Internet of Things-Enabled Logistic Warehouse Scheduling Management With Human Machine Assistance

Ziwen Zhang, Tianjin Bohai Vocational Technical College, China*

ABSTRACT

Logistics management is part of the supply chain management process to meet consumer requirements. In most instances, consumers find it challenging to identify the product, as they have to start it manually due to time-consuming storage rooms. This paper has suggested the IoT-assisted human-machine interface (IoT-HCI) framework as a logistic warehouse management system. A warehouse management framework is designed to eliminate this issue and immediately release updates and inform people about the operations. The proposed method demonstrates the aspects and the exact methodology of the product manufacturing and distribution. This system is developed through the internet of things, which can continuously enable communication between the management layers. Warehouses are the units for the transport and storing goods and items before they are shipped from the location. In most situations, there are no mixed environments in which automated systems and humans interact.

KEYWORDS

Human-Machine Interface, IoT, Logistics, Warehouse Scheduling Management

INTRODUCTION

Changing environment appears to affect the value of economic challenges in digitalization: social population transitions, urbanization, globalization, safety, and ecological advances are scarce in capital, Industries 4.0 (Zhu et al.2018; Abosuliman et al.2021). Company projects have to consider social, environmental, and economic changes in realizing their goals and procedures to ensure positive progress through this shift (Molano et al.2018). It gives businesses a significant obstacle to satisfy the associated needs (Raza et al.2020). The social and cultural drivers of Industry 4.0 are essential to evaluate in this sense.

A summary of the existing automotive situation can explain all aspects of the issue, a digression into the historical perception of manufacturing and workforce innovations (Su et al.2021). The word Industries 4.0 was invented in Germany. In Industries 4.0, the relevance of existing logistics is based on the traditional understanding of logistics (Shah et al.2020; Jiang et al.2017). Technological innovations which affect the operations of the organization during the computerization period are introduced. The main logistical aspects are primarily focused on the tactical viewpoint (Hu et al.2020). New subsequent conditions for logistics emerge during the digital era (Manogaran et al.2020).

From the perspective of the main elements, a modern strategy presents the following logistics conditions under Industries 4.0 (Sathishkumar et al.2020). Increased deployment of the self-sufficient networks leads to a debate about reducing the internal logistics of many work (Gao et al.2020). In
this sense, the emphasis is on improvements in the individual work atmosphere and interventions to
overcome the difficulties of digitalization (Manogaran et al. 2020). The role of people in the upcoming
industrial work world is essential to research (Masud et al. 2021).

As a result of technical, social, and business developments in the global economies (Nguyen et
al. 2021). The story of growth and delivery has moved from programming activities to the extent to
which machine operators and robots operate independently using artificial intelligence (AI) systems
and growing consumer requirements for cost efficiency, sustainability, fastness, and tailor-money
solutions (Sutrula et al. 2021). Human-computer interaction’s potential nature and efficiency (HCI)
is a critical issue accompanying these innovations (Manogaran et al. 2021).

In history, robots and people were mainly segregated in the fields of manufacture and distribution.
The functions were evident in cases of collaboration such as driving trucks and manufacture, and
human employees have carried out the mechanical activities of manufacturing in management and
decision-making, machinery, and robotics. As optimization reaches a new stage in AI implementations,
this situation is evolving (Ahmed et al. 2021; Taheri et al. 2020). Through manual interference, robots,
computers, and instruments such as tanks or transport machinery can take increasingly sophisticated
judgments while supervising and monitoring the existing labor (Zeb et al. 2020).

The criteria for human qualifications would transition in a ‘understand’ domain to collaboration
with the implementation of artificial intelligence (Chekired et al. 2018): In case of possible danger or
unexpected shifting circumstances, people must acknowledge and resolve to overwrite and interrupt
automatic processes.

The contributions of this article are:

1) For IoT request planning and data analysis, a decentralized multi-tier framework is developed.
The design depends on the server implementation in the cloud environment.
2) Stochastic model for comparing the utility of fog services between flattened and centralized fog.
The decentralized fog framework has a better processing performance to minimize computational
and communication losses is proved.
3) The proposed scheduling paradigm for the planning of IoT data is implemented. IoT applications
are separated into two importance ranges (high and low); It gives high-importance applications
(e.g., emergency applications).

