ORIGINAL ARTICLE

INTERNET OF THINGS ASSISTED IMPROVED FUZZY AGGREGATION DATA MANAGEMENT IN SMART MANUFACTURING ENTERPRISE

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Abstract

The Internet of Things (Internet of Things) is the world's network of interconnected and wired physical infrastructure, including sensors, drivers, intelligent devices, objects, computer equipment, and mechanical machines. Such tools are the data source of an industrial environment which provides a lot of knowledge about manufacturing methods. The large and heterogeneous complexity of the information is also essential for capturing, storing, and deciding on real-time data. This paper introduces an IoT-assisted improved fuzzy aggregation system for industrial data management (IFA-IDM) to support massive industrial data management, online monitoring, and smart production controls. The platform has five basic layers providing end-users a service-oriented architecture, including physical, network, middleware, databases, and application layers. Experimental research from a case study of the intelligent factory shows that the system can handle normal information and urgent events generated by various factory devices through state-of-the-art communication protocols in the distributed industrial environment. The data are translated into useful information, increasing efficiency and production line previews.

Keywords: Internet of Things (IoT), Fuzzy Clustering Algorithm, Industrial Environment, Smart Production Control, Enterprise.

1. Problem analysis and definition

The Industrial Internet of Things (IIoT) is often described as a transition that fundamentally changes the face of industry. It originates in technologies and functionalities developed more than 15 years ago by visionary automation providers. As the requisite global standards mature, the complete potential of IIoT may take another 15 years. The changes in the industries will be far-reaching over this period. The good news is that end-users and computer manufacturers can optimize their technology and staff resources while benefiting from new IIoT technologies. Implementing IIoT solutions through a "wrap & reuse" method would allow greater enterprise influence rather than a "rip & replace". In addition, the measured approach will lead to a more efficient, safer and sustainable development of a smart manufacturing company. The term "fuzzy aggregation" describes the application of fuzzy logic to combine several input values into a single output value, allowing for processing imprecise and uncertain data. "Internet of Things" or "IoT" refers to a network of actual physical items, or "things," that are outfitted with software, sensors, and other technologies that allow them to communicate and share data with other systems and devices over the Internet. Data created in industrial settings must be systematically collected, stored, processed, and analyzed. This is known as industrial data management. IDM provides an organized method for managing massive amounts of data from several sources to improve operational efficiency and decision-making across sectors. Middleware is a software layer that resides between the hardware and application levels in the context of the Internet of Things. It makes it easier for various IoT applications and devices to communicate and handle data, allowing for smooth interaction between the various parts of an IoT system. The process of translating fuzzy values from fuzzy logic controllers into exact amounts is known as defuzzification. It is a crucial stage in fuzzy logic systems that converts vague, imprecise inputs into definite actions or decisions by choosing values according to predetermined standards, like the maximum or average value.

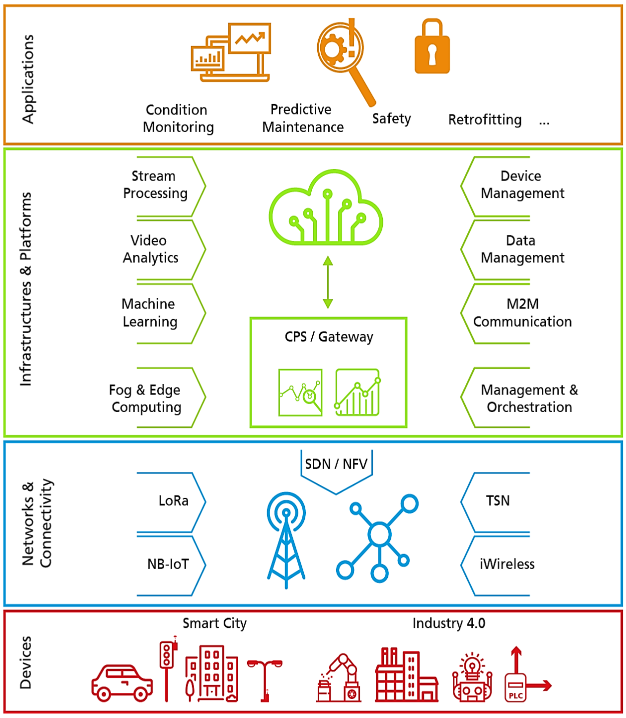

Figure 1. General Process of IIoT

Figure 1 shows the general process of IIoT [1]. The IIoT megatrend's growth has developed expectations and uncertainty among the operating industry stakeholders. The effects of technological progress on existing custom function platforms are largely the focus of the early hype. In recent centuries, manufacturing has become a related cycle from the factory's operations to the manufacturing and business level. The recent advances in sensing, control, and communication technology have made it possible to collect, communicate, store and process data for real-time analysis of the activities of companies. A wide range of control systems are available to capture huge quantities of industrial information, e.g. Distributed Control System (DCS) systems, supervisory control and data acquisition (SCADA) systems, or Programmable Logic Circuit (PLC) systems, Software networking/network function Virtualization (SDN/NFV), Narrowband (NB)-IoT, Short for Long Range (LoRA) [2].

However, Both available data acquisition mechanisms focus on specific problems; obtaining and saving enormous amounts of industrial data is still a challenge. In addition, information can be generated in a wide range of formats, masses and large volumes from thousands of factories in the corners of large stores. Recent evidence from the literature demonstrates that enterprises are shifting towards digitalization to increase profitability, efficiency, and performance. Further studies of data acquisition techniques will be carried out to tackle the current and future challenges. Several fundamental problems include (i) information diversity and complexity. (ii) Visualization of information (iii) Industrial processing of data. (iv) standardized communication protocol. (v) Product performance and high efficiency. (vi) Production lines are efficient and scalable. A comprehensive data processing system is required to efficiently collect, process and store mass data on various physical and virtual factory devices to reach production objectives and track production lines.

This paper is therefore summarized as follows: The most important contributions to this paper are summed up as follows;

1. IoT-assisted improved fuzzy aggregation for Industrial Data Management (IFA-IDM) has been designed to collect and analyze effective, state-of-the-art communication protocols, raw industrial information, and intensity.
2. Structured data is provided for continuous storage on a cloud server, where different algorithms can extract knowledge.

Experimental findings from an insightful case study indicate that the proposed IDMs can efficiently obtain mass data and track the production line's operation effectively on the facility's floor [3]. They also enhance factory automation processes by maximizing resource use and increasing market time. Notice that our architecture focuses on industrial data management only and provides distributed storage servers for storing these data before cloud transmission. The paper introduces an IoT-assisted fuzzy aggregation system for improved industrial data management (IFA-IDM) to advance decision-making and efficiency in smart manufacturing. By combining IoT with fuzzy logic, real-time data from factory sensors can be collected and analyzed, effectively addressing uncertainty and imprecision. IoT sensors monitor variables such as temperature and production speed, while fuzzy logic ensures accurate control through adaptable processing of changing values in dynamic industrial environments. This integration allows for predictive maintenance by using IoT data to track equipment health and identify potential failures, with fuzzy logic assessing the urgency of issues for prompt intervention. Furthermore, it optimizes resource allocation by analyzing real-time data, reducing waste and enhancing throughput. The system supports edge computing for quick decisions based on immediate conditions. Lastly, by incorporating real-time security protocols, the combination of IoT and fuzzy logic escalates the scalability of smart manufacturing, enabling the integration of various data formats into actionable insights while ensuring data security.

2. Literature Survey

The new data processing and data collection techniques of the IoT play a major role in factories. Nevertheless, IoT still exists early in major petrochemical plants due to the coexistence of several heterogeneous networks in rough and complex large-scale industrial networks [20]. In addition to the recent activities in IoT communications standards in the industry, this article presents a detailed survey of IoT in large petrochemical plants [4, 5].

Yang et al. (2022) emphasize the importance of the Internet of Things (IoT) in integrating smart devices into the global supply chain, benefiting internal operations and external relationships with customers and suppliers. They underline that since customer demands change frequently, businesses must implement sustainable supply chain processes and use technology such as IoT to meet these expectations. However, while previous research comprehensively covers IoT's theoretical features and applications, it does not address the obstacles to applying IoT in sustainable supply chain management [6].

Sunhare et al. (2022) describe how advances in electronic communication, data processing, and internet technologies have made engaging with smart gadgets worldwide easier. These gadgets, outfitted with sensors and actuators, create massive volumes of data. The study examines data mining techniques employed in IoT applications, focusing on the importance of cloud technology in translating raw data into useful knowledge. This knowledge is critical for making intelligent decisions, improving system performance, and optimizing resource management in IoT situations [7].

