IOT-HML: A Hybrid Machine Learning Technique for IoT Enabled Industrial Monitoring and Control System

Kota P.N. (✉ kotapn.66@gmail.com)

Modern Education Society's College of Engineering

Chandak A.S.

Cusrow Wadia Institute of Technology

Patil B.P.

Army Institute of Technology

Research Article

Keywords: industrial 4.0, hybrid machine learning, IoT enabled industrial, clustering, cluster head (CH)

Posted Date: April 19th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-365980/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

IOT-HML: A hybrid machine learning technique for IoT enabled industrial monitoring and control system

^{1*}P.N. Kota, ²Dr. A.S. Chandak, ³Dr. B.P. Patil

^{1*}Department of Electronics and Telecommunication Engineering, Modern Education
Society's College of Engineering, India

²Department of Electronics and Telecommunication Engineering, MES's Cusrow Wadia
Institute of Technology, India

³Department of Electronics and Telecommunication Engineering, Army Institute of
Technology, India

^{1*}Corresponding Author Email: kotapn.66@gmail.com

Abstract

Industry 4.0 makes manufacturers more vulnerable to current challenges and makes it easier to adapt to market changes. This will increase the speed of innovation, make it more customer-oriented and lead to faster design processes. It is essential to focus on monitoring and controlling the production system before complex accidents occur. Moreover, an industrial control system facing information security problems in recent times because of the nature of IoT which affects the evaluation of abnormal predication. To overcome above research gaps, we shift to industrial 4.0 which combine IoT and mechanism learning for industrial monitor and manage. We propose a hybrid machine learning technique for IoT enabled industrial monitoring and control system (IoT-HML). Here, we concentrate both information security issues with accurate monitoring and control system. The first section of proposed IoT-HML system is to introduce the cat induced wheel optimization (IWO) algorithm for cluster formation. The process consists of clustering and cluster head (CH)

selection. The source node forward information to destination through CH only which avoids the unwanted data loss and improve the security, because the information travel through trusted path. For route selection process, we utilize the cuckoo search algorithm to compute the optimal best path among multiples. In second section, we illustrate a coach and player learned neural network (CP-LNN) for monitoring the industrial and prevent from accidents by basic control strategies. Finally, the proposed IoT-HML system can evaluate with different set of data's to prove the effectiveness.

Keywords: industrial 4.0, hybrid machine learning, IoT enabled industrial, clustering, cluster head (CH)

1. Introduction

In the future, with the advent of Industry 4.0, computers will be able to interact and make decisions without human intervention. The combination of web physics system, the Internet of Systems (IoS) and Internet of Things (IoT) allows Business 4.0 to become a better industry. The manufacturing industry is busy converting goods, materials or products into new products. Plants, mills, or factories that produce products for general consumption are often owned by manufacturers. Machinery and tools are often used in the manufacturing process. This includes food, chemicals, textiles, machinery and equipment [1]. It contains all the refined metals and minerals extracted from the ores. This includes wood, timber and wood products. Production is the production of materials using labor, machinery, equipment, chemical or biological processing or work. This is the essence of the second sector of the economy. The term can cover a wide range of person behavior, from handicraft to high-tech, but it is also often used for manufacturing mean, in which raw materials are converted into large-scale finished goods. Such products are available to other manufacturers of other

complex products [2]. The IoT model, first introduced by Kevin Ashton in 1998, has paying attention a lot of notice in education and manufacturing. By incorporating mobile adapters into short gadgets and everyday distances, IoT allows a new dimension of communication between people and objects, giving a whole original measurement to the world of in sequence and communiqué [3].

There is no doubt that this has a huge impact on many aspects of daily life and the behavior of potential users. From a private consumer perspective, the most obvious outcome of IoT is employment and the domestic sector [4]. In this regard, appropriate living conditions, smart homes, offices, hygiene and modern training are just a few examples of the situation in which a new model will play an important role in the future. Similarly, from the point of view of business customers, very clear results can be equated with areas such as automation, industrial construction, logistics, business process management, and intelligent transportation of people and goods [5]. Many scientific endeavors in the manufacturing sector reflect such an impact on IoT technologies. The Organizes information in a process environment related to the assembly of IoT large aircraft components [6]. Process automation uses a general application model and IoT framework to simplify the process environment. The increasing impact of IoT on enterprise systems (ES) [7] for modern manufacturing domains was discussed. The relationship between IT infrastructure and enterprise organizations was examined to identify technical gaps in companies' adoption of IoT policies as IT infrastructure. The analyzed IoT technology applications are considered within the framework of cloud computing (CC) [8]; CC & IoT based cloud manufacturing (CMFG) service system (also known as CCIODCMFG) and its structure [9-11]. Based on IoT, an intelligent concept of production sources and available architecture was developed and proposed. Its key technologies are described in the context of cloud-based building systems; a

prototype has been developed to change attitudes [12]. The evolution of the industrial ecosystem is related to the advancement of information technology (IT) systems [13].

Product communication, processing, usage logic and decision making are the factors that support the development of production methods. In addition, companies rely heavily on a variety of professional IT tools and solutions to manage different positions in their industry [14]. Today, the rapid growth of miniature systems and the general interest in global inventions are leading to the next generation of industrial habitats that can use low power networks to monitor and control operations [15]. Most of these systems work with modern microelectronics and wireless data communications. Some technologies such as wireless sensor and actuator networks (WSANs) [16] are increasingly used in industrial processes to monitor and control industrial processes and to detect short circuits containing energy at short distances [17]. The most effective use of an IoT-enabled product is direct data reporting. It allows users to make accurate decisions based on such data [18]. Big Data Analytics is the process of evaluating various databases, methods, contacts, market trends, and other useful information that allow companies to make informed decisions [19]. This includes the processing of any information that is considered to refer to an item or person, such as a user ID or age. The largest data analysis will be used in the operation of the most important construction plants [20].

Our contributions. A hybrid machine learning technique is proposed for IoT enabled industrial monitoring and control system (IoT-HML) to overcome problems in both information security issues with accurate monitoring and control system. The relax of the document is prearranged as follows. The connected employment corresponds to data gathering and analysis is agreed in Sect. 2. The major harms in the obtainable are listed in Sect. 3. The proposed methodology is thorough in Sect. 4. The result and comparative analysis is discussed in Sect. 5. The ending of the thesis is agreed in Sect. 6.

2. Related works

Lin et al. [21] have proposed an industry wants to create SCB to bridge the gap between 3.0 and industry 4.0. By pulling the ICU (micro controller unit) of the MCU and installing the intelligence on a single board, intelligent production can take place without changing the on-site production function. In addition, SCB can provide guidance and advice as the data collected from the instrument panel is taught in the Knowledge and Knowledge layer, as it facilitates instrument panel functions such as prophylactic maintenance. Additionally, while the MCU can accommodate the PLC, the application layer can control the performance of the tool pane.

