Prediction of Hotspots in Injection moulding by Using Simulation, In-mould Sensors, and Machine Learning*

Mandana Kariminejad[1], David Tormey[2], Christopher O'Hara[2] and Marion McAfee[1]

***Abstract*— Injection moulding is an industrial process for the mass production of plastic components, with many parameters affecting the quality of this process. Hotspot regions in the component occur due to non-optimised process variables or limitations in the cooling system and can lead to warpage or shrinkage. Hotspots should be minimised to avoid part defects and achieve the required dimensional tolerances for precision components. This work outlines a machine-learning-based approach for predicting the maximum hotspot temperature in an injection moulded component using process simulation and in-mould sensor data. The hotspots were identified through software simulation, and then their locations and temperatures were confirmed through an actual experiment using in-mould thermocouples. Two different machine learning approaches, artificial neural network (ANN) and support vector regression (SVR), were developed using the extracted data from the sensors and a design of experiment (DOE) method. The performance of linear and Gaussian kernels was compared for the SVR method. The Gaussian SVR resulted in superior performance compared to the linear kernel. The Gaussian SVR was then compared to the ANN prediction method, where ANN showed a slightly better prediction performance. This study has two primary outcomes. First, we show the simulation results can be used to identify critical areas of the part for real-time monitoring. Secondly, embedding sensors in these locations and applying a machine learning approach to the data, provides a good indication of potential quality issues such as warpage and shrinkage post-production. The use of ANN indicates an accurate prediction performance, facilitating rapid optimisation of the process for the minimisation of hotspots.**

I. INTRODUCTION

Injection moulding (IM) is a widely used process for the rapid manufacturing of plastic components in high volumes. The process contains three main stages: filling, packing, and cooling. Uneven and non-uniform temperature distribution on the cooling of the part can lead to residual stresses and, thereby, part defects such as warpage and shrinkage. Identifying and eliminating the locally heated regions or hotspots are crucial to having a uniform temperature profile and high part quality. Hence, predicting these hotspots and mapping their relationship with the key input parameters is a proposed novel approach to improve the part quality.

Different machine learning (ML) algorithms have been applied in the injection moulding (IM) process to predict the part quality factors and optimal process variables. Artificial Neural Network (ANN) is one of these well-developed methods that has been shown to be effective for modelling the IM process in a number of recent works. Bensingh et al. [1] applied ANN to improve the optical quality in the injection moulding of a bi-aspheric lens by coupling ANN and Particle Swarm Optimisation (PSO). The comparison of the results with the ANN and Genetic Algorithm (GA) approach illustrated the superiority of the ANN/PSO approach in faster convergence. Cheng Ke et al. [2] applied a multilayer perceptron neural network on a dataset extracted from a pressure curve produced by an in-mould pressure sensor to predict the part dimension of a moulded component. Moayyedian et al. [3] implemented ANN along with the Taguchi method to find the optimum process settings for producing a high-quality thin-walled part. In a recent study, Lee et al. compared ANN to linear and second-order polynomial regression, in which ANN prediction performance was relatively better than the two other methods [4].

Another popular ML method that can capture nonlinearity in data and provide a proficient prediction model is support vector machine regression (SVR). Gao et al. [5] applied SVR to predict the part dimensions in an injection moulding process using pressure and temperature data. Yan et al. [6] designed probabilistic constraints for SVR to predict the product design time, and they validated their approach in the injection moulding process. Li et al. [7] developed least squares SVR to predict the weight of the plastic parts in the injection moulding process and validated their approach through an experiment with an average error of 2%. A complete review of the application of the different ML approaches in injection moulding is summarised in [8].

