Proc. of the 9th Intl. Conf. of Asian Society for Precision Engg. and Nanotechnology (ASPEN 2022)
15–18 November 2022, Singapore. Edited by Nai Mui Ling Sharon and A. Senthil Kumar
doi://10.3850/978-981-18-6021-8_OR-08-0273

Predictive analytics for downtime prevention in Plastic Injection Molding Line

Junt Kong Chan, Shiming Ang, Hongtao Wang, and Yan Shen

Agency for Science, Technology and Research
3 Cleantech Loop, #05-06, CleanTech Two, Singapore 637143
Email: chanjk@i3.a-star.edu.sg, TEL: +65-67149420

KEYWORDS: Industrial Internet of Things, Predictive Analytics, Visualization

This paper discusses the implementation of predictive analytics a plastic injection molding production line. The production line was analyzed to understand the process and identify the machines for their function, parameters available and communication capability / protocols. Sensors for environmental parameters, water, and compressed air supply were added. An IIoT architecture was designed for communication interoperability between the edge computer and the line machines. This allowed each machine data to be captured, synchronized and stored in a database. A dashboard was designed with user friendly interface (UI), allows operators to easily comprehend production status; and process experts can analyse historical data via charts. For the analytics, the line data was studied with the process experts to identify line issues and key parameters which drive these issues. It was found that the line would shut down a few times a day for an unknown reason, at that time. Using analytic tools and studying data captured from the production line, key parameters causing the unplanned shutdown were identified. The event was able to be predicted ahead of time. Based on the findings regarding the issue root cause, the predictive analytics model was developed and fine-tuned. The model provided alerts with 10 minutes lead time at 75% confidence.

1. Introduction

The user manufactures medical products such as needles and catheters. The user is embarking on plan to digitize the manufacturing process, and has approached I3 for collaboration to build up their capability in data sciences and analytics. A project within the user's plastic injection molding plant was identified, where statistical analytics will be applied to the plastic injection molding machine parameters to predict issues on the molded parts. During the initial investigation, it was found that the injection molding sensor, process and environment parameters are currently not being collected, which is needed for performing any analytics. The project will first start by gathering the injection molding machine parameters, environment and process parameters into a database as part of the project. The user also requested to perform analytics during the POC data to determine if signals can be detected, and for an Android alert app.

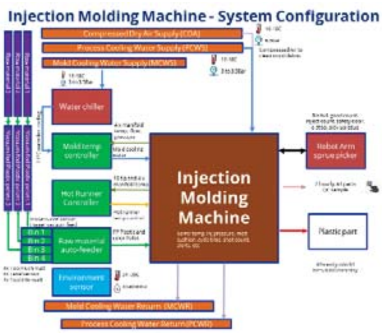


Fig. 1 Block diagram for Injection molding line

2. Predictive analytics for injection molding line

2.1 IIoT architecture

Based on studies of the line VFN17 the processes and equipment parameters will be captured :

1. Injection molding machine (Text file)
2. Hot runner controller (Text file)
3. Mold cooling solution (OPC-UA)
4. Water chiller (Modbus)
5. Raw material auto-feeder (OPC-UA)
6. Machine and Process Cooling Water Supply (MCWS and PCWS) flow, temperature and pressure (IO-Link)
7. Compressed Dry Air Supply temperature and pressure (IO-Link)
8. QC sample request sample request (Ethernet)
9. Clean Room Temperature and Humidity (REST)

The IIoT architecture for data capture was developed.

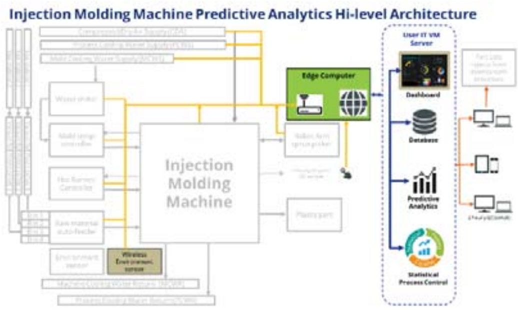


Fig. 2 Injection molding line IIoT architecture

Communications from the machines, sensors and small board computers would be integrated at HPE EL300 edge computer. Once the communications were enabled, and parameters captured, a study was done with the process experts to identify the most important parameters. In total, around 700 parameters are captured.

On the VM server, Microservice APIs were developed to pull JSON data from the Edge server and write into an SQL database.