Cohen et al. [22] have proposed a first addresses the industry 4.0 Modern readiness for assembly and production methods through a recent literary review of relevant documents. It assesses the challenges facing release and production methods. It focuses on the most promising developments in the future, the evolution of such production methods and the digitization of digital manufacturing. Finally, this manuscript describes the content of the documents selected for this particular edition. Research obtainable in this particular subject has made a significant contribution to the theory and practice in this area, and will be useful for future research.

Chen et al. [23] have proposed a feature advantage benefit (FAB) is used in Computer-Integrated Manufacturing (CIM) system, radio frequency identification (RFID) 300mm (FAB) and Semiconductor Company This is a explanation to transform the operating process pour for the features of the Fab in CIM system in the Manufacturing Execution System (MES). It uses the IoT intend plan and the structural design of this new IoT explanation scheme. As a consequence of this study, the integration of in-depth training in the IoT organization into the present CIM system demonstrates the reimbursement of FAB.

Using IoT RFID to identify work in the early stages of processing saves approximately 8 2.8 million instead of encoding. The company will be able to gain more visibility of assets, reduce labor force requirements and maintain global trend.

Hirman et al. [24] have proposed an Industry 4.0 Agreement on IoT Division Design, Feature Literature and Risk Assessment to Improve Factory Production at the plant. The data collected from the manufactured products can be generated by the manufacturer via IoT. Through digital and other analytics, the manufacturer can improve the entire product and its production process based on this data. On the other hand, because of this data, the consumer can prove that the manufacturer has used the product under certain circumstances. On paper, the IoT unit is designed using temperature and humidity sensors. Project risk analysis was performed using the semi-scale risk assessment method. Subsequently, four prototype of the performance component be fabricated and experienced. Risk analysis was performed after the test. In conclusion, a recommendation was made to reduce the risks.

Nabeel et al. [25] have proposed the information is stored in a database that can be further processed for the more expensive version. Prior to assembly, vehicle parts are monitored and connected to geometry, mechanical work, and used materials. Data area monitoring such as vibration and instrument wear detection is available during machine operation. The system runs on a microcontroller, multiple RFID, SD module, and WiFi module, and uses the SBI protocol to operate, ensuring process quality and productivity. Advanced batch RFID solution configuration integrates with data analysis machine and machine building module, allowing real-time partial quality and productivity monitoring.

Camatti et al. [26] have proposed explores how IoT industrial utility structures are constructed and how they relate to the TOGOF framework. The interpretation of the article is defined in three stages: (i) the literary review to integrate the information in the industrial context and to address the previously identified gap in addressing the various representations

of a given study; (ii) examine the various ways in which IoT applications are designed and link them to the TOGOF framework; (iii) Consider consistent critical analysis from the points discussed.

Yang et al. [27] have proposed the problem of IoT-enhanced dynamic SS has been developed in many MCs, allowing event-oriented adaptive planning when the model faces three types of uncertainties (service market, service delivery, and customer aspects, respectively). Experiments are also being carried out using different systems that demonstrate the advantages of this specific model and optimization model.

Gnoni et al. [28] have proposed a maintenance control and inspection of hazardous equipment and work environment. Its purpose is to develop a prototype platform that integrates various vertical applications that can handle four basic services: equipment, vehicle maintenance information management (based on smart labels), potential configuration error detection tool, algorithm device malfunction (e.g.) live personnel and system status. This information is used to provide workers with accurate and competitive information about the driver. The prototype is experienced live in the workplace with very good results and feedback.

Li et al. [29] have proposed a uses statistical process control (SPC) and data removal knowledge are used to examine the composed semiconductor procedure data. The live criticism algorithm is used to make convinced that each creation is artificial using multiple optimal procedure parameter. This increases productivity, increases semiconductor yields, and reduces production costs. This work focuses on scale fiction. The K-clustering algorithm is used in conjunction with real-time criticism control psychoanalysis to take out and examine all parameters moving semiconductor presentation. The grouping of live advice and SBC using historical procedure data allows the system to predict the optimal procedure parameter for the next location.

Wang [30] have proposed as higher radio broadcast technology, 5G has the potential to improve IoT and CPMS. Considering the architectural features and features of 2.5G wireless communication technologies, 5G-IIoT based architecture offered us a common use method. 5G, i.e., how innovative production solutions and production technologies are implemented, varies due to different contexts. Used to improve mobile internet, mass model communication, ultra-high reliability and low latency communication. Analyze the features of 5G IoT based on key technology and challenges.

3. Problem methodology and System model

3.1 Problem methodology

The robust overall structure of the IoT Industrial Control System is determined by a reliable operating module that measures reliability and controls for optimal performance [31]. Sensitive environment is very difficult for IoT. The cluster-based routing system used to ensure the reliability and security of a data source maintains the routing protocol efficiently and reliably. Parallel node display is recommended for scenes with multiple malicious nodes. Abnormal attacks disturb the Bayesian dynamic balance between the striker and the detection node. Industry 4.0 further weakens manufacturers of current challenges and makes it easier to adapt to changes in the market. This will accelerate innovation and make it more customer-oriented, leading to faster design processes. It is important to focus on monitoring and controlling the production system before complex accidents occur. When an existing intelligence system fails to respond to a pre-disaster situation, its rapid operation can cause the server's IoT components to crash for years. Moreover, an industrial control system facing information security problems in recent times because of the nature of IoT which affects the evaluation of abnormal predication. To overcome above research gaps, we shift to industrial 4.0 which combine IoT and mechanism learning for industrial monitor and organize. We

propose a hybrid machine learning technique for IoT enabled industrial monitoring and control system (IoT-HML). Here, we concentrate both information security issues with accurate monitoring and control system. The major donations of planned IoT-HML technique are summarizing as follows:

- The first section of planned IoT-HML scheme is to introduce the cat induced wheel optimization algorithm for cluster formation. The process consists of clustering and cluster head (CH) selection. The source node forward information to destination through CH only which avoids the unwanted data loss and improve the security, because the information travel through trusted path.
- For route selection process, we utilize the cuckoo search algorithm to compute the optimal best path among multiples.
- In second section, we illustrate a coach and player learned neural network (CP-LNN) for monitoring the industrial and prevent from accidents by basic control strategies.
- Finally, the proposed IoT-HML system can evaluate with different set of data's to prove the effectiveness.

