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SL-RI: Integration of supervised learning in robots for industry 5.0 automated application monitoring

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A R T I C L E I N F O

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A B S T R A C T

Robotic technology holds a significant role within the realm of smart industries, wherein all functionalities are executed within real-time systems. The verification of robot operations is a crucial aspect in the context of Industry 5.0. To address this requirement, a distinctive design methodology known as SL-RI is proposed. This article aims to establish the significance of incorporating robots in the Industry 5.0 framework through analytical representations. In the context of this industrial monitoring system, the implementation of a supplementary algorithm is essential for effective management, as it enables the robots to acquire knowledge through the analysis and adaptation of restructured commands. The analytical model of robots is designed to accurately monitor the precise position and accelerations of robots, resulting in full-scale representations with minimal error conditions. The uniqueness of the proposed method in robotic monitoring system is related to the application process that is directly applied in Industry 5.0 by using various parametric cases where active movement of robots are monitored with rotational matrix representations. In this type of representations the significance relies in the way to understand the full movement of robots across various machines and its data handling characteristics that provides low loss and error factors.

1. Introduction: Need for industry 5.0

Numerous industries encounter operational challenges stemming from manual processes, as the comprehensive design of various components, spanning micro, mini, and large scale segments, necessitates meticulous segregation at each stage of advancement [1]. In order to comprehensively analyze the complete attributes of corresponding components, it is imperative to integrate a smart manufacturing facility referred to as “Industry 5.0" [2]. In contrast to previous generations of industrial operations, the fourth generation of automatic operation is characterized by the utilization of advanced devices, which offer enhanced convenience. Moreover, it is feasible to observe the precise condition of each component through the utilization of a sensing device integrated with the Internet of Things (IoT), as each action results in the individual disconnection of components [3]. One significant benefit of Industry 5.0 lies in its ability to efficiently restore automated device operation in the event of failure, thereby minimizing downtime. Therefore, many industries opt for the installation of various sensing units at primary and peripheral viewpoints to ensure their uninterrupted operation. In the context of Industry 5.0, the simultaneous implementation of monitoring and automated operations presents a significant opportunity for seamless transmission of data to end users [4]. This, in turn, enables the development of intelligent decision-making systems. The decision-making system allows for a real-time connection to the physical world, enabling the production of intelligent products at each output unit. If an end user requires modifications to the output content, customization can be facilitated by the design operator at a relatively lower cost compared to industries that have undergone third-generation revolutions. In addition, it is imperative to establish fundamental elements, including digital technologies, cloud computing for data storage, data processing, and cyber-physical systems, for each operation within the context of Industry 5.0 [5].

By employing the aforementioned strategies, the Industry 5.0 can effectively function in a competitive business landscape by utilizing

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skilled humanoid personnel [6]. On the other hand, in the context of Industry 5.0, the presence of a skilled humanoid necessitates a greater level of infrastructure management to ensure the continuous operation of all systems, thereby mitigating the risk of early failures. Another significant challenge in the management system of Industry 5.0 is the limited ability to extend support from different groups due to the disclosure of all information, which in turn necessitates additional training and knowledge. In order to enhance the automation processes in Industry 5.0, it is imperative to ensure the security of transmitted data. This can be achieved by implementing a series of closed loop systems, wherein a connection management system is incorporated at each phase of operation [7].

1.1. Building blocks of industry 5.0

In the context of Industry 5.0, the integration of various components, namely machines, plants, and human resources, is observed. These components are interconnected and reliant on specific perceptions, which serve as the fundamental building blocks for their operation.

1.1.1. Reservescheduling

In order to carry out processing and management operations effectively, it is essential for data to be handled in a sequential manner, with the allocation of appropriate resources. This ensures that organizations can maintain their operational functionality within established connections.

1.1.2. IoT and industrial IoT (IIoT)

In the context of industrial operations, a significant number of connections are established between machinery and human resources. Consequently, the monitoring of these connections can only be effectively accomplished through the utilization of the Internet of Things (IoT). The role of Industrial Internet of Things (IIoT) is significant in facilitating the establishment of connections between humans and machines.

1.1.3. Artificial intelligence (AI)

As the quantity of connections increases, the computational capacity of each system continues to exhibit a sluggish rate of growth. Therefore, in order to mitigate the issue of slow connections, the process of identification is facilitated through the utilization of artificial intelligence (AI) technology, thereby replicating human intelligence at the present moment.

1.1.4. Cloud computing

In the event of an interrelationship existing among machines, humans, and other components, it is imperative to establish a connection with a remote server in order to promptly process all information. Furthermore, each activity is stored with an individual link, ensuring that the system maintains a high level of security.

In order to optimize the performance of all building blocks, it is necessary to implement more adaptable operations. This entails meeting customer demand by ensuring an ample supply of necessary components. In addition to the need for flexible operations, it is essential to maintain transparent data processing information in order to facilitate informed decision-making and to convert all units of information processing into digital representations. Fig. 1 presents a visual depiction of the connectivity aspect of Industry 5.0.

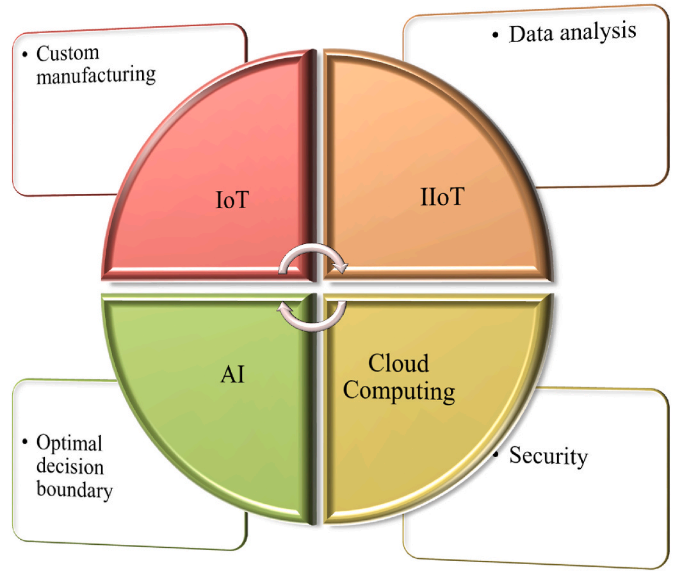

Fig. 1. Connectivity representation of Industry 5.0.

1.2. Literature survey

This section examines the majority of existing systems that offer autonomous operation through complete robotic systems. To develop a comprehensive understanding of the principles governing autonomous systems in industrial processes, it is imperative to conduct a comparative analysis of raw data across different operating conditions. Furthermore, the purpose of this comparison is to offer an up-to-date assessment of contemporary operating systems in the event of failure during automated operations, as the implementation of Industry 4.0 necessitates the utilization of modern design principles. The collection of raw data for industrial applications, as described in Ref. [1], involves the transition from conventional operational methods to intelligent manufacturing systems. In the context of conversion, the establishment of semantic internet connectivity is a crucial requirement, necessitating the execution of numerous automated procedures by robotic systems. While it is feasible to achieve similar functionality by substituting robotic systems, the presence of semantic wireless connectivity is imperative for the distinct operation of devices. In the aforementioned scenario, there is a significant potential to integrate artificial intelligence techniques with existing network technologies. However, a notable limitation in substituting robotic systems is the substantial energy requirement, which necessitates manual operation. In order to mitigate the need for manual operations, a research team has devised an experimental configuration that focuses on identifying specific shortcomings that arise from the integration of industrial operations with the Internet of Things (IoT) [2]. Due to the prevalence of web technologies in industrial operations, researchers have placed significant emphasis on the importance of data security. The process of security analysis involves establishing connections between various communication channels, with the aim of achieving a maximum accuracy rate of 99 %. However, it is important to note that in the context of real-time connectivity for autonomous operation, attaining a high level of accuracy is not feasible, even when robotic operations are implemented.

