Optimal Scheduling of Flexible Manufacturing System Using Improved Lion-Based Hybrid Machine Learning Approach

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ABSTRACT Dispatching rules are generally useful for scheduling jobs in flexible manufacturing systems (FMSs). However, the appropriateness of these rules relies heavily on the condition of the system; thus, there is no single rule that always outperforms others. In this state of affairs, diverse machine-learning technology offers an effective approach for dynamic scheduling, as it allows managers to identify the most suitable rule at each moment. Nonetheless, various machine-learning algorithms may provide diverse recommendations. The main objective of this study is to implement FMS scheduling using intelligent hybrid learning algorithms with metaheuristic improvements. The developed model involves three phases: feature extraction, optimal weighted feature extraction, and prediction. After the benchmark datasets for the FMS are gathered, feature extraction is performed using t-distributed stochastic neighbor embedding, linear discriminant analysis, linear square regression, and higher-order statistical features. Further, an optimal weighted feature extraction method is developed to select the optimal features with less correlation using the improved lion algorithm (LA), which is called the modified nomadic-based LA (MN-LA). Finally, the optimally selected weighted features are subjected to a hybrid learning algorithm with the integration of a fuzzy classifier and a deep belief network (DBN). For improving the prediction model, the membership function of the fuzzy classifier is optimized using the proposed MN-LA. Moreover, the activation function and the number of hidden neurons in the DBN are optimized using the MN-LA. The main objective of the optimized hybrid classifier is to enhance prediction accuracy. The experimental results indicate the effectiveness of the proposed heuristic-based scheduling method for FMSs.

INDEX TERMS Flexible manufacturing system, hybrid classifier, modified nomadic-based lion algorithm, optimal weighted feature extraction, rule scheduling, deep belief network, fuzzy classifier, feature extraction, prediction.

NOTATION

| Abbreviations | Descriptions          | Abbreviations | Descriptions          |
|---------------|-----------------------|---------------|-----------------------|
| FMS           | flexible manufacturing system | MN-LA         | modified nomadic-based LA |
| t-SNE         | t-distributed stochastic neighbor embedding | DBN          | deep belief network   |
| LDA           | linear discriminant analysis | GA           | genetic algorithm     |
| LSR           | linear square regression | KB-GA         | knowledge-based GA    |
| LA            | lion algorithm         | PSO           | particle swarm optimization |
| FPR           | false predictive rate  | EDA           | estimation of distribution algorithm |
| FNR           | false-negative rate    | NSBBO         | nondominated sorting biogeography-based optimization |

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I. INTRODUCTION

The flexible manufacturing system (FMS) is a production method that is engineered to adapt effortlessly for making adjustments in product type and quantity [1]. Jerome H. Lemelson, who was an American industrial engineer and inventor, developed the concept of flexible manufacturing and filed several related patents in the early 1950s [2]. Machines and computerized devices can be customized to produce a variety of components and to manage varying production levels [3], [4]. The objective of an FMS is to provide the appropriate raw materials or parts at the proper time to the proper machinery. Providing excessive materials or providing materials too early yields a backed-up in-process inventory. Providing insufficient materials or providing materials too late yields delayed work schedules and idle machines. In several cases, this results in poor capital use, e.g., excess inventory in process and/or equipment utilization. A FMS can enhance productivity and therefore reduce the manufacturing cost of a company. Flexible manufacturing can be a fundamental element of a create-to-order approach that allows customers to tailor the products that they need [5]. This flexibility can lead to increased capital costs. In particular, in contrast to more traditional systems, purchasing and installing the specialized equipment that allows such automation can be expensive [6], [7]. The process of scheduling in an FMS is defined as an NP-hard challenge. Its difficulty has increased significantly in the past few years with more complexities are introduced in FMSs.

Various methodologies are available to address the FMS scheduling problem [8], e.g., the heuristic method [9], the analytical method [10], the artificial intelligence-based method [11], and the simulation-based method [12], [13]. An FMS scheduling challenge is recognized as an optimization model with certain constraints by the analytical framework, including explicit constraints as well as the objective function. One potential approach for examining the FMS according to the structure is the Petri net (PN) diagram [14], [15]. After the PN diagram is applied, a suitable algorithm is employed to address the problem [16], [17]. However, in practice, the PN framework appears to be too broad. To replace it, another approach, e.g., a machine-learning algorithm, can be employed [18].

Because the problem is categorized as NP-hard, it is essential to use metaheuristics [19]. Filho et al. [20] evaluated the use of a genetic algorithm (GA) and its derivative, reporting that the GA is the most effective approach for overcoming FMS scheduling challenges. Kim et al. [21] established a network-based hybrid GA integrating a neighborhood search method into the mutation procedure. The objective was to improve the solution and the efficiency of the genetic search process. Prakash et al. [22] integrated knowledge management into a knowledge-based GA, and Burnwal and Deb [23] developed a cuckoo-based search strategy to reduce the penalty fees due to delays in production and enhance the utilization time of the machine. Recently proposed methodologies are normally compared with conventional methodologies, e.g., GAs, shortest processing time (SPT), particle swarm optimization (PSO), and longest processing time. Therefore, efficient FMS can be developed by adopting various machine-learning techniques and optimization algorithms [24].

The main objectives of the present study regarding the scheduling prediction in the FMS are as follows:

- to develop an intelligent model for solving the problem of predicting the best scheduling in FMS using the optimal weighted feature extraction and optimal hybrid classifier;
- to integrate two machine-learning algorithms (the fuzzy classifier and deep belief network (DBN)) for performing effective classification to identify the best scheduling rule from a set of optimal features;
- to develop a modified metaheuristic algorithm called the modified nomadic-based lion algorithm (MN-LA) that optimizes the weight functions of weighted feature extraction for attaining less correlative features; and
- to propose the optimization concept in the hybrid classifier that optimizes the membership functions of the fuzzy classifier and the number of hidden neurons of the DBN for maximizing the prediction accuracy.

The remainder of this paper is organized as follows: section II presents a literature review of the FMS; section III details the structure of the FMS, along with the system operation and a data description; section IV presents the proposed
FMS using weighted feature extraction; section V describes the development of the proposed FMS prediction model using a hybrid classifier; section VI presents an improved LA for enhancing the performance of feature extraction and classification; section VII presents the results and discussions; and section VIII concludes the paper.

II. LITERATURE REVIEW

A. RELATED WORKS

Priore et al. [25] considered and analyzed the fact that generally, for addressing the FMS in scheduling jobs, only the dispatching rules were used. However, the suitability of the dispatching rules was largely dependent on the system’s condition. Thus, no specific rule can be considered as functioning significantly better than another. Therefore, machine-learning methods were used to select a suitable rule for the system. Even when machine-learning approaches are used, each approach has different optimal rules. The proposed ensemble methods, which were structured to select the most appropriate rule over time, clarified this disadvantage. A comparison was made among the behavior of boosting, stacking, and bagging approaches. Simulation results indicated that with regard to the mean flow and mean tardiness, the suggested approach was superior to the other traditional methods.

Wang et al. [26] suggested an innovative effective estimation of distribution algorithm (EDA)-based on the place–time PN systems of the FMS to solve FMS problems. A candidate strategy was proposed as an individual method with two segments. The first segment contains the information on the route, and the second is a permutation that is replicated in parts. A highly permissive deadlock controller checks and ensures individuals’ viability. In an experimental evaluation involving benchmark examples, the proposed algorithm outperformed all traditional approaches for the described problem.

Rifai et al. [19] proposed a revolutionary strategy called nondominated sorting biogeography-based optimization (NSBBO) for optimizing the complexities of multi-loading FMS scheduling along with the shortcuts infused with re-entrant features. This approach was developed to identify relatively close-optimal tradeoff solutions that can satisfy the two targets of makepan minimization as well as overall earliness. The goal was to achieve optimal machine allocation and job sequencing while satisfying all requirements simultaneously. The construction of the NSBBO involved replacing three strategies focused on sinusoidal, quadratic, and trapezoidal systems in the generic linear emigration–immigration method. A series of test issues were evaluated to determine the effectiveness, complexity, and reliability of the proposed solutions according to the specifications of the NSBBO and NSGA-II. The experimental results indicated that the NSBBO-trapezoidal framework was successful and competitive with previously reported models. Thus, it was argued that the developed NSBBO and its derivatives are viable alternative strategies for resolving the bi-objective consistency of the re-entrant FMS scheduling issue.

Li et al. [27] focused on solving the scheduling problem of minimizing the FMS’s total energy consumption based on the FMS’s PN frameworks. On account of the different energy-consumption rates of the availability of resources under various operating circumstances, two energy-consumption functions were considered. A dynamic programming (DP) system based on PNs was established to resolve the scheduling issues. As the number of states being examined increases exponentially with the scale of the problem, the problem becomes more difficult to solve, rendering DP algorithmically impractical. A modified dynamic programming (MDP) algorithm was applied at an appropriate time to achieve an optimal or suboptimal schedule. The simulation results indicated the MDP’s effectiveness in comparison with traditional models.

Luo et al. [14] considered deadlock management problems for a general category of the FMS and developed an effective method. The method has three interesting and unique features from a software viewpoint. To define and classify the FMS, a PN system was developed to manage all the FMS characteristics. The banker algorithm-like deadlock avoidance technique was recommended. The developed policy was verified to be polynomial with regard to model size. Furthermore, experimental results indicated the efficacy of the method and its superiority to traditional systems.

Duan et al. [28] developed an iterative deadlock mitigation strategy dependent on structural analysis for devices with simple sequential processes with resources (S3PR), which comprised two stages. The first stage was called the “control of the siphons.” The strict minimal siphons (SMSs) were calculated in an S3PR network, and control places were implemented by adding P-invariants combined with extra SMS sets that do not restrict any characteristics of the legal system. The second stage, which is called non-maxmarked siphon control, was performed iteratively or incrementally if the method was not still alive. A mixed-integer linear programming (MILP) problem was built in each iteration step to measure a non-maxmarked siphon, and a control place was applied to the siphon’s first-controlled net, resulting in an enhanced and enlarged network. The iteration was conducted until all new non-maxmarked siphons were produced by a final-augmented net. To prove the superiority of the proposed method, its viability was validated and compared with that of several traditional approaches.

Dong et al. [29] introduced a sequence of recovery transitions to solve deadlock difficulties in dynamic production systems by adopting a PN. In addition to traditional deadlock management techniques that mount control places to a web template, the transitions have been used as legal ones to remove all the deadlock points. First, a series of retrieval transitions were obtained from each deadlock marking to be retrieved, relying on the reachability graph evaluation. Additionally, to calculate a recovery change to recover multiple
deadlock markings, a technique of vector intersection was introduced. Therefore, an iterative method was developed to identify a few recovery transitions to restore all the deadlock points. The results indicated that the approach for recovery of the deadlock was efficient and effective.

Bashir et al. [30] proposed offered a novel, innovative approach for computing the minimum supervisory model, which enhances the efficiency of the FMSs in the PN models. The implemented strategy utilized the structural properties of a PN model to avoid the construction of its reachability graph, which tends to be a state explosion issue. Two main algorithms were proposed. The purpose of the first algorithm was to calculate an efficient uncontrolled transition, and that of the second algorithm was to calculate the generalized mutual exclusion constraints (GMECs) for each stage of the PN FMS method. Additionally, a strategy was presented for building control places for each calculated GMEC without resolving the issue of linear integer programming, which significantly reduces the computational overheads.