3.2 System architecture of proposed IoT-HML system

Fig. 1 shows the proposed system model. The system consists of an industrial environment. In order to detect the temperature, pressure and the speed three different sensors are used i.e, temperature sensor, pressure sensor and speed sensor. For monitoring the data transmission data monitoring center is used. The vehicles will take data from the base station and it is send it to nearby nodes. The terminal ranges are used to identify the nearest node location. The nodes are clustered. The paths are formed between the nodes for the transmission. From the multiple nodes aggregated nodes are identified. The access point, base station is there for proper data transmission. The data that are sending from the sensors are given to the cloud platform after that only it will be given to the monitoring unit. When the sensor wants to send

the data to the vehicle it will check for the vehicle which is free by sending the request to the base station. The base station will check for the free vehicle. In case if the entire vehicle is busy then the sensor will hold the data in the sensor node until the base station send the acknowledgement related to the free vehicle. At that period of time the internal process of the industry will be in an interrupt form.

Fig. 1 System model of proposed IoT-HML system

4. Hybrid machine learning technique for IoT enabled industrial monitoring and control system (IoT-HML)

4.1 Clustering using cat induced wheel optimization (IWO)

The purpose of clustering is to divide the whole network into separate parts to ensure the reliability and the security data. Then, select the cluster heads with unknown nodes at the nearest cluster host terminal and its cluster number. Data clusters arise from the need to find interesting formats or groups of similar features in a given data set. Using the IWO algorithm, the security and the reliability data are transferred from the source node to the destination which is selected on the basis of the cluster head process. Clustering is a compilation process, so every member of a division has some similarities based on some similarities. A cluster is a set of objects, their similarity or proximity is bundled. A Clustering aim is to collect data / objects in clusters, as each cluster contains similar data. This technique does not contain any information about the cluster or group method, which is why clusters should be included in the supervised study. Cluster complex and linearly indistinguishable data sets, without prior knowledge of the number of groups in nature. Unlike most existing clustering techniques, specific algorithms do not require prior knowledge of the data. In super wide wheels that are wider than other rover wheels, the shape of the profile can significantly change the performance of the drive or reduce side curves with lateral deflection. To get the optimal shape of the wheel with more traction and resist lateral overturning with less torque, following objective functions are defined. The required torque of motor for generating the wheel angular velocity ω_m of nominal magnitude is minimized by the first objective. In the real case the angular velocity ω is generated by the torque of motor τ . The fraction of the real torque and the nominal torque of angular velocity is represented in the first objective function.

$$D_1 = \left(\frac{|\tau|}{|\omega|} \right) \left(\frac{\tau_m}{\omega_m} \right)^{-1} \quad (1)$$

Where τ_m denotes the torque of the ideal magnitude. The tractive and torque relation can be denoted by the effective radius of the wheel. The radius of the effective s_{eff} is equal to

the radius of the wheel average s_{whe} in the ideal slip less rigid contact. Thus, the 2nd objective function is,

$$D_2 = s_{whe} s_{eff}^{-1} = s_{whe} \left(\frac{\tau}{g_r} \right)^{-1} \quad (2)$$

The rover platform depends on the third objective. To avoid the slipping of lateral, the force of lateral is used as a parameter when the rover front axis is rotated. The force of lateral resists against the rover steering once the front axis is fixed. Then, the third objective function is,

$$D_3 = \frac{|g_k|}{|g_d|} \quad (3)$$

The total function of the objective is defined as sum of these functions as

$$D_t = \sum_{j=1}^3 \psi_j D_j \quad (4)$$

Where ψ_j indicates the coefficient of priority which evaluates the significance of the function D_j in design.

The seeking mode and the tracing mode are the two modes in the behaviour of the cat characteristic which is used to solve the different optimization problem. Cats spend a lot of time relaxing, but are always wary of their surroundings in seeking mode.

$$Y_{l,r} = \begin{cases} [1 + (2 \times rand - 1) \times SRD] \times Y_{i,r}, & \text{if } D \in n \\ Y_{i,r}, & \text{otherwise} \end{cases} \quad (5)$$

On updating the values, the equation is

$$U_{i,r} = z \times U_{i,r} + s_1 \times d_1 \times (Y_{best,r} - Y_{i,r}) \quad (6)$$

The tracing of target is modelled in tracing mode as follows:

$$Y_{i,r} = Y_{i,r} + U_{i,r} \quad (7)$$

Calculate the Informative score IS_{il} by using the equation,

$$IS_{il} = Tg_{il} \times \log \left(\frac{m}{m_l} \right) \quad (8)$$

The working function of cluster formation using cat induced wheel optimization is given in Algorithm 1.

Algorithm 1 Cat Induced Wheel Optimization

Input : τ, ω, s, g, m

Output : D_t, IS_{il}

- 1 Assume the values for the input τ, ω, s .
 - 2 Calculate the first objective function using the τ
 - 3 On substituting the value of s , find D_2
 - 4 Overall objective function is calculated using the equation $D_t = \sum_{j=1}^3 \psi_j D_j$
 - 5 Compute the $U_{i,r}$ and $Y_{i,r}$
 - 6 Evaluate the IS_{il}
-

4.2 Optimal best path using cuckoo search algorithm

Data can go through many intermediate paths and need to select the best optimal nodes for data transfer. These optimal nodes contribute to the optimal operation of the network. Extensive work has been done to improve the efficiency of network routing and to identify the best route to prevent congestion. There are many techniques for finding optimal path, here we are describing about cuckoo search algorithm. The main function of the router is the best way to send packets. To determine the best path, the router searches its routing list for a network address that matches the packet's target IP address. The idea of this method is based on the spread of parasites on some cuckoo. There are two instances of cuckoo eggs in other bird cages. The high quality egg nest selected for the new generation coincides with the

ability to lay a new egg cuckoo. First, it usually emerges from the nest if it cannot find the first-born cuckoo eggs or extra little birds of the crowd. Second, it fixes and removes the host bird. The Levy plane has an imperative responsibility to explore the given investigate space:

$$Y_j^{NEW} = Y_{Best_j} + U_j^{NEW,LEVY} \quad (9)$$

$$U_j^{NEW,LEVY} = \alpha \times RAND[0,1] \times (Y_{BEST_j} - F_{BEST}) \times LEVY(\beta) \quad (10)$$

Levy flight creates the individual value j , where $U_j^{NEW,LEVY}$ is the velocity. The new and best position of the individual j are Y_j^{NEW} and Y_{BEST_j} . The value of coefficient range α is 0 and 1. Until the current iteration the current best solution f_{BEST} . The distribution coefficient range β is of 0 and 3. 1.5 is set to typical. To use the search space described below, the Exotic Egg Detection Technique uses random technology:

$$Y_j^{NEW} = Y_{BEST_j} + U_j^{NEW,RANDwalk} \quad (11)$$

$$U_j^{NEW,RANDwalk} = RAND[0,1] \times Z(j,:) \otimes (Y_{BEST_i} - Y_{BEST_z}) \quad (12)$$

