https://doi.org/10.52131/jcsit.2021.0201.0009

iRASD Journal of Computer Science and Information Technology

Volume 2, Number 1, 2021, Pages 40 - 51

Journal Homepage:
https://journals.internationalrasd.org/index.php/jcsit

Performance Analysis Internet of Things Based on Sensor and Data Analytics

Muhammad Bilal Alamgir[1]

[1] National College of Business Administration and Economics (NCBA&E), Bahawalpur, Pakistan.
Email: baasimalamgir@gmail.com

ARTICLE INFO

Article History:

Received:	September 10, 2021
Revised:	October 19, 2021
Accepted:	December 27, 2021
Available Online:	December 31, 2021

Keywords:
Internet of Things (IoT)
Data Analytics
Sensors
Analysis
Smart systems
Series Partitioning
Quality of data

ABSTRACT

The Internet of Things (IoT) is a transformative development. Sensors are known in scientific science as a prospective field. IoT sensors are used successfully to develop an intelligent world in different IoT implementations. To make a familiar operating image, ubiquitous sensing abilities provide shared knowledge. IoT systems can fail if one of the sensors stops working due to any failure, which causes serious living problems to some families. Thus, the problem consists of predicting when the subsequent loss will occur. A two-phase approach is proposed. First, an exploration of the provided data will take place. The purpose of such analysis is threefold: (1) to get familiar with the data, (2) to assess the quality of data and decide which methodology to employ accordingly, (3) to determine the features of interest. This research will serve as the basis for further theoretical work in the same field in the prospect. Analyzing these sensor-derived data is an important task that can find valuable latent information in addition to the data itself. Since the Internet of Things includes some sensors, the measurement data obtained by these sensors are multi-type data, often including information from the time series. Depending on the configuration flow rate, vibration, impeller speed, and even temperature, the sensors with solid correlation can be closely correlated with some delay involved. Data ranges investigation was done before correlation check. Results indicate that our procedure is accurate for the machine's regular, damaged, and recovering state.

Corresponding Author's Email: baasimalamgir@gmail.com

1. Introduction

An array of network media is used to connect artefacts. The Internet of Things (IoT) aims to make things more dynamic and understandable. Linking anything that moves and doesn't move via the Internet of Things (IoT) opens up new and exciting possibilities. Numerous objects are given the ability to behave intelligently (appliances). Other embedded computing technologies like sensors and RFID tags have been employed to enhance the functionality of IoT-enabled entities (Sehrawat & Gill, 2019). Individuals may now communicate and improve their systems because of the Internet of Things (IoT). Numerous innovative applications make use of it, and as a result, there are numerous potential markets for it (Chifor, Bica, Patriciu, & Pop, 2018). Internet of Things (IoT) is a broad word that encompasses a wide range of technologies, including the cloud, intelligent gadgets, virtual worlds, sensors, and radio frequency identification (RFID). Cloud-based IoT networks are also a result of IoT-based networks, which offer many intelligent services.

In this revolutionary Internet of Things (IoT) environment, devices can exchange data and provide a wide range of helpful services. Alexa-enabled devices, such as the Echo and many other intelligent IoT-enabled gadgets, offer an array of possibilities to their owners, such as the ability to operate a wide range of home and outdoor electronic items via voice command or remote control (Sehrawat & Gill, 2019). Audio and video chats, music and video playback, and news updates are available through various apps. As well as seeing calendars and tasks, they can also keep tabs on traffic and social networking pages like Facebook. Figure 1 displays IOT based on sensors and data analytics. These devices can link to Alexa Echo devices and use cloud-based voice services using far-field speech recognition. Amazon's new "Tap to Alexa" feature can assist those unable to exchange.

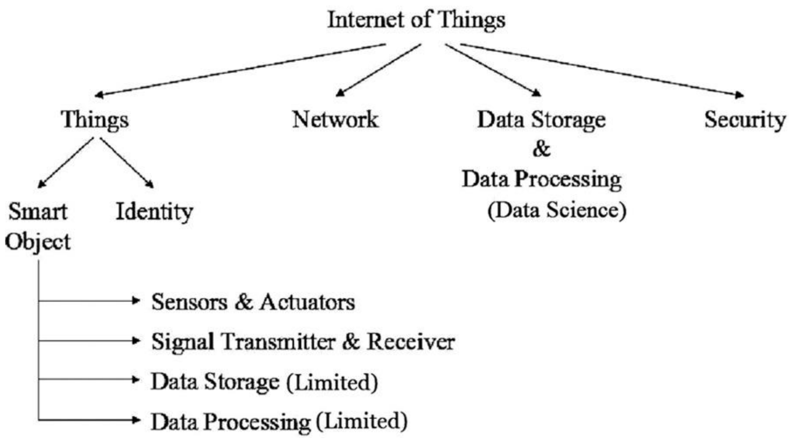


Figure 1: IOT based on sensors and data analytics

Users can do well-known "Alexa" pranks by touching the screen. Those with disabilities, such as blind or deaf, are better served by this. IoT-enabled devices are utilized for entertainment, such as listening to music, setting a timer, receiving news notifications, and receiving weather updates. You may buy these products on the market with or without a screen. Devices without a computer can provide audio; however, screen devices often assist with a display. The Internet of Things (IoT) has transformed how we interact with the world around us. With so many people's lives at stake, there is a risk that any sensor failure could cause the entire IoT system to fail. Many details regarding the sensor that can analyze and anticipate system failures are provided in this study. Here are the paper sections: Section 2 outlines the system's evolution. Section 3 focuses on predicting system failures, while Section 4 is the final section.