Therefore, in order to optimize the operations of industry 4.0, it is imperative to incorporate sustainable capabilities that leverage the advanced functionalities of robotic systems [3]. There is ongoing debate regarding the ability of most robotic systems to solely execute tasks through collaborative schemes, as it cannot always be guaranteed that the overall cost of operation will remain low. In order to mitigate the financial burden associated with automated operations, it may be prudent to disregard certain high-level automated tasks. Instead, robotic systems should only perform operations that are specifically required. However, it is important to note that robotic systems often incur significant operational costs, leading to the execution of tasks only in scenarios where the likelihood of failure exceeds the anticipated operating thresholds. In order to mitigate the complexity of high-level tasks, it is possible to extract relevant corporate context from machine learning techniques. This involves analyzing key components within task performance modes [4]. One potential approach to mitigate certain complex tasks is through the integration of sensing devices equipped with sensors, which enables the autonomous system to make informed decisions. The integration of sensors with automated devices enables the provision of self-diagnosis capabilities in the event of failures occurring during task execution. In the event of an automatic processing system experiencing failure, there are multiple reasons that can be attributed to the failure, resulting in minimal impact on the production chain. Furthermore, within the context of Industry 4.0, it has been observed that certain instances exist where complete self-automation is not implemented across the integrated system. In such scenarios, a decision tree is employed as a preventive measure against operational failure [5]. The utilization of decision trees offers the opportunity to exercise supervisory data control in industry 4.0 settings, thereby mitigating potential risks associated with hypothetical scenarios involving robotic systems and navigation architectures [6]. The utilization of control establishment enables a peripatetic robot to employ an open loop procedure rather than relying on combined closed view representations. The implementation of an open loop procedure enables the robot to autonomously perform operations in unobstructed environments, thereby avoiding collisions.

Several researchers have demonstrated the capabilities of autonomous operations in various environments, including both unrestricted and challenging conditions [7]. These operations require individual characteristics and self-adaptation procedures. The majority of historical advancements indicate the necessity of an intelligent warehouse for seamless automated operations, ensuring meticulous oversight of all relevant aspects without any potential points of failure. While ensuring the prevention of failure points is a crucial process, it is possible to establish an active research environment for next generation networks by implementing flexible manufacturing facilities. Several challenges in the current research areas of automatic operations in industry 4.0 can be addressed by implementing solutions derived from human-centric procedures [8]. The primary objective of many human-centric processes is to enhance the description of future scenarios. This objective can also be applied to the industrial revolution, specifically by implementing security measures to address potential risks associated with digital twin technology. By identifying and mitigating failure modes in derivative components, the overall performance and reliability of industrial processes can be improved. Furthermore, this study also presents a comprehensive elucidation of the pertinent methodologies employed to articulate the characteristics of autonomous functioning, particularly in the context of cognitive systems integrated with cutting-edge technological platforms. Therefore, Fig. 1 is generated to offer an overview of the prevailing methodologies employed for automated operations in the context of Industry 4.0. The visual representation depicted in Fig. 2 presents the cumulative count of techniques that have been implemented in preceding epochs starting from the year 2020.

The analysis of Fig. 1 reveals that collaborative procedures are employed in all autonomous industrial operations, necessitating the integration of an industry 4.0 method with a measurement technique. Table 1 presents a comparative analysis of various existing methods.

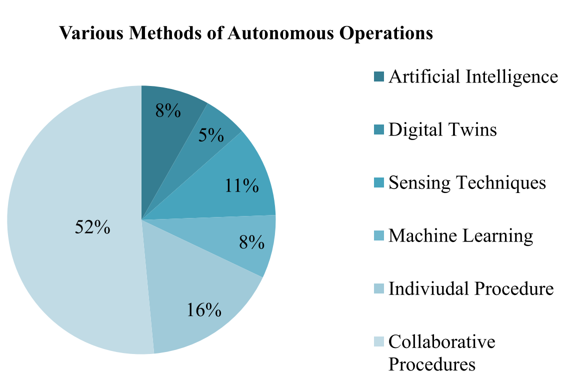

Fig. 2. Existence of previous methodologies for autonomous operation.

1.3. Research gap and motivation

Before conversing the related works in industrial process from first generation to third generation an outline is provided with the following arguments that indicate the challenges and various developments [-22–26].

- The need of Industry 5.0 in various application fields are discussed in order to provide a deep insight about working operations. The operation of Industry 5.0 is based on achieving effective (smart) solutions in order to satisfy specific purpose. In practical systems Industry 5.0 aims to provide real time outcomes at much faster rate.
- As a secondary objective the benefits of robotic technology in Industry 5.0 that entirely replaces human interface system is provided in a systematic way. The advantage of robots is completely based on type of sensors that is collective with human skills in case of monitoring.
- Finally, the modification that is present in industrial systems for monitoring different applications using IoT is described in order to achieve a complete automated network even in case of data transfer technique.

1.4. Major contributions

The major contributions of the proposed work is based on developing a robotic system for monitoring Industry 5.0 applications where an arm movement will be created for providing active movements that assure the following parametric objectives as it is considered as one of the additional design for achieving the robotic objectives.

- To provide free movements to robotic system thereby increasing the acceleration points with exact position mapping which leads to exact monitoring states.

Table 1
Comparison of state-of-the-art.

References	Methods espoused	Contributions
[9]	Intelligent tools with IoT and artificial intelligence	Automatic vehicle monitoring systems under industry 4.0
[10]	Robotic operation with IoT	Cyber physical representation systems for automatic industrial process
[11]	Real time navigation systems	Robot control and management for industrial operations
[12]	Radio frequency identification systems using robotic technology	Collaborative autonomous industrial manufacturing process
[13]	Centering resonance and leveraging	Productive industrial and automation process
[14]	Secured industrial process with IoT	Large scale industrial network monitoring process under 4.0
[15]	Deep extraction and modification of industrial components	Non-linear dynamic distribution of automated industrial components
[16]	Data path techniques for enterprises	Data analysis in automated way for enterprise industry 4.0
[17]	Attribute based competency maturity model	Automatic transformation of future skill extraction
[18]	Inductively coded industrial operation	Additive manufacturing technology with automatic monitoring systems
[19–21]	Security based data operations	Data processing scheme with secured automation

- To represent the full scale model for robotic system where a comparison is made between previous and current knowledge at maximized energy rates.
- To make certain that robotic actions (full scale movements) are carried out with low error representations thereby loss functions are minimized.
- To operate the robotic systems at high strength at dynamic conditions by using machine learning algorithms thereafter maximum amount of secured operation can be carried out.

2. Proposed system model

The proposed system model with Supervised Learning in Robotics Industry (SL-RI) incorporates a robotic design specifically tailored for industrial applications. This design is based on an energetic model, which enables the determination of robot movements. Designing a robot with unrestricted arm movement is of great significance, as it enables the accurate determination of key factors such as applied velocity, acceleration, and position. Mathematical representations play a crucial role in Industry 5.0, as they enable the identification of parameters in a distinct manner.

2.1. Active movements

In the context of Industry 5.0, it is imperative for robots to execute a series of actions in accordance with prescribed commands. Consequently, it becomes essential to seamlessly adjust the positioning of their arms without any interruptions. Furthermore, it is imperative to actively regulate the velocity of robots. To achieve this, a robust force formation system is devised [3], employing Equation (1) in the following manner.

$$f_d = max\sum_{i=1}^{n}\begin{bmatrix} b_1 & \cdots & b_p \\ \vdots & \ddots & \vdots \\ b_a & \cdots & b_1 \end{bmatrix} + \begin{bmatrix} f_1 & \cdots & f_i \\ \vdots & \ddots & \vdots \\ f_i & \cdots & f_j \end{bmatrix} \tag{1}$$

2.2. Full representation model

When the applied force and inherent forces are combined, the comprehensive model of the robotic system undergoes modifications, while the existing knowledge remains in a state of zero predetermination. The aforementioned statement suggests that the robot should commence from the initial position ($p = 0$), thus allowing for the modification of the rotation condition as described in Equation (2) [4].

$$T_f = max\sum_{i=1}^{n}(R_1 + .. + R_j) + K_{in} \tag{2}$$

2.3. Robotic energy

In the context of Industry 5.0, it is imperative to design robotic systems that optimize energy utilization. To achieve this, it is necessary to establish a distinct connection that facilitates the integration of heavy loads with the positional aspects of the system. If there is a connection between the aforementioned energies, it is possible to represent a base coordinate system with a gearbox device [6], as indicated in Equation (3).

$$D_t = \sum_{i=1}^{n}(H_1 + .. + H_i) + (pos_1 + .. + pos_i) \tag{3}$$

2.4. Robot error

In the context of robotic design, it is conceivable that errors may arise as a result of variations in initial conditions and other contributing factors, resulting in an amplification of discrepancies at each joint. Therefore, it is imperative to identify two errors that correspond to deformation factors in axis representations. Therefore, it is imperative to minimize the occurrence of error conditions by utilizing Equation (4) in the following manner.

$$Error_i = min\sum_{i=1}^{n}\begin{bmatrix} \delta_1 & \cdots & \delta_i \\ \vdots & \ddots & \vdots \\ \delta_i & \cdots & \delta_n \end{bmatrix} + \beta_i \tag{4}$$

Equation (4) is utilized to ascertain the minimization of errors, encompassing both axis and circular errors. If there is any alteration in the axis, it is imperative to execute robotic actions while adhering to the initial state conditions, as this is crucial for preventing undesired outcomes across various industries.