By random walk technique the individual j creates the velocity value of $U_j^{NEW,RANDwalk}$. Z is a binary matrix defined by $Z = RAND(C,M)$. The individuals chosen randomly are Y_{BEST_j}, Y_{BEST_j} . The below equation describes the solution of candidate in continuous domain:

$$y_j = [y_1, y_2, \dots, x_C] \quad (13)$$

Where, y_j is the solution j ($j = 1, 2 \dots M$) in the population. The number of binary bits represents the problem in control variable in the binary version. The following equation represents the candidate solution.

$$y_j = [y_1, y_2, \dots, y_{M_{BITS}}] \quad (14)$$

The below equation determines the dimension of problem i.e. M_{BITS}

$$M_{BITS} = M_{BIT} \times C \quad (15)$$

The continuous variable in the double domain is represented by digit of binary bits M_{BITS} . Based on the equation, 50% has value 1 and remaining has value 0.

$$y_j = RAND(1, M_{BITS})0.5 \quad (16)$$

When deciding on a binary domain candidate, each person should switch to a nonstop domain to appraise health performance. This revise uses the technique of converting an individual scale binary domain into a continuous domain. The binary domain is represented by Y_i which determines the quantization value by the following equation.

$$Y_{Quanti} = \sum_{n=1}^{M_{BIT}} BIT[n] \times 2^{-n} / \sum_{n=1}^{m_{BIT}} 2^{-n} \quad (17)$$

The quantization value of Y_i^{Quant} in the range of [0, 1]. The bit $n=1, 2, \dots, BIT_m$ with status $BIT[n]$. The limits of $(Y_{High i} - Y_{Low i})$ with continuous domain value of Y_i is calculated as follows:

$$Y_i = Y_{Quanti} \times (Y_{High i} - Y_{Low i}) + Y_{Low i} \quad (18)$$

Equation (21),(22),(23) updates the new position

$$R(U_j^{NEW LEVY}) = Transfer_function(U_j^{NEW LEVY}) \quad (19)$$

$$Y_j^{NEW} = \begin{cases} (Y_{BEST_j})^{-1}, & \text{if } [0,1] < R(U_j^{NEW LEVY}) \\ Y_{BEST_j}, & \text{if } [0,1] \geq R(U_j^{NEW LEVY}) \end{cases} \quad (20)$$

where transfer function is a transport meaning which maps speed values into likelihood standards. The new and current position are Y_j^{NEW} and Y_j . $(Y_j)^{-1}$ is the inverse of Y_j . Like the Levy's aviation system, EPCSA's discovery of a strange egg creates another new solution for the population.

$$Y_{f_{BEST(j)}} = [Y_1, Y_2, \dots, X_C] \quad (21)$$

Then, in order to generate new solution approximately the best explanation of all time, you need to configure the existing solution for all control bits starting the worth of 0 to 1 or vice versa.

$$Y_{f\ BEST}(j) = [y_1, y_2, \dots, y_c, \dots, y_{NEW}] \quad (22)$$

$$Y_{NEW} = [y_1, y_2, \dots, y_{cNEW}, \dots, y_{NEW}] \quad (23)$$

$$y_{c,NEW} = \begin{cases} 1, & \text{if } y_c = 0 \\ 0, & \text{if } y_c = 1 \end{cases} \text{ with } c = 1, 2, \dots, M_{BITS} \quad (24)$$

So far there are two conventional transmission functions with S shaped and V shaped.

$$R(U_j^{NEW}) = 1/(1 + e^{-U_j^{NEW}}) \quad (25)$$

$$Y_j^{NEW} = \begin{cases} 0, & \text{if } RAND[0,1] < R(U_j^{NEW}) \\ 1, & \text{if } RAND[0,1] < R(U_j^{NEW}) \end{cases} \quad (26)$$

The control variable position is updated by equation (20)

$$R(U_j^{NEW}) = |\tanh(U_j^{NEW})| \quad (27)$$

$$R(U_j^{NEW}) = \left| \frac{2}{\Pi} \text{Arc tan} \left(\frac{\Pi}{2} \times U_j^{NEW} \right) \right| \quad (28)$$

The individual position is updated by combining equation (25) and (26) the position is set by 0 or 1. Therefore, cuckoo search algorithm selects the appropriate transmission function to solve the NR problem.

Algorithm 2 Optimal best path using CSA

Input : $Y_j^{NEW}, U_j^{NEW, LEVY}$

Output : $R(U_j^{NEW})$

- 1 Initialize cuckoo position and parameters
 - 2 Randomly generate positions and calculate fitness
-

3 Compute the position by using

$$Y_i = Y_{Qunat i} \times (Y_{High i} - Y_{Low i}) + Y_{Low i}$$

4 Update the new position by

$$R(U_j^{NEW LEVY}) = Transfer_function(U_j^{NEW LEVY})$$

5 The individual position is calculated by

$$R(U_j^{NEW}) = 1/(1 + e^{-U_j^{NEW}})$$

6 Control variable is updated by

$$R(U_j^{NEW}) = |\tanh(U_j^{NEW})|$$

7 Return

4.3 Data monitoring coach and player learned neural network (CP-LNN)

Here is a specific training program for coaches and players with intermediate networks. During the training phase, the coach and player networks teach simultaneously with the confirmation system. The major idea of our training program is those coach and player recession networks use similar skin tone beginning communal conversion network so that the player relapse system can simply copy the coaching network. These training programs allow a system of players to maintain excellent performance when they have a limited number of options. On the using the concept of the CP-LNN algorithm the data are monitored in the industrial field and also prevent the accidents using the basic control strategies. FIG. 2, at the end of the transition layers the two network branches are divided into coach and player intermediate network. The fully related coating of the back coach complex is called the T-FC. The associated layer on the player log complex is called STD-FC, which has a 1 to 1 jump and a universal standard pool.

Fig. 2 working function of coach and player learning model

Features are integrated into the coach latency network and the player latency network. Note that the functions of the coach and the player's intermediate network are encoded with the usual layers of data verification. Completely associated layer play an important role in the FLD complex as the CNN feature makes the map an important strategy. As a result, collective training requires loss target operations, so the STD-FC layer is the D-FC layer. To do this, according to the proposed law, the loss is divided into three functions. The first branch is for the Coaches Regression Network and the next branch is for the Player Regression Network. All network are taught from the end with three loss functions (M^1, M^2, M^3). The second loss function M^3 , is responsible for reducing the error production of the player's middle network. The third loss function, M^3 , is difference flanked by the loss output vectors T-FC and STD-FC. In preparation, the loss M^3 reflected in all three sub-networks: unit switching network, coach regression network, and player regression network. The three terms of loss terms (M^1, M^2, M^3) can be printed as follows:

$$M^1(x, Z_{CNN}, Z_S) = \frac{1}{n} \sum_{j=1}^n \|x_j - b(g(y_j; Z_{CNN}), Z_S)\|_1 \quad (29)$$

$$M^2(x, Z_{CNN}, Z_{STD}) = \frac{1}{n} \sum_{j=1}^n \|x_j - h(g(y_j; Z_{CNN}), Z_{STD})\|_1, \quad (30)$$

$$M^3(q, p) = \frac{1}{n} \sum_{j=1}^n \|q_j - p_j\|_1, \quad (31)$$

Where n is the digit of teaching imagery, j is the directory of an input picture, x_j is position fact facial marker organize and y_j is the input picture. The $g(\cdot)$ is the meaning of common problem complex parameterized by Z_{CNN} . $b(\cdot)$ is the meaning of the coach regression network parameterized by Z_S . $h(\cdot)$ is the occupation of the player regression network parameterized by Z_{STD} . And q_j is output vector of S-FC and p_j is that of STD-FC. The algorithm 3 represents the working function of the coach and player learning neural network.