Although ML methods have been implemented in injection moulding to predict different part quality factors or process variables, limited research has been conducted to predict the part temperature profile and hotspots. Several studies have been done to minimize hotspots by modifying the mould tools, such as sophisticated cooling channel design [9]–[11] or runner systems [12]. These modifications require costly modifications to machine tools. Also, temperature differentials and hotspots will lead to post-process shrinkage and warpage, which are often not apparent for a long time after production. For high-precision components such as medical devices, product release may be delayed for up to

*This research is supported by an ATU Sligo Bursary and also by a research grant from Science Foundation Ireland (SFI) under Grant Number 16/RC/3872 and is co-funded under the European Regional Development Fund and by I-Form industry partners.

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two weeks post-production to allow for quality assurance metrology to be conducted after the relaxation of residual stresses in the parts. Prediction of the hotspots and temperature differentials in situ could reduce the metrology quality controls, production lead time, and scrap rates. Such a real-time method could also be used for process optimisation and control and to optimise design changes should they be needed.

Moreover, most optimisation and prediction studies conducted to date have used data on machine variables rather than process parameters and, thereby, do not capture inherent variability in the process. Hence using in-mould sensors for extracting real-time and inline data from the process is essential for effective control and monitoring of the process [13].

This research presents a novel approach, incorporating in-mould sensors and simulation, for predicting the hotspots and mapping their relationship with eight input process parameters. The component and the related mould tools were simulated in Autodesk Moldflow Insight 2019 to identify the temperature distribution and probable hotspot locations in the component. Based on this temperature profile, three Kistler temperature sensors were embedded into the moulds to validate the simulation data. A DOE method was implemented to generate and analyse real-time data of eight machine parameters as inputs and the sensor readings from a thermocouple embedded in the IM tooling as an output. The dataset was used in two ML methods, ANN and SVR, to predict the hotspot temperature in the part. The simulation and prediction results are outlined in section III, followed by the conclusion and future research associated with this study.

II. METHODOLOGY

A. Part description & Simulation

The product investigated is a medical device component referred to as a ‘Clip’. The main dimensions are in millimetres, and the isometric view is illustrated in Fig.1. An industrial partner in this research work provided the initial process settings for the simulation. The clip material is POM (Polyoxymethylene). Current clip production sees component quality issues such as shrinkage and warpage, meaning the part currently suffers from an unacceptably high failure rate due to not meeting the precise dimensional tolerances that are required.

For the simulation of the Clip, a CAD model of the mould with the cooling channels (Fig. 2 (a)) was imported into the Moldflow simulation software. A 3D mesh, as shown in Fig. 2 (b), was used to capture the details of the geometry. The melt and mould temperatures were set at 215 °C and 90 °C, respectively, with the coolant in the cooling channel, assumed to be water. The other process settings were adjusted based on the details provided by the industrial partner. The injection location and runner system were designed based on the production tools. For simulation of the cooling stage and temperature distribution throughout the part, the Cool (FEM) method with flow solver was used in Moldflow. This solver

