IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 2 February 2023, accepted 12 March 2023, date of publication 16 March 2023, date of current version 24 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3258407

RESEARCH ARTICLE

Smart Decision-Making and Communication Strategy in Industrial Internet of Things

KESAVAN GUNASEKARAN[1], V. VINOTH KUMAR[2], A. C. KALADEVI[3], T. R. MAHESH[4], C. ROHITH BHAT[5], AND KRISHNAMOORTHY VENKATESAN[6]

[1]Department of Electronics and Communication Engineering, Siddartha Institute of Science and Technology, Puttur, Andhra Pradesh 517581, India
[2]School of Information Technology and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu 632014, India
[3]Department of Computer Science and Engineering, Sona College of Technology & Saveetha School of Engineering (SIMATS), Salem 636005, India
[4]Department of Computer Science and Engineering, JAIN (Deemed-to-be University), Bengaluru 562112, India
[5]Department of Computer Science and Engineering, Saveetha School of Engineering (SIMATS), Chennai 600124, India
[6]Department of Mathematics, Units of Basic Sciences, Arba Minch University, Sawla Campus, Arba Minch 4400, Ethiopia

Corresponding author: Krishnamoorthy Venkatesan (krishnamoorthy.venkatesan@amu.edu.et)

ABSTRACT Smart machine-machine (M2M) interactions, such as those enabled by the Internet of Things (IoT), have enabled people and machines to communicate and make decisions together. Furthermore, these systems have become increasingly important in the commercial and industrial sectors over the previous two decades. The Industrial Internet of Things (IIoT) is a smart system comprising engineering equipment which can connect to one another to improve manufacturing operations. This task would become more complicated if the amount of energy used by the IIoT ecosystems, as well as the amount of network traffic they generate, increased dramatically. Consequently, decision-making processes during communication are essential for autonomous interaction in critical IoT infrastructure. Smart factories employ communication technology to track and gather information in real-time to enhance the output, effectiveness, and predictability while lowering the overall cost of vital operations. In this context, Industry 4.0 not only limits to addresses the issues of integrating technologies, but it also focuses on data collection, dissemination, utilization, and organization and also improves the delivery of the solution or services quicker with more sustainability. This study intends to create an NF-based communication system for IIoT platforms to leverage those benefits. The proposed model includes smart decision-making procedures to deal with communication issues. Compared with the many methods already in use, the suggested mechanism's functional viability in the automated system is found to be optimal. Outcomes from simulations reveal that the suggested method has improved the accuracy and communication reliability of the IIoT platforms in comparison with the previous methods. Aside from these, the suggested model keeps the throughput of the local automation unit at 96.03% and the throughput of the production hall at 95.58% on average while maintaining the lowest average PLR of about 26.48% across different data rates.

INDEX TERMS IIoT, Neuro-fuzzy, reliability, routing strategy, industry 4.0, decision-making, EANFR and FBCFP.

I. INTRODUCTION

Within the past two decades, the IoT has attracted a lot of scientific investigative work. As one of the practical breakthroughs, it offers a treasure trove of solutions to issues addressed in many sectors. The Internet acts as a network's communicative spine, allowing data to be sent across the global networking infra [36]. In 1999, Kevin Ashton of MIT's Auto-ID laboratory first coined the term "Internet of Things." Kevin envisioned a scenario in which the various domains of the globe are connected via the Internet [38]. Such a scenario would require numerous pervasive sensing devices and an infrastructure built on real-time observations. This seems to have enormous capability to strengthen the present convenience in accessing information, security, and autonomy. The IoT refers to the network comprising gazillions of

The associate editor coordinating the review of this manuscript and approving it for publication was Wenbing Zhao.

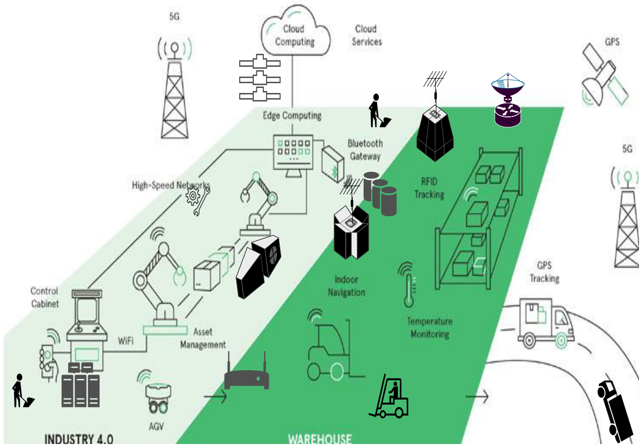

FIGURE 1. Generic anatomy of IIoT-based industry 4.0 infrastructure.

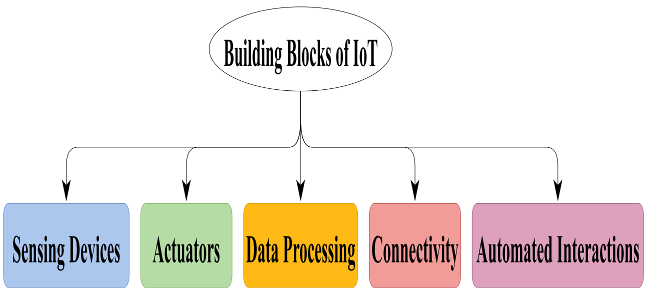

FIGURE 2. Building blocks of IoT.

interconnected digital equipment and industrial robots that can collect data from their surroundings and relay it to others without any external intervention [14]. Figure 1 depicts the generic anatomy of IIoT-based Industry 4.0 infrastructure [6].

The building blocks of the IoT have presented a deeper understanding of the IoT's purpose and operation. Figure 2 depicts the five critical components necessary to achieve the IoT's capabilities: sensing devices and actuators, data processing, connectivity, and automated interactions. For interoperability with currently available devices, communication protocols such as IEEE 802.15.4, Wi-Fi, LTE, Z-wave, and Bluetooth were all employed. RFID, NFC, and other similar technologies were employed for their precision during information exchange across the network. Services offered through the IoT will allow smart objects to become malleable participants in ideological agendas and economical operations. They might share resources and work together to pass things around [32], [33]. Each sensing device communicates with the others. They can also respond autonomously to actual events, and their ready-to-use technique can motivate workouts and create organizations with minimal to no help from a human hand.

The IIoT is a decentralized branch of the IoT that aims to improve manufacturing operations via the universal interconnection of machines [31], functional prototypes, and various supply chains [11]. Industry 4.0's vital objective is to improve the way things are made using different technologies like the IoT, CPS, ML, virtual computing, and business intelligence. The IIoT is gaining popularity due to its potential to improve workers' living and working conditions, boost productivity and prolong the lifespan of manufacturing equipment. Both physical and cyber platforms are essential to the IIoT. Automation, communication, and computational capabilities are all part of the cyber-infrastructure that makes Industry 4.0 possible. The machinery and operational platforms that employ such industrial gadgets to carry out specific outputs and automated activities constitute the physical processes. The IIoT is predicated on the idea that all the equipment employed in manufacturing processes has access to a unified network that can be accessed from anywhere in the world.

Conversely, in the previous era, factory-floor connectivity was relatively straightforward, with gauges, controllers, and motors all being linked locally for individual automation processes [21]. Ultimately, standardization and the connectivity of equipment at the scale of the manufacturing space and across businesses throughout the globe will enable deeper synchronization inside and across manufacturing facilities. In addition, it will make equitable operations more efficient by allowing for regional and international adjustments to be made to the production line.

In the past years, Fieldbus, as well as Ethernet, have dominated as the preferred means of connectivity in factory automation due to their ability to establish localized connections between sensing devices, robots, and embedded processors [21]. Due to Fieldbus services, the number of cables required for an installation has been drastically reduced, along with the associated costs, and multiplex peer-to-peer communication has been enabled across a common communications platform [25]. However, the intended purpose of establishing a consistent model to guarantee universal and interoperable alternatives has fallen short since several specifications relying on individual vendors have evolved throughout time. Foundation Fieldbus H1 [27], INTERBUS [16], and PROFIBUS [26] are only a few well-known variants.

The usage of wireless technologies like 3GPP-LTE is a unique strategy towards the IEEE-based principles that are frequently used in non-licensed bandwidths [3]. Wireless technologies [37] have an advantage over other connectivity options because they use a previously established, universally accessible network design that is intended to allow for freedom of movement and confidentiality. Using licensed bandwidths also makes it easier for equipment to work together. However, the existing LTE protocol does not consider secure, minimally delayed M2M connectivity [22]; hence, supporting the overwhelming amount of M2M services [34], [35] is a crucial necessity for the forthcoming 5G norm. Although the future 5G norm is expected to satisfy the needs of the IIoT, the likelihood that it will be implemented in the industrial management sector continues to be high.