2. Background

Machine learning and the Internet of Items can be used to keep track of things and aid in illness detection, manufacturing costs, early warning systems and better management decisions. Some studies have revealed that IoT-based surveillance systems can be advantageous. Mora, Gil, Terol, Azorín, and Szymanski (2017) developed an IoT-based system for monitoring vital human signs. Footballers' heart rhythms were studied during a game as a case study. Using the proposed strategy, we were able to watch the participants' vital signs and consider various scenarios in addition to the worst-case scenario (i.e. death by accident). The Internet of Things (IoT) by (Zhang, Zhang, Li, Zhang, & Yang, 2017) to control the agriculture sector.

An irrigation and fertilization system monitored citrus soil moisture and nutrients. Using case studies, researchers have found that the proposed strategy has helped growers make better decisions, enhance citrus production, and reduce labour expenses and chemical fertilizer emissions. Using a distributed control system, Manes et al. exposed a mechanism to trace leaks and gas stages in hazardous situations(Manes et al., 2016). The sensor data was collected via a wireless sensor network. Remote servers received environmental sensor data and displayed it on a user interface. A warning was issued via the proposed system whenever a significant event was detected. To keep an eye on the safety of construction sites, Cheung and his colleagues came up with an information modelling and wireless sensor network (Cheung, Lin, & Lin, 2018).

A remote server has received data from wireless sensor nodes concerning harmful gas concentrations and the surrounding environment (such as temperature and humidity). An alarm or warning was issued when the suggested system discovered something ordinary. In a case study, this is how it looked: Managers will be able to make better real-time judgments with the help of the suggested technology because it would increase construction site safety. Sensors based on the Internet of Things (IoT) are being used in current studies to learn about a specific location's environment and display the sensor data in real-time. Many research areas, such as intelligent building and healthcare, require sensors that leverage the Internet of Things (IoT). For IoT-based sensors, there has been much research that has improved the system and shown substantial outcomes. Smart buildings can be monitored using IoT-based sensors developed by (Plageras, Psannis, Stergiou, Wang, & Gupta, 2018).

The proposed system was tested in a computer simulation. An intelligent building with many Internet of Objects (IoT) sensors may make it easier to maintain tabs on things. Using this strategy, not only will smart buildings be more environmentally friendly, but they will also be more energy-efficient. Blanco-Novoa et al. recommended installing an Internet of Things (IoT) sensor inside a building to monitor its radon levels. Detection systems may notify users when a specified level of radon gas is detected. Radon gas levels could be observed, pre-programmed measures could be taken, and individuals could be alerted when a particular group of radon gas is achieved using the approach presented. Indoor air quality in various ways by Benammar et al. (Benammar, Abdaoui, Ahmad, Touati, & Kadri, 2018). Sensors like CO_2, CO, SO_2, NO_2, O_3, Cl_2, temperature, and humidity could be used to gather information.

A single-board computer known as a Raspberry Pi was utilized as a gateway. According to the test results, in-home air quality can be monitored for up to six different gases and temperature and humidity. A system that uses wearable sensors to detect and stop the spread of the Chikungunya virus using IoT technology. It was possible to determine whether or not a person's health, environment, medical history, physical location, and local weather conditions made them susceptible to infection. Using the proposed device, governments and health institutions can be alerted to the presence of ill persons. Arduino and Raspberry Pi to create an IoT-based sensor that could aid Healthcare by (Bayo-Monton et al., 2018).

A proposed sensor was compared to a computer in terms of how it worked. eHealth systems can benefit from an IoT-based sensor, according to the findings. Many tests in the manufacturing business have shown how IoT-based sensors may improve working environments, reduce mistakes, detect problems and predict the output. Managers may now make better decisions because of this. The sensor developed by Moon et al. types use of the Internet of Things. To collect and transmit data from the sensors that monitor temperature, humidity and CO_2, a wireless connection was used. Experiments have shown that the proposed gadget is stable enough to correctly measure the quality of the factory's environment in real-time. Its purpose is to assist managers in maintaining an ideal working environment for the factory's workers. Low-cost Internet-of-Things (IoT) sensors haven't stopped Salamone et al. from developing an additive developed design method.

Temperature and humidity readings were recorded using sensors. It was discovered in the study that understanding the surrounding environment throughout the design phase in additive manufacturing could help to avoid any blunders. Li et al. used IoT sensors to track down the source of a challenging with their excavation erecting system (Juanli Li, Xie, Yang, & Li, 2018). A diagnostic can be improved by using sensors from the IoT (IoT). Lee et al. devised a method for predicting a commodity's output and improving process organization using IoT and machine learning. The metal casting was used to demonstrate how the system would operate in the actual world. The proposed method was able to determine the consistency and controllability of the metal casting precisely suggested by Calderón Godoy et al. (Calderón Godoy, González Pérez, & Networks, 2018) that sensors and the SCADA system could be helpful in the framework for the fourth industrial revolution. According to the experiments, that which is supposed to assist managers in adapting to the new environment of Industry 4.0 is working.

Sensors and other components with IoT connections have skyrocketed in popularity. With the help of the Internet of Things, manufacturing processes can be shifted quickly from old-fashioned to digital ones. As the number of sensors increases, the demand for new technologies like big data that can handle large amounts of data increases. Big data and IoT technology combined to form a strategic framework that aided Ge et al. in making critical decisions (Ge, Bangui, & Buhnova, 2018). Managers can benefit from big data analytics by handling and comprehending a large amount of data from various sources (sensor devices).

3. Proposed Approach

Failure of sensors causes serious living problems to some families. Thus, the problem consists of predicting when the subsequent loss will occur. To this end, a two-phase approach is proposed. First, an exploration of the provided data will take place. The purpose of such inquiry is threefold: (1) to get familiar with the data, (2) to assess the *quality* of data and decide which methodology to employ accordingly, (3) to determine the features of interest. At the end of this first phase, it is expected to have a clean, ready to work data set, which will be used throughout the second phase. The predetermined methodology will be implemented to tackle the prediction problem in this phase. Figure 2 demonstrate the proposed approach for IoT and Data analytics.

