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Development of an IoT-based real-time remote monitoring device for the maintenance of injection moulding machines in plastic industries

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Abstract

The remote monitoring of industrial equipment for real-time predictive maintenance reduces downtimes and losses brought on by unforeseen failures. An IoT-Based intelligent system developed for real-time remote monitoring and failure prediction of process parameters in the Injection Moulding Machine is presented in this work. The developed system captures data from the equipment, analyses, and transmits the data to the ThingSpeak IoT web server for further fault prediction analysis in MATLAB, with subsequent feedback to users - all in real-time. The software component of the system is developed using MINITAB, MATLAB, ThingSpeak IoT platform, and C++ in Arduino Integrated Development Environment. The hardware component of the system is developed using MLX90614 infrared temperature sensor, ultrasonic proximity sensor HC-SR04, and wifi-enabled Esp32 WROOM-32 Microprocessor. When implemented on the injection moulding machine, the system achieved real-time data capture, analysis, and feedback through its easy-to-understand user interface. Comparative analysis of the developed system's measured data with that of the traditional method, showed a Pearson Correlation Coefficient of 0.995242, indicating a perfectly positive correlation and consistency of measured data. The system may be beneficial to plastic manufacturing industries for reliable remote monitoring and failure prediction of the process parameters of Injection Moulding Machines towards achieving reduced maintenance cost, downtime, and cost of re-work.

Keywords: intelligent system, remote monitoring, data, real-time, sensors, parameters, failure prediction, injection moulding machine.

1. Introduction

Injection moulding is one of the most popular cyclic manufacturing technologies and is extensively used to produce a variety of industrial products. In a complex manufacturing process, there are various factors like machine conditions, product characteristics, process parameters, raw materials, and several disturbances that affect the production plan and the final product quality (Zhang et al., 2016). To compete effectively in the plastics marketplace, manufacturers, and researchers have focused on improving product quality by adopting different methodologies. Predictive maintenance (PdM) predicts equipment failures to optimize maintenance efforts (Selcuk 2017; Tortorella 2018). The technology is based on real-time monitoring of equipment and processes, by this maintenance is carried out only when needed. Remote monitoring helps in supervising and controlling intelligent systems by means of locally installed agents that can be accessed by a management service provider. So, the equipment can be diagnosed without the expert compulsorily present in the production facility.

Fault diagnosis is a crucial factor in any industry to detect the failure of equipment and schedule maintenance. Researchers have also developed a Data Acquisition (DAQ) system that employed cavity sensors and analysed the resulting data for potential faults (Gordon et al. 2017). Although the performance of the introduced method in terms of injection moulding monitoring is reliable, consistent quality in moulded products requires more than just a monitoring strategy. The process is still dependent on the skills of the operator and process engineers. The lack of an online feedback system makes it difficult to develop robust monitoring and control techniques. A major portion of the recent research prefers the use of artificial intelligence (AI) technologies to control moulding processes as such technologies are better suited to identifying the relationships between measurable and unmeasurable parameters (Ogorodnyk & Martinsen 2018).

Conventionally machine operator’s assistance is needed to conduct experiments and adjust process parameters based on observed quality feedback. To overcome such issues a combination of sensors is introduced, and a model has been developed to collect cavity and nozzle pressure data. After the extraction of essential data, the same model is used to diagnose the process conditions (Baek 2014). As modern moulding machines can generate large quantities of data, recently, the literature (Kozjek et al. 2017), used a big-data management approach to identify faults. A structured query language (SQL) database, stored data from every cycle, and Python programming is used to develop a fault-prediction model with an accuracy of 57%. Based on the prediction control measures can be taken by the operator instantly. Although the performance of the introduced method in terms of injection moulding monitoring is reliable, consistent quality in molded products requires more than just a monitoring strategy. Park et al. suggested that an AI-based moulding process can improve product consistency and quality. Chen et al. assigned injection moulding variables to three levels which include machine variables such as temperature, and pressure; process variables such as melt temperature, melt pressure; and quality definitions such as shrinkage and warpage.

Kangalakshmi et al., Schiffers et al., & Wang et al. have tried to address quality-related problems by applying model-based proportional-integral-derivative (PID) control, adaptive process control, and phase diagram control, respectively with each achieving some encouraging results. To overcome the complexities of sensor installation, data collection, and the difficulties of inter-relationship derivation between process parameters and failure, a research object with simple geometry is chosen. Cavity temperature and pressure sensors are used for data collection, and simulations are conducted to validate their models using different tools in all the above-introduced monitoring and control strategy. Considerable research efforts have been devoted to the reduction of quality failure rates in injection moulding, but the application of the developed system is either theoretical or just in simulation models. Furthermore, their practical implementation in industrial applications is still a distant job.

Kumar et al. (2020), presented an engineering analysis model to analyze the process behavior of injection moulding in a cyber way because a fully experimental approach is a lengthy, costly, and impractical option. Tayalati et al. (2022), identified different phases for a look-out for faults during the injection moulding process: first, during the initial setting when we try to identify the initial parameters for a new plastic part; and second, during mass production when there is a deviation in the production process. Vasco et al. (2023), developed an intelligent system for processing equipment malfunctions, and environmental variations of injection moulding machines, to detect them at an early stage to avoid production in unsuitable processing conditions. They introduced an automatic self-correction to processing conditions and provided key performance indicators (KPI) for operation, maintenance, production, and quality control, with a local or remote interface. Tripathi et al. (2023), analyzed the process variable data from injection moulding processes to identify the key causal interactions between influential and dependent process variables in different product categories using variable lagged transfer entropy measure. They used variable lagged transfer entropy measurements to construct directed networks by calculating significant pairs of process variables for each production process (of each material). Wu et al. (2023), developed a generative machine learning-based multi-objective optimization model. Such a model can predict the qualification of parts produced under different processing variables and further optimize processing variables of injection molding for minimal energy consumption and weight difference amongst parts in one cycle.

Albertin et al. (2023), used Artificial Intelligence as Machine Learning model to recognize when something changes in the data’s behavior collected up to that moment, also helping companies to gather a preliminary dataset for future Predictive Maintenance implementation. Araujo et al. (2023), demonstrated the in-cavity pressure monitoring feasibility for failure diagnosis and injection moulding process optimization. Chen et al. (2022), provided online insight into process monitoring of injection moulding machines by utilizing a monitoring system with in-mould sensors. To meet these objectives, an artificial neural network (ANN) and multiple linear regression (MLR) were used to build the prediction model that was integrated with the monitoring system. Farahani et al. (2022), introduced a generalized framework for the implementation of predictive maintenance in the injection moulding process by integrating a variety of different data sources available in this process and taking advantage of both cloud and edge computing. Hu et al. (2022), proposed an integrated “processing–matching–classification–diagnosis” concept based on machine vision and deep learning that allows for efficient and intelligent diagnosis of injection moulding in complex scenarios. Nunes et al. (2023), proposed a flexible architecture for PdM to recommend maintenance actions in injection moulding, The proposed architecture is based on containerized microservices on intelligent edge devices together with a hybrid model which fuses generalized fault trees (GFTs) and anomaly detection. Bogedale et al. (2023), introduced a novel approach to modelling injection moulding processes using only time series data and evaluates the quantitative influences of varying sampling times on calculation of integral values and model quality. Gomes et al. (2023) developed an affordable, simple system for injection moulding machine parameter monitoring, it boosts of a real-time data acquisition and display in an intuitive Graphical User Interface (GUI), while being open-source firmware and software-based. Pierleoni et al. (2020), explored multiple sensors' data extracted from an injection moulding machine, with the final aim of developing a Predictive Maintenance model tailored on the specific machine utilization. Moreira et al. (2020), integrated a custom pressure sensor into an injection tool to monitor the different pressure levels along the process cycle, together with a commercial off-the-shelf accelerometer, coupled at the surface of the tool. Both sensors recorded the events over regular productive cycles, being this information, in the long-term, is paramount for smart predictive maintenance. These intelligent systems are developed using Industry 4.0 technologies, which promise huge potential through new business models, increased resource productivity, and cross-value chain efficiencies, enabling smart factories that are capable of profitably producing customer-specific items in an agile way (Okeagu & Mgbemena 2022).