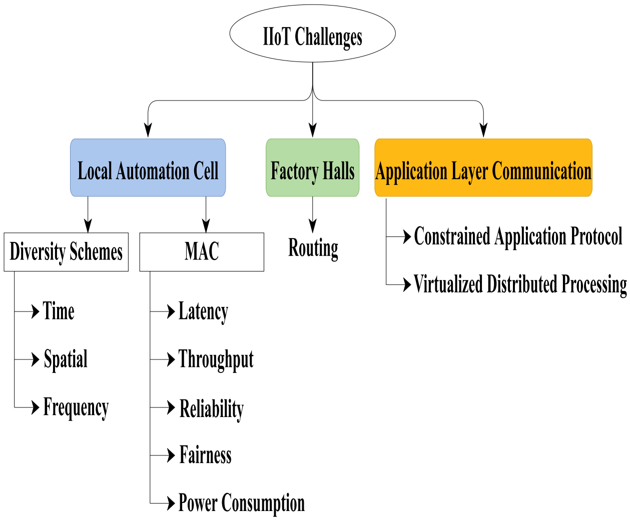

FIGURE 3. **Challenges in IIoT.**

The IIoT comprises various controllers, connected devices, and sensing units linked with cutting-edge technology to form skilful platforms that can communicate with one another through the Internet. In addition to this necessary framework, we discovered a small assortment of common elements that together provide comprehensive establishments of communication inside the IIoT at a large scale. However, there are unique difficulties associated with every element that is needed to be resolved in order to provide a holistic, unified, and adaptable solution, as dealt with in the previous research [13], [29], [30].

Figure 3 provides a high-level summary of the various IIoT communication elements and the issues they pose. We catalogue the concerning elements that usually combine to create an IIoT infra with a wide establishment of connectivity and communication. As such, we furnish a brief rundown of the IIoT's communication mechanisms and the difficulties they pose.

Individual industrial automation units in a factory space are responsible for performing a distinct set of functions. To ensure coherence and flexibility among the factory's automated operations, those units must be coupled together along the production lines' main concourse. In order to do this, each piece of equipment must be assigned a unique address (on the basis of the manufacturing unit), as well as the communications network, must enable routing to interconnect the units to a process console and facilitate connectivity between equipment in holding units. Moreover, a factory may have a single entry point or numerous ports that connect to the Internet to enable communication across facilities.

Units for local automated mechanization are clusters of sensing devices, controllers, and associated actuators located in a large manufacturing hall. A communications network connects all of this equipment together. Wireless connections should be prioritized for convenience and inexpensive setup and upkeep costs. The physical and MAC layers are highly pertinent for addressing the rigorous communication constraints required in security systems and essential feedback controllers. As a virtue of the broadcasting capability of the transmission channels in the wireless network, in the vast majority of instances, devices that are part of the same automated unit have the capability to interact with one another directly.

Application Layer Interaction paves the way for the use of IIoT applications with the synchronization of manufacturing operations throughout workplaces and the subsequent adaptation of operations via other virtual services [28]. However, connecting limited equipment to the network effectively via benchmark approaches is a crucial difficulty, too, just as it is in the more conventional IoT infra's.

A. ROUTING ISSUES IN IIoT

Establishing a reliable and optimal route is among the objects considered in routing-centric data communication. Such a method handles specific routing-based critical characteristics of IIoT networks, including energy utilization, traffic, latencies, and response with time bounds. Various routing strategies can be implemented, each catering to the specific needs of an IIoT network based on its topological dynamism. When components are not mobile, a static and stable approach can be employed for use with a hardwired network. Every router has a route cache with entries for all the destinations it can send data to and the paths to reach them.

The planned IIoT, on the other hand, would rely heavily on wireless connectivity channels to ensure that industrial configurations can be modified easily. Because of this, the routes must be flexible to some extent, making a definitive appropriate response unattainable. It is possible to use either preexisting communications infra or ad-hoc methods to learn ways to go from one node to another in the absence of a predefined/static topology. Knowledge about the network's components, such as newly discovered neighbors, link conditions, and service requirements, is compiled by a centralized instantiation of an IIoT connectivity strategy. The centralized instantiation compiles global data and indicators to determine the best route for each channel connection in the system. Still, it then pushes that information out to the required devices via routing. These indicators include the necessary hop count to reach a target, the connection bandwidth, the delay, or even the energy demand, which is very important for devices that run on batteries. One of the benefits of such a routing technique is that it reduces the amount of processing power needed at individual nodes while still providing access to global data. Figure 4 signifies the major routing issues in IIoT networking system. Furthermore, this system offers some degree of adaptability as a result of the nodes sending revisions of the aforesaid specific features. Conversely, there are drawbacks, such as a non-negligible processing cost at the centralized controller and a sole breakdown spot if no secondary or failover strategy is established. Ad-hoc networking

FIGURE 4. Routing issues in IIoT networking systems.

systems are self-organizing systems where every node must transit the data, similar to wireless mesh [2] or MANET [7].

Reactive and proactive route strategies are both employed in such networking environs. Thus, we emphasize these fundamental layouts, notwithstanding the existence of hybrid options. The purpose of a proactive approach [10] is always to have a birds-eye perspective of the whole network. In order to accomplish this, nodes regularly disseminate their routing information, relying on knowledge about their immediate vicinity learned via scheduled discoveries. The route data is always accessible, which is a significant benefit of this strategy. Yet, the critical drawback is the sluggish consolidation in the event of reorganization or connection breakdowns. In addition, controlling and upkeep communication complexity is exceptionally high whenever substantial data volumes are limited (sensed data or actuating instructions). The proactive routing procedures, which employ up-to-date route discovery across the entire network, resolve the path identification problem but demand a regulated schedule.

B. MOTIVATION

Some of the most fundamental requirements for establishing route discovery in a complex network rely on factors like the number of route hops, the form of connectivity and communication used to construct that route, the availability of the target, the pace at which mobile nodes could move, and so on. Particularly in adaptive routing algorithms (where network creation starts only after requests), dealing strictly with path formation and data transfer is necessary. If this doesn't happen, it will have a devastating effect on the network's efficiency. However, increased network instability may impede numerous crucial transmissions required to correctly deliver the observed data. However, a more intricate routing algorithm would need additional stability measures for a set of distributed devices in order to communicate with the target devices. Although developing routing algorithms for IIoT-based dynamic infrastructure introduces new challenges, the mobility idea identifies ways to cut the node count involved in data transfer, hence decreasing latency. With instantaneous route selection based on the concept of various possibilities approaching the endpoint and minimal overheads, the channel's unbalancing implications can be mitigated, and the nodes' tolerance for malfunctions/failure may be accounted for. Providing such immediate route selection alternatives, particularly in dynamic networking, requires the use of a sophisticated inference process.

Among these cutting-edge inference systems, the neuro-fuzzy approach is a popular choice at the moment. Ever since fuzzy mechanisms [19] began to see widespread use in industry, researchers have known that creating a system with a strong showing is no simple feat. In order to solve MF and rule-based issues, a significant amount of experimentation is often required. After realizing this, the concept of using learning techniques in conjunction with fuzzy systems emerged. The NN has been proposed as a means to either fully or partially simplify the operation via automated adjustments in fuzzy systems due to its powerful learning techniques. To reap the benefits of both NN as well as fuzzy systems and to address the limitations of each, they should be used in tandem. The computability properties of NNs are introduced to fuzzy systems, where they provide both a means of interpreting such systems and a more precise way of representing them. Thus, the benefits of NNs make up for the shortcomings of fuzzy logic control. These strategies must be employed jointly since they complement one another. Therefore, in this research, we use an NF strategy to provide a theoretically sound model for reliable communication in IIoT infra.

The entire article is structured systematically and delineated as follows. Section II discusses the most relevant existing methodologies and their working processes for identifying research gaps. Section III elaborates on the clustering and sub-clustering processes, appropriate CH selection strategies, and the NF-based communication process. Section III-A discusses the performance of the proposed system relative to existing models in various aspects. Finally, section III-B summarizes the study with key points and exposes the future enhancement plan.

II. RELATED WORK

As a new field of study, IIoT genuinely expects investigators to tackle complex problems in sectors like design and architecture, networking, and stability. IIoT relies heavily on routing because of its pervasiveness. Throughout this section, we'll go over some of the fundamentals of IIoT infrastructure and the NF idea, which is crucial to ensuring reliable routing [18]. The subsequent phase deals with the observation and communication difficulties that arise in a networking system based on IIoT. This section also concludes with a review of the available literature.

Brante et al. [9] present a mechanism for an influential roster of CHs to extend the system's longevity beyond the use of surplus power. When nodes are grouped into a cluster, the CH takes on the extra work of data collection, aggregation, and connectivity with the primary node (BS). For this reason, current data is required to predict situations, like bottlenecks, that affect the CH nodes. Fuzzy rules may be used to deal with this ambiguity since FL allows for a range of input values (0 to 1) and the ability to make decisions based on incomplete data. FL was formerly widely utilized by scientists to deal with uncertainty in a diverse range of situations.

Ari et al. [4] published a novel approach for selecting intermediaries; it used a decision-making framework influenced by FL. With the use of fuzzy inference, Gupta et al. [15] managed to choose qualified candidates for the role of CH and execute the routing procedure via the cluster leaders. To a limited degree, the efficiency of these approaches improved. The precision, however, has to be increased so that better choices may be made. Expanding the scope of fuzzy inference is possible by considering a more extensive set of qualities. Because of this, Kim et al. [20] created a fuzzy-based routing approach using path length and energy as crucial factors. However, owing to the sensor nodes' inherent limitations, the energy consumption issue was unable to be addressed entirely. To effectively manage the uncertainty concern and make predictions, developing a more impactful learning approach that can be coupled with FL is required.