Lee and Shin [31] have introduced a faulty assumptions about the nature of the function. It uses a linear regression as a learning algorithm, and also the learning would be quick and easy, but the accuracy of the algorithm would suffer due to high bias error that comes, when using a linear regression on nonlinear data. In reducible and variance error the amount of function learned from one training data set would change if a different training data set were used.

Chu et al. [32] have developed a modern industrial technology, which implements cellular manufacturing systems (CMSs) as a solution for complex production. It consists of multiple manufacturing units, each of which includes multiple tasks. In CMS, each worker has one or more skills. It can demonstrate cross-training with learning and forgetting effect for the worker assignment problem. In this, the proposed hybrid bacteria foraging algorithm is used to solve the joint decision model of worker assignment and production planning in cellular manufacturing systems.

Cavalcante et al. [33] have introduced the resilient supplier selection that utilizes the advances in data analytics when avoiding the two major inconveniences, namely the need to estimate the likelihood of disruptions and forecasting the performance impacts. The proposed data-driven decision-making model for resilient supplier selection can be exploited for the design of risk mitigation strategies in supply chain disruption management models, re-designing the supplier base or investing in most important and risky suppliers.

Wang et al. [34] have proposed an improved symmetric SCA with adaptive probability selection (SSCA-APS). APS was used to integrate original operators and the proposed operators. To combine the new symmetric sine cosine operator with the original sine cosine operator, there are two solutions, the first one is that the probability of choosing the new operator and the original operator is fixed. The other is to select strategies adaptively according to the success rate of offspring.

Kamboj et al. [35] have proposed nature-inspired search algorithm. It consist of two operators namely mutation and crossover which are used to maintain the amplitude of the search-space boundaries and search-direction matrix, that helps to improve the capabilities of the powerful exploration and exploitation.

Wang et al. [36] proposed a modified ALO (MALO). It has a strong exploration ability that is utilized to search for the optimal ants and adapt to the discrete optimization problem. It consist of two categories supervised and unsupervised. The supervised models need to know the class label of each training sample in advance, which results in a better classification result than unsupervised models in most cases.

B. REVIEW

Machine learning, big data analysis, Internet of things (IoT), etc. are contemporary trends and have applications in almost every research domain [37], [38]. Even though numerous scheduling models for the FMS have been developed, a few questions must be answered in future studies. A few of the important advantages and disadvantages of the existing methods are explained in detail in Table 1. Among them, support vector machines (SVMs), inductive learning, back-propagation neural networks (BPNs), and case-based reasoning (CBR) increase the mean tardiness and mean flow time and improve the dynamic efficiency of the FMS [25]. However, they lack the element of knowledge-based refine-ment, and for better results, several types of decisions must be implemented in the established FMS. Although the EDA [26] is sufficient for extracting the desired genes and will not become stuck in the optimum local solution, it has limitations, e.g., its complexity. Research must be performed to improve the developed algorithms. NSBBO [19] can achieve bi-objective satisfaction in the FMS scheduling problem and has high levels of diversity and effectiveness. However, in the field of tool magazines, which involves the availability of cutting tools and material handling systems, further study must be performed. MDP [27] achieves the ideal or sub-optimal solution within the appropriate time, and the model inherently has good performance. However, as the number of examined states increases, the size of the problem increases, which makes the problem difficult to solve. This will be examined in future studies to maximize the total energy consumption and satisfy the time-related goal. The modified banker’s algorithm [14] has exhibited superiority and higher efficiency compared with other models and appears to be capable of handling large-scale structures. However, it demands the count of the functions to be addressed; no new process can be initiated while executing it. Additionally, it requires the count of resources to stay static; no resource can be reduced for any reason without the likelihood of a deadlock. Bio-inspired meta-heuristics are becoming popular for various applications these days [39], [40]. MILP [28] can solve various kinds of complex problems; however, it does not provide an optimal solution to large problems, and its computational time is long. In contrast to other conventional
| Author [citation] | Methodology | Features | Challenges / Disadvantages |
|------------------|-------------|----------|----------------------------|
| Priore et al. [25] | SVMs, inductive learning, BPNs, and CBR | It enhances the mean tardiness and mean flow time. It also improves the dynamic efficiency of the FMS. | More decision types must be employed in the developed FMS for better results. It lacks the knowledge-based refinement element. |
| Wang et al. [26] | EDA MVNS | It is capable of mining the desired genes. It does not become trapped in local optimal solutions. | Studies must be performed to enhance the developed algorithm. The system is complex. |
| Rifai et al. [19] | NSBBO | It can attain the bi-objective satisfaction for the problem of FMS scheduling. It has high levels of diversity, efficiency, and effectiveness. | Research must be performed in the field related to tool magazines, e.g., on the availability of cutting tools and material handling devices. |
| Li et al. [27] | MDP | The optimal solution is attained within an acceptable time. The performance of the system is effective in nature | As the number of explored states increases, the size of the problem increases, making the problem difficult to solve. Optimizing total energy consumption and satisfying the time-related objective will be analyzed concurrently in future studies. |
| Luo et al. [14] | Modified banker’s algorithm | It outperforms other models. It is capable of handling large-scale systems. | It demands the number of functions to be resolved; when implementing it, no extra processes can begin. It demands that the number of resources remains fixed; without the possibility of a deadlock, no resource can go down for any reason. |
| Duan et al. [28] | MILP | It can solve all types of discrete and continuous problems. | It does not produce the optimal solution for large problems. The computational time is long. |
| Dong et al. [29] | Iterative intersection approach | It is effective and efficient compared with other conventional methods. | The structural minimality of the system must be improved. Yet, to neglect computing of the net model’s reachability graph for further increasing the efficiency. |
| Bashir et al. [30] | GMECs | It reduces the computational cost. | Research must be extended to generalized S3PR systems. |
| Lee et al. [31] | ANN and DNN | It can lower the product and service costs, speed up business processes, and serving customers better. It can quickly identify opportunities and potential benefits, effectively and then communicate to stakeholders. | High variance error typically occurs when a model is overfitted to a training dataset that contains random noise. It can affect accuracy. |
| Chu et al. [32] | CMS | It can increase the productivity and flexibility of a manufacturing system. It is effective in optimizing the trade-offs between cross-training and workload balance. | The placement of bottleneck machines are needed to be addressed during cell formation. When volume of production changes, number of workers is adjusted and workers are reassigned to various cells. |
| Cavalcante et al. [33] | resilient supplier selection | It is more evident when considering larger data sets. It includes faster processing times and better causality recognition. | Irregular to be accurately identified, estimated, and forecasted. |
| Wang et al. [34] | SSCA-APS | It has better performance in searching precision, and stability. | The speed of convergence is very slow. |
| Kamboj et al. [35] | HHO | It is easy to get trapped into local search space for constrained engineering optimization problems. | It is not efficient to solve non-differentiable, non-continuous problem and also large scale real world multimodal problem. |
| Wang et al. [36] | MALO and WSVM | It is efficient to improve the accuracy and efficiency of classification. | The position of the ants cannot be updated directly. It does not derive the problem for obtaining global optimum. |

methods, the iterative intersection approach [29] is effective and efficient and does not require ILPPs (integer linear programming problem) to be solved. However, to increase the efficiency and structural minimality of the system, it is necessary to neglect the calculation of the reachability graph of the net model. GMEC [30] does not require the ILPP to be addressed and minimizes the cost of computing. However, further research must be performed on popular S3PR systems.
Hence, the aforementioned challenges must be overcome in future studies, and a better FMS must be developed.

### III. STRUCTURE OF FMS: SYSTEM OPERATION AND DATA DESCRIPTION

#### A. FMS STRUCTURE

The structure of the FMS [29] includes a loading or unloading station, three automatic guided vehicles (AGVs), four pairs of input/output buffers (IB/OB) for each CNC (computerized numerical control) machine, and four CNC machines. Fig. 1 shows the structure of the FMS. The four CNC machines are denoted as $MC_1$, $MC_2$, $MC_3$, and $MC_4$.

#### B. SYSTEM OPERATIONS

The system operations performed by the four machines are presented in Table 2. Three types of parts are processed. Some operations are performed on more than one machine, and some of them are performed only on one machine. Table 3 presents a list of the required operations and due dates. The arrival intervals of the parts are generated randomly. The operations are denoted as $Opr_1$, $Opr_2$, $Opr_3$, $Opr_4$, $Opr_5$, and $Opr_6$.

The operations and assumptions used in the FMS simulation model are presented below.

| Operation | $MC_1$ | $MC_2$ | $MC_3$ | $MC_4$ |
|-----------|--------|--------|--------|--------|
| $Opr_1$   | -      | 10     | -      | -      |
| $Opr_2$   | 12     | 15     | -      | -      |
| $Opr_3$   | -      | -      | 13     | 17     |
| $Opr_4$   | -      | 18     | 8      | 16     |
| $Opr_5$   | 7      | -      | 12     | -      |
| $Opr_6$   | 5      | -      | -      | -      |

TABLE 3. Parts and required operations [41].

| Part type | Required operations | Due date (unit time) |
|-----------|---------------------|----------------------|
| $pt_1$    | $Opr_1 \rightarrow Opr_3 \rightarrow Opr_2 \rightarrow Opr_1$ | 1000                 |
| $pt_2$    | $Opr_5 \rightarrow Opr_4 \rightarrow Opr_2 \rightarrow Opr_5 \rightarrow Opr_4$ | 1400                 |
| $pt_3$    | $Opr_1 \rightarrow Opr_2 \rightarrow Opr_1$ | 1200                 |

1. The loading or unloading station capability is not restricted.
2. Raw materials are transferred to CNC machines using AGVs, one part at a time.
3. On each machine, only one part can be processed at a time.
4. The processing time of the machine includes the setup time.
5. AGVs and breakdowns of machines are not considered.
6. The closest inactive AGV carries a part, which requires transport.
7. When more than one machine performs an operation that a part requires, that part is transferred to the input buffer with less waiting time.

The simulation model of [41] involves three system attributes to manufacture the model, which define the dynamic operations of the FMS: the input or output buffer size of each machine, the part arrival rate, and the speed of the AGV. In the input buffers, the dispatching rules used for the machines are first come first served (FCFS), SPT, and earliest due date (EDD). These six attributes are considered as inputs, and the optimal scheduling rules are the outputs.

#### C. DATASET DESCRIPTION

The index of the performance of the FMS is based on minimizing the load unbalances and machine duplication and maximizing the utilization of resources [42]. The maximization of resource utilization is performed according to the index. The data gathered in the developed FMS based on [41] (Table 4) are used for further processing, particularly for predicting the best scheduling rule.