The injection moulding process continues to face quality failures such as sink marks, short shots, warpage, and flashes. Existing solutions like conformal cooling channels manufactured with 3D printing technology and process parameter optimization systems are incapable of maintaining quality consistency due to variations in process parameters, and process instability associated with the machine and environmental factors. This results in large quantities of scrap parts, reduction of productivity, and wastage of resources. A more efficient molding process is therefore in high demand. From the previous works reviewed, it could be clearly seen that none dealt with a real-time feedback system for the process control in the injection moulding process. The absence of the feedback mechanism denies communication between the developed system and the job floor which greatly affects the efficiency of the system. However, researchers have opined that alarm feedback is the best, as it is easier to understand. To overcome this difficulty, this paper introduces an IoT-based real-time remote monitoring system for predictive maintenance of Injection Moulding machines that can reduce quality failures and increase productivity with the application of an improved monitoring system. The primary goal of the presented research is to develop a smart monitoring and control system and validate it with real industrial experiments. The developed system boosts of robust feedback mechanism, and will drastically reduce downtime, reduce the cost of re-work, and reduce maintenance costs – for higher profitability.

2.0 Materials and Methods

Analysis model for describing real-world process behavour is developed and tested using MINITAB. The hardware component is of the system is then developed using Arduino microprocessor, temperature, and proximity sensors. The software component of the system is developed using Arduino IDE, MATLAB, and ThingSpeaks IoT platform. Development of the fault prediction and control model is done using MATLAB. The intelligent system is developed by integrating and synchronising the various components of the system, followed by the testing and validation of the developed system.

The analysis model is developed from the historical data of the identified parameters, using MINITAB. The digital model is tested to ensure it represents the real condition of the equipment. The sensors are now trained to capture and transmit data for real-time monitoring and control. The sensors transmit the data to an IoT server, from which the data is exported to the fault prediction and control model. At this point, the intelligent system is fully functional and controlled using appropriate lines of code in MATLAB. The methodology applied in this study is a data-driven approach to predictive maintenance, the entire process is basically on the capturing, transmission, and analysis of injection moulding parameter data for fault prediction and real-time feedback.

2.1 Design of Hardware Components

The following hardware was selected for this research;

a) By-906 Infrared Arduino Temperature Sensor

With a Temperature range of -70C to 382.2C, the component will cover robustly, the Injection machine mould temperature (ranging from 30C to 80C). It offers a standard accuracy of ±0.5C around room temperature. It has a very low noise amplifire, and provides high precision for the thermometer.

Figure 1 By-906 Infrared Arduino Temperature Sensor

b) HC-SR04 ultrasonic proximity sensor

The products produced needs to be captured and transmitted in real-time without disrupting the process, a sensor that detect the ejecting products without touching it or causing abrasion/damage to the product, is desirable. This ultrasonic sensor detects and transmit the presence/passage of objects electrically without having to touch them (www.ia.omron.com). It has a measuring distance of 2cm to 400cm, while the area of coverage (ejection exit of the Injection moulding) is 64cm.

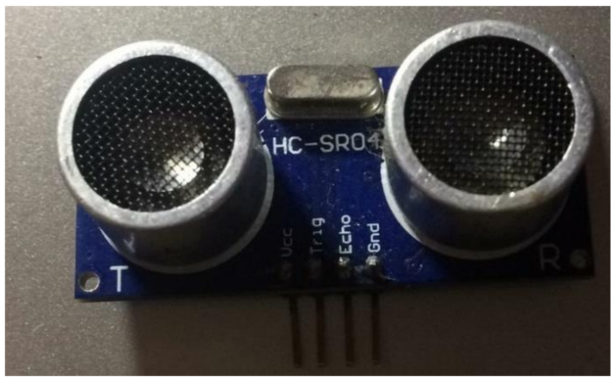


Figure 2 HC-SR04 ultrasonic proximity sensor

c) Wifi enabled Esp32 WROOM-32 microprocessor

The microprocessor module allows microcontrollers to connect to a wi-Fi network and make simple connections using Hayes-style commands. The sensors are manipulated through the microprocessor due to its flexibility and efficiency.

Figure 3 Wifi enabled Esp32 WROOM-32 microprocessor

2.2 Design of Software Components

The Computer Aided Engineering (CAE) tools are deployed at different stages in the system. MINITAB is for the generation/testing of the analysis model; Excel Data Analysis ToolPak is used for analysis model selection, Arduino IDE is used for the training of the sensors through the microprocessor. The ThingSpeak IoT platform receives/exports data between the sensors and the fault prediction model. MATLAB performs the final data analysis and fault prediction. These tools are integrated with the hardware to develop the intelligent system.

2.2.1 Development/testing of the analysis model for describing real-world process behavior using MINITAB

Schiffers et al. (2016), assigned injection moulding variables to three levels; machine variables, process variables, and quality definitions (final response). These variables will produce a robust monitoring and control model for adaptive control of process parameters. The mould temperature, injection speed and the number of products is grouped under process parameters. Finding an empirical relationship between the parameters can be made possible using CAE. The input variables are injection speed, the number of products produced per interval of failure and the mould temperature. The model is to predict 'time to failure' in real-time using regression analysis. The output variable is recorded using a stopwatch, the injection speed and the number of products are displayed on the dashboard, while an infrared temperature gun was used to record the mould temperature. These data were monitored and collected for about a period of 1 month, at an interval of 30mins during working hours. The comprehensive data table contains machine readings at this rate, but was later filtered to generate/test an accurate analysis model using MINITAB. The analysis model is tested using MINITAB.

2.2.2 Development of fault prediction and control model using MATLAB.

A control algorithm to recognise process parameters, to analyze the data and make failure predictions is developed in MATLAB using MATLAB Language. The analysis model is imported into the environment, for real-time fault prediction, the environment gets the input data from ThingSpeak. The MATLAB environment also hosts the feedback control.

2.3 Development of the Intelligent System by Integrating and Synchronising the Various Components of the System

To connect the system components and provide real-time remote monitoring and fault prediction, an integrated control system is programmed using the commercial tools. Data is extracted from the sensors, to the IoT data base, then exported to the MATLAB environment for analysis, monitoring, fault prediction and feedback. At this point, the system is developed and can be controlled using appropriate lines of code.

2.4 Experimental Setup and Validation

The functionality of the developed system is tested on the machine under study, **Injection Moulding Machine (LSF-148S Longsheng Machinery**). Two locations are involved in the test, the remote location and the production unit. A total of 2 participants are selected for the exercise, the expert monitoring remotely and the equipment operator, who is a worker in the production cluster. The expert is a volunteer, and the quality control officer of the company with proficiency in CAE tools; similarly, the equipment operator has been trained on the workings of the hardware. The total cost of the system is about $150, and the components of the system are readily available in the market. This requires a 5mins setup time as it needs the user to call up the MATLAB environment through the computer screen in a remote location with a strong internet presence. At this time, the sensors are strategically positioned, up and running for real-time data capturing and transmission. By-906 Infrared Arduino Temperature Sensor has a field of view of 90^0, the sensor is installed at an angle of 45^0 to the mould, and at a distance of 15cm from the mould. HC-SR04 ultrasonic proximity sensor with a range of 2cm to 400cm, and a field view of 15^0, is installed at a distance of 32cm from the object, and at a normal angle (Angle 0) to the object.