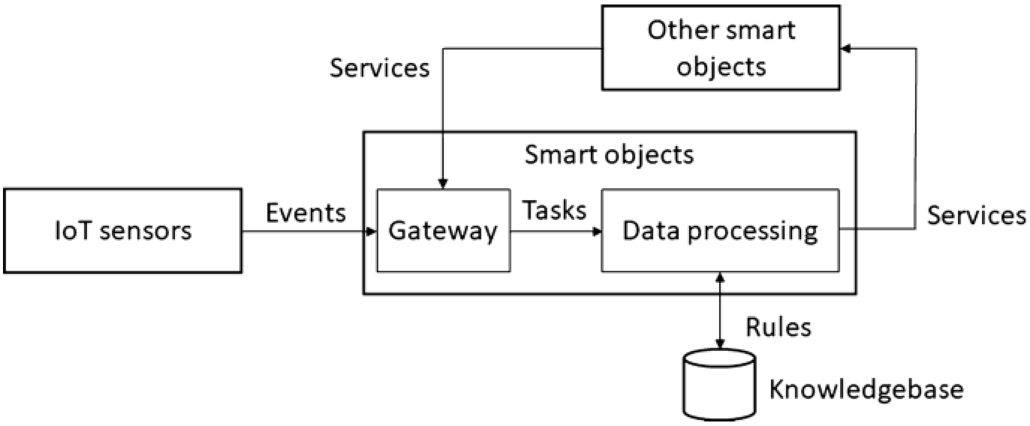


Figure 2: Proposed approach for IoT and Data analytics

3.1. Methodology

To predict the failure anomaly detection, 53 sensors were used, which recorded data at a 1min time-sample. Since there are 220320 recordings, the current data set represents 153 days. Figure 3 displays Time Stamp And Machine Status Moreover, and the measurements have different scales. Since NaN values exist, it is crucial to inspect the impact of eliminating them.

	Unnamed: 0	timestamp	machine_status
0	0	2018-04-01 00:00:00	NORMAL
1	1	2018-04-01 00:01:00	NORMAL
2	2	2018-04-01 00:02:00	NORMAL
3	3	2018-04-01 00:03:00	NORMAL
4	4	2018-04-01 00:04:00	NORMAL

Figure 3: Time Stamp And Machine Status

Hence, there are NaN values in every row and column of interest. The only thing one can do is replace NaN values with some other value. Since one is only interested in knowing the available data at this phase, a simple way to normalize data and replace NaN values with 0. Moreover, the Normalizer method uses partition data in features (X) and labels (y). Figure 4 represents Machine State Values

	0	1	2	3	4	5	6	7
0	0.967194	0.830145	0.949651	0.960396	0.792969	0.764598	0.602731	0.6
1	0.967194	0.830145	0.949651	0.960396	0.792969	0.764598	0.602731	0.6
2	0.959089	0.834736	0.949651	0.962196	0.798611	0.735461	0.598829	0.6
3	0.965264	0.830145	0.948877	0.962196	0.785156	0.769891	0.598505	0.6
4	0.959475	0.830910	0.949651	0.962196	0.795573	0.765891	0.600130	0.6

Figure 4: Machine State Values

In turn, y is a categorical feature. Thus, it needs to be one-hot encoded. Figure 5 shows the Normal, Broken and Recovering States

	BROKEN	NORMAL	RECOVERING
0	0	1	0
1	0	1	0
2	0	1	0
3	0	1	0
4	0	1	0

Figure 5: Normal, Broken and Recovering States

Up until now, the following data: X: normalized sensors' measurements (1) shape: (220320, 51), (2) Y: categorical labels, corresponding to the machine status (*Normal*, *Broken*, *And Recovering*) (3) shape: (220320, 1) (4) one_hot: a one-hot encoded data frame of **y**. To get a graphical, clearer representation of the data to be processed, consider the following figures representing each sensor measurement trend.(Bi, Jin, Maropoulos, Zhang, & Wang, 2021) Figure 6 shows the Sensor Capacity Trend.

Figure 6: Sensor Measurement Trend

As can be seen, there is a design being taken by the sensors (e.g. measurements 0, 6, 13). In turn, some signals are very noisy and seem to follow no trend in particular (e.g.

measurements 40-51). The problem at hand consists of determining when the machine will fail. Another way of addressing the issue is to select when the device changes from Normal to any other status (Unal et al., 2021).

For computational and problem tractability reasons, one can reduce the number of relevant features, i.e., choose the best kk features based on the prediction. The assumption here is that having 51 simultaneous and independent measurements of the same system produces redundant data. For many practical reasons, it may be essential to have redundant sources of information (e.g. security, maintenance, etc.). However, redundancy produces nothing but noise (Jianhua Li et al., 2017). Therefore, to choose the best kk features, one can use the sci-kit learn's SelectKBest method, as follows. Figure 7 represents Dataset Comprising Signals 0 To 12.

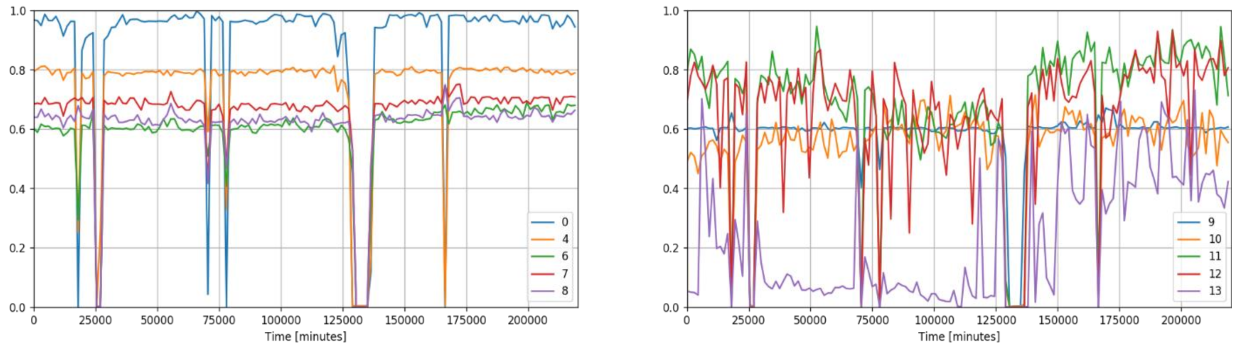


Figure 7: Dataset Encompassing Signals 0 To 12

As can be implicit, most capacities (except signal 13) monitor the same trend. Therefore, one may focus on a dataset comprising signals 0 to 12 to develop a prediction model. The final data set is presented below, including a superposition of the machine status (Kumarage, Khalil, Alabdulatif, Tari, & Yi, 2016). Figure 8 demonstrate the Superposition of The Machine Status.

