Design and Improvement of New Industrial Robot Mechanism Based on Innovative BP-ARIMA Combined Model

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***Abstract*—The main innovation of Industry 4.0, which involves human-robot cooperation, is transforming industrial operation facilities. Robotic systems have been developed as modern industrial solutions to assist operators in carrying out manual tasks in cyber-physical industrial environments. These robots integrate unique human talents with the capabilities of intelligent machinery. Due to the increasing demand for modern robotics, numerous ongoing industrial robotics studies exist. Robots offer advantages over humans in various aspects, as they can operate continuously. Enhanced efficiency is achieved through reduced processing time and increased industrial adaptability. When deploying interactive robotics, emphasis should be placed on optimal design and improvisation requirements. Robotic design is a very challenging procedure that involves extensive development and modeling efforts. Significant progress has been made in robotic design in recent years, providing multiple approaches to address this issue. Considering this, we propose utilizing the Backpropagation Autoregressive Integrated Moving Average (BP-ARIMA) combination model for designing and improving a novel industrial robot mechanism. The design outcomes were evaluated based on performance indicators, including accuracy, optimal performance, error rate, implementation cost, and energy consumption. The evaluation findings demonstrate that the suggested BP-ARIMA model offers optimal design for industrial robotics.**

***Keywords*—Industry 4.0; robotics; design; backpropagation autoregressive integrated moving average (BP-ARIMA); and operation facilities**

I. Introduction

An industrial robot is a revolutionary machine designed to ease the burden of repetitive factory tasks. Assembly plants are examples of highly dynamic settings that have significantly benefited from this invention. These robots are installed as fixed, imposing features of the factory space, with various other workers' activities revolving around them [1]. Industrial robots are movable platforms with sensors, processors, and actuators that can function autonomously. These systems equip robots to perform discrete operations inside elaborate processing or production pipelines. These devices have three or more axes of motion and may be programmed to carry out various tasks, which is why they are sometimes referred to as robotic systems [2]. Multiple mechanisms power these automated systems; the most common are electric motors, hydraulic drives, and pneumatic controls. In terms of price-to-performance, electric motors are the way to go because of their reliable power source and straightforward construction. Their increasing popularity may be attributed to the wide variety of jobs they can do, which includes welding joints, selecting and arranging things, piercing, and sawing. In addition, their effectiveness exceeds that of traditional propulsion methods. Fig. 1 shows some of the many ways industrial robotics technology is being used, demonstrating the far-reaching impact of robotics [3].

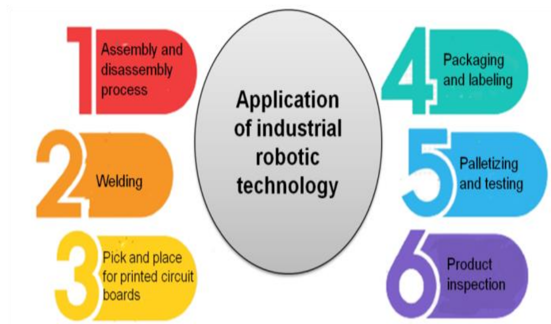

Fig. 1. Application of industrial robotics technology.

These robots also greatly aid monitoring efforts for controlling industrial processes and assuring product quality. The efficiency of future factories and enterprises will significantly benefit from their influence. Robotic calibration aims to discover statistical approaches that more accurately represent the machine's capabilities, taking precision beyond the level of nominal kinematic models. The price tag is manageable for all the quality gains we're making. Manipulators, end effectors, input gear, controllers, and locomotion systems are the fundamental building blocks of every effective industrial robot [4]. As a measure of technical progress, the degree of automation achieved may be defined by the extent of its integration. While robots have come a long way in intelligence, they still often need human aid to deal with unpredictable workloads and environmental conditions. Precision and endurance are where robots thrive, but humans have the upper hand when it comes to things like intuition, responsiveness, and flexibility. This collaboration makes the most of each party's capabilities. As the field of autonomous systems continues to grow and adapt to new applications and problems, route planning has become more important [5]. There are unique challenges and necessities for industrial robot systems as they become more flexible. Traditional online training and offshore procedures are two prominent uses for industrial robots. These methods are constantly developing to keep up with the increasing complexity of today's projects and software. Industrial robots are on the cusp of altering the assembly line and the global economy. These robots are set to spearhead this shift because of their rising intelligence, mobility, interaction, and adaptability capabilities. Even while people are still in the driver's seat in intelligent factories, automation is closing the gap [6].