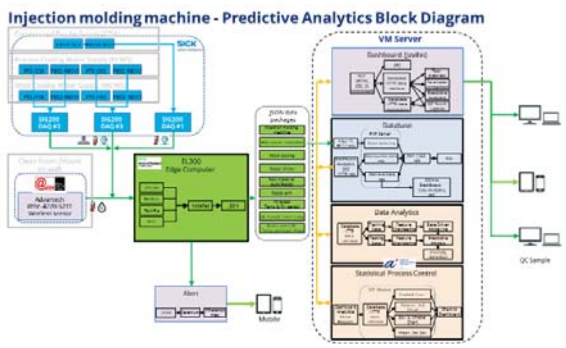


Fig. 3 Block diagram for the Injection molding machine predictive analytics

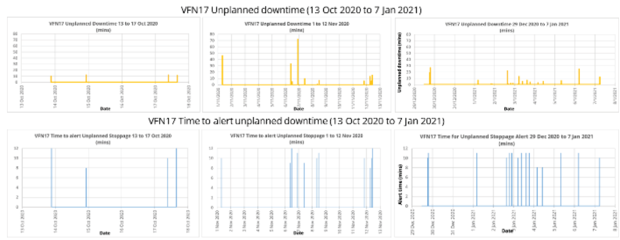
The database was designed to be easy to scale, with a sensor ID, data columns and timestamp.

A dashboard based on user inputs, was developed to display the line status, parameters, alerts and charts.

Fig. 4 Dashboard for Injection Molding Line

2.2 Data Analysis

The data captured was analysed to identify issues which were happening on the line. It was observed that a shutdown of the Injection Molding Machine would happen 36 times between 13



October 2020 and 7 Jan 2021. All shutdown events required operator intervention.

Fig. 5 Material starvation data charts

2.3 Predictive analytics model

The predictive analytics model was built following the data analysis pipeline below.

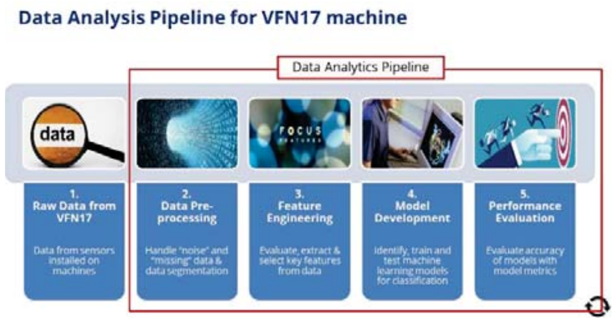


Fig. 6 Data analysis pipeline

2.3.1 Raw Data from VFN17

From the raw data, there were 36 VFN17 unplanned stoppage events :

1. 33 events from Raw material auto-feeder Bins
2. 1 event due to water chiller Fault 6
3. 2 events "Others" (e.g. Robot loss grip)

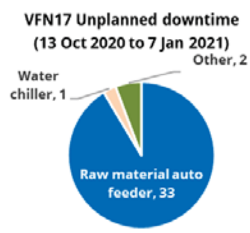


Fig. 7 VFN17 unplanned stoppage events

2.3.2 Data Pre-processing

The average period of VFN17 first alert to stoppage is found to be 10 minutes, and this period was used for data labelling.

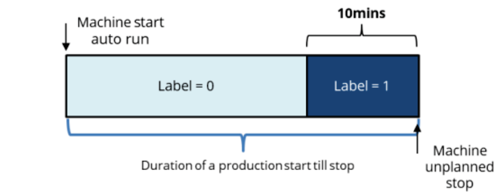


Fig. 8 VFN17 data labelling

For the period of analysis there were 7,847 segments, used to create a balanced dataset.

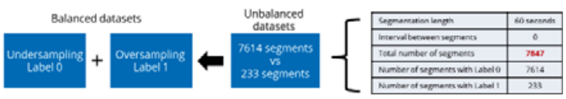


Fig. 9 VFN17 data segmentation

2.3.3 Feature Engineering

205 key parameters were identified during feature extraction. 15 time-domain features were applied to these parameters.

Total number of segments (A)	7847
Number of key parameters (B)	205
Number of time-domain features (C)	15
Total number of extracted features (A x B x C)	**~24 million**