2.5. Comparative errors

The error functions mentioned above are determined solely by changes in axis and circular movement, but they are not restricted to functions that measure changes in relational errors exclusively. Therefore, it is necessary to make a determination regarding the relative error functions in this scenario, which is applicable when a greater number of robots are involved in the same operation within industries [9].

$$rel_e = min\sum_{i=1}^{n}\frac{\theta_i - \widehat{\theta_i}}{\theta_t} \tag{5}$$

Equation (5) indicates that comparative errors are made by finding the difference between initial and final position of robots thereby total errors can be found.

2.6. Robot loss functions

If the number of relative errors exceeds a certain threshold, the loss functions in robotic design will be maximized, resulting in an inability to achieve stable operation. Therefore, it is imperative to ensure consistent and uninterrupted functioning without any associated decrease in efficiency, a goal that can only be accomplished by minimizing the losses outlined in Equation (6).

$$loss_i = min\sum_{i=1}^{n}\rho_l(i) + other_l(i) \tag{6}$$

Equation (6) ascertains the losses that manifest during the design phase, thereby signifying the mitigation of mechanical losses within the system. Therefore, by effectively mitigating such losses, it becomes feasible to operate the robot for monitoring various applications without encountering any interruptions.

2.7. Robot strength

The longevity of extracting valuable information from gathered raw data points is contingent upon the robot's maximum strength. Therefore, in order to carry out any given task, it is imperative to optimize the power output of robotic systems, as denoted by Equation (7).

$$strength_i = max\sum_{i=1}^{n}\frac{\omega_d}{\omega_t} \times 100 \tag{7}$$

2.8. Robotic safety

In Industry 5.0 if industrial productions are made with respect to different materials then it is essential to improve the safety measures. Whenever a product is created by human interface system or by any robots then it is essential to create a safety data measurement unit that is carried out by integrating safety sensors at the head position of each robot. Therefore the safety measures for data monitoring system for a particular product can be monitored by using Equation (8) as follows.

$$SY_i = max \sum_{i=1}^{n} encrypt_p(i) + KF_i \quad (8)$$

2.9. Objective functions

The aforementioned equations are integrated to formulate the objective function with min-max criteria, allowing for the attainment of a multi-objective framework through the utilization of a parametric monitoring system, as denoted by Equation (8).

$$obj_1 = min \sum_{i=1}^{n} Error_i, rel_e, loss_i \quad (9)$$

$$obj_2 = max \sum_{i=1}^{n} f_d, T_f, strength_i \quad (10)$$

The objective function in Equations (8) and (9) represents the essential min-max conditions that must be combined with an appropriate optimization algorithm in order to achieve maximum accuracy, as discussed in the following section.

3. Optimization algorithm

In the proposed method the robotic systems are used for full scale representations where exact training is needed. Therefore it is essential to provide a supporting algorithm that is processed by using machine learning algorithms where every set of data is labeled for proper identification. In order to identify the target in Industry 5.0 it is essential to train the robot with location and object identification parts as every Industrial process requires more number of objects which is treated as obstacles. But if machine learning algorithms are used then each robot will be trained thereby a difference between obstacle and necessary objects will be identified thus providing powerful insights over Industry 5.0 with necessary actions.In order to attain optimal solutions for each robotic process, it is imperative to engage in optimization, thereby enabling the adoption of every solution through the implementation of desirable methodologies. Therefore, the proposed method selects an optimization algorithm as a distinctive pattern, thereby resolving any deficiencies in the system model. In the context of industrial monitoring systems aimed at facilitating intelligent operations, it is imperative for robots to acquire specific functionalities through the utilization of pre-established functions via machine learning algorithms for industrial applications (SL-RI). Hence, the complete dataset is gathered and subjected to machine learning algorithms, enabling the generation of intelligent decisions, even in the context of extensive networks. In every designed robot, specified commands are utilized to carry out crucial tasks such as mainframe visualization, artificial intelligence, and self-learning [27–30].

In addition, a supervised learning algorithm is employed to execute robotic actions, which possesses the capability to reveal comprehensive understanding through the utilization of a labeled training dataset. One of the primary obstacles encountered in the implementation of supervised learning algorithms is the significant time consumption associated with varying inputs. However, due to the robots' ability to efficiently recognize and respond to changing inputs within the specified time frame, it is feasible to implement an effective combined strategy utilizing a supervised learning algorithm. When the proposed system model is integrated with a supervised machine learning algorithm, the resulting robot can be classified as a knowledge-based system. This classification allows for the potential implementation of the robot in various commercial applications. Therefore, it is possible to obtain further information by collecting data and analyzing it before making any decisions. Moreover, the detection of any modifications in the robot's position, acceleration, and other relevant factors can only be accomplished through the utilization of supervised learning algorithms in conjunction with a fundamental feedback control system.

3.1. Supervised machine learning

In supervised machine learning algorithms, labeled data is used as input-output pairs, where each output label represents the prediction process performed by the robots. Each robot involved in the labeling process is equipped with an identification function that enables it to receive action insights, facilitating its comprehension of environmental factors. Furthermore, the utilization of supervised machine learning in the proposed system model is highly relevant. This is due to the fact that each input is contingent upon its preceding form, allowing the robotic system to effectively discern and interpret any alterations that occur. The utilization of robotic systems enables the establishment of decision boundaries that can effectively adapt to changes within shorter time intervals. Consequently, the integration of robotic systems in various industries holds the potential to attain a heightened level of control. In order to facilitate the visualization and identification of data patterns, it is imperative to establish a connection between robotic systems and labeled datasets, as this enables clear differentiation of the output. The aforementioned implication can be directly associated with the use of pick and place robots in the industrial sector. In this context, the robot is provided with comprehensive information regarding previous products and their respective arrangements, along with labeled data, to facilitate its learning process. By utilizing a dataset that has been appropriately labeled, the robot is able to select a component and accurately position it, facilitating the collection of information for each product in a straightforward manner. The mathematical formulation for representing data in a supervised machine learning algorithm for robots can be expressed using Equation (10) in the following manner.

$$current_i = \sum_{i=1}^{n} \begin{bmatrix} W_1 & \cdots & W_i \\ \vdots & \ddots & \vdots \\ W_i & \cdots & W_j \end{bmatrix} + \tau_i \quad (10)$$

Equation (10) delineates the relationship between the current output values and the various weight representations, as well as the summation of the preceding set of values. However, it should be noted that the output units are also directly influenced by the inputs that are being considered. As a result, Equation (11) can be expressed in the following manner.

$$SL_o = \sum_{i=1}^{n} (\nabla_1 + .. + \nabla_i) \quad (11)$$

Equation (11) delineates the process by which diverse knowledge representations are generated to approximate the values of measurements. Therefore, the loss function that accounts for the overall cost of implementation in industries can be denoted by Equation (12) in the following manner.

$$modified_{loss} = min \sum_{i=1}^{n} (\vartheta_i - \mu_i) + I_i \quad (12)$$

Equation (12) demonstrates the process of minimizing loss functions by reducing the discrepancy between authentic and forecast values to a level lower than the anticipated values. The implementation steps with programming code [31] for the supervised machine learning algorithm are presented, and the block diagram illustrating the combined model is depicted in Fig. 3.