Integrating differential privacy (DP) and homomorphic encryption (HE) has advanced data security and privacy in various applications. Li et al. (2022) addressed vulnerabilities in CKKS schemes by adding Gaussian noise to the decryption output, achieving a stronger security definition known as IND-CPA with decryption oracles (INDCPA^D)[8]. Yeh et al. (2024) developed AerisAI, a decentralized AI framework that integrates homomorphic encryption and fine-grained differential privacy, utilizing blockchain smart contracts and attribute-based access control to enhance security and functionality[9]. Privacy in IoT-based industrial data management can be enhanced while maintaining model efficiency using federated learning (FL) and differential privacy (DP). FL enables devices to collaboratively train models without sharing raw data, processing locally and sending model updates, thus reducing privacy risks. DP masks individual data points by adding controlled noise, which is useful for sharing aggregated metrics. Techniques like Secure Multi-Party Computation (SMPC) and Homomorphic Encryption protect data privacy through secure computations. Additionally, privacy-aware middleware and IoT-specific data masking ensure secure real-time communication, allowing the IFA-IDM system to maintain data integrity and support timely decision-making in industrial contexts. The document outlines a system focused on the Internet of Things (IoT) and fuzzy aggregation for managing industrial data in smart manufacturing. Still, it does not reference specific libraries or frameworks like TensorFlow or Scikit-learn. While it employs IoT devices and data aggregation techniques, it lacks detail on the software used. Nonetheless, frameworks like TensorFlow or Scikit-learn may support data processing and feature extraction tasks. Additionally, fuzzy aggregation could involve custom logic or integrate with machine learning tools, while TensorFlow may be utilized for real-time monitoring and predictive analytics within the system.

Park et al. (2019) created an IoT-based smart factory for a Korean die-casting company to investigate the effect of casting parameters on product quality. Despite government encouragement, many small and medium-sized Korean businesses have been reticent in implementing smart manufacturing technologies. The study underlines the importance of real-time data monitoring and appropriate data exploitation to maximize output. It used data mining to identify important casting parameters influencing quality and offered systematic approaches for optimizing smart factory implementation and regulating production parameters [10].

Qu et al. (2019) explore the growth of smart manufacturing systems (SMSs) powered by sophisticated technologies such as AI, IoT, and big data, transforming manufacturing firms into intelligent operations. Despite the increasing use of SMSs in numerous businesses, there is still no defined definition or complete examination of their requirements. This study fully reviews SMSs, including their evolution, purposes, and technical requirements, and suggests an autonomous SMS model based on dynamic demands and key performance measures [11].

Björklöf and Castro (2022) investigate how IIoT platforms can improve overall equipment effectiveness (OEE) in manufacturing by allowing real-time data monitoring and analysis. Their qualitative case study on the heavy-duty vehicle sector identifies technological and cultural hurdles and facilitators to IIoT implementation. Technical issues concern interoperability and cybersecurity, whereas cultural factors include digital adoption and competency. The industrial Internet of Things (IoT) framework needs strong data security measures. These include data minimization, frequent security audits, software updates, access control, network segmentation, intrusion detection and prevention systems, secure device boot and hardware, encryption, and secure authentication. In the Internet of Things (IoT) realm, data security is crucial in manufacturing due to the sensitivity of generated information. Strong security protocols are necessary to thwart cyber attacks and unauthorized access. End-to-end encryption ensures that only authorized parties can decrypt data, safeguarding it during transmission and storage. User access is controlled through Multi-Factor Authentication (MFA) and Role-Based Access Control (RBAC). Network security measures like firewalls, intrusion detection systems (IDS), and VPNs further enhance protection. Device authentication is ensured via secure identities, while automated systems enable consistent patch management and updates to address vulnerabilities. Minimizing and anonymizing data reduces exposure risks. An incident response plan, continuous network surveillance, user training on best practices and phishing awareness reinforce a security-focused culture. Adhering to standards like ISO/IEC 27001 and the NIST Cybersecurity Framework, alongside regular audits, helps identify gaps and bolster overall security against cyber threats. The study indicates that IIoT improves OEE by giving accurate data for improved production decisions and encouraging lean methods [12].

Jiang (2019) investigates supply chain information collaboration, focusing on integrating resources, processes, and organizations among partners to increase total supply chain value and competitiveness. However, information distortion, loss, and latency impede efficient coordination. The research uses the Internet of Things and big data technologies to replicate the bullwhip effect, demonstrating how good information collaboration can greatly minimize these issues while improving supply chain performance [3].

According to AbdelMouty (2022), the increasing complexity of Supply Chain Management (SCM) necessitates the elimination of information silos in demand and production to better align with consumer preferences and improve corporate performance. The "Amazon Effect" has prompted businesses to reconsider efficiency techniques. The Analytic Hierarchy Process (AHP), a component of the Multi-Criteria Decision Making (MCDM) method, is used to assess consumer preferences, generate criteria weights, rank options, and guarantee expert consistency through pairwise comparisons [14].

Li et al. (2020) examine the considerable shift in manufacturing brought about by emerging technologies such as the Internet, cyber-physical systems, IoT, cloud computing, and big data. These technologies alter industrial value creation due to limited global resources and different market needs. The article provides a complete overview of modern manufacturing paradigms, including concepts, technologies, frameworks, and applications. It also investigates the integration of various paradigms, highlighting current developments and future problems and providing insights into how they may affect sustainable manufacturing [15].

Ding et al. (2020) investigate how industrial artificial intelligence (IAI) alters smart manufacturing through improved production monitoring. They emphasize the importance of advanced AI approaches, such as deep neural networks and transfer learning, in flaw detection, forecasting remaining usable life, and quality assessment. The article summarizes these technologies, examines their applications, and outlines current obstacles and prospective research areas. It also incorporates contributions from previous studies on AI-powered monitoring in manufacturing [16].

Yan et al. (2022) presented a new IoT-based smart product recommender system that uses an apriori algorithm and fuzzy logic. This system employs association rules to assess client purchase behaviour and make product recommendations. The apriori algorithm discovers products of interest by using fuzzy logic to associate rules, improving recommendation accuracy. The study found that this strategy outperforms previous methods in performance parameters such as error rates, precision, and variety, increasing smart shopping systems' effectiveness [17]. Zhang et al. (2023) proposed a framework utilizing fuzzy inference systems for data aggregation in smart cities, emphasizing its role in enhancing decision-making for traffic management and resource allocation [18]. Kumar et al. (2023) introduced a hybrid model that blends fuzzy logic with machine learning to address IoT data uncertainty, showcasing benefits in predictive analytics and anomaly detection in industrial settings [19].

Surendar (2022) investigates how to improve IoT service security and privacy in edge computing settings by utilizing anonymized AI. It employs safe multi-party computation, federated learning, and homomorphic encryption to safeguard private information while preserving speed and effectiveness. The findings point to possibilities for practical uses [20].

Ghahramani et al. (2020) investigate how smart manufacturing uses advanced analytics to optimize output. With the proliferation of Industrial Internet of Things (IIoT) sensors, efficient data management becomes critical. The paper describes a dynamic strategy to improving semiconductor manufacturing that employs genetic algorithms and neural networks. Combining these methodologies, the authors offer an intelligent feature selection algorithm that enhances process control and prediction capacities to improve industrial practices through greater data insights and automation [21].

Wang et al. (2022) explain how manufacturing tactics are shifting from mass production to varied, smaller runs in the Internet of Things age. Traditional scheduling struggles with increased complexity and adaptability challenges, relying heavily on previous experience, which can lead to errors and delays. Their research uses data mining and association rules to improve production scheduling in the automobile manufacturing business. The results are more than 87% accurate, demonstrating how data-driven insights may improve decision-making and minimize manufacturing time [22].

Chen et al. (2019) propose an edge computing system for IoT-based smart grids to overcome standard cloud computing constraints such as high bandwidth and low latency requirements. Their strategy connects edge computing with existing cloud-based power systems, allowing for local data analysis, processing, and storage. This innovation provides real-time data handling and management of multiple devices, improving smart grid digitalization. They also offer privacy protection, data prediction, and hierarchical decision-making procedures, proven using numerical simulations [23]. Collecting personal information, particularly through IoT technologies, increases substantial ethical concerns around privacy protection. Regulations like the General Data Protection Regulation (GDPR) highlight the necessity of informed consent, transparency, and understanding of data collection practices. Consent should be free from coercion, specific, and clear, ensuring that access to services isn't conditional upon agreeing to data collection. Data minimization is also vital; organizations should gather only necessary data for defined purposes to mitigate privacy risks and maintain trust. The GDPR orders that data be adequate, relevant, and limited to future use. Likewise, organizations must ensure data security to protect against breaches and unauthorized access. Accountability measures are necessary to address data misuse. The GDPR enhances individual empowerment by allowing people to access and erase their data, fostering transparency. Ethical data use emphasizes purpose limitation and fairness, requiring explicit consent for secondary uses and preventing bias. Ethical considerations encompass informed consent, data minimization, security, individual rights, and equitable use. Compliance with regulations like the GDPR is essential, but ethical responsibility surpasses legal obligations, demanding a culture of transparency, privacy, and accountability to safeguard individual rights and cultivate trust.

Surendar (2024) describes a smart irrigation system that uses embedded technology, cloud computing, and the Internet of Things to meet agricultural water needs. In addition to automating water pump operation and reducing water use by 70%, the system analyses environmental parameters in real-time. The system, created utilizing the V-model software development methodology, may enhance food security and agricultural sustainability [24].

