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APPLICATION OF MACHINE LEARNING IN THE PRECISE AND COST-EFFECTIVE SELF-COMPENSATION OF THE THERMAL ERRORS OF CNC MACHINE TOOLS – A REVIEW

The current development of production engineering takes place through the innovative improvement of machine tools and machining processes at the constantly growing application of intelligent self-improvement functions. Machine learning opens up possibilities for machine tool self-improvement in real time. This paper discusses the state of knowledge relating to the application of machine learning for precise and cost-effective thermal error self-compensation. Data acquisition and processing, models and model learning and self-learning methods are also considered. Three highly effective error compensation systems (supported with machine learning) are analysed and conclusions and recommendations for future research are formulated.

1. INTRODUCTION

The constantly growing demand for higher multiparametric manufacturing efficiency makes it necessary to engage modelling and numerical simulations, supported with the latest knowledge and increasingly advanced artificial intelligence tools, in its improvement. Efficiency improvement through the reduction of machining errors, introduced into the tool path along the controllable axes by the machine tool, the cutting tool and the cutting process, plays a major role in this respect. It is necessary to increasingly more efficiently recognize disturbances and errors and correct and compensate them in real time. For this purpose the determination of precise error functions, supported with machine learning is needed. The current tendency is towards greater autonomy of machine tool and machining improvement processes. The support of these processes with machine learning to increase their efficiency is currently a major challenge.

Therefore the application and improvement of AI models and tools are highly desirable. It is also necessary to search for innovative machine learning methods through a holistic

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analysis of machine learning. This paper deals specifically with the improvement of machine learning as applied to the self-compensation of thermal errors, which recently have been the subject of extensive research.

Changes in temperature cause the deformation (variable in time and space) of the machine tool's individual parts and whole assemblies [1]. This results in the displacement of the cutting tool relative to the workpiece and in significant deterioration of machining precision. Changes in temperature can also contribute as much as 75% of workpiece dimensional and geometrical errors [1]. The machine tool thermal error practically cannot be directly measured during machining. Therefore for determining this error in real time methods of its modelling supported with machine learning are employed [2–48].

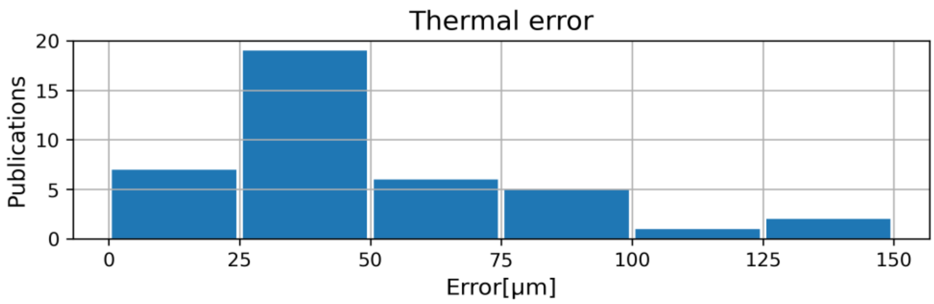

Fig. 1. Most often compensated machine tool thermal errors

The heat sources which can contribute to the thermal error are: the machine tool environment, the machine tool itself, the machine tool operators and the cutting process [47]. The error can be reduced by minimizing the impact of the above-mentioned sources. The remaining error can be compensated in the controllable axes by means of an accurate error model and the control system.

In the literature on thermal error minimization reviewed in this paper the maximum absolute error is assumed as a measure of the thermal error. Figure 1 shows an exemplary thermal error histogram based on 40 publications from the last 10 years. It indicates that errors of up to 100 µm, and particularly errors in the range of 25–50 µm, are most often compensated. This is so because of the current machining precision requirements.

Thermal errors can be effectively reduced by compensating them using advanced machine learning methods. Section 2 explains what machine learning consists in and discusses the application of machine learning in thermal error self-compensation. Sections 3, 4 and 5 present the preferred self-compensation methods, including measurements, data preprocessing, machine learning models and learning and self-learning methods. Section 6 discusses the usefulness of thermal error self-compensation systems showing the highest precision and adaptability.

2. GIST OF MACHINE LEARNING

Using machine learning one can improve modelling and implement the idea of an artificial operator learning on the basis of previous experience and adapting to changes in the machine tool operating conditions, including the thermal ones [49]. Machine learning also makes it possible to achieve precise thermal error compensation in real time. Machine learning model adaptation to changes in thermal conditions is realized through self-learning.

Machine learning consists in training the model of specific relation, using data on the natural behaviour of an object or a process. Machine learning application in thermal error compensation consists in training the model this error on the basis of data acquired from an experiment and/or a numerical simulation. In the machine tool control system the thermal error compensation value is calculated in real time using a machine learning model and it is entered into the tool path. Compensation corrections are entered directly into the interpolator or through a special procedure with which the open CNC controller is equipped [50]. This can also be done via G-code correction, but this is rarely used because it is difficult to perform in real time and practically it cannot be applied on an ad hoc basis in series production.

