以振動訊號進行塑膠射出成型產品重量虛擬量測

Plastic injection molding is a critical manufacturing process, vital to meet growing industrial demand for high-quality products. Geometric appearance and part weight are key quality attributes. To address this, we employ Vibration Analysis and Artificial Neural Networks (ANN) to predict these qualities cost-effectively.

We collected vibrational data using an accelerometer on the injection molding machine's toggle pin bearing. Analyzing low-frequency vibrations during the injection process, we used this data as inputs for two feed-forward ANNs. The first ANN classifies parts into normal, over, or short shots with 100% accuracy. The second ANN predicts part weights with a maximum error of 0.715 %, surpassing Support Vector Regression's 6.287 % error in a prior study.

The ANNs' superior performance is attributed to the abundant vibrational signatures used as inputs. This approach enhances the efficiency and effectiveness of plastic injection molding, ensuring products meet specific quality requirements amid growing competition.

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Plastic, due to its versatile nature, has found immense application globally, leading to the prominence of plastic injection molding in the polymer processing sector (He et al., 2000). This method, which involves injecting hot molten plastic into molds and solidifying it, is pivotal for crafting a diverse array of cost-effective components varying in size and complexity (Tang et al., 2007). The intricate injection molding process is delineated into six stages, encompassing everything from the initial feeding of the granular thermoplastic material to the eventual ejection of the final product. The phase where molten plastic fills the mold, known as the filling stage, stands out in its significance to the overall product quality (Lou et al., 2003). Studies, such as those by Sadeghi, underscored the pivotal role of mold cavity pressure in determining the product's quality. Further, while mold cavity pressure, nozzle pressure, and hydraulic pressure are intricately linked to product quality, the challenges of sensor installations, including their cost and the need for frequent replacements, are undeniable (Sadeghi, 2000). Thus, emerges the appeal of vibration analysis as an innovative and cost-effective solution.

Vibration analysis, extensively employed for machine condition monitoring, leans on accelerometers to record vibrational nuances (Vishwakarma et al., 2017; Ravi et al., 2005). The vibrational data, particularly within the frequency domain, holds rich insights into part quality. Notably, the low trending frequency range within the recorded vibrational signal offers valuable insights into product quality. Augmenting this with artificial neural networks (ANN) offers a potent combination. ANNs, initially conceptualized to mimic mammalian brain functionalities, have burgeoned across disciplines, driven by their prowess in handling intricate non-linear systems (Olden et al., 2004; Chow et al., 2002; Cook et al., 2000; Woll and Cooper, 1997; Chen and Ramaswamy, 2002). Of the myriad ANN algorithms, Bayesian regularization has showcased superior performance, a finding supported by rigorous testing (Kayri, 2016). Building on this foundation, the current research employs MATLAB's neural network tools to train the Bayesian regularization algorithm, aiming to oversee the performance of a plastic injection molding machine.

Injection molding, with its unparalleled capability to produce high volumes swiftly, is a darling of the industry. This efficiency, however, is coupled with the challenge of ensuring consistent quality, which hinges on design intricacies and meticulous processing (Yeung and Lau, 1997; Dimla et al., 2005; Lau and Tse, 1997; Masood and Song, 2004). While the process has historically been somewhat of a 'black art', relying substantially on experiential knowledge, modern advancements offer a glimmer of methodical precision. Techniques like numerical simulations and intelligent systems have been championed for monitoring and optimizing the injection molding process (Lou et al., 2003; Sadeghi, 2000; Espejo, 2006; Yang et al., 2000; Li et al., 2008). Central to this research is the ambition to harness vibration analysis for monitoring variations in product quality during the plastic injection molding process. Highlighted are two pivotal attributes of moulded parts: their weight and physical appearance. The physical manifestations can be segmented into three categories, showcased in **Figure 1(a)** for over- shot, **1(b)** for short-shot, and **1(c)** for normal shot. The first two are deemed defective, resulting from either an excess or dearth of molten material. Achieving the ideal 'normal shot' necessitates precise parameter adjustments by the machine operator. As production scales up, the traditional reliance on manual checks becomes untenable, amplifying the likelihood of quality degradation. Addressing this, the research advocates the integration of machine learning for an automated and precise monitoring system.

