate Occurrences may be quickly constructed using the Generator program, the provided datasets (EDU and benchmark d36) can be utilized for a variety of applications.

Table 1. Outline of iMOPSE EDU datasets (Myszkowski et al., 2019).

Instances	Activities	Materials	Interactions	Abilities
10-3-5-3	10	3	5	3
10-5-8-5	10	5	8	5
10-7-10-7	10	7	10	7
15-3-5-3	15	3	5	3
15-6-10-6	15	6	10	6
15-9-12-9	15	9	12	9

3.2 Data Pre-Processing using Adaptive Median Filter (AMF)

The ordinary median filter has been enhanced by the AMF technique. Impulse noise is decreased using spatial processing. To assess whether noise is present or not, the AMF identifies each pixel in the skin picture together with its surrounding pixels. Because it protects the subtle visual features and lowers non-impulse noise, it performs better than other filters. Furthermore, there's a significant probability it can adapt to sudden loudness. Both the mean channel and the median channel have the same effect on a picture's disorder. As in Formula (1), the median channel for two descriptions may change.

$$med(n_k) = \{n_i + 1^a = 2i + 1(ODD)) \ \frac{[n_i + n_{i+1}]}{2} a = 2i(even) \qquad (1)$$

Here n_i is the i[th] the biggest observed data and n_1; n_2; n_3... n_i are the observed data. Consider a situation where there are seven samples overall in the data collection 2, 3.5, 1, 3, 1.5, 4 and the median filter yields an output of 2.5. The signal will be maintained if the pulse is n + 1 or longer; else, it will be dropped from the series. The median filter is distinct from other filters since it has the potential to reduce pulse noise while preserving local features. The signal produced by this approach is then sent to the feature extraction step.

3.3 Feature Extraction by using Kernel Principal Component Analysis (KPCA)

An approximate covariance matrix of the data in Formula (2) is diagonalized using a basis transformation known as Principal Component Analysis (PCA).

$$D = \frac{1}{k}\sum_{i=1}^{k} \quad v_l v_i^S \qquad (2)$$

The orthogonal projections onto the Eigenvectors or the new coordinates in the tile Eigenvector basis are principal components. In this work, this setting is further developed into a nonlinear setting of the following kind. If the data were initially nonlinearly mapped onto a feature space using Formula (3),

$$\Phi: Q^M \rightarrow E, v \rightarrow V \qquad (3)$$

We'll show that, for certain values, even if it has arbitrarily large dimensionality, we can still do KPCA in E.

For now, let's assume that Formula (4) translates data into feature space. KPCA for the covariance matrix,

$$\underline{D} = \frac{1}{k}\sum_{i=1}^{k} \quad \Phi(v_l)\Phi(v_l)^S \qquad (4)$$

Applications for denoising and wavelet transforms often employ KPCA, a nonlinear variant. The traditional PCA approach tries to reduce the number of dimensions when the manifold is linearly buried in the observation space. The manifold is linearized using the kernel technique, one of the two components, to satisfy the requirements of the PCA, the second component of KPCA. To automatically convert data into a pairwise formula between the mapped data in the feature set, KPCA employs feature mapping. The kernel calculates this pairwise formula. It is difficult to find an appropriate kernel that linearizes the surface in the feature space while taking into consideration the geometry of the input space. The nonlinear dimensionality reduction of KPCA would be ineffective for a suboptimal projection that does not satisfy these conditions.

3.4 Classification based on Hybrid Dynamic Genetic-Adaptive Improved Gravitational Optimization Algorithm (HDG-AIGOA)

Genetic algorithms and an enhanced gravitational optimization method are combined in the HDG-AIGOA algorithm. The gravitational forces present in nature serve as an inspiration for the gravitational optimization technique. Each answer to the optimization problem is regarded as a celestial body, simulating the interactions between celestial bodies. The gravitational forces are used to iteratively update the locations of these entities, which results in the identification of ideal or nearly ideal solutions. The HDG-AIGOA algorithm combines enhanced gravitational optimization and genetic algorithms to make use of each other's advantages. The algorithm's dynamic and adaptive properties relate to the integration of dynamic and adaptable parameters throughout the optimization process, which enables the algorithm to modify its behavior in response to the specifics of the issue being addressed. According to the paper's description, the HDG-AIGOA algorithm's goal is to generate optimum or very close-to-optimal plans for production scheduling issues to increase effectiveness and lower costs. The key components of the genetic-adaptive and gravitational optimization algorithms are described in greater depth below:

a) Genetic-Adaptive Algorithm (GAA)