Among the machine learning models one can distinguish linear models and artificial neural networks. Linear models are the simplest machine learning models, whereby they can be implemented directly on the CNC controller. The linear models used in thermal error compensation are: the linear regression model [43], the autoregressive moving average (ARMA) [35] and the grey model [38]. Artificial neural networks (ANNs) are more complex models which are difficult to implement on the CNC controller. Therefore an industrial computer is used to implement them [23]. The ANNs most often used in thermal error modelling are: a multilayer perceptron (MLP) [4, 6, 7, 9, 14, 15, 17, 21, 24, 26, 29, 33, 35, 40–44] and a radial basis function (RBF) network [8, 9, 16, 19, 20, 27, 28, 34, 36, 38]. Linear models have usually shown an accuracy of a few/10-20 micrometres, while artificial neural networks have usually shown an accuracy of few micrometres. It is demonstrated in section 5 that ANNs showed higher accuracy (in μm and %) than linear models. Thanks to thermal error compensation based on a machine learning model the machining error was reduced by at least 30% [10, 11, 14, 15, 17, 23, 26, 32].

The preparation of a machine learning model for implementation involves the following steps: problem analysis, training and testing data acquisition, collected data processing and model training and testing. In order to acquire model training data one must simultaneously measure (as precisely as possible) displacements and temperatures in selected points of the machine tool structure. After the model is trained, its accuracy is verified using the testing data. The size (defined as the duration of measurements) of the testing set has usually not exceed 100 hours and the testing set has constituted 10–70% of the whole data set. If the model is sufficiently accurate, it is used by an error compensation algorithm in real time. If the model's accuracy is insufficient, it should be improved by collecting a larger amount of data, changing the data processing method or changing the model.

When the model is implemented, there are still too many factors which can worsen thermal error compensation precision during machining. Exemplary causes of precision deterioration can be: the degradation of structural components, the translocation of the machine tool, daily and yearly changes in ambient temperature, the action of heat sources (e.g. people, machines) in the neighbourhood of the machine tool or a change in the machining program. The model's accuracy can be restored through self-learning consisting in model updating on the basis of additionally (autonomically) acquired temperature and thermal error measurements [45, 47, 48]. The cost of an improvement in model accuracy is a reduction in machine tool productiveness. In order to minimize the idle time resulting from self-learning the autonomous acquisition of measurements should start only when it is evident that the model has lost the required accuracy. Active learning algorithms, e.g. Query By Committee, are used to recognize the proper instant for starting measurements [51]. The criteria for evaluating the whole self-compensation system are: precision, impact on machine tool productivity, and autonomy. The autonomy of the self-compensation systems studied so far consists in this that human participation is limited to the setting of key parameters (e.g. maximum allowable thermal error, model fine-tuning frequency).

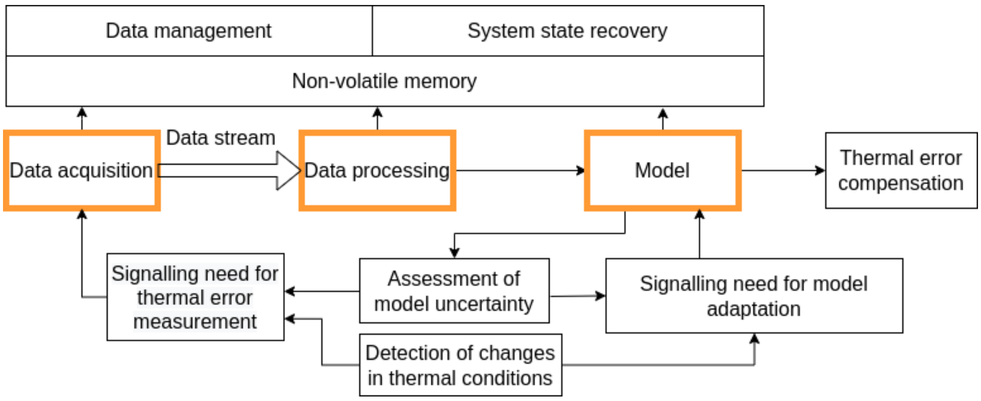

Fig. 2. Self-compensation system structure with highlighted main machine learning components

A self-compensation system operating in real time should also work correctly after a failure. In order to make it possible to bring the system back to operation the current state of the system should be cyclically saved to permanent memory. Over a long time interval a large amount of data will be collected. The data should be properly managed using data processing methods. Data stream processing frameworks are helpful in implementing such a system [52, 53]. The structure of a self-compensation system operating in real time is shown in Fig. 2.

The main criterion for evaluating a compensation system is thermal error modelling accuracy. The accuracy of a machine learning model is checked using the testing set. The accuracy determined by model testing depends on:

- the machine tool design,
- the method of acquiring measurements,
- the methods of data preprocessing,
- the kind of machine learning model,
- the data in the testing set.

Publications [2–48] present research on thermal error modelling for various machine tools. In nearly all the studies the testing set proved inadequate to check the long-term accuracy of thermal error modelling.

We selected three solutions showing the highest accuracy to determine the direction of further search for thermal error modelling methods. The solution which shows high accuracy for one machine tool may turn out to be inaccurate for other machine tools. Thus the selection of a few best solutions may turn out to be insufficient to determine the direction of further search. That is why we grouped solutions and selected the group in which solutions most often showed a high (80% or more) thermal error reduction on various machine tools. Besides evaluating the methods used so far, we turned our attention to methods which have been successfully used in other fields.

It is worth to mention about automated machine learning, which can save time and money spent on searching effective machine learning methods. Searching for thermal error modelling method may be supported by double-loop learning [54], n-loop learning [55, 56]. F. Hutter et al. performed review of automated machine learning (AutoML) methods [57].