The rest of the research work is as follows. Section 2 deals with the background and the literature
on logistics and IoT. The proposed IoT-assisted human-machine interface (IoT-HCI) framework is
designed and implemented in section 3, and the software analysis and performance evaluation are
illustrated in section 4. The conclusion and future scope are discussed in section 5.

BACKGROUND TO LOGISTICS AND IOT

Logistic effects are significant in the 4th phase of industrialization. Logistics is affected by both
ability and limitation as a cross-cutting function (Zhou et al. 2021). Many literature reviews and
articles address the link between transportation and industrial production. Ding et al. explain the
direct impact on logistics of Industry 4.0 drivers, including state-of-the-art innovations, environmental
problems, and individual consumer models (Ding et al. 2020). It demonstrates a growing strength of
teamwork and team management. Industry 4.0 has been defined, and its requirement about the issue
of complexity is arising.

In addition to these limitations, prove that the emphasis is adapting technical compounds of
Industry 4.0 as Cyber-Physical Structures and the Internet of Things and Structures as necessary
(Thürer et al. 2019). It demonstrates that its function develops into an innovative decision-maker
capable of interacting and collaborating with IoT-HCI and the intellectual community. The primary
roles of logistics are discussed in several journals. It contains the evolution from the 4 R logistical variables to the 8 R logistical variables (Bhatia et al. 2020). Any adjustment takes into account future specifications and patterns. And without consistency, the use of IoT in industrial optimization is minimal. Industrial computerization IoT applications continue to evolve. As already stated, fog-based strategies can satisfy the current industrial system architecture. The most recent work focuses on centralized computing systems that use cloud technology for data management and industrial optimization control processing. In the framework of cloud technology in industrial automation, the plurality of established technologies and applications concentrate on elevated amounts than in the ground (Lyu et al. 2020).

The scholars study a prototype for IoT sensors to interface with a production field cloud-based system (Qing et al. 2018). This research covers the mitigating tools to cope only lessen the losses in interaction induced by the infrastructure and overlook computational limitations and cloud storage capabilities. By integrating computation with AI, the investigators accurately represent the success of IoT (Golpîra et al. 2021). They create an effective way to achieve a limit by comparing the efficiency of various computation methods to show how they can be applied to functional IoT implementations (Leithon et al. 2019). The quality assessment part equates the computing effectiveness of the research with this. The participants ignore data delays and syncing time, mainly if computers are looped (Lu et al. 2020).

The decentralized computing function only takes into account a few parts. Instead of transmitting some data to a centralized server, the study proposes an Edge Grid computing methodology that dispenses decision-making tasks among these endpoints (Lam et al. 2019). Edge Grid has many advantages, such as a localized treatment, low latency, and failure resistance. In the centralized network, the participants neglect the task allocation issue (Du et al. 2019). A recent study has addressed the concept of decentralized IoT data management of fog and cloud technology. The articles talk about the current problems of information processing dimensions in IoT (Tsang et al. 2021). By combining fog processing and cloud technology, a modular platform is designed. The data obtained is analyzed and maintained by the endpoint or the cloud service based on time delay specifications (Yang et al. 2020). The results assessment portion equates the findings with these two (Wang et al. 2020). This article discusses problems to reduce connectivity and data collection delays in the intelligent factory of object systems. Fog databases are structured into a layered structure to meet the requirements for industrial items and interpret real-time information.

The goal is to optimally combine and unload the IoT load demand that surpasses lower fog server capabilities on higher levels on other databases. It distributes the supplies on high-level servers to plan the downloaded workloads. The approach can manage vast quantities of demands for IoT products and data from various factory hardware elements. The research is one of the first efforts to develop and further enhance its success by reducing fluctuations in communication with a modern centralized Fog Server model for IoT environments.

**PROPOSED IOT-ASSISTED HUMAN-MACHINE INTERFACE (IOT-HCI) FRAMEWORK**

**Architecture**

The architecture system combined cyberspace program elements and physical IoT computers. It is necessary to think about IoT installation. Businesses must consider the cost of integration and the security and scalability of IoT devices within their present inventory management system. Cyber-attacks on the supply chain can have disastrous consequences for all parties involved. As a result, logistics companies must invest in methods to protect sensitive data and information. Employees should be informed about the risks of opening questionable emails and clicking on unknown URLs, links, and attachments. Preventing employees from downloading unapproved software and apps is best
practice. In the proposed method, the intellectual IoT edge computation device (iNode) is equivalent to an intelligent design, which works on a network edge system from fog-abled networking technology.