The principles of natural selection and genetics serve as the basis for genetic algorithms. They work with a population of possible answers, represented as people or chromosomes. To produce new children, these people perform genetic operations like selection, crossover, and mutation. An objective function is used to assess each person's fitness, and those who do better are more likely to pass on their skills to the next generation. The parameters and operators of the genetic algorithm are continuously adjusted in a genetic-adaptive algorithm throughout the optimization process. These modifications may be based on factors unique to the challenge or variables in contexts that are constantly changing. The algorithm may successfully balance exploitation (exploiting potential regions for improved solutions) and exploration (examining various parts of the solution space) by adjusting the parameters and operators. By adjusting to the dynamics and features of the issue, the use of a genetically adaptive algorithm aims to increase the efficiency and efficiency of the optimization process.

Mathematical model of GAA

This section introduces a revolutionary adaptive genetic algorithm and describes the new crossover and mutation operators in more depth. Two chromosomes are chosen as parents by the global best-crossover (GB-crossover) operator. One of these is chosen at random from the mating pool, while the other is the population's best chromosome for the GAA method. The chosen chromosome is then replaced in the child produced by the chosen parents.

Let $\vec{V}_j(s+1) = \vec{V}_{gbest}$ respectively, the chosen chromosome and the world's finest chromosome. The offspring is then determined using Formula (5)

$$\vec{V}_j(s+1) = \vec{V}_{gbest} + \vec{q}_1\vec{V}_{gbest} - \vec{q}_2\vec{V}_j(s) \quad (5)$$

Based on the GAA principles, A variety of chromosomal values in the general population are intelligently changed using the quasi-sliding surface-mutation (QSS-mutation) operator. Let $\vec{V}_j(s)$ represent a randomly chosen chromosome, then Formula (6) defines the QSS mutation.

$$\vec{V}_j(s+1) = \vec{V}_j(s) + \left(\vec{b} \times \mu\right) \quad (6)$$

where $\vec{V}_j(1)$ is the initial position and equal to $\vec{V}_j(1), \vec{b}\ \epsilon\ [0,1]^C$ is a random vector,

The adaptation factor μ will be calculated by the following Formula (7), (8), and (9)

$$\mu = 10^{\frac{-1}{\sqrt{|s|}}} \quad (7)$$

Which

$$t = f + f; f = e\left(\vec{V}_j(1)\right) \quad (8)$$

$$f = \frac{e\left(\vec{V}_j(1)\right) - e\left(\vec{V}_j(1-1)\right)}{s-(s-1)} = e\left(\vec{V}_j(1)\right) - e\left(\vec{V}_j(1-1)\right) \quad (9)$$

Where $e\left(\vec{V}_j(1)\right)$ the fitness is value of $\vec{V}_j(1)$ and t is the iteration number.

b) Gravitational optimization Algorithm (GOA)

A prospective solution to an optimization issue is represented by each mass in the GOA algorithm's simulation of the interactions between masses in a gravitational field. The search space is first randomly initialized with a population of masses (possible solutions). Each mass is assigned a place and a mass value. The program then repeatedly modifies the masses' placements by the gravitational pull of other masses. The mass and separation of two masses affect the gravitational force that exists between the mass. The underlying tenet is that masses with higher fitness values produce larger gravitational forces that pull other masses toward their places. The GOA method has been used to solve several optimization issues, including feature selection, parameter estimates, and function optimization. It has shown positive outcomes and has been discovered to be competitive with other well-known optimization techniques. The law of gravity served as the inspiration for the GOA, a population-based optimization method. To find the best answers to optimization issues, it models the interactions between masses in a gravitational field.