Shen et al. [23] proposed an NF approach with output embedding that is more complicated to design but offers a substantially finer control interface. Defuzzification interpretation is performed by summing and dividing layers. The top weights in the summing component are meant to be the expected readings, whereas the bottom values are intended to be the actual ones. Due to the similarity between neural activity and neuro-fuzzy systems in terms of cell processes (like message basic arithmetic), the design of NF systems is often compared to that of machine learning models.

In order to better distribute periodic routing, a methodology to determine averaged single-hop latencies per transaction using a computational model via NN. Furthermore, swarm intelligence, a dependable, self-organized, and decentralized routing approach, was employed as a reliable indicator for an adaptive NF inference approach to tackle the path cost minimization issue.

Taheri et al. introduced a novel and energy-aware route discovery strategy as well as a stochastic and distributed clustering-based density estimation protocol. This methodology employs three different processes, including a stochastic CH voting procedure, using FL for making decisions, and implementing on-demand grouping. This approach, much similar to the LEACH procedure, continually does clustering since it is concerned with all iterations. In order to efficiently implement clustering-oriented packet forwarding, the HEED method is described through various methods that uses the likelihood function to pick the CHs in a randomized fashion. But HEED adjusts the CHs most consistently throughout the whole network system via numerous rounds of experimentation within narrower cluster boundaries. Further, while the HEED mechanism is not receiving any CH declarations from adjacent nodes, any node might emerge as CH by cycling across the responsibilities and employing their likelihood function. One positive aspect of HEED is the way it uses a rotation strategy to choose which CHs to assign to each participant. Further, better rule application has enhanced the decision-making procedure. Unfortunately, the majority of the aforementioned methods simply assisted in CH choosing to utilize FL, while only a handful of methods assisted in cluster formation. Furthermore, prior efforts primarily addressed routing instead of using machine learning techniques in the network and relied on FL for decision-making.

According to the work of Abbas et al. [1], an NF system is implemented to describe the features of the restrictions related to picking the ideal inspiring path in accordance with the driver's individualized interests. If the suggested system detects traffic problems along the chosen route, it may proactively choose an alternate path. With the help of a route rating, the user may make more nimble and future-oriented choices. By doing this, they could determine the course based on the user's selections at a much lower cost. In the method that has been developed, all potential routes are analyzed for their expenses, and the most cost-effective one is chosen. In summary, this method selects to go in the direction that will lead to the lowest overall cost. Using vehicle-to-vehicle communication, this study may be expanded to include practical applications.

Thangaramya et al. [24] offer a novel communication technique known as NF-based cluster formation protocol (FBCFP) that executes connectivity learning by taking into account four vital aspects: the cluster hub, existing energy levels, its range from the mobile sink, the variation in the distance among the cluster's members and the CH because of the node's movement, and the cluster hub's degree. Researchers employed a convolutional NN with fuzzy inference for weight modification to update the network parameters for this task. Furthermore, they performed cluster-based networking and effective cluster creation using a fuzzy inference technique. After a CH has indeed been chosen, all the non-CH endpoints in the network employ the Mamdani fuzzy inference process to implement those four criteria for each CH, with the most significant proportion of energy being taken into account when determining which will succeed as a CH. Researchers compare the suggested routing method's efficiency to that of FLCFP, LEACH, and HEED. This work's empirical findings demonstrate that the suggested approach, called FBCFP, significantly increases the overall lifespan of the network when compared to FLCFP, LEACH, and HEED. Furthermore, it is demonstrated that the suggested FLCFP decreases energy consumption and strengthens QoS in IoT-based networking systems by maintaining the uniform number of clusters and optimizing power usage through the rule-based application knowledge gained from the training process with an ML algorithm and employing the rules to determine impactful routing determinations. It was demonstrated via experiments carried out in this study that the usage of convolutional NN for training in the suggested technique improves the packet distribution ratio and decreases the other QoS metrics, notably latency and power usage.

The novel Energy-Aware Adaptive Fuzzy-Neuro Clustering (EAANFC-MR) with a WSN-aided IoT method is presented by Daniel et al. [12]. Based on EAANFCs, EAANFC-MR proposes two fundamental phases: clustering as well as multi-hop data transmission. First, the EAANFC-based clustering approach is employed to choose CHs dependent on the remnant power of all the deployed nodes, as well as their proximity and node orientations. Afterwards, the QOBFO technique is applied as a multi-path routing strategy to choose the best routes to the end target. For the purpose of selecting a reliable CH system, researchers employed the idea of an adaptable neuro-fusing inference algorithm. Initially, EAANFC incorporates clustering notions and principles. The QOBFO is then utilized to determine optimal destination pathways using a multi-path routing mechanism (QOBFO). Finally, the proposed EAANFC-MR concept is performed in MATLAB, and the findings are analyzed from multiple perspectives.

To address the issue of high-powered IoT devices, Jeevanantham and Rebekka [17] offer an energy-aware neuro-fuzzy routing model (EANFR) that utilizes a vector space created via the deep-neural system to determine routing choices and manage the clustering process. The EANFR approach can be trained to determine the best CH nodes along with the most efficient, simplest, and optimal pathways. After running extensive simulations, a scientific study showed that the suggested EANFR model had the fewest training losses. Moreover, associated with network lifespan, the EANFR appears to be better than published studies, in particular when compared to energy-aware cluster analysis with the ML approach (an improvement of 89.23 per cent), radial basis NF network inference scales (20.63 per cent), and intuitive Q-learning (67.21 per cent). Furthermore, their study showed that the suggested EANFR paradigm significantly increased the network lifetime and QoS capabilities of the network, which makes it ideal for IoT-based surveillance applications.

III. METHODOLOGY

The IIoT infrastructure relies on minimally-powered and lossy networks comprising many macro and micro-level interconnected embedding devices. Saving energy and making efficient use of resources are two areas where routing can really helps out. Selecting the most appropriate routes via smart decision-making methodologies helps devices save more energy and ensures that networks operate longer with minimal downtime. The routing technique utilizes route variables such as traffic load, device energy, projected transmission cost, connection measure, and hop count to determine the most reliable path for transmitting data. In addition, a well-thought-out clustering approach is essential for coordinating the various pieces of communication hardware and ensuring their compatibility with future expansion. As a result, in this research, we utilize neuro-fuzzy strategies to maintain a reliable connection between various heterogeneous devices. In addition, we also adopted a unique clustering approach to managing the communication devices of the IIoT.

A. DISTRIBUTION OF COMPONENTS IN IIoT

Connectivity to nearby devices is a crucial characteristic of IIoT infrastructure components and equipment. A component with no connectivity (0 degrees) cannot share information with other nodes. A more highly-degreed node increases the network's communication probabilities and resilience to connection failure. When choosing the node to connect to next, the one that has the highest degree among its neighbors will be prioritized. This section deals with the computation of a component's distribution in the network. Let Q components (static or mobile) are deployed in the network environment. Every component's degree implies a binomially distributed nonlinear function that is the aggregate of Q-1 autonomously attributable factors. Let κ denote the likelihood that a connection exists, and δ stands for the arbitrary element that represents the degree of the relationship. This degree of component dispersion is calculated using equation (1).

$$\boldsymbol{P}\left(\boldsymbol{\delta}=\boldsymbol{L}\right):\longrightarrow\left(\mathbf{1}-\boldsymbol{\kappa}\right)^{(\boldsymbol{Q}-\boldsymbol{L}-\mathbf{1})}\cdot\left[\frac{(\boldsymbol{Q}-\mathbf{1})}{\boldsymbol{L}}\right]\cdot\boldsymbol{\kappa}^{\boldsymbol{L}} \tag{1}$$

where, $\left[\frac{(\mathrm{Q}-1)}{\mathrm{L}}\right]$ states the total quantity to choose L channels/links from *Q-1* possibilities, and $(1-\kappa)^{(\mathrm{Q}-\mathrm{L}-1)}\cdot\kappa^{\mathrm{L}}$ represents the absolute likelihood of choosing available L links from $(Q-L-1)$.

B. CLUSTERING

This subsection delineates the novel clustering process, namely homocentric clustering, which exhibits a concentric formation of sub-clusters around the central controller. Figure 5 signifies the graphical representation of the homocentric clustering process.

The homocentric clustering follows the base principles of concentric circle formation, in which the common controller determines the boundary region of each circle based on the computation exhibited in equations (2) and (3).

$$\sum\nolimits_{i=1}^{k}\boldsymbol{b}_{\boldsymbol{r}_i}=\boldsymbol{T}_{\boldsymbol{C}_l}^{\boldsymbol{R}}-\boldsymbol{r}_i \tag{2}$$

$$\boldsymbol{r}_i\mid\boldsymbol{h}_i=\left[\boldsymbol{T}_{\boldsymbol{C}_l}^{\boldsymbol{R}}/\mathbf{2}\right]\times\boldsymbol{h}_i \tag{3}$$

where, b_{r_i} denotes the concentric clustering range, $T_{C_l}^{R}$ represents the transmission range of common l^{th} controller, C_l, r_i indicates the boundary distance of concentric clusters from C_l, h_i signifies the hop counts.

