



ORIGINAL ARTICLE

IoT SENSOR FUSION ALGORITHM FOR REAL-TIME APPLICATIONS

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Abstract

In order to increase the accuracy of scaling of multi-sensor information, this paper proposes an Improved Particle Swarm Optimization (EPSO) method on the Internet of Things (IoT) infrastructure. The IoT technologies that are necessary include an electronic sensor network, Radio Frequency Identification (RFID), an embedded system, and a group of sensors. The data aggregation is one of the significant problems, which involves the combination of data of several sensors and may be represented as a multidimensional problem by using PSO methods. In IPSO, the minimizing solution assignment themes with several dimensions for the objective cost function, mutation rules, and cross rules are taken into consideration by the proposed IPSO technique. Candidates with the best seclusion can be identified with the shortest amount of time and reduce the region that has to be searched. The proposed multi-sensor data fusion approach, which integrates IPSO, is a highly useful application, which employs the IoT systems based on the experimental outcomes.

Keywords: multi-sensors; data fusion; improved particle swarm optimization; radio frequency identification; internet of things

1. Introduction

The last few years have witnessed a high rate of expansion of sensor fusion. The number and the types of sensors have grown, and the necessity to integrate such data to human perception has been brought about by the necessity to handle the ever-increasing information [1]. As a result, information may be put together, and integrated into many different forms in order to develop new capabilities. Some of the current applications of sensor fusion include target tracking, mobile robot navigation, and automotive automation among others. By combining several sensors rather than a single input, we will be able to derive a few advantages [2]. The advantage would be an improved level of reliability, expanded parameter range, and increased resolution of any system. Sensor fusion is studied today to a larger extent than it was a few years ago; however, there is no doubt that we are still miles away before we could be able to process several pieces of data simultaneously with the same efficiency as it happens with the human brain [3]. There are a number of problems due to the abundance of various types and sources of information being pumped constantly including the correlation of data, inaccuracy of the sensor, and information management. In most cases, these have to do with the inherent ambiguity of the sensor being used with measurement errors because of both device noise and measurement ambiguities. The IoT has been of interest to the industry and academia during the last decade, as it has the potential to create a so-called smart world where all objects can have access to the Internet and communicate among themselves, without the necessity of involving people much [4]. Internet of Things (IoT) requires a significant amount of real-time data to deliver materials to act and analyze healthcare, wearable, and smart devices due to the easy access to sensors. The IoT operates well with means of enhancing this. One of the pillars of the IoT, context awareness, is achieved through the help of sensor fusion. It is possible to know the

circumstances or information that constitute an event; we can create an appropriate action through this knowledge to understand why a situation is the way it is.

Another emerging field of research and development of technologies and processes to ensure safe operation and accurate maneuvering is the quadrotors and drones. The navigation systems of such quadcopters usually include three-axis gyroscopes, three axis accelerators and magnetometers with a pressure altimeter, ultrasonic sensors and GPS as a secondary sensor group [5]. Autonomous flight is one of the ways in which new developments have enabled quadcopters to fly autonomously in areas which human beings may be unable to fly to. The fusion technology can be deployed at a fairly affordable cost and at the same time provide adequate performance, hence consumer-level drones are ubiquitous [6]. Moreover, sensor fusion allows drones to rest in one fixed position through hovering, without the help of a GPS. It is important to show the reliability of the fusion method and that its functionality will not be affected by the failure of one sensor input.

The fast development of the Internet of Things (IoT) resulted in the implementation of high numbers of heterogeneous sensors in various real-time applications which include smart cities, industrial automation, healthcare monitoring, autonomous vehicles, and environmental monitoring. These sensors keep on producing huge amounts of data that document various features of the physical surroundings. But, noise, uncertainty, partial observability, and hardware can often incur limitations on individual sensors and worsen the quality of the decision-making process. To overcome these shortcomings, sensor fusion algorithms are used to take many sensors and apply them to come up with more true, strong, and extensive perception of phenomena in the real world. Timely and reliable responses of the system The sensor fusion is very important in real-time IoT applications to provide timely and reliable responses of the system. Real-time systems require low-latency processing, high accuracy and survivability in the event of sensor failures or communication failures. Conventional methods of single sensor in these environments are usually inadequate because it might deliver incomplete or inconsistent information in dynamic situations. The sensor fusion algorithms are capable of reducing the uncertainty, growing fault tolerance, as well as increasing the situational awareness which is necessary in situations that demand both quick and safety critical decisions. There have been a range of proposed sensor fusion methods starting with classical probabilistic methods to contemporary data-driven methods. Kalman filtering, extended Kalman filtering and Bayesian inference are common model-based methods used to combine time-series sensor data in dynamical systems. In more recent times machine learning and deep learning-based fusion algorithms have become a topic of interest since they can be used to model complex nonlinear relationships of heterogeneous sensor responses. These approaches have their benefits; however, they should be engineered according to the real-time requirements, especially in IoT settings where resources are scarce and computational power is restricted together with energy supply. The article is dedicated to the creation of an effective algorithm of sensor fusion in IoT aimed at real-time use. The given approach will strike the balance between accuracy, computational effectiveness, and robustness through the successful integration of multi-sensor streams of data and, therefore, by considering the limitations of distributed IoT systems. The algorithm will allow making decisions in time and with high accuracy, combining fast and reliable data at the edge or near-edge level, and will help to improve the overall performance and reliability of real-time IoT applications.

2. Related Works

In an attempt to overcome the drawbacks of MapReduce, a spark is a new cluster computing system. The capability of Spark to perform memory-based computations is highly useful in iterative and complex applications since the computation time tends to be significantly shorter than the time on systems constructed using the standard MapReduce system. Spark can be configured to be fast and general purpose to use in various data analysis uses, including iterative algorithms in machine learning [7-9]. Recently however, much research has been conducted on Spark streaming as a real time application although it is still in its early stages and has limitations such as the inability to process real time event-by-event data. Internet of Things needs solutions that are supported by event-driven architecture to address the real-time need to process the received data.