Fog computing extends cloud computing to the network’s edge, allowing for better resource usage and performance in latency, bandwidth, and energy consumption. Fog computing is not a replacement for cloud computing, but it does allow for data storage and processing at the network’s edge and connection with cloud data centers. Fog computing is a promising technique for various applications that require real-time processing yet have high latency. The use of fog computing in logistics systems is investigated in this research. The advantages of deploying fog computing in an intelligent logistics center are examined. The link and transfer can refer to the data capture and preprocessing methods like RFID or sensors middling in the iNode and enterprise-integration system and sales knowledge gathering system in the Cloud utilizing a 3 Tier framework on cognitive collection and software development facets of Cloud-based Production System (IoT-HCI). Cloud computing is a new enabling technology that provides centralized processing, adaptable storage systems, and extensible services. It is feasible to use cloud computing technology to integrate and supply industrial resources and competencies in cloud services in the manufacturing setting. This work aims to design a function IoT-HCI mechanism to connect multiple types of performance equipment. A cloud-based infrastructure is used to provide a service pool that keeps these resources operational.

For the Cloud-based production system, the suggested solution offers a transparent and interconnected media environment. The 3 Tier cyber level is identical to the iNode logic system, and the automation element of the 3 Tier configuration levels is the same as the iNode steering System. The 3 Tier group includes most functionality systems in the IoT cloud. The current architecture model of IoT-HCI in an Industrial 4.0 sense reflects many software systems in the iNode. Most hardware devices in the device remain unchanged. The reliability of the services is likely the most significant reason why manufacturers would appeal to the clouds. Manufacturers can prepare themselves for full-scale production by combining product management and building information with supply chain data and communications. Products can progress from idea to engineering to prototype to small production to full-scale manufacture and shipment faster with comprehensive integration. Furthermore, by facilitating communication throughout the supply chain, these software systems ensure that firms have enough raw materials on hand and easily adjust orders to fit their future productivity levels.

Figure 1. The architecture of the iNode
Fig. 1 shows the architecture of the iNode. The iNode has a reasoning module, control module, and middleware to interface with the vision module; the embedded database is used to store the knowledge database can access it. PLC and sensor middleware is used to manage the control module. The entire modules are controls the communication module.

The suggested system uses Ultra High Frequency (UHF) RFID as the principal IoT infrastructure. A static UHF RFID tags, UHF printers fixed & hand-held scanner, robotics, conveyor systems, human-machine interface (HMI), and intelligent IoT nodes are included IoT-based PL scheme. It consists of the management and configuration of manufacturing machinery and the above-listed items with IoT. The iNode also can be addressed later in the IoT-HCI. An active RFID tag may be explicitly inserted into a framework for Tbike or a system that has been installed on the base, or in a locking brace connected to the chassis, based on Tbike selling prices.

During the startup period, consumer and output information can be submitted to the storage of the RFID system based on Tbike’s label encryption algorithm. The IoT technologies used the label and encryption of objects, non-line-of-sight processes, transparency in real-time and quality control, and decentralized offline storage. This functionality can make market and product designs based on IoT easier, as explained below:

- Mass customization: An electric bike with various modifications and component choices can be ordered by each user. The unique production requirements which be entered in the database of each consumer’s RFID tag. The RFID reader can read and manipulate each unique manufacturing process embedded in the marked work material. The IoT system allows Tbike to customize the integrated manufacturing line for each vehicle in large quantities.

- Decentralized processing: IoT is an entirely decentralized platform, where each iNode controls its actions in the performance of development tasks. As the manufacturing performance can be represented in the RFID system at the initiation point, iNode can select and perform the exact development process, without linking to the database or the cloud infrastructure, based on the integrated label information on the manufacturing line. The dispersed offline computational power of the IoT framework allows the distribution system to be more stable. A single loss spot can be avoided, and expanded production methods and properly formulated manufacturing plants can be quickly reduced.

- Prevention of theft: If the RFID is incorporated into a bike framework, it is much easier to quickly identify and restore a damaged or stolen bike to the holder. It could minimize bike robbery and improve the likelihood of robbed bikes restoration.

- Check and confirm after selling: The RFID tag inserted on each bike enables the motorcycle stores to conveniently analyze the information stored in the label to verify the guarantee without collecting data from anywhere.