Initially, C_l determines the boundary region of each concentric cluster based on its transmission range and

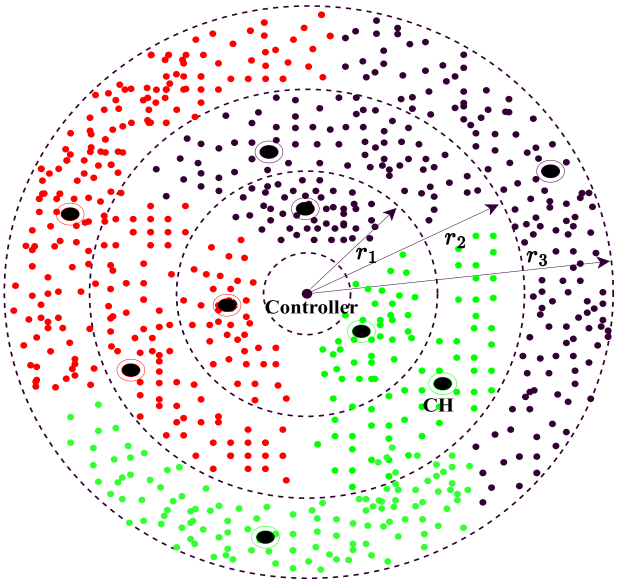

FIGURE 5. Homocentric clustering.

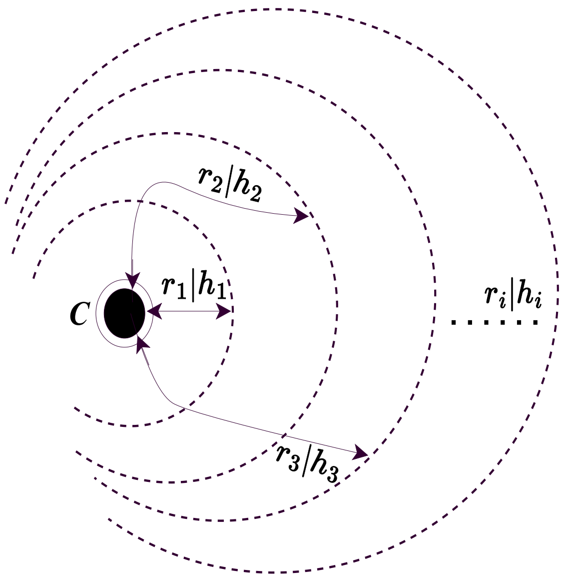

FIGURE 6. Inter-cluster communication process.

reachability (hop counts). The first concentric cluster includes all the primary components incorporated into the IIoT infra. Sequentially, the second concentric cluster includes secondary components of the IIoT that are directly associated with the primary components. In a similar fashion, each concentric cluster is constructed based on the hop count and transmission range. All of the first-level concentric cluster components can communicate C_l in a single hop. In contrast, the next-level of concentric clusters can communicate C_l according to the computation process of equations (2) and (3). Figure 6 indicates the inter-cluster communication process with C_l.

C. FORMATION OF SUB-CLUSTERS

Each machinery components in all the concentric clusters are again grouped into several sub-clusters with appropriate

TABLE 1. Algorithm for sub-clustering.

Input: d_i, dist (d_i)
Output: sub-clusters (ϑ)

1: Randomly select initial centroid μ_i within each r_i, ($\mu_i \in r_i$); the initial count of $\mu_i$starts with 3 and increases for everyb_{r_i}.

1a: Select next μ_i; where $\mu_i = d' \in r_i$with $p\left({dist(d')^2}\Big/{\sum_{d\in r_i}(d)^2}\right)$

1b: repeat 1a until all the $\mu_i$of each b_{r_i}

2: Determine the Euclidean distance (Li et al., 2010) between every d_i in the r_i and all μ_i. and later than it will be placed in the sub-cluster whose μ_i is closest to the given coordinate of d_i.

3: Ensure the revised mean estimate is reflected in the current centroids value.

4: It is necessary to perform steps 2 and 3 repeatedly until convergence is reached. Then, if the convergent condition is met, the loop can be severed.

CH to communicate to C_l. For the purpose of sub-clustering, we opted K-means++ algorithm [5]. In the case of finding initial centroids using Lloyd's algorithm for K-Means clustering, randomization process is utilized. The initial k-centroids were picked randomly from the data points (d). This randomization of picking k-centroids points results in the problem of initialization sensitivity. This problem tends to affect the final formed clusters. The final formed clusters depend on how initial centroids were picked.

K-means++ is a smart centroid initialization technique and the rest of the algorithm is the same as that of K-Means. The steps to follow for centroid initialization are given table 1.

D. CH SELECTION

Each sub-cluster selects its CH component based on two parameters: the communication device assigned to perform the least number of operations (α) and the device with the maximum count of interconnected equipment (γ). CH changes over time, t whenever the role of the communication device changes. During the commencement of the initial communication process, CH is randomly chosen. Later, each communication device regularly verifies it's α and γ values and shares the massage with the current CH. Thus, based on the computational values, the current CH selects a new CH, which may reform the boundary of the sub-cluster if necessary. Equation (4) represents the computation process for CH selection. Around 50 per cent of the equipment is considered static, while the remaining 50 per cent is considered to be in mobile mode.

$$S_{t_n}^{CH_i} = \begin{cases} \boldsymbol{min}\,(\boldsymbol{\alpha})\,, -\infty \leq \boldsymbol{\alpha_t} \leq \infty \\ \boldsymbol{max}\,(\boldsymbol{\gamma})\,, -\infty \leq \boldsymbol{\gamma_t} \leq \infty \end{cases} \tag{4}$$

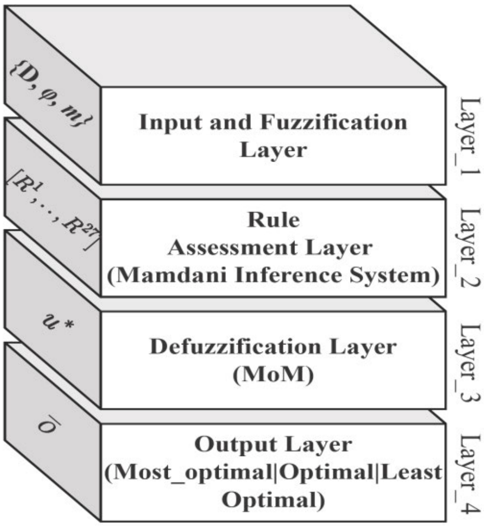

FIGURE 7. Architecture of NFIS.

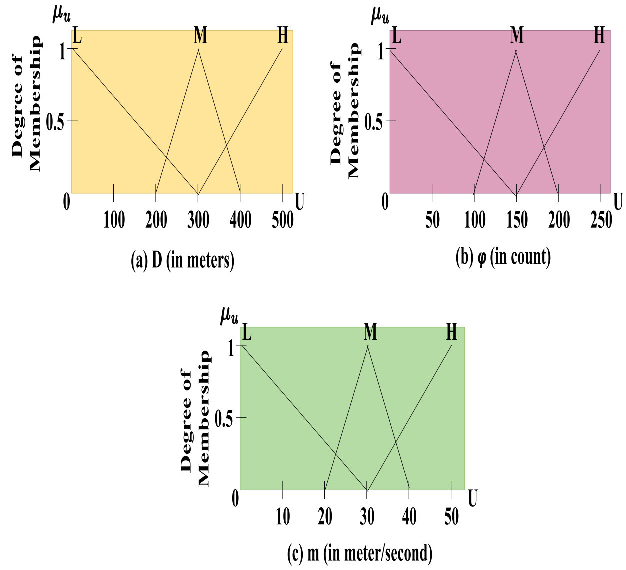

FIGURE 8. MF of (a) D, (b) φ, and (c) m.

E. COMMUNICATION STRATEGY

The communication processes are handled in two stages: intra-cluster communication and inter-cluster communication. Before the commencement of communication at both stages, discovery of multi-path routing is performed via neuro-fuzzy inference strategy.

NFIS is a hybrid of standard inference methods and the more recent and sophisticated approaches of NN and FL. Iteratively tuning the NN's hidden (customizable) layers with input data points implies the defining features of fuzzification and the inference process via rule base. The framework initially exemplifies the learning actions of a NN, and then, for more precise exegesis, operation, and system depiction, it also illustrates the action patterns of an FL.

An inevitable conclusion is to strengthen the technical aspects of understanding fuzzy structures. To automate or assist in the calibration of the fuzzy inference, NN, which consists of a set of practical learning procedures, has conventionally been considered a viable solution.