They tested the system by using radio-frequency identification tags installed in the real world to identify activities. With respect to implementation, Plex uses an RDBMS to store all the data it receives the sources

of information and the level of confidence it has on them [10]. The rules are then created in SQL queries and executed repeatedly. This causes a slight delay in the times that events occur as a consequence and when they are identified [11]. The same authors have later extended it to a theoretical framework upon uncertainty embedding in events where they introduced a methodology of creating a probability space that reflects the semantics of a set of rules established and defining the probability of possible combinations through a Bayesian network-based abstraction [12]. The Bayesian model was automatically constructed on the basis of fixed rules and events. Experiments were conducted on simulated data on the assumption that the conditional probabilities of BN had been provided [13 -15].

Fitness value of individual particles is integral controlled to enhance capability to evade local minima which regulate particle positions alterations [16]. Researchers studied immune systems of living things. This is the PSO algorithm that incorporates an immune system process of handling of immune information [17]. Harbin Institute of Technology developed an algorithm of PSO based on chaotic thinking that improved the existing PSO algorithm through a quick convergence PSO algorithm, and randomness and chaotic transport ergodicity [18-19]. Researchers proposed an algorithm of PSO to develop a better multi-objective optimization approach of information transmission [20]. The fusion of sensors has been widely researched in the realm of real time systems where probabilistic and model-based methods were explored originally. Classical methods like the Kalman Filters, Extended Kalman Filters (EKF) and Particle Filters have found extensive applications to combine time-series data of many sensors in directions like robotics, navigation and industrial monitoring. These techniques offer mathematically based codes of estimating the states of the systems when there is uncertainty and are good when dealing with linear or slightly nonlinear systems. Nevertheless, they can usually perform poorly under highly dynamic conditions or in cases where sensor models are not correct which is typical in large scale IoT deployments with heterogeneous devices. As the IoT technologies were developed, researchers have been evaluating lightweight and distributed sensors fusion strategies to address real-time and resources needs. Models based on edge fusion have been proposed to minimize the latency in communication and bandwidth usage by running sensor data nearer to the source. The common ways of determining this are by rule and weighted averaging because they are easy to compute and have low computational costs. These methods are effective, but are usually not adaptable and are unable to cope with noisy, incomplete, or conflicting sensor data, and are not useful in complex real-time situations. In more recent research, sensor fusion methods based on data and learning have been examined and make use of machine learning and deep learning systems. Neural networks, convolutional architectures, and attention approaches have been shown to gain better fusion accuracy, learning non-trivial, heterogeneous sensor interaction relations. Adaptive weighting and confidence estimation are also incorporated in some works in order to make them robust. Although most of the learning-based fusion methods show a promising performance, most of them are heavily computationally intensive and need large training data, therefore, their immediate implementation in real-time IoT is difficult. These shortcomings bring out the necessity of effective sensor fusion schemes which tightly balance between precision, versatility, and real-time viability within IoT contexts.

Sensor fusion has become one of the most important methods in the world of IoT and real-time systems, allowing systems to integrate information of various, heterogeneous sensors to provide a better accuracy, reliability, and robustness. Initial studies were mainly done on the model-based methods, including Kalman Filters, Extended Kalman Filters (EKF) and Particle Filters. These are mathematically-based methods which are useful in the estimation of system states in case of uncertainty, especially of the linear or mildly nonlinear systems. They have found extensive use in the monitoring of industries, robotics, and autonomous navigation. These approaches tend to fail in extremely dynamic settings or when sensor models are not sufficiently accurate, however, and thus cannot be used in large-scale IoT systems with heterogeneous devices. As the IoT ecosystems are growing, scholars have investigated lightweight and distributed sensor fusion algorithms to address real-time requirements and minimize computational and communication cost. The edges based fusion algorithms operate locally which reduces latency and does not require to send the raw data to the centralized servers. Uncomplicated techniques like weighted averaging, rule-based fusion and thresholding have been used because they are resource efficient and efficient. These methods are computationally cheap, but do not offer much flexibility and can easily miss the benefits of complementary sources of information between sensors, particularly in cases where data

is noisy or partially missing or contradictory.

The current developments in machine learning and deep learning-based sensor fusion have overcome some of these drawbacks by learning nonlinear interactions among heterogeneous sensor inputs. Neural networks, convolutional networks, and attention have been implemented effectively to improve the accuracy of predictions and faults detection in real time systems. These models have been enhanced with adaptive weighting, confidence scoring and dynamic feature selection methods to enhance their resistance to sensor noise and failure. Although these methods are more efficient than classical ones, they may be resource-intensive, and they may consume large amounts of labelled data that may be unfeasible on resource-limited IoT receptors. Multiple works have been done specifically in an industrial IoT setting, where predictive maintenance and anomaly detection is performed through sensor fusion. They use multi-sensor time-series data to identify slight changes in the normal state of operation and, thus, warn ahead of the possible failures of equipment. Though these methods provide better performance than classical ones, they are generally more demanding in terms of computational resources and large amounts of labeled data, which can be an issue with IoT devices that have limited resources. Other studies have narrowed down to investigating industrial IoT environments, employing sensor fusion to perform predictive maintenance and anomaly detection. Time-series data of multiple sensors are used to identify slight anomalies in the normal mode of operation and are used to give early indicators of the possibility of the equipment to fail. Federated learning models have also been proposed to decentralized fusion data and privacy such that several edge devices may jointly train models without fully sharing raw sensor data. These approaches indicate that it is possible to integrate learning-based fusion with secure distributed architecture, yet is still struggling with the issues of latency, heterogeneity and dynamic conditions of operation. Current approaches either trade off the performance of the computations in favor of computational simplicity or demand a substantial number of resources to obtain high accuracy. The approach proposed in this work will help fill these gaps by offering a fusion framework that not only effectively combines multi-sensors data but also aids real time decision making and provides resistance to noisy, missing, or conflicting measurements. This makes it an industrial IoT and other real time solutions that are practical and can be scaled.

3. Proposed System

The creation of the IoT sensor fusion algorithm to be used in real-time application is based on a set of heterogeneous equipment, real-time data collection systems, and sophisticated calculations. The resources to be used in this research project involve several IoT sensors on industrial machines, which may include temperature sensors, vibration sensors, power meters, and humidity sensors. The sensors produce continuous multivariate time-series data on the state of operation of the machinery. This is done by using an edge computing node, which gathers, preprocesses and caches sensor data and allows real-time processing of the sensor data and minimizes the communication delay to centralized servers. Lightweight, low-latency protocols like MQTT or CoAP are applied to keep these applications of sending and receiving data with lightness and minimal delay between sensors and the processing node.