The IoT web server (ThingSpeak) is also active to receive data from the sensors and export to the model for prediction and control. Validation is done using Pearson Correlation, the formula to calculate the Pearson correlation coefficient (r) between two variables X and Y can be expressed as:

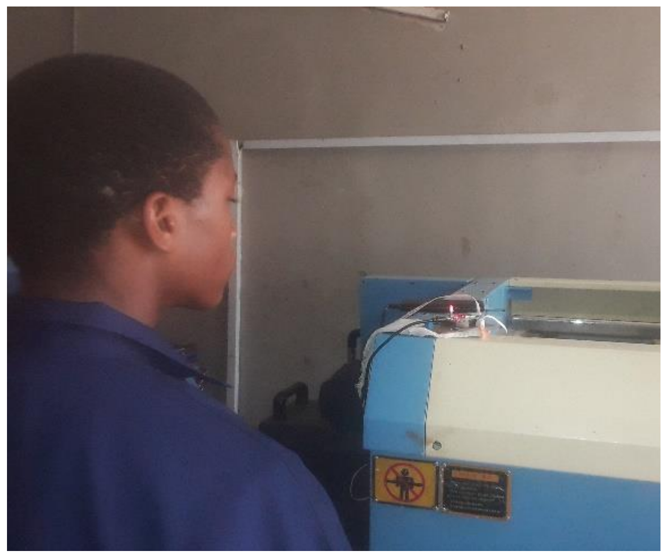
$$r = cov(X,Y) / (std(X) * std(Y)) \qquad (1)$$

Where cov(X,Y) is the covariance between X and Y, std(X) is the standard deviation of X, and std(Y) is the standard deviation of Y. MATLAB was used to write the program for calculating the Pearson Correlation Coefficient of the actual values, and the predicted value by the developed system. The system is easy to implement because the interface is designed in a simple and interactive way. The experimental setup shows the machine under study Fig. 4a, the location/position of the proximity sensor Fig.4b, the location/position of the temperature sensor Fig. 4c, and location/monitoring of the microprocessor by the machine equipment Fig. 4d.

(a) Injection Moulding Machine (LSF-148S Longsheng Machinery)

(b) Installation of the Proximity Sensor

(c) Installation of the Temperature Sensor



(d) Monitoring of the Arduino Microprocessor

Figure 4 Experimental Setup for Testing the Developed System

3.0 Results and Discussion

3.1 Development/Testing of the Analysis Model for Describing Real-World Process Behavior Using MINITAB

These data are monitored and collected for about a period of 1 month, at an interval of 30mins during working hours. The data is filtered to generate an accurate analysis model that perfectly represents the real-world process behavior of the machine as shown in Table 1.

3.1.1 Data Fitting

The type of regression model that best fit the data, to ensure accurate analysis is determined by the use of Excel Data Analysis Toolpak. From table 1, the input variables are plotted individually against the output variable. Different types of regression models are used, and the model with the best R^2 value is selected for the modelling.

Specifically, the model depicts the relationship between the process parameters and the output parameter under study. The results are summarized in Table 2 and the best model selected. The regression models considered are linear, exponential, logarithmic, polynomial and power.

Table 1 Parameter Data

S/N	X_1 (mm/s)	X_2 (pcs)	X_3 (C)	Y (minutes)
1	40	622	87	220.24
2	40	692	90	245.12
3	40	735	92	260.19
4	40	651	89	230.55
5	40	646	93	228.41
6	40	672	91	238.08
7	40	749	96	265.11
8	40	731	92	258.53
9	40	719	87	254.44
10	40	755	94	267.17
11	40	699	88	247.13
12	40	762	95	273.26
13	40	647	96	229.06
14	40	686	99	242.5
15	40	637	86	225.27
16	40	680	91	240.32
17	40	620	95	219.36
18	40	752	90	266.18
19	40	703	88	248.47
20	40	764	89	270.15
21	40	728	87	257.41
22	40	695	86	243.15
23	40	730	89	258.19
24	45	720	94	254.57
25	40	654	87	231.26
26	40	665	92	235.23
27	40	744	88	263.21
28	40	713	90	252.12
29	40	747	87	264.34
30	40	730	94	258.24
31	40	734	90	260.2
32	40	761	97	269.29
33	40	715	87	253.13
34	40	722	100	255.49
35	40	640	89	226.46
36	40	674	95	239.15
37	40	635	90	224.47
38	40	728	96	256.16
39	40	643	94	227.37
40	40	623	98	220.34
41	40	598	87	212.35
42	40	671	97	237.46
43	40	617	89	218.27
44	40	630	88	224.52
45	40	644	91	227.56
46	40	659	98	233.19
47	40	605	90	214.12
48	40	626	94	221.33
49	40	610	86	215.57
50	40	630	89	223.06

Where X_1 = Injection speed, X_2 = Number of products produced per interval of failure, X_3 = Mould temperature & Y = Time to failure

Table 2 Model Selection Summary Table

S/N	Independent Variables	Dependent Variables	Linear (R^2)	Exponential (R^2)	Logarithmic (R^2)	Polynomial (R^2)	Power (R^2)
1	X1	Y	0.9947	0.0102	0.0102	0.0102	0.0102
2	X2	Y	1	0.9788	0.9766	0.9982	0.9982
3	X3	Y	0.9938	0.0159	0.0187	0.0208	0.0186

The model with R^2 value of 1 or closest is the best fit, thus linear model was selected for the modelling.

3.1.2 Creation of the analysis model

The model is created using MINITAB. The parameter data in Table 1 is used to develop a multiple linear regression model for analysis, time to failure is the output variable, while injection speed, number of products produced per interval of failure and mould temperature are the input variables. The MINITAB results are shown below.

Regression Analysis: Y versus X1, X2, X3

The regression equation is

Y = 0.05 - 0.058 X1 + 0.354 X2 + 0.0214 X3

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.055	6.590	0.01	0.993	
X1	-0.0585	0.1573	-0.37	0.712	1.018
X2	0.354352	0.002234	158.59	0.000	1.026
X3	0.02141	0.02877	0.74	0.460	1.025

S = 0.771510 **R-Sq = 99.8%** R-Sq(adj) = 99.8%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	15372.0	5124.0	8608.45	0.000
Residual Error	46	27.4	0.6		
Total	49	15399.4			

Durbin-Watson statistic = 2.01119

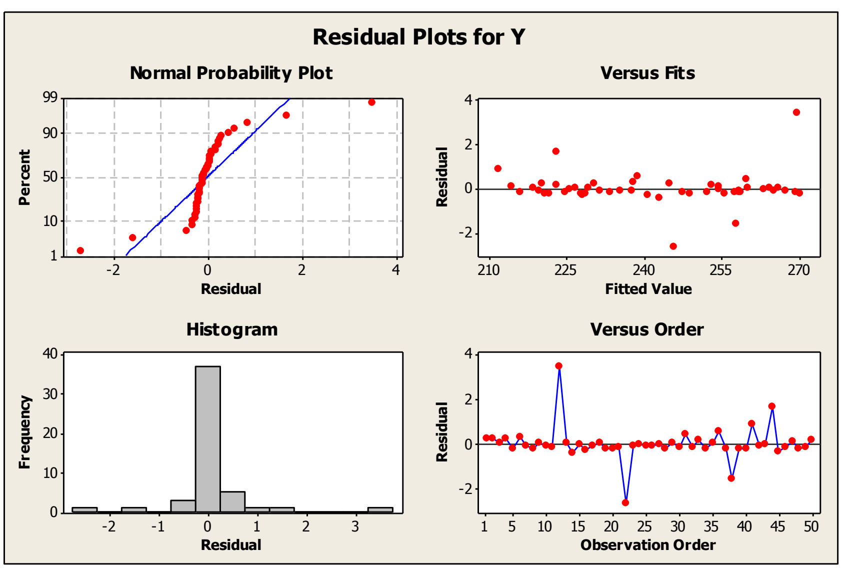


Figure 4: Residual Plots for Y

3.1.3 Linear regression analysis

The equipment time to failure for the conditions under study can be predicted using the linear regression model. The coefficients of the predictors in the equation as obtained from MINITAB package are:
$\alpha = 0.05$, $X_1 = 0.058$, $X_2 = 0.354$, $X_3 = 0.0214$

therefore, the predictive model becomes,

$$Y = 0.05 - 0.058X_1 + 0.354X_2 + 0.0214X_3 \quad (1)$$

Where X_1 = Injection speed, X_2 = Number of products produced per interval of failure, X_3 = Mould temperature & Y = Time to failure.