Algorithm 3 Working function of coach and player learning

Input	$y_j, \alpha = 1, \beta = 0, \gamma = 0$
Output	Z_{CNN}, Z_S, Z_{STD}

1. For $s=1$ to S do
2. Feed y_j to shared convolution network: $g(y_j; Z_{CNN})$
3. Feed $g(y_j; Z_{CNN})$ to the coach regression and player regression network:
 $b(g(y_j; Z_{CNN}); Z_S), h(g(y_j; Z_{CNN}); Z_{STD})$
4. Calculate (M^1, M^2, M^3)
5. $\{Z_{CNN}^*, Z_S^*, Z_{STD}^*\} \leftarrow \arg \min_{Z_{CNN}, Z_S, Z_{STD}} \{\alpha M^1(x, Z_{CNN}, Z_S) + \beta M^2(x, Z_{CNN}, Z_{STD}) + \gamma M^3(q, p)\}$
6. $Z_{CNN} \leftarrow Z_{CNN}^*, Z_S \leftarrow Z_S^*, Z_{STD} \leftarrow Z_{STD}^*$

7. Increase β, γ

8. End

The totality defeat starting the divided point is definite as $M_{branch} = \alpha M^1 + \beta M^2 + \gamma M^3$. They α, β, γ indicate the value of all defeat. Because all fatalities influence all network, we will set these settings correctly. Through training, the trainer should be trained regularly as the regression network should perform well. If the coach's intermediate net is not working properly, the player's intermediate net is not working properly. Therefore, we fixed $\alpha = 1$ from opening to end to attain the best presentation. Then, we augment β, γ from 0 to 1 steadily (i.e. $\beta = \gamma = 1 - e^{-1}$ or $\beta = \gamma = \tan g(s)$, where s is s -th epoch), which they shape to the coach and player regression network and communal difficulty network together. If we originally set $\beta = \gamma = 1$, the coach regression network presentation is drenched before it achieves the best presentation. Thus, at the beginning of the preparation, the overall transformation network and coaching network dominate. Once that, the players' intermediate network is gradually trained. Algorithm 3 describes the operation of the coach and the player learning model. Indicates the type of in-depth machine training of the neural network when multiple layers of input are used for computer tasks for optimal performance. This means that the data is very constructive and concise. We teach the player the correct knowledge by integrating the knowledge of several coaches to improve accuracy after the abstract. We have optional several authors within the framework of information filtering, the logits vector shaped by the player network for an input video $U_i, i = 1, \dots, L$ represented by $(A_R)_i$, where the dimension of vector $(A_R)_i = [(A_R)_i^1, \dots, (A_R)_i^d]$ is the number of categories d . the SOFTMAX layer converts the logits vector $(A_R)_i$ to a probability distribution $(q_R)_i = [((q_R)_i^1, \dots, (p_R)_i^d)]$ describes as,

$$(q_R)_i = \text{SOFTMAX}((W_T)_j) \quad (32)$$

where

$$(q_R)_i^j = \frac{\exp((A_R)_j^i)}{\sum_Z \exp((A_R)_j^Z)}, \quad \text{for } j = 1, \dots, d \quad (33)$$

On the other hand, the logits vector bent by the coach network for an input video $U_i, i = 1, \dots, L$ is represented by $(A_S)_i^d$, where the dimension of vector $(A_S)_i = ((A_R)_i^1, \dots, (A_R)_i^d)$ is the number of categories d . By introduce a parameter called warmth s , the widespread SOFTMAX layer FSOFTMAX converts the logits $(A_S)_i^d$, to soft probability distribution

$$(q_S^s)_i = [(q_S^s)_i^1, \dots, (p_S^s)_i^d]$$

$$(q_S^s)_i = F \text{ SOFTMAX}(A_S)_i, s \quad (34)$$

$$(q_S^s)_i^j = \frac{\text{EXP}((A_R)_j^i / s)}{\sum_Z \text{EXP}((A_S)_j^Z / s)}, \quad \text{for } j = 1, \dots, d \quad (35)$$

The first objective function $w1$ minimizes the cross entropy with the soft labels $(q_S^s)_i$, and the soft probability $(q_R^j)_i$, produced by the player model. $(q_R^s)_i$, is computed by FSOFTMAX with the same warmth t as the coach model,

$$(q_R^s)_i = F \text{ SOFTMAX}(A_T)_i, s \quad (36)$$

where

$$(q_R^s)_i^j = \frac{\exp((A_R)_j^i / s)}{\sum_Z \exp((A_R)_j^Z / s)}, \quad \text{for } j = 1, \dots, d \quad (37)$$

The first objective function $w1$ is

$$\underset{M}{\text{ARGMIN}} \quad w1(M) = \underset{M}{\text{ARGMIN}} - \frac{1}{Ld} \sum_{i=1}^L \sum_{D=1}^d (q_S^s)_i^D \ln(q_R^s)_i^D \quad (38)$$

where $(q_S^s)_i^D$, fashioned by the player is the possibility that the i -th video belongs to the D -th class, $(q_S^s)_i^D$, is the soft label shaped by the coach, w is the weights of the student, L

is the number of teaching videos, and d is the number of total classes. The second meaning function w_2 minimize the cross entropy with the hard labels Y_{true} and the probability $(q_R)_i$, fashioned by the student.

$$ARGMIN_M w_2(M) = ARGMIN_M - \frac{1}{Ld} \sum_{i=1}^L \sum_{D=1}^d (y_{ture})_i^D \ln(q_R)_i^D \quad (39)$$

Where $(q_R)_i^D$, shaped by the player is the possibility that the j-th video belongs to the b-th Class, $(y_{ture})_i^D$ is the hard label in sequence, and $(y_{ture})_i^D = 1$ if the i-th video belong to the D-th class, otherwise. $(y_{ture})_i^D = 0$ M is the weights of the student, L is the number of training videos, and d is the number of total classes. The overall objective meaning w is a prejudiced regular of two diverse purpose function.

$$ARGMIN_M w(M) = ARGMIN_M \lambda s^2 w_1 + (1 - \lambda) w_2(M) \quad (40)$$

Where M is the weights of the player and λ is a relative weight.