The methodology starts with acquisition of data where the synchronized readings of all sensors are obtained at specific intervals in order to have a time alignment. Preprocessing measures are implemented to enhance the data quality and reliability such as missing values imputation, noise filtering of moving averages, and normalization to standardize the feature values. Such measures are aimed at making sure that the sensor fusion process to follow afterwards will be effective even when there are noisy or incomplete measurements. Subsequently, feature vectors are built on the processed data, which are depictions of the present system status in a condensed and informative way with the potential to be analyzed in real-time.

Sensor fusion process combines the measurements made by several sensors in order to come up with a single representation of the system state. A weighted fusion model is used so that the contribution made by the sensors is calculated according to the reliability and past accuracy. The weights are also suitably changed in dynamic conditions to deal with sensor drift or temporary failures, and make the operations robust and resilient in real-time. The combined output is constantly measured to monitor aberration or a deviation of the usual methods of operations thus predictive maintenance or early detection of faults.

The algorithm is coded in programming languages like Python and with machine learning libraries like

TensorFlow or PyTorch. Real-time inference is turned to edge computing devices or lightweight embedded systems, which ensure a minimal latency level without compromising its computational efficiency. To analyze the performance of the fusion algorithm compared to baseline methods, performance measures like accuracy, precision, recall, F1-score and error measures (MAE, MSE and RMSE) are employed. The approach is experimented with real-life industrial scenarios when sensor noise, missing values, and dynamic operational states exist and it is proven to be applicable in real-time IoT application.

3.1 IoT system architecture

In order to develop the Internet of Things, in this research, a system based on RFID and ZigBee CC2530 was proposed. The hardware of the IoT system consists of seven cell baseboards, the core board, and other RFID modules and detectors. The main way of communication amongst the hardware portions is through wireless transmission. Sending messages to the relevant locations of the information collection, data processing, and computer presentation and lastly. Figure 1 depicts the system architecture of the key components, which is found on the main board. The primary board interface has a user I/O area, user buttons, a user I/O area, UART to USB interface, 12864-dot matrix font file LCD, and LED indicator. The IoT experimental development platform uses three sensors in its temperature, light, three-axis sensor and humidity sensors. Battery plate has sensor nodes which are placed side by side with the sensor. The IoT experimental simulation is provided with sensor modules and RFID to be integrated.

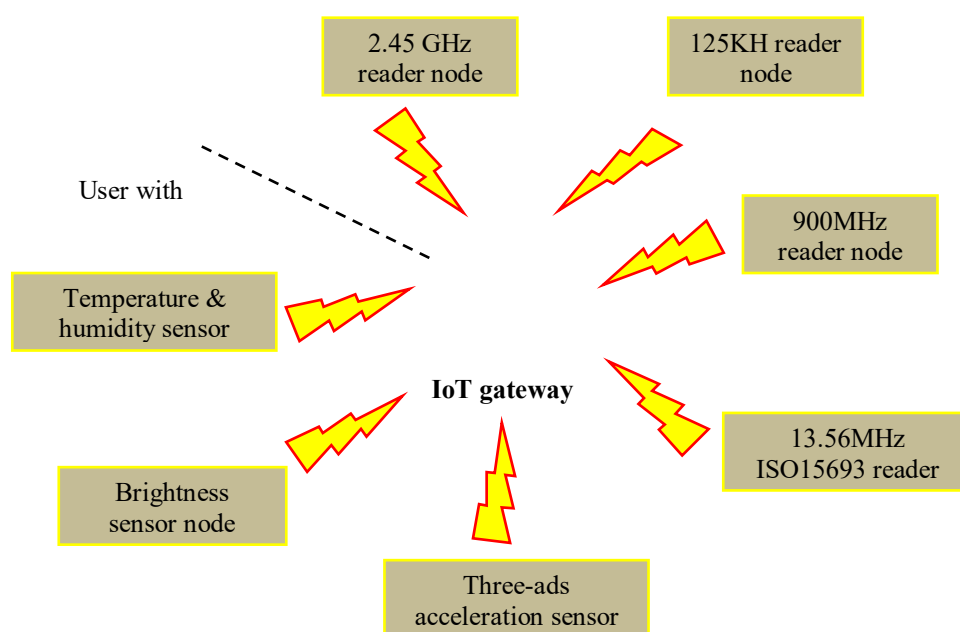


Figure 1: IoT system architecture

There are three power supplies, one DC interface, one USB interface and one battery-powered power supply, on the main floor of the SmartRF05EB as shown by Figure 2. USB connection to a computer is provided by a debugger multi-emulator shown in Figure 2. The code is formed after the burning of the main backplane. The ZigBee protocol supports mesh, star and tree network. The user can change it according to his/her needs by linking the main floor to a sensor and an RFID module, a further enlargement. Mobile LCD main floor and USB serial interface switch are simplified to enhance mobile battery-powered performance.