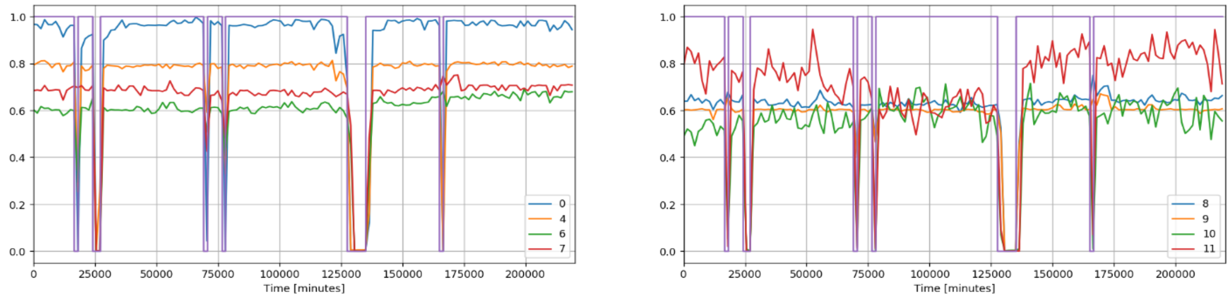


Figure 8: Superposition Of The Machine Status

Data shows that 6 (not 7) failures were recorded. Given the problem at hand and the available data, the best approach is to use recurrent neural networks (RNN) since the primordial goal is to predict the system's future behavior (Yu & Li, 2019). To this end, a data set will be constructed using the following data partitioning:

- Each sensor's measurement will be broken into six subseries, where the breaking point is when machine status switches to NOT NORMAL—such a partitioning results in 6×8=486×8=48 time-series.
- Then, the 48 time-series will be further divided into Train and Test sets.

The following section focuses on the data set creation.

3.2. Data set creation for a regression problem

In the previous section, a data exploration took place, from which a set of features of interest were determined. Moreover, a data set creation methodology was devised based on the data. This section focuses on building such a data set. Reminiscence that during the exploration, NaN values were relieved by 0 and data were normalized without inordinate argument.

Such data processing was performed to enable an easy familiarization with data. However, to build a data set, one does not want to corrupt data, i.e. one must be very careful of its preprocessing since the model building methodology is very sensitive to such data manipulations. Therefore, the data set creation will have a bottoms-up approach, i.e. starting with the raw data, features will be selected and manipulated individually and aggregated at the end.

3.3. Data imputation

Recall from the previous section that the data set at hand had NaN values in every row and column. To address this problem, unacceptable values were relieved by 0. However, that is a poor approach since the studied system is continuous. Forcing the time series to switch from a given value to 0 intermittently corrupts the signal, creating patterns that may be learned by the RNN, which would be counter-productive. Thus, the best way to address the problem is to infer somehow what is the most likely one to appear in place of NaN from a neighborhood of values. As a starting point, consider this example. Consider the series defined as follows,

Any person would be able to infer NaN should be replaced by 6. Several methods were developed to teach a machine to assume the same. Arguably, the simplest one consists of averaging, as follows. Let $x_i x_i$ represent the sequence element in position ii. Consider the situation in which a NaN value is at position ii, i.e. x_i=NaN. Then, one can infer its value as follows, Xi =xi−1+xi+1/2. The figures below represent a chunk of several of the features of interest. Figure 9 displays the Linear Trend Between Points.