The values of statistical criteria; Coefficient of determination, R^2 = 99.8%, Adjusted R^2 = 99.8% and F-distribution = 8606.45 point to the fact that the multiple linear regression model as shown by equation (1) is very robust in predicting the equipment breakdown in real-time. The model can be used by the management of the company in predicting machine breakdown and scheduling maintenance appropriately.
However, X_1 remained almost constant; thus, its coefficient in the equation is modelled as 40.

3.1.4 Testing of the developed analysis model

To further verify the accuracy of the analysis model, the model was applied to a randomly selected resulting time to failure from table 3.1 (1st, 5th, 10th, 15th, 20th, 25th, 30th, 35th, 40th and 50th) as shown in Table 3 below. Comparing the results in Table 1 to the predictions obtained by the model, we can see that the calculated error is highly negligible and the predictions quite accurate. Therefore, it can be concluded that the model perfectly represents the real-world process behavior of the machine under study.

Table 3 Prediction Accuracy of the Proposed Model

Observation	Results	Predictions	Error
1st	220.240	219.986	0.254
5th	228.410	228.619	0.510
10th	267.170	267.265	0.202
15th	225.270	225.280	-0.010
20th	270.150	270.347	-0.197
25th	231.260	231.325	-0.065
30th	258.240	258.406	-0.166
35th	226.460	226.407	0.053
40th	220.340	220.576	-0.236
50th	223.060	222.864	0.170

3.2 Development of the Hardware and Software Components of the Intelligent System.

The sensors were trained using the **Arduino IDE (Integrated Development Environment)** software, the programming language used is **C++.** The two sensors were trained through its microprocessor, to capture and transmit data in real-time to ThingSpeak through channel id 2014053. There are 3 fields in the ThingSpeak channel, the first field receives the mould temperature data from the Arduino temperature sensor, the second field receives the number of cups from the ultrasonic proximity sensor, and the ultrasonic sensor was trained to capture cup passage within 64cm range; this range being the space through which the products eject from the machine. The third field gets feedback from the prediction model for control. The data transmission is done at intervals of 30 seconds, this gives a robust real-time condition of the machine. The sensors, microprocessor, and other supporting components that formed the system's hardware component (such as buzzer, resistors capacitors LED, transistors, and push button), are connected/built on a vero board. The sensors are connected to the board using 4 pins header wire as shown in Fig. 5.

Figure 5 The Hardware Component of the Developed System

3.3 Development of a Fault Prediction and Control Model Using MATLAB.

The model environment was created using MATLAB Language. The analysis model in equation (1) is imported into the MATLAB environment by plotting each of the input variable against time to failure while injection speed is modelled as 40 (constant). The model also hosts the control of the system, that's the reset button and the alarm feedback mechanism. The model gets its data from ThingSpeak and also give feedback to the sensors through ThingSpeak still, enabling a robust synchronization between the model and the hardware on the production facility. A detailed architecture of the fault prediction and control model is represented in the flow chart in figure 6.

3.4 Development of the Intelligent System by Integrating and Synchronising the Various Components of the System.

The intelligent system was developed by integrating the various software and hardware components of the system. At this point the system is fully ready for deployment, and can be controlled using the appropriate lines of code. The system behavior is described in Fig. 7, while Fig. 8 shows the components integration and synchronization right from data collection to failure control.

3.5 Experimental Results and Discussions

The setup time for both participants is 5minutes each. The hardware was connected to a power source, which turns the indicator light on the microprocessor board red. But immediately it was connected to internet through the microprocessor's customized hotspot, the indicator turns blue and start data capturing and transmission to the web server. At every 30seconds the system transmits data, the indicator light turns white and then returns back to blue to start a new process. The model gets this data from ThingSpeak and make the fault predictions. Different predictions were recorded at different times as shown in figure 9.