#### IV. PROPOSED FMS PREDICTION MODEL WITH WEIGHTED FEATURE EXTRACTION

#### A. PROPOSED RULE SCHEDULING IN FMS

Scheduling is an important feature of computing models, hard real-time environments, etc. and is one of the significant research areas related to combinatorial optimization issues. The use of multi-processor systems is efficient for reducing the computational speed of multiple programs. Decisions regarding production in real dynamic FMSs are frequently made using a small amount of data. The limited scheduling data availability is an issue for applying machine learning in these kinds of problems. The machine-learning approach has been utilized by numerous researchers [24], and the model proposed herein is intended to improve the accuracy of machine learning in FMS scheduling with small datasets.
TABLE 4. Sample data considered for training FMS model [41].

| Buffer size | Arrival rate of parts | AGV speed | FCFS performance in machine utilization | SPT performance in machine utilization | EDD performance in machine utilization | Best scheduling rule |
|-------------|-----------------------|-----------|----------------------------------------|----------------------------------------|--------------------------------------|---------------------|
| 12          | 32                    | 84        | 83                                     | 73                                     | 64                                   | FCFS                |
| 11          | 38                    | 105       | 69                                     | 88                                     | 60                                   | SPT                 |
| 10          | 34                    | 98        | 64                                     | 74                                     | 82                                   | EDD                 |
| 10          | 36                    | 111       | 75                                     | 91                                     | 92                                   | EDD                 |
| 12          | 36                    | 113       | 66                                     | 85                                     | 76                                   | SPT                 |
| 9           | 34                    | 101       | 70                                     | 90                                     | 80                                   | SPT                 |
| 12          | 38                    | 118       | 65                                     | 83                                     | 75                                   | SPT                 |
| 9           | 32                    | 109       | 69                                     | 83                                     | 84                                   | EDD                 |
| 12          | 31                    | 74        | 83                                     | 82                                     | 68                                   | FCFS                |
| 8           | 33                    | 101       | 71                                     | 89                                     | 82                                   | SPT                 |
| 8           | 33                    | 100       | 66                                     | 84                                     | 75                                   | SPT                 |
| 10          | 34                    | 99        | 66                                     | 77                                     | 84                                   | EDD                 |
| 12          | 31                    | 83        | 77                                     | 85                                     | 67                                   | SPT                 |
| 11          | 34                    | 111       | 67                                     | 78                                     | 85                                   | EDD                 |
| 12          | 37                    | 109       | 71                                     | 89                                     | 84                                   | SPT                 |
| 12          | 36                    | 92        | 81                                     | 87                                     | 69                                   | SPT                 |
| 12          | 31                    | 84        | 75                                     | 83                                     | 65                                   | SPT                 |
| 10          | 29                    | 81        | 67                                     | 83                                     | 80                                   | SPT                 |
| 9           | 28                    | 97        | 67                                     | 78                                     | 84                                   | EDD                 |
| 12          | 34                    | 87        | 79                                     | 87                                     | 68                                   | SPT                 |
| 13          | 35                    | 82        | 87                                     | 84                                     | 70                                   | FCFS                |
| 9           | 35                    | 113       | 66                                     | 80                                     | 81                                   | EDD                 |

A block diagram of the proposed optimal scheduling model for the FMS is shown in Fig. 2.

The proposed model consists of three steps: feature extraction, weighted feature extraction, and classification. First, the standard datasets related to FMS scheduling are collected from [41]. Here, the best scheduling rule of the FMS is predicted using input attributes e.g., the buffer size, arrival rate of parts, AGV speed, FCFS, SPT, and EDD. Later, these input attributes are subjected to feature extraction, where t-distributed stochastic neighbor embedding (t-SNE), linear discriminant analysis (LDA), and linear square regression (LSR) features are extracted, among others. Once the feature extraction is complete, the corresponding feature vector is converted into another form by multiplying it by a weighted function. Consequently, the scaling of each feature is performed according to the value of the weight function, allowing high-speed classification. As a novel contribution, the weight functions to be multiplied by each feature vector are optimized by an improved metaheuristic algorithm called the MN-LA. The optimal weight function generated by the MN-LA is implemented such that the correlation between the features is minimized. Finally, the optimally tuned features are subjected to a hybrid classifier that combines DBN and fuzzy classifiers. Moreover, the proposed MN-LA is used for optimizing the activation function and number of hidden neurons of the DBN and the membership limits of the fuzzy classifier. The optimized DBN is enhanced by the MN-LA such that the classification accuracy is maximized. Thus, the output of the developed system provides three classes for the best scheduling rule: FCFS, SPT, and EDD. In order to analyze the performance of the proposed MN-LA, comparison was made with the existing metaheuristics algorithms, such as PSO, GWO, WOA, and LA. The other algorithms were also coded to ensure that all the algorithms run on the same platform and computational power.

B. FEATURE EXTRACTION

Using the collected data related to the FMS, feature extraction is performed to reduce the amount of data for processing.
without losing relevant or significant information. Features such as t-SNE, LDA, LSR, and higher-order statistics are considered. The descriptions of the features are as follows:

**t-SNE [43]:** This is a dimensionality-reduction approach that reduces high-dimensional information into a low dimensional embedding space for visualization implementations. Moreover, t-SNE measures the pairwise similarity distribution, attempting to optimize the visualization in a low-dimensional space by matching the distributions according to the Kullback–Leibler (KL) divergence. Additionally, the pairwise similarities of t-SNE methods among the points in both low- and high-dimensional spaces. The probability that a point \( u_{ji} \) is expressed by Eq. (2).

\[
\begin{align*}
    u_{ji} &= \frac{\exp \left( -\frac{||y_i - y_j||^2}{2\sigma_i^2} \right)}{\sum_{k \neq i} \exp \left( -\frac{||y_i - y_k||^2}{2\sigma_i^2} \right)}, \quad (1) \\
    v_{ji} &= \frac{\left( 1 + ||y_i - y_j||^2 \right)^{-1}}{\sum_{k \neq i} \left( 1 + ||y_k - y_j||^2 \right)^{-1}}. \quad (2)
\end{align*}
\]

Subsequently, t-SNE minimizes the KL divergence among the distributions, which preserves the local structure of the data points across the high- and low-dimensional spaces. Moreover, t-SNE utilizes gradient descent for minimizing the KL divergence with the gradient measured using Eqs. (3) and (4).

\[
\begin{align*}
    \frac{\partial C}{\partial y_j} &= 4 \sum_j \left( u_{ij} - v_{ij} \right) v_{ij} \left( y_i - y_j \right), \quad (3) \\
    W &= \sum_{k \neq i} \left( 1 + ||y_k - y_j||^2 \right)^{-1}, \quad (4)
\end{align*}
\]

where \( u_{ij} \) and \( v_{ij} \) represent the symmetric joint probabilities of \( u_{ij} \) and \( u_{ji} \), such that \( u_{ij} = \frac{u_{ij} + u_{ji}}{2N} \). The t-SNE gradient computation is reformulated as the N-body simulation difficulty by reorganizing the terms into attractive and repulsive forces, as given by Eqs. (5) and (6), respectively. The combined attractive and repulsive forces are given by Eq. (7).

\[
\begin{align*}
    At_{fe} &= \sum_{j \in \{1, \ldots, N\} \neq i} u_{ij} v_{ij} W \left( y_i - y_j \right), \quad (5) \\
    Re_{fe} &= -\sum_{j \in \{1, \ldots, N\} \neq i} v_{ij}^2 W \left( y_i - y_j \right), \quad (6) \\
    \frac{\partial C}{\partial y_i} &= 4 \left( At_{fe} + Re_{fe} \right). \quad (7)
\end{align*}
\]

Thus, the extracted t-SNE features are denoted as \( FS^{t-SNE} \).

**LDA [45]:** This is an improved feature-extraction and dimension-reduction technique that is widely used in the fields of face recognition, speech recognition, and multimedia information retrieval. The main objective of LDA is to forecast the optimal transformation according to the high-dimensional information, which is divided into classes. For solving the problems related to the optimal discrimination projection matrix, the within-class and between-class scatter matrix is forecasted. The numerical formula for determining the optimal discrimination projection matrices are as follows:

\[
M_{topd} = \arg \max_{M} \frac{M^{t}BC_{class}M}{M^{t}WC_{class}M}. \quad (8)
\]

Here, \( WC_{class} \) and \( BC_{class} \) represent the within- and between-class scatter matrices, respectively. To compute \( WC_{class} \) and \( BC_{class} \), Eqs. (9) and (10) are used, respectively. Moreover, Eq. (11) gives the eigenvectors of the projection matrix \( M_{t} \).

\[
\begin{align*}
    WC_{class} &= \sum_{k=1}^{L} \left( f_{vk} - \mu_{NK} \right) \left( f_{vk} - \mu_{NK} \right)^{t}, \quad (9) \\
    BC_{class} &= \sum_{k=1}^{L} J_k \left( \mu_{k} - \alpha \right) \left( \mu_{k} - \alpha \right)^{t}, \quad (10) \\
    M_{t} &= \text{eig} \left( R_{K}^{-1} BC_{class} \right). \quad (11)
\end{align*}
\]

In the above equations, the term \( R_{K} \) is given by \( R_{K} = BC_{class} + WC_{class} \), and the attributes of the data are denoted as \( f_{vk} \). \( \alpha_{NK} \) and \( NK \) represent the data vector and the data samples of class \( K \), respectively. Hence, the term \( FS^{LDA} \) represents the feature extracted via the LDA method.

**LSR [46]:** This is a novel supervised dimensionality-reduction process. The LSR is used for extracting details from the data. Eq. (12) describes the optimization issue of LSR. Here, the class indicator matrix is denoted as \( Y_n = \{y_1, y_2, \ldots, y_N\} \), and the matrix with \( K^{th} \) columns has a dimensionality vector, which is denoted as \( d^{*} + 1 \) on the basis of Eq. (13). \( V^{*} \) represents the optimal transformation matrix. The pseudo-inverse of \( V^{*}V^{*\dagger} \) is expressed as \( \left( V^{*}V^{*\dagger} \right)^{\dagger} \).

\[
\begin{align*}
    I(Z^{*}) &= \min_{Z^{*}} \frac{1}{2} \left\| Z^{*}V^{*} - Y_o \right\|_S^2, \quad (12) \\
    Z^{*}_{lsr} &= \left( V^{*}V^{*\dagger} \right)^{\dagger} V^{*}Y^{*} \quad (13)
\end{align*}
\]

Finally, the features extracted via LSR are expressed as \( FS^{LSR} \).

**Higher-Order Statistics:** The higher-order statistics, such as the skewness, kurtosis, root mean square (RMS), entropy, and energy, are extracted.

**Skewness:** This is the degree of distortion from the normal distribution in a set of data. Skewness can be positive, negative, zero, or undefined. The skewness is calculated using Eq. (14), where \( m_3 = \frac{\sum (x_i - \bar{x})^3}{n} \) represents the third-moment dataset.

\[
skn_1 = \frac{m_3}{m_2^2} \quad (14)
\]
Kurtosis: This is a statistical measure, which is used to explain the distribution. It measures extreme values in tail. Distribution with high kurtosis display tail data, which are usually smaller than the tails of the normal distribution, are given by

\[ \text{kurt}_4 = \frac{m_4}{m_2^2}. \] (15)

Here, \( m_4 = \frac{\sum (x_i - \bar{x})^4}{n} \), and \( m_2 = \frac{\sum (x_i - \bar{x})^2}{n} \); \( m_4 \) represents the fourth moment, and \( m_2 \) represents the variance (\( \sigma^2 \)).