3. DATA ACQUISITION

The representativeness of the acquired measurement data has a significant impact on thermal error modelling accuracy. The more representative the learning data, the more accurate the machine learning model. In order to ensure compensation system autonomy, measurements should be performed automatically. When preparing a thermal error self-compensation system one should plan the data acquisition process. For this purpose it is helpful to know the approach of researchers to the acquisition of measurements for training and testing thermal error models.

A system of acquiring measurements for thermal error modelling consists of two integrated subsystems: an input quantities measurement system and a thermal error measurement system. Detailed information about the measured input quantities used for thermal error prediction is given in subsection 3.1. The thermal error measurement methods used are presented in subsection 3.2.

The major measurement parameters are: sampling frequency and total measurement performance time. The sampling period would amount to at least 1s [32] and usually did not exceed a few minutes. The measurements acquisition time usually did not exceed 30 h. The size of the largest set of data used to model the thermal error amounted to 160 h [3]. The sampling period should be adjusted to the rate of change in thermal conditions in order to precisely monitor changes at the minimum use of resources such as memory and computing power. For example, the self-adaptation of the sampling period can be based on a model of the future changes in temperature [58]. Moreover, it is important to perform measurements over a long machine tool operation time interval in order to acquire data in various thermal conditions.

The data should be balanced (acquired in various conditions) and acquired in conditions close to the ones in which machining takes place. Such data enable the training of a model resistant to changes in machine operating conditions. The acquisition of measurements in proper conditions is possible if controllable heat sources are used. The use of a climate chamber facilitates the control of machine tool ambient temperature.

In industrial applications it is essential that compensation be effective long-term. On the basis of the acquired data it has usually been impossible to verify the model over a long time horizon (e.g. 1 year). One of the ways of enabling model training and testing over a longer time horizon consists in acquiring data from different seasons of the year [27]. Another solution is to use cyclic model fine-tuning [45, 47, 48].

Thus it is important to monitor the thermal conditions and the thermal error over a long interval of machine tool operation time. It is worth equipping the machine tool with temperature control to set conditions close to the ones prevailing during machining. The autonomy of the measurements acquisition system can be increased through the use of sampling frequency self-adaptation.

3.1. MEASUREMENT OF INPUT QUANTITIES

The thermal error has been mainly modelled on the basis of temperature measurements in the particular points located on machine tool structure components, characterized by various heating intensity, thermal capacity and heat exchange conditions. Temperature measurement points have often been located on large structural components and close to heat sources. Sometimes a larger number of temperature measurement points would be selected and various methods of selecting key measurement points would be used [2, 6, 26, 27, 33, 35, 36, 39, 40]. A different method of selecting measurement points consisted in analysing an infrared camera image [7]. Figure 3 shows a distribution of the number of temperature sensors used in the research described in 47 publications. It appears that most often a few or 10–20 sensors have been used.

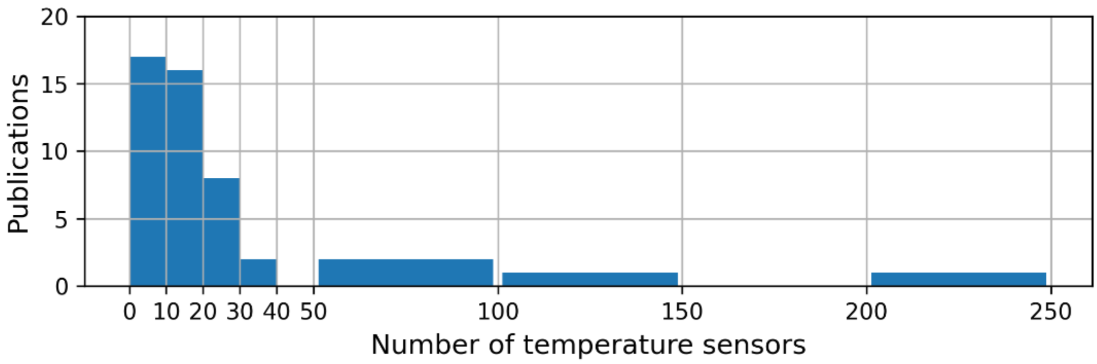

Fig. 3. Frequency of use of various n umbers of temperature sensors for data acquisition

In the most accurate thermal error modelling methods the following numbers of sensors were used: 12 temperature sensors [20], 8 temperature sensors [23] and 6 temperature sensors and an infrared camera [10]. In order to determine a sufficient number of sensors, we divided the modelling methods into three groups using: a few, 10–20 and more than 20 temperature sensors. High modelling accuracy characterized about 60% of the modelling methods using a few sensors, about 70% of the modelling methods using 10–20 sensors and about 60% of the modelling methods using more than 20 sensors. The above statistics indicate that 10–20 temperature sensors is the number sufficient for the accurate modelling of the thermal error. However 10–20 temperature sensors may be insufficient for precision thermal error compensation in long time. In general, the more temperature measurement points, the more possibilities of key points selection, the more possibilities of reaching high thermal error modelling accuracy.

The thermal error has also been modelled as a function of: an infrared camera image [6, 10], temperature and spindle rotational speed measurements [13, 23] or measurements of temperatures and deformations of specific machine parts [7]. The rotational speed of the spindle has a direct effect on the heating of specific machine tool structure components. Temperature itself contributes to the deformation of specific machine parts, whereby also measurements of these deformations can be used to predict the thermal error. Infrared camera and measurement of deformations of specific machine parts may be very expensive, therefore we advice against using these tools. The thermal error also depends on the position (e.g. of the spindle [1]) and so it is worth including the latter among the model input variables.