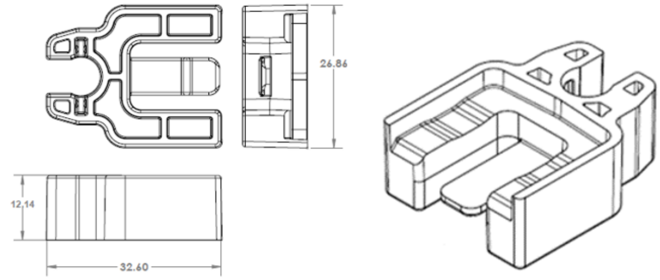


Fig. 1: Isometric view and main dimensions of Clip

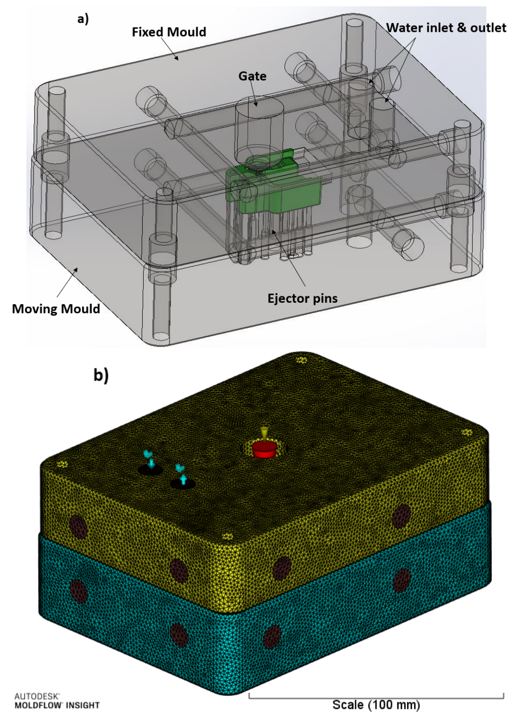


Fig. 2: a) CAD and b) meshed moulds in Moldflow

can calculate the excessive shear heating in flow and variation of the wall thickness.

B. Sensor selection

Sensors are required to measure the temperature distribution in the physical experiment and are used to extract accurate data for ML methods. For the direct in-mould temperature measurement in which the sensor is in contact with the polymer melt, Kistler high-temperature thermocouples (type 6193B0) were chosen. The sensor temperature durability is up to 450°C, the voltage range is 0 to 10V, and they are small enough (diameter of 1mm) to fit into the cavity in direct contact with the polymer melt with a measurement error of less than ±0.5.

C. Experimental Setup

The sensorised mould tools were manufactured to validate the simulation results of the temperature distribution in the component and for the hotspot predictions of the ML methods.

For the experimental setup, the injection moulding machine variables were adjusted using key process settings, as identified in the simulation, to generate temperature readings in the expected hotspot locations; these were measured by the embedded thermocouples. A DOE methodology was applied for data collection and analysis. A recent study revealed that fractional factorial design is an efficient approach to model the injection moulding process using ANN [14]. Hence this research used a fractional factorial design with eight input variables.

The input variables were: mould temperature, melt temperature, holding time, holding pressure, shot size, switch-over position, injection speed, and cooling time. The number of experiments for the fractional factorial method with 1/16 fraction and eight two-level variables can be calculated as (1). The experiment designs are listed in Table I.

$$2^{(8-4)} = 16 \tag{1}$$

Each experiment was repeated for ten shots, or cycles, in the injection moulding machine, and thereby, the full dataset collected from the injection moulding process was 160 shots. The desired output is the maximum hotspot temperature from the sensor with the maximum measurements among the three thermocouples.

D. Machine Learning methods

In this research, two different machine learning regression methods were compared to map the relationship between 8 input parameters and the maximum hotspot temperature. The first method is a support vector machine regression (SVR), and the second is an artificial neural network (ANN).

Support vector machine was initially developed for pattern classification and then was extended to solve the regression problem by definition of a margin of tolerance (ε) [15]. In the ε-insensitive SVR (loss function), the goal is to find a cost function in which the error on the training points is no greater than ε.

For applying support vector regression (SVR) in nonlinear problems and computing with the dot product of two vectors, a kernel function is applied to transform data to a high dimensional feature space for linear mapping. Different kernel functions for the transformation to linear space include linear, polynomial, and Gaussian functions. In this paper, the performance of linear and Gaussian kernels was compared. The dot product of observation j and k can be replaced with (2) and (3) for Gaussian and linear kernels, respectively. ε value and the kernel scale (σ) were selected as 0.2 and 0.7 respectively.

$$K(x_j, x_k) = x_j^T x_k + c \tag{2}$$

$$G(x_j, x_k) = exp(-\frac{-\|x_j - x_k\|^2}{2\sigma^2}) \tag{3}$$

For the ANN approach, a feedforward network with two fully connected layers of size 10, Rectified Linear Units (ReLU) activation function [16], and one final fully connected layer for regression was designed. The network structure is shown in Fig. 3.