No	Feature	Equation
1	Average Amplitude	$p_1 = \frac{1}{k}\sum_{i=1}^{k} s(i)$
2	Standard Deviation	$p_2 = \left(\frac{\sum_{i=1}^{k}(s(i)-p_1)^2}{k-1}\right)^{1/2}$
3	Root-mean-square amplitude (RMS)	$p_3 = \left(\frac{1}{k}\sum_{i=1}^{k} s(i)^2\right)^{1/2}$
4	Square of mean root absolute amplitude (SMRA)	$p_4 = \left(\frac{1}{k}\sum_{i=1}^{k}\sqrt{\lvert s(i)\rvert}\right)^2$
5	Peak Value	$p_5 = \max\lvert s(i)\rvert$
6	Skewness Coefficient	$p_6 = \frac{\sum_{i=1}^{k}(s(i)-p_1)^3}{(k-1)p_2^3}$
7	Kurtosis coefficient	$p_7 = \frac{\sum_{i=1}^{k}(s(i)-p_1)^4}{(k-1)p_2^4}$
8	Peak Factor	$p_8 = \frac{p_5}{p_3}$
9	Margin Factor	$p_9 = \frac{p_5}{p_4}$
10	Waveform factor	$p_{10} = \frac{p_3}{\frac{1}{k}\sum_{i=1}^{k}\lvert s(i)\rvert}$
11	Impulse factor	$p_{11} = \frac{p_5}{\frac{1}{k}\sum_{i=1}^{k}\lvert s(i)\rvert}$
12	Min amplitude	$p_{12} = \min(s(i))$
13	Max amplitude	$p_{13} = \max(s(i))$
14	Max - min	$p_{14} = p_{13} - p_{12}$
15	Peak - mean	$p_{15} = p_5 - p_1$

Fig. 10 Feature extraction

Fisher's Ratio was used identify key features for model development. The top 3 VFN17 unplanned stop features was from the Raw material auto-feeder machine.

Top 3 Ranked Feature Areas	Rank
Raw Material auto-feeder Mixing Chamber Level	1
Raw Material auto-feeder Bin 1 Too Little Material	2
Raw Material auto-feeder ac Weight	3

	Top 20 Ranked Features	Ratio
Raw Material auto-feeder Mixing Chamber Level	sfLevelMixingChamber_max	1992.3
	sfLevelMixingChamber_peak	1992.3
	sfLevelMixingChamber_MarginFactor	689.8
	sfLevelMixingChamber_RMS	234.4
	sfLevelMixingChamber_WaveFormFactor	79.0
	sfLevelMixingChamber_CrestFactor	79.0
	sfLevelMixingChamber_mean	74.4
Raw Material auto-feeder Too Little Material	acC1TooLittleMaterial_min	35.2
	acC1TooLittleMaterial_ImpulseFactor	35.2
	acC1TooLittleMaterial_SMRA	34.4
	acC1TooLittleMaterial_mean	33.4
	acC1TooLittleMaterial_RMS	32.3
	acC1TooLittleMaterial_peak	30.0
	acC1TooLittleMaterial_max	30.0
	acC1TooLittleMaterial_CrestFactor	25.2
	acC1TooLittleMaterial_WaveFormFactor	25.2
	sfLevelMixingChamberSMRA	23.3
Raw Material auto-feeder acWeight	acWeight_max	9.2
	acWeight_RMS	7.4
	acWeight_peak	5.2

Fig. 11 Feature selection

2.3.4 Model Development

Neural Network was chosen as it was able to learn by example and more fault tolerant.

A predictive model was then built to predict VFN17 unplanned stoppage events.

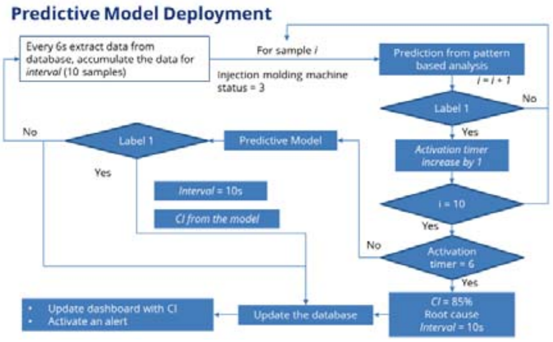


Fig. 12 Predictive model for VFN17

2.3.5 Performance Evaluation

The metrics for evaluating the ML model performance :

Accuracy (ACC)	$\frac{\textit{number of correctly classified instances}}{\textit{total number of instances}}$
True-Positive-Rate (TPR)	$\frac{\textit{number of correctly classified positive instances}}{\textit{total number of positive instances}}$
True-Negative-Rate (TNR)	$\frac{\textit{number of correctly classified negative instances}}{\textit{total number of negative instances}}$
Area Under Curve (AUC)	*Defined as the trade off between TPR & TNR*

Fig. 13 Classification metrics

From the data analysis undertaken, Neural Network TPR value was the highlight. For predictions obtained using the ML model, the message to users is "Injection Molding Machine is going to stop in 10mins"