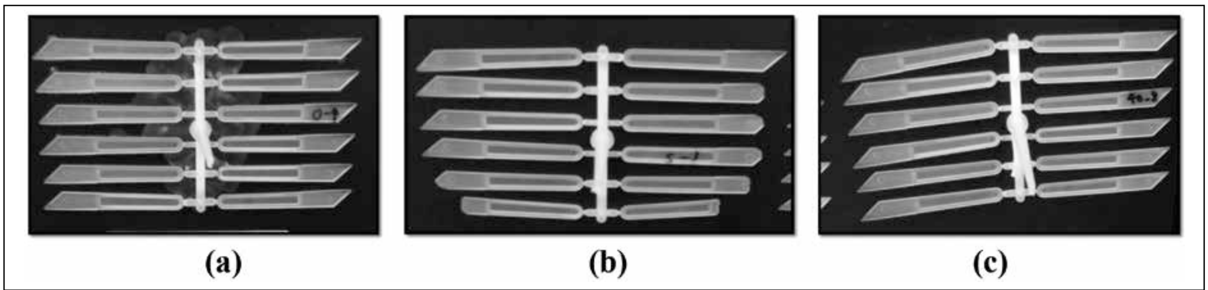


Figure 1. Photo of (a) over-shot, (b) short-shot, and (c) normal shot

Experimental Details

The research utilized CHUAN LIH FA's CLF-60TX plastic injection moulding machine, consisting of a plastic injection unit and a mould clamping unit (**Figure 2(a)**). The injection unit is responsible for melting thermoplastics and injecting them into the shaping mould. The clamping unit ensures mould alignment, keeps it closed during the injection, and controls its opening and closing. For consistency, a single shaping mould was used to produce a disposable cake knife, chosen for its simple geometry (**Figure 2(b)**).

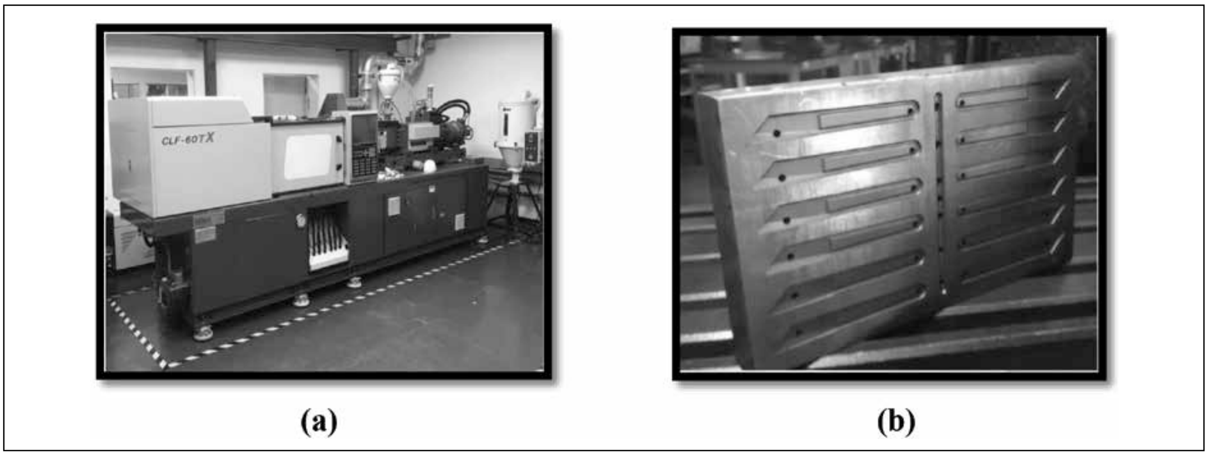


Figure 2. Photo of the (a) CLF-60TX plastic injection molding machine, (b) Disposable Cake Knife shaping mold

In the experimental setup, two accelerometers, Acc1 and Acc2, were attached to the injection screw bearing (**Figure 3(a)**) and the toggle pin bearing (**Figure 3(b)**) respectively. A strain gauge was positioned on the clamping unit's tie-bars. These sensors fed data to an IMC Data Acquisition System, which was linked to a laptop for data logging.