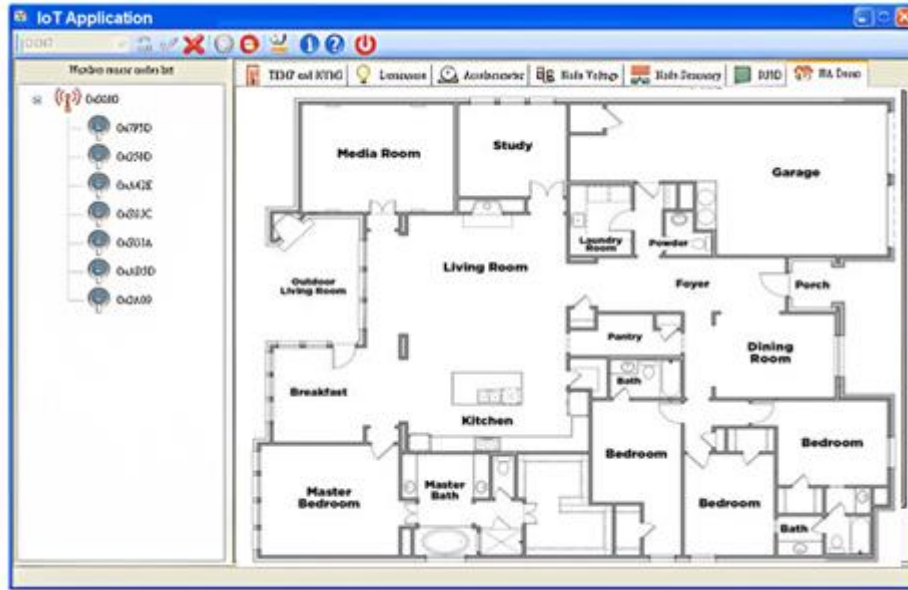


Figure 2: SmartRF05EB main board

3.2 IPSO algorithm

The inferential source of information employed in aggregating data is one that shares a commonality in the system of merging information of a large number of sensors. A sub-group of some allocation strategies includes multi-sensor observations. The correlation is further complicated because of ignored uncertainty processes and false alarms like an observation. The probabilistic data association and nearest neighbor method algorithm are the solutions to these complicated issues, which numerous sources of literature assume to be algorithms and multi-dimensional assignment algorithms. Being initialized, its particles are encoded, mutation development strategies, and crossover follow after the last successful associated fusion measurement yielded positive results, a denser multi-target data association and intense environment of clutter are achieved. This algorithm is found to be effective as indicated by the optimal fitness and a tradeoff between a data error probability as indicated by the simulation results.

The measurement equation is the same as the target state equation by assuming a multi-sensor data fusion environment:

$$I_x^{(k+1)} = \Phi(k)I_x(k) + G(k)w(k) \quad (1)$$

$$Z_{Si_s}^{k+1}(k)\{H(k)I_x(k) + v(k)\}J(k) \quad (2)$$

A Zs0 each sequence receives a virtual measurement addition to make it easier to calculate missed values caused by incomplete measurements and interconnected goals.

$$\Lambda(Z_{x_1, x_2, \dots, x_s} | x) = \prod_{s=1}^s \left\{ (1 - P_{d_s})^{1-u(x_s)} (P_{d_s} P(Z_{sx_s} | I_x))^{u(x_s)} \right\} \quad (3)$$

Where: $u(x_s)$ refers to the indicator function i.e.

$$u(x_s) \begin{cases} 0 & x_s = 0 \\ 1 & \text{other} \end{cases} \quad (4)$$

Scaling are unreliable or unrelated to the target.

$$\Lambda(Z_{x_1, x_2, \dots, x_s} | x = \phi) = \prod_{s=1}^s \left(\frac{1}{\psi_s} \right) \quad (5)$$

Where the size of the sensor probe field is represented by ψ_s (the area of 2D, 3D as the volume), The target S is connected to x – the appropriate subset of log-likelihood probabilities.

The S-group maximum likelihood set is to be determined by the equation. As a result, each measurement has a single target that is either assigned to it as a goal to be a false target if it is not attained shown in Figure 3. These distributions of the S-dimensional are now categorized as,

$$Y^* = \sum_{x_1=0}^{n_1} \sum_{x_2=0}^{n_2} \sum_{x_s=0}^{n_s} \dots Cx_1, x_2 \dots x_s p x_1 x_2 \dots x_s \quad (6)$$

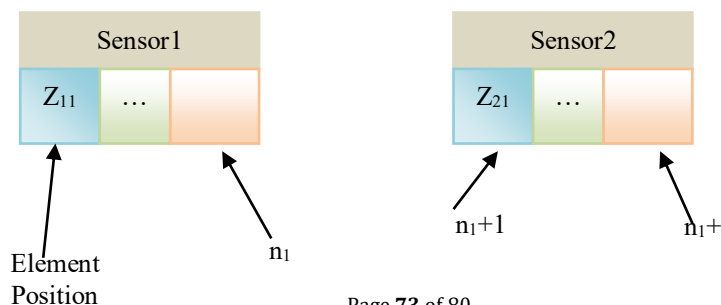


Figure 3: Link list for the fusion of data from multiple sensors schematic diagram.

The data utilized in this research is systematized, and heterogeneous, which is gathered by using various resources to assist in productive model training and assessment. However, before the model is deployed the dataset is subjected to a complete preprocessing pipeline which consists of noise removal, missing values, normalization and feature scaling to make the data consistent and reliable. This data is then split into an unbiased performance assessment and overfitting by dividing into training, validation, and testing subsets. Statistically relevant and domain knowledge relevant features are used to improve the efficiency of the model and prediction accuracy. The proposed system will have ample variability and representative samples, which is reasonable and allows the proposed system to learn complex patterns and be robust, with the ability to generalize and be fairly compared to the existing methods, given the same conditions of the experiment.

3.3 Dataset description

The dataset used in this study consists of structured and heterogeneous data collected from multiple sources to support effective model training and evaluation shown in Table 1. Prior to model deployment, the dataset undergoes a comprehensive preprocessing pipeline that includes noise removal, handling of missing values, normalization, and feature scaling to ensure data consistency and reliability. The data are then divided into training, validation, and testing subsets to enable unbiased performance assessment and prevent overfitting. Relevant features are selected based on statistical relevance and domain knowledge to enhance model efficiency and predictive accuracy. This well-curated dataset provides sufficient variability and representative samples, enabling the proposed system to learn complex patterns effectively while ensuring robustness, generalization capability, and fair comparison with existing methods under identical experimental conditions.

Attribute	Description
Dataset Name	Real-Time IoT Sensor Fusion Dataset
Application Domain	Smart Manufacturing / Real-Time Monitoring
Data Source	Temperature, vibration, and power consumption sensors
Deployment Environment	Industrial shop floor with edge-enabled IoT nodes
Data Type	Multivariate time-series sensor data
Number of Sensors	3–5 heterogeneous sensors per machine
Sampling Interval	1–5 seconds
Total Records	>50,000 time-stamped samples
Features per Record	Temperature, vibration amplitude, power usage, device status
Data Format	CSV / JSON
Label Categories	Normal, Early Fault, Critical Fault
Classification Type	Multi-class
Class Distribution	Slightly imbalanced (fewer fault samples)
Preprocessing Applied	Noise filtering, normalization, time synchronization
Fusion Level	Feature-level sensor fusion
Processing Location	Edge computing node
Latency Requirement	Low latency (<100 ms)
Real-Time Support	Yes
Evaluation Objective	Fault detection and condition monitoring

