Int J Adv Manuf Technol (2008) 36:43–52
DOI 10.1007/s00170-006-0807-9

ORIGINAL ARTICLE

Development of artificial neural network-based in-process mixed-material-caused flash monitoring (ANN-IPMFM) system in injection molding

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Received: 9 August 2006 / Accepted: 11 September 2006 / Published online: 1 March 2007

Abstract This paper describes the development of an artificial neural network-based in-process mixed-material-caused flash monitoring system (ANN-IPMFM) in the injection molding process. This proposed system integrates two sub-systems. One is the vibration monitoring sub-system that utilizes an accelerometer sensor to collect and process vibration signals during the injection molding process. The other, a threshold prediction sub-system, predicts a control threshold based on the process parameter settings, thus allowing the system to adapt to changes in these settings. The integrated system compares the monitored vibration signals with the control threshold to predict whether or not flash will occur. The performance of the ANN-IPMFM system was determined by using varying ratios of polystyrene (PS) and low-density polyethylene (LDPE) in the injection molding process, and comparing the number of actual occurrences of flash with the number of occurrences predicted by the system. After a 180 trials, results demonstrated that the ANN-IPMFM system could predict flash with 92.7% accuracy.

Keywords Injection molding process · Flash · Artificial neural network · Mixed material · Accelerometer sensor

1 Introduction

The plastic injection molding process is the most commonly used manufacturing process in the plastics industry due to its capability for mass production at a relatively low cost. In this relatively simple process, plastic is melted and then forced into the cavity of a closed mold under high pressure. After sufficient cooling time, the molten material solidifies into the desired shape, the mold is opened, and the part is removed. Then next injection cycle then begins [1].

The demand for injection-molded products has grown tremendously in recent years. More and more plastics have been consumed and discarded, which has resulted in a shortage of petroleum, as well as waste disposal and pollution problems [2, 3]. Therefore, recycled plastics from defective parts, trimmings, and other manufacturing scraps have been widely used in the injection molding process, ranging in use from very small-scale reprocessing in small companies to huge programs that utilize several tons of recycled materials per year [4].

Recycling plastics can often result in aggregate material with differing thermal and mechanical properties that can vary significantly from batch to batch. When mixed material is processed by injection molding, careful attention must be given to process parameters, regrind composition, and moisture content.

This study describes "mixed material" as a composition of plastic aggregate containing two different materials that differ in thermal and mechanical properties. Product defects may result from using mixed materials due to their different

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melting temperatures, resulting in inconsistent flow rates into the mold [5]. One of the more common defects is flash, which occurs when material flows outside of the edge of the mold cavity (Fig. 1).

Flash can harm both the injection mold and the molded parts. Mold damage results when excess plastic flakes stick to the mold. The presence of flash on injected parts requires removal by an automatic or manual method. The manual method of trimming flash from the injected parts is often used and can be very labor intensive, affecting both productivity and quality. In the plastic injection molding industry, 100% flash inspection is costly since this process is still plagued by complex process dynamics, material properties, and high cost. This process usually requires manual removal of excess material and routine off-line inspection.

Machinists in an injection molding operation can control flash by setting proper process parameters. Some of those process parameters include proper material drying, mold clamp pressure, cylinder temperature, holding and injection pressure, and injection speed. However, even if parameters are controlled appropriately, flash may still occur. Therefore, a system that could monitor the occurrence of flash online would greatly improve process efficiency [6].

An in-process flash prediction system that can predict flash occurrence in real-time and online with a high degree of accuracy could prevent flash from occurring between routine inspection times. In recent years, considerable research has been conducted on in-process defect prediction systems in the injection molding process. For example, a few systems have been developed to monitor part weight or dimensions [7–9]. In these systems, when the part weight or dimensions are out of tolerance, the system notifies the operator that a defect has occurred and requires inspection immediately. Lee and Young [10] developed an on-line part shrinkage monitoring system to predict the shrinkage range of crystalline polymers and thus identify defective parts. Other systems have been developed [11–13] to allow the effective setting and resetting of processing parameters based on the various part defects, such as flash, short shot, weld line, and cracking.

Fig. 1 Injection-molded specimen without and with flash

These systems were shown to work successfully in establishing process parameters and minimizing defects. Once these parameters are set to an optimal value, flash or other defects rarely happen if virgin or a homogeneous material is used. However, when recycled mixed materials are used in injection molding, flash often occurs, even at the optimum processing parameter settings. This research focuses on developing an in-process, mixed-materials-caused flash monitoring system (IPMFM) operating within optimum injection molding processing parameters.