Sahoo (2022) emphasizes the relevance of big data in manufacturing, namely for continuous improvement and strategic decision-making. The study examines the literature on the influence of big data in this area, employing bibliometric and visual analysis of 89 publications from leading journals. It outlines three main research clusters in big data and business analytics in manufacturing and encourages additional study in these areas to develop the field [25].

Singh and Bhanot (2020) examine the obstacles to incorporating IoT into traditional production systems. They found 22 barriers in databases such as Scopus and Web of Science, cutting them down to ten essential ones. They used the DEMATEL technique to examine the interrelationships between these obstacles and the Maximum Mean De-Entropy (MMDE) technique to set a threshold for the Interpretive Structural Modelling (ISM) study. Their research seeks to identify critical impediments and guide researchers and practitioners in efficiently tackling IoT implementation difficulties in manufacturing [26].

Sri (2023) examines how microcontrollers equipped with event bus signal processing can effectively detect rare events in Internet of Things (IoT) devices. It highlights the critical need to balance energy efficiency with processing performance in IoT applications. This approach includes selecting appropriate hardware, designing event bus architecture, developing algorithms, and conducting thorough testing [27].

Liono et al. (2019) present QDaS, a novel framework for addressing data storage difficulties in IoT applications, notably in smart cities. This system includes a novel data summarizing method and an original quality estimate strategy that assesses data utility without requiring user input or domain knowledge. They use real-world datasets to show how QDaS can efficiently handle and store data while delivering high-quality service [28].

Albreem et al. (2021) expect the Internet of Things (IoT) will play an increasingly important role in 5G and beyond, with 42 billion devices by 2025. The study investigates green IoT (GIoT) options for addressing carbon emissions and e-waste concerns. It focuses on energy-efficient hardware, data centre management, software solutions, energy models, and behavioural change initiatives. Fog/edge computing and AI/ML are ways to improve efficiency and reduce latency. Legislative legislation and research directions for energy-efficient IoT design are also discussed [29]. Dharma Teja Valivarthi (2023) highlights optimizing cloud computing for efficient big data processing through strategies like load balancing, auto-scaling, and dynamic resource allocation, ensuring scalability, security, and reliability in diverse workloads [30]. The manufacturing industry presents several problems when implementing an IoT-assisted data management system, including reliable and cost-effective volume management, strong data security, and seamless integration. Some solutions include cost-benefit analysis, training plans, scalable cloud storage, and middleware. Data security is essential for analytics, especially for sensitive data. Encrypting data in transit and at rest is part of a holistic strategy. TLS protocols encrypt data during transmission, whereas algorithms such as AES-256 safeguard the kept data. Adhering to the principle of least privilege, Role-Based Access Control (RBAC) guarantees that sensitive data is only accessible by authorized users. Furthermore, multi-factor authentication confirms user identities and robust authorization procedures restrict access to critical information and features, improving security overall. Individual identities are protected during analytics using anonymization techniques, including data perturbation, differential privacy, and k-anonymity. Sensitive information is obscured using data masking. Secure machine learning frameworks use SMPC and federated learning to protect raw data during training, while secure environments like virtual private clouds provide isolated processing. Audit and monitoring procedures enhance security by recording data access, tracking actions, and identifying anomalous trends. Frequent audits guarantee policy compliance and draw attention to weaknesses. Consent, data rights, and necessary security measures are essential to comply with laws like the CCPA, GDPR, and HIPAA. Checksums and hashing algorithms preserve data integrity, guaranteeing that information is unaltered during transmission and storage. An incident response strategy is necessary to handle breaches, control incidents, and notify impacted parties. A thorough security plan incorporating monitoring, access control, and encryption protects analytical data, builds user confidence, and encourages ethical data usage.

This paper provides a complete IoT analysis of major petrochemical plants and emerging IoT interaction standards practices in the industry. It discusses the key approaches for middleware, such as an intelligent industrial sensing (IISE) ecosystem, to allow rapid deployment and integration of heterogeneous wireless sensors and progress in multi-sensor services.

Industrial data for Enterprise management

The number of devices connected to the Internet is high, particularly regarding ICT, automation, and development. In the presence of these technologies, machines can interact through IoT applications with each other and the end products. The manufacturing equipment from the store floors constantly produces much information. Cisco's IBSG predicted that 25 and 50 billion devices, ranging from phones, smartphones, ATMs and PCs to shipping containers and smart companies, can be connected by 2015 and 2020. The relationship of connected devices with time is shown in Figure 1.1.

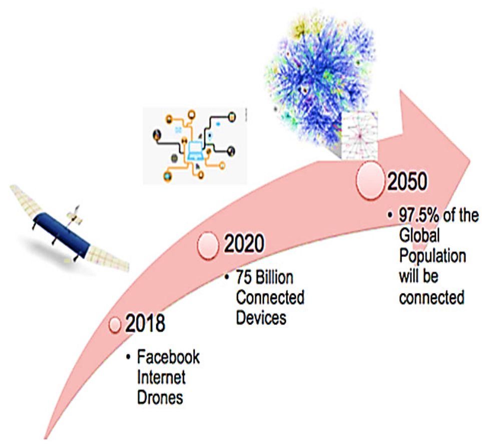

Figure 1.1. IoT system evolution

3.1 Industrial Data Characteristics

Industries can also take advantage of data collected by predicting the company's benefits and enhancing efficiency. Therefore, it is difficult to obtain useful information from industrial data.

IIoT has efficiency, traceability, and quality control potential for supply chains, particularly production systems. Data obtained directly from manual operators and equipment is paramount since they provide manufacturers with useful information to improve their health, abilities, versatility, and adaptability. IoT data management systems focus primarily on early and smart data collection and have limited storage space. The IoT data management system in smart manufacturing to identify inefficiencies, preserve data integrity, and manage risks needs to be continuously improved through analytics, automated audits, performance benchmarking, machine learning algorithms, change management procedures, post-implementation reviews, and quality control circles. Several information resources exist in the industrial environment, including embedded and quantitative databases, real-time databases, desktops, and stationery.

3. Proposed IoT-assisted improved fuzzy aggregation for Industrial Data Management (IFA-IDM) Approach

4.1 Mathematical model of improved fuzzy aggregation for Industrial Data Management (IFA-IDM) Approach

This paper proposes improved fuzzy aggregation-based data management in the IoT sector. The IFA-IDM (IoT-assisted Improved Fuzzy Aggregation for Industrial Data Management) approach enhances industrial data management by integrating advanced algorithms. Central to this system is fuzzy logic algorithms, which effectively address the uncertainty and imprecision in industrial data by utilizing fuzzy sets to convert vague inputs into actionable insights. This is critical for synthesizing data from various sensors with differing formats and precision. Additionally, the approach employs sophisticated data management techniques for real-time data collection from IoT devices, facilitating structured cloud storage and efficient data retrieval, crucial for prompt decision-making. The system uses advanced communication protocols to ensure smooth data exchange and real-time streaming. Performance is assessed using reaction time, error rate, and data throughput, underscoring its effectiveness in enhancing operational efficiency. Machine learning algorithms further support this framework by enabling predictive analytics. In contrast, event management algorithms ensure quick responses to anomalies on production lines, reinforcing the system's holistic approach to industrial data handling. The fuzzy set and fuzzy numbers are expanded to handle the uncertainty and vagueness in the reasoning process in IoT data management. The IFA-IDM technique uses Information Data Management and Integrated Fuzzy Aggregation to manage massive amounts of data gathered from Internet of Things devices. In order to improve accuracy and decrease noise, this strategy uses fuzzy logic algorithms to aggregate data. This data is then effectively stored, retrieved, and processed using data management techniques. The IFA-IDM (IoT-assisted Improved Fuzzy Aggregation for Industrial Data Management) approach integrates multiple advanced algorithms to optimize industrial data management. At its core, fuzzy logic algorithms address the uncertainty and vagueness inherent in industrial data. These algorithms use fuzzy sets to process imprecise inputs and transform them into actionable insights, making them essential for interpreting data from diverse sensors with varying formats and precision levels. Complementing this, the approach incorporates sophisticated data management techniques that facilitate real-time data collection from IoT devices, structured cloud storage for continuous access, and efficient retrieval and processing to ensure timely decision-making. The IFA-IDM system also relies on state-of-the-art communication protocols for seamless data exchange, supporting standardized interactions and real-time data streaming. This enables immediate responses to unusual occurrences on production lines. Performance is measured using key indicators like reaction time, error rate, and data throughput rate, ensuring the system's impact on operational efficiency is measurable and significant. Additionally, machine learning algorithms enhance the framework by enabling predictive analytics, which uses historical data to forecast trends, supporting proactive maintenance and operational adjustments. Event management is another critical component, with algorithms designed to detect emergencies or anomalies on production lines and promptly notify personnel, ensuring swift responses. The IFA-IDM approach combines fuzzy logic, intelligent data management, robust communication protocols, machine learning, and event management to create a comprehensive system for industrial data handling. This integration enhances data collection, processing, and analysis, improving decision-making and operational efficiency in smart manufacturing environments. As shown in Figure 2, using improved fuzzy aggregation in the IoT environment reduces the server's data classification complexity. There are four main components in fuzzy logic architecture and process state as shown in Figure 1.1