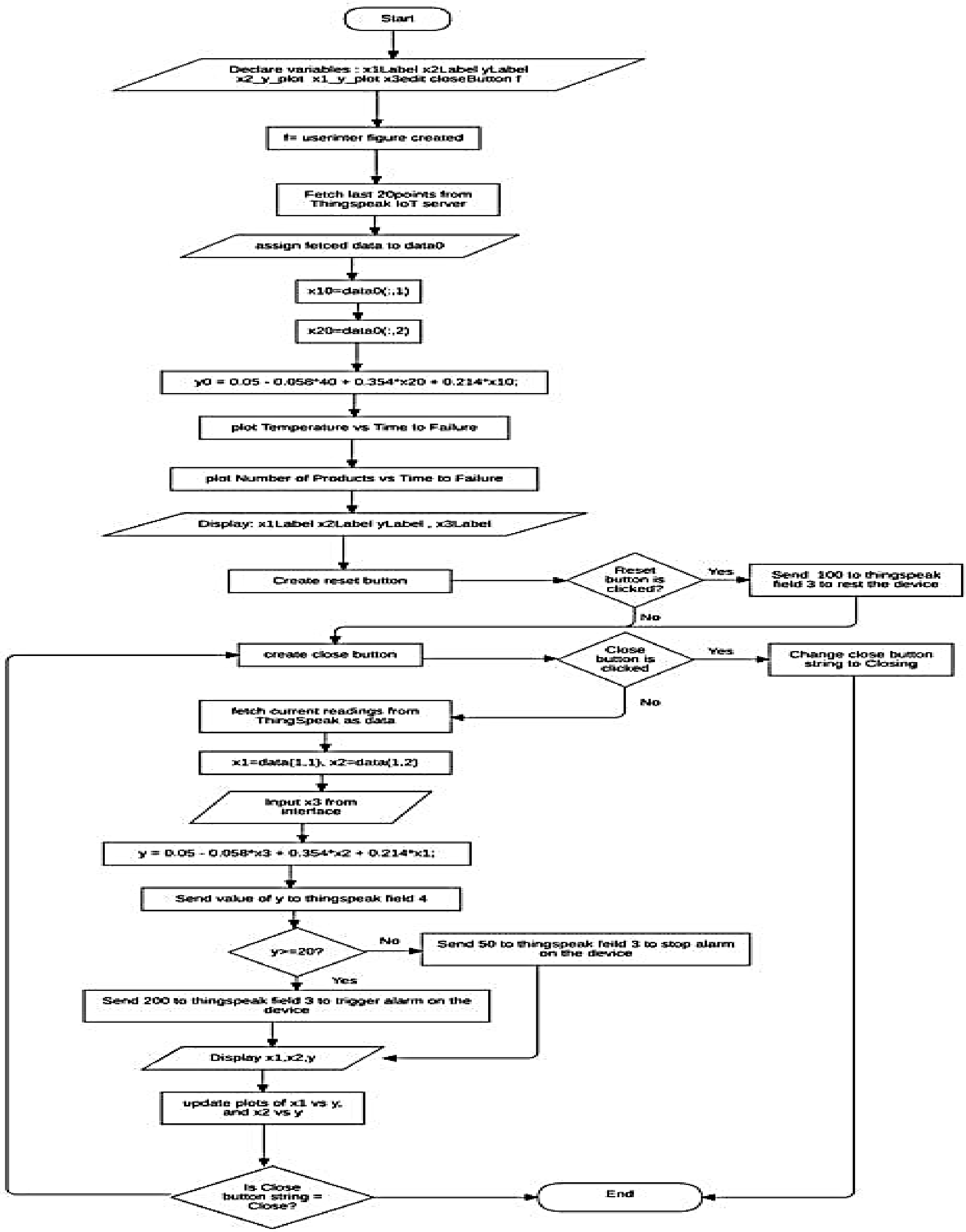


Fig. 6 Fault Prediction and Control Model Architecture

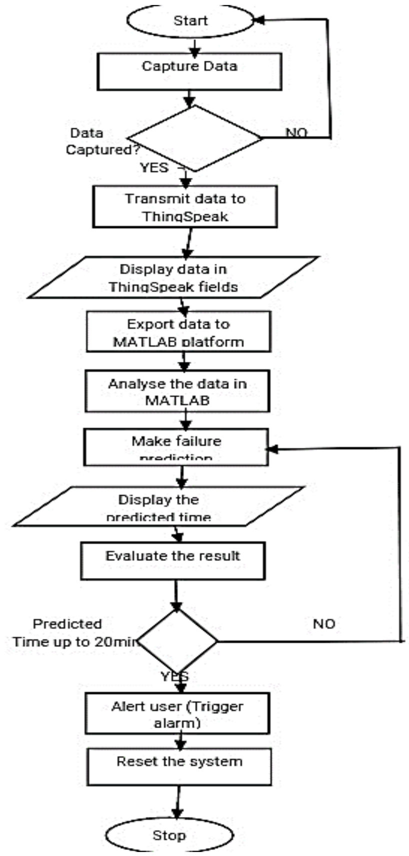


Figure 7 System Flowchart

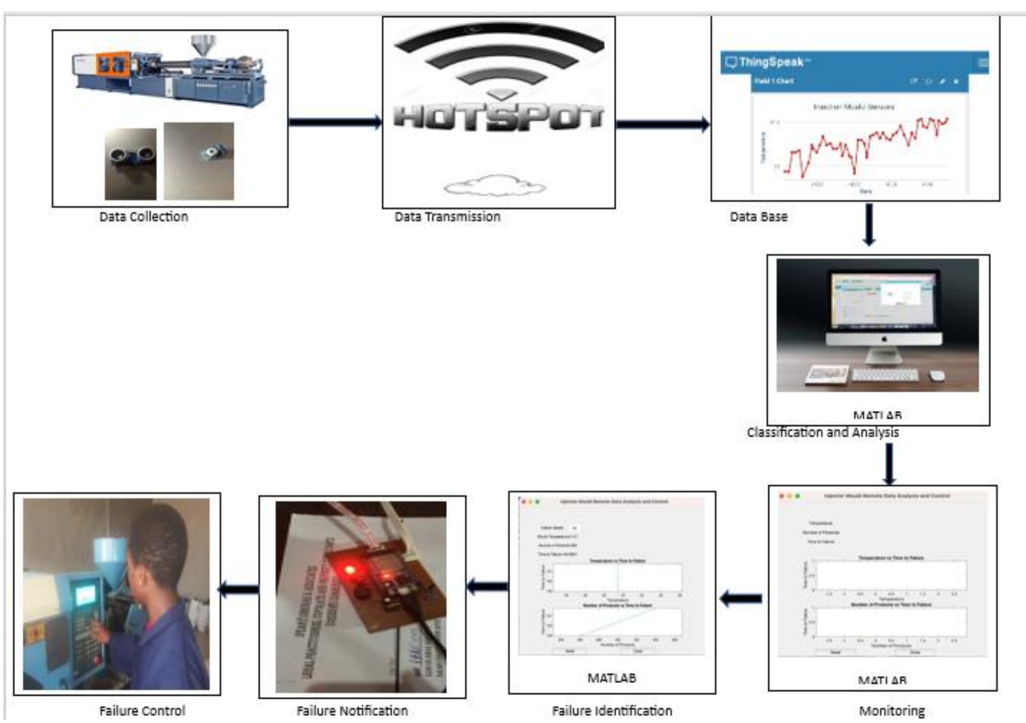


Figure 8 System Synchronization and Integration

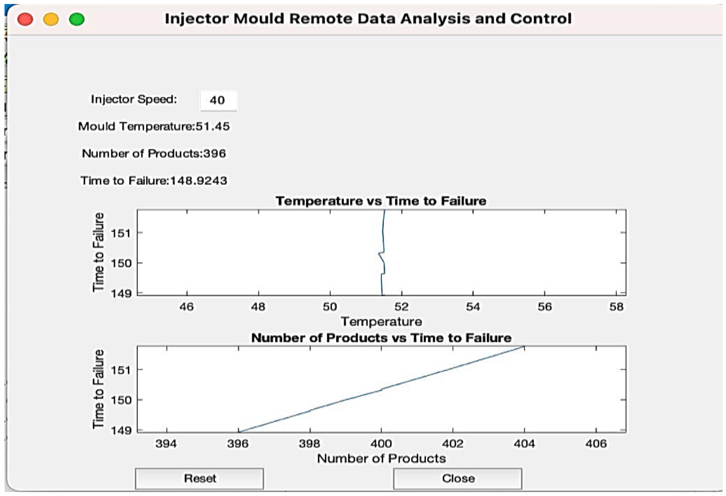


Figure 9 Real-time Prediction of Machine Time to Failure

The prediction shown in Fig. 9 was made using the real-time data from the web server at about 14:41 GMT+0100 as proved in Fig. 10 & 11 below;

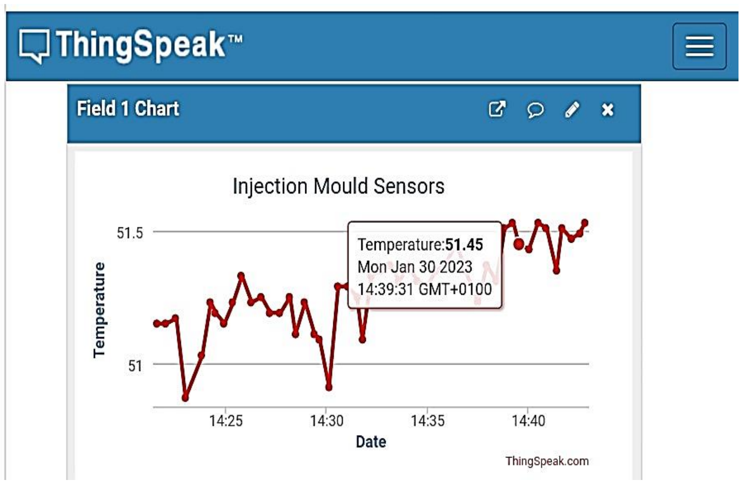


Figure 10 Real Time Temperature Data Used for the Prediction

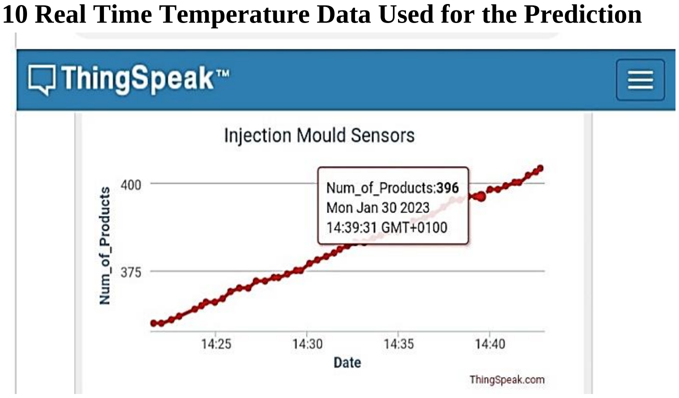


Figure 11 Real Time Number of Cups Data Used for the Prediction

The predicted time to failure is evaluated by the model, and triggers an alarm when It's remaining exactly 20minutes to machine failure. From the experiment in Fig. 9, the alarm went off at about 16:49 GMT+0100, exactly 20minutes to the predicted machine failure. Then at about 17:14 GMT+0100, 5mins late from the predicted time, the failure occurred. The failure occurred as a result of abnormal increase in mould temperature. So, the increase does not allow the product to get the degree of cooling required for the cup formation and solidification, so during ejection, the product is damaged. Immediately this happens, the machine immediately stops, halting production and causing downtime. The alarm feedback as demonstrated using the developed system addresses the gap in the reviewed articles and forms the major innovative aspect of the study.