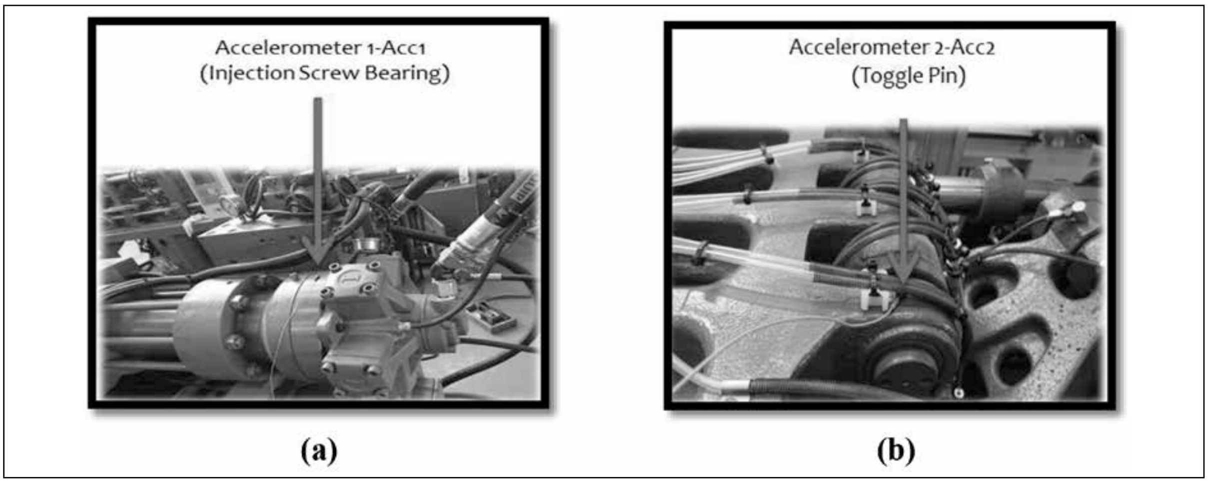


Figure 3. Photo of an accelerometer mounted on the (a) Injection screw bearing, and (b) toggle pin bearing

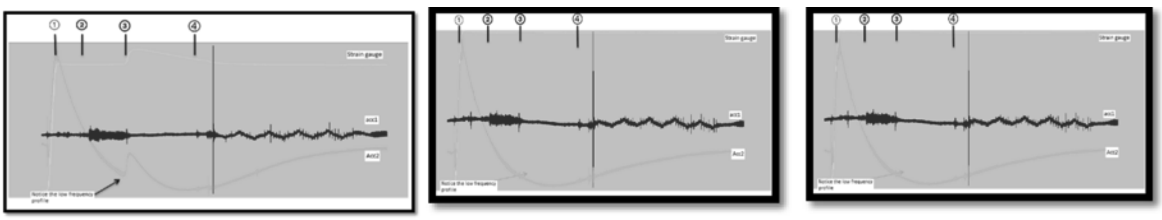
Injection moulding's quality is influenced by machine input parameters like injection speed, packing time, material temperature distribution, and holding force (Brydson, 1995; Pötsch and Michaeli, 1995; Sadeghi and Akbarzadeh, 2011; Rosato and Rosato, 2000; Chiang and Chang, 2006; Huang and Tai, 2001; Wang, 2002). To study these effects, a Local Sensitivity Analysis was employed, streamlining the understanding of input parameter variations on the output. The steps for data collection began by identifying a parameter combination for a 'normal shot', measuring the weights of produced parts, and then systematically varying individual parameters, measuring the weights, and recording vibrational signals. The data collected is summarized in **Table 1**, which details 11 tests with varied parameters. The first test combination resulted in an ideally moulded part, while the subsequent tests involved parameter adjustments. Varied parameters are highlighted in purple in the table, with visual classifications of parts produced by different combinations.