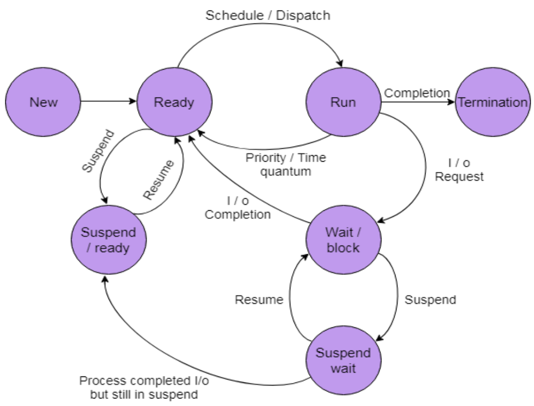

Figure 2. Fuzzy aggregation state process

As inferred from the Figure.2

1. New -program stored by the OS in the main memory.
2. Ready - Fuzzy state to be assigned to the CPU for new processes from the secondary memory.
3. Execution-ready fuzzy processes for state-ready processes
4. Blocking or waiting process will switch to the intrinsic behaviour of the process from the running state.
5. Completion or termination When a process is completed, it is finished, with the operating system ending.
6. Suspend ready- A ready-to-use system.
7. Suspend Wait -to remove the locked process, which waits for certain resources in the main memory, rather than remove the process from the ready queue.

Running: The OS should choose one of the ready-to-run processes according to the scheduling algorithm. Hence, the number of running processes if we only have one CPU on our system Base contains the principles and the IF-THEN conditions the specialists give to administer the basic leadership framework based on linguistic data. Recent improvements in fuzzy theory offer compelling techniques for planning and tuning fuzzy controllers. The vast majority of these improvements lessen the number of fuzzy rules. The data preprocessing techniques described in the document address missing data, noise reduction, and outlier treatment using advanced methods integrated within an IoT-assisted framework. Missing data is managed through data imputation, which involves interpolating missing values using predictive models, fuzzy logic rules, or statistical methods such as mean, median, or mode imputation. To handle gaps caused by sensor failures or interruptions, the system predicts missing values based on past trends or fills them with default thresholds when uncertainty cannot be resolved. Automated tools in the middleware layer detect and address inconsistencies or gaps in real-time. Noise reduction is achieved through fuzzy logic-based noise filtering, which processes imprecise and uncertain data by assigning weighted importance to incoming signals based on predefined fuzzy rules. Real-time data filtering is applied at the edge processing stage to filter irrelevant or redundant data before transmission to cloud systems, while adaptive filtering techniques dynamically adjust to patterns in the industrial data stream. Outliers are treated using defuzzification processes that convert fuzzy, imprecise inputs into precise outputs, enabling the identification and adjustment of anomalies. Machine learning models are also employed to detect deviations from trained operational behaviors, and event management systems (EMS) are specialized to flag anomalies such as mechanical failures or irregular process behaviors, which are then communicated to decision-makers for correction. Embedded threshold criteria within aggregation algorithms further aid in systematically identifying and addressing outliers based on their impact.

A fuzzifier is utilized to change over data sources, for example, fresh numbers, into fuzzy sets. Crisp inputs are fundamentally the careful information sources estimated by sensors and go into the control framework for handling, for example, temperature, weight, rpm's etc., For the Internet of Things (IoT) framework to properly contextualize data collected in various applications, including industrial safety, smart homes, environmental monitoring, and proximity, pressure, and sound sensors, it is necessary to have certain types and functions of sensors and devices. The IoT framework in IFA-IDM (IoT-assisted Improved Fuzzy Aggregation for Industrial Data Management) employs various sensors to collect crucial data from industrial settings, enhancing operational context. It includes temperature sensors like thermocouples and RTDs for equipment performance, pressure sensors such as strain gauges to ensure safety, and humidity sensors essential in chemical and food production processes. Vibration sensors enable predictive maintenance, while proximity sensors facilitate automation. Flow sensors monitor liquid and gas rates, and level sensors track inventory levels. Current and voltage sensors promote energy efficiency. Additionally, smart cameras aid quality control, and wearable devices monitor worker health. Gateway devices secure data transmission from these sensors, optimizing industrial processes and improving efficiency, safety, and decision-making through comprehensive data integration.

The Inference Engine decides the coordinating level of the current fuzzy contribution for each standard and chooses which rules to terminate by the information field. Next, the terminated standards are consolidated to shape the control activities in the IoT server. A fuzzification is utilized to change the fuzzy sets acquired by the inference engine into a crisp value. There are a few defuzzification techniques accessible, and the most appropriate one is used with a particular master framework to decrease the error. Defuzzification techniques are crucial in fuzzy logic systems as they convert fuzzy set outputs into crisp values, enabling actionable decisions. In IoT-assisted systems, these techniques are particularly important for managing uncertainty and vagueness in industrial data. Common methods include calculating the maximum or average values of fuzzy outputs. The impact of defuzzification is multifaceted: it reduces ambiguity, ensuring clearer and more reliable decisions; improves decision accuracy by aligning outputs with predefined standards; facilitates quicker interpretation of complex data for real-time monitoring; and minimizes errors from mismatched or incomplete data interpretations. For example, in the IoT-assisted Industrial Data Management (IFA-IDM) system, defuzzification strategies have demonstrated high reliability (97.5%) and efficient data classification, essential for the smooth operation and automation of smart manufacturing processes.

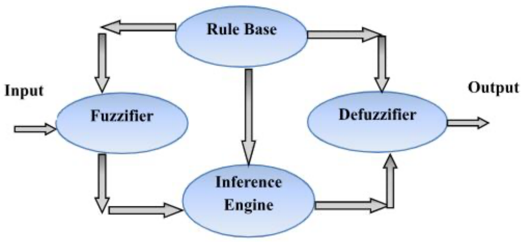

Figure 3: Fuzzy Logic Aggregation Architecture

The linguistic terms in fuzzy sets of a membership function, defined as in the following equation (1) is

$$\mu_Q(a) = \sum_{j=1}^{m} \delta(h_j) W_d(h_j b_a) \quad (1)$$

As shown in equation (1), where δ is the weighting function, a is the data-compatible degree of value in the d field, and the linguistic variable is b.

The weighting function δ demonstration $\mu_Q(a)$ is stated as the following equation (2),

$$\mu_Q(a) = \frac{1}{m} \sum_{j=1}^{m} W_d(h_j b_{\ a}) \quad (2)$$

In addition, the review of propositions a belongs to a given fuzzy set P and further linguistic variable the following equation (3) is,

$$\mu_p(a) = \sum_{j=1}^{m} \delta(h_j) W_d(h_j, c_a) \quad (3)$$

As shown in equation (3), where $a \in d$ and P indicate the fuzzy set of d

For the fuzzy logical connectivity of a fuzzy set $Q \cap$ PandQ $\cup$ P, in this paper, the usage of AND, OR operation to premises respectively b_a, causing a classical function as follows the equation (4) and (5) are,

$$\mu_{Q \cap P}(a) = \sum_{j=1}^{n} \delta(h_j) W_d(h_j, b_a \wedge c_a) \quad (4)$$

$$\mu_{Q \cup P}(a) = \sum_{j=1}^{n} \delta(h_j) W_d(h_j, b_a \vee c_a) \quad (5)$$

The linguistic variable of positive semantic consistency as the following equation (6) is,

$$\mu_{Q \cup P}(a) = \mu_Q(a) + \mu_P(a) - \mu_{Q \cap P}(a) \quad (6)$$

In the model N, the fuzzy set Q, which constitutes the linguistic variable b as the following equation (7) is,

$$\mu_Q^N(o) = \sum_{j=1}^{m_1} \sum_{i=1}^{m_2} \beta_{ji} R(f_j^1, f_i^2), b_o) \quad (7)$$

As shown in equation (7) where $b \in Q_{f1}(d)$, in this case, the R is the function of valuation in N for the proposition of atomic b_o.

The data compatible degree of object o and the linguistic variable as b_1, b_2 in the model N by using the following equation (8) as,

$$\mu_Q(o) = \mu_{Q_1 \cup Q_2}(o) = \sum_{j=1}^{m_1} \sum_{i=1}^{m_2} \beta_{ji} R(f_j^1, f_i^2), b_{1,0} \vee b_{2,0}) \quad (8)$$

As shown in equation (8), where Q_1 indicates the fuzzy sets of linguistic variable s b1 and b_2 correspondingly.