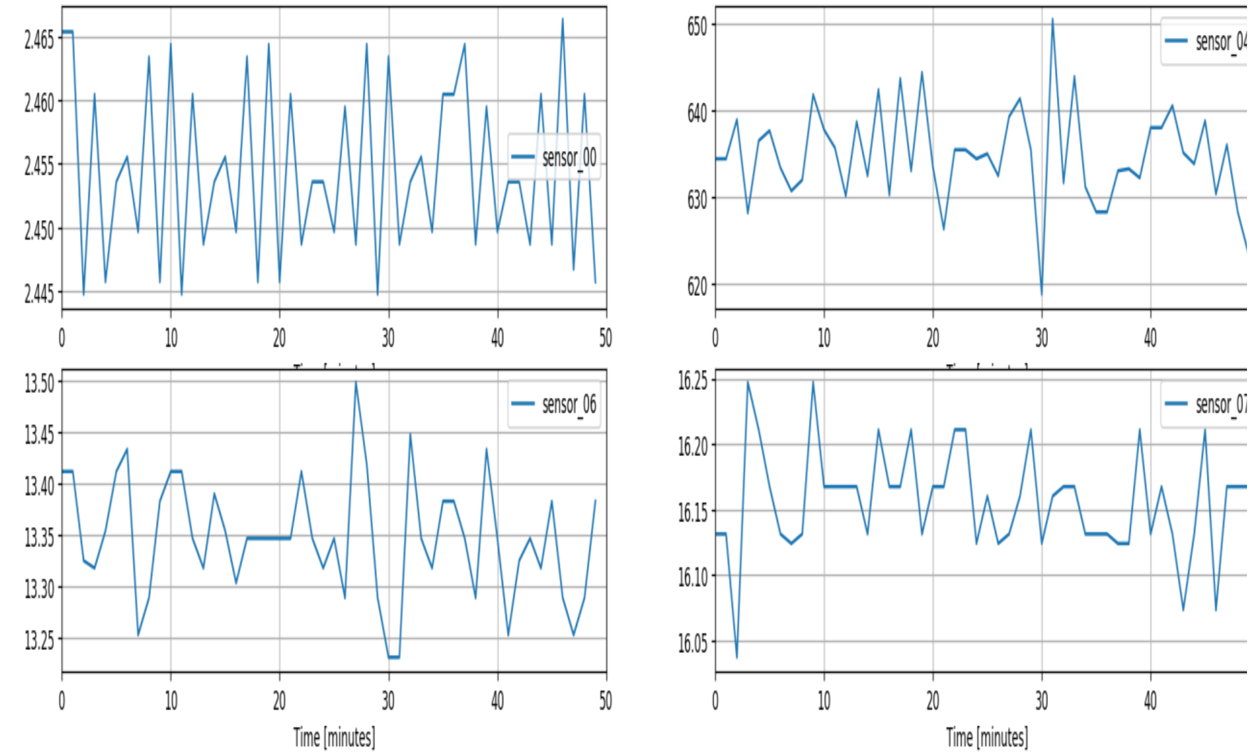


Figure 9: Linear Trend Between Points

The measurements seem to follow a linear trend between points; thus, one can exploit this information and perform data imputation resorting to linear interpolation.

3.4. Data partitioning

After data imputation, one can proceed to partition data. To this end, one starts by keeping only the features of interest (i.e. sensors 0, 4, 6, 7, 8, 9, 10, and 11) and drop the rest. Then, one performs feature normalization to bring all values into the range [0, 1] [0, 1]. After, one truncates the time-series following the machine status information.

Starting by dropping new features, the normalization process is done, and before proceeding to truncate data, the researcher saved the new data set for future research avenues. The last step in data preprocessing is trimming each time series (i.e. feature) according to the machine status. Namely, one is interested in partitioning data, as shown in Figure 10.

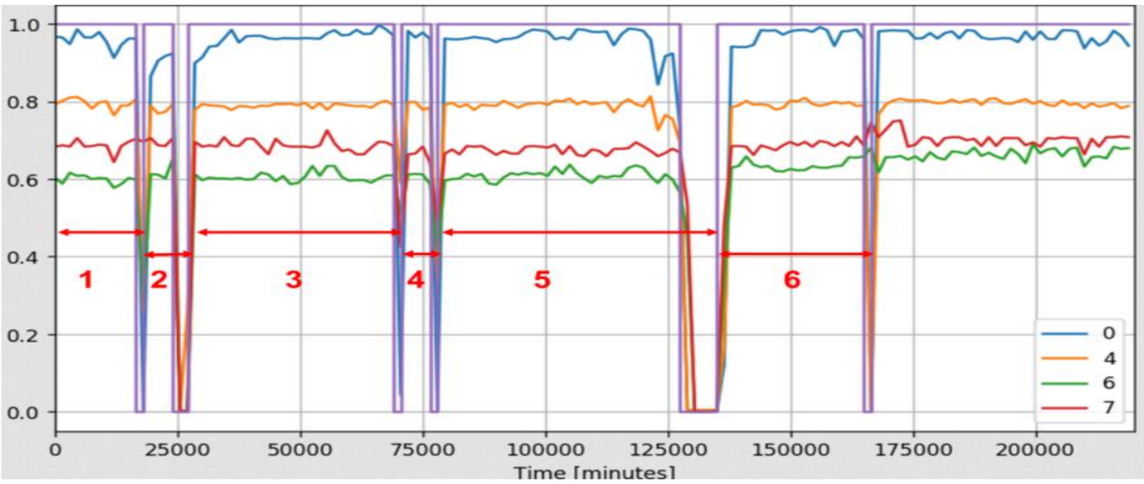


Figure 10: The System's Expected Behaviour

However, after breaking up eight-time series into 48 new ones, it appears that information is being lost. This means that you may be confident that the model will function because the data used to train, validate, and test the prediction model includes both the event you wish to forecast (failure) and the system's expected behaviour (legal status).

To this end, function, find_gaps, will be defined to determine gaps between the indexes that correspond to a normal status of the pump system. Then, this information is used to create a look-up table (fail_ind**),** which consists of a 6x2 array in which each row corresponds chunks of data (as seen in the figure above), and columns represent the starting and finishing indexes of the fail status. After resorting to series partitioning, one can initiate the partitioning process.

3.5. Results and Discussion

This work focused on the first of a two-phase approach to a failure reduction problem. The devised methodologies focused on data exploration. Two significant results were achieved:

- The features of position were determined, i.e. the measurements achieved by sensors 0, 4, 6, 7, 8, 9, 10, 11;
- A set of clean, ready to work data sets, which will be used throughout the second phase, was also constructed (please refer to sxx_1.csv, sxx_212csv, sxx_3.csv, sxx_4.csv, sxx_6.csv, sxx_8.csv).

Moreover, an extra data set (sensor_new_data.csv) was also built, consisting of the eight features of interest, plus the binary label (machine_status, i.e. either NORMAL or FAILURE). The analysis Technique phase focuses on simple techniques to get more info about the system. First, load the data and convert timestamps. For preliminary investigation, it was checked. Dt is equal - we can treat every column as an evenly sampled series of data - with simplified analysis. Figure 3.10 shows the Sampled Series of Data, and Figure 11 represents together With the Machine Status.