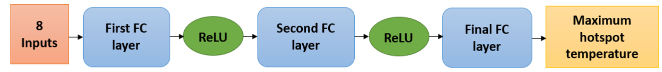


Fig. 3: ANN net structure

For all the methods, 5-fold cross-validation was used to avoid overfitting. The dataset was divided into two parts, 110 samples for training by 5-fold cross-validation and 50 samples for testing to examine the network performance.

III. RESULTS & DISCUSSION

A. Simulation & Experiment

After the simulation of the mould tools and Clip using Moldflow software, the temperature distribution and hotspot locations were identified as presented in Fig. 4 [11]. Two hot spot regions are illustrated with circles in two different cross-sections in Fig. 4, and their maximum temperature is almost 105°C. As mentioned in the previous section, two sensors were located in the moulds to measure the high-temperature points. Sensor A is located near the gate in the fixed half, and sensor B is located in the moving half to measure the hotspots in regions 1 and 2 (Fig. 4 (a, b)). Also, sensor C was located at the average temperature location to compare the sensor measurements.

The sensors were embedded in the cavity based on the simulation result in Fig. 4. The location of sensors A, B, and C in the moulds is illustrated in Fig. 5.

After embedding the sensors, moulds were manufactured for conducting the experiments. The actual sensorised tool with the sensors A, B, and C is illustrated in Fig. 6.

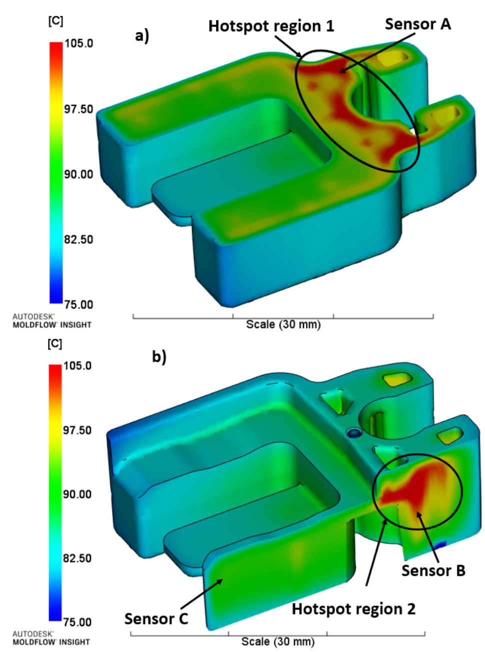


Fig. 4: Temperature distribution in Clip (a) xy cross-section (b) zx cross-section

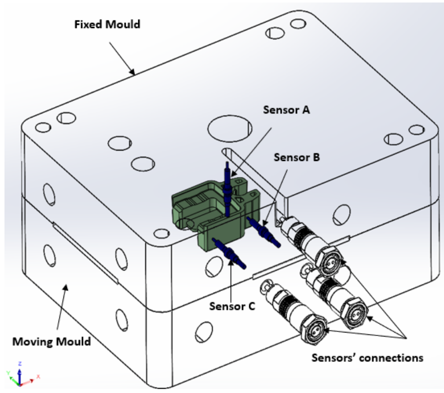


Fig. 5: sensor location in the moulds

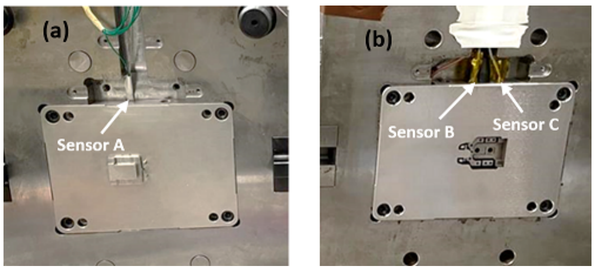


Fig. 6: The manufactured tools a) fixed half, b) Moving half

Next, the injection moulding process was conducted with the same process settings as the simulation. The measurements of the three sensors are shown in Fig. 7 for fifteen cycles to ensure process stability. The results in this figure indicate that the temperature measurements of sensors A and B (located in the hotspot regions 1 and 2) are higher than sensor C (located in an average temperature region) and confirm the simulation results in Fig. 4. The maximum temperature measurement of sensors A and B is 102.7°C and 105.05°C, respectively, and agree with the maximum temperature in simulation results (Fig. 4) which is 105°C.