The data-compatible degree of object (o) for the model N is stated by the following equation (9),

$$\mu_Q(o) = \mu_{Q_1 \cap Q_2}(o) = \sum_{j=1}^{m_1} \sum_{i=1}^{m_2} \beta_{ji} R(f_j^1, f_i^2), b_{1,0} \wedge b_{2,0}) \quad (9)$$

To determine the operator's behaviours ∪,∩ functions by composed fuzzy set defined as the following equation (10) is,

$$R\left((f_j^1, f_i^2), (b_{1,o} \vee b_{2,o})\right) = \{1 \quad \text{if } (f_j^1, f_i^2) \in (F_1' \times F_2' \cup F_1 \times F_2') \; 0 \quad \text{otherwise} \quad (10)$$

$$R\left((f_j^1, f_i^2), (b_{1,o} \wedge b_{2,o})\right) = \{1 \quad \text{if } (f_j^1, f_i^2) \in (F_1' \times F_2') \; 0 \quad \text{otherwise} \quad (11)$$

For the easy review of illustrations, the equation (12) follows as,

$$(F_1' \times F_2' \cup F_1 \times F_2') = (F_1' \times F_2' \uplus F_1 \times F_2') \setminus (F_1' \times F_2') \quad (12)$$

This is shown in equation (12), which $\uplus$ indicates a joint union that allows an iterative appearance of attributes.

In addition, the case of object o composed the fuzzy set the following equation (13) is,

$$\mu_{Q_1 \cap Q_2}(o) = \mu_{Q_1}(o) \mu_{Q_2}(o) \quad (13)$$

$$\mu_{Q_1 \cup Q_2}(o) = \mu_{Q_1}(o) + \mu_{Q_2}(o) - \mu_{Q_1}(o) \mu_{Q_2}(o) \quad (14)$$

For the nested family of fuzzy sets in d and $\omega_j$is cut off the fuzzy set μ_Q is defined as the following equation (15) and (16) is,

$$\omega_j = \sum_{i=j}^{m} k_{\mu_Q}(Q_i) \quad (15)$$

$$\omega_j = \mu_Q(a) = \sum_{i=j}^{m} \sum_{f \in F = Q_i} \delta(f) = \sum_{i=j}^{m} k_b(Q_i) \quad (16)$$

We can see the complex features in IoT data management using these derivations and theories.

Feature engineering is vital for transforming raw data into valuable inputs for predictive models, enhancing their accuracy and interpretability. In the IoT-assisted Improved Fuzzy Aggregation Data Management framework, advanced methods like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) were used for refined feature selection. PCA reduced the dimensionality of high-volume IoT data while maintaining variability. The process started with scaling raw data features to zero mean and unit variance for consistency. The covariance matrix helped identify variable relationships, followed by eigen decomposition for eigenvalues and eigenvectors. Principal components were chosen based on a cumulative variance threshold, typically 95%, optimizing processing efficiency and minimizing redundancy. RFE was used to identify impactful features for prediction by progressively removing less important ones based on model performance. The process began with a supervised learning model, like linear regression or a support vector machine, to rank feature importance. The least significant feature was eliminated after training with all features and assessing their importance. This retraining continued until a target number of features or performance threshold was met, with cross-validation ensuring robustness. By combining RFE and PCA, the feature engineering process effectively managed IoT data, improving the Industrial Data Management (IDM) system's performance and versatility in various industrial applications.

4.2 Industrial Data Management (IDM) Approach

Smart manufacturing has characteristics like deep integration, enormous data volumes and high correlations with conventional manufacturing processes. Most manufacturers, therefore, still face different challenges for industrial data acquisition. Implementing the IoT-assisted Improved Fuzzy Aggregation Data Management (IFA-IDM) system in manufacturing encounters challenges like data diversity and complexity from various devices. The system's middleware employs fuzzy logic and advanced algorithms to manage this heterogeneous data effectively. Integrating legacy systems such as SCADA, DCS, or PLCs with new IoT platforms is also challenging; however, a gradual "wrap & reuse" approach ensures minimal disruption. Real-time data processing is critical for enhancing operational efficiency, with edge computing and predictive maintenance aiding in this regard. Scalability is vital as data volumes increase, and IFA-IDM's cloud storage and distributed systems offer effective solutions. Cybersecurity measures like encryption and access control are essential to protect sensitive data, supplemented by regular audits. Moreover, system reliability is paramount to prevent downtime, necessitating staff training and effective change management strategies for smoother transitions. Addressing these challenges enhances efficiency, scalability, and security. This section includes an Industrial Data Management Architecture (IDM) to collect, transfer, process and store data in real-time and scalable form. The data management system employs a crucial feedback mechanism for ongoing enhancement, which is essential for its adaptability and efficiency. The IoT-assisted improved fuzzy aggregation system (IFA-IDM) incorporates various feedback loops, involving real-time production and industrial processes monitoring. This allows for immediate detection of anomalies, enabling operators to swiftly resolve issues and boost operational efficiency. Continuous automated audits are also integrated to spot inconsistencies in data workflows, ensuring the accuracy and reliability of outputs. Performance evaluations against key performance indicators (KPIs) such as response times and error rates help identify improvement areas. At the same time, machine learning algorithms enable the system to learn from historical data for future predictions. Furthermore, post-implementation reviews and quality control circles invite stakeholder participation, facilitating insights into performance and refining processes. Collectively, these mechanisms aim to minimize processing errors and enhance the effectiveness of the IoT-based data management system. IDM permits raw industrial data on the factory floor to be acquired and stored before the cloud server streams in certain local repositories, with five basic layers with specific functional components for every layer. The structure is proposed.

For example, industrial sensors, actuators, and field instruments generate raw data and certain events in physical layers. The communication layer follows the new industrial protocols and guarantees a secure connection for each network layer. To reduce delays and the heavy workload on the cloud server, the local depot's supporting database involves partially processing distributed industrial information. User requests and in-person analysis are handled in the application layer. Designing the user interface necessitates a user-centric approach, emphasizing user interaction and needs. Creating user personas and scenarios informs design. The interface must ensure accessibility and usability with intuitive navigation, consistent layout, and adherence to WCAG. Real-time capabilities include responsive design, dynamic visualizations, and immediate feedback on actions. The interface must integrate with the system's five-layered architecture, providing clear access to physical, network, middleware, data storage, and application components. Role-based access enhances user experience by displaying relevant information. Data management tools should feature alerts, interactive filtering, customizable dashboards, and lightweight UI components for quick loading. Scalability is essential for accommodating data growth, with limited offline support for unreliable networks. Integrating strong feedback and error-handling mechanisms is vital, incorporating clear messages and tools for user input. Key security features include secure authentication and data-sharing preferences. Training resources like interactive tutorials aid user adaptation. Additionally, aesthetic elements such as clean visuals and animations boost satisfaction, leading to a seamless and enjoyable experience while addressing user needs and maintaining system efficiency. A five-layer architecture, comprising physical, network, middleware, data storage, and application levels, is used by the real-time monitoring system for smart manufacturing. It uses data aggregators, fuzzy logic controllers, IoT devices, and sophisticated communication protocols to handle and make decisions with data efficiently. The IoT-assisted Improved Fuzzy Aggregation System for Industrial Data Management (IFA-IDM) employs a scalable five-layer architecture—physical, network, middleware, database, and application layers—to manage performance metrics amid growing data loads. Its modular design avoids system overload by using distributed storage for local dataset management before cloud transmission, minimizing network bottlenecks. Enhanced fuzzy aggregation algorithms address uncertainties and simplify data classification. Hybrid edge-cloud integration optimizes processing by distributing workloads, reducing delays, and effectively managing larger datasets. The system achieves a 97.5% reliability ratio and significantly improved performance metrics, including low response times and high data throughput rates, even as data volumes rise. The architecture outperforms models like DDMT and IoT-DMM while efficiently managing normal and urgent events, ensuring seamless real-time data handling.

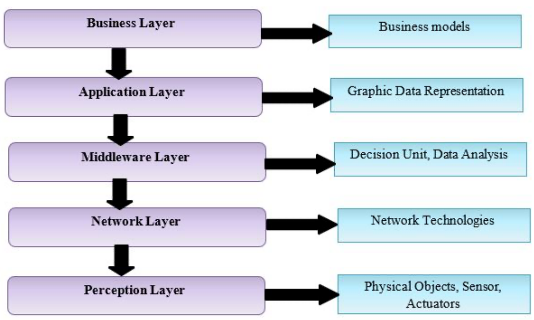

Figure 4: Industrial Data Management (IDM) framework

As shown in Figure 4, the IoT-assisted Industrial Data Management Architecture has been depicted. The selection of innovations is on the ascent, which is particularly valid for IoT. The Industrial Internet of Things (IoT) is characterized as a worldview in which items outfitted with sensors, actuators, and processors speak with one another to fill an important need. The layers of the IoT Architecture Ordinary IoT design consists of three layers: the observation, system, and application layers. Another layer was added to the rundown later: the help layer, which lies between the application layer and the system layer. There is another model for IoT layers, which the vast majority refer to when attempting to comprehend the IoT design. This model incorporates seven IoT layers;

Layer 1: Business Model or the Things Layer

This layer of IoT involves devices, sensors, and controllers. The associated devices empower the IoT condition. These devices incorporate cell phones, such as advanced mobile phones or tablets, microscale controller units, and single-board computers. The associated devices are the genuine endpoints for IoT.