This system consists of two major components. The first, the sensing mechanism, detects key characteristics of the injection molding process. The second, the decision-making mechanism, analyzes the sensor signal and performs monitoring functions.

Several sensing mechanisms have been used in-process to predict defects in the injection molding process. Traditional sensors such as thermocouples and pressure sensors have been employed in monitoring and controlling molding and other processes [14]. These sensors, like others, have limitations, such as slow response, instability, and non-repeatability [15]. Therefore, more advanced measurement sensors are continually being sought for process monitoring and control.

One such sensor, the accelerometer, has many applications in process monitoring and control. It has successfully been used to monitor cutting vibrations in an on-line surface roughness prediction system in milling operations [16]. Accelerometers were used to detect vibration signals caused by a change in cutting parameters. Using these signals, the on-line system predicted the surface roughness of a milled surface in real-time with reasonable prediction accuracy. Similarly, the current study explores a similar application of the accelerometer-to collect the in-process vibration signals formed during injection molding.

To develop a real-time decision-making mechanism, this study employed artificial neural networks (ANN). These systems can model arbitrary input data by adjusting their internal network connections. These adjustments systematically minimize the margin of error between the network output and the desired response. This process of supervised learning reduces the network error using a training set of matching input-output vectors [17].

Artificial neural networks have remarkable advantages because of their ability to generalize by inductive learning. Based on the connectionist model of the human brain, neural networks exhibit a number of desirable properties comparable to conventional computation systems, including the ability to accept parallel computation, robustness in the presence of noise, the ability to adapt to any non-linear function, and the ability to generalize [13].

Artificial neural networks have been widely used in plastics engineering to monitor part quality [7, 18] and shrinkage (10), as well as to control processing parameters [11, 12, 19]. For example, Choi, Lee, Chang, and Kim [11] used artificial neural networks to optimize processing parameters and predict injection molding part defects.

In summary, this research serves to develop an ANN-based in-process mixed material-caused flash monitoring (ANN-IPMFM) system in the injection molding process. The system has two capabilities: 1. to collect and analyze vibration signatures generated during the injection molding process; and 2. to determine and alert an operator when flash has occurred.

2 Structure of the ANN-IPMFM system

The structure of the ANN-IPMFM system (Fig. 2) integrates two sub-systems, vibration monitoring and threshold prediction.

1. The vibration monitoring sub-system detects the occurrence of flash caused by mixed materials during the injection molding cycle. This system utilizes an accelerometer sensor to monitor the difference in the vibration signals between injection-molded specimens with flash and without flash during the last period of the injection filling stage. Using statistical analysis, we calculated a process characteristic indicator, γ, as the subsystem parameter for determining whether flash has occurred.
2. The threshold prediction sub-system predicts the control threshold value, based on training data, according to the current processing parameter settings. These input process parameter settings may differ in value from the parameters used by the vibration monitoring sub-system. If this is the case, the threshold prediction sub-system adapts and produces results based on the adjusted input processing parameter settings. The significant processing parameters (injection speed, holding pressure, and melt temperature) are the inputs to this sub-system. The ANN training process incorporates results based on a combination of parameter settings within the optimum setting range.

The flash control threshold values were determined through a statistical process control (SPC) methodology. A component of the X-bar control charting procedure was followed when calculating the cutoff values. The upper and lower control limits were calculated, where the upper control limit represented the cutoff values for the flash control threshold. These values were generated from the data collected during cycles when no flash occurred (i.e., control material). In testing the ANN model, the output of the threshold prediction sub-system is the proposed flash control threshold value (θ).

3 Experimental setup

The schematic diagram in Fig. 3 illustrates the setup of the IPMFM system. This setup consists of a *BOY 22M* injection molding machine outfitted with a *Procan MD* microprocessor control (Pennsylvania, USA); a Windows-based personal computer with *DaqView 8.0* from IOtech,