Algorithm Supervised Machine Learning

BeginPROCEDURE SML

Given

$w_1+..+w_i+..w_j$: Input data weight functions

τ_i: Previous data values

for$i$=1:n**do**

1. $\nabla_1+..+\nabla_i$ formeasuring complete knowledge inputs
2. $\vartheta_i - \mu_i$ for finding the difference between actual and predicted values

endfor

else

for all i=1:n**do**

3. $modified_{loss}$ for monitoring the loss values with intercepted values

end for all

end PROCEDURE

```
Input data = GD();
Supervised training = PDdata;
layers = defineSML();
output = trainSMLrobots(layers, Supervised training);
prediction = output(prediction, supervised training);
typedefompl::base::SE2StateSpace::StateType State;
#include "node3d.h"
#include "node2d.h"
#include "visualize.h"
#include "collisiondetection.h"
namespaceHybridAStar {
class Node3D;
class Node2D;
class Visualize;
static Node3D* hybridAStar(Node3D& start,
const Node3D& goal,
Node3D* nodes3D,
Node2D* nodes2D,
int width,
int height,
CollisionDetection&configurationSpace,
float* dubinsLookup,
Visualize& visualization);
#ifndef COLLISIONDETECTION_H
#define COLLISIONDETECTION_H
#include <nav_msgs/OccupancyGrid.h>
#include "constants.h"
#include "lookup.h"
#include "node2d.h"
#include "node3d.h"
namespaceHybridAStar {
namespace {
inline void getConfiguration(const Node2D* node, float& x, float& y, float& t) {
x = node->getX();
y = node->getY();
// avoid 2D collision checking
t = 99;
}
inline void getConfiguration(const Node3D* node, float& x, float& y, float& t) {
x = node->getX();
y = node->getY();
t = node->getT();
}
}
/*!
*/
classCollisionDetection {
public:
/// Constructor
CollisionDetection();
float cost = 0;
float x;
float y;
float t;
// assign values to the configuration
getConfiguration(node, x, y, t);
if (t == 99) {
return !grid->data[node->getIdx()];
}
if (true) {
cost = configurationTest(x, y, t) ? 0 : 1;
} else {
cost = configurationCost(x, y, t);
}
return cost <= 0;
}
endif // COLLISIONDETECTION_H
```

Fig. 3 describes the block representations of supervised learning algorithm where a step-by-step approach is carried out for predicting the output functions. To predict the output functions the input data is generated by choosing initial weight conditions (load) of each robot where input data is considered from previous state representations. Further after generating the data knowledge inputs based on current state conditions are achieved and a modification is made between actual and generated values thus providing a labeled data set with added layers. In addition during formation of new layers a comparison is made and loss functions are checked and if any industrial process by robots is not carried out in an active way then prediction of output data cannot be completed efficiently. Table 2 represents the information about considered variables.

4. Results

This section presents a real-time experimental analysis aimed at determining the application of robotic technology in industrial processes (SL-RI). Specifically, five distinct robots have been chosen to execute various actions within industrial settings. This article examines the performance of a physical supervised robot utilizing a supervised learning algorithm. The evaluation is conducted in real-time, comparing the results with a simulation setup. The simulation analysis is performed in a robotic tool using an individual bot system, allowing for the monitoring of automated operations throughout the process. During the initial phase of operation, a dataset consisting of approximately 5000 sets of data is trained and used as input for the robots. This dataset includes important factors such as knowledge-based inputs and weight-associated matrices, which are utilized in the functioning of the robots. After the necessary inputs have been provided, the robotic system is activated through an individualized configuration process, which includes selecting the initial starting position. The acceleration of robots is maintained at a consistent rate of approximately 5 km/h as a result of careful supervision and arrangement procedures. However, if the acceleration were to exceed this threshold, the arrangement process would become significantly more complex. Consequently, the robot undergoes forward motion with a consistent rate of acceleration, enabling it to systematically perceive and store each individual object encountered. Moreover, the existing data stored within robotic systems is compared with the current values to ascertain the present operational conditions. Hence, the examination process is conducted using five primary

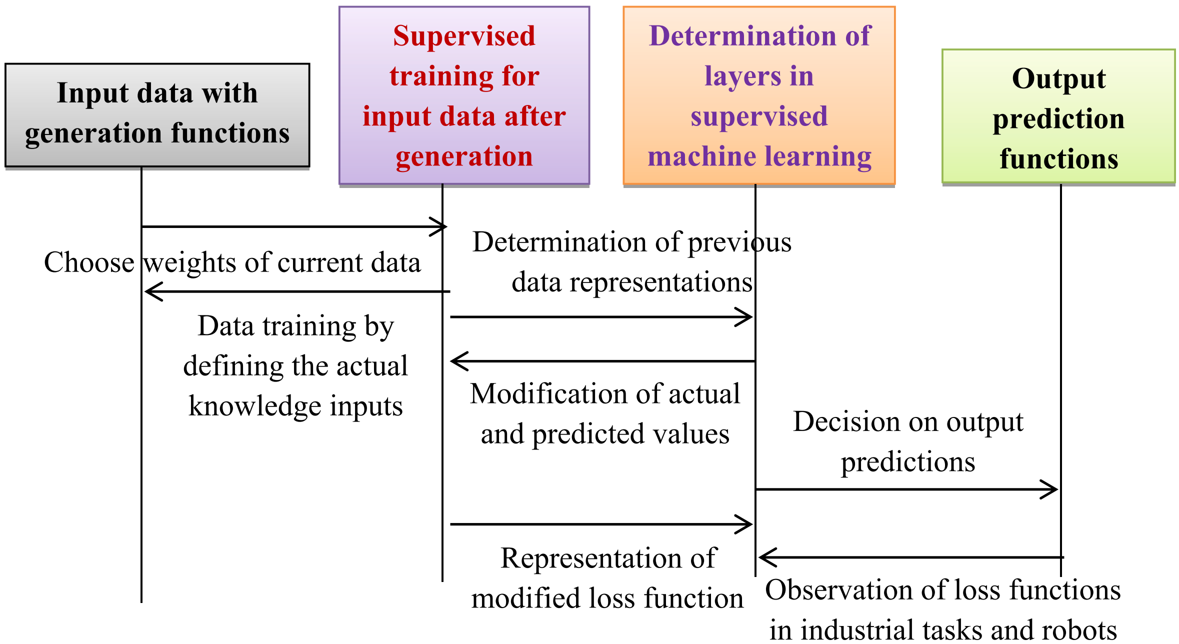

Fig. 3. Block representations of supervised machine learning in industries.

scenarios, which are outlined below. The significance of these designed scenarios is presented in Table 3.

Scenario 1: Active movement demonstrations
Scenario 2:Robotic energy representations
Scenario 3:Error functions
Scenario 4: Loss measurements
Scenario 5: Robotic strength

4.1. Discussions

All of the aforementioned scenarios are executed in real-time using the MATLAB robotic tool, wherein simulations are conducted with precise value determinations. The analysis is conducted using a three-dimensional simulation model, which enables precise monitoring of all outcomes. This stands in contrast to robotic systems, which only provide two-dimensional outcomes. The effectiveness of robotic applications relies heavily on active movements, thus necessitating the provision of an acceleration constant during the initial phase. Table 4 presents the requisite environments for conducting simulation analysis.

The manufacturing process in Industry 5.0 is heavily reliant on the level of automation implemented to enhance operational efficiency. Industry 5.0 encompasses a wide range of automation types, including augmented reality and digital twin representations. However, the primary focus of analysis in the context of Industry 5.0 is on the consideration of both quality and quantity. Therefore, it is imperative to incorporate an automated system that relies on robotic techniques for all industrial applications utilizing artificial intelligence methodologies. Robots have the capability to execute tasks that closely resemble those performed by humans, thereby enabling the implementation of additive manufacturing techniques in comparison to alternative automated digital representation systems. However, when comparing the two cases, the robotic system that is enabled has the capability to efficiently carry out productive operations within a shorter time frame. As a result, this leads to a reduction in overhead costs associated with the original manufacturing processes. Negative impact on robots defines that most of the time periods there are certain constraints where a robot is fails to operate in the desired point where the operational units suffers from major drawback thereby changing the functionality to cause intervention for human systems. Also the negative impact implies that every robots with predefined programming model with autonomous operation can never be guaranteed as most of the programming modes can be

Table 2
Representation of system model variables.