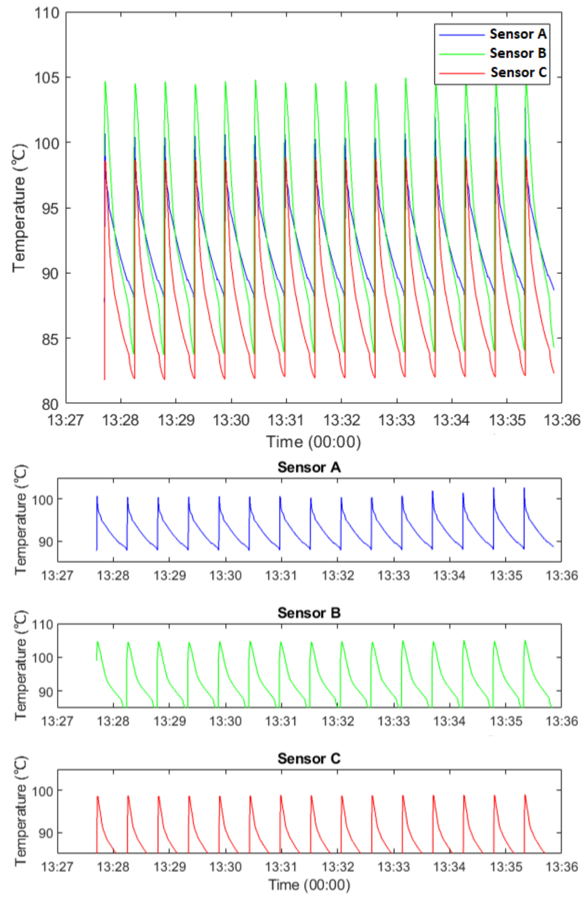
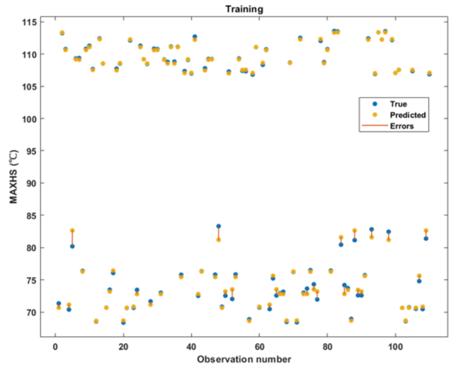


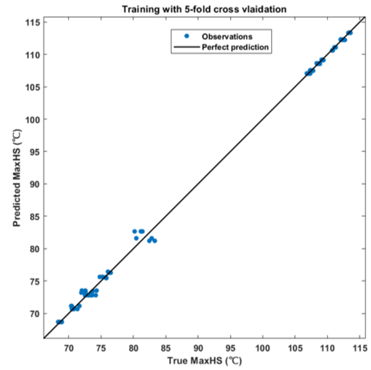
Fig. 7: The temperature measurement by sensors A, B, and C during 15 cycles