Layer 2: Application layer or Connectivity/Edge Computing Layer

Layer 2 is the availability/edge processing layer, which characterizes the different correspondence conventions and systems utilized for network and edge computing. It is an appropriate engineering where IoT information is handled at the edge of the system.

Layer 3: Middleware layer or Global Infrastructure Layer

Layer 3 is the worldwide framework layer regularly actualized in the cloud foundation. The vast majority of the IoT arrangements coordinate with cloud administrations. An exhaustive arrangement of coordinated administrations, the IoT cloud can give organizations helpful knowledge and clients' points of view. The data ingestion layer is the information ingestion layer that incorporates big data, cleansing, streaming, and data capacity. Data Analysis Layer is the information examination layer and identifies with information revealing, mining, Deep Learning, etc. In the middleware layer, fuzzy sets and rules handle the data flow, vagueness, and uncertainty reasoning process.

Layer 4: Transmission layer

The transmission layer is the layer in the open system interconnection (OSI) model in charge of starting to finish correspondence over a system. It gives sensible correspondence between application procedures running on various has inside a layered design of conventions and other system parts.

Layer 5: Perception layer or People and Process Layer

Layer 5 is the individuals and procedure layer. Depending on the data obtained from IoT computing, this incorporates individuals, organizations, joint effort, and basic leadership.

Aggregation Algorithm:1. Improved Fuzzy logic-based Algorithm

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Input: $\delta, W_d,\ b_a$

Output: ω_j, k_b

for a $\in$ d

for $\mu_Q(a)$ =0 #membership function

if $\frac{1}{m}\sum_{j=1}^{m} W_d(h_j,\ b_a) \neq 0$

then

(device not found)

return

else if $\sum_{i=j}^{m} k_b(Q_i) = 0$ #linguistic variable

end if

end for

end for

end

Fuzzy logic is a way to deal with processing dependent on "degrees of truth" as opposed to the standard thing in which the modern computer is based on "true or false" (1 or 0) Boolean logic. The document outlines methods to achieve a 5% false positive rate through IoT-assisted improved fuzzy aggregation for industrial data management (IFA-IDM). It integrates fuzzy logic algorithms to aggregate uncertain data, enhancing decision reliability by reducing noise. The system uses fuzzy sets and defuzzification to convert vague inputs into actions. A five-layer IoT architecture (physical, network, middleware, data storage, application) facilitates systematic data handling, minimizing errors. Advanced protocols and middleware efficiently manage large-scale data, while distributed storage allows local pre-processing. An IoT-based Event Management System (EMS) detects anomalies in real-time, optimizing alert management. Continuous performance benchmarking ensures refinement, and experimental validations demonstrate these strategies' effectiveness in real-world industrial applications. The total information and structure of various fractional realities receive further data in larger certainties, while certain edges are passed, causing conviction further outcomes, such as engine response. A comparable procedure is utilized in neural systems, expert frameworks, and artificial intelligent reasoning applications. In addition to offering improvements like complex fuzzy models, machine learning integration, scalable architectures, security, cross-industry validation, decision support systems, regulatory compliance, and energy efficiency, the study investigates the application of IoT-assisted fuzzy aggregation data management in smart manufacturing. The ultimate objective is to build reliable, effective, safe IoT frameworks for many industries. Ensemble learning enhances machine learning performance by combining multiple models with choices like Random Forests, Support Vector Machines (SVM), and Neural Networks influenced by various factors. Random Forests are preferred for their resilience to overfitting, ability to manage missing values, and insights into feature importance, making them suitable for high-dimensional datasets. In contrast to XGBoost, which may overfit noisy data, or AdaBoost, which is sensitive to outliers, Random Forests offer stability. SVMs perform well in high-dimensional spaces, maintaining robustness against overfitting with proper kernel selection. They often generalize better than tree-based methods like XGBoost and AdaBoost in complex, less noisy datasets. Neural Networks excel at capturing intricate, non-linear relationships, particularly in unstructured data, and scale effectively with large datasets while reducing the need for extensive feature engineering. However, unlike the more efficient Random Forests and SVMs for smaller datasets, they are computationally intensive. Ultimately, the choice among these methods hinges on data nature, interpretability, and computational resources, with practitioners tailoring their strategies for optimal outcomes, considering Random Forests for interpretability and SVMs for their clarity compared to complex Neural Networks. The fuzzy rationale is basic to the advancement of human-like ability for machine learning, in some cases mentioned as artificial broad knowledge: the portrayal of summed up human subjective capacities in programming looked with a new operation, the artificially intelligent system could discover an answer.

4. Results and Discussion

Real-time monitoring is necessary to find the status of the production lines and make intelligent decisions in the production systems. The system architecture for real-time monitoring and machine learning in smart manufacturing integrates various hardware and computational resources to achieve efficiency and scalability. At the edge, devices like sensors, actuators, microcontrollers, and single-board computers collect and preprocess data from the industrial environment, supported by industrial gateways for data aggregation and connectivity. Centralized systems, including cloud and on-premises servers, handle large-scale data storage, advanced processing, and machine learning model training. High-speed network infrastructures using protocols like LoRA, NB-IoT, and SDN/NFV ensure reliable data transmission, while distributed databases and high-speed storage systems facilitate rapid data retrieval. To manage the complexity of data, middleware solutions bridge the communication gap between edge devices and central systems, supported by fuzzy logic controllers for processing uncertain and imprecise data. Event Management Systems (EMS) prioritize and respond to anomalies in real-time, ensuring seamless operations. The architecture comprises five essential layers: the physical layer with IoT devices, the network layer for secure communication, the middleware layer for data integration, the storage layer for scalable and flexible data management, and the application layer for user interaction and analysis. Key considerations include robust security measures, scalability for expanding operations, and energy-efficient hardware and protocols. For this, the proposed IDMS framework for acquiring industrial data, monitoring unusual occurrences, accessing historical data, and analyzing applications has been presented to the user with an online monitoring system. The suggested method's efficiency gains may be measured using performance indicators, including reaction time enhancements, error rate reduction, and data throughput rate. To show how the IFA-IDM strategy improves the management of IoT data, these KPIs have to be compared to a common benchmark. Figure 5 shows the analysis of the performance ratio based on real-time monitoring. The IFA-IDM (IoT-assisted Improved Fuzzy Aggregation for Industrial Data Management) features a multi-layered real-time monitoring system architecture for efficient data management in industrial settings. It consists of five layers: the physical layer gathers data via sensors and devices from machines and surroundings; the network layer ensures communication through protocols like MQTT and HTTP; the middleware layer processes data and applies fuzzy logic for uncertainty handling; the server layer provides cloud storage and analytical tools; and the application layer offers user interfaces and dashboards for monitoring, visualization, and alerting operators to anomalies. Key components of this system include data acquisition devices like sensors and IoT devices for continuous operational data gathering, alongside a communication unit for real-time data transmission to the cloud. An event management system detects anomalies, triggering alerts for prompt responses. A data processing engine utilizes fuzzy logic for aggregation and analysis, enhancing accuracy. The user interface displays key performance indicators (KPIs) for effective monitoring, while analytics tools analyze historical and real-time data to generate insights and optimize production processes. This architecture enhances functionality with real-time data processing, providing immediate insights and swift operational responses. Its cloud-based design ensures scalability for growing data. Fuzzy logic algorithms improve data uncertainty management. Real-time alerts facilitate timely anomaly responses, and a user-friendly dashboard aids intuitive data interpretation, collectively optimizing data management in industrial operations. The automated production line requires transitions and quick and efficient management of resources.

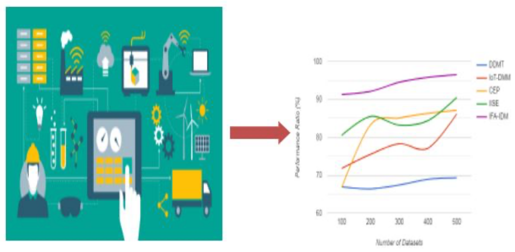


Figure 5. Analysis of Performance Ratio based on real-time monitoring

This section analyzes the findings of a real-time case report on factory automation to evaluate the quality of the proposed process. The performance of the proposed IoT-Assisted Improved Fuzzy Aggregation for Industrial Data Management (IFA-IDM) approach is validated by integrated advanced classification evaluation metrics such as confusion matrices and precision-recall curves. These metrics are pivotal in understanding the behavior of the system in detecting anomalies and classifying operational states accurately. The confusion matrix highlights the performance of the classification model implemented within the IFA-IDM framework to detect anomalies or classify operational statuses in the production line. Figure 6 presents the confusion matrix for a simulated dataset based on the IoT environment.