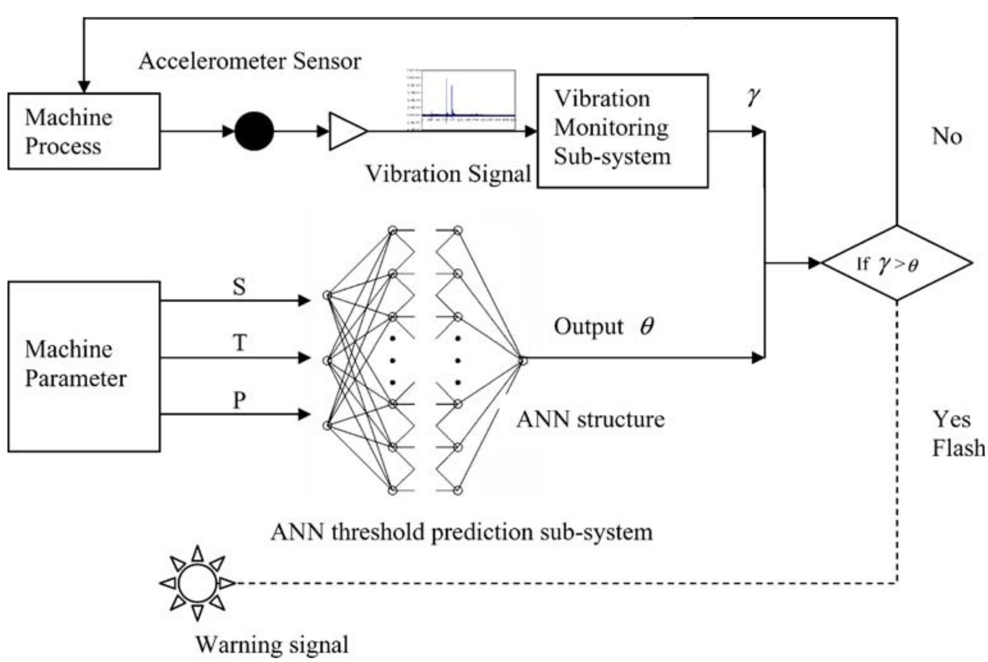

Fig. 2 The structure of the ANN-IPMFM system (*S* denotes injection speed, *T* denotes melting temperature, *P* denotes holding pressure.)