Table 1. List of 11 combinations of 12 varying experimental parameters

			Material temperature											
Parameter combination number	Number of cycles	Injection Speed (mm/s) (100% = 162 mm/s)	(1)	(2)	(3)	(4)	(5)	Clamping Force (Tons)	Packing Time(s)	Packing Pressure (bar)	Initial Screw Position (mm)	Mean weight of parts (g)	Visual Classification
1	14	20%	200	200	190	190	180	20	2	20	32	13.14	Normal
2	14	30%	200	200	190	190	180	20	2	20	32	13.15	Normal
3	14	10%	200	200	190	190	180	20	2	20	32	13.10	Normal
4	14	20%	210	210	200	200	190	20	2	20	32	13.03	Normal
5	17	20%	180	180	170	170	160	20	2	20	32	13.10	Normal
6	14	20%	200	200	190	190	180	30	2	20	32	13.00	Normal
7	14	20%	200	200	190	190	180	10	2	20	32	13.95	Over
8	14	20%	200	200	190	190	180	20	4	20	32	13.18	Normal
9	14	20%	200	200	190	190	180	20	0	20	32	12.54	Normal
10	14	20%	200	200	190	190	180	20	2	20	35	14.72	Over
11	14	20%	200	200	190	190	180	20	2	20	29	12.67	Short

Signal Processing

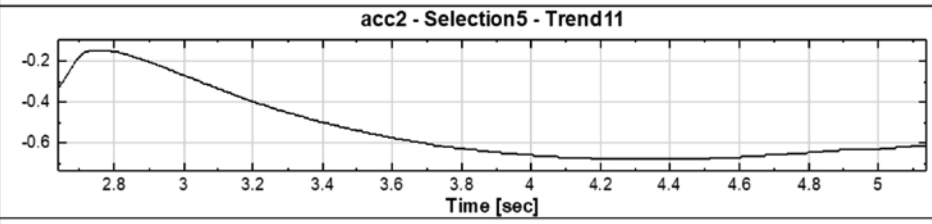
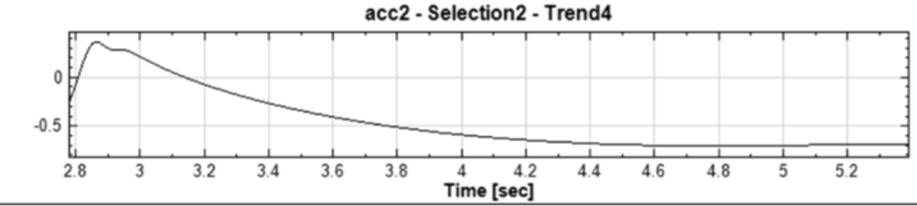
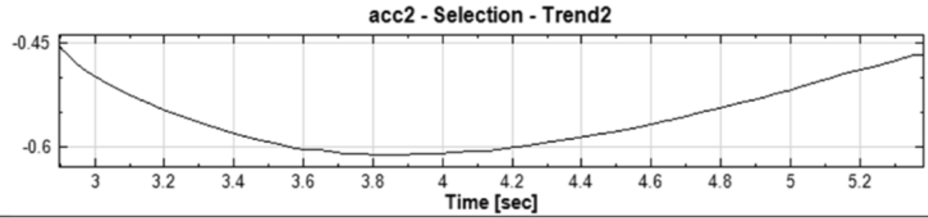
Acc1 and the strain gage were used to delineate the stages of the injection cycle, as shown in **Figures 4(a)-(c)**. Acc2 provided insights into part quality, with distinct impulse profiles observed for different shot types (**Figures 4(a)-(c)**), detailed in **Table 2**.



(a) (b) (c)

Figure 4. General vibrational profiles recorded by Acc1, Acc2 and Strain gauge for (a) a normal shot, (b) an over shot, (c) a short shot. Position 1~4 refer to: 1=Closing of mould, 2=Injection screw moves forward, 3=Injection screw stops spinning and injection starts, 4=End of injection period/start of packing period

Table 2. Vibrational profiles of the injection period acquired by Acc2 for a normal, over and short shot. The unit for y-axis is ms^{-2}

Shot Classification	Vibration Profile of Acc2 for injection period
Normal	
Over Shot	
Short Shot	