- Control of lifecycle: RFID facilitates both read and printing labeled electric bikes product placement details and provides data on after-sales services such as servicing or maintenance keys. Such time progress can also be changed if appropriate in the IoT cloud framework. Every bicycle should use IoT development to provide the consumer life cycle details that can be used in various phases of the material life process to help and improve customer experience.
Fig. 2 shows the IoT architecture of the proposed IoT-assisted human-machine interface (IoT-HCI) framework. It contains many units such as HMI, wireless sensor network, conveyer, robot, UHF RFID tag, an RFID reader. The vision sensor unit is used to sense and control the logistic device. The physical world includes three types of objects listed below in the suggested IoT-HCI architectural design:

1. Tagged items: Completed material and components can be used as tagged items. Like a 2D QR code, many marking technologies, High-Frequency RFID, Ultra High-Frequency RFID, etc., are available. Even so, only Ultra High-Frequency RFID is evaluated in this study.
2. IoT gadgets: RFID tags, vision monitors, iNodes, and different sensor categories are known to be part of the IoT family to collect system or atmosphere information.
3. Production-related devices and facilities: standard factories such as Machine parts, robotic arms, conveyor belts, and Human-Machine Interfaces (HMI) are devices. The suggested scheme of IoT-HCI design comprises the iNode and IoT cloud distributed device.

Figure 3. Big data architecture of the proposed IoT-assisted human-machine interface (IoT-HCI) framework
Fig. 3 shows the big data architecture of the proposed IoT-assisted human-machine interface (IoT-HCI) framework. In logistics, big data may be utilized to eliminate inefficiencies in last-mile delivery, increase supply chain transparency, optimize deliveries, safeguard perishable items, and automate the entire process. The Internet of Things enables the connecting of components in multiple locations, allowing for effectively processing containers, trucks, and ships in numerous ports. All devices at the port are connected, allowing for data mining and integration and full visibility of all regions of the port. It contains big data storage, analytics tools, shop floor data capturing modules, iNode management modules, enterprise data integration modules, and digital product counterparts. The process of automatically detecting and gathering information concerning objects/goods, subsequently logging that data in a computer, is known as automated identification and data capture (AIDC). AIDC is a term that refers to a variety of data collection devices. Barcodes, fingerprinting, RFID, electromagnetic stripes, mobile payments, OCR, and voice commands are examples of these technologies. Retail, warehouses, transportation & transportation, and field service are just a few industries where AIDC devices are used. Because of RFID’s capacity to track moving objects, it has now been used in various applications, including AVI systems.

An iNode is a metadata structure that contains any Linux file data save its details and information. The node is a special disc block produced by the creation of the file system. Inode numbers restrict the number of total files/directories kept within the file system. Inode number The effective implementation of the concept to provide safe warehouse management through intelligent product responsiveness against major hazards. An HMI can be combined with an iNode to enable human-machine collaboration and for Touchscreen User Interface implementations. An independent entity iNode can transform different sensor information for helpful information from RFID, sight, etc., to available sensor information. Activity precise management over a workspace or development cell with industrial robots is monitored to demonstrate the features of endpoint knowledge in the suggested IoT-HCI system.

The iNode also communicates in various operative politics and environmental modifications with its neighboring iNodes to manage output activities and demonstrate the flexible control capacity of iNode. IoT cloud continually tracks iNodes operations, gathers and saves information from iNodes, analyses content, changes market rules or controls iNodes logics. At the correct period, the IoT Platform can also include administration consoles to allow iNode configuration by the systems engineer. The suggested architectural structure for the IoT-HCI system comprises two sections. The first section of the model is the iNode integrated model and the second section is the IoT network. Below are the components of each element:

**Smart IoT Node (Inode)**

iNode’s device framework adopts the development agent model and includes the following components.

1. **iNode Device**: The logic module collects operating information from the iNode control unit and mission-specific notifications from the nearby iNodes and IoT Network. On that basis, iNode knows the actual physical state and selects the next target to serve due to environmental adjustments.

2. **Controller Module iNode**: The controller captures logic module commands, gathers and transforms physical information from the device via RFID, View module, Programmable Logic Circuit (PLC), and detector middleware. The central controller picks available projects from the iNode expert system based on operating information and market rules and performs the controller encoded in a schedule. These plans describe a formula for output or some other activity in connection with a procedure.