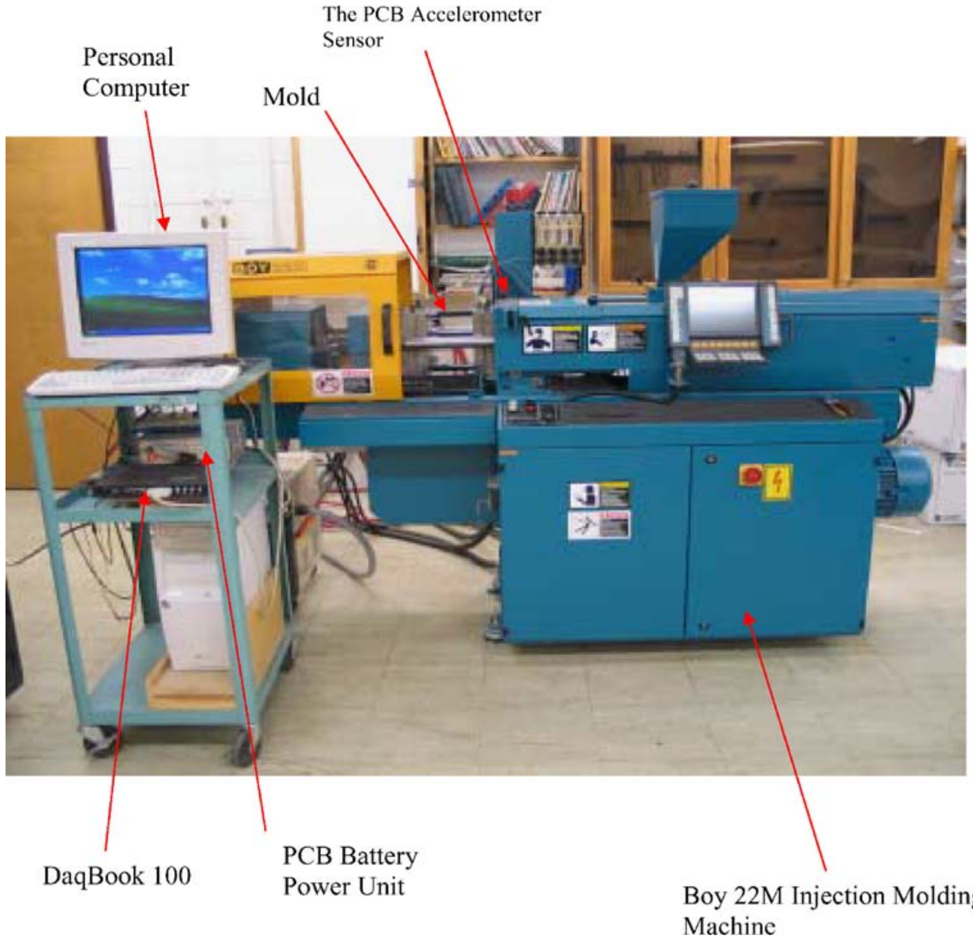

Fig. 3 Experimental setup

Inc. (Ohio, USA) installed; a PCB Piezotronics model 356B08 3-axis accelerometer sensor (New York, USA); an IOtech model *DBK11A* screw terminal expansion card; and an IOtech *DaqBook 100* data acquisition system (Ohio, USA). The accelerometer sensor was installed on the top-center of the stationary mold-half with its Z- axis parallel to the travel of the movable platen. The X-axis was perpendicular-vertical and the Y-axis was perpendicular-horizontal to platen travel. A PCB model 480E09 (New York, USA) signal conditioner was used to power the accelerometer, amplify the signal, and filter noise before the signal is passed to the data acquisition system. Figure 3 illustrates the location of the accelerometer sensor on the injection molding machine. An example of the vibration signal collected during the injection molding cycle is shown in Fig. 4. The first main signal peak is generated when the mold closes; the second main signal peak shows the beginning of the plastic injection filling stage.

4 Vibration monitoring sub-system development

The vibration monitoring sub-system was developed by devising an experimental design to collect and analyze data, generate the process characteristic indicator for flash determination, and build the decision-making mechanism.

4.1 Experimental design

The goal of the experimental design was to capture the difference in the vibration signals between the specimens with and without flash. The polymer materials used in this research were Polystyrene (PS) 147F manufactured by INEOS Styrenics and low-density polyethylene (LDPE) 2072 manufactured by the Huntsman Corporation. PS was considered the control material, while a PS and LDPE mix was the treatment material.

The treatment material was a mixed material consisting of artificially mixed PS and LDPE (90% PS+10% LDPE). This aggregate composition simulated aggregate compositions of virgin and regrind material often used in the injection molding process.

The specimen molded was a tensile bar measuring 4.95×0.5 inches (see Fig. 1). The specimen had a weight of 0.35 ounces and a volume of 0.62 in^3. This research utilized processing parameter settings suggested by the material manufacturers to establish optimal processing ranges for the injection molding process in this study.

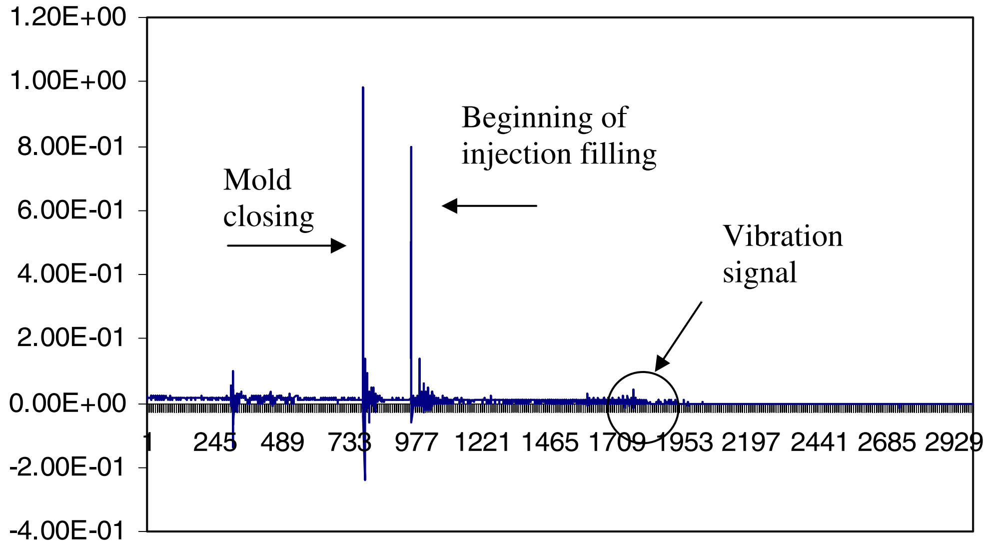

Fig. 4 An example of an injection molding processing vibration signal for a good specimen

4.2 Experimental setup and procedures

After the injection molding machine stabilized, the researchers collected and recorded vibration data from 15 consecutively molded specimens. Researchers reviewed each specimen visually for the presence of flash.