Variables	Implications
$b_1 + \ .. + \ b_i$	Build matrix
b_p, b_a	Build matrix with respect to position and acceleration vectors
$f_1 + \ ..f_i + \ ..f_j$	Applied robotic force in arms
$R_1 + \ .. + \ R_j$	Rotation matrix at each movement
K_{in}	Attained knowledge of previous states
$H_1 + \ .. + \ H_i$	Heavy load in the industrial system
$pos_1 + \ .. + \ pos_i$	Position of loads
$\delta_1 + \ ..\delta_i + \ ..\delta_n$	Axis change errors
β_i	Circular error changes
$\theta_i, \widehat{\theta_i}$	Relative error positions
θ_t	Total error points
ρ_l	Loss functions due to connected motors
$other_l$	Losses that occurs due to associated supports
ω_d, ω_t	Ratio of disintegration and total dynamisms in each robot
$W_1 + \ ..W_i + \ ..W_j$	Weight of current data
τ_i	Previous data representations
$\nabla_1 + \ .. + \ \nabla_i$	Knowledge inputs
ϑ_i, μ_i	Authentic and forecast values
I_i	Intercepted values
$encrypt_p(i)$	Products that are available with encryption
KF_i	Total number of key factors for a product

Table 3
Significance of scenarios.

Scenarios	Significance
Active movement demonstrations	To determine the maximum association in monitoring process using build matrix
Robotic energy representations	To examine the movement of robots at maximized energy rate
Error functions	To monitor the industrial systems at minimized error rate
Loss measurements	To prevent severe loss functions with associated supports
Robotic strength	To provide high power for robots to carry high loads

changed by other users which also causes severe impact on human systems. In future there is possibility that every robotic system plays a major role in developing industries and in Industry 5.0 operations it is always essential that more amount of control techniques must be enabled by using various algorithmic patterns. Hence a direct control technique is established that prevents entire human system from utilizing the skill patterns in industrial sectors. In every industries where more number of products are created the amount of emissions are much higher which needs to be monitored continuously by using corresponding sensors. If it is monitored then a comparison can be made with reference values thus in an automated way it is possible to minimize the impact of emissions. Whenever there is more human interaction in industries then all materials under creation point faces the major challenge on emission which needs to be reduced as with human interaction it is possible to provide only manual control. However if automatic monitoring system is present then the status of every machine can be monitored at short time period thereafter reducing the amount of emission in every machine. One significant benefit of incorporating robots in the context of Industry 5.0 pertains to their ability to navigate around obstacles and streamline the sorting process, thereby reducing the time required for these tasks compared to human counterparts. The sorting process involves the scanning of designated codes, resulting in the arrangement of each product in a systematic manner. This enables the manufacturer to differentiate between recognized and non-recognized products. Alternatively, if a machine encounters any obstacles, it can be resolved through the utilization of a robot sensing process. This involves accurately identifying the precise location of the obstruction, followed by executing the necessary steps for its removal. Therefore, the capabilities of robots in the fourth industrial revolution are significantly extensive, enabling them to ensure comprehensive safety in the context of industrial automation. The following is a comprehensive account of the designed scenarios, providing a thorough description for each.

4.1.1. Scenario 1: Active movement demonstrations

In this particular scenario, the comprehensive motion of robots is observed through an individualized constructed matrix, wherein a discerning system is triggered. To enable dynamic robotic motion, adjustments are made to both position and acceleration points, thereby facilitating the application of active forces in robotic arms. The movement of the robot is observed to be influenced by active forces, resulting in its displacement relative to specific positions and subsequent activation of comprehensive representations. The subsequent step in this procedure involves the assembly of a comprehensive structure, wherein each building matrix is combined with its corresponding forces in robotic arms. This ensures that the entire mechanism is taken into account, allowing for the active and unrestricted movement of the robots. Furthermore, each movement is exemplified through the utilization of previously acquired knowledge obtained during earlier stages. The proposed methodology involves the identification of the rotation period of robots, as well as the utilization of prior state knowledge to identify and execute active movements. Simulation outcomes for active movement demonstrations are presented in Fig. 4.

Table 4
Simulation parameters.

Bounds	Requirement
Operating systems	Windows 8 and above
Platform	MATLAB and Robot studio
Version (MATLAB)	2015 and above
Version (Network simulator)	2023.1
Applications	Robotic design for industrial applications
Data sets	Weight functions for Supervised learning with build up matrix
Environmental parameters	Energy, strength and active movements

According to the findings presented in Fig. 4 and Table 5, it can be observed that the proposed method leads to significantly higher levels of active movements for robots. This can be attributed to the method's ability to monitor the entire industrial extent over the specified time period. The implementation of dynamic movements has led to the complete integration of automated processes in various industries. During the simulation analysis, it was observed that the robot initiates its movement from an initial position denoted by zero. The robot then proceeds to perform slow movement processing, enabling comprehensive observations of the full scale. In order to demonstrate the active movements of robots, a series of rotational values are examined, specifically 14, 17, 23, 27, and 32. Correspondingly, the total number of constructed systems is analyzed, with values of 19, 26, 34, 37, and 44 being considered. The current methodology identifies the active movement of robots to be 51, 54, 57, 59, and 61. However, the proposed approach increases the active movements to 76, 79, 83, 86, and 88%, respectively. Therefore, the proposed method for Industry 5.0 actively monitors every industrial process, in contrast to the existing approach [4,6,8,10].

Even though active movements of robots are maximized in the proposed system it is observed that some of the error occurs with three dimensional segments where uncertainty exists. In repeated ways the uncertainty conditions which is considered as major limitations are monitored and in most of the cases it is avoided but to complete extent the error functions with respect to dynamic movement of robots can never be neglected. Therefore if there is any change in the position it is denoted with respect to new position values thereby all new position values are marked and it is observed that at least equivalent dynamic representations are made. In case if dynamic representations are not provided then with marginal changes then it denotes that position changes are not accurate even if fast robotic movements are observed. Hence it is essential to determine the total error functions that is described in Scenario 3 and for the same scenario simulation comparisons are also made.

4.1.2. Scenario 2: Robotic energy representations

The proposed method involves utilizing an energy identification procedure to identify heavy load conditions within a robotic system. In order to execute the energy representation process, the total quantity of loads is determined, with specific attention given to identifying heavy loads. In the context of Industry 5.0, the identification and discernment of the corresponding positions of heavy loads occur. Therefore, all instances of heavy loads being transported by robotic systems are documented, and efforts are made to optimize the energy expended during the carrying process up to a specific threshold. The utilization of high-capacity systems facilitates the marking of positions, followed by the implementation of an identification smear through the establishment of distinct links for both loads and positions. In the context of link generation in industrial robotic systems, it is observed that these systems typically operate at low energy levels. However, in the event of sudden increases in load conditions, individual energy supplies are provided. Fig. 5 illustrates the energy representations of robotic systems within the context of Industry 5.0.