Mathematical model of GOA

To create a mathematical model of GOA, numerous elements of the area are often quantified using mathematical formulas or represented in (Figure 2). Take into consideration a situation where n decision-making factors and an objective function dependent on GOA. Each variable has a lower limit and an upper bound, according to Formula (10).

$$vk^c \text{ and } vw^c \text{ are the lower and the upper bounds of variable } c \quad (10)$$

The bounds of factors create an area known as the search field with an amount of n, where Formula (11) shows that:

$$vk^c \leq v^c \leq vw^c \quad (11)$$

GOA searches randomly through this space using N objects trying to find the sub-optimum. The position of the j^{th} object in the search space is defined as Formula (12).

$$V_j = \left(v_k^1, \dots, v_j^c, \dots, v_j^n\right), j = 1,2, \dots, M \quad (12)$$

$N_{bj}(s), N_{oj}(s)$ are the active, passive, and inertia mass, respectively $N_{jj}(s)$ is the agent's goal value j at the time (s) . The value of mass will increase in proportion to how well the goal function performs. The agent's mass in its active, passive, and inertial states j is determined using the goal function it currently has, as shown by Formula (13),

$$N_{bj}(s), N_{oj}(s) \; and \; N_{jj}(s) \qquad (13)$$

The gravitational law as amended before determining the agent's acceleration with the use of the law of motion Formula (14), the total forces from a group of heavier objects applied to the agent should be calculated using Formula (15). By deducting the agent's current velocity from its acceleration Formula (16), the subsequent velocity of the agent is then calculated. The next step is to use Formula (17) to find the agent's position.

$$E_j^c(s) = \sum_{i\epsilon lbest, i\neq j} \quad rand_i E_{ji}^c = \sum_{i\epsilon lbest, i\neq j} \quad rand_i H(s) \frac{B_{bi}(s) N_{oj}(s)}{Q_{ji}(s)^O + \varepsilon} \left(v_i^c(s) - v_j^c(s)\right) \qquad (14)$$

$$b_j^c\,(s) = \frac{E_j^c(s)}{N_{bj}(s)} \qquad (15)$$

$$x_j^c(s+1) = rand_j \times w_j{}^c(s) + b_j^c(s) \qquad (16)$$

$$v_j^c(s+1) = v_j^c(s) + x_j^c(s+1) \qquad (17)$$

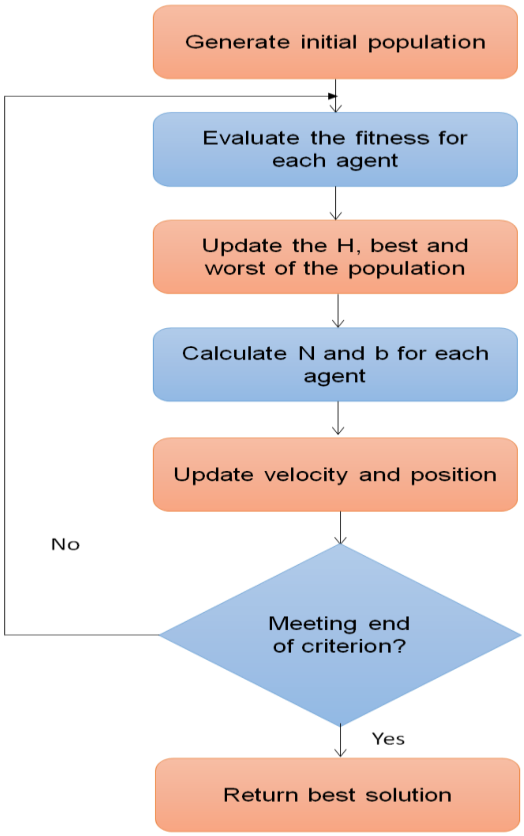

Figure 2. Flow chart of GOA

4. RESULTS AND DISCUSSION

4.1 Results

Optimizing Production Scheduling typically provides detailed information about the performance metrics used, the specific problem instances tested, and the comparative suggested method with other algorithms or existing approaches.

a) Accuracy

The HDG-AIGOA algorithm's correctness would be assessed based on how closely its produced schedules match the ideal ones or how well they adhere to the predetermined production scheduling goals, such as minimizing setup times or optimizing resource use. According to a high accuracy score, the recommended model helps optimize production and eliminate false positives and false negatives (missing anomalies). To calculate the accuracy, use Formula (18).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (18)$$

Table 2. Numerical Outcomes of Accuracy for existing and proposed methods.