Energy-efficient methods, such as green manufacturing, are in high demand because of rising worldwide concerns about pollution and resource depletion. Techniques that reduce pollution and waste during production are emphasized [7]. Automation and robotization, in which machines, rather than humans, do laborious, repetitive activities, are becoming more common. Industrial robots can currently perform various tasks, mimicking human agility and productivity. Unlike humans, they never tire, giving them a distinct edge [8]. Researchers have shown that robotization has significant advantages for enterprises, including higher productivity, lower manufacturing costs, and better utilization. Industrial robots increasingly perform machining processes, including chamfering, deburring, grinding, and polishing.

Compared to conventional machining centers, they provide many benefits, including adaptability, enough space for work, and low initial investment costs. Industrial robot efficiency is measured by creating different control systems and paths. High-speed cameras monitor mobility information, assessing velocity, acceleration, and direction accuracy [9]. A laser tracker-based adjustment method is offered in the pursuit of precision. This method detects residual errors through tool location measurements, enhancing motion planning and ensuring obstacle-free operations—the trajectory of robotization points toward the proliferation of industrial robots in various sectors. According to projections by the Boston Consulting Group, a global automation revolution is on the horizon as industries approach the point where robotization becomes economically feasible [10].

As for the remainder of the paper, Section II provides the relevant research and suggested approaches. Section III provides a description, Section IV displays the findings, and Section V shows the final results of the article.

II. Related Works

The study [11] suggests a technique based on innovation performance standards that can conduct a topology optimization for industrial robots applicable across the board in the workplace or while using a specific set of pathways in Industry 4.0. The best robot designs or trajectories for which extreme performance will be reached are calculated and repeatedly modified to require the selected efficiency indicators to be applicable worldwide. It uses the elastic models' structural features to lower the computational burden of these performance metrics and thereby lessen the computing time needed to calculate them. The Linearization Method, our last optimization technique, produces results in computing time comparable to conventional topological optimization algorithms. Still, its implementation is more straightforward, making it simple to do customization or enhancement. The study [12] analyses industrial robot control performance and dependability while considering the impact of unknown factors. Initially, the Denavit-Hartenberg technique is used to create the kinematic models of industrial robots, which assumes the connection extents and component rotational degrees to be unknowable factors. To do the durability study, the sensitive factors are identified using the Sobol approach, which is also used to examine the sensitivity of unknown factors for the strategizing accuracy of industrial robots. The research [13] thoroughly analyzes chatter-related concerns that arise throughout robotic machining activities, covering processes, mitigating tactics, and techniques for identifying regeneration chatter and mode coupling chatter. Industry robots' weak stiffening and relationship design may cause regeneration and talk-in-phase couplings under various cutting circumstances. A set of recommendations are offered to assist in differentiating between the double chatter mechanisms utilized in robotic machining after a comparison of the two is conducted.

The research [14] proposes an intelligent failure detection method for multi-joint industrial robots based on attitude data. The attitude change of the final joint is used to represent the transmission defect of robot components based on the study of the transmission mechanism. The multi-joint robot's last joint is equipped with only one attitude sensor as part of an affordable data-collecting method. The study [15] outlines using the virtual reality (VR) digital twin of physical architecture to analyze how people respond, including predictable and random robot movements. Human responses are analyzed, and the VR environment's efficiency is validated using various existing measures and a newly created Kinetic Energy Ratio meter. It has made it more difficult for governments to enact laws governing whether people and machines must coexist near one another, as well as the development of human-robot collaboration tactics. The research [16] offers the first thorough analysis of how the employment of industrial robots affects the emissions intensity of production. It discovered that industrial robots might significantly increase the energy intensity of production, and our hypothesis survived several robustness tests. Also, the technical advancement impact and complementing effect among workers and industrial robots play a role in these economic benefits. Lastly, they discovered a complex relationship between production emission intensity and industrial robots. Instead of sustainable energy intensity, robotic systems may impact non-renewable energy intensity. The author in [17] presents a method for analyzing how people respond to both expected and unanticipated robot movements. It employs an augmented actuality digital twin of a physical structure.