The observation from Fig. 5 and Table 6 reveals that the requisite energy is supplied to robots to facilitate the transportation of heavy loads in a smooth and uninterrupted manner. In the initial state, a minimum amount of energy is allocated for the robot to transport equal weights. However, as time progresses, the supplied energy level fluctuates and eventually stabilizes at its maximum level. In order to substantiate the energy representation case study, a series of heavy loads are examined, specifically with values of 56, 74, 89, 95, and 100. These loads are associated with position separations of 2.5, 3.2, 4.7, 4.8, and 5.6, respectively. Based on the aforementioned distinction in positions, it becomes evident that a minimum of 70 % energy is necessary to power all of the given loads. However, in order to address full load conditions, it is imperative to employ the entirety of available energy. In the

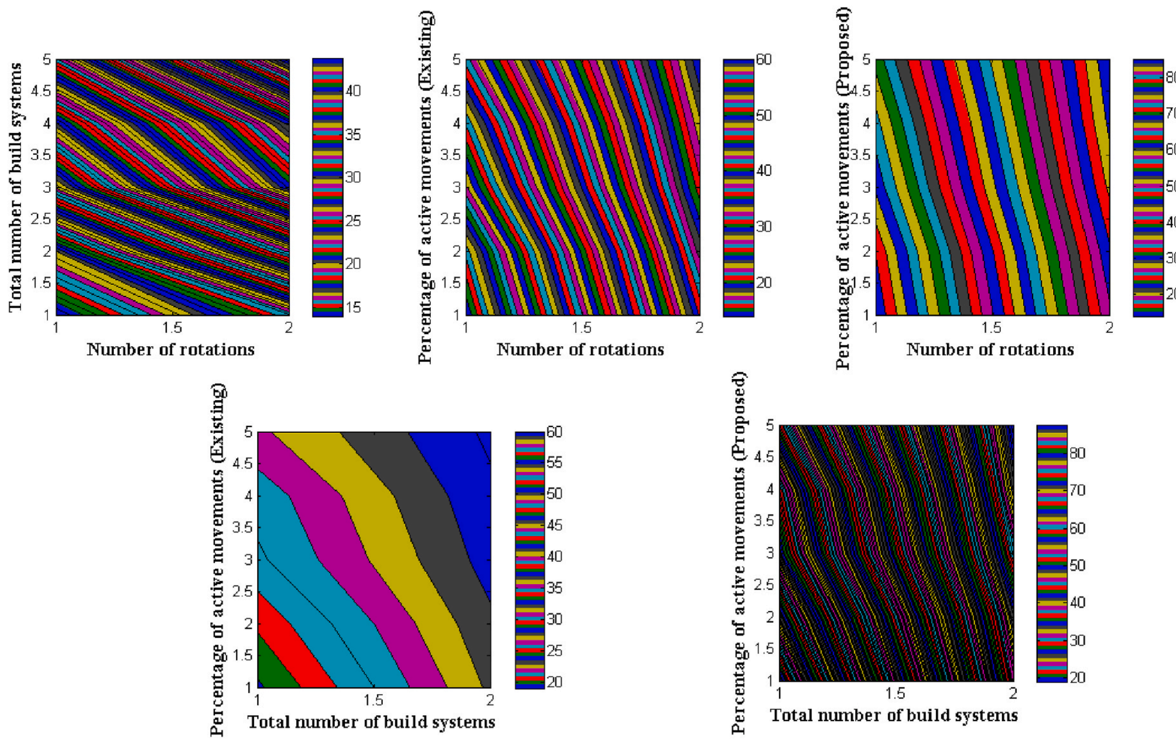

Fig. 4. Total number of build systems and active movement of robots.

Table 5
Active movement of robots with build systems.

Number of rotations	Number of build systems	Percentage of active movements (Existing)	Percentage of active movements (Proposed)
14	19	51	76
17	26	54	79
23	34	57	83
27	37	59	86
32	44	61	88

proposed approach, the energy representations are measured at percentages of 86, 89, 94, 97, and 98, signifying the comprehensive utilization of energy. However, the existing approach [4,6,8,10] does not fully utilize the available energies, resulting in energy percentages of 76, 79, 82, 85, and 87, respectively.

4.1.3. Scenario 3: Error functions

The utilization of robotic systems for monitoring industrial processes gives rise to errors that are primarily associated with issues pertaining to positioning and movements. Therefore, in this particular scenario, error functions are evaluated and modeled in two categories: robotic errors and comparative errors. The occurrence of robotic errors often arises from a shift in the robot's axis, causing it to deviate from its intended trajectory and instead follow a different path that includes changes in direction. The aforementioned modifications will manifest in the event of any alteration in the internal programming mechanisms of the robot. Another type of error is associated with comparative error, which arises from the influence of neighboring robots. As a result of the errors exhibited by these neighboring robots, subsequent robots will also exhibit high error rates. Therefore, the occurrence of comparative errors is regarded as a significant factor contributing to the failure of robotic systems in industrial monitoring. As a result, it is imperative to reduce these errors to ensure optimal performance. The total error measurements pertaining to axis position can be mitigated by ensuring that the robots adhere to a consistent path. Fig. 6 depicts the simulated output of the robot as well as the comparative errors.

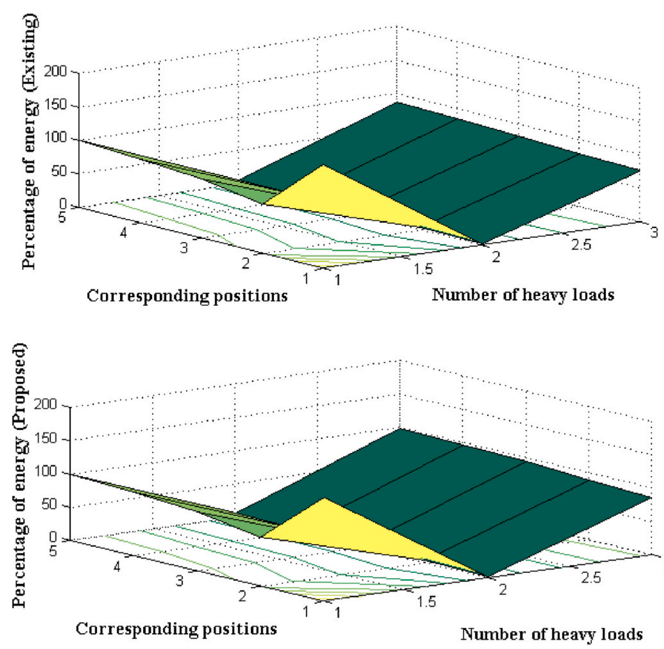

Fig. 5. Total allocated energy for heavy load and position variations.

Table 6
Energy representations for loading conditions.

Number of heavy loads	Corresponding positions	Percentage of energy (Existing)	Percentage of energy (Proposed)
56	2.5	76	86
74	3.2	79	89
89	4.7	82	94
95	4.8	85	97
100	5.6	87	98

Based on the findings presented in Fig. 6 and Table 7, it can be inferred that the proposed method effectively minimizes error measurements in comparison to the existing approach. In order to demonstrate the likely results of error measurements, the analysis focuses on circular movements performed by robots. This is achieved by designing distinct paths that vary in axial directions. Consequently, it can be observed that initially, all robots adhere to a consistent circular trajectory without any deviations. However, once the loading procedure commences, there exists a potential for each robot to undergo alterations in acceleration, consequently affecting the circular path movements. Hence, axis change errors are incorporated alongside circular error positions, wherein error conditions are accurately determined. During the real-time experimentation, we observed errors in the five-axis changes, specifically 7, 10, 12, 15, and 18. These errors were attributed to variations in the paths that were being considered. The aforementioned errors pertaining to changes in the axis result in a consistent total error point distribution of 43, 52, 59, 67, and 74, respectively. Consequently, the total error percentage for the existing approach [4,5,7,8] is 29 %, 26 %, 23 %, 21 %, and 18 %, while the projected model maintains an error percentage of 16 %, 13 %, 8 %, 6 %, and 4 %.

4.1.4. Scenario 4: Loss measurements

In the event that a robotic system contains a higher quantity of errors, it is plausible that there will be a consequential loss in all related supports, thereby directly impacting the functionality of the robots. The accuracy of loss measurements in robotic systems is typically observed through the combination of learning algorithms. As a result, the industrial measurement process evaluates two loss functions. The initial loss occurs as a result of motor or arm segment failure, while subsequent loss functions, after the learning process, are referred to as data value loss. The monitored conditions of industries remain at a stationary state, resulting in significant losses. Consequently, it is necessary to assess the disparity between the actual values and the projected values. Furthermore, the disparity between the output and intercepted values is incorporated in robotic systems. As a result, the suggested approach yields measurement values with minimal loss. However, in the context of mechanical losses, the lifespan of monitoring robots must be interconnected and, in numerous instances, cannot be entirely mitigated.