3.2. MEASUREMENT OF THERMAL ERROR

Since the overall precision of thermal error compensation depends on the modelling accuracy and the thermal error measurement precision, it is important that the measurement of the thermal error be very precise. The thermal error has been measured by means of: an inductive sensor [13, 16, 17, 21, 23, 25, 26, 30, 33–38, 42], a capacitive sensor [14], a laser interferometer [9, 19, 31] and a laser reflective sensor [7, 24, 43, 44]. The thermal error measurement procedures used in 5-axis machine tools have been: the R-test [46] and ETVE [25]. Thermal error measurements have also been performed on the machine by means of a measuring probe [5, 29, 45, 47]. This way of measuring made automatic thermal error measurement (with repeatability below 1μm) between machining processes possible [47].

Since in 5-axis machine tools it is possible to compensate the thermal error along the rotational axes it is worth using the R-Test and ETVE procedures which make it possible to measure the thermal error simultaneously along the rotational and linear axes. In order to ensure compensation system autonomy one should use the automatic thermal error measurement procedure. When selecting a thermal error measuring method one should pay attention to measurement precision as the measurement error is one of the components of the compensation system error. Measurement precision depends on the sensors and thermal error measuring procedures used. The future challange is implementation of autonomous thermal error measurement system in 3-axis machine tool.

4. DATA PROCESSING

The next step in the preparation of a machine learning model is data processing. Preprocessing is a tool which improves accuracy, reduces productivity losses and supports the management of the self-compensation system's non-volatile memory. In order to maximally use the potential of measurement data preprocessing it is essential to get know the methods used for this purpose. In Fig. 4. showed division of thermal error modelling methods with regard to data processing.

In the thermal error modelling methods showing the highest accuracy the following data preprocessing methods have been used: partial correlation analysis [20], scaling [23] and infrared camera image filtration [10]. In order to evaluate the usefulness of data preprocessing we compared two groups of thermal error modelling methods: methods using preprocessing and methods not using preprocessing. High accuracy (above 80%) was attained by less than 45% of the solutions without preprocessing and over 70% the solutions with preprocessing. This means that the use of data preprocessing methods increases the chances of achieving higher thermal error modelling accuracy.

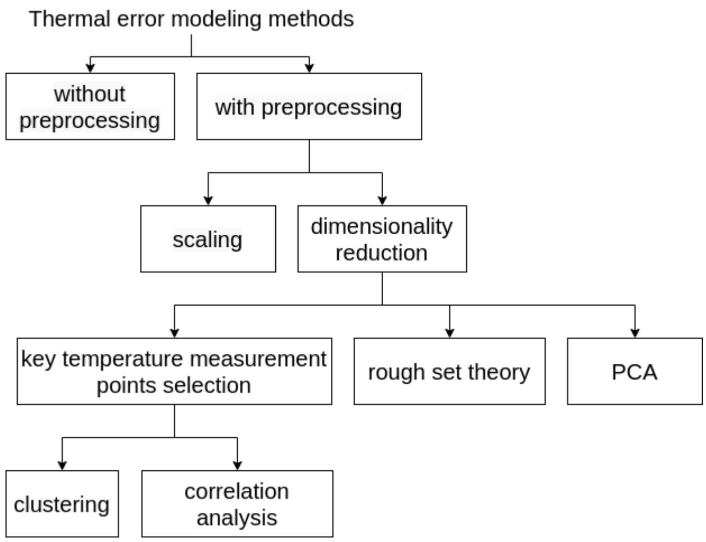

Fig. 4. Division of thermal error modelling methods with regard to data processing

After data acquisition it may turn out that the number of measurements taken in proper conditions is small. In order to solve this problem one can modify the data set using resampling methods [59]. Resampling should balance the data set and increase the share of the measurements taken in conditions similar to the ones in which machining takes place.

Key temperature measurement points are often selected by applying clustering (grouping) methods and methods of assessing the effect of temperature on the thermal error. A group of machine tool structure points in which temperature measurements are similar is called a cluster. The following clustering methods are used: fuzzy c-means clustering [2, 6, 7, 16, 22, 27, 40], hierarchical clustering [26, 33, 35, 36], k-means clustering [45], Kohonen network clustering [39] and density peaks clustering [44]. After clustering is performed representatives of each cluster are selected by assessing the effect of temperatures on the thermal error [2, 6, 26, 27, 33, 35, 36, 39, 40]. In this way temperature measurement points which are not closely correlated with one another and have the strongest effect on the thermal error are selected. The following methods of assessing the effect of temperature on the thermal error are used: correlation analysis [14, 16, 22, 26, 28, 33, 35, 36, 38, 40], grey correlation analysis [2–4, 6, 7, 9] and the grey relational analysis method (GRAM) [5, 15, 27, 39].

The modelling method showing the highest accuracy (about 98.5%) consisted in selecting 2 key points from 12 on the basis of an analysis of partial correlations [20]. In order to evaluate the usefulness of using selection methods we compared two groups of solutions: solutions not using preprocessing methods and solutions using the selection of key points. High accuracy (above 80%) was attained by about 85% of the solutions using the selection of key temperature measurement points. Thanks to the use of such selection high thermal error modelling accuracy was attained more often than when the methods without data preprocessing were used. Over 90% of the solutions using the selection of key points reduced the number of sensors to below 10. Whereas about 70% of the solutions without data preprocessing used fewer than 10 sensors. In comparison with the solutions without data preprocessing, the solutions with the selection of key points more often used fewer than 10 temperature sensors. This means that selection methods help to increase thermal error modelling accuracy and reduce the cost of producing an intelligent system of thermal error compensation.