Several standard measures and a newly created Kinetic Energy Ratio metric are employed to analyze user responses and confirm the efficacy of the VR environment. It has made it more difficult for governments to enact laws governing how people and robots should coexist near one another, as well as the development of human-robot collaboration tactics. In the study [18], 460 senior managers and owners of ACMCs in India were surveyed on their intentions to adopt and plans to deploy InRos in their organizations. 4.0 Industry Compatibility is one of the critical factors influencing InRos adoption intention, according to the study, external pressure, perceived advantages, and vendor support. Interestingly, the study also shows that official backing and IT infrastructure have little impact on a person's decision to embrace InRos. The data further reveals that perceived cost concerns adversely affect the association between adoption intention and probable InRos usage in ACMCs.The research contributes to the theory by using the conventional TOE framework and finding, counterintuitively, that Indeed facilities are not a primary factor of technology acceptance.

III. Materials and Method

Robot implementations have become prominent because of the industrial sector's increasing demand for versatility, cost-effectiveness, and performance. Industrial robots combine a workspace and collaborate with human employees in these settings. For industrial robotics design, the BP-ARIMA is recommended.

Backpropagation Autoregressive Integrated Moving Average (BP-ARIMA) for industrial robotic design

Backpropagation combines the precision of ARIMA models with the adaptability of neural networks, Autoregressive Integrated Moving Average (BP-ARIMA) performs very well when applied to robotics. This integration may allow more accurate modeling and prediction of robotic systems' dynamic behaviors and time-varying patterns. Foreseeing these nonlinear correlations and complex linkages is essential to robotic operations. BP-ARIMA's use of neural networks for feature extraction and the backpropagation approach for iterative refinement makes this possible. BP-ARIMA's adaptability makes it useful for various robotic applications, including defect detection, efficiency enhancement, and sensor data prediction.

The high nonlinear adaptation capability of backpropagation (BP) has resulted in its widespread application in several prediction disciplines. In dependability design, this approach is relatively uncommon. As a result, a reliable robotic design technique based on BP has been established. The intake layer, concealed layer, and output layer are the three layers that compose aBP neural network. The incoming layers are implicitly linked to the output nodes by concealed neurons. The link between two neurons' weight attributes reflects the relationship's degree. Establishing a BP model entails choosing the number of neurons for the hidden layer, the number of source and outcome neurons, and the weight ratios of the linkages. The BP algorithm's principle may be concisely explained as follows. The output is produced in the first phase when the inputs spread outward. The discrepancy between the created and actual results is determined in the second stage, transmitted back to the entry layer, and the connection lifts are modified to lower the error. Once the resultant network resembles the trained data sufficiently, that is, till the errors between the expected and actual outcomes are suitably modest, this procedure of modifying the connectivity weights is maintained.

A BP system is implemented by identifying the number of neurons for the input and output layers, finding out how many neurons are in the concealed layer, and figuring out the weights of the connections. There are three input criteria, and their related inputs are the industrial model, optimized energy, and efficient performance. There is just one outgoing neuron that, under various circumstances, relates to the optimal performance design. The following equation 1 may be used in designing even if there is no chance to precisely compute the ideal number of concealed layer neurons depending on data.

