CRACK DETECTION IN INJECTION MOLDS

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ABSTRACT

Paper presents measurement of acoustic emission (AE) signals during injection molding of polypropylene with new and damaged mold. The damaged injection mold was fitted with a steel insert with cracks induced by laser surface heat treatment. Standard test specimens were injection molded, commonly used for examining the shrinkage behavior of various thermoplastic materials. Resonant piezoelectric AE sensors were attached to the tool steel inserts via AE waveguides. To improve the tool integrity prediction with smaller defects, AE signal frequency characteristics are implemented and a measure of AE signal amplitude probability distribution is introduced. A multi-dimensional feature vector with real-valued explanatory variables is introduced, providing the defining points in an appropriate multidimensional space to characterize the state of injection molding tool. A neural network pattern recognition is introduced to classify feature vectors. The results of our experiments confirm that acoustic emission measurement during injection molding of polymer materials is a promising technique for characterizing the integrity of molds with respect to crack occurrence, even with resonant sensors.

Key words: acoustic emission, injection molding, cracks, feature vector, pattern recognition.

1. Introduction

Injection molding is still regarded as the most important and very popular manufacturing process because of its simple operation steps. The plastic material solidifies into a shape that conforms to the mold contours. A typical production cycle begins when the mold closes, followed by the injection of melt into the mold cavity. Once the cavity is filled, holding pressure is applied to compensate for the material shrinkage. In the next step, the screw turns, feeding the material for the next shot to the screw tip. This causes the screw to retract as the next cycle is almost ready. Once the molded part is sufficiently cooled, the mold opens and the part is finally ejected.

Chen and Turng [1] defined three categories of variables that fill the hierarchy and dependencies of an injection-molding control system. The first level variables are defined as machine variables and include barrel temperatures in several zones, pressure, sequence and motion, etc. The second level variables are process-dependent variables that include melt temperatures in the nozzle, runner and mold cavity, melt pressure in the nozzle and cavity, melt-front advancement, maximum shear stress, rate of heat dissipation and cooling. The third level incorporates quality
measures such as part weight and thickness, shrinkage and warpage, etc. Current research mostly deals with the control tasks at the first two levels. For quality control purposes, this is often achieved indirectly through online dynamic process control or offline statistical process control (SPC). The majority of commercially available in-mold sensors for monitoring second level variables are pressure and temperature sensors.

Correlation of basic AE burst signals parameters (peak amplitude, energy, RMS value, RA value, burst count, …) and crack propagation in steel is well described in accessible literature. We used AE parameters to confirm presence of damaged area in tool. We focused also on possibility of damage detection based on frequency characteristics of AE signals with defined time length and AE signals amplitude probability distribution [2]. Also the detection of cracks in molds during the injection molding process is a topic that has not gained a sufficient coverage in the accessible literature.

Biancolini et al. [3] investigated fatigue crack nucleation and propagation on steel using the fractal analysis and box counting method described with Richardson diagram and defined time lag. Box counting method offers definition of fractal dimension that is defined with tangent of inclination in Richardson diagram. Box counting method incorporates definition of time lags and counting of time lags containing at least one AE data above a specified threshold. In our research we used the idea of defining the box in a way to measure AE signals in a form of “boxes” with defined time length (duration).

2. Experimental Procedure

Experiments were conducted on a hydraulic injection molding machine KM 80 CX-SP 380 KraussMaffei, for a broad spectrum of injection molding process parameters. Acoustic emission signals were captured during the production cycle of standard test specimens that are intended for shrinkage evaluation of various polymer materials. Acoustic emission measurement system AMSY-5 from Vallen-Systeme GmbH was used for capturing and analyzing the AE signals.

![Fig. 1: A tool steel insert on a hydraulic injection molding machine with two PZT sensors on acoustic waveguides.](image)
Two piezoelectric AE sensors VS150-M (resonant at 150 kHz) were mounted with silicone grease with two sensor holders on the tool steel insert from both sides as shown on Figure 1. Both PZT sensors were connected via two preamplifiers AEP4 with a fixed gain of 40 dB. Experiments were conducted using a new injection mold tool and a damaged tool, respectively. Surface cracks were generated by successive local laser surface hardening of the tool steel. Both tools were tested using magnetic particle testing with fluorescent magnetic suspension.