In our theoretical analysis, the Root Mean Square (RMS) is calculated as:

$$RMS = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}} \tag{1}$$

The vibrational signal from Acc2 aligned with an over-damped second-order impulse response. Using a second-order transfer function (TF) presented as:

$$G(s) = \frac{b}{s^2 + as + b} \tag{2}$$

we derived insights about natural frequency (ω_n) and Damping ratio (ζ) using:

$$\omega_n = \sqrt{b} \tag{3}$$

$$\zeta = \frac{a/2}{\omega_n} \tag{4}$$

The TF, $G(s)$, can also be represented as:

$$G(s) = \frac{k}{(T_1 s + 1)(T_2 s + 1)} \tag{5}$$

Transforming this yields:

$$G(s) = \frac{k / T_1 \times T_2}{S_2 + \frac{T_1 + T_2}{T_1 \times T_2} \times S_2 + \frac{1}{T_1 \times T_2}} \tag{6}$$

From which:

$$a = \frac{T_1 + T_2}{T_1 \times T_2} \tag{7}$$

$$b = \frac{1}{T_1 \times T_2} \tag{8}$$

For feature extraction, the vibrational data from Acc2 underwent conversion. A low-pass filter isolated the low-frequency profile, then the injection impulse response time was extracted. Using MATLAB's PIDTOOL, the profile was matched to a transfer function across 142 injection cycles. This process for a normal shot is illustrated in **Figures 5(a)-(d)**, and similarly, over shot and short shot processes are depicted in the same way.

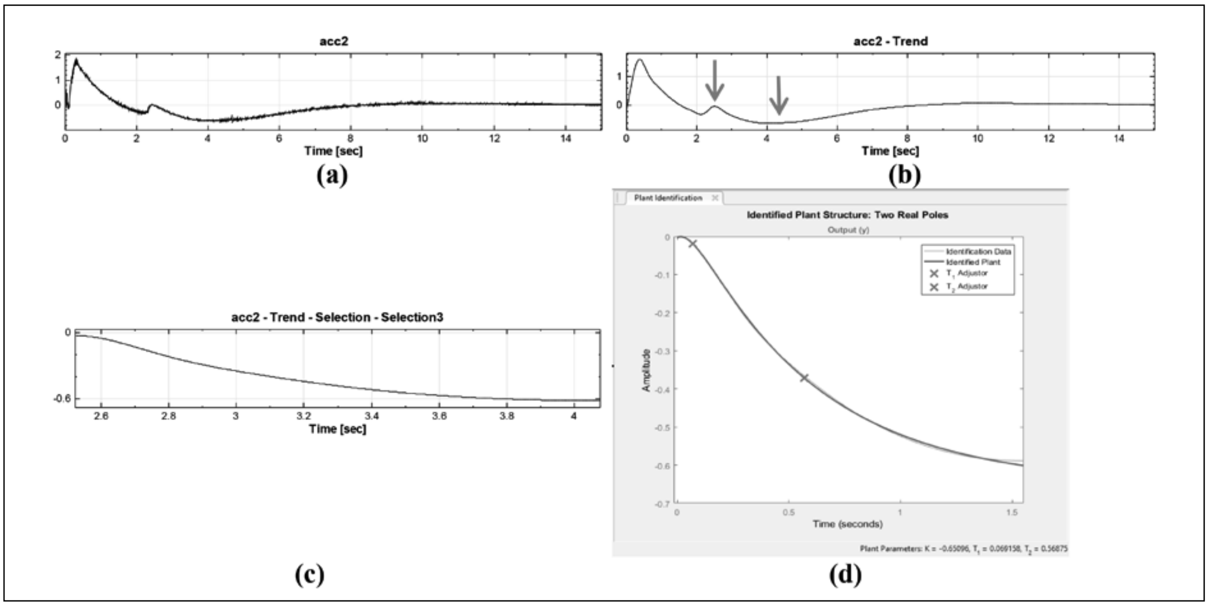


Figure 5. Illustration of the steps taken to generate the transfer function for a normal shot (a) Raw vibrational profile for a normal shot; (b) Low frequency trending signal; (c) Extracted injection impulse response area bounded by red arrows in Fig. 5(b); (d) Generated transfer function for a single normal shot

Results and Discussion

A total of 10 machine control parameters and 8 vibrational features as shown in **Table 3** were used as inputs for the neural network. The vibrational features were obtained from fitting the injection profiles to a specific transfer function $G(s)$.