$$c = \sqrt{i + o + a} \tag{1}$$

Where a is steady between 1 and 10, c is the quantity of concealed layer neurons, i is the number of incoming layer neurons, o is the number of output layer neurons, and a is changed to reduce the prediction error to attain the optimum matching effectiveness. During the training phase, the weight levels of linkages are continuously modified until the design inaccuracies are decreased under a predefined level. The symmetric randomized design approach, which has homogenous distribution and fair evaluation, is used to choose the training data.

$$b_i = \frac{a_i - \min a_i}{\max(a_i) - \min(a_i)} \tag{2}$$

The preceding part provided the training design information. The sampling information is standardized using equation 2 to assure resolution; max (a_i) and $\min(a_i)$ denote the greatest and lowest values within the group of the-th input. a_i And $b_i$denote the raw and standardized data of the i-th input, correspondingly. The information is re-ranged between 0 and 1 after the standardization procedure. The BP incorporates two processes, data forward propagating and erroneous backward propagating, both dependent on gradient reduction. While the system is training, the data is sent from the intake layer to the output layer. If the outcomes do not match the desired results, the gradient is sent back into the system to modify the load and skew of each neuron and reduce the error between anticipated and actual data. Equation 3 describes the BP's goal functionality.

$$G = \frac{1}{2 \times a} \sum_{i=1}^{N} \sum_{j=1}^{L} x \left(\frac{x_{ij} - \hat{x}_{ij}}{a} \right)^2 \tag{3}$$

where a is the learning sample amount, L is the output variable's size, and x_{ij} and $\hat{x}_{ij}$ are the actual result and estimation data, correspondingly. Equation 4 defines the system x_k's output value.

$$x_k = f(\, z_{1k} \times o_1 + \cdots + z_{jk} \times o_j + \cdots + z_{nk} \times o_n + a_k \,)$$

o_j is the output level of the jth concealed layer neurons, z_{jk} is the weighted connecting the jth hidden layer nodes and the k^{th} output layer neurons, and a_k is the biased value of the kth output layer nodes and stands for the activating factor. The networking design weights and biases must be changed following the training inaccuracy for the output values to be near the intended value. Equation 4 and 5 modifies the value upgrade equation for concealed layers and distortions.

$$z'_{jk} = w_{jk} - \frac{a}{n} \sum_{k=1}^{n} \Delta v - o_j \tag{4}$$

$$a'_j = a_j - \frac{1}{n} \sum_{k=1}^{n} \Delta v \tag{5}$$

Where n is the total amount of nodes in the output layer, w'_{jk} is the updated weights connecting the nodes in the jth concealed layer and the kth output units, a'_jnd is the modified bias of the kth output layer nodes. V is the learning variance, which was adjusted to be $\Delta v = x_k - \hat{x}_k$.

Unfortunately, the numerical accuracy frequently falls short of the standards. Numerous academics enhance the BP variables to increase the design reliability of BP.

Autoregressive Integrated Moving Average (ARIMA) is among the greatest widely used procedures for designing optimal robots. It is a flexible approach that can accommodate different time series behaviors. The essential need is for the information to be stable, meaning they maintain their statistical features throughout the process. Differentiation and other nonlinear transitions, such as the logistic function, can convert non-stationary series into static ones. The ARIMA functions as a filter that tries to isolate the signal from the earlier noise using the signal framework to enhance it. The term ARIMA comprises three parts that are united to make the model. The Autoregressive (AR) portion is the first component. This section aims to demonstrate the effect of earlier data. It is executed by regression using the most recent p values from the series. Equation 6 serves as the model for AR.

$$\hat{c}_k = s + \sum_{j=1}^{p} \emptyset_j c_{k-j} + \epsilon_k \tag{6}$$

When s is steady, $\emptyset_j$ is a modeling variable used to weigh prior variables and an arbitrary inaccuracy. Incorporation is the second element (I). By comparing the information by level d, it achieves its goal of making it stable. The final component is the Moving Average (MA), which eliminates arbitrary information fluctuations and retrieves value from the prior inaccuracy components. The MA of the most recent p predicted inaccuracies is used to produce it. Equation 7 provides the MA system.