3. Experimental Results and Discussion

During AE testing, we detect signals carrying energy released from an active source rather than being supplied by the test method. Furthermore, acoustic emission testing can detect dynamic processes associated with the degradation of structural integrity [4,5]. The major AE signal sources detected by NDT are crack growth and plastic deformation of the steel [6]. Acoustic emission (AE) as transient elastic waves [7] has drawn a great attention because of its applicability to on-line surveillance and capability to acquire data with high sensitivity [8].

The cracks detected on the damaged tool steel insert are presented in Fig. 2. After 24 hours, the standard injection molded polypropylene test specimens were scanned with an optical ATOS II SO 3D-digitizer. The cracks on the damaged tool steel insert are also reflected on the surface of injection molded specimens, as shown in Fig. 2. Deviations from the ideal surface are noticeable, with specified values from ideal shape of D2 ISO test specimen.

![Fig. 2: Cracks in the tool steel insert and accompanying PP specimen.](image)

For classification we used sample vector that is AE signal with defined length of 52.4 ms \( X = (x_1, x_2, \ldots, x_n) \) where \( n = 262144 \). We will use term AE signal for specified sample vector (box).

We selected length of 52.4 ms for AE signal to cover also long AE bursts expected during injection molding process. AE signal can incorporate several AE bursts or burst cascades. An AE burst is over, when the duration discrimination time elapses due to the absence of threshold crossings. If a burst is over and a threshold crossing is detected before the rearm time elapsed, a new burst is processed by the channel as a subsequent burst in the frame of a burst-cascade. AE burst peak amplitude, duration and energy are derived from the first burst of the burst cascade. We used 3.2 ms rearm time and 3.1998 ms duration discriminant time. Absence of cracks in a new tool offers us classifying measured AE signals as process orientated signals. On the other hand, the presence of damaged area in steel insert causes a considerable increase in the number of AE bursts detected during the filling phase, in an amplitude range between 40 and 60 dB. Consequently, we can ascribe the additional signals measured during the filling phase to active AE sources from injection mold defects. A rapid increase in mold pressure during the filling phase could stimulate plastic zone formation, stacking and slipping of dislocations ahead of the crack tip and crack extension [9, 10] in tool steel. Plastic deformations in the vicinity of the crack...
in the steel, mostly related to sliding dislocations, and crack growth cause distinctive AE bursts [11].

If the mold material cracks are relatively small or less explicit, the decision about the acceptability of a damaged mold based on burst rate and cumulative number of AE bursts is difficult. It is therefore reasonable to introduce AE signal frequency characteristics and AE signal amplitude probability distribution into the decision criteria.

To improve the prediction of injection mold state, we introduced the kurtosis and skewness parameters describing the amplitude distribution of recorded AE signal. Kurtosis is a measure of the "peakedness" of the probability distribution for a real-valued random variable. In our case we calculated the kurtosis of measured AE signal amplitude values. Kurtosis was used in our research to characterize infrequent extreme deviations of amplitude values in AE signal, which can be attributed to active sources in damaged area, as opposed to frequent modestly sized deviations of amplitude values, which can be attributed to process orientated signals. Crack propagation yields AE signals with a high positive excess kurtosis with leptokurtic distribution. Skewness S is defined as a third central moment of amplitude values in AE signal X about its mean value. Skewness is in our research used as a measure of asymmetry about the mean amplitude value of AE signal.

Fig. 3: Change of a parameter PL/PS and kurtosis K during the production cycle in injection molding with a new and damaged mold.