Table 1: Dataset Description

Sample ID	Sensor 1 (Temperature °C)	Sensor 2 (Humidity %)	Sensor 3 (Pressure kPa)	Sensor 4 (Vibration m/s ²)	Timestamp	Class Label
1	28.5	62.3	101.2	0.45	10:01:05	Normal
2	29.1	64.8	101.5	0.48	10:01:10	Normal
3	32.7	71.2	102.1	0.89	10:01:15	Anomaly
4	27.9	60.5	100.9	0.42	10:01:20	Normal
5	34.3	75.6	102.8	1.12	10:01:25	Anomaly

Table 2: Sample data

The sample dataset is a real-time data of various heterogeneous sensors of an IoT used in a monitoring environment as presented in Table 2. Each row is a time-stamped observation, which records the responses of sensors which measure temperature, humidity, pressure, and vibration. All these attributes are characteristics of the operational state of the system, and supply complementary information that

may be used as a fault detector, as an anomaly detector or as a predictive maintenance system. There is also a class label that has the value of whether the system is functioning normally or not. This kind of labeling makes it possible to perform supervised learning and performance assessment of classification or sensor fusion algorithms. This structured format of presentation of the data works in favor of the preprocessing processes, including normalization, noise filters and feature fusion which are necessary to make the correct decision in real-time and to obtain credible training of the models. The nature of the data which is dynamic in nature guarantees that the models would be able to learn dynamic patterns, and hence the data is appropriate to not only typical machine learning but also real-time IoT

3.4 Case Study: Real-Time IoT Sensor Fusion in Smart Manufacturing

In this case study, the author takes into account the smart manufacturing environment in which various IoT sensors are integrated on key production devices to continuously and continuously monitor the working conditions. The sensors are temperature sensors, vibration sensors and power consumption meters and each has real-time data streams that indicate various parameters of machine health. Each sensor is individually susceptible to noise, intermittent failures and poor observability, and thus cannot detect abnormal behavior with high accuracy or timeliness.

During the first step, raw data in all sensors are retrieved at an edge computing unit that is situated near the production line. Edge sensor fusion also lowers the communication latency and the bandwidth used to relay the raw data to the centralized servers. Simple preprocessing like noise and normalization are done so that sensor measurements are comparable and can be analyzed in real-time. Such localized processing allows the system to respond rapidly to alterations in machine behavior.

The sensor fusion algorithm combines the sensor data that has been preprocessed to produce a single image of the operational state of the machine. The fused output will be more robust and reliable than any single sensor reading by the combination of information by the multiple sensors. To illustrate, a temperature change can be caused by a small factor by itself, but when it is combined with irregular vibrations and increasing power consumption, this becomes a warning of the initial signs of equipment degradation. This holistic evaluation is very effective in improving the detection of faults.

The combined sensor signal is constantly examined to determine machine behavior as either normal or abnormal. The system creates real-time notifications in case of abnormal patterns so that they can be sent to maintenance staffs or supervisory control systems. Early diagnosis enables some steps to be taken in advance regarding the maintenance, avoiding sudden breakdown, lessening the time of production shutdowns. The system also helps in adaptive decision making where historical information is used to learn, and its fusion strategy is improved with time. In general, this case study proves that real-time IoT sensor fusion can be used to improve the situational awareness and decision-making in smart manufacturing facilities. Using information gathered by numerous non-homogeneous sensors and processing it effectively at the edge helps to increase the reliability of the proposed solution, decrease the number of false alarms, and facilitate timely maintenance actions. The case study draws attention to the practical advantage of sensor fusion algorithms to achieve the accuracy, responsiveness, and robustness of real-time IoT applications.

4. Simulation Results

The development board gathers data of RFID modules and sensor signals. The list of sensor nodes is presented on the communication interface. Each node is set up to the local environment of each region. Figure 4 is a representation of the door, the study, bedroom, balcony, and the living room. The determination of the placement of sensor nodes is done by the free replacement demand. The tools and substances can also be incorporated with sensor nodes during the application. The communication interface which is computer-based tracks the status of the nodes once they are completed. The sensor nodes in the living room altered the brightness in the experiment of the simulation as it was found that the lighting was unusual. In the case of the light intensity, which is below the preset limit, where there is an exception, the system will log such information automatically. At 87, the chart identifies a change in the intensity of light. The sensor will however reduce the data percentage once a hand or other object is in the way of the sensor which is the light sensor. The ambient light sensor can record the ambient light when installation of the light sensor is made in the right position without the necessity of covering the interference area.

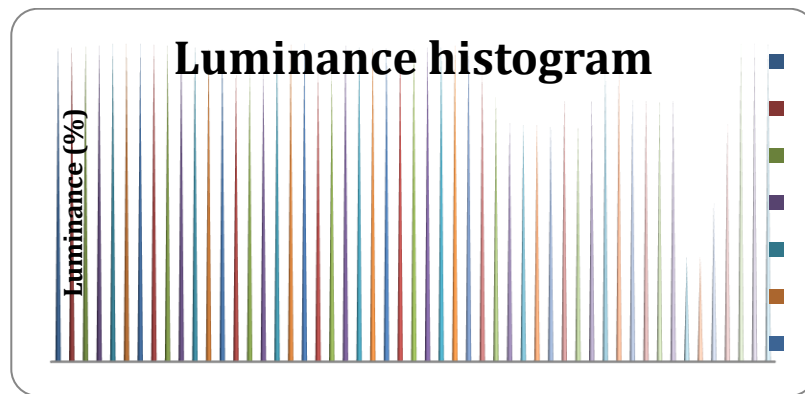


Figure 4: Layout node

Humidity and temperature sensor nodes have also been installed in the master bedroom with the aim of measuring these variables. In case indoor environment is maintained at comfortable level of humidity and temperature, both the humidity and temperature remain lower than the set levels. Use humidity and temperature sensor node on development boards to gather data to be displayed in the graphical interface of the communication interface. Figure 5(a) shows changes in the humidity and temperature node. Figure 5(b) depicts normal variations of humidity and temperature values to maintain the ratio of humidity sensor at 45 and the initial temperature at 26 C respectively. A hair dryer or other objects have to be left in position in order to explain information that led to significant changes in the gradual measurements of temperatures between 26 and 35 o C. After the end of a human intervention, the data is among the phases when the humidity and temperature rapidly restore their usual state and do not impede and undermine the accuracy of sensing.