NFIS framework comprises four layers which utilizes Mamdani inference procedures to attain the outcome. Figure 7 depicts the architecture of NFIS. All the layers are briefly elaborated as follows,

Input and Fuzzification Layer: Any fuzzy set 'F'' (can be denoted as F_d) is the degree set in U to which the MF$\rightarrow$ $\mu(u)$ is applied (positively).

$$\boldsymbol{F_d} \longrightarrow \left\langle \boldsymbol{u} \in \boldsymbol{U} \mid \boldsymbol{\mu_{F_d}}(\boldsymbol{u}) > 1 \right\rangle \tag{5}$$

The range of degrees in U in which the MF $\mu_{F_d}(u) = 1$ is considered the core of a fictitious dimension (F_d) (kernel) described in the U (universe of disclosure).

$$\boldsymbol{core}(\boldsymbol{F_d}) \longrightarrow \left\langle \boldsymbol{u} \in \boldsymbol{U} \mid \boldsymbol{\mu_{F_d}}(\boldsymbol{u}) = 1 \right\rangle \tag{6}$$

Any fuzzy set's MF is expressed in terms of a triangle MF in the suggested model which is expressed as,

$$\boldsymbol{\mu_{F_d^r}}(\boldsymbol{\mu}) = \begin{cases} \mathbf{1} - \left[2\left|\boldsymbol{u} - \bar{\boldsymbol{u}}^r\right| / \boldsymbol{\tau}^r\right] & , \boldsymbol{if}\ \left(\boldsymbol{\tau}^r/2\right) = \geq \left|= \boldsymbol{u} - \bar{\bar{=}}\boldsymbol{u}^r\right| \\ \mathbf{0} & , \boldsymbol{otherwise} \end{cases} \tag{7}$$

In equation (7), both $\bar{u}^r$ and τ^r denote the MF's core (centre) and spread (width), correspondingly, as determined by equation 1.3. As per the premise in layer 1, the 'centroid' is considered to be a specific position in the core of the triangle MF. In accordance with the premise in layer 2, the distribution of (Fd) determines the spread in specific MF.

The layer 1 include the elements that actualize the MF $\mu_{F^r_{d_x}}(\bar{u}_x)$, for r = 1,…,N and x = 1,…,n. The precise input feed $[(\bar{u}_x),\ldots,(\bar{u}_n)]$ is compiled of vector components $\overline{u} = [\bar{u}_r,\ldots,\overline{u}_n]^T$. The preceding section (antecedent) of the fuzzy sets $F^r_{d_1},\ldots,F^r_{d_n}$ for r = 1,…,N at the laconic degree $\mu_{F^r_{d_x}}(\bar{u}_x)$, produces the fuzzified values. Thus, the total components' count equalizes $(n.N)$, where n denotes the input while N represents the set of rules in IF-THEN format. So, the preceding component of the fuzzifier is represented by the MF in layer 1. The primary objective of NFIS is to discover a set of optimal intermediate communicative components and essential routes. For this, three vital factors are considered: the distance (D), maximum operational time of i^{th} equipment (φ), and mobility (m).

Figure 8(a), 8(b), and 8(c) represent the input MF D, φ, and m, respectively. Each fuzzy set of input linguistic variables is categorized into three linguistic terms, namely, L, M, and H, which are utilized to infer the fuzzified values via rule base.

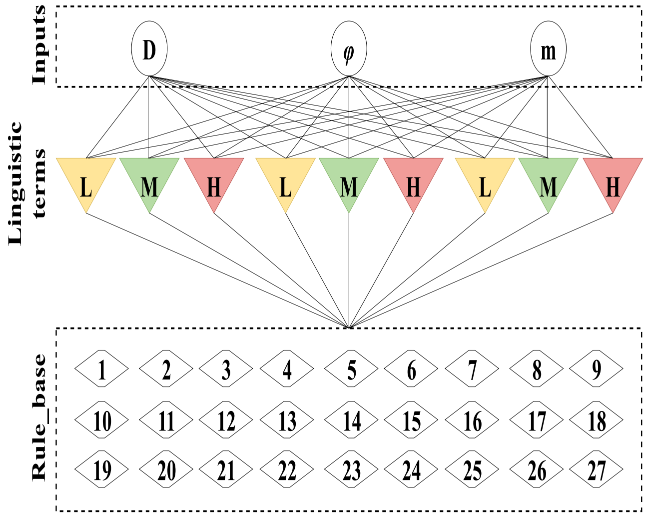

FIGURE 9. Rule base inference.

Rule Assessment Layer: The second layer consists of the elements that validate the Cartesian product (implement the min. function) of the variables of the MF $\mu_{F^r_{d_x}}(\bar{u}_x)$ where x is an integer ranging from 1 to n. A set of defined rules R^k corresponds to the collection of N components that make up this layer's composition. The expression in equation (8) describes the set of the objective rule base.

$$R^k : if \left[(u_1 \rightarrow F^r_{d_1})\&\&(u_2 \rightarrow F^r_{d_2})\&\& \cdots (u_n \rightarrow F^r_{d_n})\right] Then \left(v \rightarrow o^k\right) \tag{8}$$

where $\bar{u}_k, \ldots, \bar{u}_n$ and v are the input and output linguistic variables, respectively and $k = 1, \ldots, N$. Additionally, the values of the defined variables are drawn from a set of pre-configured MF depending on various linguistic terms. Both $F^r_{d1}, \ldots, F^r_{dn}$ and o^k refers the linguistic terms of input and output, respectively.

To infer rules, the Mamdani inferring technique [8] is used, which is based on the precise "IF-THEN" rule-base. In this way, the 27 rule guidelines in the rule-base are formed by the three input variables used together to decide the various alternatives for data routing through an intermediary route. Figure 9 shows the rule-base and the potential rule firings for simpler comprehension. Ultimately, the established routes' defined rules are sorted into categories for training and decision-making. Typically, the n_i that performs NF inferring procedures will focus on the best possible route node along the path. If the likelihood of receiving the optimal route node is low, the subsequent set of ideal nodes is chosen as a backup. This form of backup strategy increases the network's reliability in communication, particularly during data transfer. Table 2 provides a classification of the rules that may be used to find a degree of optimality (optimal, better, least optimal) to choose route nodes.

Defuzzification and Outcome Layer: Both defuzzification, as well as crisp outcome layers, are defined in the remaining two NF layers. The Mean of Maximum (MoM) [19] is applied for the defuzzification process, and it generates a measurable result centered on the fuzzy sets, $\bar{F}^k_d$, k = 1,…,N. An expression represented in the equation (9) characterizes the defuzzification procedure.

$$u^* = \sum (u_i) \in \left[e^{u_i}/|e|\right] \tag{9}$$

In this case, |e| denotes the cardinality of the F_d, and 'e' is used to normalize the heights of the F dk. The level of antecedent compatibility is denoted by the hook's expression$\xi_k = \mu_{F^r_{d_x}}(\bar{o}^k)$. On the other hand, that ξ_k is the primary cause of the procedure in the linearization layer since it is the result of the new stage and has been fed as input to the defuzzification layer. To a large extent, the neural system's weights are determined by the values of $\bar{u}^k$, which are propagated from the initial layer (first). Therefore, the procedure stated involves a division operation carried out by the layer's last element in order to provide a precise result, $\bar{o}$ and expressed as,

$$\bar{o} = \xi_k / \sum\nolimits_{k=1}^{N} (\xi_k) \cdot \sum\nolimits_{k=1}^{N} \left(\bar{u}^k\right) \tag{10}$$

TABLE 2. Compilation of rules and consequences.

R1	R2	R3	R4	R5	R6	R7	R8	R9
R10	R11	R12	R13	R14	R15	R16	R17	R18
R19	R20	R21	R22	R23	R24	R25	R26	R27
	Most Optimal			Optimal			Least Optimal	

IV. PERFORMANCE EVALUATION

A. EMPIRICAL SETUP

To test and evaluate the proposed model, we utilized IoTIFY. It is a testing, hyper-scalable application that can handle thousands of connected devices. This form of network model aids in the resolution of IIoT network challenges by modeling many IoT virtualized interfaces and end-points. Working in tandem with the IoT Application Integration Environment, IoTIFY provides a versatile and adaptable IoT equipment testbed that speeds up the creation, validation, and implementation of large-scale IIoT solutions supporting thousands of devices. Data packet loss ratio, out-of-order transmission, delay, and concurrency are brought into networking by LoRaWAN's unpredictable communication medium. We use the essential experimental specifications to assess the effectiveness of the suggested model, which are all listed in Table 3.

B. DISCUSSION

In a sequence of simulations carried out in two contrasting IIoT settings (local automation unit and factory hall), the

TABLE 3. Experimental settings and parameters.

Experimental Parameter	Range/specifications
Operating System	Windows 10 pro
Network Radius	Local Automation Cells: 150 meters Factory Hall: 1000 meters
Simulation Time	1 hour, 30 Minutes
Controller Transmission Range	100 meters
Device Transmission Range	50 meters
Initial Energy	1000-1500 mA
Data Reception Energy Range	20 mA
Data Transmission Energy Range	4 mA
Transmission Amplifier Energy Range	8 mA
Sensing Energy Range	1000-1300 µA
Intra-Cluster Data Aggregation	1.2 mA
Inter-Cluster Data Aggregation	1.4 mA
Energy Decay Exponent	2
MAC	6LoWPAN
Number of Equipments	Local Automation Cells: 250 Factory Hall: 25
Mobility	5 m/s (Intra-Cluster) 8 m/s (Inter-Cluster)

proposed model's efficacy is compared to that of two established methods (EANFR and FBCFP). For analysis purposes, a few basic metrics are considered. They are throughput, PTP, PLR, communication delay, and reliability checks against device failures.