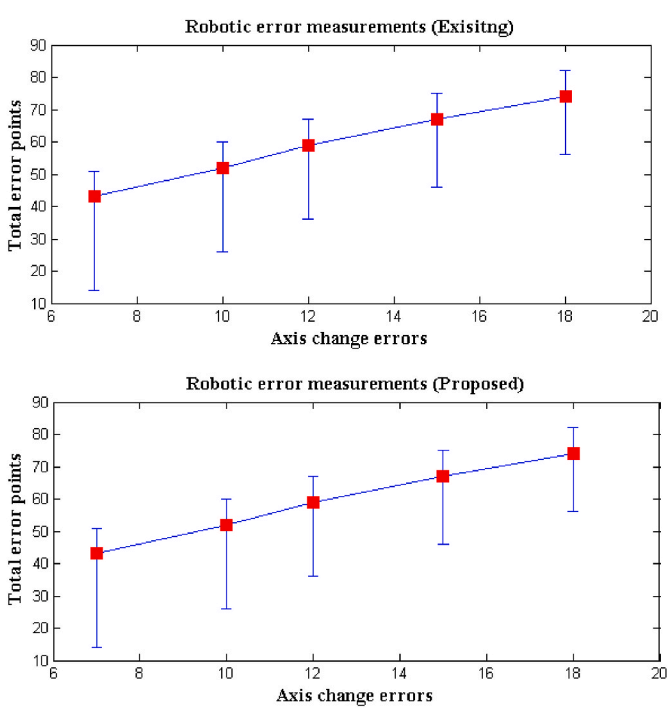

Fig. 6. Error representations pointed during axis modifications.

Table 7
Comparison of error during axis changes.

Total number of axis change errors	Total error points	Percentage of error (Existing)	Percentage of error (Proposed)
7	43	29	16
10	52	26	13
12	59	23	8
15	67	21	6
18	74	18	4

Simulated output in Fig. 7 encompasses loss measurements encompassing both mechanical and data losses.

The analysis of Fig. 7 and Table 8 reveals that the proposed method exhibits significantly reduced loss measurements in comparison to the existing approach. In order to validate the accuracy of the loss measurements, the provided data points consisting of pairs of observed values and corresponding forecast values are considered: {26,20}, {34,27}, {39,28}, {45,31}, and {49,33}. For the set of values mentioned above, it can be observed that the difference in measurements remains consistently low. This suggests that there is a reduction in mechanical losses. The proposed method for monitoring states in robotic systems demonstrates a reduction in loss measurements, resulting in a loss percentage of less than 5 %. The accuracy and predictability of the aforementioned values, {45,31} and {49,33}, can be demonstrated through empirical evidence. In both cases, the loss percentages are determined to be 4 % and 2 %, respectively. However, when comparing the values, it can be observed that the current methodology yields a loss percentage of 7 and 5, suggesting that mechanical losses are relatively elevated. In the alternative set of values, the losses persist at 11, 8, and 6 in the proposed method, while in the existing approach [2,6,7], they are observed to be 17, 13, and 9, respectively. Therefore, the implementation of measures to mitigate high losses during the initial stages effectively prevents the system from experiencing significant robotic loss values.

4.1.5. Scenario 5: Robotic strength

In order to execute a given set of actions, it is imperative that each robot possesses distinct capabilities and varying characteristics. Therefore, in this particular scenario, the manifestation of robotic strength is evident in the context of industrial monitoring, encompassing the performance of disintegration and dynamic measurements. The term "disintegration value" pertains to a robot that experiences an abrupt disconnection from specific operations, resulting in distinct alterations within the system. In situations involving dynamic operations, it is imperative for the robotic system to bear the entire load without encountering any points of obstruction. Consequently, it becomes necessary to disregard a majority of the changes within the system. If the robot chooses to utilize additional force, which is quantified in terms of power, then the supply must be modified to determine the disintegration procedure. However, it is crucial to fully utilize the capabilities of robots, as their entire strength should not go untapped. This is because every operation carried out by a robotic system in the industrial sector can only be accomplished by leveraging their inherent strengths. Fig. 8 illustrates the relationship between robotic strength and the proportion of disintegration and dynamic modes.

Based on the analysis of Fig. 8 and Table 9, it is evident that the potential of robotic systems remains underutilized in the proposed method when compared to the existing approach. The robotic system under consideration for the proposed method employs a minimal amount of energy in order to carry out monitoring tasks. In the event of high load conditions, a greater quantity of energy is required, and the robotic system in question efficiently utilizes this energy without any supplementary utilization. In order to validate the simulation pertaining to the strength of robotic systems, disconnection occurrences are taken into account. These disconnections are quantified as 8, 13, 17, 22, and 25, while their corresponding dynamic ranges are measured as 15, 19,

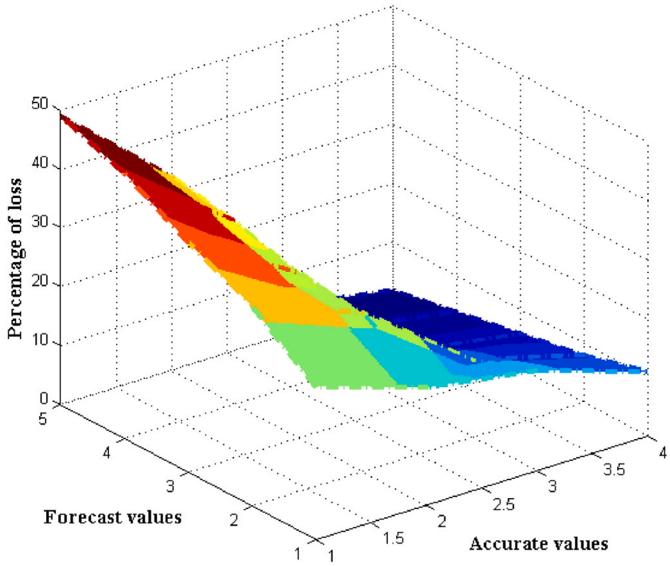

Fig. 7. Loss representations with comparison of accurate and forecast values.

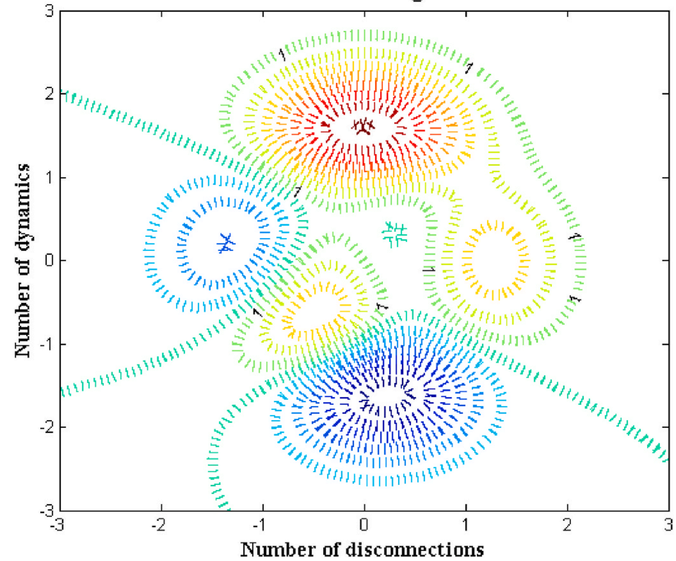

Fig. 8. Contour representations in terms of total strength for dynamic movements.

Table 8
Robotic design loss for existing and proposed approach.

Accurate values	Forecast values	Loss (Existing)	Loss (Proposed)
26	20	17	11
34	27	13	8
39	28	9	6
45	31	7	4
49	33	5	2

Table 9
Output strength of robotic systems during disconnections.

Number of disconnections	Number of dynamics	Percentage of strength (Existing)	Percentage of strength (Proposed)
8	15	3	1
13	19	2	0.4
17	24	1	0.2
22	28	0.6	0.1
25	36	0.3	0.1

24, 28, and 36, respectively. The measured disconnection percentages for the existing approach [3,5,6,8] are observed to be 3, 2, 1, 0.6, and 0.3. In contrast, the proposed method maintains a percentage of utilized strength at 1, 0.4, 0.2, and 0.1, followed by a constant rate. The proposed method effectively harnesses the capabilities of robots, resulting in improved performance across all operations when compared to the existing approach.