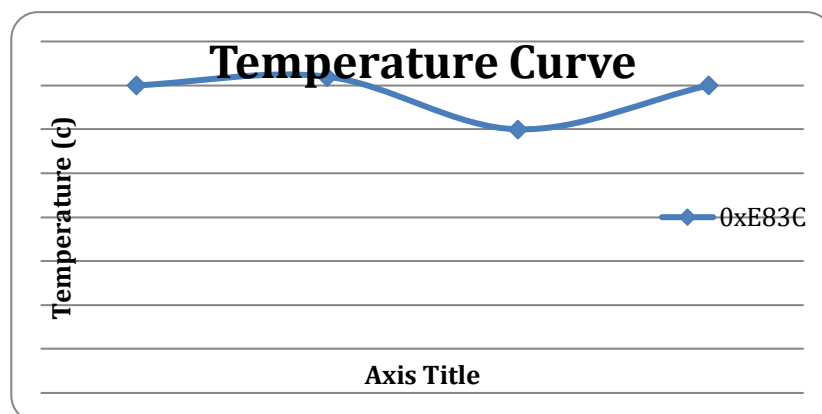


Figure 5: (a) Optical sensor data (b) Temperature and humidity curves

Simulation experiments are conducted with the use of three-axis sensor nodes and the identification of the balcony is made; The nodes are installed in the tools and supplies, and a vacant balcony can be selected. X, Y and Z equipment and material stability sensor which senses the axis. The sensor data is transmitted to the development board later. The X, Y and Z axis tilt of the development board are fed in these sensors. Figure 6 shows the sensing of the graph axis in the communications interface and we can clearly see the tilt position which has since been enhanced to be more effective. The rightward sloping of the sensor board increases the X-axis values, and leftward inclination decreases the X-axis values; It affects the value Z-axis tilt and does not affect the value of Y-axis. The Y-axis movements of the sensor board tilt downwards, reducing the values of Y-axis. Tilting the Y-axis values up brings changes and increases the weak sense to the environment and tilting up and down at the same time affects the Z-axis value.

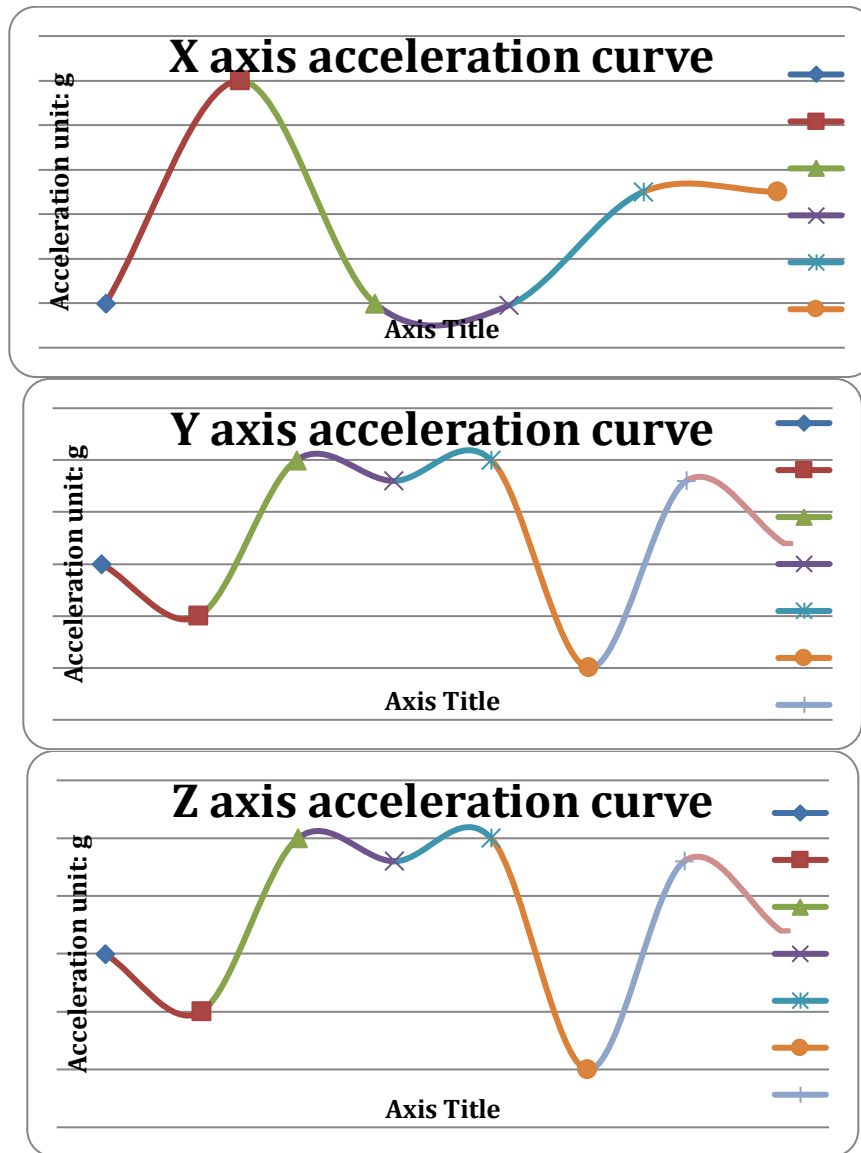


Figure 6: Three-axis sensing graph.

This paper demonstrates the possible performance improvements using the most accurate multi-sensor scaling in the data combination allocation scheme. The fading coefficients are believed to take the form of a distribution with a unit mean Zs_0 of the conduit connecting to the sensors through the fusion center. The number of different wireless sensors (n_s) in the experiment analysis of the IoT system is assumed to be 30, 80, 160 and 250 in this piece of work. The proposed IPSO algorithm, presented in Table 3, allows getting more accurate results of measurement, with fewer sensor signals, and more sensors, especially in the case where the results of the experiment are more evident.