TABLE I: Fractional factorial design

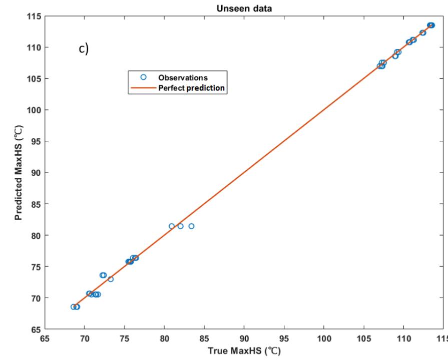
No	Holding time (s)	mould temperature (°C)	Holding pressure (bar)	shot size (mm)	Switch over position (mm)	Injection velocity (mm/s)	Melt temperature (°C)	Cooling time (s)
1	3	40	400	6	10	40	230	10
2	3	90	400	6	5	40	210	30
3	6	90	200	12	5	20	210	30
4	6	90	200	6	10	40	210	10
5	3	90	200	6	10	20	230	30
6	6	90	400	6	5	20	230	10
7	6	40	200	6	5	40	230	30
8	6	40	400	6	10	20	210	30
9	6	40	400	12	5	40	210	10
10	3	40	200	12	10	40	210	30
11	3	90	400	12	10	20	210	10
12	3	40	200	6	5	20	210	10
13	3	90	200	12	5	40	230	10
14	3	40	400	12	5	20	230	30
15	6	90	400	12	10	40	230	30
16	6	40	200	12	10	20	230	10



(a) training

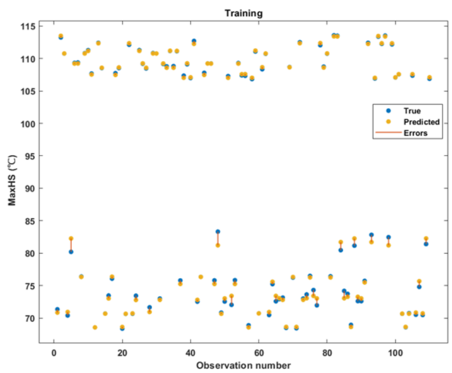


(b) training with cross validation

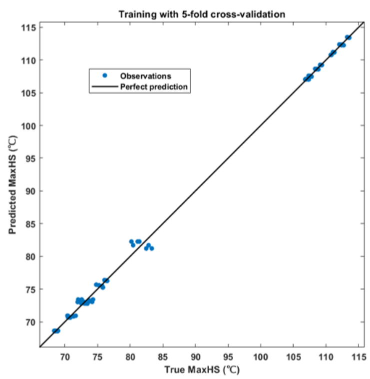


(c) testing

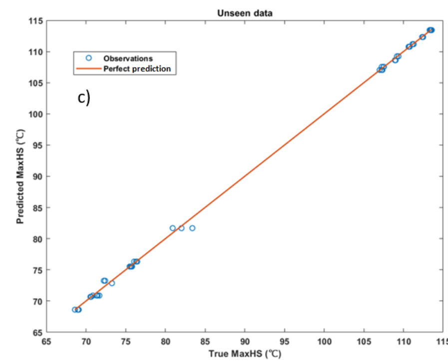
Fig. 8: Gaussian SVR regression results



(a) training



(b) training with cross validation



(c) testing

Fig. 9: ANN regression results

This temperature is reduced to 96.5°C for sensor C, which measures the estimated normal (average) temperature of the Clip.

B. Prediction of the hotspot temperature by Machine Learning

After verifying the simulation results by experiment, the performance of two machine learning algorithms in predicting the maximum hotspot temperature was compared. The desired output for the prediction was the maximum temperature of sensor B since this sensor has the maximum thermocouple measurements, as shown in Fig. 7. For selecting a suitable kernel function in SVR, the prediction performance of linear and Gaussian kernels was compared. The linear SVR had a validation and test RSME (Root Mean Square Error) of 1.62°C and 1.27°C, respectively. Compared to the Gaussian SVR, with an RSME of almost 0.5°C for both training and testing. The prediction results for Linear and Gaussian SVR are summarised in Table II.

After selecting a suitable kernel for SVR, the performance of Gaussian SVR and ANN in the hotspot prediction were compared in Fig. 8 and Fig. 9, respectively. Fig. 8 (a) and Fig. 9 (a) evaluate the training performance by 5-fold cross-validation and compare the actual values and predicted values by showing the error bars. The error bars for both methods are small except for a few observations in the 80 to 85°C range. The error bars in this region are larger since only ten samples were available for training with this range of hot spot temperatures. In other words, only one of the experiment designs from table I resulted in a hotspot with a temperature between 80°C to 85°C.