Key points were usually selected (on the basis of the measurements used to train the model) only once. Such selection takes no account of changes in thermal conditions over a long time horizon [45]. In order to adjust model inputs to changing conditions, adaptive selection methods were applied. K-means clustering combined with the timeseries cluster kernel (TCK) increased model resistance, whereby machine tool productivity loss was reduced by 45% [45]. In comparison to TCK, Group-Lasso combined with particle swarm optimization (PSO) reduced the mean error from ±14μm to ±11μm (a reduction of about 21%) along the linear axes and from ±32 μm/m to ±22 μm/m (a reduction of about 31%) along the rotational axes [60]. Thus it was demonstrated that the Group-Lasso method combined with PSO is significantly better than k-means clustering combined with TCK. Thanks to the adaptive selection of key points one can increase the cost-effectiveness of the thermal error self-compensation system and the resistance of the model to changes in conditions.

The selection of key points reduces the dimension of the model input space whereby model training becomes more effective. Thanks to a reduction in dimensionality also the amount of data stored in permanent memory can be reduced. Apart from input variables selection, the following methods of dimensionality reduction have been used in thermal error modelling: principal component analysis (PCA) [8, 21, 41] and rough set theory [9, 41]. It is also worth to use dimensionality reduction algorithms (e.g. kernel principal component analysis (KPCA), RReliefF) which have been successfully used in other fields [61].

For data processing two kinds of scaling: scaling to an interval [23, 42, 43] and normalization [37, 45] have been used. Scaling is used to improve modelling accuracy [62]. One of the solutions showing the highest modelling accuracy (about 98.4%) used scaling to interval <0, 1> [23]. In order to evaluate the usefulness of scaling we compared two groups of solutions: solutions without preprocessing and solutions with scaling. About 70% of the solutions using scaling showed high accuracy (above 80%). In comparison with modelling without data preprocessing, the use of scaling more often results in high modelling accuracy. This means that the use of scaling enhances the chances of thermal error modelling improvement.

Using the dimensionality reduction methods (including the selection of input variables) one can increase model accuracy and resistance to changes in thermal conditions and save non-volatile memory space. Resampling methods are used to balance the data set, while scaling increases modelling accuracy. Also filtering is a noteworthy method of measurements processing as it has been used to remove noise from measurement series [43] and infrared camera images [10]. Moreover, the dynamics of thermal changes can have a significant bearing on the thermal error and so it should be taken into account by calculating the rate of temperature change over time. The methods of measurements preprocessing constitute a tool increasing the accuracy and cost-effectiveness of the self-compensation system and suppor-ting the automatic management of permanent memory. The self-compensation system can be further improved using the resampling methods and the dimen-sionality reduction algorithms which are successfully used in other fields.

5. MACHINE LEARNING MODELS

A major step in thermal error modelling is model learning which follows measurements acquisition and data preprocessing. By supporting the machine learning processes with advanced learning algorithms the thermal error will be modelled more accurately. It is essential to use algorithms for adapting the model to changes in conditions.

Among the machine learning models one can distinguish linear models and artificial neural networks. The following linear models are used in thermal error compensation:

- the linear regression (LR) model [11, 18, 21, 22, 25–28, 35, 40, 43],
- the autoregressive moving average (ARMA) model [25, 35, 37, 45–48],
- the grey model (GM) [5, 7, 38, 42].

The following artificial neural networks are used in the modelling of the thermal error for compensating the latter:

- the multilayer perceptron (MLP) [4, 6, 7, 9, 14, 15, 17, 21, 24, 26, 29, 33, 35, 40–44],
- the radial basis function (RBF) network [8, 9, 16, 19, 20, 27, 28, 34, 36, 38],
- the adaptive neuro-fuzzy inference system (ANFIS) [2, 4, 6],
- the convolutional neural network (CNN) [10, 12, 43],
- the grey neural network (GNN) [3, 7, 42] and
- the recurrent neural network (RNN) [23].

The thermal error is most often modelled using MLP neural networks, linear regression and RBF networks.

Figure 5 shows data on the performance of thermal error models. Most of the models made it possible to reduce the thermal error to below 10 μm. Thermal error models usually were able to improve machine tool precision by a few tens of micrometers. After compensa-tion the thermal error would often decrease by over 80%.

In the solutions showing the highest performance the following neural networks were used: RBF [20], BiLSTM [23] and CNN [10]. Three groups of machine learning models: linear models, MLP and RBF networks and more complex models based on neural networks (ANFIS, CNN, GNN, RNN and others) were used. The linear models would usually model the thermal error with an accuracy of a few/10–20 μm, while the neural networks would usually attain the accuracy of a few micrometres. High accuracy (over 80%) was attained by about 45% of the solutions using linear models and by about 60% of the solutions using MLP or RBF networks. Over 80% of the solutions using more complex models attained high accuracy. MLP and RBF networks more often helped to attain high accuracy than linear models. In comparison with the other two groups of models, more complex models would most often attain high accuracy.