$$\hat{c}_k = \mu_k + \sum_{i=1}^{p} \theta_j \epsilon_{k-j} + \epsilon_k \tag{7}$$

Where is the series' average up to moment k, k = $\hat{c}_k - c_k$I s the prediction's inaccuracy in the prior, and j is a modeling variable that accounts for previous mistakes. The entire ARIMA structure is shown in Equation 8, where c is the differenced series created by combining Equations 7 and 8. The three variables, p, d, and q, may be changed to emphasize some components more than others. With various settings, many prototypes that could be used with multiple series may be produced.

$$\widehat{c'}_k = s + \sum_{j=l}^{p} \emptyset_j c'_{k-j} + \sum_{i=1}^{p} \emptyset_j \, \epsilon_{k-j} + \epsilon_k \tag{8}$$

Likewise, efficient robotic design is incorporated into the industrial sector.

IV. Result and Discussion

1) Performance analysis: This study introduces a brand-new design measure built on BP-ARIMA to enhance the industrial sector and improve robot design. In this section, the evaluation is discussed. Accuracy, optimal performance, error rate, implementation cost, and energy consumption are used to evaluate the effectiveness of the suggested system. The existing techniques used for comparison are the hybrid Grasshopper optimization algorithm and Nelder–Mead (HGOANM) [19], fuzzy wavelet neural networks (RFWNNs) [20], and radial basis function neural network (RBFNN) [21].

A. Accuracy

In industrial robots, accuracy and repeatability are essential. The robot's ability to reliably go to a given spot is measured by its repeatability. The difference between the position the robot is planned to reach and the value of the work the robot arrives at is known as accuracy. Analyzing the design accuracy of time intervals provides information about the performance of the suggested framework. Fig. 2 indicates the accuracy of the proposed method. The accuracy outcome of the recommended way is shown in Table I.

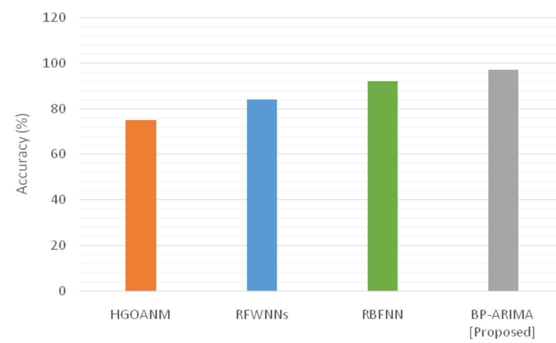

Fig. 2. Accuracy of the proposed and existing techniques.

TABLE I. OUTCOME OF ACCURACY

Methods	***Accuracy (%)***
HGOANM	75
RFWNNs	84
RBFNN	92
BP-ARIMA [Proposed]	97

B. Optimal Performance

Optimal performance describes an optimal state where individuals are wholly absorbed in the activity. Industrial robots use optimization to locate the most effective method for enhancing 3D space accuracy, decreasing vibrations, selecting ideal robot base points for applications to cut down on required times, and discovering creative or operational factors that guarantee lower energy consumption. Fig. 3 suggests the optimal performance of the proposed method. The outcome of the optimal performance recommended method is shown in Table II. It shows the suggested approach is more Optimal than the existing approach.

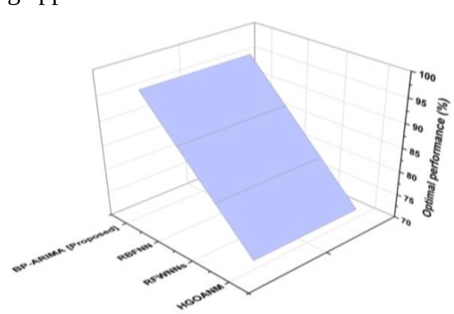

Fig. 3. Optimal performance of the proposed and existing techniques.