Fig. 8 (b and c) and Fig. 9 (b and c) show the regression plots for the training and testing datasets, respectively. For both methods, the predicted values are almost equal to the actual values meaning the R-squared is near 1. In these graphs, it is also noticeable that the predicted and actual values in the 80-85°C range had a more significant difference because of fewer available samples in this range.

The Root Mean Square Error (RSME) of the training by 5-fold cross-validation and testing is also summarised in Table II. The RSME of the Gaussian SVR is almost 0.5°C for both training and testing, and the RSME of the ANN has a slightly better performance in prediction by RMSE of nearly 0.4°C. Fig. 10 compares the prediction results of Linear SVR, Gaussian SVR, and ANN in one plot for the region of 68°C to 74°C to see the differences in the performance of each approach for the testing data in more detail.

It is also noteworthy to mention that there is not any data available between almost 85°C to 105°C since the dataset was prepared by using a two-level fractional factorial design, and so the corresponding hotspot temperatures were mainly dispersed in two regions.

TABLE II: Linear SVR, Gaussian SVR and ANN results for training and testing

Method	RMSE training	RMSE testing	R-squared training	R-squared testing
Linear SVR	1.62	1.27	0.99	0.99
Guassian SVR	0.57	0.51	1	1
ANN	0.45	0.41	1	1

IV. CONCLUSION

This research compared the performance of two machine learning algorithms in predicting the hotspot temperature of an injection moulded component.

The hotspot regions were identified through simulation in Moldflow Insight, two in-mould thermocouples were embedded into these regions on a manufactured mould. An additional thermocouple was placed in a region of average temperature. The simulation results were compared to physical experimental results collected from an injection moulding machine. This validated the simulation results and showed the thermocouples presented higher temperature readings in the hotspot regions (see Fig. 4).

For data collection and analysis, a fractional factorial design was used. Two machine learning approaches, artificial neural network (ANN) and support vector regression (SVR), were then applied to predict and map the relationship between eight input parameters and the maximum hotspot temperature from sensor readings. Linear and Gaussian SVR were compared to select a proper Kernel function in which the Gaussian method had a better performance with RSME of 0.5°C. Furthermore, by comparison of Gaussian SVR and ANN, the ANN method was shown to be slightly more accurate in its predictions, with an RMSE of almost 0.4°C (see Table II).

The results indicate that ANN can achieve excellent prediction accuracy, even with a simple structure; however, SVR did not perform well with a linear kernel function. In this study, the hyperparameters of ANN and SVR were selected manually. For a better comparison of the methods, the hyperparameters should be tuned through an optimisation approach to ensure the maximum efficiency of the methods.

Using simulation results and inline data from the process in the machine learning approach is a novel method to predict the hotspots and find the optimum process setting for an even temperature distribution throughout the moulded part, thereby reducing scrap rates and increasing product quality. Experiment results in this study validated the reliability of the simulation tool; further research can investigate using simulation software to develop an adaptive closed-loop control system for real-time optimisation of the machine variables.

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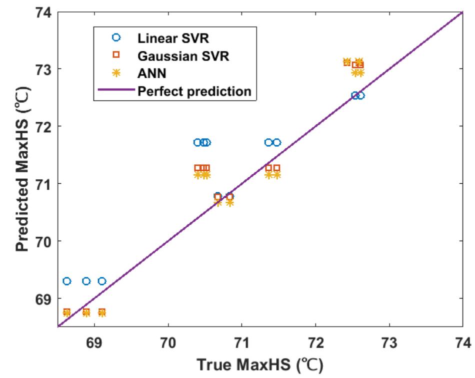

Fig. 10: Comparison of prediction results of three methods for testing dataset

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