3. **RFID Module**: When the flux density for the RFID transmitter identifies significant artifacts, it can collect the Radio waves from active RFID tags from an RFID scanner. These indicators may describe entity IDs to render these data and information by filtering RFID interfaces. RFID
Middleware can also translate original filtered details to object sensor information, such as event logs, compared to the event ID, storage, period, and market contextual information. RFID results are dealt with differently from other detectors, such as movement or temperature sensors, as RFID data, including network data, when other sensory data is useless.

(4) **Vision Module**: Several production companies use various camera types to conduct video surveillance immediately on the manufacturing line, mainly to increase quality command and oversight. The device should be incorporated video analytical processing. Video surveillance can translate Camera footage and transform information into organizational metadata for contextualized events. Tbike can suggest video analysis in the painting to check the performance of the artwork of its bike frames.

(5) **PLC And Device Server Software**: The IoT-HCI architecture not only implies that the iNode communications and connectivity with the PLC and processor wired or wireless sensing devices are essential for the iNode’s web services. A system to translate basic PLC/sensor information into organizational metadata must contain PLC and detector software.

(6) **iNode Information Database**: iNode database stores company rules and control theory. Various control frameworks are organized into functional schedules, which describe formulas or activities of development.

(7) **Integrated Repository**: As iNode can run in an offline computing state, an integrated dataset is needed to support transient caching data within the system. The stored information can be exported to IoT servers and cloud-based processing.

**IoT Cloud**

(1) **Floor Data Capture Module Factory**: The floor information gathering system is closely linked to a sensing device. The production Logistic (PL) scheme is configured to monitor and manage components and is captured and stored in the massive processing system within our network. Any of this information can be processed either in the Cloud environment or specifically in the MES repository. It is recommended that most sensor information in the picture, from RFID and the notice period, is saved in the IoT platform distributed databases.

(2) **Stored Data**: IoT distributed storage processing can provide organized (such as SQL) and unorganized information. The existing major database infrastructure supports SQL and NoSQL data collection, Oculus data warehouses, and the repository is logically split into two classes. The digital product conserves life cycle data, including output pedigrees, for each produced bike. Data recorded in the RFID system must be synchronized with a device’s digital equivalent within a specific time. The other files, including database, sensor readings, and transactions, are stored in ample information storage.

(3) **Big Data Research Tool**: Big data analytics is carried out offline in the system. Various proprietary applications for computational, data gathering or open-source computing may be seen as platforms for big data analytics. Big information processing offline produces new insights, transforming them into company rules and command logics and updating the iNodes.

(4) **iNode Control Device**: This system gave a device setup iNode Control Controller, market rules, iNode control, and upgrading iNodes’ information. This module allows output procedures to be transferred to an iNode database.

(5) **Business Data Management Module**: This device is intended to integrate PL company information technology. The device utilizes techniques to conduct a two-fold data processing between company structures and the IoT-HCI. PL is synonymous with Industry resources management (IRM), consumer relationships maintenance (CRM), marketing execution scheme (MES), and supplier chains maintenance (SCM).
Model Preference Queuing Algorithm For Iot Data Planning

A range of cloud structures or data centers is considered, in which each data center contains spatially distributed processors. These databases manage the planning and measurement data from various items built in the industrial plant. Data, demands, and data from diverse industries and the sensors, such as disaster applications, are of different significance. High-priority requests must be efficiently planned and analyzed. By the basic assumption, it defines the queuing scheme to enhance.

Assumption 1: Input is data periods in each category are independent of each other, and probability distributions are standard errors. The source comprises the overlap of these groups of two separate renewal systems. It must be remembered that it is not a renewal mechanism for the entire inputs of IoT data irrespective of their category.

Assumption 2: Each fog level contains s databases. The schedule periods of IoT applications are randomly initialized, that each other is different. Their allocation is identical for applications of the same category, although it differs from other varieties.

Assumption 3 (Queue Restraint): 0 for lower importance categories and 1 for higher importance categories are three sets. A class 1 order is served before a class 0 client. The starting point first comes with each type and is made with precautionary training. The category 0 query concern is returned to the top end of its category’ queues in the pre-emptive situation and waiting until the freshly submitted category 1 application is accepted.