RMS: The RMS is defined as the square root of the mean squared, where the mean squared is the arithmetic mean of the squares of numbers. The RMS is also called the quadratic mean:

\[ \text{RMS} = \sqrt{\frac{1}{n} \sum t_1^2 + t_2^2 + \cdots + t_n^2}, \] (16)

where the items under observation are represented by \( t_n^2 \), and the total number of pixels is represented by \( n \).

Entropy: This is a statistical measure of uncertainty that accurately reflects the intraset distribution when a set of patterns is provided. The entropy is given by Eq. (17), where \( Q_c \) represents the probability of obtaining the \( c \)th value.

\[ \text{Entropy} = - \sum_{c=1}^{n} Q_c \log_2 Q_c \] (17)

Energy: The square root of the ASM (angular second moment) texture character is used as the Energy, which is in the range [0,1]. The sum of the square elements in the GLCM (gray level co-occurrence matrix) is computed via the entropy calculation, according to Eq. (18).

\[ \text{Energy} = \sum_{x,y=0}^{\text{max}} Q (x - y)^2 \] (18)

The attained higher-order statics are denoted as \( FS^{\text{HIGH}} \).

The features obtained via the aforementioned techniques, e.g., t-SNE, LDA, LSR, and higher-order statistics, are presented in Eq. (19). The combined form of the extracted features \( FS_i \) is changed according to Eq. (20).

\[ FS_i = FS^{\text{SNE}} + FS^{\text{LDA}} + FS^{\text{LSR}} + FS^{\text{HIGH}} \] (19)

\[ FS_i = \{ FS_1, FS_2, \cdots, FS_N \} \] (20)

The merged features \( FS_i \) are further used for weighted feature extraction, to alter the scaling of the features, so that each feature will be less correlative over other by proving unique information for the prediction. In Eq. (20), \( NF \) represents the total number of features extracted.

C. WEIGHTED FEATURE EXTRACTION

To extend the value of the feature vector at a large scale, a weight function \( WF_i \) is multiplied by the feature vector*, as follows:

\[ FS_i^* = FS_i \times WF_i. \] (21)

Hence, the weighted feature vector \( FS_i^* \) is extracted, in which the weight function is tuned or optimized by the proposed MN-LA for minimizing the correlation between the features. Finally, the optimal weighted feature vector \( FS_i^* \) is subjected to the optimal hybrid classifier to predict the best scheduling rule.

V. DEVELOPMENT OF PROPOSED FMS PREDICTION MODEL USING HYBRID CLASSIFIER

A. DBN

The DBN consists of several layers, similar to the neural network (NN) [47]. The visible and hidden neurons are present in the input and output layers, respectively. The DBN employs a Boltzmann network for obtaining the results effectively. The result from the DBN is denoted as \( \text{opt} \), and it has a binary format. Additionally, the result comprises the probability of the sinusoidal function \( Bzn_{\text{prb}} (\lambda) \) A, as indicated by Eqs. (22) and (23). Here, the pseudo-temperature parameter, which is denoted as \( \text{prb} \), holds the probability’s noise level. Eq. (24) refers to the stochastic model. The Boltzmann system is modeled according to the Boltzmann distribution to accurately design the input parameters.

\[ \text{opt} = \begin{cases} 1, & \text{with } 1 - Bzn_{\text{prb}} (\lambda) \\ 0, & \text{with } Bzn_{\text{prb}} (\lambda), \end{cases} \] (22)

\[ Bzn_{\text{prb}} (\lambda) = \frac{1}{1 + e^{-\lambda}}, \] (23)

\[ \lim_{\text{prb} \to 0^+} Bzn_{\text{prb}} (\lambda) = \begin{cases} 1, & \text{for } \lambda < 0 \\ \frac{1}{2}, & \text{for } \lambda = 0 \\ 0, & \text{for } \lambda > 0. \end{cases} \] (24)

The energy of the Boltzmann model for configuring the neuron states and the mathematical equation is given by Eq. (25). Here, the term \( nse \) represents the neuron states, the weights of the neurons are denoted as \( B \), and the biases of the neurons are denoted as \( \beta \). The Boltzmann system in the DBN encircles the neurons according to Eq. (26).

\[ \text{BZE}(nse_1) = \sum_{c<d} B \cdot nse_c \cdot nse_d - \beta_c nse_d \] (25)

\[ \Delta \text{BZE}(c) = \sum_d nse_c \cdot B + \beta_c \] (26)

The configuration between the visible and hidden neurons with respect to the energy is given by Eqs. (27)–(29). In these equations, the terms \( vs_c \) and \( hd_d \) refer to the visible and the hidden neurons, respectively. The bias weights are denoted as \( \text{vs}_c \) and \( \text{hd}_d \), respectively. The terms \( bs_c^* \) and \( bs_d^* \) represent the biases considered.

\[ \text{BZE}(vs^*, hd) = - \sum_{c,d} B \cdot vs_c \cdot hd_d + \sum_c vs_c \cdot bs^*_c - \sum_d hd_d \cdot hd_d \] (27)
The training set of the restricted Boltzmann machine (RBM) reduces the considered probabilities during the training of the DBN, as the parameter of the weight function restricts the probability distribution of input data. Moreover, it has the ability to allot the probability to each visible and hidden neuron with the assistance of the energy function, as indicated by Eq. (30). Here, the partition function pf is given by Eq. (31).

\[
\Delta \text{BZE}(v_{s}, h_{d}) = \frac{1}{pf} e^{-D(v_{s}', h_{d})} \tag{28}
\]

\[
\Delta \text{BZE}(v_{s}', h_{d}') = \frac{1}{pf} e^{-D(v_{s}', h_{d}')} \tag{29}
\]

The proposed DBN optimizes the activation function and the number of hidden neurons using the proposed MN-LA.

**B. FUZZY CLASSIFIER**

The major benefit of the fuzzy classifier is that the fuzzy set theory can articulate and influence the uncertainty and vagueness [44]. The starting procedure of the traditional fuzzy classifier is for providing the rules. Here, the actual classification of the data is provided by the triangular membership function, as given by Eq. (33). The membership function of \( y \) in \( C \) is represented by \( \mu_{C}(Y) \), and the low, medium and high operators are represented as \( lw, med \), and \( hg \), respectively. The universe of discourse is denoted as \( Y \), and the concerned element is denoted as \( y \).

\[
\mu_{C}(Y) = \begin{cases} 
0, & y \leq lw \\
\frac{y - lw}{mg - lw}, & lw < y \leq med \\
\frac{hg - med}{hg - y}, & med < y < hg \\
0, & y \geq hg 
\end{cases} \tag{33}
\]

We assume \( \hat{r}_{i} = \{E_{g}, F^{h}\} \), where \( F^{h} \) represents the output. The limiting factor \( \delta_{1} \) is given by Eqs. (34) and (35), and \( MF_{LN} \) indicates the number of linguistic variables.

\[
\delta_{1} = \max (\hat{r}_{i}) - \min (\hat{r}_{i}) \tag{34}
\]

\[
\delta_{1}' = \frac{\delta_{1}}{MF_{LN}} \tag{35}
\]

The minimum and maximum limits of the linguistic variables are given by Eqs. (36)–(38).

\[
L_{w}^{\text{min}} = \min (\hat{r}_{i}) \\
L_{w}^{\text{max}} = \min (\hat{r}_{i}) + \delta_{1}' \tag{36}
\]

\[
med^{\text{min}} = L_{w}^{\text{max}} + 0.1 \\
med^{\text{max}} = \min (\hat{r}_{i}) + 2\delta_{1}' \tag{37}
\]

\[
H_{g}^{\text{min}} = \min (\hat{r}_{i}) + 2\delta_{1}' + 0.1 \\
H_{g}^{\text{max}} = \max (\hat{r}_{i}) \tag{38}
\]

Because the limits of the membership function play a vital role in determining the output degree, the function must be tuned properly. Hence, in this study, the proposed MN-LA was used to optimize the membership limits, which had a positive effect on the final membership function.

**C. OPTIMIZED HYBRID CLASSIFIER**

The results obtained from the optimized DBN and the fuzzy classifier (with the proposed MN-LA) are merged via the logical AND operation. The AND operation is performed on each pair of input bits for performing the binary operations, which considers two same-length binary depictions and therefore assumes the output of both classifiers. A diagram of the optimized hybrid classifier is shown in Fig. 3.
VI. IMPROVED LION ALGORITHM (LA) FOR ENHANCING PERFORMANCE OF FEATURE EXTRACTION AND CLASSIFICATION

A. OBJECTIVE MODEL

In the proposed FMS scheduling model, the developed MN-LA optimizes the weight function in weighted feature extraction, as well as the activation function and number of hidden neurons in the DBN and the membership limits of the fuzzy classifier. There are two main objectives for the prediction model of FMS scheduling.

(a) Minimizing the correlation between features: While optimizing the weight functions in weighted feature extraction, the first objective of this model is to minimize the correlation between the features. When the correlation between the two features is minimized, it is probable that different classes can be distinguished accurately. The correlation between the two features \( u \) and \( v \) is expressed as follows:

\[
\text{Correlation} = \frac{n \sum u v - \sum u \sum v}{\sqrt{n \sum u^2 - (\sum u)^2} \sqrt{n \sum v^2 - (\sum v)^2}}.
\]  

(39)

Hence, the first objective function, which is given by Eq. (40), depends on Eq. (39).

\[
FR_1 = \min_{WF_1, WF_2, \ldots, WF_{NF}} \text{Correlation} \quad (40)
\]

(b) Maximizing the classification accuracy: The second objective of the proposed prediction model is to optimize the activation function, as well as and the number of hidden neurons of the DBN and membership limits of the fuzzy classifier, for maximizing the classification accuracy. The accuracy is defined as “the ratio of the number of exact predictions to the total number of predictions. The accuracy is given by Eq. (41), where \( trp \) and \( trn \) represent the numbers of true positives and true negatives, respectively, and \( fap \) and \( fan \) represent the numbers of false positives and false negatives, respectively.

\[
\text{Acc} = \frac{trp + trn}{trp + trn + fap + fan} \quad (41)
\]

Accordingly, the second objective of the proposed prediction model is defined as follows:

\[
FR_2 = \max_{AF, N_{HN}} (\text{Acc}) \quad (42)
\]

Here, \( AF \) represents the activation function of the DBN.

B. SOLUTION ENCODING

As the proposed MN-LA is used in two places (weighted feature extraction and classification), the objectives tend to solve the correlation between features and classification accuracy. The solution encoding of weight optimization in weighted feature extraction is shown in Fig. 4.

Moreover, Fig. 5 shows the solution encoding for the optimized DBN.