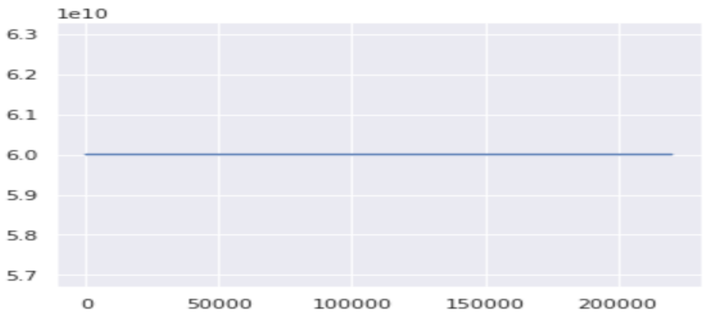


Figure 11: Sampled Series of Data

Sensors that have more than 2% of nans - let's see it together with the machine status:

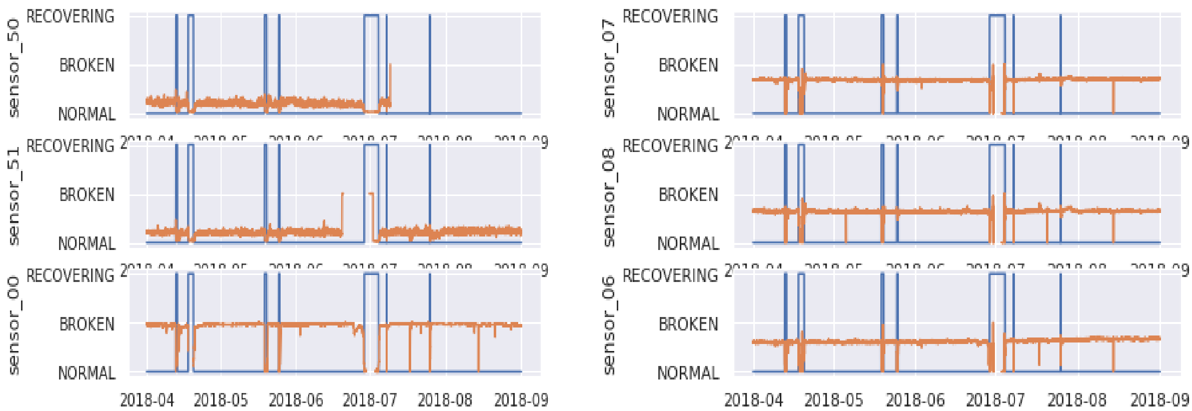


Figure 12: Together with The Machine Status

From these plots, we can also assume that the 5th failure may correspond to a different failure mode than the others - but we don't confirm that fact. Let's also remove the sensor_50 - we don't have 1/3 of the data and reproduce the missing ones.

- Sensor 50 fails after the 6th failure of the pump, and its reading is not available until the end of our data frame. Maybe it's not crucial for system operation, and its repair is not economically justified.
- Sensor 51 fails before the 5th failure of the pump but during recovering from that failure gets back to regular operation.
- Sensors 00, 07, 08, 06 - have a significant period of nan's during recovering state after 5th failure of the pump, but we may assume that their data coverage for failure prediction is correct.

Initially, there were 52 sensors, and we removed the 15th and 50th. Now we have 50 sensors and don't know what they is (temperature, flow, pressure, vibration, pump motor current). Data ranges investigation was done before correlation check. We found that some sensor correlates, as shown below. Figure 13 displays Correlation Values For Sensors.

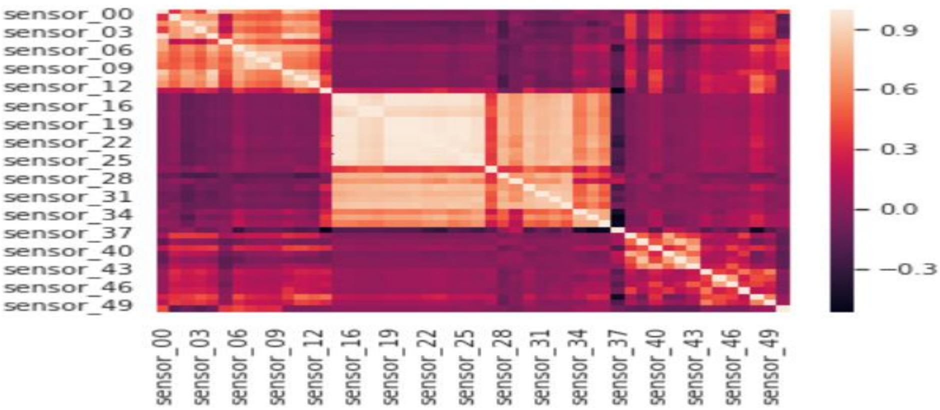
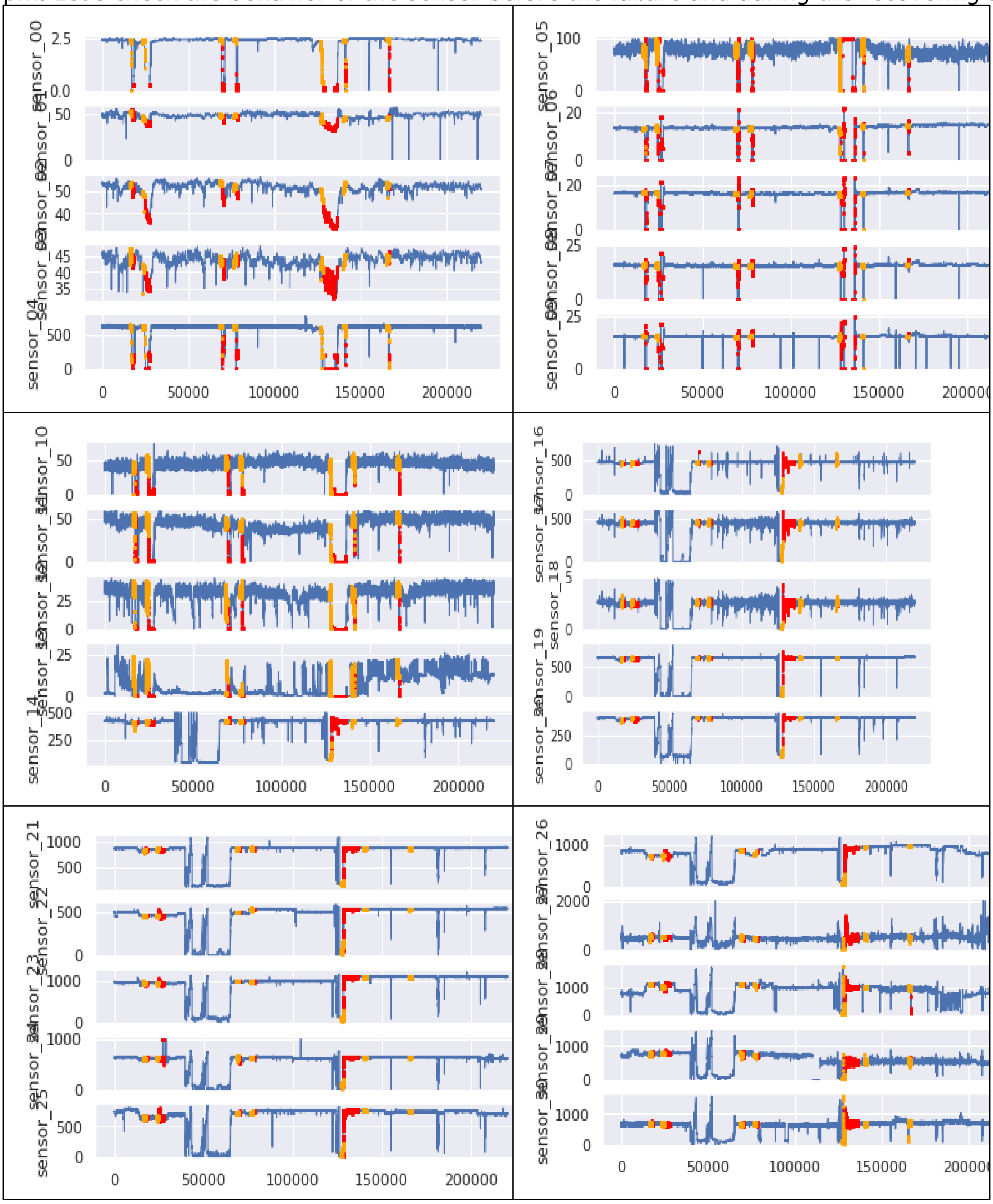