Table 3. Input parameters to the ANN obtained from the machine controller and the vibrational feature extraction

Machine Control Input Parameters	Vibrational Features Input Parameters
Part Number	K
Injection Speed (mm/s)	T1
Clamping Force (Tons)	T2
Packing Time (s)	a
Packing Pressure (bar)	b
Initial Screw Position (mm)	$\frac{k}{T_1 \times T_2}$
Material temperature 1	Natural Frequency
Material temperature 2	Damping Ratio
Material temperature 3	
Material temperature 4	
Material temperature 5	

The artificial neural network classified parts and predicted weights. Trained using a Bayesian Regularization Algorithm, the feed-forward neural network used 19 features as inputs. Data from 142 injected parts were used, with 85 for training, 7 for validation, and 50 for testing. The neural network achieved 100 % classification accuracy, as detailed in **Figure 6**.

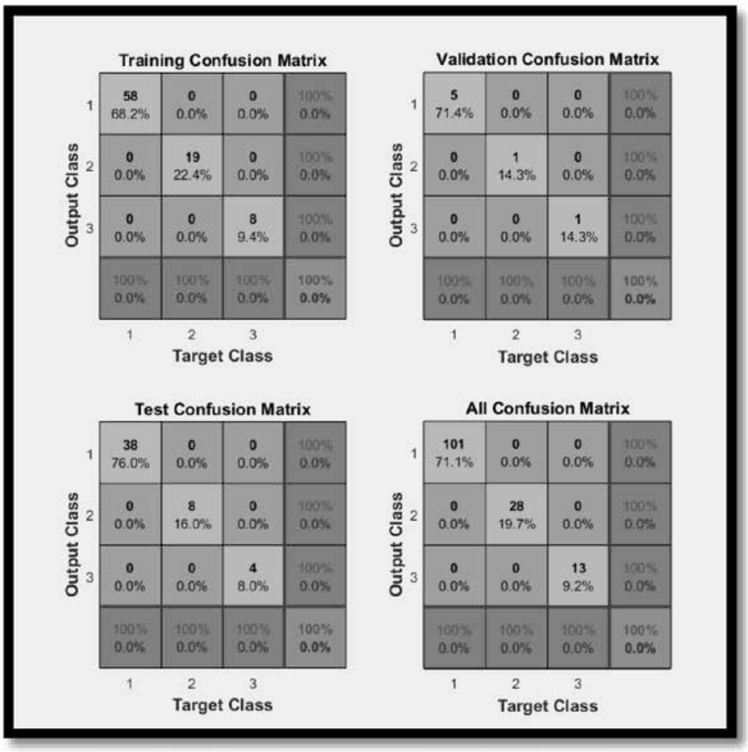


Figure 6. Confusion matrix displaying the ANN’ s performance

For weight prediction, another feed-forward neural network processed data from 142 injected parts. The predictions deviated by approximately ± 0.09 g (**Figure 7**). This approach had a lower error than the method by Li, Hu, and Du (2008). **Figure 8** compares the actual measured part weight to the neural network's prediction. The maximum weight difference was approximately 0.08726 g.