Methods	Accuracy (%)
ANN (Zhao et al., 2005)	28
DNN (Zonta et al., 2022)	42
CNN (Liu et al., 2022)	73
HDG-AIGOA (Proposed)	85

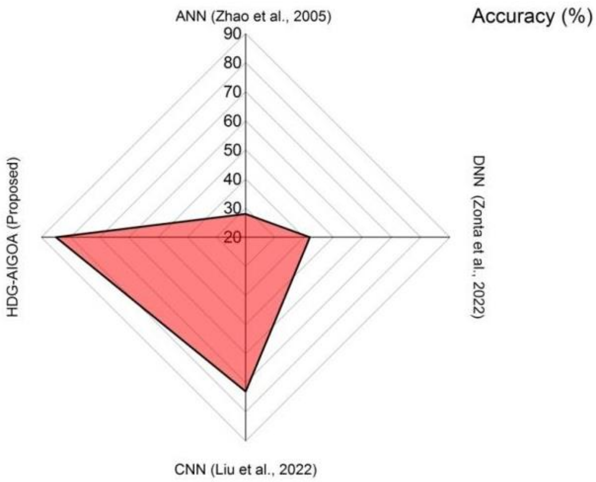

Figure 3. Comparison of accuracy for existing and proposed methods

(Figure 3) compares the accuracy for the recommended and existing techniques. The suggested method exceeds the already in-use ANN (28%), DNN (42%), and CNN (73%), with a high accuracy performance of 85%. The recommended technique HDG-AIGOA is shown in (Table 2), and it performed better in terms of data classification accuracy than other approaches already in use.

b) Root Mean Square Error (RMSE)

The average size of inaccuracy in predictions based on quantitative data is measured by the RMSE. It may be conceptualized as the vector of anticipated values' normalized distance from the vector of observed (or real) values. Instead of utilizing RMSE to gauge the efficiency of HDG-AIGOA for production scheduling, it is preferable to take into account the particular performance indicators connected to the scheduling optimization objectives. These metrics would be used to assess the algorithm's performance in terms of production scheduling activities, including optimization results, efficiency gains, and cost savings. The RMSE is calculated using Formula (19).

$$RMSE = \left[\frac{1}{m}\sum_{j=1}^{m} \quad (\hat{\phi}_j - \phi_i)\right]^{\frac{1}{2}} \tag{19}$$

n − Total number of samples

$\hat{\phi}_j$ − Prediction Values

ϕ_j − Actual Values

Table 3. Numerical Outcomes of RMSE for Existing and proposed methods.

Methods	RMSE (%)
ANN (Zhao et al., 2005)	25
DNN (Zonta et al., 2022)	40
CNN (Liu et al., 2022)	53
HDG-AIGOA (Proposed)	58

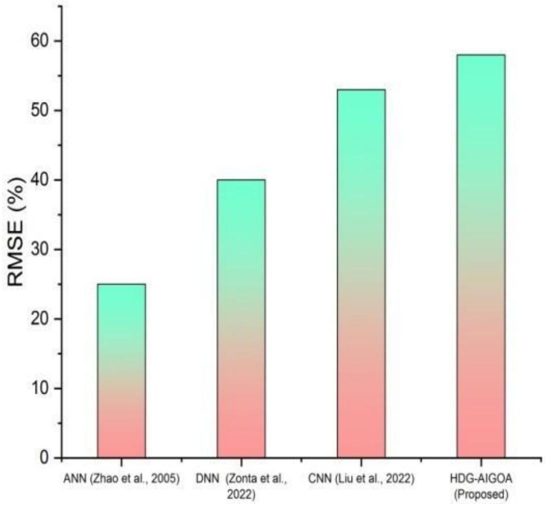

Figure 4. Comparison of RMSE for existing and proposed methods

(Figure 4) compares the RMSE for the recommended and existing techniques. With a low performance of RMSE of 58%, the suggested method exceeds the ones already in use, including ANN (25%), DNN (40%), and CNN (53%). The recommended technique HDG-AIGOA is shown in (Table 3) and outperformed other approaches currently in use in terms of data classification RMSE.