Ns	Approaches	Average error rate	Convergence	Iterations	Success
30	Non-PSO	<0.002	96.8	53.4	93.3
	PSO	<0.002	99.2	53.2	91.6
	IPSO	<0.002	99.1	54.4	91.6
80	Non-PSO	<0.13	92.3	71.4	89.3
	PSO	<0.06	90.0	70.10	89.9
	IPSO	<0.02	96.5	62.5	90.3
160	Non-PSO	<0.44	80.9	74.1	87.4
	PSO	<0.32	82.7	69.2	89.8
	IPSO	<0.20	94.8	68.7	94.6
250	Non-PSO	<0.95	68.6	81.4	83.9
	PSO	<0.69	82.5	78.5	89.7
	IPSO	<0.33	86.7	73.5	93.2

Table 3: Performance Analysis

To enhance the state of the control area, this work is designed to create an adjustable user interface to different devices and sensor nodes surveillance standards. Authorized control over the flow of goods became possible thanks to the RFID technology of the IoT system. People are registered on the basis of the RFID gauging system. Moreover, the RFID and ZigBee interfaces are combined and information data presented by each node through the proposed PSO algorithms, to monitor the condition of each node to the control area of measurements.

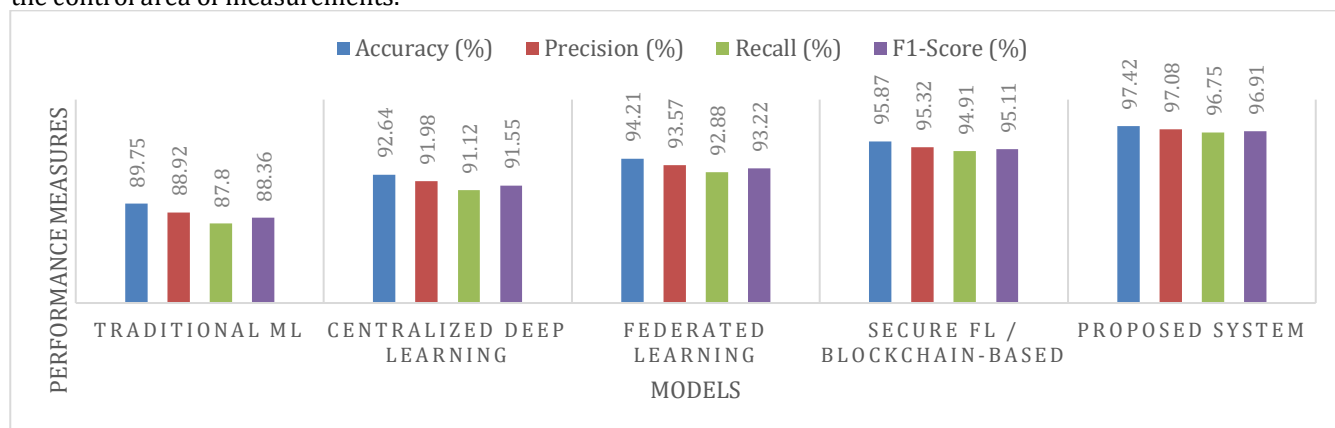


Figure 7: Comparison of performance measures

The proposed system beats all the four existing systems in all the major performance indicators shown in Figure 7. It is more accurate and precise, and has better recall and F1-score which means that it is more effective in detecting anomalies and classifying machine states. The benefits of the proposed sensor fusion and real-time processing model in improving predictive accuracy and robustness in industrial IoT settings are exhibited by the incremental benefits over the traditional, centralized, federated, and secure federated systems.

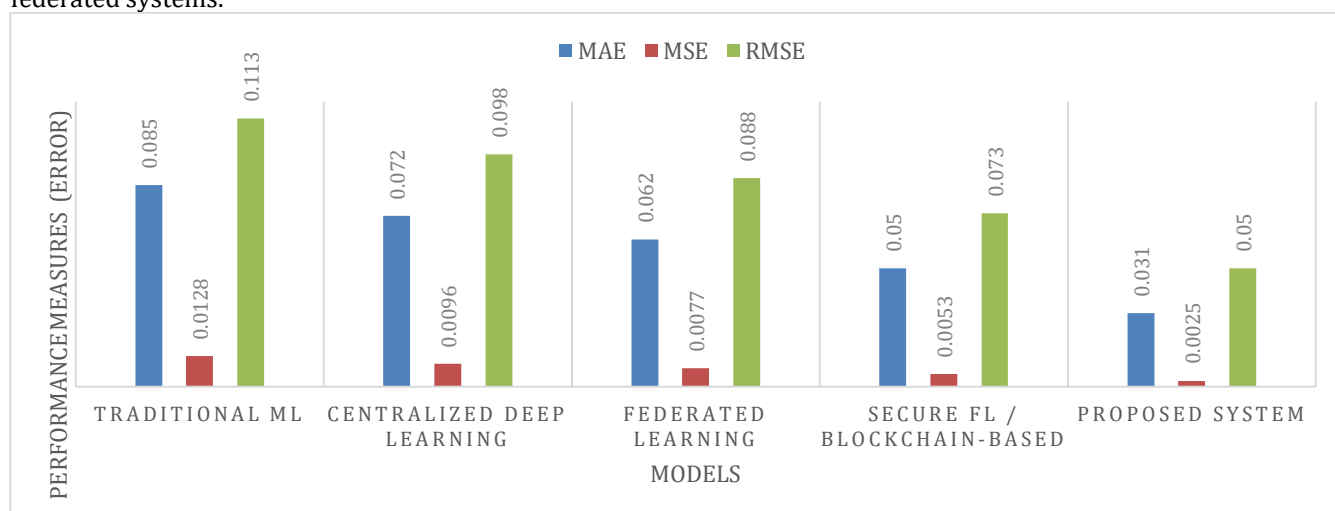


Figure 8: Comparison of performance measures (Error)

The proposed system has the lowest MAE, MSE, and RMSE values in a comparison with all the approaches, and it is more robust and predictive shown in Figure 8. The lower error measures show that the new sensor fusion algorithm would be able to accurately estimate the actual system state with minimum deviations even in the conditions of noisy and dynamic IoT. The proposed model is more stable and accurate in decision-making during industrial monitoring in comparison with the traditional, centralized, and secure federated solutions.