The injection filling time was set at 1.7 seconds. The data collection time was set to 6 seconds at a scanning frequency of 500 Hz, which was enough time to record activity during the mold closing and after the filling stage. Therefore, 3000 data points, including X-, Y-, and Z-axis accelerations, were recorded for each specimen. Only the Z-axis vibration data were used for analysis in this paper. Once the pilot data collection and analysis were complete, the monitoring sub-system processing characteristic indicator ($\overline{\gamma_j}$) was determined.

4.3 Processing characteristic indicator

Flash occurred in conjunction with stronger vibration signals during the last period of the filling stage (0.4 seconds). Figure 4 shows specimens with flash, and Fig. 5 shows specimens without. Comparing these two figures reveals that specimens with flash exhibited stronger vibration signals than those without during the final stage of the injection filling phase.

An approach for data treatment was then developed to compare the signals in the last period of the injection filling stage. The researchers utilized the following procedure to calculate a processing characteristic indicator ($\overline{\gamma_j}$) to compare the signals in the last period of the filling stage:

Step 1: Start from the point when the mold initiates closing, collect 3000 Z-axis vibration data points.

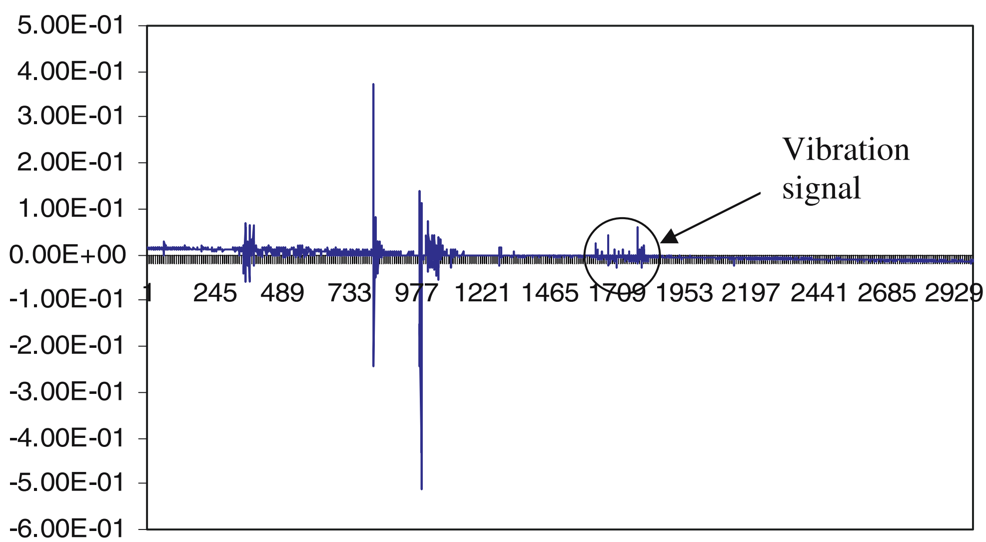

Fig. 5 Z-axis vibration signal sample with flash

This data collection covers vibration signals from the moment the machine initiates mold closing until the end of the injection filling stage (see examples in Figs. 4 and 5).

Step 2: Locate the second peak of the Z-axis vibration signal, which represents the beginning of the injection filling stage.

Step 3: Start from the second peak point, collect 850 (1.7 seconds) Z-axis data points. (Z_{ij},i=1,2,...850, j=1,2...15, where i denotes the data point and j denotes the specimen number used in this research.)

Step 4: Find the maximum absolute peak value Z_{jmax} within the last 200 data points:

$$Z_{j\max} = Max|Z_{ij}| = Max\{|Z_{651j}|, |Z_{652j}|, \ldots |Z_{850j}|\} \quad (1)$$

Step 5: Calculate the average absolute peak value of the 200 (0.4 seconds) points:

$$\overline{Z_j} = \frac{\sum_{i=651}^{850} |Z_{ij}|}{200} \quad (2)$$

Step 6: Calculate the ratio of the maximum peak value over the average peak value. This is called the max-avg. ratio γ_j, which has the following formula:

$$\gamma_j = \frac{Z_{j\max}}{\overline{Z_j}}, \text{ where } j \text{ is number of experiments} \quad (3)$$

Step 7: Save the max-avg. ratio as γ_j.