5. Results and Discussion

In this segment, we appraise the planned IoT-HML system with two different test cases are data gathering and data analyzing (for monitoring). The simulations were performed using network simulator for data gathering phase and the anaconda simulator for data monitoring phase. The simulations are carried out with metrics for both proposed protocol and existing. The proposed IoT-HML system with C-IWO based data gathering is evaluate though three different test scenarios are impact of sensor nodes, impact of bad nodes and impact of node movement. The performance of proposed C-IWO based data gathering is compare with the obtainable state of art data gathering technique are cluster based and AODV routing. The different metrics are worn to examine the presentation of proposed steering such as delay, energy consumption, throughput, data delivery ratio and data loss ratio. The number of sensor

nodes randomly placed in the given network size $1200 \times 900 \text{ m}^2$ and the number of node is taken from 100 to 500 for this analysis. The average mobility of sensor node is 10 mps. For each sensor node, the initial energy is fixed as the 18720J. The average transmission range is 50m. The summary of simulation parameters are given in Table 1.

Table 1 Simulation parameters

Parameters	Values
Network size	$1200 \times 900 \text{ m}^2$
Number of nodes	50, 100, 150, 200 and 250
MAC type	IEEE 802_11
Antenna model	Omni Antenna
Transmission range	50m
Packet size	512 bytes
Interference range	50m
Initial Energy	10J
Mobility model	Random model
Maximum speed	10mps
Minimum speed	1mps
Simulation time	100s

5.1 Performance comparison of data gathering phase

5.1.1 Impact of node density

In this situation, we differ the digit of nodes as 100, 200, 300, 400 and 500 with the fixed network size as $1200 \times 900 \text{ m}^2$. Fig. 3 shows the delay comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average delay of proposed C-IWO based routing is 23.2% lower than cluster based routing and 38.4% lower

than AODV routing protocol. For 100 sensor nodes, the delay of proposed C-IWO based routing is 10% and 55% for cluster based, AODV correspondingly. Fig. 4 shows the energy consumption contrast of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average energy consumption of planned C-IWO based routing is 14% lower than cluster based routing and 22.8% lower than AODV routing protocol. For 200 sensor nodes, the energy consumption of proposed C-IWO based routing is 15% and 26% for cluster based, AODV correspondingly. Fig. 5 shows the Throughput judgment of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average Throughput of proposed C-IWO based routing is 10.6% higher than cluster based routing and 20.2% higher than AODV routing protocol. For 300 sensor nodes, the Throughput of proposed C-IWO based routing is 18% and 23% for cluster based, AODV respectively.

Fig. 3 Delay comparison with nodes

Fig. 4 Energy consumption comparison with nodes

Fig. 5 Throughput comparison with nodes

Fig. 6 shows the Delivery ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Delivery ratio of proposed C-IWO based routing is 1.6% higher than cluster based routing and 6% higher than AODV routing protocol. For 400 sensor nodes, the Delivery ratio of proposed C-IWO based routing is 1% and 2% for cluster based, AODV respectively. Fig. 7 shows the Loss ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Loss ratio of proposed C-IWO based routing is 24% lower than cluster based routing and 34.6% lower than AODV routing protocol. For 500 sensor nodes, the Loss ratio

of proposed C-IWO based routing is 52% and 58% for cluster based, AODV respectively. The summary of comparative analysis of proposed and existing data gathering protocols is given in Table 2.

Fig. 6 Delivery ratio comparison with nodes

Fig. 7 Loss ratio comparison with nodes

Table 2 Comparative analysis of routing protocols over node density

Loss ratio (%)	3	29	33	34	39	40
	2	25	29	31	32	33

Nodes	Delay (s)			Energy consumption (mJ)			Throughput (Mbps)				Delivery ratio (%)			
	1	2	3	1	2	3	1	2	3	1	2	3	1	2
100	0.9	1	2	11	13	15	48.1	39	37	98	97	96	12	12
200	1.2	2	2.3	12.9	13.5	16	35	32	30	97	96	95	20	20
300	1.9	2.3	2.9	13	15	17	34	32	28	95	94	90	25	25
400	2	2.9	3	14.2	17	18	30	28	24	90	87	82	29	29
500	2.5	3	3.2	15	19	20	29	25	21	87	80	75	30	30

5.1.2 Impact of bad node density

In this situation, we differ the digit of bad nodes as 10, 20, 30, 40 and 50 with the fixed number of node as 500 and network size as 1200×900 m². Fig. 8 shows the delay comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV.

The average delay of proposed C-IWO based routing is 21.4% lower than cluster based routing and 39.6% lower than AODV routing protocol. For 10 sensor nodes, the delay of proposed C-IWO based routing is 23% and 37% for cluster based, AODV correspondingly. Fig. 9 shows the energy consumption contrast of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average energy consumption of proposed C-IWO based routing is 11.8% lower than cluster based routing and 18.2% lower than AODV routing protocol. For 20 sensor nodes, the energy consumption of proposed C-IWO based routing is 17% and 31% for cluster based, AODV correspondingly. Fig. 10 shows the Throughput judgment of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average Throughput of proposed C-IWO based routing is 6% lower than cluster based routing and 15% lower than AODV routing protocol. For 30 sensor nodes, the Throughput of proposed C-IWO based routing is 12% and 21% for cluster based, AODV respectively.

Fig. 8 Delay comparison with bad nodes

Fig. 9 Energy consumption comparison with bad nodes

Fig. 10 Throughput comparison with bad nodes

Fig. 11 shows the Delivery ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Delivery ratio of proposed C-IWO based routing is 5.2% higher than cluster based routing and 7.4% higher than AODV routing protocol. For 40 sensor nodes, the Delivery ratio of proposed C-IWO based routing is 11% and 5% for cluster based, AODV respectively. Fig. 12 shows the Loss ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Loss ratio of proposed C-IWO based routing is 16.2% lower than cluster based

routing and 29.2% lower than AODV routing protocol. For 50 sensor nodes, the Loss ratio of proposed C-IWO based routing is 25% and 34% for cluster based, AODV respectively.