C. CONVENTIONAL LA

The LA is inspired by the distinctive social behavior of the lion [48]. There are two special behaviors in the conventional LA algorithm: territorial defense and takeover. Moreover, the conventional algorithm includes six phases: pride generation, fertility evaluation, mating, territorial defense, territorial takeover, and termination.
1) PRIDE GENERATION
The terms \( D_{\text{male}} \), \( D_{\text{female}} \), and \( D_{\text{nomad}} \) correspond to a territorial lion, its lioness, and a nomadic lion, respectively. The vector elements of the given vector representation are \( d_{k, \text{male}} \), \( d_{k, \text{female}} \), and \( d_{k, \text{nomad}} \), which are arbitrary elements differing among minimum and maximum values when \( n > 1 \), where \( k = 1, 2, \ldots, K \). The term \( K \) represents the length of the lion and can be calculated as
\[
K = \begin{cases} q, & n > 1 \text{(general case)} \\ r, & \text{otherwise (special case).} \end{cases} \tag{43}
\]
where \( q \) and \( r \) are the terms utilized for defining the length of the lions.

2) FERTILITY EVALUATION
This is helpful for skipping local optimal solutions. When \( D_{\text{male}} \) and \( D_{\text{female}} \) are saturated on the basis of their fitness, both can obtain global or local optima, from which it is not probable to acquire the best solution. The term \( D_{\text{male}} \) denotes laggardness, which is indicated by \( I_r \). When \( f(D_{\text{male}}) \) is greater than \( f_{\text{ref}} \), the term \( I_r \) is increased by 1. Territorial defense occurs when \( I_r \) reaches its maximum value \( f_{\text{max}} \). The sterility rate of the lioness \( G_r \) is employed to denote the fertility of \( D_{\text{female}} \), and the lioness is increased by 1. If \( G_r > G_{\text{max}} \), \( D_{\text{female}} \) is updated.

The update process is performed until the female generation count \( S_r \) reaches \( S_{\text{max}} \). The updated \( D_{\text{female}}+ \) is given by Eqs. (44)–(46).
\[
d_{k, \text{female}}^{+} = \begin{cases} d_{m, \text{female}}, & \text{if } k = m \\ d_{k, \text{female}}, & \text{otherwise} \end{cases} \tag{44}
\]
\[
d_{m, \text{female}}^{+} = \min \left[ d_{m, \text{max}}, \max \left( d_{m, \text{min}}, \nabla_m \right) \right] \tag{45}
\]
\[
\nabla_m = \left[ d_{m, \text{female}} + (0.1c_2 - 0.05) \left( d_{m, \text{male}} - c_1 d_{m, \text{female}} \right) \right] \tag{46}
\]

In Eqs. (44)–(46), the \( k \text{th} \) and \( m \text{th} \) factors of \( D_{\text{female}}^{+} \) are denoted as \( d_{k, \text{female}}^{+} \) and \( d_{m, \text{female}}^{+} \), respectively. The upgraded female function is denoted by \( \nabla_m \). The random integers are indicated by \( c_1 \) and \( c_2 \), which lies in between the interval 0 and 1.

**Mating:** This consists of crossover and mutation, and the additional phase is called “gender clustering.”

**Lion operator:** This offers a large search space that is useful for overcoming the local optimal solution and obtaining different outcomes with equal fitness values. The conditions that must be fulfilled to select \( D_{\text{nomad}}^{e} \) are given by Eqs. (47)–(49).
\[
f \left( D_{\text{nomad}}^{e} \right) < f \left( D_{\text{male}} \right) \tag{47}
\]
\[
f \left( D_{\text{nomad}}^{e} \right) < f \left( D_{\text{cub}}^{m} \right) \tag{48}
\]
\[
f \left( D_{\text{nomad}}^{e} \right) < f \left( D_{\text{cub}}^{l} \right) \tag{49}
\]

When \( D_{\text{male}} \) is conquered, the pride is updated, whereas when \( D_{\text{nomad}}^{e} \) is conquered, the nomad coalition is updated.

**Termination:** The process is terminated when the following two conditions are satisfied:
\[
h > h_{\text{max}}, \quad f(D_{\text{male}}) - f(D_{\text{optimal}}) \leq e_T. \tag{50}
\]
Here, \( h \) and \( h_{\text{max}} \) represent the new generation and maximum new generation, respectively, and \( e_T \) represents the error threshold. The pseudocode for the existing LA is presented in Algorithm 1.

**Algorithm 1** Pseudocode for the Existing LA [48]

Set the values of \( D_{\text{male}} \), \( D_{\text{female}} \), and \( D_{\text{nomad}}^{l} \).

Determine the values of \( f(D_{\text{male}}) \), \( f(D_{\text{female}}) \), and \( f(D_{\text{nomad}}^{l}) \).

Initialize \( f_{\text{ref}} = f(D_{\text{male}}) \) and \( h = 0 \).

Reserve the values of \( D_{\text{male}} \) and \( D_{\text{female}} \).

Conduct the fertility evaluation.

The mating is performed, and the cub pool is obtained. \( D_{\text{cub}}^{m} \) and \( D_{\text{cub}}^{l} \) are obtained via gender clustering.

Set \( U_{\text{cub}} = 0 \).

The cub-growth task is executed.

The territorial defense is performed; if the results obtained from the defense are 0, update the values of \( D_{\text{male}} \) and \( f(D_{\text{male}}) \). Continue the evaluation.

If \( U_{\text{cub}} < U_{\text{max}} \), the cub growth is performed.

The territorial defense is performed, and the values of the updated \( D_{\text{male}} \) and \( f(D_{\text{male}}) \) are obtained.

The value of \( h \) is increased by 1.

If the condition of termination is not satisfied, update the values of \( D_{\text{male}} \) and \( f(D_{\text{male}}) \) again. Continue the evaluation process.

D. PROPOSED MN-LA
The existing LA is based on the behavior of lions. It is robust and effective for acquiring a global or near-global optimum value. This method is useful for solving high-dimensional problems and is scalable. It takes less time to converge and it is reliable. Even though the LA has several advantages, it has a few disadvantages, such as the complex component design and the requirement of more parameters. In previous studies, optimization models were improved to obtain a new model suitable for complex problems. In conventional LA, the nomadic lion is updated using the mutation operation. To improve this, both the male and female nomadic lions are updated using the new formula. Accordingly, Eq. (52) gives the updated formula for the male nomadic lion, where \( AQ \) represents the coefficient computed using Eq. (53), and \( Dist_{\text{male}} \) represents the distance between the solution to the male lion, which is determined using Eq. (54).
\[
D_{\text{nomad}}^{m} = D_{\text{male}} - AQ \left( Dist_{\text{male}} \right) \tag{52}
\]
\[
AQ = 2 \times \text{rand} - 1 \tag{53}
\]
\[
Dist_{\text{male}} = \text{abs} \left( 2 \times R_{\text{male}} \times D_{\text{male}}^{m} - D_{\text{cub}}^{m} \right) \tag{54}
\]
In Eq. (53), rand represents a random number. In Eq. (54), \( R_{\text{male}} \) refers to the male rate, whose value is 0.15.

Similarly, the nomadic female lion is updated using Eq. (55), which is based on Eq. (45).

\[
\nabla_m = \left[ d_{\text{female}}^m + (0.1c_2 - 0.05) \left( d_{\text{f}}^m - c_1d_{\text{cub}}^m \right) \right]
\]

(55)

In this work, the parameters have been tuned by the trial and error method, which is a fundamental method of problem solving. It is characterized by repeated, varied attempts, which were continued until success. The pseudocode of the proposed MN-LA is presented in Algorithm 2.

Algorithm 2 Pseudocode of the Proposed MN-LA

- Set the values of \( D_{\text{male}}, D_{\text{female}}, \) and \( D_{\text{nomadic}} \).
- Determine the values of \( f(D_{\text{male}}), f(D_{\text{female}}), \) and \( f(D_{\text{nomadic}}) \).
- Initialize \( f_{\text{ref}} = f(D_{\text{male}}) \) and \( h = 0 \).
- Reserve the values of \( D_{\text{male}} \) and \( f(D_{\text{male}}) \).
- The fertility evaluation is conducted.
- The mating is performed, and the cub pool is obtained.
- \( D_{\text{cub}}^m \) and \( D_{\text{cub}}^f \) are obtained via gender clustering.
- Set \( U_{\text{cub}} = 0 \).
- The cub-growth task is executed.
- Update the nomadic male lion using Eq. (54).
- Update the nomadic male lion using Eqs. (45) and (55).
- The territorial defense is performed; if the results obtained from the defense are 0, update the values of \( D_{\text{male}} \) and \( f(D_{\text{male}}) \). Continue the evaluation.
- If \( U_{\text{cub}} < U_{\text{max}} \), the cub growth is executed.
- The territorial defense is performed, and the updated values of \( D_{\text{male}} \) and \( D_{\text{female}} \) are obtained.
- The value of \( h \) is increased by 1.
- If the condition of termination is not satisfied, update the values of \( D_{\text{male}} \) and \( f(D_{\text{male}}) \) again. Continue the evaluation process.

VII. RESULTS AND DISCUSSIONS

A. EXPERIMENTAL SETUP

The developed optimal scheduling for the FMS using the optimized intelligent model was implemented using MATLAB 2018a, and the performance of the model was evaluated. The population size was fixed as 10, and the number of iterations was fixed as 25. The performance of the proposed MN-LA-based Fuzzy+DBN (FDBN) was compared with that of traditional algorithms, such as PSO-FDBN [49], grey wolf optimizer (GWO)-FDBN [50], whale optimization algorithm (WOA)-FDBN [50], and LA-FDBN [48]. Additionally, the proposed method was compared with traditional machine-learning algorithms, e.g., the SVM [51], NN [52], DBN [47], fuzzy classifier [44], and FDBN [44, 47]. The performance was analyzed according to the relevant performance measures, e.g., the accuracy, sensitivity, specificity, precision, FPR, FNR, NPV, FDR, F1 score, and Matthew’s correlation coefficient (MCC).

B. PERFORMANCE MEASURES

In this study, the following 10 performance measures were used to evaluate the performance:

(a) Accuracy: given by Eq. (40)

(b) Sensitivity: measures the number of true positives, which are recognized exactly.

\[
\text{Sen} = \frac{\text{trp}}{\text{trp} + \text{fap}}
\]

(56)

(c) Specificity: measures the number of true negatives, which are determined precisely.

\[
\text{Spe} = \frac{\text{trn}}{\text{fan}}
\]

(57)

(d) Precision: It is the ratio of the number of positive observations that are predicted exactly to the total number of observations that are positively predicted.

\[
\text{Pr}_e = \frac{\text{trp}}{\text{trp} + \text{fap}}
\]

(58)

(e) FPR: It is computed as the ratio of the number of false-positive predictions to the number of negative predictions.

\[
\text{FPR} = \frac{\text{fap}}{\text{fap} + \text{trn}}
\]

(59)

(f) FNR: It is the proportion of positives that yield negative test outcomes.

\[
\text{FNR} = \frac{\text{fan}}{\text{trn} + \text{trp}}
\]

(60)

(g) NPV: It is the probability that subjects with a negative screening test truly do not have the disease.

\[
\text{NPV} = \frac{\text{fan}}{\text{fan} + \text{trn}}
\]

(61)

(h) FDR: It is the number of false positives in all of the rejected hypotheses.

\[
\text{FDR} = \frac{\text{fap}}{\text{fap} + \text{trn}}
\]

(62)

(i) F1 score: It is defined as the harmonic mean between precision and recall. It is used as a statistical measure to rate performance.

\[
\text{F1score} = \frac{\text{Sen} \cdot \text{Pr}_e}{\text{Sen} + \text{Pr}_e}
\]