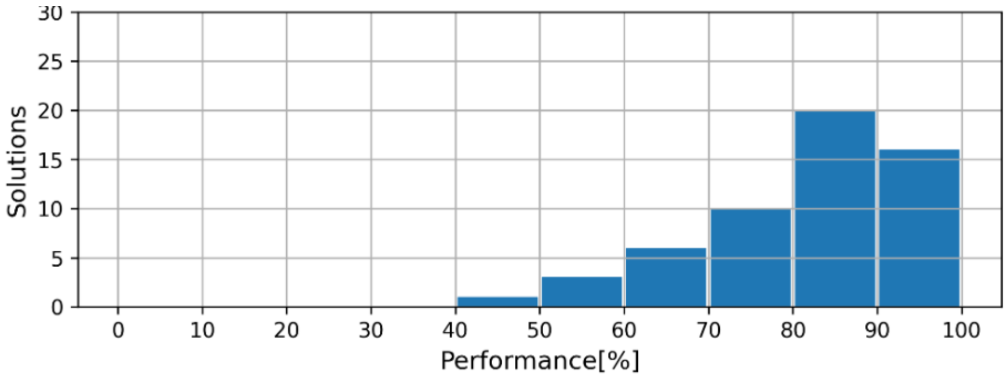

Fig. 5. Thermal error compensation performance of machine learning models

Transfer learning is successfully used in image recognition [63] and natural language processing [64]. An exemplary application of transfer learning and ensemble learning consisted in predicting milling process stability [65]. As transfer learning has been found to be effective in solving other problems, it is worth considering applying it in a similar way as it was used to predict milling process stability [65]. First a set of training data was generated using milling machine FE simulations. Then the whole data set was divided into N_{net} subsets. Each of the N_{net} MLP networks was trained on a different data subset (pre-training) and then it was fine-tuned on a set of data from an experiment. In order to predict the stability of the milling process the predictions made by all the N_{net} networks were averaged. Owing to this way of modelling both the knowledge contained in the FE model and the measurements taken during the experiment can be utilized. Thermal error modelling can be performed in a similar way.

Since it is not always possible to measure the thermal error it is worth employing semi-supervised learning methods which are able to use sample containing temperature measurements without thermal error measurements. These methods enable one to use temperature measurements alone during the machining process. Exemplary semi-supervised learning methods are: co-training and pre-training [66]. The application of co-training to thermal error modelling consisted in iterative training of two RBF models [19], while the application of pre-training consisted in unsupervised training and then supervised training of a deep belief network (DBN) [30].

The operating conditions of a machine tool can change to such in which the model will inaccurately estimate the thermal error. Hence it is necessary to use model algorithms for adapting the model to changing operating conditions (concept drift) [67]. Such algorithms were based on updating model parameters or applying ensemble learning algorithms. The self-compensation systems investigated to date have been based on model parameters updating [45, 47, 48]. Using ensemble learning algorithms one can save time and computing power when there is a need to respond to cyclic changes [67]. This means that the preferred thermal error model adaptation methods are ensemble methods which make it possible to more effectively respond to cyclic changes in machine tool ambient temperature. Exemplary ensemble learning algorithms are: addictive expert ensembles (AddExp), dynamic cross-company learning (DCL), on-line weighted ensemble (OWE) and dynamic and on-line ensemble regression (DOER) [68].

Change detecting algorithms make it possible to determine the timestamp at which a change occurs and the significance of this change, whereby they aid model adaptation [67]. Changes are detected on the basis of current measurements and/or the model's current accuracy. Change detection based on the current model accuracy requires thermal error measurement, which entails a reduction in machine tool productivity. Hence it is preferred to frequently use change detection methods based on current temperature measurements combined with the infrequent use of methods of detecting changes on the basis of the current model accuracy. Change detection based on the current model accuracy can take place periodically and/or when thermal error model uncertainty is too high. Active learning methods (e.g. Query By Committee) make it possible to assess thermal error model uncertainty without measuring the error itself [51].

It emerges from the thermal error modelling research to date that the use of complex machine learning models increases the chances of attaining high accuracy. Also it is recommended to use ensemble learning algorithms to make the thermal error model adapt to changes. Thus it is advisable to model the thermal error using the ensemble model being a combination of various machine learning models. Advanced model learning methods (transfer learning and semi-supervised learning) make it possible to use the knowledge contained in the FE model and in the temperature measurements taken during machining. Z. Niu et al. performed review on attention mechanism [69], which enables embedding adaptive key temperature measurement points selection into machine learning model. Change detection algorithms and active learning algorithms support model adaptation. Using the ensemble model combined with the above-mentioned learning and adaptation methods one can create an cost-effective and precise self-compensation system.

6. CASE STUDY

This case study describes three thermal error modelling methods which showed the highest accuracy [10, 20, 23]. Then research on long-term thermal error compensation desirable in industrial applications is discussed. Finally the direction for further research on thermal error modelling by means of machine learning is indicated.

The highest thermal error modelling accuracy amounted to about 98.5% [20]. In the latter study the thermal error along axis Z and temperature in 12 points were simultaneously measured at every 3 minutes. The training set size was 6 h while the testing set size was 5 h. Using partial correlation analysis two key points were selected from twelve temperature measurement points. The thermal error was modelled using the RBF network. Thanks to this modelling method the thermal error was reduced from ±55 μm to ±0.8 μm (a reduction of about 98.5%).