The IIoT-based network's throughput is defined as the rate at which data is transferred between components at the local automation unit level as well as the factory hall level and the computation is expressed in equation (11). As a result, the network's efficiency is enhanced, as data transmission distribution is optimized and packet latency is reduced.

$$T = \sum\nolimits_{c=1}^{N} rd_c^{LAU} + \sum\nolimits_{c=1}^{N} rd_c^{FH} \tag{11}$$

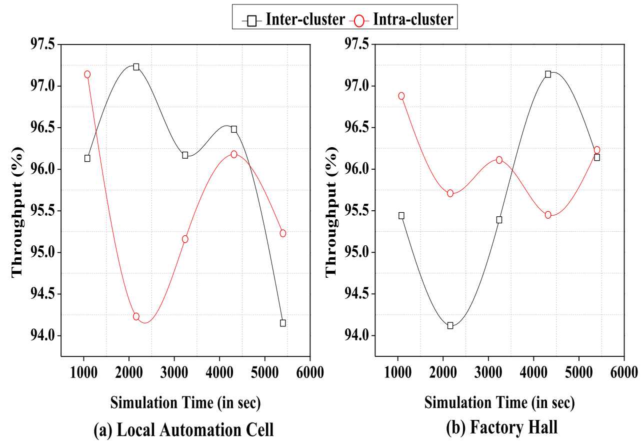

FIGURE 10. Throughput analysis at (a) local automation unit, (b) factory hall level.

Figures 10(a) and 10(b) demonstrate the suggested NF-based routing throughput rate. In terms of the network's throughput, NF-based routing outperformed EANFR and FBCFP routing approaches. It accurately estimated the data transmission rate from origin to destination throughout the network. Overall, the suggested methodology is determined to have an average result of over 95%, whether applied to local automation or the whole factory hall. The investigation is performed on multiple stages (i.e., across and within clusters), revealing an average throughput of 96.03% at the local automation unit and 95.58% at the manufacturing hall. Additionally, it was shown that the suggested model outperformed the EANFR and FBCFP methods by a margin of 7% which is evident from the outcome exhibited in figure 11. Such a high level of functioning is achieved because of the NF inference engine, which is touted as a sophisticated method for choosing the intermediate routing equipment and distinguishing packet losses incurred by wireless-generated faults.

The packet transmission proportion indicates the percentage of data streams sent ρ_s by the sources that actually reach the target, ρ_r. It is determined by comparing the total proportion of packets sent across the IIoT network to the total proportion of packets intercepted at the terminal/end-point. The computation of this metric is expressed in equation (12).

$$PTP = \left({}^{\rho_r}/_{\rho_s} \right) \tag{12}$$

Estimating the amount of data transferred from one device connected to another is called PTP throughout the network. Figures 12(a) and 12(b) depict the effectiveness of the PTP for the proposed routing approach under varied payloads at the LAU and FH levels, respectively. Inter-communication at the LAU level has an average PTP percentage of 87.4%, while intra-communication at the FH level averages 91.2% due to the predominant use of NF-based methods in routing with finer decision-making on choosing suitable intermediate routing devices/equipment.

Inter-communication PTP resultants at the FH level average 84.6%, whereas intra-communication PTP resultants

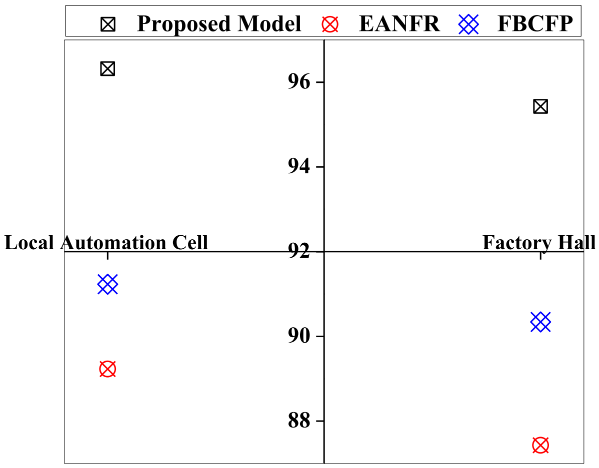

FIGURE 11. Throughput resultant comparison.

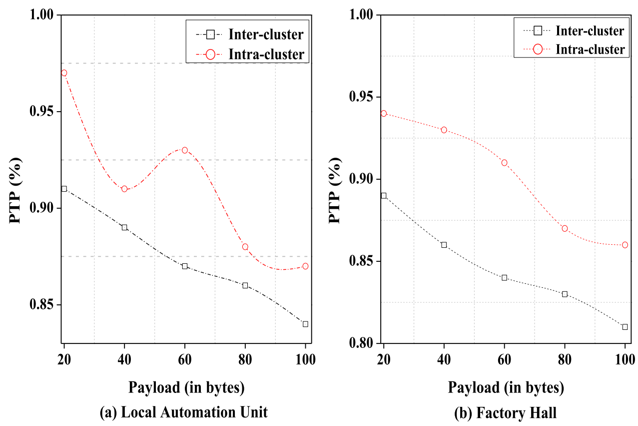

FIGURE 12. PTP analysis at (a) Local automation unit, (b) Factory hall level.

average 90.2%. The PTP result shows that the conceptual model outperforms competing approaches in intra-cluster communication situations, suggesting prospective usage in a vast scope of intra-cluster settings. Figure 13 shows that when the performance of the proposed model is compared to that of the current models, the NF-based routing approach bolstered the suggested model for superior performance, and this is true regardless of whether or not intra-cluster communication outcomes are included.

Figure 14 depicts the reliability check against a device/equipment failure rate ranging from 5 to 25%. It is found that the proposed model is highly reliable because it tends to provide a tolerable communication service in the presence of device/equipment failure. On the other hand, the existing model failed to provide complete reliability due to a higher failure rate.

The packet loss rate (PLR) is the proportion of successfully delivered packets relative to the overall count of packets sent across different sources and targets. Figure 14 shows the resulting impact on the packet loss ratio for the proposed model, EANFR, and FBCFP approaches by changing

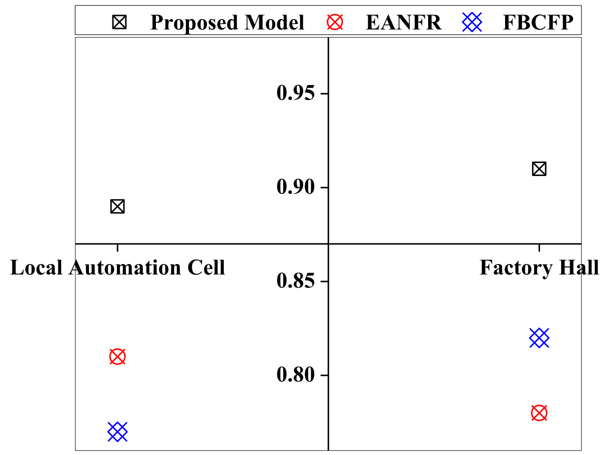

FIGURE 13. PTP resultant comparison.

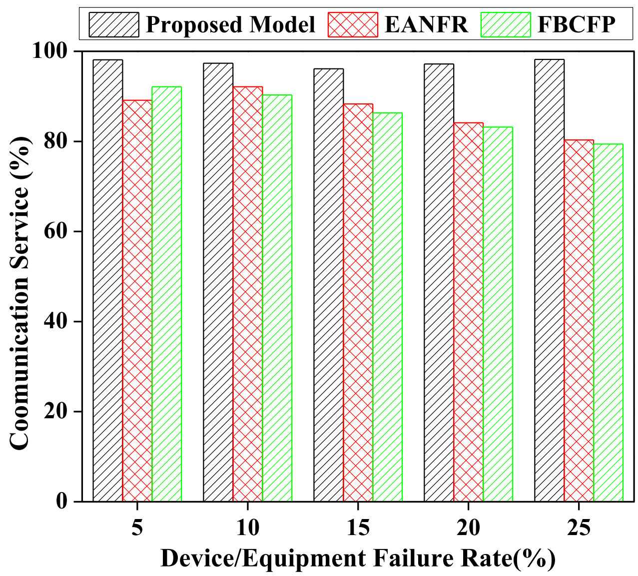

FIGURE 14. Reliability check.

the data transfer rate of transmission packets per minute (1 pac/m, 5 pac/m, 15 pac/m and 20 pac/m). It has been shown that NF-based routing strategies have a lower PLR than EANFR and FBCFP methods across the range. Packet loss rose by 20.12%, 28.58%, and 30.76% for the proposed models, EANFR, and FBCFP, respectively, at a data transmission rate ranging from 1 to 20 pac/m (see Figures 15(a), 15(b), 15(c), and 15(d). The possibility of packet loss escalating in tandem with the data transfer pace is also noted. This occurs as a result of the unrestricted involvement of intermediary devices/equipment inside the clusters. This realization highlights the significance of limiting or fixing the data transmission rate throughout the IIoT-based networking infrastructure.