Figure 13: Correlation Values For Sensors

We can see a strongly correlated group of sensors - from sensor_14 to sensor_26. Some other correlated groups are also not as strong as the mentioned one.

4. Failure data investigation

We saw that the first six failures happened late evening/night - the only 7th was at 2 pm. Let's check the behavior of the sensor before the failure and during the recovering state:



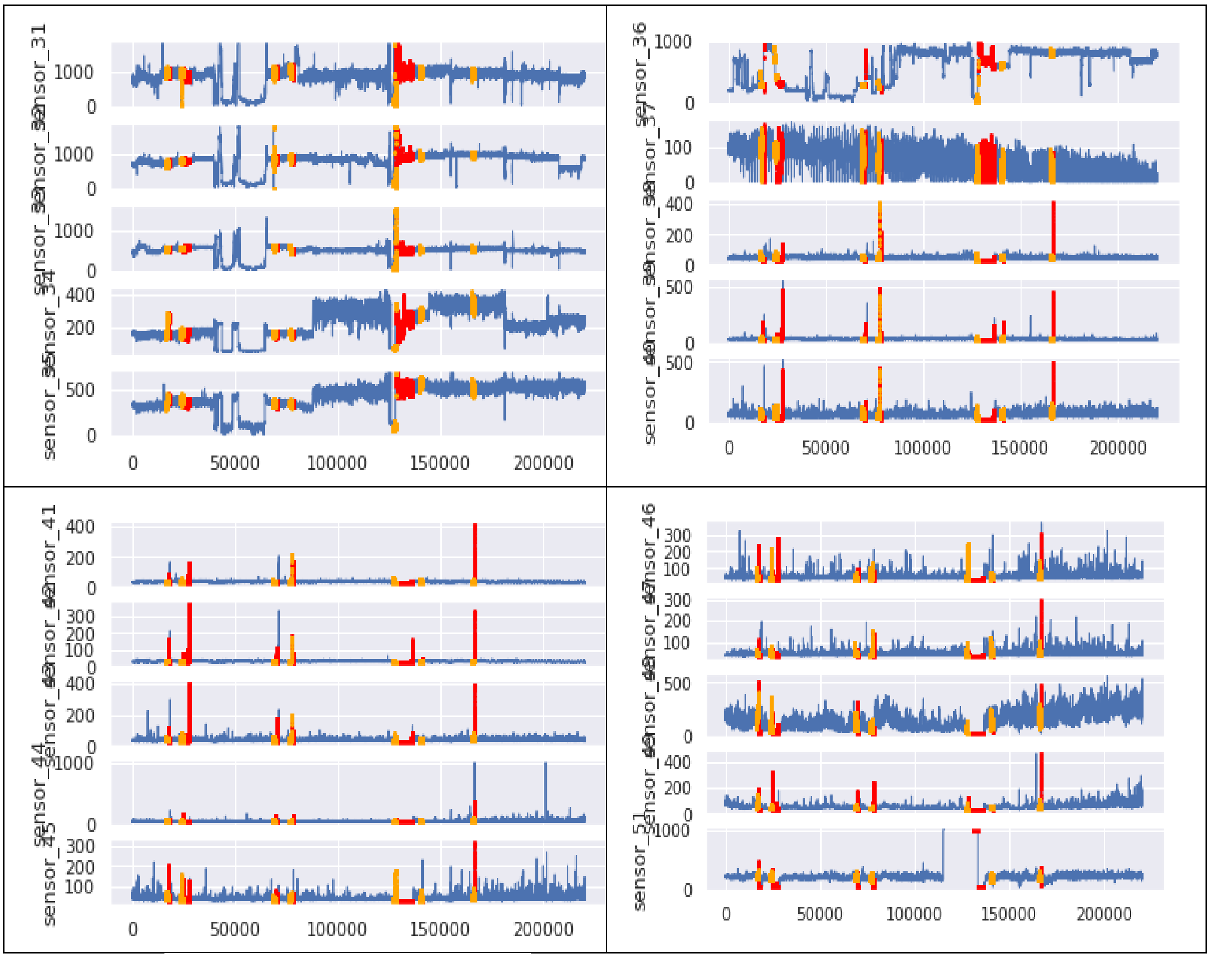


Figure 15: During Recovering State

5. Conclusion and future work

The IoT sensor network is undergoing a paradigm shift because of new technologies like cloud, fog, and edge computing. Data processing, fusion, and sensor data analytics may now be done at a higher level. Sensor data analysis is critical, and this paper explains why in great detail. Using 50 sensors, we could determine a correlation between them. Depending on how the equipment is set up, there can be a delay in the relationship between the flow rate, vibration, speed of the impeller, and even the temperature. Linking anything that moves and doesn't move via the Internet of Things (IoT) opens up new and exciting possibilities. The data ranges were examined before the correlation assessment. Based on the results, we can confidently say that our approach works in any machine state: normal, broken, or recovering.

5.1. Future work

Anomaly Detection, Analysis based on data collected from 51 sensors and LSTM, we can predict future temperature, humidity, light and voltage readings based on the given time series data. It is the case of multidimensional and multivariate time series models.

References

Bayo-Monton, J.-L., Martinez-Millana, A., Han, W., Fernandez-Llatas, C., Sun, Y., & Traver, V. J. S. (2018). Wearable sensors integrated with Internet of Things for advancing eHealth care. *18*(6), 1851. doi:10.3390/s18061851

Benammar, M., Abdaoui, A., Ahmad, S. H., Touati, F., & Kadri, A. J. S. (2018). A modular IoT platform for real-time indoor air quality monitoring. *18*(2), 581. doi:10.3390/s18020581

Bi, Z., Jin, Y., Maropoulos, P., Zhang, W.-J., & Wang, L. J. I. J. o. P. R. (2021). Internet of things (IoT) and big data analytics (BDA) for digital manufacturing (DM). 1-18. doi:10.1080/00207543.2021.1953181

Calderón Godoy, A. J., González Pérez, I. J. J. o. S., & Networks, A. (2018). Integration of sensor and actuator networks and the scada system to promote the migration of the

legacy flexible manufacturing system towards the industry 4.0 concept. *7*(2), 23. doi:10.3390/jsan7020023