A very high modelling accuracy (98.4%) was attained by the BiLSTM network [23]. The thermal error along axis Z in a horizontal machining centre was modelled. First the thermal error (measured by a capacitive sensor) and the temperature in 8 points (measured by PT101 sensors) and the rotational speed were simultaneously measured at every 2 s. The training set size amounted to about 30 min, while the testing set size amounted to about 90 min. Data preprocessing with scaling was employed to improve modelling accuracy. Thanks to this modelling method the thermal error along axis Z was reduced from ±80 μm to ±1.3 μm (a reduction of about 98.4%) and the total machining error along axis Z was reduced from about ±100 μm to ±15 μm (a reduction of about 85%).

Also the thermal error along the X and Z axes of a milling machine was very accurately modelled using CNN (an accuracy of 94.3%) [10]. First the thermal error (measured by an inductive LVDT sensor), the temperature in 6 points (measured by PT100 sensors) and the thermogram (measured by a FLUKE Ti400 infrared camera) were simultaneously measured. The training set size was 15 h, while the testing set size was 5 h. First the initial thermogram was removed from the infrared camera images and thermogram noise was reduced using a median filter. Then thermogram transformations (symmetrical reflections and trimmings) were applied to generate a larger amount of data. Thanks to this modelling method the thermal error was reduced from ±12 μm to ±1μm along axis *X* and from ±35 μm to ±2 μm along axis *Z*. Thus the maximum machining error was reduced from ±35 μm to ±2 μm (a reduction of 94.3%).

Even though they performed well on the testing set, the above methods may not work in industrial applications as the testing procedure did not verify the long-term accuracy of thermal error modelling. Only methods which work long-term are useful in industrial applications.

Several attempts at realizing long-term thermal error compensation have been made [27, 45, 47, 48, 60, 70]. One of the ways to realize long-term compensation is to train and test the model on data from different seasons of the year [27]. First the thermal error along axis *Z* and the temperatures in 7 points were simultaneously measured at every 3 min. In total, 48 h of data (the training set – 32 h, the testing set – 16 h) from different seasons of the year were collected. Using c-means clustering and GRAM combined two key temperature measurement points from seven were selected. The following modelling methods: linear regression and the RBF network were compared. Linear regression, reducing the thermal error from ±70 μm to ±6 μm (a reduction of about 91%), was found to be the better model.

There is always a risk that the model trained in this way will become inaccurate in the future due to a change in the conditions. In order to prevent this, self-learning has been employed [45, 47, 48, 60, 70]. The R-Test procedure was used to measure the thermal error by means of a measuring probe. This method enables the automatic measurement of the thermal error, which is necessary in the practical application of self-learning. In the above-mentioned works the thermal errors was modelled using the linear ARMA model. The firsts applications of cyclic model fine-tuning consisted in thermal error modelling on the basis of temperature measurements in 2 points [47, 48]. In next study into self-learning 25 temperature sensors were used [45]. First the model was trained on a data set of 12 h. Then for 96 hours the model was cyclically trained at every 12 h. At the beginning of each model fine-tuning cycle the measurements were scaled and using the x-means algorithm the number of clusters into which the temperature measurement points could be divided was determined. Then using k-means clustering and the TCK method combined the key temperature measurement points were selected. At the end of the fine-tuning cycle the ARMA model parameters were updated. Thanks to the use of such a method the thermal error was reduced from ±22 μm to ±6 μm (a reduction of about 73%). Owing to the use of the adaptive selection of key points the loss of machine tool productivity was reduced by 45%.

Then an investigation into increasing the cost-effectiveness of the self-compensation system by using the detection of changes in the thermal conditions, based on a one-class support vector machine (SVM), was carried out [70]. Thanks to such detection the machine tool productivity loss was reduced by 78% with no significant decrease in self-compensation system precision. It appears from the latest research on the autonomous compensation system that a system based on the adaptive selection of input variables and the updating of the ARMA model by means of the Group-LASSO method combined with the PSO algorithm is in a long time horizon (a few months) more precise than the previously investigated system by at least 20% [60].