It is evident through the observed results from figure 16 (a) and 16 (b), which exhibits the average communication service of the three different models at varying scalability. The

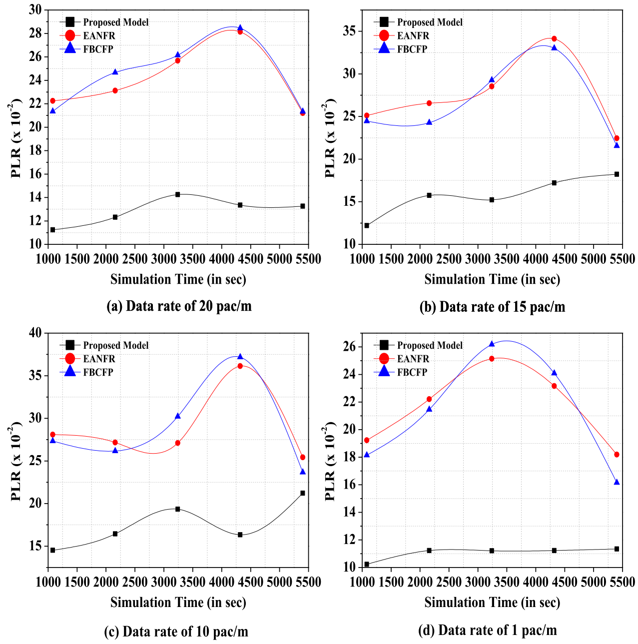

FIGURE 15. **PLR analysis at varying data transfer rate.**

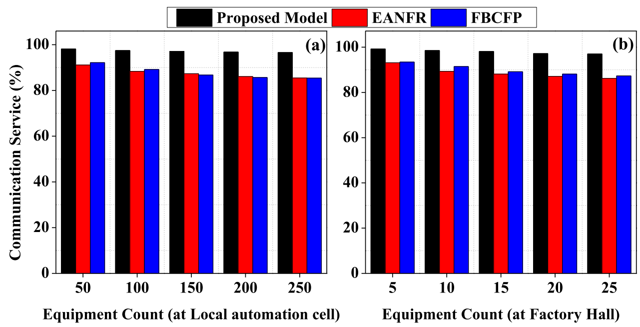

FIGURE 16. **Scalability analysis.**

proposed model maintains the above 96% communication service across varying scalability at local automation cells (ranging from 50 to 250 equipment), which dominates the existing models. Similarly, at the factory hall level, though the equipment count varies from 5 to 25, the communication service is maintained at above 97%. This observation reveals that the proposed model is highly compatible and adaptable in different scenarios.

Though the performance of the proposed model excels in all departments, they are a few identified limitations which are considered in future work. They are (i) the processing time of the NF system and (ii) exceeding observation of PLR (above 15%)

V. CONCLUSION AND FUTURE WORK

The IIoT is an intelligent system made up of interconnected components of machine parts designed to boost production in industrial settings. As a result, self-governing communication in mission-critical IIoT-based networks necessitates decision-making procedures during communication. Therefore, in this research, we developed an NF-based strategy to provide stable and reliable communication across all devices. To solve communication problems, the suggested model implements ingenious decision-making mechanisms. The presented model surpassed the two most relevant current approaches in several aspects and yielded positive results for standard QoS measures as a consequence of the fine-tuning experiments. The NF inference engine, hailed as a cutting-edge mechanism for selecting the intermediate routing hardware and identifying packet losses brought on by wireless-generated defects, is responsible for this impressive degree of functionality. We intended to test the proposed methodology under high mobility conditions, particularly to determine its reliability in such scenarios. In addition, we also planned to consider the limitations of the proposed model (i) the processing time of the NF system and (ii) exceeding observation of PLR (above 15%).

FUNDING

This research received no external funding.

DATA AVAILABILITY STATEMENT

The dataset used for the findings is included in the manuscript.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest exists.

REFERENCES

[1] S. Abbas, M. S. Khan, G. Ahmed, M. S. Abdullah, and U. Farooq, "Bio-inspired neuro-fuzzy based dynamic route selection to avoid traffic congestion," *Int. J. Sci. Eng. Res.*, vol. 2, no. 6, pp. 284–289, 2011.

[2] I. F. Akyildiz and X. Wang, "A survey on wireless mesh networks," *IEEE Commun. Mag.*, vol. 43, no. 9, pp. S23–S30, Sep. 2005, doi: 10.1109/MCOM.2005.1509968.

[3] S. Andreev, O. Galinina, A. Pyattaev, M. Gerasimenko, T. Tirronen, J. Torsner, J. Sachs, M. Dohler, and Y. Koucheryavy, "Understanding the IoT connectivity landscape: A contemporary M2M radio technology roadmap," *IEEE Commun. Mag.*, vol. 53, no. 9, pp. 32–40, Sep. 2015, doi: 10.1109/MCOM.2015.7263370.

[4] A. A. A. Ari, B. O. Yenke, N. Labraoui, I. Damakoa, and A. Gueroui, "A power efficient cluster-based routing algorithm for wireless sensor networks: Honeybees swarm intelligence based approach," *J. Netw. Comput. Appl.*, vol. 69, pp. 77–97, Jul. 2016, doi: 10.1016/j.jnca.2016.04.020.

[5] D. Arthur and S. Vassilvitskii, "K-means++: The advantages of careful seeding," Stanford, Stanford, CA, USA, Tech. Rep. 829, 2006.

[6] *AVNET: Quality Electronic Components & Services*. Accessed: Apr. 13, 2022. [Online]. Available: https://www.avnet.com/wps/portal/abacus/manufacturers/m/te-connectivity/industrial-iot/

[7] S. Basagni, M. Conti, S. Giordano, and I. Stojmenović, *Mobile Ad Hoc Networking*, vol. 461. New York, NY, USA: IEEE Press, 2004.

[8] S. Bova, P. Codara, D. Maccari, and V. Marra, "A logical analysis of Mamdani-type fuzzy inference, I theoretical bases," in *Proc. Int. Conf. Fuzzy Syst.*, Jul. 2010, pp. 1–8, doi: 10.1109/fuzzy.2010.5584830.

[9] G. Brante, G. de Santi Peron, R. D. Souza, and T. Abrao, "Distributed fuzzy logic-based relay selection algorithm for cooperative wireless sensor networks," *IEEE Sensors J.*, vol. 13, no. 11, pp. 4375–4386, Nov. 2013, doi: 10.1109/JSEN.2013.2269798.

[10] T. Clausen and P. Jacquet, Eds., "Optimized link state routing protocol (OLSR)," Oct. 2003, doi: 10.17487/rfc3626.

[11] T. R. Cutler, "The Internet of Manufacturing Things," *Ind. Eng.*, vol. 46, no. 8, pp. 37–41, 2014.