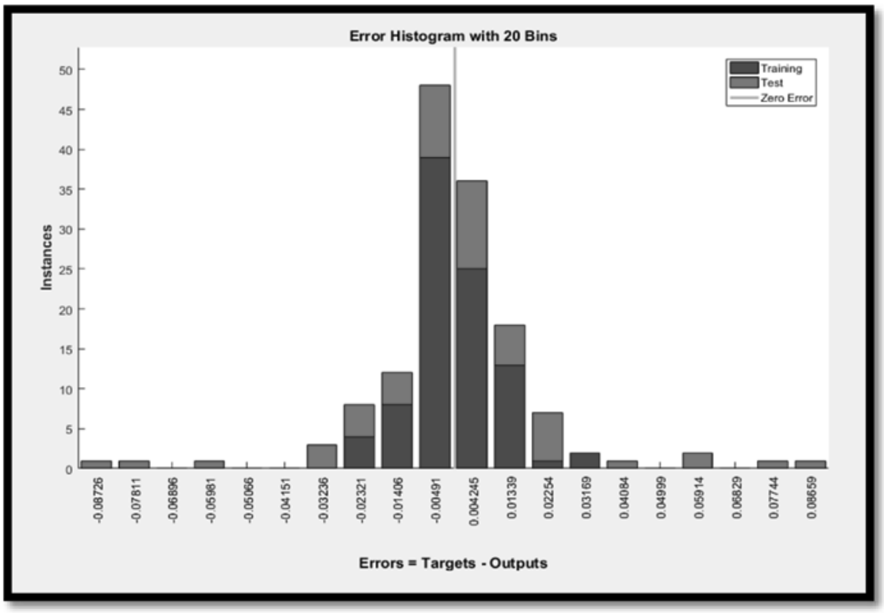


Figure 7. Error deviation for the input-output predictor ANN

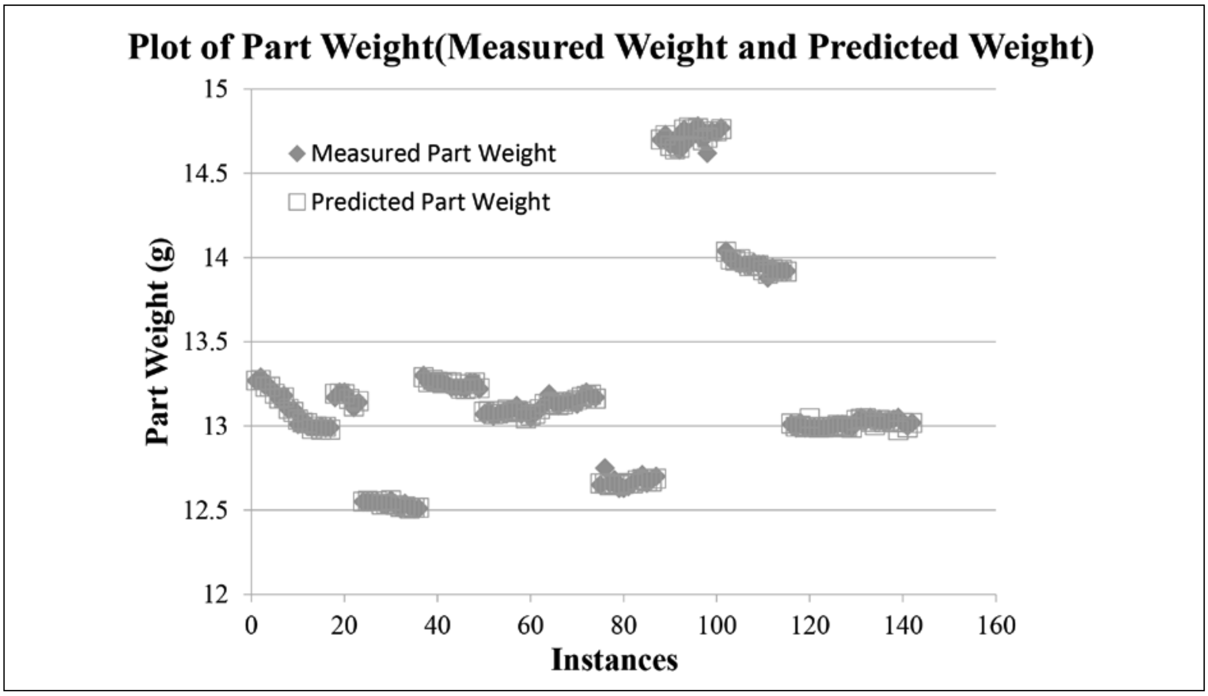


Figure 8. Plot of measured part weight superimposed on the ANN's weight prediction

A comparison between the machine's moulding accuracy and the ANN's accuracy revealed the ANN provided more accurate weight predictions for most parameter combinations, except for two cases highlighted in red as shown in **Table 4**.