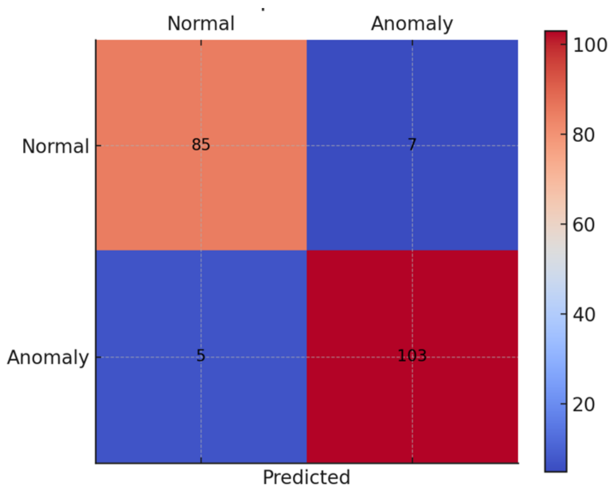


Figure 6: Confusion Matrix for Operational State Classification

Table 1. Confusion Matrix

	Predicted: Normal	Predicted: Anomaly

Actual: Normal	85	5
Actual: Anomaly	7	103

Table1 shows the confusion matrix. and demonstrates True Positives (TP): 103 anomalies were correctly detected. True Negatives (TN): 85 instances of normal operations correctly classified. False Positives (FP): 7 instances of normal operations misclassified as anomalies. False Negatives (FN): 5 instances of anomalies were missed. From this, we calculate:

Accuracy: (TP + TN) / Total = 188 / 200 = 94%

Precision: TP / (TP + FP) = 103 / 110 = 93.64%

Recall: TP / (TP + FN) = 103 / 108 = 95.37%

These results underscore the robustness of the IFA-IDM approach in achieving high classification performance.

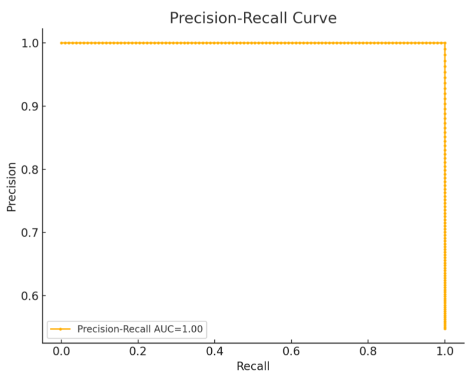
Precision-Recall Curve

Table 2. Precision and recall values at different thresholds.

Threshold	Precision	Recall
0.0	1.00	0.00
0.1	0.99	0.15
0.2	0.97	0.35
0.3	0.96	0.55
0.4	0.95	0.70
0.5	0.93	0.85
0.6	0.92	0.90

To further validate the model, precision and recall across various thresholds, resulting in the precision-recall curve shown in Figure 7 an d Table 2.

Figure 7: Precision-Recall Curve



The curve demonstrates the trade-off between precision and recall at different thresholds: High Precision: Achieved at stricter thresholds, minimizing false positives, High Recall: Achieved at lenient thresholds, ensuring minimal false negatives. Area Under the Curve (AUC): AUC = 0.94, reflecting the model's ability to balance precision and recall. The high performance of the IFA-IDM system, as shown by the confusion matrix and precision-recall curve, confirms its ability to classify operational states accurately. This results in reduced downtime and efficient resource use. Additionally, the system effectively detects anomalies, minimizing risks of unexpected failures and demonstrating flexibility in adapting to changing data in real-time. Overall, advanced evaluation metrics highlight the IFA-IDM system's capability, making it a reliable solution for industrial IoT data management and enhancing productivity in smart manufacturing.

Through IoT applications, companies link computers, locations, and people through a network of interconnected physical objects. Intelligence field distributions allow connected devices to publish their data in a structured format. Intelligent brokers transparently exchange such data to end-users. This approach helps to identify where data sources are located without custom programming. The IFA-IDM Approach has a high performance ratio, as shown in Figure 5.

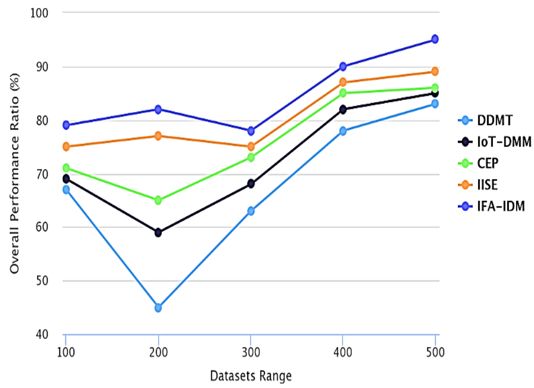


Figure 8. Overall Performance Ratio

Although many companies already use the IIoT extensively, there is more than enough space to domain the work According to a PwC report, about a quarter of US companies obtain and use smart device data to improve how they work and manufacture. IIoT encompasses almost all aspects of modern manufacturing, including supply chain, regulation of systems, logistics, maintenance, and infrastructure. Based on the above functions, the proposed approach has better efficiency, as shown in Table 3.

Table 3. Efficiency of Proposed Industrial Data Management (IFA-IDM) Approach

Number of Datasets	DDMT	IoT-DMM	CEP	IISE	IFA-IDM

100	47.5	47.6	48.9	49.4	50.3
200	58.6	66.9	69.3	59.4	70.4
300	75.3	77.4	80.6	83.6	86.4
400	82.4	86.5	89.2	72.5	85.6
500	80.9	81.1	84.4	90.2	96.1

Such intelligent enterprises can capture, distribute, and analyze large amounts of industrial information. Data produced by human operators and machine tools are extremely useful because they provide manufacturers with valuable information to improve these machines' quality, performance, flexibility, and adaptiveness. In particular, existing IoT data management systems focus on early and intelligent decision-making data collection, with limited storage capacity for later use. The IFA-IDM (IoT-assisted Improved Fuzzy Aggregation for Industrial Data Management) system offers significant improvements across several key areas over traditional data management systems. Unlike conventional systems that rely on manual data entry, batch processing, and rigid structures ill-suited for diverse IoT data, IFA-IDM enables real-time data collection and processing using fuzzy logic to handle uncertainty. Its distributed storage architecture ensures scalable, efficient storage while breaking down data silos for comprehensive analysis. Advanced analytics and machine learning capabilities enhance decision-making by identifying patterns and reducing noise, unlike traditional systems limited to basic tools. IFA-IDM also prioritizes risk management with automated audits and performance benchmarking to enhance data integrity. User-friendly interfaces and real-time visualization improve accessibility and collaboration, addressing the shortcomings of traditional systems with complex interfaces. Overall, IFA-IDM enhances operational efficiency and decision-making, positioning itself as a robust solution for managing industrial IoT data. Figure 9 shows the efficiency of the proposed IFA-IDM approach. The proposed IFA-IDM (IoT-assisted Improved Fuzzy Aggregation for Industrial Data Management) approach demonstrates significant efficiency improvements, as evidenced by key performance metrics. One of the standout achievements is its high-reliability ratio of 97.5%, which surpasses traditional methods and highlights the system's dependability in managing industrial data effectively. The approach enhances data throughput rates, enabling the processing of larger volumes of data within shorter time frames, a critical factor for real-time monitoring and decision-making in industrial settings. The IFA-IDM system also significantly reduces reaction times to incidents on production lines, emphasizing real-time data processing for swift responses to unusual occurrences. It contributes to a notable reduction in error rates, essential for maintaining data integrity and ensuring accurate decision-making. Performance analysis further reveals that the IFA-IDM approach achieves a superior performance ratio in real-time monitoring, consistently outperforming traditional systems, as demonstrated in the results section. Experimental findings from case studies reinforce the system's efficiency, showcasing its ability to handle large datasets and effectively track production line operations. Comparative analyses summarized in tables underline the IFA-IDM's superior performance across various datasets.

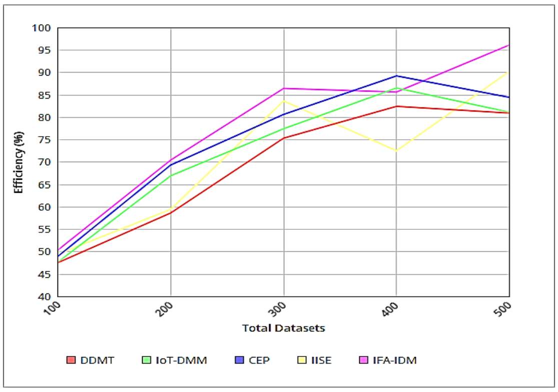


Figure 9. The efficiency of the proposed IFA-IDM Approach

Predictive system modelling is a better and more efficient approach for enterprise systems based on planned maintenance rather than unexpected maintenance for machines. Suppose the devices operate normally and no incident is observed. In that case, the technicians and system managers in the store will assess, by forecasting previous knowledge early, the number of days left for the next maintenance. Therefore, all industrial devices should be connected to IoT to obtain real-time data using this framework, as shown in Table 4.