(63)

(j) MCC: It is a correlation coefficient computed using four values.

\[
\text{MCC} = \frac{\text{trp} \times \text{trn} - \text{fap} \times \text{fap}}{\sqrt{(\text{trp} + \text{fap}) (\text{trp} + \text{fan}) (\text{trn} + \text{fap}) (\text{trn} + \text{fan})}}
\]

(64)
C. PERFORMANCE ANALYSIS USING T-SNE+LDA+LSR

The performance of the proposed and conventional models using the features t-SNE+LDA+LSR to optimize the DBN with respect to the learning percentage is shown in Fig. 6. As shown in Fig. 6(a), the accuracy of the proposed MN-LA-FDBN method was 0.2% higher than that of GWO-FDBN, 0.5% higher than that of WOA-FDBN, and 1% higher than that of LA-FDBN at a learning percentage of 35%. From Fig. 6(b), the sensitivity of the proposed MN-LA-FDBN method is 33.84% greater than PSO-FDBN, 15.38% greater than that of GWO-FDBN, 30.76% greater than that of WOA-FDBN, and 21.53% greater than that of LA-FDBN at a learning percentage of 65%. The precision of the improved MN-LA-FDBN was determined accurately, and it is shown in Fig. 6(c). At a learning percentage of 85%, the precision of the proposed MN-LA-FDBN was 35.1% higher than that of LA-FDBN and 42.8% higher than that of WOA-FDBN. On considering Fig. 6(d), at a learning percentage of 75%,
TABLE 5. Overall performance analysis of proposed and conventional models for optimal scheduling using t-SNE+LDA+LSR with different Heuristic-Based FDBNs.

| Performance measure | PSO-FDBN [49] | GWO-FDBN [53] | WOA-FDBN [50] | LA-FDBN [48] | MN-LA-FDBN |
|---------------------|---------------|---------------|---------------|---------------|------------|
| Accuracy            | 0.88          | 0.90667       | 0.84667       | 0.91333       | 0.9        |
| Sensitivity         | 0.82          | 0.72          | 0.78          | 0.74          | 0.7        |
| Specificity         | 0.91          | 1             | 0.88          | 1             | 1          |
| Precision           | 0.82          | 1             | 0.76471       | 1             | 1          |
| FPR                 | 0.09          | 0             | 0.12          | 0             | 0          |
| FNR                 | 0.18          | 0.28          | 0.22          | 0.26          | 0.3        |
| NPV                 | 0.91          | 1             | 0.88          | 1             | 1          |
| FDR                 | 0.18          | 0             | 0.23529       | 0             | 0          |
| F1 score            | 0.82          | 0.87321       | 0.77228       | 0.85057       | 0.82353    |
| MCC                 | 0.73          | 0.79472       | 0.65679       | 0.80924       | 0.78019    |

the FPR of the proposed MN-LA-FDBN method is 90.6% better than PSO-FDBN, and 84% better than WOA-FDBN. As shown in Fig. 6(e), the FNR of the improved MN-LA-FDBN was 100% higher than those of WOA-FDBN and PSO-FDBN. In Fig. 6(f), the F1 score of the proposed MN-LA-FDBN method is 11.76% superior to PSO-FDBN, 8.23% superior to GWO-FDBN, 17.64% superior to WOA-FDBN, and 29.41% superior to LA-FDBN at a learning percentage of 85%. The overall performance of the proposed MN-LA-FDBN and the conventional machine-learning techniques with t-SNE+LDA+LSR features is presented in Table 5. The accuracy of the improved MN-LA-FDBN was 2.2% higher than that of PSO-FDBN, 0.7% higher than that of GWO-FDBN, 6.2% higher than that of WOA-FDBN, and 1.4% higher than that of LA-FDBN. Moreover, the precision of the implemented LA was 21.9% higher than that of PSO-FDBN and 30.7% higher than that of WOA-FDBN. The results confirm that the proposed MN-LA-FDBN model was effective for predicting the optimal scheduling in the FMS.

D. PERFORMANCE ANALYSIS USING HIGHER-ORDER STATISTICS

The performance of the proposed MN-LA-FDBN and the different metaheuristic-based FDBN methods using the higher-order statistical features with respect to the learning percentage is shown in Fig. 7. The accuracy of the proposed MN-LA-FDBN was high for all learning percentages, as shown in Fig. 7(a). For a learning percentage of 85%, the accuracy of the proposed MN-LA-FDBN was 0.5% higher than that of LA-FDBN, 4.8% higher than that of PSO-FDBN, and 6.1% higher than that of WOA-FDBN. In Fig. 7(b), the sensitivity of the proposed MN-LA-FDBN method is 38.46% superior to PSO-FDBN, 16.92% superior to GWO-FDBN, 33.84% superior to WOA-FDBN, and 27.69% superior to LA-FDBN at a learning percentage of 65%. Additionally, the precision of the proposed MN-LA-FDBN was high for all the learning percentages. As shown in Fig. 7(c), the precision of the proposed MN-LA-FDBN method was 11.1% higher than that of PSO-FDBN and 12.3% higher than that of FDBN. When considering Fig. 7(d), at a learning percentage of 35%, the FPR of the proposed MN-LA-FDBN method is 91.42% upgraded than PSO-FDBN, and 94.28% upgraded than WOA-FDBN. In Fig. 7(e), the FNR of the proposed MN-LA-FDBN method is 83.07% better than PSO-FDBN, 64.61% better than GWO-FDBN, 89.69% better than WOA-FDBN, and 76.92% better than LA-FDBN at a learning percentage of 65%. On considering Fig. 7(f) at a learning percentage of 85% the F1 score of the proposed MN-LA-FDBN method is 14.11% improved than PSO-FDBN, 16.47% improved than WOA-FDBN, and 15.29% improved than LA-FDBN. Table 6 presents the overall performance of the modified MN-LA-FDBN and the traditional optimization-based FDBN methods with higher-order statistics. As shown, the accuracy of the proposed MN-LA-FDBN was 6.9% higher than those of PSO-FDBN and WOA-FDBN, 0.7% higher than that of GWO-FDBN, and 2.9% higher than that of LA-FDBN. Additionally, the precision of the proposed MN-LA-FDBN was higher than those of the other algorithms. It was 21.6% higher than those of PSO-FDBN and WOA-FDBN. Therefore, the proposed MN-LA-FDBN method was superior to the conventional methods for predicting the optimal scheduling in the FMS.

E. PERFORMANCE ANALYSIS FOR T-SNE+LDA+LSR+HIGHER-ORDER STATISTICS

The performance of the developed MN-LA-FDBN and the traditional algorithms with t-SNE+LDA+LSR+higher-order statistics with respect to the learning percentage is presented in Fig. 8. As shown in Fig. 8(a), the accuracy of the proposed MN-LA-FDBN was high for all the learning percentages. It was 0.5% higher than that of GWO-FDBN, 2.7% higher than that of WOA-FDBN, and 7.5% higher than that of PSO-FDBN at a learning percentage of 75%. From Fig. 8(b) the Sensitivity of the proposed MN-LA-FDBN method is 38.46% superior to PSO-FDBN, 16.92% superior to GWO-FDBN, 33.84% superior to WOA-FDBN, and 27.69% superior to LA-FDBN at a learning percentage of 65%. Additionally, the precision of the proposed MN-LA-FDBN was high for all the learning percentages. As shown in Fig. 8(c), the precision of the proposed MN-LA-FDBN method was 11.1% higher than that of PSO-FDBN and 12.3% higher than that of FDBN. When considering Fig. 8(d), at a learning percentage of 35%, the FPR of the proposed MN-LA-FDBN method is 91.42% upgraded than PSO-FDBN, and 94.28% upgraded than WOA-FDBN. In Fig. 8(e), the FNR of the proposed MN-LA-FDBN method is 83.07% better than PSO-FDBN, 64.61% better than GWO-FDBN, 89.69% better than WOA-FDBN, and 76.92% better than LA-FDBN at a learning percentage of 65%. On considering Fig. 8(f) at a learning percentage of 85% the F1 score of the proposed MN-LA-FDBN method is 14.11% improved than PSO-FDBN, 16.47% improved than WOA-FDBN, and 15.29% improved than LA-FDBN. Therefore, the proposed MN-LA-FDBN method was superior to the conventional methods for predicting the optimal scheduling in the FMS.
MN-LA-FDBN was 100% better than those of WOA-FDBN and PSO-FDBN. In Fig. 8(e) the FNR of the proposed MN-LA-FDBN method is 58.82% better than PSO-FDBN, 50.58% better than GWO-FDBN, 76.47% better than WOA-FDBN, and 42.35% better than LA-FDBN at a learning percentage of 85%. On considering Fig. 8(f) at a learning percentage of 75% the F\textsubscript{1} score of the proposed MN-LA-FDBN method is 4% improved than PSO-FDBN, 13.33% improved than WOA-FDBN, and 10.66% improved than WOA-FDBN. The performance of the proposed MN-LA-FDBN and the existing models for t-SNE+LDA+LSR+Statistics is presented in Table 7. The accuracy of the proposed MN-LA-FDBN was 6.9% higher than that of PSO-FDBN, 0.7% higher than that of GWO-FDBN, and 2.9% higher than that of WOA-FDBN. The precision of the proposed MN-LA-FDBN was 27.5% higher than that of PSO-FDBN and 19% higher than that of WOA-FDBN. The results indicate that the implemented MN-LA-FDBN method with the combined features was suitable for predicting the optimal scheduling in the FMS and was superior to the other models.
TABLE 6. Overall performance analysis of proposed and conventional models for optimal scheduling using Higher-Order statistics with different Heuristic-Based FDBNs.

| Performance measure | PSO-FDBN [49] | GWO-FDBN [53] | WOA-FDBN [50] | LA-FDBN [48] | MN-LA-FDBN |
|---------------------|---------------|---------------|---------------|--------------|------------|
| Accuracy            | 0.86          | 0.9133        | 0.86          | 0.8933       | 0.92       |
| Sensitivity         | 0.74          | 0.74          | 0.74          | 0.68         | 0.76       |
| Specificity         | 0.92          | 1             | 0.92          | 1            | 1          |
| Precision           | 0.82222       | 1             | 0.82222       | 1            | 1          |
| FPR                 | 0.08          | 0             | 0.08          | 0            | 0          |
| FNR                 | 0.26          | 0.26          | 0.26          | 0.32         | 0.24       |
| NPV                 | 0.92          | 1             | 0.92          | 1            | 1          |
| FDR                 | 0.17778       | 0             | 0.17778       | 0            | 0          |
| F1 score            | 0.77895       | 0.85057       | 0.77895       | 0.80952      | 0.86364    |
| MCC                 | 0.67893       | 0.80924       | 0.67893       | 0.76564      | 0.82375    |

TABLE 7. Overall performance analysis of proposed and conventional models for optimal scheduling using t-SNE+LDA+LSR+Statistics with different Heuristic-Based FDBNs.