4.2. Performance metrics

4.2.1. Economic analysis

The robotic procedures for automated monitoring in Industry 4.0 must be designed in such a way for ensuring low cost operations. In real time applications if the robotic system is implemented at low cost then it is possible that every individual operations can be replaced thereby providing exact monitoring with reduced emissions. In addition if small scale industries are designed with robotic monitoring then every material wastage can be reduced in such a way to make another product with same specifications. With the use of robotic monitoring it is also possible to control high error variations where if human interactions are present then there is a possibility that a material can be created at varying specifications. This type of low cost operation provides major advantage for every smart industries to achieve good decision based on all products thereafter ensuring maximized feasibility. Fig. 9 provides simulation outcomes of implementation cost with respect to number of robotic units are corresponding materials.

From Fig. 9 it is apparent that implementation cost of projected robotic model is reduced as compared to existing approach [5]. The major reason for reduction in cost is that every designed robot can able to learn all input specification of every material where wastage of material in this case is reduced. Moreover the status of every machine is monitored properly thereby reducing the amount of time for material creation which results in power cost savings. Furthermore it is possible to reduce the cost of each robotic unit in proposed system by implementing proper operational nodes at each point in the machine thereby establishing appropriate data to control centres. To verify the implementation cost number of robotic units are considered as 4,6,8,10 and 12 with total number of materials as 176,211,259,312 and 344 where the total cost is observed to be 109,101,96,92 and 87 dollars in case of existing approach. But in proposed method the implementation cost is reduced to 81,74,65,59 and 52 dollars respectively.

4.2.2. Time complexity

Since the entire process is carried out for monitoring every industrial process the time measurements are analyzed where entire complexity can be found out. In the proposed method time complexities denotes the total period for making active movement of robots and in addition the amount of time taken for learning the input sources are examined. As supervised learning is integrated in proposed system model the time complexities for learning the nature of material and corresponding creation units are higher but due to appropriate position representation of robots it is possible to reduce the time complexity in projected model. Moreover the input weights for every robotic unit are much lesser in case of considered industrial process therefore time complexities are reduced in real time applications. Further in real time applications the robotic units takes much less time for monitoring entire industry if axis direction is properly followed in accordance with dynamic movements. Fig. 10 illustrates the time complexities of proposed and existing approach.

From Fig. 10 it is observed that time complexity of proposed model is reduced in case of both monitoring and learning as compared to existing approach. To prove the time complexity representations number of iterations are considered from 10 to 100 in step variations where

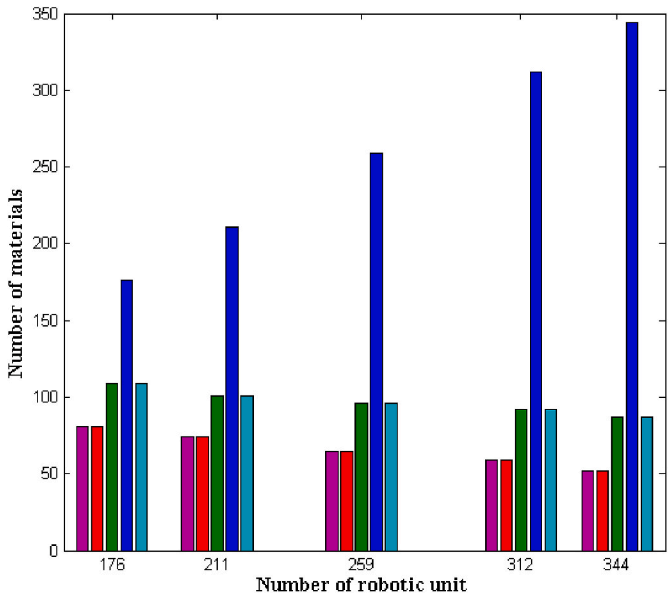

Fig. 9. Economic feasibility with varying materials.

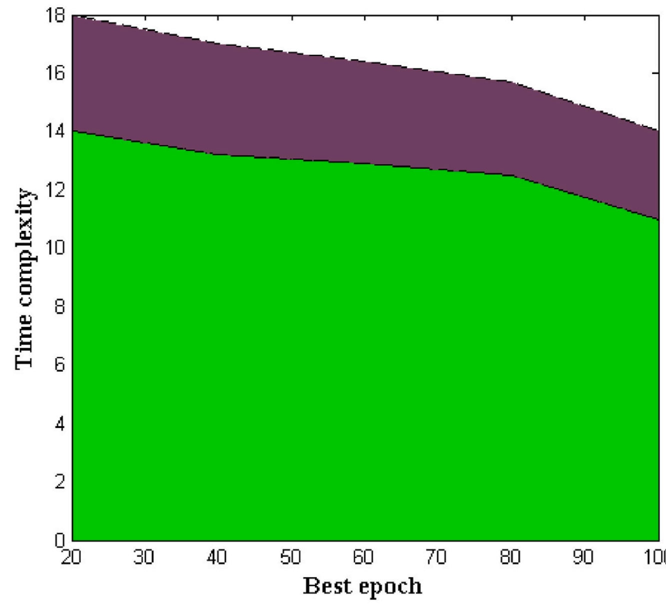

Fig. 10. Time complexities with best epoch periods.

negligible changes are present in each set thus best epoch values with 20,40,60,80 and 100 is taken and the output is simulated. Due to increase in robotic movements where complete active points are enabled the axis directions are followed which results in reduction of time periods. Hence the proposed method provides low time complexity for high iteration periods which remains at 3 % whereas at same conditions existing approach [5] provides more complexity with respect to time periods and it is observed as 11 %. Hence with reduced time complexity it is possible to maximize the efficiency of robotic system for proper monitoring of industrial units.

5. Conclusions

The industrial 5.0 operations with robotic systems are carried out with supervised learning algorithm where every active movements are monitored with respect to each objects in the system. Hence in the proposed method a full scale representation is made for examining current status of every device in industries where strength is observed at each time periods. Moreover with respect to each movement the data set patterns are observed which is transmitted to devices that provides secured operation as compared to normal operational units.The presence of various types of robots enables their utilization in real-time applications, facilitating the completion of complex tasks within a short timeframe. By comparing individuals, it is possible to perform offloading tasks with programming codes at a high level of efficiency. Hence, the proposed approach integrates a robotic system to perform diverse task functions, and a novel mathematical model is developed using parametric representations. The parametric representation model is utilized to monitor the active movements of robots, employing full-scale representation values to accurately determine energy representations. In order to enhance the efficiency of robotic systems, supervised learning algorithms are often integrated into full-scale representations. Furthermore, the design of robots incorporates sensing modules, enabling the simultaneous monitoring of both their performance and activity. Given that a significant number of robotic systems experience failures during specific operations due to insufficient strength, it is imperative to thoroughly analyze the loss functions associated with the identification of maximum errors. The examination of the combined outcomes on learning algorithms with proposed system formulations is conducted using Robotic Studio, which is integrated with MATLAB representations. The outcome analysis involves the design of five scenarios based on different parameters in the system model, including active movements, robotic energy, error functions, loss measurements, and robotic strength. The results of each scenario demonstrate that the proposed method, utilizing a min-max objective function, performs better than the existing approach, which shares similar functionalities. Additionally, it can be observed that the proposed system exhibits a low error rate of 2 %, consequently enhancing the robustness of the industry. The monitoring of operations with a 5.0 approach.

5.1. Limitations and implementation challenges

Even though the proposed method is suitable for implementing in real time applications using robotic system model the procedure of dynamic movement changes are susceptible with more number of disconnections that needs to be reduced. In addition the dynamic changes makes the robot to deviate from axis movements hence corresponding machine movements are not monitored with proper balancing mode. Further the major limitations in the proposed work is only some of the operational constraints are considered as movement of robots in Industry 5.0 is evaluated thereby analysis of unlabelled data set is not considered with noise level, temperature, humidity etc.

In every country the advanced model on robotic system for Industrial applications is on the way of developments with major challenges in real time such as high implementation cost, failure of robotic monitoring units, change in dynamic movements and more amount of energy utilization. However the proposed method on supervised learning with automatic monitoring units provides solutions for addressing all major challenges by making the robot to be active at all crossing movements where no change in axis directions are ensured. Further the amount of energy for all active movements are determined with a gear box model where a base coordinate system is designed.

5.2. Future work

Therefore in future the proposed method on robotic model for Industry 5.0 can be extended by ensuring various operational objectives such as three dimensional movements with emotional feeding system that is carried out in an efficient way with advanced algorithms such as deep learning with neural networks.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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