3.6 Control Strategy for Avoiding the Predicted Failure

The control strategies presented in this study is experimented by the machine operator, and failure was averted. From literatures, the predicted machine failure can be averted by increasing the cooling time of the process, by one or two seconds. This allows the product to stay longer in the mould, so as to cool off and solidifies before ejection. The melting temperature and the nozzle temperature is be reduced by 10C each, this will considerably reduce the amount of heat that is been injected into the mould, Table 4 below.

Table 4 Control Strategy for Avoiding Failure

Case	Failure Type	Control Actions
High Mould Temperature; leading to machine breakdown and product fracture	Machine Breakdown	➢ Increase cooling time by one or two seconds ➢ Reduce melting temperature by 10C ➢ Reduce Nozzle temperature by 10C

3.7 Developed System Validation

Experimental results are randomly selected for validation Table 5. The program written for calculating the Pearson Correlation is done using MATLAB. Stopwatch is used to record the actual machine time to failure, to validate the failure time predicted by the developed system. Using Pearson Correlation method, results is obtained through the different plots in Fig. 12, with a Pearson Correlation Coefficient of 0.995242. In Fig. 12a, measured time to failure is plotted against modelled time to failure; in Fig. 12b time to failure is plotted against time; in Fig. 12c, time to failure is plotted against the devices, in Fig. 12d frequency is plotted against measurement. The results shows that the developed system is very robust and reliable for failure prediction of the machine under study.

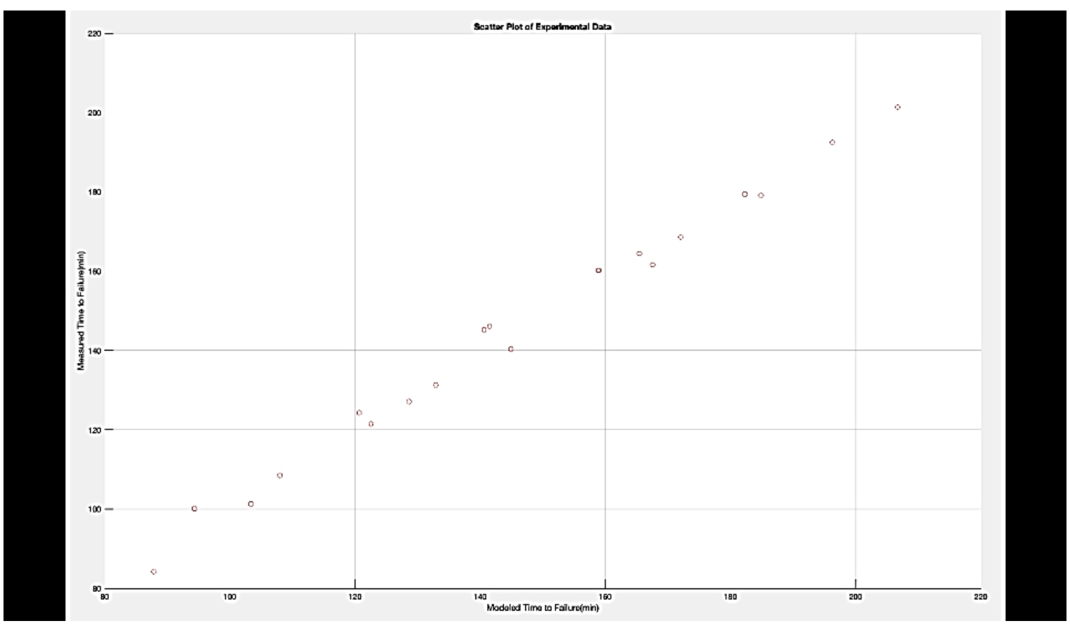
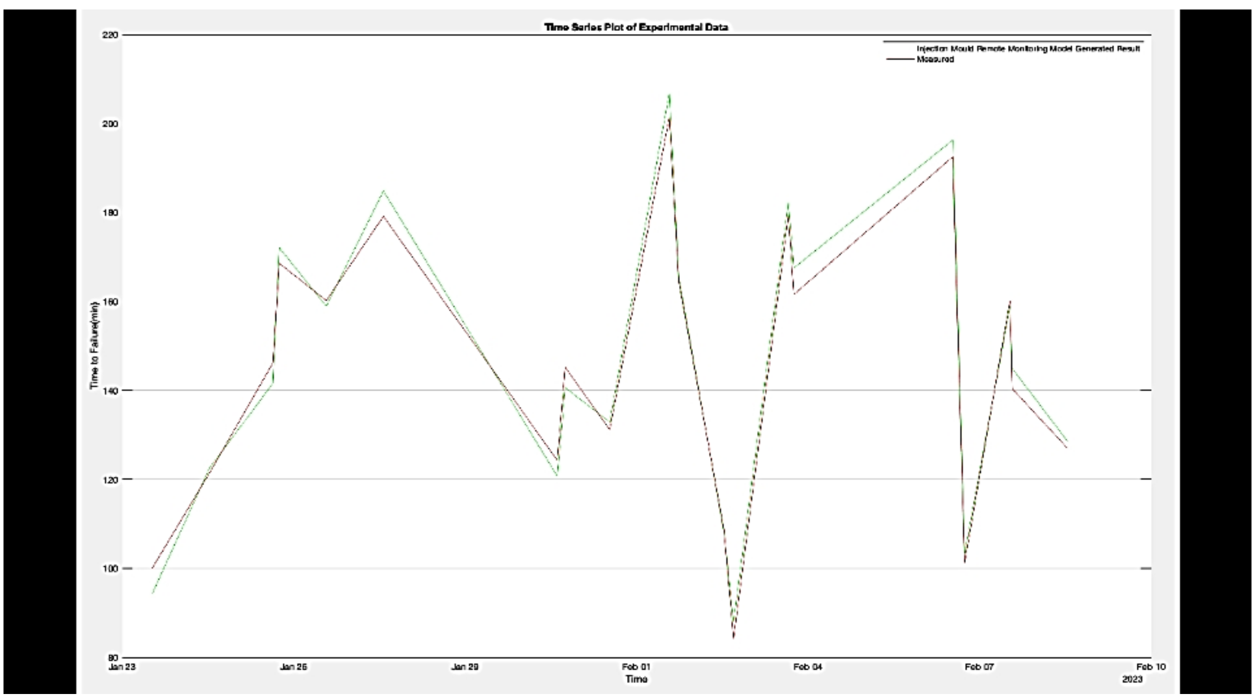