Cheung, W.-F., Lin, T.-H., & Lin, Y.-C. J. S. (2018). A real-time construction safety monitoring system for hazardous gas integrating wireless sensor network and building information modeling technologies. *18*(2), 436. doi:10.3390/s18020436
Chifor, B.-C., Bica, I., Patriciu, V.-V., & Pop, F. J. F. G. C. S. (2018). A security authorization scheme for smart home Internet of Things devices. *86*, 740-749.
Ge, M., Bangui, H., & Buhnova, B. J. F. g. c. s. (2018). Big data for internet of things: a survey. *87*, 601-614. doi:10.1016/j.future.2018.04.053
Kumarage, H., Khalil, I., Alabdulatif, A., Tari, Z., & Yi, X. J. I. C. C. (2016). Secure data analytics for cloud-integrated internet of things applications. *3*(2), 46-56. doi:10.1109/MCC.2016.30
Li, J., Xie, J., Yang, Z., & Li, J. J. S. (2018). Fault diagnosis method for a mine hoist in the internet of things environment. *18*(6), 1920. doi:10.3390/s18061920
Li, J., Zhang, T., Jin, J., Yang, Y., Yuan, D., & Gao, L. (2017). *Latency estimation for fog-based internet of things.* Paper presented at the 2017 27th International Telecommunication Networks and Applications Conference (ITNAC).
Manes, G., Collodi, G., Gelpi, L., Fusco, R., Ricci, G., Manes, A., & Passafiume, M. J. S. (2016). Realtime gas emission monitoring at hazardous sites using a distributed point-source sensing infrastructure. *16*(1), 121. doi:10.3390/s16010121
Mora, H., Gil, D., Terol, R. M., Azorín, J., & Szymanski, J. J. S. (2017). An IoT-based computational framework for healthcare monitoring in mobile environments. *17*(10), 2302.
Plageras, A. P., Psannis, K. E., Stergiou, C., Wang, H., & Gupta, B. B. J. F. G. C. S. (2018). Efficient IoT-based sensor BIG Data collection–processing and analysis in smart buildings. *82*, 349-357. doi:10.1016/j.future.2017.09.082
Sehrawat, D., & Gill, N. S. (2019). *Smart sensors: Analysis of different types of IoT sensors.* Paper presented at the 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI).
Unal, D., Hammoudeh, M., Khan, M. A., Abuarqoub, A., Epiphaniou, G., Hamila, R. J. C., & Security. (2021). Integration of federated machine learning and blockchain for the provision of secure big data analytics for Internet of Things. *109*, 102393. doi:10.1016/j.cose.2021.102393
Yu, B., & Li, H. J. I. J. o. D. S. N. (2019). Anonymous authentication key agreement scheme with pairing-based cryptography for home-based multi-sensor Internet of Things. *15*(9), 1550147719879379. doi:10.1177/1550147719879379
Zhang, X., Zhang, J., Li, L., Zhang, Y., & Yang, G. J. S. (2017). Monitoring citrus soil moisture and nutrients using an IoT based system. *17*(3), 447. doi:10.3390/s17030447