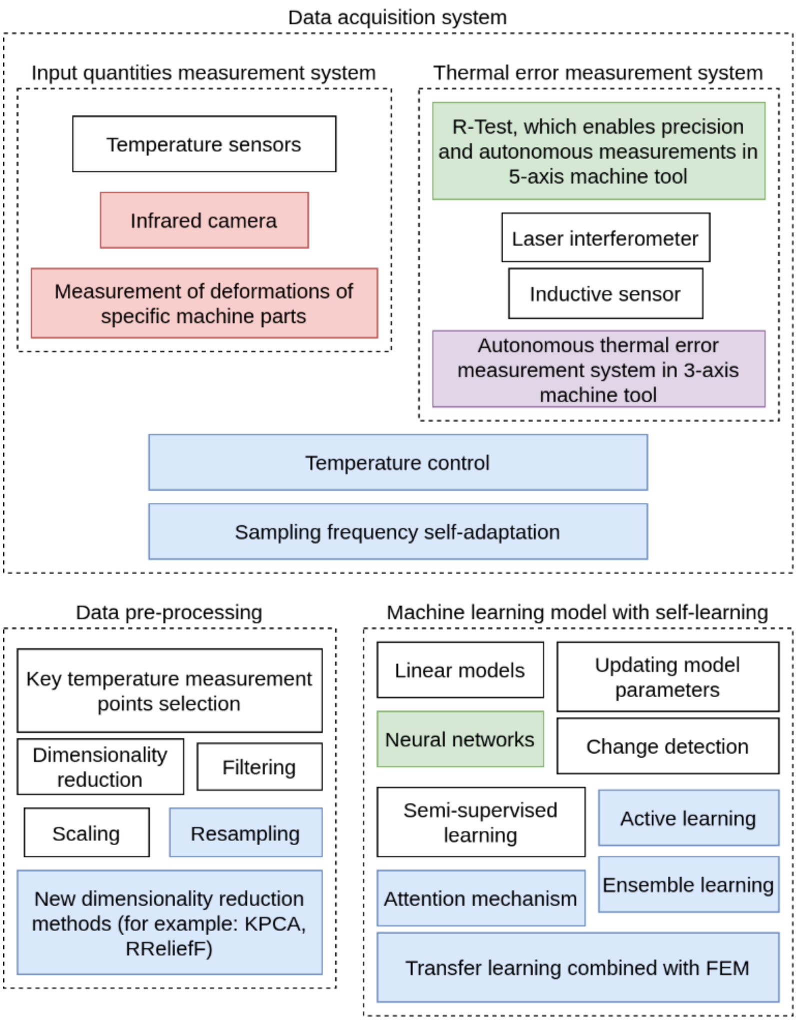

Fig. 6. Graphical representation of this review results. It is showed that, thermal error compensation is developed in three areas (data acquisition, data pre-processing and machine learning model with self-learning). Legend: green – preferred methods, red – very expensive methods, blue – new possibilities of improvement, purple – future challenge

An additional improvement increasing the autonomy of this system was the use of maximum allowable error adaptation (through the choice of the maximum error during model fine-tuning). Thanks to this system over a long time the mean error was reduced from ±28 μm to ±11 μm (a reduction of about 61%) along the linear axes and from ±36 μm/m to ±22 μm/m (a reduction of about 39%) along the rotational axes.

Thermal error compensation is used in order to increase machining precision. Therefore the most important requirement which thermal error modelling methods must meet is their long-term accuracy in conditions close to the ones in which machining takes place. In order to increase self-compensation system usefulness one should take thermal error measurements in conditions which temperature measurements are closest to those taken during machining.

Autonomy, precision and cost-effectiveness of thermal error self-compensation system can be further improved by improving data acquisition, data processing, the models and adaptation to changes in thermal conditions. Thanks to measurement sampling frequency adaptation the autonomy of this system will increase, while the use of resampling and dimensionality reduction methods which have been successfully used in other fields will make it possible to increase the accuracy of modelling and to support the automatic management of permanent memory. Ensemble learning algorithms will help to increase the model's accuracy and adaptability to changes in conditions. Modelling accuracy can also be further improved through the use of advanced learning methods (transfer learning and semi-supervised learning) which are able to use the knowledge contained in the FE model and in the temperature measurements taken during machining. Through the proper use of active learning methods it will be possible to minimize the machine tool productivity losses resulting from the taking thermal error measurements. The above-mentioned methods open up possibilities for further improving the quality of self-compensation systems. Figure 6. shows new possibilities of improvement in the field of thermal error compensation of machine tools.

7. CONCLUSION

Owing to machine learning one can create, a precise and inexpensive to maintain, machine tool thermal error self-compensation system which will operate in real time and automatically adapt (through self-learning) to changes (caused, e.g., by a change of the machining program) in the thermal conditions. Moreover, by means of transfer learning machine learning can be combined with other modelling techniques (e.g. the finite element method). The above analysis of the thermal error modelling methods, covering in detail the measurement methods, data preprocessing and the models used, has indicated the possibilities of improving thermal error compensation. This improvement consists in enhancing the autonomy, precision and cost-effectiveness of the self-compensation system. A huge potential lies in the use of ensemble models which make it possible to combine various machine learning models and to use more effective self-learning algorithms.

A special challenge is posed by the implementation and comparison of precise and cost-effective methods of thermal error model adaptation (self-learning). These methods should be tested on naturally (in operating conditions) changing conditions and on artificially generated changes in the conditions. The publication (e.g. on GitHub or OpenML) of reference data sets so that they are available to third parties would help to compare modelling and adaptation methods. The publication of reference data set documentation in the form of an article (the so-called data paper), which should include a description of the data set and information about its accessibility, is very important. Frank Hoffmann presented general recommendations concerning reference data set publication [71]. Such a data set should contain temperature and thermal error measurements and temperature measurements taken during machining. The published data set would make it possible for researchers to verify modelling and adaptation methods without performing measurements on the machine tool. When testing adaptation methods one should treat the data set as a data stream.

The conclusions drawn from the existing research will be useful in the future research on thermal error self-compensation. Also a way of increasing the usefulness of the solutions described in the literature has been proposed. Further comparative studies will make it possible to evaluate which of the modelling and adaptation methods are more effective as regards machine tool precision and productivity. The future challenge is implementation of autonomous thermal error measurement system in 3-axis machine tool. Another very important challenge is improvement of thermal error modelling and self-learning methods in terms of precision and productivity losses of machine tool.

The implementation of a precise and cost-effective thermal error self-compensation system brings benefits resulting from raising the quality of the manufactured products at no significant increase in the production costs. In the further future it will be possible to integrate the self-compensation system with an autonomous machine tool to increase its machining precision while preserving its autonomy.

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