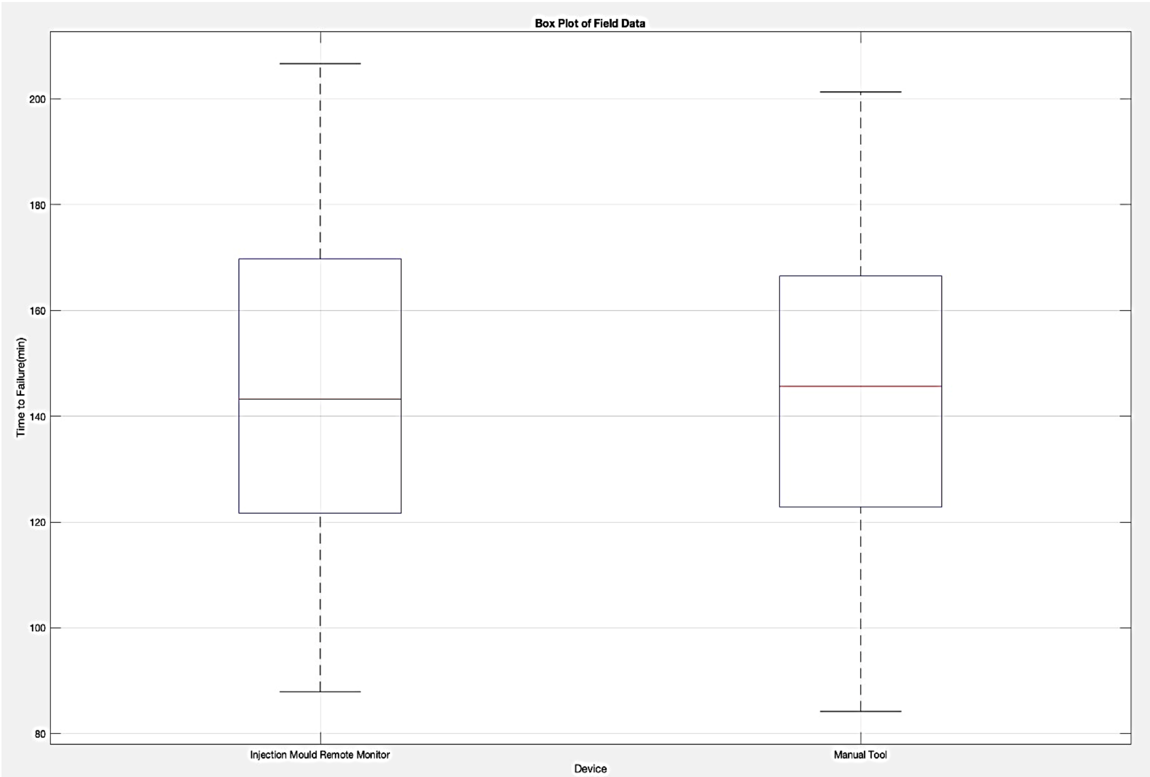
Figure 12(a) Scattered Plot of Experimental Data

Table 5 Result Validation Data

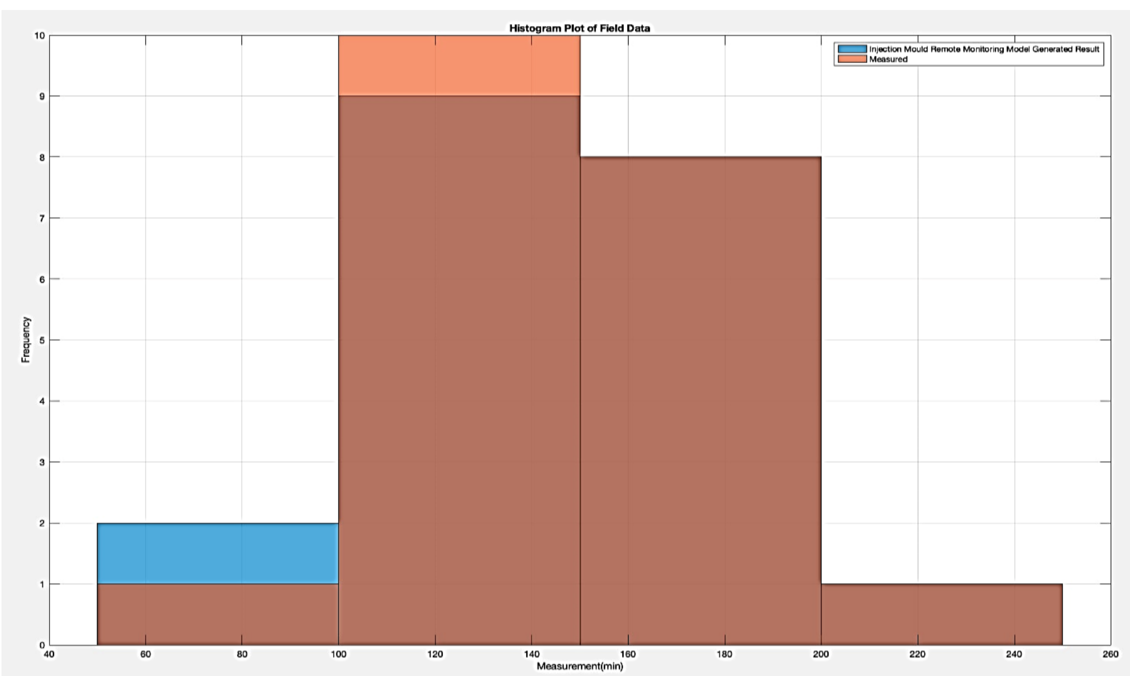
Observation	Mould Temp. (C)	Number of Cups (Pcs)	Predicted Time (Mins)	Actual Time (Mins)
2023-01-23T13:02:41+00:00	48.2	267	94.3474	100.1
2023-01-24T13:02:41+00:00	50.64	322	122.5571	121.45
2023-01-25T11:08:15+00:00	53.24	403	141.5313	146.12
2023-01-25T15:05:01+00:00	56.27	489	172.0401	168.54
2023-01-26T12:31:11+00:00	54.09	452	158.8955	160.18
2023-01-27T13:24:51+00:00	58.46	525	184.831	179.12
2023-01-30T10:00:18+00:00	50.63	318	120.6801	124.24
2023-01-30T14:20:38+00:00	51.45	396	140.599	145.15
2023-01-31T12:40:11+00:00	50.92	351	132.883	131.2
2023-02-01T09:41:21+00:00	60.1	580	206.6561	201.31
2023-02-01T13:30:31+00:00	55.32	465	165.3838	164.44
2023-02-02T10:24:33+00:00	49.63	305	107.982	108.52
2023-02-02T14:13:31+00:00	47.45	249	87.8874	84.17
2023-02-03T08:36:22+00:00	57.06	512	182.247	179.37
2023-02-03T12:40:41+00:00	54.5	471	167.5143	161.56
2023-02-06T09:40:41+00:00	59.16	551	196.254	192.47
2023-02-06T13:42:12+00:00	50.15	292	103.3392	101.28
2023-02-07T10:50:21+00:00	56.12	447	158.9569	160.18
2023-02-07T14:50:42+00:00	52.26	408	144.9102	140.35
2023-02-08T10:22:10+00:00	51.07	339	128.665	127.1



12(b) Time Series Plot of Experimental Data



12(c) Box Plot of Field Data



12(d) Histogram Plot of Field Data

4.0 Conclusion

In this paper, an IoT-based real-time remote monitoring system for predictive maintenance of Injection Moulding machines, is presented. Predictive Maintenance is a viable strategy adopted when dealing with maintenance issues given the increasing need to minimize downtime and associated costs. The methodology has been implemented in a real environment on the example of a plastic industry using an Injection Moulding Machine (LSF-148S Longsheng Machinery). The identified parameter data was collected manually as presented in Table 1; the data were used to create an analysis model using MINITAB. The sensors were trained (Using Arduino IDE) and deployed for real-time data capturing and transmission. Data are then transmitted to the fault prediction/control model domicile in MATLAB through an IoT web server (ThingSpeak). The system was then developed by integrating and synchronizing its hardware and software components Fig. 8; the system behavior was also explained using a flowchart in Fig. 7. Several experimental Tests were carried out, and validation was done using Pearson Correlation. Random results of the actual values of the failure time and that of the failure time predicted by the developed system were selected Table 5. A Pearson Correlation Coefficient of 0.995242 was recorded, which shows that the developed system is very robust and reliable for failure prediction of the machine under study. The fault predictions helped to avert the machine failure that could led to a waste of time, material & labor. A control strategy for the identified failure was also summarized in Table 4. These involve; increasing the cooling time for the product by 1 or 2 seconds, and reducing the melting temperature and the nozzle temperature simultaneously, by 10C.