The priority and data rate for entering and departure packets in the First-In-First-Out (FIFO) queue is expressed in Equations (1) and (2)

\[ \lambda = \lambda_1 + \lambda_0 \]  \hspace{1cm} (1)

\[ \mu = \mu_1 + \mu_0 \]  \hspace{1cm} (2)

Where \( \lambda_1 \) and \( \mu_1 \) have top importance, the rates of entry and the operating time \( \lambda_0 \) and \( \mu_0 \) are the low importance arrival and operation levels of request. IoT queries can put in separate server stacks, with two high- and low-priority resources when it arrives. The processing rate of the entering and the departure of iNode are expressed in Equation (3)

\[ \rho_i = \frac{\lambda_1}{\mu}, \quad \rho_o = \frac{\lambda_0}{\mu}, \quad \text{and} \quad \rho = \rho_i + \rho_o \]  \hspace{1cm} (3)

The processing rate of the entering and the departure of iNode are expressed as \( \rho_i \) and \( \rho_o \). As a simulation process, the expected norm of queuing up is described in the structure definition utilizing Markov chains. Each condition in the Markov process correlates to IoT applications in the two stacks. That condition changes occur as new IoT applications are made and IoT applications are served.

The model takes two scenarios into account: when the amount of awaiting queries, defined by \( r \), is \( r < s \) in each cloud tier and \( s \) is the database number, then the total completion percentage is \( r \mu \). The next is the level of demand \( r \geq s \) to wait for the whole server, meaning that the entire \( s \mu \) is busy. Using a reciprocal illustration, it can acquire the general steady process status to differentiate between \( r \mu \) and \( r \) accordingly.
If $r < s$, the expression of the steady-state process $\pi_r$ is expressed in Equation (4)

$$\pi_r = \pi_0 \left( \frac{\lambda + \lambda_0}{\mu} \right)^2 \frac{1}{r!}$$

(4)

$\lambda$ and $\lambda_0$ are denoted the arrival rate of the request and the delivery of the iNode. The priority of the received packet is represented as $\mu$. The reciprocal of the importance of the pack is denoted as $r$. The initial steady-state process is described as $\pi_0$.

Figure 4. Pictorial representation of $\pi_r$

Fig. 4 shows the pictorial representation of $\pi_r$. Where the arrival rate of the demand and the delivery of the proposed system are denoted as $\lambda$ and $\lambda_0$. The reciprocal of the arrival rate is denoted as $r$. The initial state of the common process is represented as $\pi_0$.

If $r > s$, the steady-state process is expressed in Equation (5)

$$\pi_r = \pi_0 \left( \frac{\lambda + \lambda_0}{\mu} \right)^2 \frac{1}{s!s^{r-n}}$$

(5)

The incoming and the outgoing data packets are denoted as $\lambda$ and $\lambda_0$. The $\mu$ is denoted as the priority of the data packet processed. The serviced packages are marked as $s$. $r$ is the remaining packets in the stream, and the $n$ is denoted as the number of packets processed in the system per time. $\pi_0$ is denoted as the steady-state response of the proposed system.

The condition of complete task is expressed in Equation (6):
\[
\pi_0 = \left[ \sum_{r=1}^{s-1} \left( \frac{\rho_H + \rho_L}{r!} \right)^s + \left( \frac{\rho_H + \rho_L}{s!} \right)^s \frac{1}{s!} s^{r-n} \right]^{-1}
\]

The higher rate and the lower rate of the arrival of packets are denoted as \( \rho_H \) and \( \rho_L \). The remaining packet is denoted as \( r \), and the serviced data are represented as \( s \). We describe the average time of expectations (low \( E(W_0) \)) and (high \( E(W_1) \)) are expressed in Equations (7) and (8)

\[
E(W_0) = \frac{\lambda_0}{\mu_0} + \frac{\lambda_1}{\mu_1} \frac{\mu_0^2 - \mu_1^2}{(1 - \rho_1)(1 - \rho_0 - \rho_1)}
\]

\[
E(W_1) = \frac{\rho_1}{(1 - \rho_1)\mu_1}
\]

The arrival rate, the priority, and the processing rate of the request and service are denoted as \( \lambda_0, \lambda_1, \mu_0, \mu_1, \rho_0, \rho_1 \). The weight of the input and output architecture is denoted as \( W_0 \) and \( W_1 \).

**Logistic Collaboration (Human-Computer Interface)**

Three barriers or resistance zones may describe human engagement with artificial intelligence systems and optimization. The three barriers reflect a growing yet transient opposition following the ever-increasing frequency of direct intrusions in the three practical regions of AI (x-axis).