Table 4. Injection Moulding Machine's Deviation compared to ANN's Prediction Deviation

Parameter combination number	Number of cycles	Injection Speed (mm/s)	Material temperature (1)	(2)	(3)	(4)	(5)	Clamping Force (Tons)	Packing Time(s)	Packing Pressure (bar)	Initial Screw Position (mm)	Mean weight of parts (g)	Visual Classification	Standard deviation of mean from actual weight	Standard deviation of ANN Prediction from actual weight
1	14	20%	200	200	190	190	180	20	2	20	32	13.14	Normal	0.03197221	0.011350784
2	14	30%	200	200	190	190	180	20	2	20	32	13.15	Normal	0.028137448	0.020314162
3	14	10%	200	200	190	190	180	20	2	20	32	13.10	Normal	0.018008486	0.018784718
4	14	20%	210	210	200	200	190	20	2	20	32	13.03	Normal	0.017227641	0.024141928
5	17	20%	180	180	170	170	160	20	2	20	32	13.10	Normal	0.108796499	0.012963144
6	14	20%	200	200	190	190	180	30	2	20	32	13.00	Normal	0.010792536	0.000267279
7	14	20%	200	200	190	190	180	10	2	20	32	13.95	Over	0.036766006	0.015581742
8	14	20%	200	200	190	190	180	20	4	20	32	13.18	Normal	0.021648073	0.012511308
9	14	20%	200	200	190	190	180	20	0	20	32	12.54	Normal	0.016923077	0.00749245
10	14	20%	200	200	190	190	180	20	2	20	35	14.72	Over	0.047645671	0.001257307
11	14	20%	200	200	190	190	180	20	2	20	29	12.67	Short	0.033085866	0.000902711

Understanding input parameter importance aids machine operators. Although the ANN was considered a 'black box', input parameter importance can now be ranked using a Connection Weight Approach (Olden and Jackson, 2002). The most sensitive machine input parameters were identified as initial screw position, packing time, and clamping force as shown in **Table 5**.

Table 5. Ranking importance of input parameters

Input	Rank	Weight Importance percentage
Initial Screw Position (mm)	1	30.639
Packing Time (s)	2	17.069
Clamping Force(Tons)	3	17.009
K	4	14.533
k/T1T2	5	6.256
T1	6	4.133
Damping Ratio	7	2.939
T2	8	1.574
Part Number	9	1.082
a	10	0.909
b	11	0.869
Injection speed (mm/s)	12	0.864
Temperature 5	13	0.381
Temperature 4	14	0.381
Temperature 3	15	0.381
Temperature 2	16	0.381
Temperature 1	17	0.381
Natural Frequency	18	0.216

Conclusion

Plastic products have gained immense popularity over the years, largely attributed to their unique properties such as corrosion resistance, chemical resistance, low density, and ease of manufacturing (Chen and Shiou, 2003). Among the various methods of producing plastic items, injection molding stands out as one of the most prevalent techniques. It's imperative that plastic injection molding machines maintain high production volumes consistently.

However, over time, the performance of injection molding machines can vary, necessitating the presence of an onsite machine operator to vigilantly supervise the entire process. This operator is tasked with inspecting every molded part to ensure stringent quality control. Yet, given the large-scale nature of this task, it becomes laborious and prone to human errors.

This research introduces a novel method that combines vibrational analysis with artificial intelligence to meticulously monitor the quality and weight of molded parts. The study revealed that the accelerometer, when positioned on the toggle pin bearing, offers substantial insights related to part quality and weight, especially within the low-frequency domain. Specifically, the time span associated with the injection impulse response was found to be rich in critical vibrational data. This vibrational information, combined with machine input parameters, was instrumental in training a feed-forward classification artificial neural network. Impressively, the trained network demonstrated the capability to flawlessly categorize the physical appearance of each injected part as a normal shot, over shot, or short shot. Furthermore, a second feed-forward network, mirroring the structure of the classification network, was trained to estimate the weight of each molded part. Preliminary results showed that the ANN could predict the part's weight with an impressive accuracy, deviating by a mere 0.715 % from the actual weight.

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