TABLE II. THE OUTCOME OF OPTIMAL PERFORMANCE

Methods	***Optimal performance (%)***
HGOANM	72
RFWNNs	80
RBFNN	88
BP-ARIMA [Proposed]	96

C. Error Rate

The error rate measures how much a model deviates from the genuine model in its predictions. For design techniques, the phrase error rate is often used. The error rate gauges how far a model's improvement strays from reality. The error rate of a sector is the percentage of operational errors made by that sector. Given the expense of correcting errors, manufacturing errors should be avoided at all costs. By dividing the overall amount of incorrect predictions on the testing sample by every one of the statements on the testing dataset, on the other hand, it is possible to get the error rate. The recommended method's error rate is shown in Fig. 4. The results of the suggested technique are shown in Table III. It demonstrates how the recommended approach has a lower mistake rate than the existing approach.

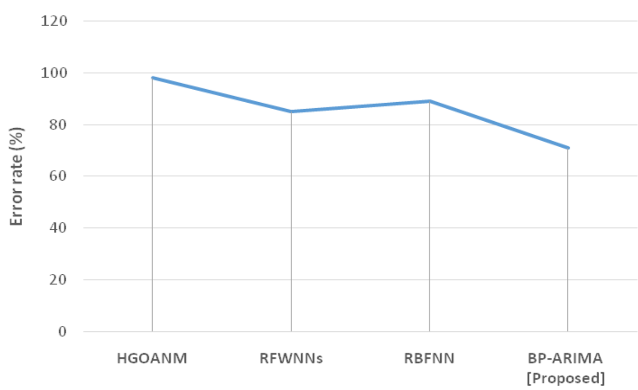

Fig. 4. Error rate of the proposed and existing techniques.

TABLE III. THE OUTCOME OF THE ERROR RATE

Methods	***Error rate (%)***
HGOANM	98
RFWNNs	85
RBFNN	89
BP-ARIMA [Proposed]	71

D. Implementation Cost

Manufacturers may use the cost of quality to evaluate and enhance their quality requirements. In contrast to the expenses related to inner and outer breakdowns, it is a technique for identifying and quantifying when most of an organization's resources are spent on prevention and maintaining product quality. Implementation costs are those associated with planning and carrying out a strategy for implementing particular or much particular proof treatment. These factors include labor, power, resources, life-long process maintenance, and manufacturing inputs to operate a robot properly. According to the company sector and scale of the operation, these expenses differ wildly because of the various kinds of production facilities. The recommended method's implementation cost is shown in Fig. 5. The implementation cost results of the suggested technique are shown in Table IV. It proves that the proposed method uses less cost.

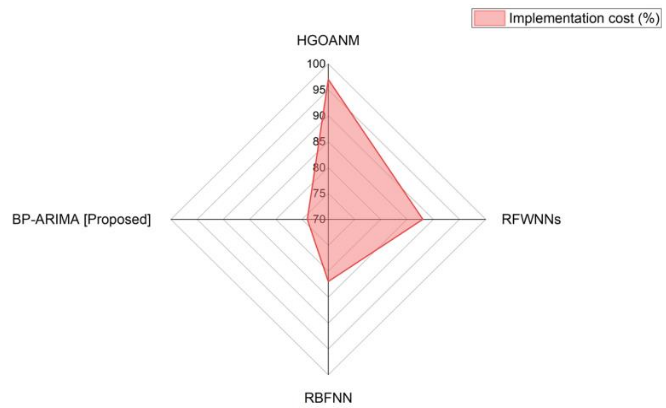

Fig. 5. Implementation cost of the proposed and existing techniques.

TABLE IV. THE OUTCOME OF THE IMPLEMENTATION COST

Implementation cost (%)	***Implementation cost (%)***
HGOANM	97
RFWNNs	88
RBFNN	82
BP-ARIMA [Proposed]	74

E. Energy Consumption

The controllers, conditioning air, engine, and friction at the robotic connection are some parts of the robotic system that use energy. Energy and other sources like gasoline engines or compressed gasses may be used to power action. Electric actuators are most often used in smaller, interior robotics of the kind that the beginning constructor is far more able to design. A comprehensive and realistic industrial robot model using less energy consumption has been presented. The recommended method's energy consumption is shown in Fig. 6. The energy consumption outcome of the suggested technique is shown in Table V.