Classification Results

The best TPR is 75.54% using Neural Network with accuracy of 94.7%

Neural Network

	ACC	TPR	TNR	AUC
5	0.985472	0.570815	0.998161	0.784488
10	0.983688	0.686695	0.992776	0.839736
15	0.983433	0.695279	0.992251	0.843765
20	0.983306	0.695279	0.99212	0.843699
25	0.978718	0.699571	0.98726	0.843416
30	0.98063	0.703863	0.989099	0.846481
35	0.978336	0.708155	0.986604	0.847379
40	0.979355	0.703863	0.987786	0.845824
45	0.980247	0.699571	0.988836	0.844204
50	0.977061	0.729614	0.984634	0.857124
55	0.976424	0.72103	0.98424	0.852635
60	0.967758	0.708155	0.975703	0.841929
65	0.962151	0.729614	0.969267	0.84944
70	0.921116	0.712446	0.927502	0.819974
75	0.938193	0.699571	0.945495	0.822533
80	0.934752	0.716738	0.941424	0.829081
85	[illegible]	0.72103	[illegible]	[illegible]
90	0.946731	0.755365	0.952587	0.853976
95	0.933478	0.746781	0.939191	0.842986
100	0.94329	0.716738	0.950223	0.833481

Logistic Regression

	ACC	TPR	TNR	AUC
5	0.978336	0.575107	0.990675	0.782891
10	0.983561	0.695279	0.992382	0.843831
15	0.983306	0.695279	0.99212	0.843699
20	0.980757	0.690987	0.989624	0.840306
25	0.975277	0.699571	0.983714	0.841643
30	0.974258	0.703863	0.982532	0.843197
35	0.961259	0.703863	0.969136	0.836499
40	0.965592	0.699571	0.973733	0.836652
45	0.965847	0.686695	0.974389	0.830542
50	0.959475	0.725322	0.96664	0.845981
55	0.956344	0.699571	0.964408	0.831989
60	0.938448	0.725322	0.94497	0.835146
65	0.938958	0.72103	0.945626	0.833328
70	0.918058	0.695279	0.924875	0.810077
75	0.917803	0.72103	0.923825	0.822427
80	0.929782	0.708155	0.936564	0.822359
85	0.925449	0.716738	0.931836	0.824287
90	0.921126	0.738197	0.926714	0.832456
95	0.930674	0.746781	0.936302	0.841541
100	0.928253	0.738197	0.934069	0.836133

N-Nearest Neighbors

	ACC	TPR	TNR	AUC
5	0.677456	0.626609	0.679012	0.652811
10	0.71161	0.618026	0.714473	0.66625
15	0.963171	0.665236	0.972288	0.818762
20	0.848477	0.712446	0.85264	0.782543
25	0.842233	0.746781	0.845154	0.795967
30	0.850771	0.746781	0.853953	0.800367
35	0.845928	0.729614	0.849488	0.789551
40	0.861221	0.725322	0.86538	0.795351
45	0.849242	0.725322	0.853034	0.789178
50	0.860456	0.733906	0.864329	0.799117
55	0.8732	0.755365	0.876806	0.816085
60	0.876004	0.742489	0.880089	0.811289
65	0.87269	0.72103	0.877331	0.799181
70	0.901491	0.712446	0.907276	0.809861
75	0.894482	0.733906	0.899396	0.816651
80	0.895247	0.738197	0.900053	0.819125
85	0.902893	0.738197	0.907933	0.823065
90	0.900599	0.729614	0.905831	0.817723
95	0.891678	0.72103	0.8969	0.808965
100	0.897413	0.725322	0.902679	0.814001

Neural Network		
ACC (Accuracy)	94.67%	indicates the ability to predict normal & unplanned stoppage at 94.7% of the time.
TPR (True Positive Rate)	**75.54%**	**implies that when there are 100 instances of unplanned stoppages states, 75.54 instances can be predicted correctly**
TNR (True Negative Rate)	95.26%	implies that when there are 100 instances with state of running smoothly, 95.3 instances can be predicted correctly
AUC (Area Under Curve)	85.40%	the value for the trade-off between TPR and TNR

Fig. 14 Classification results

The predictive analytics results are displayed on the dashboard.

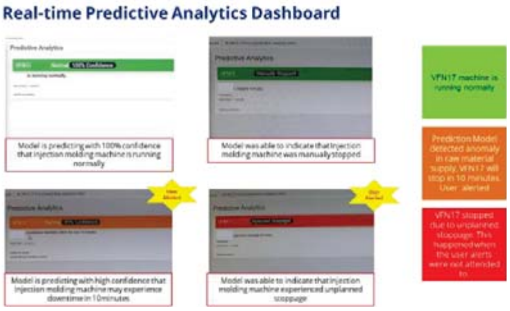


Fig. 15 Real-time predictive analytics dashboard

3. Conclusions

The IIoT architecture with predictive analytics to predict injection molding downtime was developed successfully. Key parameters can be captured by integrating various communication protocols. The data was synchronized and stored in a database. The data will also displayed on the dashboard, live. The solution has been deployed on-line successfully and can predict VFN17 upcoming downtime 10 minutes ahead of time.