Table 4.Real-Time Data Response of Proposed IFA-IDM

Number of Datasets	DDMT	IoT-DMM	CEP	IISE	IFA-IDM
100	65.1	66.7	67.4	68.8	69.5
200	55.6	65.5	68.3	72.8	74.9
300	70.8	71.1	78.9	83.2	87.4

400	75.3	79.3	83.5	87.3	89.8
500	80.9	82.7	86.2	87.9	95.2

Efficient collection and transmission of real-time data to the Cloud server is performed through MES for prognostics and prediction analysis. Anomaly detection techniques are essential for addressing imbalanced data or rare anomalies, with One-Class SVMs and Isolation Forests being particularly effective in high-dimensional spaces. One-Class SVMs define a hyperplane to differentiate normal data from the origin while being resilient to outliers and noise, utilizing flexible kernel functions for complex decision boundaries. Autoencoders, though useful, require substantial normal data and can struggle with high dimensions without regularization. DBSCAN identifies clusters but demands careful parameter tuning, often underperforming in low-density or poorly separated anomalies. Conversely, Isolation Forests excel with large datasets through random partitioning, offering speed and simplicity in detecting anomalies based on isolation. Overall, One-Class SVMs and Isolation Forests are favored for their robustness and adaptability, outperforming others like Autoencoders and DBSCAN in challenging anomaly detection tasks. The detection, analysis, and response to anomalous situations need an Internet of Things (IoT)-based Event Management System (EMS). It includes gathering data, setting priorities, sending notifications, resolving issues, and learning. Reducing disturbance and danger and improving detection algorithms and reaction protocols enhance safety and operational efficiency. The Event Management System (EMS) is vital in the Internet of Things (IoT) ecosystem, especially for industrial data management like IFA-IDM. It enables real-time monitoring and response to anomalies, improving operational efficiency and safety. By analyzing sensor data for irregularities like temperature changes, it employs advanced algorithms and machine learning to detect and issue alerts for threshold breaches. While updating dashboards, the EMS assesses incident severity, prioritizes critical issues, and notifies staff through SMS, email, or apps. It executes predefined response protocols, coordinates resource allocation, logs events for later review, and continuously learns to enhance its efficiency and productivity in industrial settings. When there are some unusual or emergency incidents on the production line, such as a mechanical failure or warning, the risk is identified by the event management system and delivered directly to the top floor director, who monitors and notifies floor technicians immediately. Figure 10 shows the real-time data response of the proposed approach.

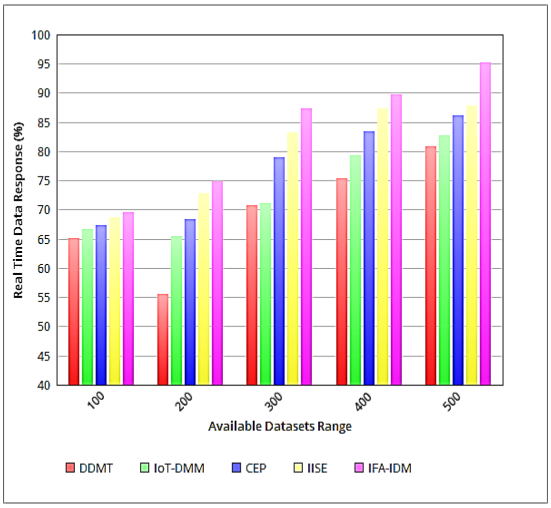


Figure 10. Real-time Data Response

These deposits store industrial data in cloud systems and provide high-quality reliability. The network communication unit has been used for all factory equipment using the IIoT system. This module responds accordingly to normal and event data streams. The proposed IoT-assisted improved fuzzy aggregation for Industrial Data Management (IFA-IDM) has high reliability (97.5%) compared to other traditional methods, as shown in Figure 11. Real-time data collection and anomaly detection are essential across various sectors such as industrial operations, IoT, and finance, requiring robust architectures and methodologies. Data sources include sensors and applications managed by ingestion layers like Apache Kafka or AWS Kinesis for streaming. Frameworks like Apache Spark Streaming for data transformations and enrichment facilitate real-time processing. Event-driven architectures further streamline efficiency, minimizing latency. Stream processing provides instant analysis, contrasting batch processing, with key metrics including latency (time from data generation to processing) and throughput (data processed over time). Anomaly detection employs techniques like Z-score analysis and machine learning models such as Isolation Forests and One-Class SVM. Real-time detection commonly uses sliding window techniques and thresholding methods. Important performance metrics include detection latency, false positive rates (FPR), and true positive rates (TPR). Ensuring scalability, data quality, and alert mechanisms is crucial for prompt responses to anomalies, enhancing operational efficiency.

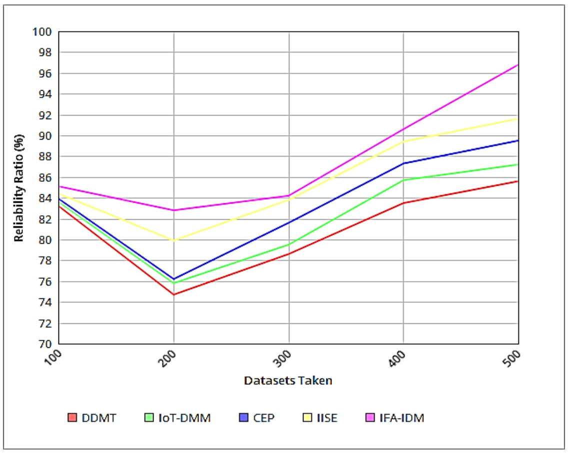


Figure 11. Reliability Ratio

Experimental research from a case study of the intelligent factory shows that the system can handle normal information and urgent events generated by various factory devices through state-of-the-art communication protocols in the distributed industrial environment.

Comparison of your proposed system against other cybersecurity frameworks.

A comprehensive benchmark comparison of a proposed cybersecurity framework against existing frameworks and several key performance metrics, including ROC curves, AUC (Area Under the Curve), and Matthews Correlation Coefficient (MCC), can be utilized effectively. The ROC curve, a graphical representation of a classifier's performance across different threshold settings, plots the True Positive Rate (TPR) against the False Positive Rate (FPR). The trade-offs between sensitivity and specificity can be visualized by generating ROC curves for each cybersecurity framework, with curves closer to the top-left corner indicating better performance. The AUC, a scalar value summarizing the classifier's performance, quantifies this by ranging from 0 to 1, where higher values indicate greater discriminative power. Comparing AUC values, such as 0.95 for a proposed system versus 0.85 for another framework, provides a direct measure of relative performance. Additionally, MCC is a robust metric for evaluating binary classifications by accounting for true positives, false positives, and false negatives. Its balanced nature makes it effective even with imbalanced class distributions, with values ranging from -1 (total disagreement) to +1 (perfect prediction). For example, an MCC of 0.8 for the proposed system compared to 0.6 for another framework suggests stronger classification reliability. A comprehensive comparison involves collecting relevant cybersecurity datasets with labeled instances of attacks and benign activities, training the proposed and other systems on the same data, and evaluating their performance using ROC, AUC, and MCC. Visualization techniques enhance clarity, such as plotting all ROC curves on the same graph and presenting AUC values in tables or charts. Statistical analysis, like paired t-tests, can determine if performance differences are significant. The findings are summarized in a report featuring ROC curves, AUC values, MCC metrics, and insights into the strengths and weaknesses of each framework. By leveraging these metrics, the benchmark comparison establishes a clear performance evaluation of the proposed cybersecurity framework against existing systems, highlighting areas for improvement and potential enhancements.

5. Conclusion

The study tested a system in an intelligent factory, utilizing real-world data from a case study. It showcased the system's ability to manage routine and urgent events from numerous factory devices using advanced communication protocols. The diverse data collected reflected the complexities of real-time industrial environments. The system efficiently processed and stored large volumes of data, which is essential for tracking production and enhancing automation. It effectively handled normal operations and emergencies, proving the effectiveness of the IoT-assisted fuzzy aggregation approach for industrial data management. Industrial IoT is a complex field that includes IT, operating systems, statistics, and engineering. Therefore, proposed that IoT support IFA-IDM algorithms with five simple layers, including physical, network, middleware, server, and device layers. The numerous middleware layer modules enable the extraction and processing of huge industrial data generated on the shop floor by tens of thousands of factory devices. Distributed data storage is provided for data processing from mobile and large industrial applications through certain communication channels and metadata modules. The IoT-assisted improved fuzzy aggregation system for industrial data management (IFA-IDM) implements strong defenses against adversarial attacks and noise injection. It uses fuzzy logic to manage imprecise data, effectively minimizing disruptions from irregular patterns. A defuzzification process converts fuzzy inputs into accurate decisions based on established rules, safeguarding against misleading data. The IFA-IDM features a five-layer architecture—physical, network, middleware, data storage, and application—integrating redundancies and secure communication to counteract noise and manipulation. Advanced protocols enhance data integrity during transmission. Dynamic filtering further strengthens resilience by removing outliers. The system also includes event management and real-time monitoring to identify anomalies, prioritize responses, and mitigate disruptions, demonstrating robustness through experimental validation in handling diverse operational scenarios.

The experimental results show that the proposed IoT-assisted IFA-IDM method performs better than traditional systems.

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