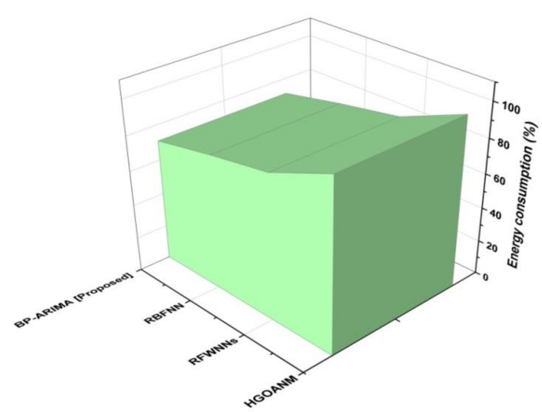

Fig. 6. Energy consumption of the proposed and existing techniques.

TABLE V. OUTCOME OF THE ENERGY CONSUMPTION

Methods	*Energy consumption (%)*
HGOANM	99
RFWNNs	84
RBFNN	78
BP-ARIMA [Proposed]	71

V. DISCUSSION

The HGOANM may take more work to implement and comprehend due to the multiple optimization methodologies it incorporates. Due to its sensitivity to beginning circumstances, the Nelder-Mead method's convergence rate may be sluggish for high-dimensional or non-convex problems. Because of the complexity of their construction, some of the interpretability gained by using fuzzy logic in conjunction with neural networks may be lost when using fuzzy wavelet neural networks. Additional challenges that restrict the efficacy of radial basis function neural networks in high-dimensional environments include their inability to scale and the possibility of underfitting or overfitting. The BP-ARIMA model combines the ARIMA models' predictive ability and neural networks' flexibility. This combination accurately models and predicts complex time series data while considering nonlinear linkages and temporal interdependence. Financial forecasting, environmental monitoring, and industrial processes may benefit from BP-ARIMA's capacity to automatically identify significant characteristics and employ backpropagation for iterative learning to manage dynamic behaviors and changing patterns. BP-ARIMA implementation may need more processing resources than regular ARIMA models due to the neural network component, and its performance depends on parameter variation and training data quality. Consider these parameters to increase the model's predictive ability. Technology may reduce jobs, rising inequality, and unemployment. Robots and humans value work safety. Risk assessments and safety measures avoid harm. Teamwork robots need instruction. Mistakes and inefficiencies lower production and quality without training. Industrial human-robot cooperation requires morality, safety rules, and well-structured training.

VI. CONCLUSION

Robots are utilized more often in the workplace today to substitute people, especially for monotonous activities. The heterogeneous integration of a wide range of innovations marks industrial robot growth. It must be noted that the primary markets for industrial robots nowadays are the automobile sectors, particularly their supply networks. This indicates that a significant portion of the advancement of robots is driven by the needs arising from this production process. Thus, most robots nowadays are ideally suited to adaptable, high-volume, cost-conscious manufacturing in a highly dynamic context. This has forced robot makers to put a lot of work into meeting the fundamental standards for cost-effectiveness, high dependability, and efficiency. The creation of an industry-specific optimum design was the goal of this research. This study presents the Backpropagation Auto-Regressive Integrated Moving Average (BP-ARIMA) as an efficient method. The traditional system is evaluated and compared for accuracy, optimal performance, error rate, implementation cost, and energy consumption. The results show that the suggested method offers an improvement and effective design for industrial robots. The performance of the proposed system may be increased in the future by using optimization techniques. Combining the BP-ARIMA model with creating a novel mechanism has several prospects for industrial robotics. When applied to industrial robots, BP-ARIMA provides a game-changing method for enhancing performance, adaptability, and prediction.

FUNDING STATEMENT

Supported by Scientific and Technological Innovation Programs of Higher Education Institutions in Shanxi（2020L0768）

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