Step 8: Calculate the average of two consecutive max-avg. ratio data to generate the sub-group statistic $\overline{\gamma_j}$ from γ_j (sub-group size=2):

$$\overline{\gamma_j} = \frac{\gamma_j + \gamma_{j+1}}{2}, \text{ where } j = 1, 2 \ldots 15 \quad (4)$$

$\overline{\gamma_j}$ would then be considered as a processing characteristic indicator for monitoring the injection molding process.

5 Threshold prediction sub-system development

Figure 6 shows the architecture of the threshold prediction sub-system, including its inputs, layers, and output. Training of the ANN is at the heart of this sub-system development.

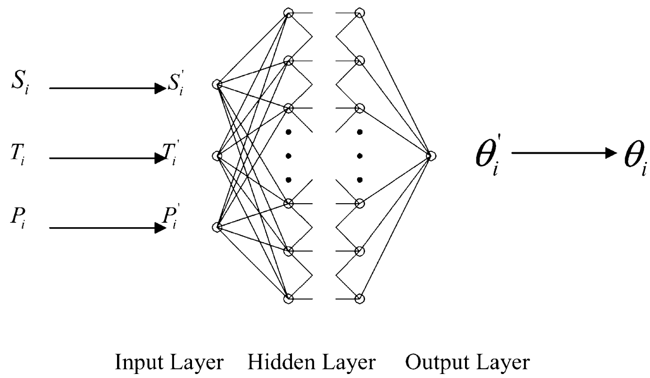

Fig. 6 Architecture of the ANN-IPMFM threshold prediction sub-system

Neural networks learn from input data. These systems pattern-analyze new data according to previously stored examples and react to new data based on past input or "experience".

Backpropagation (BP) is one of the most widely used and successfully applied supervised learning methods in many different neural network applications [20]. Backpropagation networks are usually layered, with each layer fully connected to surrounding layers by weighted connections.

Given an input, values propagate forward from the input layer of the processing units through each internal layer to the output layer. The output units then provide the ANN's response. When neural networks correct their internal parameters, the correction mechanism starts with the output units and backpropagates through each internal layer to the input. This process repeats until the weights of the networks reach the final state where the root mean square (RMS) error approaches and converges with the acceptable minimum value range.

Since backpropagation is a supervised learning method, it requires an indicator that may be either a training data set or an observer evaluating ANN performance [21]. The indicator, which already "knows" the correct output, provides the gradient descent on the error obtained from the difference between the target (correct) output and the inferred output. A rule that gives the effect of the total input on the activation of the unit is also required. A transfer function (F_i) is used as the rule, taking total input $i_i(t)$ and the current activation $a_i(t)$, and producing a new activation value for the unit i:

$$a_i(t+1) = F_i(a_i(t), i_i(t)). \quad (5)$$

Often, a sigmoid (S-shaped) function is used as the transfer function (F_i) as in:

$$a_i = F(i_i) = \frac{1}{1 + \ell^{-i_i}}. \quad (6)$$

The output of *jth* neuron in the *nth* layer is a non-linear function of the output of the (*n-1*)*th* layer defined as follows:

$$a_j^n = F\left(S_j^n\right) \tag{7}$$

where $S_j^n = \sum_i w_{ij}\ a_i^{n-1} - \theta_j$ (summation function)

w_i weight of *ith* connection of *jth* neuron
θ_j a bias or offset term of *jth* neuron.

The following equation is used to adjust the weights of the connections between units:

$$\Delta w_{ij} = \mu(d_i - a_i)a_j \tag{8}$$

where

Δw_{ij} the adjusted weight between the *ith* neuron in (*n-1*)*th* layer and the *jth* neuron in *nth* layer.
μ a positive constant of proportionality representing the learning rate
d_i the desired activation provided by the teacher.

This process repeats itself until the desired or minimum error between the target output value and the inferred output value is obtained.

After training procedures, the output of the test data is predicted using the weights matrix and bias terms obtained from training. The following four steps were used to develop the threshold prediction sub-system:

Step 1. Construct an experimental design to collect data for ANN training

The ANN required sufficient training in order to achieve an accurate flash monitoring system. Training data for a variety of processing parameters (i.e., injection speed, melt temperature, hold pressure) was obtained via a factorial experiment. Processing parameters of injection speed (*S*), melt temperature (*T*), and holding pressure (*P*) were recognized as significantly influencing the occurrence of flash and were used as inputs [5].