| Performance measure | PSO-FDBN [49] | GWO-FDBN [53] | WOA-FDBN [50] | LA-FDBN [48] | MN-LA-FDBN |
|---------------------|---------------|---------------|---------------|--------------|------------|
| Accuracy            | 0.86          | 0.9133        | 0.8933        | 0.92         | 0.92       |
| Sensitivity         | 0.8           | 0.74          | 0.84          | 0.76         | 0.76       |
| Specificity         | 0.89          | 1             | 0.92          | 1            | 1          |
| Precision           | 0.78431       | 1             | 0.84          | 1            | 1          |
| FPR                 | 0.11          | 0             | 0.08          | 0            | 0          |
| FNR                 | 0.2           | 0.26          | 0.16          | 0.24         | 0.24       |
| NPV                 | 0.89          | 1             | 0.92          | 1            | 1          |
| FDR                 | 0.21569       | 0             | 0.16          | 0            | 0          |
| F1 score            | 0.79208       | 0.85057       | 0.84          | 0.86364      | 0.86364    |
| MCC                 | 0.68664       | 0.80924       | 0.76          | 0.82375      | 0.82375    |

F. PERFORMANCE ANALYSIS FOR OPTIMAL WEIGHTED FEATURES

The performance of the improved MN-LA-FDBN and the traditional FDBN with the optimal weighted feature according to the learning percentage is shown in Fig. 9. The accuracy of the proposed MN-LA-FDBN was high compared with the other algorithms, as shown in Fig. 9(a). It was 1.4% higher than that of PSO-FDBN, 1.5% higher than that of WOA-FDBN, 2% higher than that of LA-FDBN, and 2.6% higher than that of PSO-FDBN for a learning percentage of 35%. From Fig. 9(b), the sensitivity of the proposed MN-LA-FDBN method is 67.27% greater than PSO-FDBN, 54.54% greater than that of GWO-FDBN, 56.36% greater than that of WOA-FDBN, and 49.09% greater than that of LA-FDBN at a learning percentage of 55%. In Fig. 9(c), the precision of the proposed MN-LA-FDBN was 4.7% higher than that of WOA-FDBN and 5.3% higher than that of PSO-FDBN for the learning percentage of 35%. As shown in Fig. 9(d), the FNR of the proposed MN-LA-FDBN method is 85.71% better than PSO-FDBN, 82.85% better than GWO-FDBN, 88.57% better than WOA-FDBN, and 71.42% better than LA-FDBN at a learning percentage of 35%. As indicated by Fig. 9(f), the FNR of the proposed MN-LA-FDBN is correctly defined the false-negative observations from all the observations for all the learning percentages. The FNR of the proposed MN-LA-FDBN was 37.5% higher than that of WOA-FDBN, 52.3% higher than that of GWO-FDBN, and 60% higher than that of LA-FDBN. The overall performance of the proposed MN-LA-FDBN and conventional models with optimized weighted features is presented in Table 8. As shown, the accuracy of the improved MN-LA-FDBN was 14.1% higher than that of PSO-FDBN, 6.6% higher than that of GWO-FDBN, 13.2% higher than that of WOA-FDBN, and 5% higher than that of LA-FDBN. Moreover, the precision of the proposed MN-LA-FDBN was 28.9% higher than that of PSO-FDBN and 30% higher than that of WOA-FDBN. Thus, the proposed MN-LA-FDBN exhibited good performance for optimal scheduling with the optimized weighted features.

G. EFFECT OF T-SNE+LDA+LSR ON MACHINE LEARNING

The performance analysis of the developed MN-LA-FDBN and the conventional classifiers with t-SNE+LDA+LSR with respect to the learning percentage is presented in Fig. 10. As shown in Fig. 10(a), the accuracy of the improved MN-LA-FDBN has exactly defined the positive observations from the whole observations for all the learning percentages. It was 1% higher than those of the FDBN and DBN, 6.5% higher than those of the fuzzy classifier and the NN, and 3.1% higher than that of the SVM for a learning percentage of 35%. As shown in Fig. 10(b) at a learning percentage of 85%, the Sensitivity of the proposed MN-LA-FDBN is 5.88% higher than those of FDBN and DBN, 27.05% higher than fuzzy classifier, 23.52% higher than NN, and 12.94% higher than SVM. For all the learning percentages, the precision of the implemented MN-LA-FDBN high and it is correctly defined the true values from all the values, as shown in Fig. 10(c). For a learning percentage of 85%, the precision of the proposed MN-LA-FDBN was 42.8%
higher than those of FDBN and DBN, 100% higher than that of the fuzzy classifier, 81.8% higher than that of NN, and 66.6% higher than that of the SVM. On considering Fig. 10(d) at a learning percentage of 55% the FPR of the proposed MN-LA-FDBN method is 72.72% improved than SVM, 74.54% improved than NN, 90.90% improved than DBN, 78.18% improved than fuzzy classifier, and 94.54% improved than FDBN. In Fig. 10(e), the FNR of the proposed MN-LA-FDBN method is 80% better than DBN, and fuzzy classifier at a learning percentage of 35%. When considering Fig. 10(f) at a learning percentage of 75% the F₁ score of the proposed MN-LA-FDBN method is 4% superior to SVM, 6.66% superior to NN, 5.33% superior to DBN, 1.33% superior to fuzzy classifier, 8% superior to FDBN. The overall classification analysis of the proposed MN-LA-FDBN and the conventional classifiers with t-SNE+LDA+LSR is presented in Table 9. As shown, the accuracy of the proposed MN-LA-FDBN was 8.8% higher than that of the SVM, 5.4% higher than that of the NN, 3.8% higher than that of the DBN, 12.5% higher than that of the fuzzy classifier, and 3% higher than that of the FDBN. Moreover, the precision of the proposed MN-LA-FDBN was 52% higher than that of the SVM, 44% higher.
FIGURE 9. Performance analysis of the proposed and conventional methods using optimal weighted features with the optimized FDBN: (a) accuracy, (b) sensitivity, (c) precision, (d) FPR, (e) FNR, and (f) F1 score.

than that of the NN, 28.5% higher than that of the DBN, 60% higher than that of the fuzzy classifier, and 26.1% higher than that of the FDBN. The results indicate that the proposed MN-LA-FDBN outperformed the conventional algorithms and is reliable for optimal scheduling.

H. EFFECT OF HIGHER-ORDER STATISTICS ON MACHINE LEARNING

We analyzed the proposed MN-LA-FDBN and the conventional machine-learning algorithms with the use of higher-order statistics for different learning percentages, as shown in Fig. 11. The accuracy of the proposed MN-LA-FDBN was high for all the learning percentages, as shown in Fig. 11(a). It was 4.9% higher than those of the FDBN and DBN, 28.7% higher than those of the fuzzy classifier and the NN, and 21.4% higher than that of the SVM for a learning percentage of 85%. On considering Fig. 11(b) at a learning percentage of 55% the Sensitivity of the proposed MN-LA-FDBN method is 81.81% upgraded than SVM, NN and fuzzy classifier, 54.54% upgraded than DBN and FDBN. When
TABLE 8. Overall performance analysis of proposed and conventional models for optimal scheduling using weighted feature with different Heuristic-Based FDBNs.

| Performance measure | PSO-FDBN [49] | GWO-FDBN [53] | WOA-FDBN [50] | LA-FDBN [48] | MN-LA-FDBN |
|---------------------|---------------|---------------|---------------|---------------|-------------|
| Accuracy            | 0.84667       | 0.90667       | 0.85333       | 0.92          | 0.96667     |
| Sensitivity         | 0.76          | 0.72          | 0.8           | 0.76          | 0.9         |
| Specificity         | 0.89          | 1             | 0.88          | 1             | 1           |
| Precision           | 0.77551       | 0             | 0.76923       | 1             | 1           |
| FPR                 | 0.11          | 0             | 0.12          | 0             | 0           |
| FNR                 | 0.24          | 0.28          | 0.2           | 0.24          | 0.1         |
| NPV                 | 0.89          | 1             | 0.88          | 1             | 1           |
| FDR                 | 0.22449       | 0             | 0.23077       | 0             | 0           |
| F1_score            | 0.76768       | 0.83721       | 0.78431       | 0.86364       | 0.94737     |
| MCC                 | 0.65334       | 0.79472       | 0.67356       | 0.82375       | 0.92582     |

TABLE 9. Overall performance analysis of proposed and conventional machine-learning models for predicting optimal scheduling in FMS with t-SNE+LDA+LSR.

| Performance measure | SVM [51] | NN [52] | DBN [47] | Fuzzy [44] | FDBN [44, 47] | MN-LA-FDBN |
|---------------------|----------|--------|----------|------------|---------------|-------------|
| Accuracy            | 0.82667  | 0.85333| 0.86667  | 0.8         | 0.83733       | 0.9         |
| Sensitivity         | 1        | 1      | 0.84     | 1          | 0.84          | 0.7         |
| Specificity         | 0.74     | 0.78   | 0.88     | 0.7        | 0.89          | 1           |
| Precision           | 0.65789  | 0.69444| 0.77778  | 0.625      | 0.79245       | 1           |
| FPR                 | 0.26     | 0.22   | 0.12     | 0.3        | 0.11          | 0           |
| FNR                 | 0.74     | 0.78   | 0.88     | 0.7        | 0.89          | 1           |
| FDR                 | 0.34211  | 0.30556| 0.22222  | 0.375      | 0.20755       | 0           |
| F1 score            | 0.79365  | 0.81967| 0.80769  | 0.76923    | 0.81533       | 0.82353     |
| MCC                 | 0.69774  | 0.73598| 0.70711  | 0.66144    | 0.73992       | 0.78019     |

TABLE 10. Overall performance analysis of proposed and conventional machine-learning models for predicting optimal scheduling in FMS with Higher-Order statistics.

| Performance measure | SVM [51] | NN [52] | DBN [47] | Fuzzy [44] | FDBN [44, 47] | MN-LA-FDBN |
|---------------------|----------|--------|----------|------------|---------------|-------------|
| Accuracy            | 0.82667  | 0.85333| 0.84667  | 0.81333    | 0.85333       | 0.92        |
| Sensitivity         | 1        | 1      | 0.78     | 1          | 0.78          | 0.76        |
| Specificity         | 0.74     | 0.78   | 0.88     | 0.72       | 0.89          | 1           |
| Precision           | 0.65789  | 0.69444| 0.76471  | 0.64103    | 0.78          | 1           |
| FPR                 | 0.26     | 0.22   | 0.12     | 0.28       | 0.11          | 0           |
| FNR                 | 0.74     | 0.78   | 0.88     | 0.72       | 0.89          | 1           |
| FDR                 | 0.34211  | 0.30556| 0.23529  | 0.35897    | 0.22          | 0           |
| F1 score            | 0.79365  | 0.81967| 0.77228  | 0.78125    | 0.78          | 0.86354     |
| MCC                 | 0.69774  | 0.73598| 0.65679  | 0.67937    | 0.67          | 0.82375     |

considering Fig. 11(C) at a learning percentage of 85% the precision of the proposed MN-LA-FDBN method is 47.05% superior to SVM, 49.41% superior to NN and fuzzy classifier, 23.52% superior to DBN, and FDBN. From Fig. 11(d) the FPR of the proposed MN-LA-FDBN method is 72.30% better than SVM, and fuzzy classifier, 61.53% better than NN, 92.30% better than DBN, and 95.38% better than FDBN at a learning percentage of 65%. In Fig. 11(e) the FNR of the proposed MN-LA-FDBN method is 80% better than DBN, and FDBN at a learning percentage of 35%. For the learning percentage of 85%, in Fig. 11(f) the F1 score of the proposed MN-LA-FDBN was 4.1% higher than those of the FDBN and DBN, 15.3% higher than those of the fuzzy classifier and the NN, and 11.9% higher than that of the SVM, as shown in Fig. 11(i). The overall classification performance with the use of higher-order statistics for the proposed MN-LA-FDBN and the traditional algorithms is presented in Table 10. The accuracy of the proposed MN-LA-FDBN was 11.2% higher than that of the SVM, 17.8% higher than that of the NN, 8.6% higher than that of the DBN, 13.1% higher than that of the fuzzy classifier, and 7.8% higher than that of the FDBN. As indicated by Table 10, the precision of the proposed MN-LA-FDBN was 52% higher than that of the SVM, 44% higher than that of the NN, 30% higher than that of the DBN, 55.9% higher than that of the fuzzy classifier, and 28.2% higher than that of the FDBN. The results confirm that the proposed MN-LA-FDBN performed well and is appropriate for optimal scheduling.