c) Mean Square Error (MSE)

MSE is yet another often-used statistic for assessing the efficiency and performance of predictive models, especially in regression research. Although the HDG-AIGOA method is not specifically related to prediction tasks, we can nevertheless analyze the optimization results attained by the algorithm for production scheduling by adapting MSE. An indicator of the average squared difference between the goal values and the expected optimization results would be provided by the HDG-AIGOA-adapted MSE for production scheduling. An improvement in optimization outcomes, closely matching the intended or ideal values, is indicated by a decreased MSE value, which HDG-AIGOA has attained. The MSE is determined by using Formula (20).

$$MSE = \frac{1}{m}\sum_{j=1}^{m} \quad (\hat{\phi}_j - \phi_j)^2 \tag{20}$$

Table 4. Numerical Outcomes of MSE for Existing and proposed methods.

Methods	MSE (%)
ANN (Zhao et al., 2005)	30
DNN (Zonta et al., 2022)	45
CNN (Liu et al., 2022)	48
HDG-AIGOA (Proposed)	62

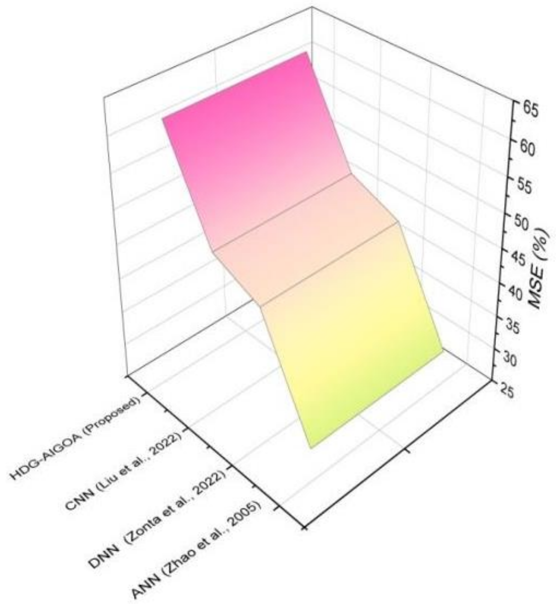

Figure 5. Comparison of MSE for existing and proposed methods

(Figure 5) compares the MSE for the recommended and existing techniques. The suggested method beats others already in use, such as ANN (30%), DNN (45%), and CNN (48%), with MSE doing poorly (62%). In terms of data classification MSE, the recommended strategy HDG-AIGOA fared better than other approaches already in use (Table 4).

d) Mean Absolute Error (MAE)

An additional often-used statistic for assessing the accuracy and effectiveness of prediction models is MAE. As part of Optimizing Production Scheduling using Hybrid Dynamic Genetic-Adaptive Improved Gravitational Optimization Algorithm (HDG-AIGOA), MAE may be modified to quantify the absolute difference between the anticipated and target values of pertinent optimization goals. A measure of the average absolute difference between the expected optimization results and the target values would be provided by the HDG-AIGOA-adapted MAE for production scheduling. A lower MAE number means that HDG-AIGOA has more successfully optimized the system, producing values that are near the intended or ideal values. Formula (21) is used to compute the MAE.

$$MAE = \frac{1}{m}\sum_{j=1}^{m} \left|\hat{\phi}_j - \phi_j\right| \quad (21)$$

Table 5. Numerical Outcomes of MAE for Existing and proposed methods.