We extracted from the acquired AE signals additional parameters significant for damaged area prediction in the injection molding tool. We calculated the PL parameter, characterizing the lower part of the power spectrum of each AE signal acquired during the filling phase with the new and damaged mold, respectively (a=90 kHz, b=190 kHz). Parameter PH characterizes the higher part of power spectrum (a=250 kHz, b=350 kHz), and parameter PS covers all power spectrum frequencies (a=50 kHz, b=550 kHz). The parameters PL, PH and PS carry information about the energies at various frequencies in a sensor’s frequency spectrum.
\[
P_j = \sum_{i=1}^{b} \frac{y_i y_j}{m}
\]
\[
m = \max(Y \cdot \hat{V})
\]

\(Y = (y_1, y_2, \ldots, y_n)\) represents the vector of discrete Fourier transform using FFT.

Change of a parameter \(PL/PS\) and kurtosis \(K\) during the production cycle in injection molding with a new and damaged mold is shown in Fig. 3.

Based on the measured AE signals, we set the vector \(V = (PH, PL/PH, PL/PS, K, S)\) as a 5-dimensional feature vector or instance with real-valued explanatory variables. Vector \(V\) offers us defining points in appropriate multidimensional space to characterize the process. We used classification to identifying the category or sub-populations based on a training data set, containing instances whose category membership is known. We can characterize the injection molding process with regard to the presence of mold defects as shown in Fig. 4. Small hollow black markers represent feature vectors during injection molding using the new and damaged mold, where the mold pressure in damaged mold is below activation level of defects in the tool steel. Red markers (\(-, \times, +\) and \(*\)) represent the feature vectors during injection molding with the damaged mold, where the mold pressure is above the activation level of tool steel defects. The encircled region indicates the presence of defects in the injection mold.

![Fig. 4: Definition of damaged mold based on feature vectors.](image)

We used neural network pattern recognition to classify data. Training data consist of a set of 634 input vectors \(V\). Input vectors acquired with the intact tool during the filling phase were all designated with target \(C = (0,1)\). Input vectors acquired with the damaged tool during the filling phase were designated by \(C = (0,1)\) if the injection pressure is low and with \(C = (1,0)\), if the injection pressure is high. If the location of individual bursts was detected, AE signals including those bursts and designated as presence of damage, had to have location inside of damaged area of the tool steel insert. For neural network pattern recognition we used feed-forward network with the F Tan-Sigmoid transfer function in both the hidden and the output layer. We used 12 neurons in hidden layer and two output neurons, because there are two target categories associated with each input vector. The network is trained with scaled conjugate gradient backpropagation.

For training of our network, data were randomly distributed into three subsets. Training subset (70 \% of the data) is used for computing the gradient and updating the network weights \(W\) and
biases B. In the validation subset (15% of the data) the error is monitored during the training process. The network weights and biases are saved at the minimum of the validation subset error. Testing subset (15% of the data) has no effect on training but provide independent measure of network performance during and after training. The highest number of misclassified vectors was 23. These are vectors labeled as presence of damage and classified by the network as absence of damage. The number of misclassified vectors labeled as absence of damage and classified as presence of damage is smaller and is 15. None of these 15 vectors were acquired with intact tool. These results mean that with intact tool we could not get output C = (1,0). With a damaged tool we can get signals with indications of intact tool, but the probability that all acquired signals during one filling phase would be misclassified as intact tool, is very small. The probability of not detecting damaged tool during injection molding is so very small.

3. Conclusions

The aim of this research work was to develop an AE monitoring system able to detect the damaged tool in injection molding. For this purpose, we made a close comparison of AE signals captured from a new mold and a damaged mold under the same processing conditions. Experimental results prove useful information about the presence of damaged mold area can be obtained by measuring AE signals during injection molding. The most useful information about the mold’s condition is gained during the filling stage of injection molding process, when the mold pressure is high enough. To improve the tool integrity prediction with smaller defects, AE signal frequency characteristics are implemented and a measure of AE signal amplitude probability distribution is introduced. A 5-dimensional feature vector with real-valued explanatory variables is proposed. Classification of feature vectors with neural network pattern recognition provides applicable information for detection of mold defects.

References