Table 1 lists the processing parameters of the experimental design at different treatment combinations. These data include injection speeds at three levels (85%, 90%, and 95% of the machine injection speed capacity), melt temperature of PS at two levels (430 and 450°F), and holding pressure at two levels (900 and 1100 psi). Based on the selection of these three factors and corresponding levels, there were twelve experimental runs designed for the training scheme. For the control (i.e., polystyrene) and treatment (i.e., 90% polystyrene+10% low density polyethylene) material each experimental condition had a replication of fifteen consecutively produced specimens.

Experimental runs were not executed randomly. For each run, a flash control threshold was calculated based on the average-maximum ratio (γ_j) (Eq. 3). The flash control threshold (θ), also called the subgroup statistic, was calculated with size n=2. The formula can is defined as follows:

$$\text{Subgroup average}: \quad \overline{\gamma_j} = \frac{\gamma_j + \gamma_{j+1}}{2}, \quad j = 1, 2...15 \tag{9}$$

$$\text{Subgroup range}: \quad R_j = \left|\gamma_{j+1} - \gamma_j\right|, \quad j = 1, 2...15 \tag{10}$$

The upper and lower control limit can be calculated as:

$$UCL_\gamma = \overline{\overline{\gamma}} + A_2\overline{R}, \tag{11}$$

$$LCL_\gamma = \overline{\overline{\gamma}} - A_2\overline{\overline{R}}, \tag{12}$$

where

$\overline{\overline{\gamma}}$ is the average of $\overline{\gamma_j}$, j=1,2...15;
$\overline{R}$ is the average of R_j, j=1,2...14;
A_2= 1.88 is the control chart coefficient if subgroup size is 2 [22].

The calculated upper control limit, UCL_γ, also called flash control threshold (θ), was used to train the ANN as the target output. With the training data listed in Table 1, the ANN-IPMFM adaptive sub-system was ready for training data collection.

Step 2. Assignment of input and output variable to form data sets

The input and output variables, as shown in Fig. 6, were next assigned to construct the threshold prediction sub-system. There were three input factors in this sub-system, which were injection speed (*S*), melt temperature (*T*), and holding pressure (*P*). The output factor was the flash control threshold (θ). The 12 runs of data collected for training were evaluated and broken into data sets. Each data set was expressed as:

$$[S_i, T_i, P_i; \theta_i], \quad i = 1 \text{ to } 12. \tag{13}$$

Step 3. Scale and prepare the data set before ANN training

In order to give the same importance to input neuron data in the neural networks system, each input value had to be re-scaled and transformed. A data scaling method was needed in order to avoid excessive training errors created by larger values of some input or output data set, and to obtain good training and monitoring results. The simple mapping scaling method, which involves converting all input and output factors to a corresponding number

Table 1 Training data for the ANN-IPMFM sub-system

Run number	Injection speed (%)	Melt temperature (°F)	Hold pressure (psi)	Flash control threshold (θ)
1	95	450	1100	5.69
2	95	450	900	5.81
3	95	430	1100	5.57
4	95	430	900	5.63
5	90	450	1100	5.60
6	90	450	900	5.75
7	90	430	1100	5.32
8	90	430	900	5.48
9	85	450	1100	5.50
10	85	450	900	5.56
11	85	430	1100	5.24
12	85	430	900	5.28

between 0 and 1 was applied. This mapping method is expressed as:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{14}$$

where X' is the scaled value, $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of the factor respectively, and X represents the original data of the factor.

For example, from the training data listed in Table 1, if the maximum value of the injection speed is 95 and the minimum value is 85, then the scaled injection speed can be expressed as:

$$S'_i = \frac{S_i - 85}{95 - 85}, \tag{15}$$

After data scaling, the data set was expressed as:

$$\left[S'_i, P'_i, T'_i, \theta'_i\right], \quad i = 1 \text{ to } 12. \tag{16}$$

Step 4. Determine the optimal ANN model

The ANN-BP learning algorithm used by [23] was applied. When the neural networks model was trained, the weight of each link for the input, hidden, and output layers was calculated and iterated until optimized using the neural networks package, PCNeuron. Backpropagation was the learning method used in this model, and the structure best able to predict the output layer was obtained based on the least RMS error between the calculated and target output. The best configuration containing two hidden layers with seven hidden neurons in each layer was selected as the final ANN-threshold prediction sub-system model. Based on this, a 3-7-7-1 ANN-threshold prediction sub-system was developed (three input layers, two levels of seven hidden layers, and one output layer).