I. EFFECT OF T-SNE+LDA+LSR+STATISTICS ON MACHINE LEARNING

The classification performance of the improved MN-LA-FDBN and the traditional classifiers with t-SNE+LDA+LSR+Statistics according to the learning percentage is shown
in Fig. 12. For a learning percentage of 85%, the accuracy of the proposed MN-LA-FDBN was 1.2% higher than those of the FDBN and DBN, 72% higher than that of the fuzzy classifier, 26.1% higher than that of the NN, and 17.1% higher than that of the SVM, as shown in Fig. 12(a). When considering Fig. 12(b) at a learning percentage of 65%, the sensitivity of the proposed MN-LA-FDBN method is 53.84% superior to SVM, NN, and fuzzy classifier 38.46% superior to DBN, and FDBN. As indicated by Fig. 12(c), for a learning percentage of 35%, the precision of the proposed MN-LA-FDBN was 3% higher than that of the FDBN, 21.9% higher than that of the fuzzy classifier, 4.1% higher than that of the DBN, 23.4% higher than that of the NN, and 21.9% higher than that of the SVM. From Fig. 12(d) the FPR of the proposed MN-LA-FDBN method is 72.72% better than SVM, 69.09% better than NN, 90.90% better than DBN, and FDBN and 70.90% better than fuzzy classifier at a learning percentage of 55%. In Fig. 12(e), the FNR of the proposed MN-LA-FDBN method is 80% better than DBN, and FDBN at a learning percentage of 35%. When
considering Fig. 12(f), at a learning percentage of 85% the F1 score of the proposed MN-LA-FDBN method is 24.70% superior to SVM, 25.88% superior to NN, 23.52% superior to DBN, and FDBN and 17.64% superior to fuzzy classifier. The overall classification analysis of the proposed and conventional models with t-SNE+LDA+LSR+Statistics is presented in Table 11. As shown, the accuracy of the proposed MN-LA-FDBN was 15% higher than that of the SVM, 7.8% higher than that of the NN, 10.4% higher than that of the fuzzy classifier, and 8.6% higher than that of the FDBN. Moreover, the precision of the proposed MN-LA-FDBN was 60% higher than that of the SVM, 44% higher than that of the NN, 37.8% higher than that of the DBN, 49.9% higher than that of the fuzzy classifier, and 27% higher than that of the FDBN. The results indicate that the proposed MN-LA-FDBN outperformed conventional classifiers.

J. EFFECT OF OPTIMAL WEIGHTED FEATURES ON MACHINE LEARNING
A classification analysis of the proposed MN-LA-FDBN and the classical methods with weighted features according to the
FIGURE 12. Performance analysis of the proposed and conventional machine-learning algorithms using t-SNE+LDA+LSR+Statistics with the optimized FDBN: (a) accuracy, (b) sensitivity, (c) precision, (d) FPR, (e) FNR, and (f) F1 score.

learning percentage was performed, as shown in Fig. 13. The accuracy of the proposed MN-LA-FDBN is high for all the learning percentages, as shown in Fig. 13(a). For a learning percentage of 35%, the accuracy of the proposed MN-LA-FDBN was 3.1% higher than those of the FDBN and DBN, 7.6% higher than that of the fuzzy classifier, 4.2% higher than that of the NN, and 5.3% higher than that of the SVM. On considering Fig. 13(b) at a learning percentage of 55% the Sensitivity of the proposed MN-LA-FDBN method is 81.81% upgraded than SVM, NN and fuzzy classifier, 54.54% upgraded than DBN, and FDBN. As shown in Fig. 13(c) at the learning percentage of 35%, the precision of the proposed MN-LA-FDBN was 5.2% higher than that of the FDBN, 21.9% higher than that of the fuzzy classifier, 6.3% higher than that of the DBN, 17.6% higher than that of the NN, and 20.4% higher than that of the SVM. From Fig. 13(d) the FPR of the proposed MN-LA-FDBN method is 73.33% better than SVM, 66.66% better than NN, and fuzzy classifier, 86.66% better than DBN, and 89.33% better than FDBN at a learning percentage of 75%. In Fig. 13(e) the FNR of the proposed MN-LA-FDBN method is 77.33% better than DBN, and FDBN at a learning percentage of 75%. When
considering Fig. 13(f) at a learning percentage of 65%, the F1 score of the proposed MN-LA-FDBN method is 23.07% superior to SVM, 24.61% superior to NN, 29.23% superior to DBN, and FDBN, and 20% superior to fuzzy classifier. Table 12 presents the overall performance of the improved MN-LA-FDBN and conventional models using weighted features. As shown, the accuracy of the proposed MN-LA-FDBN was 11.5% higher than that of the SVM, 17.8% higher than those of the fuzzy classifier and the NN, 10.6% higher than that of the DBN, and 9% higher than that of the FDBN. Similarly, the precision of the proposed MN-LA-FDBN was 39.9% higher than that of the SVM, 54% higher than those of the fuzzy classifier and the NN, 24.3% higher than that of the DBN, and 19.5% higher than that of the FDBN. Thus, the proposed MN-LA-FDBN was more effective than the conventional methods and was suitable for optimal scheduling in the FMS.

K. ANALYSIS BASED ON COMPUTATIONAL TIME
The computational time of the proposed and existing methods is analyzed and listed in Table 13. On considering the computational time, the proposed algorithm is better than...
TABLE 11. Overall performance analysis of proposed and conventional machine-learning models for predicting optimal scheduling in FMS with t-SNE+LDA+LSR+Higher-Order statistics.

| Performance measure | SVM [51] | NN [52] | DBN [47] | Fuzzy [44] | FDBN [44, 47] | MN-LA-FDBN |
|---------------------|----------|---------|----------|------------|--------------|------------|
| Accuracy            | 0.8      | 0.85333 | 0.82     | 0.83333    | 0.84667      | 0.92       |
| Sensitivity         | 1        | 1       | 0.74     | 1          | 0.74         | 0.76       |
| Specificity         | 0.7      | 0.78    | 0.86     | 0.75       | 0.9          | 1          |
| Precision           | 0.625    | 0.69444 | 0.72549  | 0.66667    | 0.78723      | 1          |
| FPR                 | 0.3      | 0.22    | 0.14     | 0.25       | 0.1          | 0          |
| FNFR                | 0        | 0       | 0.26     | 0          | 0.26         | 0.24       |
| NPV                 | 0.7      | 0.78    | 0.86     | 0.75       | 0.9          | 1          |
| FDR                 | 0.375    | 0.30556 | 0.27451  | 0.33333    | 0.21277      | 0          |
| F1 score            | 0.76923  | 0.81967 | 0.73267  | 0.8        | 0.76289      | 0.86364    |
| MCC                 | 0.66144  | 0.73598 | 0.59708  | 0.70711    | 0.65045      | 0.82375    |

TABLE 12. Overall performance analysis of proposed and conventional Machine-Learning models for predicting optimal scheduling in FMS with optimized weighted features.

| Performance measure | SVM [51] | NN [52] | DBN [47] | Fuzzy [44] | FDBN [44, 47] | MN-LA-FDBN |
|---------------------|----------|---------|----------|------------|--------------|------------|
| Accuracy            | 0.86667  | 0.82    | 0.87333  | 0.82       | 0.88667      | 0.96667    |
| Sensitivity         | 1        | 1       | 1        | 1          | 0.82         | 0.9        |
| Specificity         | 0.8      | 0.73    | 0.9      | 0.73       | 0.92         | 1          |
| Precision           | 0.71429  | 0.64935 | 0.80392  | 0.64935    | 0.83673      | 1          |
| FPR                 | 0.2      | 0.27    | 0.1      | 0.27       | 0.08         | 0          |
| FNFR                | 0        | 0       | 0.18     | 0          | 0.18         | 0.1        |
| NPV                 | 0.8      | 0.73    | 0.9      | 0.73       | 0.92         | 1          |
| FDR                 | 0.28571  | 0.35065 | 0.19608  | 0.33065    | 0.16327      | 0          |
| F1 score            | 0.83333  | 0.7874  | 0.81188  | 0.7874     | 0.82828      | 0.94737    |
| MCC                 | 0.75593  | 0.6885  | 0.7165   | 0.6885     | 0.7438       | 0.92582    |

TABLE 13. The computational time of the proposed and existing method.

| Methods | Computational Time (sec) |
|---------|--------------------------|
| PSO     | 99.428                   |
| GWO     | 163.29                   |
| WOA     | 134.58                   |
| LA      | 454.33                   |
| MN-LA   | 120.42                   |

the existing methods, such as PSO, GWO, WOA, and LA. The computational time of the proposed MNLA is 17.43% better than PSO, 35.60% better than GWO, 11.75% better than WOA, and 73.49% better than LA, respectively.

VIII. CONCLUSIONS

This paper introduced an effective prediction model using intelligent hybrid learning for FMS scheduling. It comprises feature extraction, optimal weighted feature extraction, and prediction. Once the data are collected from standard datasets pertaining to the FMS, features (e.g., t-SNE, LDA, LSR, and higher-order statistical features) are extracted. Next, optimal weight feature extraction is performed for selecting the optimal features with low correlation via the developed MN-LA. These features are applied to a hybrid classifier. The activation function and the number of hidden neurons in the DBN, as well as the membership function in the fuzzy classifier, are optimized by the proposed MN-LA. According to test results, with the use of the optimized weighted features, the accuracy of the proposed MN-LA-FDBN was 11.5% higher than that of the SVM, 17.8% higher than those of the fuzzy classifier and the NN, 10.6% higher than that of the DBN, and 9% higher than that of the FDBN. Hence, the proposed MN-LA is suitable for predicting the optimal scheduling in FMSs. The advantages of the proposed method include, reduced manufacturing cost, increased labor productivity, increased machine efficiency, improved product quality, increased system reliability, reduced parts inventory, shorter lead times, and increased production rate. The disadvantages include a high initial set up cost, requirements of skilled workers, and a more complicated system. Moreover, the proposed MN-LA has not been tested to solve many complex problems. In future, a 3D animation module for will be developed for better visualization of the system and results.

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