Methods	MAE (%)
ANN (Zhao et al., 2005)	35
DNN (Zonta et al., 2022)	50
CNN (Liu et al., 2022)	65
HDG-AIGOA (Proposed)	76

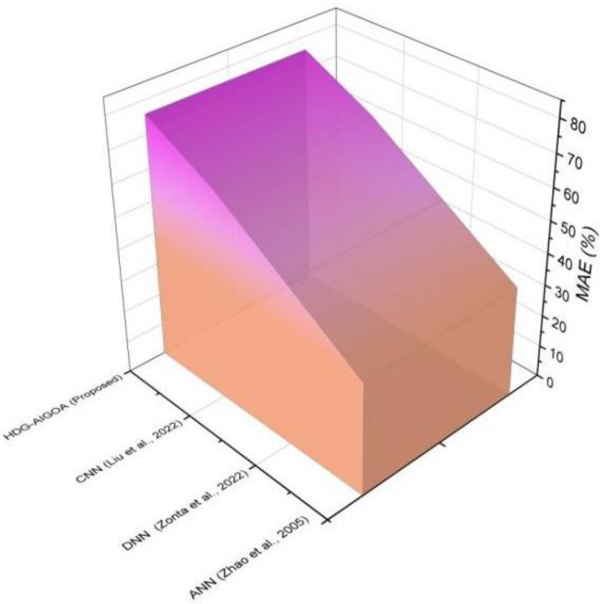

Figure 6. Comparison of MAE for existing and proposed methods

(Figure 6) compares the MAE for the recommended and existing techniques. The suggested method beats others already in use, such as ANN (35%), DNN (50%), and CNN (65%), with MAE doing poorly (76%). In terms of data categorization MAE, the suggested method HDG-AIGOA fared better than other approaches already in use (Table 5).

4.2 Discussion

Numerous sectors consider the optimization of production scheduling to be essential since it directly affects operational performance, resource usage, and overall cost-effectiveness. A viable strategy to address these issues is the HDG-AIGOA algorithm, which combines gravitational optimization, genetic algorithms, and adaptive algorithms. The hybrid character of the HDG-AIGOA algorithm is one of its main benefits. It strengthens the search process and raises the quality of the production schedules produced by incorporating several optimization approaches. By introducing variety and exploration via the use of genetic operators like crossover and mutation, the genetic algorithm component enables the algorithm to effectively explore the solution space. The algorithm may dynamically modify its parameters and operators

to adapt to the peculiarities of the problem and the state of the search. This is made possible by the adaptive algorithm component. To direct the search toward better solutions, the gravitational optimization component incorporates the idea of gravitational forces and simulates the interactions between particles. In comparison to adopting a single optimization strategy in isolation, the hybridization of these approaches in HDG-AIGOA may speed up convergence and provide higher-quality solutions. The algorithm can efficiently explore various areas of the search space and successfully exploit interesting answers by combining exploration and exploitation methodologies.

5. CONCLUSION

The Optimizing Production Scheduling using Hybrid Dynamic Genetic-Adaptive Improved Gravitational Optimization Algorithm (HDG-AIGOA) is a sophisticated algorithm designed to enhance production scheduling in a dynamic setting. The HDG-AIGOA method combines the capabilities of genetic algorithms with enhanced gravitational optimization to optimize production scheduling, as can be seen after analyzing the algorithm and its possible advantages. The HDG-AIGOA algorithm provides various benefits for production scheduling by combining these two methods and including dynamic adaption mechanisms. Various elements, including machine availability, order priority, production limits, and dynamically changing circumstances, may all be taken into consideration while handling complicated scheduling challenges in real time. The method seeks to reduce RMSE, MSE, and MAE while increasing overall operational effectiveness. It is significant to note that the unique features of the production scheduling issue at hand may have an impact on the HDG-AIGOA algorithm's performance and efficiency. The effectiveness of the algorithm may be impacted by elements like the size, complexity, and accessibility of the issue. To obtain the best outcomes in various circumstances, proper parameter adjustment and customization may be necessary. Our analysis leads us to the conclusion that the Hybrid Dynamic Genetic-Adaptive Improved Gravitational Optimization Algorithm (HDG-AIGOA) has the potential as a method for improving production scheduling in dynamic situations. It offers a solid foundation for dealing with difficult scheduling issues thanks to the integration of evolutionary algorithms, enhanced gravitational optimization, and adaptive methods. Its performance has to be validated in a variety of settings and compared to other cutting-edge algorithms via more study and testing.

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