Fig. 11 Delivery ratio comparison with bad nodes

Fig. 12 Loss ratio comparison with bad nodes

Table 3 Comparative analysis of routing protocols over bad node density

Loss ratio (%)	3	23	29	37	38	47
	2	20	23	29	37	38

Bad Nodes	Delay (s)			Energy consumption (mJ)			Throughput (Mbps)			Delivery ratio (%)			
	1	2	3	1	2	3	1	2	3	1	2	3	1
10	1	1.3	1.6	19	23.1	29.7	54	47	46	90	89	85	15
20	1.2	1.5	1.9	25.6	29.7	33.6	47	46	44	89	85	80	20
30	1.3	1.9	2.5	29.7	33.6	39.0	46	44	40	85	80	78	23
40	1.6	2	2.9	33.6	39.04	41.2	44	40	38	80	78	75	29
50	2	2.3	3	39.12	41.23	43	40	38	35	78	75	71	37

5.1.3 Impact of node mobility

In this situation, we differ the speed of nodule as 0.1, 0.2, 0.3, 0.4 and 0.5 with the fixed number of node as 500 and network size as 1200×900 m². Fig. 13 shows the delay

comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average delay of proposed C-IWO based routing is 14.4% lower than cluster based routing and 27.4% lower than AODV routing protocol. For 0.2 sensor nodes, the delay of proposed C-IWO based routing is 13% and 31% for cluster based, AODV correspondingly. Fig. 14 shows the energy consumption contrast of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average energy consumption of proposed C-IWO based routing is 12.4% lower than cluster based routing and 22% lower than AODV routing protocol. For 0.4 sensor nodes, the energy consumption of proposed C-IWO based routing is 10% and 13% for cluster based, AODV correspondingly. Fig. 15 shows the Throughput assessment of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average Throughput of proposed C-IWO based routing is 14.2% higher than cluster based routing and 32.6% higher than AODV routing protocol. For 0.6 sensor nodes, the Throughput of proposed C-IWO based routing is 12% and 23% for cluster based, AODV respectively.

Fig. 13 Delay comparison with nodes

Fig. 14 Energy consumption comparison with nodes

Fig. 15 Throughput comparison with nodes

Fig. 16 show the Delivery ratio judgment of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average Delivery ratio of proposed C-IWO based routing is 4.6% higher than cluster based routing and 8.6% higher than AODV routing protocol. For 0.8 sensor nodes, the Delivery ratio of proposed C-IWO based routing is 4% and 5% for cluster based, AODV respectively. Fig. 17 shows the Loss ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Loss ratio of proposed C-IWO based routing is 37% lower than cluster based routing

and 47.4% lower than AODV routing protocol. For 1 sensor nodes, the Loss ratio of proposed C-IWO based routing is 31% and 34% for cluster based, AODV respectively.

Fig. 16 Delivery ratio comparison with nodes

Fig. 17 Loss ratio comparison with nodes

Table 4 Comparative analysis of routing

Loss ratio (%)	3	23	29	35	39	43
	2	22	23	28	29	37

whether the given sample is normal or abnormal. When the abnormal is detected it shows that the test is positive, i.e. among the total abnormal, it shows the correct amount of positivity.

$$\frac{t_p}{t_p + f_n} \quad (42)$$

Specificity is used to predict whether the given sample is normal or abnormal. When the abnormal is absent, it shows that the test is negative i.e. among the total non abnormal and it shows the correct amount of negativity.

$$\frac{t_n}{f_p + t_n} \quad (43)$$

From the confusion matrix, we can obtain t_p, t_n, f_p, f_n ,

To categorize the affected samples, the accuracy is used to measure the ratio of samples as follows:

$$\frac{t_p + t_n}{t_p + t_n + f_p + f_n} \quad (44)$$

This is the segment to identify the incorrectly categorized samples as abnormal by using the formula,

$$\frac{f_p + f_n}{t_p + t_n + f_p + f_n} \quad (45)$$

True positive among positive is measured by the precision and calculated by

$$\frac{t_p}{t_p + f_p} \quad (46)$$

The comparative analysis for classification of the samples was shown in Table 5. It is table obviously depict the performance of planned classifier is very high contrast to obtainable state-of-art classifiers. The accuracy of proposed CP-LNN technique is very high compare to obtainable state-of-art classifiers. Not only accuracy, all other parameters are

higher than the existing classifiers. Fig. 18 show the graphical representation of planned and obtainable classifiers.

Table 5 Comparative analysis of data monitoring phase

S. No	Parameters (%)	SVM	KNN	DNN	CP-LNN
1	Accuracy	90.15	93.1	94.23	98.5
2	Sensitivity	90.39	92.5	93.5	97.3
3	Specificity	89.78	93.91	93.78	98.2
4	Precision	89.54	94.12	95.17	98.35
5	Recall	90.32	93.92	94.89	98.32
6	F-measure	91.12	92.39	96.18	97.49

Fig. 18 Performance comparison of classifiers

6. Conclusion

Background We have proposed a hybrid machine learning technique for IoT enabled industrial monitoring and control system (IoT-HML). The cat induced wheel optimization (IWO) algorithm was used for clustering which consists of cluster formation and CH selection process. The cuckoo search algorithm was utilized for the optimal best path

computation among multiple paths. A coach and player learned neural network (CP-LNN) is used for monitoring the industry and preventing accidents by basic control strategies. From simulation analysis, we proved the enhancement of proposed system over existing systems.

Statistical results For data gathering phase, the average delay of proposed C-IWO based routing protocol is 19.2% and 35% lower than the existing cluster and AODV routing protocols respectively. The average energy consumption of proposed C-IWO based routing protocol is 12.7% and 21% lower than the existing cluster and AODV routing protocols respectively. The average throughput of proposed C-IWO based routing protocol is 10.26% and 22.6% higher than the existing cluster and AODV routing protocols respectively. The average delivery ratio of proposed C-IWO based routing protocol is 3.8% and 7.33% higher than the existing cluster and AODV routing protocols respectively. The average loss ratio of proposed C-IWO based routing protocol is 16.33% and 3.9% lower than the existing cluster and AODV routing protocols respectively. For data monitoring phase, we proved the effectiveness of proposed CP-LNN classifier over existing state-of-art classifiers are SVM, KNN and DNN in terms of accuracy, precession, sensitivity, specificity, recall and F-measure.

References

1. Heterogeneous Applications, Tools, and Methodologies in the Car Manufacturing Industry Through an IoT Approach Hussein Khaleel
2. Kho, D.D., Lee, S. and Zhong, R.Y., 2018. Big data analytics for processing time analysis in an IoT-enabled manufacturing shop floor. *Procedia Manufacturing*, 26, pp.1411-1420.
3. Lu, Y. and Cecil, J., 2016. An Internet of Things (IoT)-based collaborative framework for advanced manufacturing. *The International Journal of Advanced Manufacturing Technology*, 84(5-8), pp.1141-1152.