6 ANN-IPMFM decision logic

The ANN-IPMFM system integrated a monitoring sub-system and a threshold prediction subsystems in order to monitor the occurrence of flash in process. In order for this system to function, the machine processing parameters and the inputs of the threshold prediction sub-system were first set within the optimum settings range.

The machine was then started in order to activate the system, during which the vibration monitoring sub-system began to collect and process the vibration signal. After the second specimen was molded and released, the average of two consecutive max-avg. ratios $\overline{\gamma_j}$ (Eq. 4) was generated and ready to compare with the flash control threshold value,

Table 2 The testing results for the ANN-IPMFM system

Test Run	S (%)	T (°F)	P (psi)	Flash Threshold θ_i	System Monitoring Result		Actual Result	
					# of flash	# of Non-flash	# of flash	# of Non-flash
1	94	445	1020	5.73	1	14	0	15
2	94	445	920	5.55	2	13	0	15
3	94	435	1020	5.75	0	15	0	15
4	94	435	920	5.65	1	14	0	15
5	89	445	1020	5.61	0	15	0	15
6	89	445	920	5.72	2	13	0	15
7	94	445	1020	5.38	13	2	15	0
8	94	445	920	5.57	14	1	15	0
9	89	445	1020	5.58	14	1	15	0
10	89	445	920	5.60	15	0	15	0
11	84	435	1020	5.39	13	2	15	0
12	84	435	920	5.45	14	1	15	0

Total number of test runs=180
FNN-IPMFM system accuracy=92.7%

θ_i. The comparison rule between $\overline{\gamma_j}$ and θ_i is specified as follows:

1. If $\overline{\gamma_j} = \frac{\gamma_j + \gamma_{j+1}}{2} > \theta_i$, then the system would signal the likelihood of flash and give the corresponding warning signal.
2. If not, the system would not alarm, and γ_j and γ_{j+1} would be replaced by new ratio values based on data from the next injection-molded product.

7 ANN-IPMFM system evaluation and results

The ANN-IPMFM system evaluation was based on the experimental test conditions listed in Table 2. The three process parameters were randomized within 12 testing runs. Each test run combination had fifteen replications. The system decision-making mechanism was applied to determine whether or not flash occurred.

Test runs 1 through 6 were conducted using the control material. Each test run had 15 specimens, resulting in a total evaluation of 90 test specimens. For example, in test run 1, the injection speed (89%), the melt temperature (445°F), and the holding pressure (1020 psi), were employed as input to the ANN-IPMFM threshold prediction sub-system. The material condition was the control material, and the output (predicted flash control threshold) was calculated based on the threshold prediction sub-system as θ_i=5.73. The flash occurrence was then determined by comparing $\overline{\gamma_j}$ with θ_i.

As indicated in Table 2, when the control material was used, no flash was found among any of the 90 products. Six specimens were found to have higher $\overline{\gamma_j}$ than θ_i, indicating that flash had been predicted, but had not occurred.

Test runs 7 through 12 were conducted using the treatment material; each test run had 15 specimens, for a total evaluation of 90 test specimens. All 90 specimens were identified as having flash. Seven products had lower $\overline{\gamma_j}$ than the flash threshold value θ, which indicated that no flash had occurred.

There were a total of 180 testing samples using these two material conditions. The accuracy of the ANN-IPMFM system was calculated using the total number of errors made by the system divided by the total number of testing samples. As indicated by the results of this calculation, the ANN-IPMFM system efficiently predicted flash with 92.7% accuracy.

8 Conclusions

A new approach for a neural networks-based in-process, mixed-material-caused flash monitoring (ANN-IPMFM) system in the injection molding process was developed and evaluated in this study. The completed system was shown to be able to effectively monitor flash during the injection molding operation. The main conclusions drawn from this research are summarized as follows:

1. A threshold prediction sub-system has been integrated with the vibration monitoring sub-system within optimum ranges of processing parameter settings.
2. The ANN approach used in the threshold prediction sub-system successfully predicted the flash control threshold under varying processing parameter settings.
3. The ANN-IPMFM system successfully predicted flash with 92.7% accuracy.

This research was limited to only two types of polymer (PS and LDPE) and one type of injection mold. Enlarging this system to include more materials and various types of workpiece molds could provide greater applicability to future automated machining processes and implementation in the plastics industry.

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