The proposed PdM methodology allows dynamic decision rules to be adopted for maintenance management. Preliminary results signify a proper behavior of the approach on predicting the failure of the Injection Moulding Machine, with high accuracy (95%). Generally, the system contributions are mainly on the overall cloud architecture for Industry 4.0, sensor data are transmitted using IoT, the developed system makes the predictions remotely and gives feedback in real-time, maintenance is scheduled and the danger is averted, the feedback mechanism of the developed system takes care of the gap as seen in the reviewed works. The implications of applying this intelligent system are; remote monitoring of the machine from outside the production unit, reduction in downtime, reduction in maintenance cost, and increased productivity for plastic industries. The experiment was carried out successfully, with no significant limitations. Future work will go in the direction of having a more robust data set, investigating different fault scenarios in Injection Moulding Machines, and exploring a different set of features, in particular in the fault prediction of more complex industrial equipment.

5.0 Recommendations

There is an urgent need for the top management of plastic industries to support the development of more intelligent systems, not only to predict failure along the process line but all the parts of the machine. Intelligent systems can also help in inventory and safety management. The creation of an organizational support structure for Industry 4.0 technologies is recommended. The group should include every member of the organization from management to the shop floor. This structure will promote the idea and also guarantee that everyone is carried along.

References

Albertin, U., Pedone, G., Brossa, M., Squillero, G., & Chiaberge, M. 2023. A real-time novelty recognition framework based on machine learning for fault detection. *Algorithms*; 16(2):61. https://doi.org/10.3390/a16020061.

Araújo, C., Pereira, D., Dias, D. et al. 2023. In-cavity pressure measurements for failure diagnosis in the injection moulding process and correlation with numerical simulation. *Int J Adv Manuf Technol* **126**, 291–300. https://doi.org/10.1007/s00170-023-11100-1

Baek, D.S. 2014. A studyon condition monitoring and diagnosis of injection moulding process using probabilistic neural network method. ASME 2014 Inter-national Manufacturing Science and Engineering Conference collocated with the JSME 2014 International Conference on Materials and Processing and the 42nd North American Manufacturing Research Conference vol 1, 1–7.

Bogedale, L., Schrodt, A. & Heim, H. 2023. Time series data for process monitoring in injection molding: a quantitative study of the benefits of a high sampling rate. *International Polymer Processing*, *38*(2), 167-174. https://doi.org/10.1515/ipp-2022-4258

Chen, J.C., Guo, G., & Chang, YH. 2022. Intelligent dimensional prediction systems with real-time monitoring sensors for injection molding via statistical regression and artificial neural networks. *Int J Interact Des Manuf.* https://doi.org/10.1007/s12008-022-01115-5

Farahani, S., Khade, V, Basu, S., & Pilla, S. 2022. A data-driven predictive maintenance framework for injection molding process, *Journal of Manufacturing Processes*, Volume 80, Pages 887-897, ISSN 1526-6125, https://doi.org/10.1016/j.jmapro.2022.06.013.

Gomes, T.E.P., Cadete, M.S., Ferreira, J.A.F., Febra, R., Silva, J., Noversa, T., Pontes, A.J., & Neto, V. 2023. Development of an open-source injection mould monitoring system. *Sensors 23*, 3569. https://doi.org/10.3390/s23073569

Gordon, G., Kazmer, D.O., Tang, X.Y., Fan, Z.Y., & Gao, R.X. 2017. Validation of an in-mold multivariate sensor for measurement of melt temperature, pressure, velocity, and viscosity. *International Polymer Processing*, 32/4: 406–415.

Hu, Z., Yin, Z., Qin, L., & Xu, F. 2022. A novel method of fault diagnosis for injection molding systems based on improved VGG16 and machine vision. *Sustainability*, *14*, 14280. https://doi.org/10.3390/su142114280

Kanagalakshmi, S., Manamalli, D., & Mohamedrafiq, M. 2015. Implementation of multimodel-based PID and intelligent controller for simulated and real-time temperature control of injection moulding machine. *Chemical Engineering Communications, 203/4: 452–462.*

Kozjek, D., Vrabic,9 R., Kralj, D., & Butala, P. 2017. A data-driven holistic approach to fault prognostics in a cyclic manufacturing process. *Procedia CIRP*, 63:664– 669.

Kumar, S., Park, H. S., & Lee, C. M. 2020. Data-driven smart control of injection molding process. *CIRP Journal of Manufacturing Science and Technology*, 2019. https://doi.org/10.1016/j.cirpj.2020.07.006

Moreira, E. *et al*. 2020. "Industry 4.0: Real-time monitoring of an injection molding tool for smart predictive maintenance," *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, Vienna, Austria, 2020, pp. 1209-1212, doi: 10.1109/ETFA46521.2020.9212167.

Nunes, P., Rocha, E., & Santos, J.P. 2023. Using intelligent edge devices for predictive maintenance on injection moulds. *Appl. Sci. 13*, 7131. https://doi.org/10.3390/app13127131

Ogorodnyk, O., & Martinsen, K. 2018. Monitoring and control for thermoplastics injection moulding a review. *Procedia CIRP*, 67:380–385.

Okeagu, F. N., & Mgbemena, C. E. 2022. A systematic review of digital twin systems for improved predictive maintenance of equipment in smart factories. *International Journal of Industrial and Production Engineering*, 1(1), 1–20. Retrieved From https://journals.unizik.edu.ng/index.php/ijipe/article/view/1041

Park, H.S., Phuong, D.X., & Kumar, S. 2019. AI based injection moulding process for consistent product quality. *Procedia Manufacturing*, 28:102–106.

Pierleoni, P., Palma, L., Belli, A., & Sabbatini, L. 2020. Using plastic injection moulding machine process parameters for predictive maintenance purposes," *2020 International Conference on Intelligent Engineering and Management (ICIEM)*, London, UK, 2020, pp. 115-120, doi: 10.1109/ICIEM48762.2020.9160120.

Schiffers, R., Holzinger, G.P., & Huster, G. 2016. Adaptive process control for stabilizing the production process in injection moulding machines. 10th *International Fluid Power Conference, 341–352.*

Selcuk, S. 2017. Predictive maintenance, its implementation and latest trends. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf*. 231, 1670–1679.

Tayalati, F., Azmani, M., & Azmani, A. 2022. Artificial intelligence based plastic injection process for initial parameters setting and process monitoring-review. In: Hamlich, M., Bellatreche, L., Siadat, A., Ventura, S. (eds) Smart Applications and Data Analysis. SADASC 2022. *Communications in Computer and Information Science*, vol 1677. Springer, Cham. https://doi.org/10.1007/978-3-031-20490-6_24

Tortorella, G.L. 2018. An empirical analysis of total quality management and total productive maintenance in industry 4.0. *In Proceedings of the International Conference on Industrial Engineering and Operations Management* (IEOM), Pretoria/Johannesburg, South Africa, 29 October–1 November; pp. 742–753.

Tripathi, S., Mittermayr, C., & Jodlbauer, H. 2023. Exploring the time-lagged causality of process variables from injection molding machines, *Procedia Computer Science*, Volume 217, Pages 1153-1167, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2022.12.314. (https://www.sciencedirect.com/science/article/pii/S1877050922023997)

Vasco, J. C., Martins, J., Oliveira, P., & Chaves. P. 2023. "Closed-loop control applied to the injection moulding process—an industry 4.0 refurbishment case study" *Electronics* 12, no. 2: 271.

https://doi.org/10.3390/electronics12020271

Wang, J. Ye, L., Gao, R.X., Li, C., & Zhang, L. 2019. Digital twin for rotating machinery fault diagnosis in smart manufacturing. *Int. J. Prod. Res*., 57, 3920–3934.

Wu, Y., Feng, Y., Peng, S. et al. 2023. Generative machine learning-based multi-objective process parameter optimization towards energy and quality of injection molding. *Environ Sci Pollut Res* **30**, 51518–51530. https://doi.org/10.1007/s11356-023-26007-3

Zhang, Y., Mao, T., Huang, Z., Gao, H., & Li, D. 2016. A statistical quality monitoring method for plastic injection moulding using machine built-in *sensors. The International Journal of Advanced Manufacturing Technology*, 85/9–12: 2483–2494.