4. Bandyopadhyay, D. and Sen, J., 2011. Internet of things: Applications and challenges in technology and standardization. *Wireless personal communications*, 58(1), pp.49-69.
5. Wu, Z., Meng, Z. and Gray, J., 2017. IoT-based techniques for online M2M-interactive itemized data registration and offline information traceability in a digital manufacturing system. *IEEE Transactions on Industrial Informatics*, 13(5), pp.2397-2405.
6. Lee, J., Kao, H.A. and Yang, S., 2014. Service innovation and smart analytics for industry 4.0 and big data environment. *Procedia Cirp*, 16(1), pp.3-8.
7. Wen, Y. and Li, Z., 2013. A service-integrated sensor network middleware applied to industrial solutions of IoT related. *Telecommunication Systems*, 53(1), pp.61-68.
8. Herrera, V.V., Ramos, A.V. and Lastra, J.L.M., 2012. An agent-based system for orchestration support of web service-enabled devices in discrete manufacturing systems. *Journal of Intelligent Manufacturing*, 23(6), pp.2681-2702.
9. Qu, T., Lei, S.P., Wang, Z.Z., Nie, D.X., Chen, X. and Huang, G.Q., 2016. IoT-based real-time production logistics synchronization system under smart cloud manufacturing. *The International Journal of Advanced Manufacturing Technology*, 84(1-4), pp.147-164.
10. Yanambaka, V.P., Mohanty, S.P. and Kougianos, E., 2017. Making use of semiconductor manufacturing process variations: FinFET-based physical unclonable functions for efficient security integration in the IoT. *Analog integrated circuits and signal processing*, 93(3), pp.429-441.
11. Chhetri, S.R., Faezi, S., Rashid, N. and Al Faruque, M.A., 2018. Manufacturing supply chain and product lifecycle security in the era of industry 4.0. *Journal of Hardware and Systems Security*, 2(1), pp.51-68.

12. Strandhagen, J.W., Alfnes, E., Strandhagen, J.O. and Vallandingham, L.R., 2017. The fit of Industry 4.0 applications in manufacturing logistics: a multiple case study. *Advances in Manufacturing*, 5(4), pp.344-358.
13. Wen, Z., Liu, X., Xu, Y. and Zou, J., 2016. A RESTful framework for Internet of things based on software defined network in modern manufacturing. *The International Journal of Advanced Manufacturing Technology*, 84(1-4), pp.361-369.
14. Lee, C.K.M., Zhang, S.Z. and Ng, K.K.H., 2017. Development of an industrial Internet of things suite for smart factory towards re-industrialization. *Advances in manufacturing*, 5(4), pp.335-343.
15. Zhong, R.Y., Xu, X., Klotz, E. and Newman, S.T., 2017. Intelligent manufacturing in the context of industry 4.0: a review. *Engineering*, 3(5), pp.616-630.
16. Thramboulidis, K. and Christoulakis, F., 2016. UML4IoT—A UML-based approach to exploit IoT in cyber-physical manufacturing systems. *Computers in Industry*, 82, pp.259-272.
17. Mourtzis, D., Vlachou, E. and Milas, N.J.P.C., 2016. Industrial Big Data as a result of IoT adoption in manufacturing. *Procedia cirp*, 55, pp.290-295.
18. Zhong, R.Y., Wang, L. and Xu, X., 2017. An IoT-enabled real-time machine status monitoring approach for cloud manufacturing. *Procedia CIRP*, 63, pp.709-714.
19. Chien, C.F., Hong, T.Y. and Guo, H.Z., 2017. A conceptual framework for “Industry 3.5” to empower intelligent manufacturing and case studies. *Procedia Manufacturing*, 11, pp.2009-2017.
20. Thames, L. and Schaefer, D., 2016. Software-defined cloud manufacturing for industry 4.0. *Procedia cirp*, 52, pp.12-17.

21. Lin, Y.J., Tan, C.F. and Huang, C.Y., 2019. Integration of Logic Controller with IoT to Form a Manufacturing Edge Computing Environment: A Premise. *Procedia Manufacturing*, 39, pp.398-405.
22. Cohen, Y., Faccio, M., Pilati, F. and Yao, X., 2019. Design and management of digital manufacturing and assembly systems in the Industry 4.0 era.
23. Chen, Y.Q., Zhou, B., Zhang, M. and Chen, C.M., 2020. Using IoT technology for computer-integrated manufacturing systems in the semiconductor industry. *Applied Soft Computing*, 89, p.106065.
24. Hirman, M., Benesova, A., Sima, K., Steiner, F. and Tupa, J., 2020. Design, Fabrication and Risk Assessment of IoT Unit for Products Manufactured in Industry 4.0 Factory. *Procedia Manufacturing*, 51, pp.1178-1183.
25. Srinivasan, M., Prince, E. and Padmanabhan, R., 2020. IoT architecture for advanced manufacturing technologies. *Materials Today: Proceedings*, 22, pp.2359-2365.
26. Camatti, J.A., Rabelo, G.M., Borsato, M. and Pellicciari, M., 2020. Comparative study of open IoT architectures with TOGAF for industry implementation. *Procedia Manufacturing*, 51, pp.1132-1137.
27. Yang, C., Peng, T., Lan, S., Shen, W. and Wang, L., 2020. Towards IoT-enabled dynamic service optimal selection in multiple manufacturing clouds. *Journal of Manufacturing Systems*, 56, pp.213-226.
28. Gnoni, M.G., Bragatto, P.A., Milazzo, M.F. and Setola, R., 2020. Integrating IoT technologies for an “intelligent” safety management in the process industry. *Procedia Manufacturing*, 42, pp.511-515.
29. Li, B., Chen, R.S. and Liu, C.Y., 2020. Using intelligent technology and real-time feedback algorithm to improve manufacturing process in IoT semiconductor industry. *The Journal of Supercomputing*, pp.1-20.

30. Wang, Y., 2020. Industrial Structure Technology Upgrade Based on 5G Network Service and IoT Intelligent Manufacturing. *Microprocessors and Microsystems*, p.103696.
31. Wang, C., 2019. IoT anomaly detection method in intelligent manufacturing industry based on trusted evaluation. *The International Journal of Advanced Manufacturing Technology*, pp.1-13.

Figures

Figure 1

System model of proposed IoT-HML system

Figure 2

working function of coach and player learning model

Figure 3

Delay comparison with nodes

Figure 4

Energy consumption comparison with nodes

Figure 5

Throughput comparison with nodes

Figure 6

Delivery ratio comparison with nodes

Figure 7

Loss ratio comparison with nodes

Figure 8

Delay comparison with bad nodes

Figure 9

Energy consumption comparison with bad nodes

Figure 10

Throughput comparison with bad nodes

Figure 11

Delivery ratio comparison with bad nodes

Figure 12

Loss ratio comparison with bad nodes

Figure 13

Delay comparison with nodes

Figure 14

Energy consumption comparison with nodes

Figure 15

Throughput comparison with nodes

Figure 16

Delivery ratio comparison with nodes

Figure 17

Loss ratio comparison with nodes

Figure 18

Performance comparison of classifiers