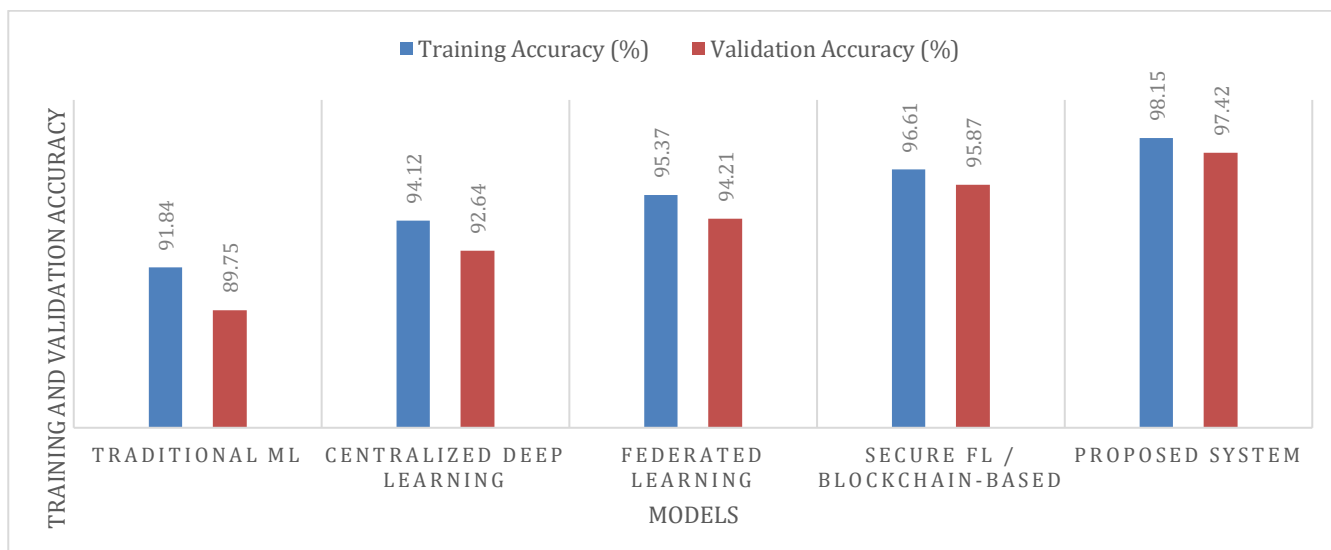


Figure 9: Comparison of training and validation accuracy

The proposed system has the highest training and validation accuracy of all methods and it means not only is it learning but it also has high generalization to unknown data shown in Figure 9. The small difference between training and validation loss indicates that the model does not overfits but provides strong predictive accuracy which shows that the proposed sensor fusion and real-time processing methodology are effective in industrial IoT systems. The slight variation between training and validation loss indicates that the model has a good generalization and the low overfitting is good enough to guarantee good performance in real-time IoT settings shown in Figure 10. This shows that the proposed sensor fusion algorithm is efficient in learning the complicated patterns and also it is highly stable and robust to varying conditions.

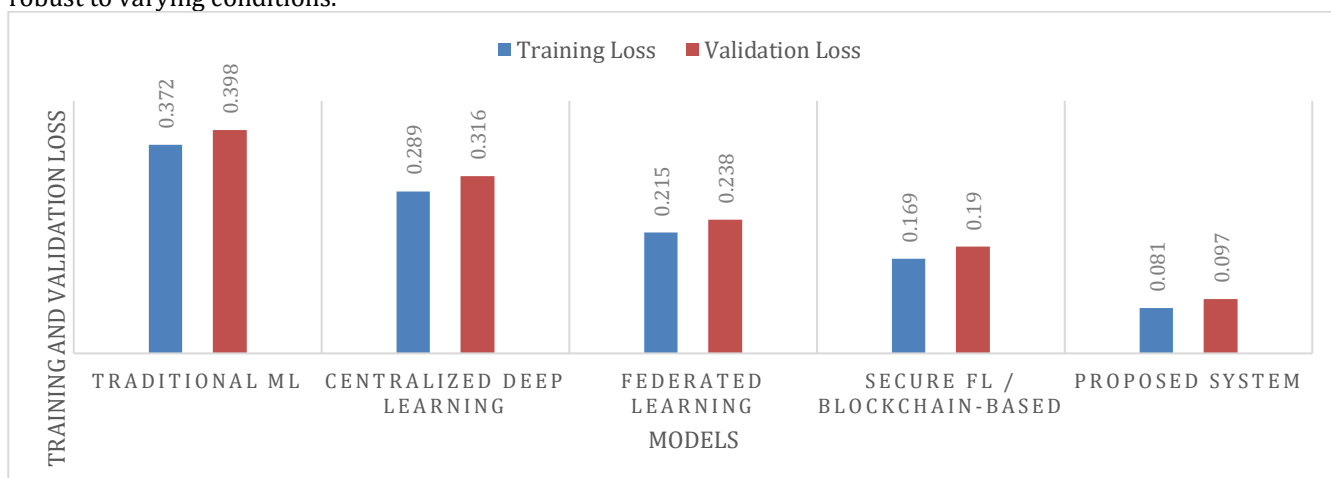


Figure 10: Comparison of training and validation loss

5. Conclusions

The IoT system employs RFID and ZigBee wireless sensor network in order to monitor the status of a particular region. The strategies of enhancing the IoT system proposed in this work are more effective in comparison with the traditional optimal solution. The overall error probability of multi sensor data fusion in computing based on the PSO is less than 0.01%. Due to its simplicity, high-quality solutions and strength, the IPSO IoT system is better than the currently studied PSO strategies due to its rapid convergence and low computing workload. The iterative nature of the IPSO algorithm renders it highly promising to be used in real-time applications, fast. Big data and Internet of Things (IoT) configurations have been the focus of attention recently. The investigators focused on big data analytics technologies based on machine learning. Machine learning is a growing trend in the field owing to its ability to recognize hidden features and trends even in very intricate data. In the study, we applied our Big Data IoT - based system in the application of a weather information processing use case. With the help of a publicly available data, we put in practice climate clustering and sensor detection approaches. In this particular application, we provided the execution information of each level of structures. We have adopted the training algorithm, ScikitLearn-based k-means cluster. The results of the information

analyses have shown that our approach can be employed to extract the data of a fairly complicated database in a meaningful manner.

Conflict of Interest Statement

There is no conflict of interest

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