1. **AI Competency**: Optimization and AI systems acquire skills in particular areas, from juggling industry sales forecasts. There are modern skills that humans become used to and are generally less scary, so the emergence of opposition to them is considerably lower. Logistics may involve automatic commercial truck gearboxes, automated tracking and navigating networks, and automated intra-logistics solutions such as order collection and storage solutions. These may include logistics technologies. They both have any final judgment, such as walking streets, which humans still make. AI advice from communication systems is not practice, an evident indication of opposition or better intelligence.

2. **AI Judgments**: AI implementations recommend and execute individual decisions that typically increase fear and resistance to people. It can discern three distinct phases for vehicle steering wheel implementations: retaining steady velocity, keeping distance from the front driver, and finally changing the speed according to the expected field characteristics.

3. **AI Independence**: AI systems make a host of diverse choices, such as conducting vehicles for longer stretches effectively and in contact with other motorists. Individualism: These technologies are at the gateway to commercial and worldwide technologies and in the development of robotics that moves independently, interacting with people, traffic, and wellbeing. These degrees or obstacles are shown in the sequence of human interference, which reaches a new condition after three difficult places: a state of confidence about an AI technology where human beings are likely to collaborate effectively and confidence in automatic systems.
SOFTWARE ANALYSIS AND PERFORMANCE EVALUATION

System Parameters
VMs are used as cloud servers for several VirtualBox; each VM has a 1.48 GHz CPU and 4 GB RAM capabilities. The networking devices are implemented using NS-2. 3 Tier cloud databases are obtained in the tests, commercial IoT activities, datasets, and the studies are performed in various hierarchical fog environments with multiple configurations and computing capacities. Cloud processors are linked through a network connection of 120Mbps. In terms of CPU times per second, a limit of 22 GHz of computing capacities is given. Any network topology VM runs MATLAB to operate all the architectures suggested.

Figure 5. (a) Buffer inventory level analysis of the proposed system with load capacity = 2

![Buffer inventory level analysis of the proposed system with load capacity = 2](image)

Figure 5. (b) Buffer inventory level analysis of the proposed system with load capacity = 5

![Buffer inventory level analysis of the proposed system with load capacity = 5](image)

Fig. 5(a) and 5(b) show the buffer inventory level analysis of the proposed IoT-assisted human-machine interface (IoT-HCI) framework with load capacity as 2, 5, respectively. The epoch time is varied from 0 to 20 minutes for the simulation analysis. The respective buffer usage is monitored and plotted in the above figures. The results show that variations in the buffer utilization concerning time. The proposed IoT-assisted human-machine interface (IoT-HCI) framework performs well all the time.
Table 1 shows the task analysis of the proposed IoT-assisted human-machine interface (IoT-HCI) framework. The task of the proposed system varied from 10 to 90 functions per second. The respect performance in each system is monitored, and their energy utilization percentage is analyzed and tabulated in the above table. The results show that all three-tier systems work well in all scenarios with lower energy utilization. The 3 tier system utilizes the lowest energy than the other two tiers.

<table>
<thead>
<tr>
<th>Tasks (tasks per 10 sec)</th>
<th>1 tier</th>
<th>2 tier</th>
<th>3 tier</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>24</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30</td>
<td>68</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>40</td>
<td>84</td>
<td>43</td>
<td>0</td>
</tr>
<tr>
<td>50</td>
<td>57</td>
<td>61</td>
<td>28</td>
</tr>
<tr>
<td>60</td>
<td>42</td>
<td>79</td>
<td>68</td>
</tr>
<tr>
<td>70</td>
<td>37</td>
<td>59</td>
<td>81</td>
</tr>
<tr>
<td>80</td>
<td>52</td>
<td>36</td>
<td>63</td>
</tr>
<tr>
<td>90</td>
<td>52</td>
<td>41</td>
<td>58</td>
</tr>
</tbody>
</table>

Table 1 shows the task analysis of the proposed IoT-assisted human-machine interface (IoT-HCI) framework. The task of the proposed system varied from 10 to 90 functions per second. The respect performance in each system is monitored, and their energy utilization percentage is analyzed and tabulated in the above table. The results show that all three-tier systems work well in all scenarios with lower energy utilization. The 3 tier system utilizes the lowest energy than the other two tiers.