[12] A. Daniel, K. M. Balamurugan, R. Vijay, and K. Arjun, "Energy aware clustering with multihop routing algorithm for wireless sensor networks," *Intell. Autom. Soft Comput.*, vol. 29, no. 1, pp. 233–246, 2021, doi: 10.32604/iasc.2021.016405.
[13] Z. Fang, J. Wang, Y. Ren, Z. Han, H. V. Poor, and L. Hanzo, "Age of information in energy harvesting aided massive multiple access networks," *IEEE J. Sel. Areas Commun.*, vol. 40, no. 5, pp. 1441–1456, May 2022, doi: 10.1109/JSAC.2022.3143252.
[14] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Generat. Comput. Syst.*, vol. 29, no. 7, pp. 1645–1660, 2013, doi: 10.1016/j.future.2013.01.010.
[15] I. Gupta, D. Riordan, and S. Sampalli, "Cluster-head election using fuzzy logic for wireless sensor networks," in *Proc. 3rd Annu. Commun. Netw. Services Res. Conf.*, May 2005, pp. 255–260, doi: 10.1109/cnsr.2005.27.
[16] J. D. Irwin, "Interbus," in *Industrial Communication Systems*. Boca Raton, FL, USA: CRC Press, 2018, pp. 493–502.
[17] S. Jeevanantham and B. Rebekka, "Energy-aware neuro-fuzzy routing model for WSN based-IoT," *Telecommun. Syst.*, vol.81, pp. 441–459, Sep. 2022, doi: 10.1007/s11235-022-00955-6.
[18] K. M. K. Raghunath and G. R. Anantha Raman, "Neuro-fuzzy-based bidirectional and biobjective reactive routing schema for critical wireless sensor networks," *Sensor Data Anal. Manage.*, vol. 2021, pp. 73–96, Nov. 2021, doi: 10.1002/9781119682806.ch4.
[19] K. M. K. Raghunath and S. Thirukumaran, "Fuzzy-based fault-tolerant and instant synchronization routing technique in wireless sensor network for rapid transit system," *Automatika*, vol. 60, no. 5, pp. 547–554, Jul. 2019, doi: 10.1080/00051144.2019.1643963.
[20] J.-M. Kim, S.-H. Park, Y.-J. Han, and T.-M. Chung, "CHEF: Cluster head election mechanism using fuzzy logic in wireless sensor networks," in *Proc. 10th Int. Conf. Adv. Commun. Technol.*, Feb. 2008, pp. 654–659, doi: 10.1109/icact.2008.4493846.
[21] P. Neumann, "Communication in industrial automation—What is going on?" *Control Eng. Pract.*, vol. 15, no. 11, pp. 1332–1347, Nov. 2007, doi: 10.1016/j.conengprac.2006.10.004.
[22] P. Popovski, "Ultra-reliable communication in 5G wireless systems," in *Proc. 1st Int. Conf. 5G Ubiquitous Connectivity*, Nov. 2014, pp. 146–151, doi: 10.4108/icst.5gu.2014.258154.
[23] Y. Shen, N. Xi, Q. Pei, and J. Ma, "The QoS-ensured vertical handoff decision in heterogeneous wireless networks," *J. Inf. Sci. Eng.*, vol. 30, pp. 875–893, Jan. 2014.
[24] K. Thangaramya, K. Kulothungan, R. Logambigai, M. Selvi, S. Ganapathy, and A. Kannan, "Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT," *Comput. Netw.*, vol. 151, pp. 211–223, Mar. 2019, doi: 10.1016/j.comnet.2019.01.024.
[25] J. P. Thomesse, "Fieldbus technology in industrial automation," *Proc. IEEE*, vol. 93, no. 6, pp. 1073–1101, Jun. 2005, doi: 10.1109/JPROC.2005.849724.
[26] E. Tovar and F. Vasques, "Real-time fieldbus communications using Profibus networks," *IEEE Trans. Ind. Electron.*, vol. 46, no. 6, pp. 1241–1251, Dec. 1999, doi: 10.1109/41.808018.
[27] J.-P. Vasseur and A. Dunkels, *Interconnecting Smart Objects with IP*. Amsterdam, The Netherlands: Elsevier, 2010, doi: 10.1016/c2009-0-20667-2.
[28] D. Wu, M. J. Greer, D. W. Rosen, and D. Schaefer, "Cloud manufacturing: Strategic vision and state-of-the-art," *J. Manuf. Syst.*, vol. 32, no. 4, pp. 564–579, 2013, doi: 10.1016/j.jmsy.2013.04.008.
[29] W. Wei, J. Wang, Z. Fang, J. Chen, Y. Ren, and Y. Dong, "3U: Joint design of UAV-USV-UUV networks for cooperative target hunting," *IEEE Trans. Veh. Technol.*, vol. 72, no. 3, pp. 4085–4090, Mar. 2022, doi: 10.1109/TVT.2022.3220856.
[30] Y. Zhang, J. Wang, L. Zhang, Y. Zhang, Q. Li, and K.-C. Chen, "Reliable transmission for NOMA systems with randomly deployed receivers," *IEEE Trans. Commun.*, vol. 71, no. 2, pp. 1179–1192, Feb. 2023, doi: 10.1109/TCOMM.2022.3230847.
[31] N. Rahmatov, A. Paul, F. Saeed, W.-H. Hong, H. Seo, and J. Kim, "Machine learning–based automated image processing for quality management in industrial Internet of Things," *Int. J. Distrib. Sensor Netw.*, vol. 15, no. 10, Oct. 2019, Art. no. 155014771988355, doi: 10.1177/1550147719883551.
[32] S. Din, A. Paul, A. Ahmad, B. B. Gupta, and S. Rho, "Service orchestration of optimizing continuous features in industrial surveillance using big data based fog-enabled Internet of Things," *IEEE Access*, vol. 6, pp. 21582–21591, 2018, doi: 10.1109/ACCESS.2018.2800758.
[33] F. Saeed, M. J. Ahmed, M. J. Gul, K. J. Hong, A. Paul, and M. S. Kavitha, "A robust approach for industrial small-object detection using an improved faster regional convolutional neural network," *Sci. Rep.*, vol. 11, no. 1, p. 23390, Dec. 2021, doi: 10.1038/s41598-021-02805-y.
[34] A. Paul, M. M. Rathore, and S. Rho, "Power aware mobility management of M2M for IoT communications," *Mobile Inf. Syst.*, vol. 2015, pp. 1–14, Jan. 2015, doi: 10.1155/2015/521093.
[35] A. Paul and S. Rho, "Probabilistic model for M2M in IoT networking and communication," *Telecommun. Syst.*, vol. 62, no. 1, pp. 59–66, Mar. 2015, doi: 10.1007/s11235-015-9982-z.
[36] M. M. Rathore, A. Paul, A. Ahmad, M. Anisetti, and G. Jeon, "Hadoop-based intelligent care system (HICS)," *ACM Trans. Internet Technol.*, vol. 18, no. 1, pp. 1–24, Feb. 2018, doi: 10.1145/3108936.
[37] R. M. Bhavadharini, S. Karthik, N. Karthikeyan, and A. Paul, "Wireless networking performance in IoT using adaptive contention window," *Wireless Commun. Mobile Comput.*, vol. 2018, pp. 1–9, Jul. 2018, doi: 10.1155/2018/7248040.
[38] F. H. Cabrini, F. V. Filho, P. Rito, A. B. Filho, S. Sargento, A. V. Neto, and S. T. Kofuji, "Enabling the industrial Internet of Things to cloud continuum in a real city environment," *Sensors*, vol. 21, no. 22, p. 7707, Nov. 2021, doi: 10.3390/s21227707.

KESAVAN GUNASEKARAN received the B.E. degree from the Electronics and Communication Engineering Discipline, University of Madras, the M.Tech. degree in applied electronics from Dr. M. G. R. University, India, and the Ph.D. degree from the Electronics and Communication Engineering Discipline, St. Peter's University, India, in 2016. He is currently a Professor with the Department of Electronics and Communication Engineering, Siddartha Institute of Science and Technology, Andhra Pradesh, India. His research interests include real-time applications, VLSI signal processing, the Internet of Things, and digital system design.

V. VINOTH KUMAR is currently an Associate Professor with the School of Information Technology and Engineering, VIT University, Tamil Nadu, India. He is the author/coauthor of papers in international journals and conferences, including SCI-indexed articles. He has published over 35 articles in IEEE ACCESS, Springer, Elsevier, IGI Global, and Emerald. His current research interests include wireless networks, the Internet of Things, machine learning, and big data applications. He is an Associate Editor of *International Journal of e-Collaboration* (IJeC) and *International Journal of Pervasive Computing and Communications* (IJPCC). He is also an editorial member of various journals.

A. C. KALADEVI received the B.Sc. degree in computer science from the Cauvery College for Women, Tiruchirappalli, the M.C.A. degree from the PSG College of Technology, Coimbatore, the M.Phil. degree in computer science from Manonmaniam Sundaranar University, Tirunelveli, the M.E. degree in computer science and engineering from the V. M. K. V. Engineering College, Salem, India, which was then affiliated to Anna University, Chennai, and the Ph.D. degree in information and communication engineering from Anna University, in 2014. She is currently a Professor with the Department of Computer Science and Engineering, Sona College of Technology, Salem. She has more than 25 years of teaching experience. She has published 21 articles in various international journals and presented 32 papers in both national and international conferences. She has coauthored three books in computer science discipline. She has conducted two national workshops titled ''Big Data and Cloud for Bigger Transformations'' funded by the Department of Science and Technology (DST), New Delhi, under BDI Scheme and ''Empowering the Tribal Women in and Around Yercaud Hills, Salem, by Inculcating Self-Employment Opportunities Using Innovative ICT-Based Skill Development Techniques'' funded by the Tamil Nadu State Council for Science and Technology (TNSCST), Chennai, under the Dissemination of Innovative Technology Scheme. She has guided more than 25 PG and 39 UG projects out of which three UG projects were funded by TNSCST under students project scheme. As an enthusiastic student counselor, she has given a great moral support to students who are now placed in a much renowned positions in their career. Her research interests include data analytics, cloud computing, and image processing.

T. R. MAHESH is currently an Associate Professor and the Program Head of the Department of Computer Science and Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bengaluru, India. He has credit more than 50 research articles in Scopus/WoS and SCIE-indexed journals of high repute. He has been an editor of books on emerging and new age technologies with publishers, such as Springer, IGI Global, and Wiley. He has served as a reviewer and a technical committee member for multiple conferences and journals of high reputation. His research interests include image processing, machine learning, deep learning, artificial intelligence, the IoT, and data science.

C. ROHITH BHAT received the engineering degree in computer science from the Dr. M. G. R. Engineering College, Chennai, and the master's and Ph.D. degrees from the Dr. M. G. R. Educational and Research Institute. He is currently a Professor with the Saveetha School of Engineering (SIMATS), Chennai. His passion for academics and research has made him the right person to be in academic sector. His academic interest has made him to pursue his research work on process mining and classification in general. He has got patents to his credit and has published journals in journals of repute. He has got immense interest in training the students for their placements. His research interests include process mining, the IoT, machine learning, and deep learning.

KRISHNAMOORTHY VENKATESAN received the bachelor's and master's degrees from the Mathematics Discipline, University of Madras, Tamil Nadu, India, the M.Phil. degree in mathematics from Tiruvalluvar University, and the Ph.D. degree from the Mathematics (Fuzzy Algebra) Discipline, Bharathiar University, Tamil Nadu, in 2016. He is currently an Associate Professor with Arba Minch University, Sawla Campus, Ethiopia. He was qualified in the eligible test of lectureship examination in the state level, in 2017. His research interests include fuzzy and intuitionistic fuzzy sets and its related fields.