Figure 6. (a) Computation time analysis of the proposed system with load capacity =2

![Figure 6. (a) Computation time analysis of the proposed system with load capacity =2](image)

Figure 6. (b) Computation time analysis of the proposed system with load capacity =5

![Figure 6. (b) Computation time analysis of the proposed system with load capacity =5](image)
Fig. 6(a) and 6(b) show the computation analysis of the proposed IoT-assisted human-machine interface (IoT-HCI) framework with load capacity as 2, 5, respectively. The workload of the system is varied from 1 to 5 demands per second for the software analysis. The computation time required for both loads is analyzed, and the measured time is plotted in the above figures. As the workload increases, the computation time for all three tiers is increased. Even the proposed system produces very low computations time for all the cases.

Table 2. Performance analysis of the proposed IoT-assisted human-machine interface (IoT-HCI) framework

<table>
<thead>
<tr>
<th>Time slot (sec)</th>
<th>Priority-based accuracy (%)</th>
<th>Content-based accuracy (%)</th>
<th>Packet-based accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>97.2</td>
<td>94.3</td>
<td>84.8</td>
</tr>
<tr>
<td>10</td>
<td>98.6</td>
<td>88.7</td>
<td>85.6</td>
</tr>
<tr>
<td>15</td>
<td>95.2</td>
<td>94.5</td>
<td>89.1</td>
</tr>
<tr>
<td>20</td>
<td>94.5</td>
<td>97.6</td>
<td>91.8</td>
</tr>
<tr>
<td>25</td>
<td>94.2</td>
<td>93.7</td>
<td>85.1</td>
</tr>
<tr>
<td>30</td>
<td>94.8</td>
<td>91.6</td>
<td>86.8</td>
</tr>
<tr>
<td>35</td>
<td>95.1</td>
<td>94.6</td>
<td>84.9</td>
</tr>
<tr>
<td>40</td>
<td>95.3</td>
<td>91.7</td>
<td>87.6</td>
</tr>
<tr>
<td>45</td>
<td>95.6</td>
<td>97.6</td>
<td>90.1</td>
</tr>
<tr>
<td>50</td>
<td>94.8</td>
<td>95.1</td>
<td>92.8</td>
</tr>
</tbody>
</table>

Table 2 shows the performance analysis of the proposed IoT-assisted human-machine interface (IoT-HCI) framework. The time slow of the proposed system is varied from 5 seconds to 50 seconds for the software analysis. The system’s performance is analyzed for priority, content, and packet levels, and the result is tabulated in the above table. The system’s respective accuracy (%) shows the effectiveness of the proposed IoT-assisted human-machine interface (IoT-HCI) framework.

Figure 7. (a) Average end to end delay analysis of the proposed system with load capacity = 2
Fig. 7(a) and 7(b) show the average end-to-end delay analysis of the proposed IoT-assisted human-machine interface (IoT-HCI) framework with a load capacity of 2, 5, respectively. The three-tier system is analyzed, and their respective end-to-end delay for the variations in the average computations per task (Giga cycles) are evaluated. The outcome is plotted in the above figures. The results show that the proposed IoT-assisted human-machine interface (IoT-HCI) framework has the highest performance in all computations and all the system’s three tiers.

The proposed IoT-assisted human-machine interface (IoT-HCI) framework is designed and implemented. The simulation outcomes, such as average end-to-end delay, accuracy, computation time, buffer inventory level, task utilization, etc., are analyzed. The proposed IoT-assisted human-machine interface (IoT-HCI) framework exhibits very high results in all situations and parameters.

**CONCLUSION AND FINDINGS**

This article suggests an optimized cloud framework for industrialized Internet implementation and presents an IoT-assisted human-machine interface (IoT-HCI) framework to the data analysis scheduling scheme. It is focused on the performance of multilevel databases on the fog layer. It created the ideal workload optimization using combined numerical software to plan various industrial system demands in real-time effectively. The simulated queueing algorithm aggregates the optimum solution to multiple levels. The approach suggested has shown the exact manufacturing and delivery dimensions and methodology of the goods. This method is built via the internet to enable collaboration between the administration layers constantly. This warehouse control approach is proposed to ensure that all of the warehouse’s products are sensitized in real-time, speeded up, and performance improvements and stock shortages are avoided.

**FUNDING AGENCY**

This research received no specific grant from any funding body in the public, commercial, or not-for-profit sectors.
REFERENCES


