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A review on transfer learning in spindle thermal error compensation of spindle

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Abstract: Data-driven approaches offer unprecedented opportunities for smart manufacturing to facilitate the transition to Industry 4.0-based production. One of the key factors affecting the accuracy of machine tools is the thermal error caused by thermal deformation. A major heat source among those that cause thermal deformation in machine tools is the spindle. Transfer learning plays a key role in developing intelligent systems for thermal error prediction in machine tools. In this paper, the opportunities and challenges of migration learning for thermal error modeling of spindles are reviewed. The main models of transfer learning are discussed, including, and their application to spindle thermal error modeling is overviewed. The purpose of this paper is to provide a basic introduction to the whole process of thermal error compensation in spindles and to give an overview of the different topics of thermal error modeling methods.

Keywords: transfer learning; domain adaption; machine tools; subspace metric; thermal error prediction

1. Introduction to data-driven smart manufacturing

As a symbol of the modern level of mechanical manufacturing, precision machine tools are becoming increasingly important. With the continuous development of industrial technology, the requirements for machine tool precision are also increasingly high [1]. The final processing accuracy of CNC machine tools is affected by many sources of error, which can be mainly categorized into:

(a) geometric and kinematic errors,
(b) thermal errors,

(c) cutting-force induced errors,

(d) other errors such as the tool wear and the errors induced by assembling and chattering.

Thermal error is generated by the deformation or distortion caused by the heat and temperature rise of the machine components, which is the main factor affecting the stability of machine tool accuracy, accounting for about 40%–70% of total machine tool error [2]. Nevertheless. Even if the static accuracy of the machine tool is very high, but in use due to changes in ambient temperature and the heating of moving parts, *etc.*, will also lead to a reduction in the accuracy of the machine tool [3]. However, due to their error items, highly coupled and complex generation mechanism, and some of the errors have time-varying and dynamic characteristics, so there are still major technical difficulties in the measurement and modeling [4].

Methods for reducing and eliminating thermal errors have been a hot research topic. The error compensation method eliminates or reduces the original thermal error by creating an artificial error, which has the advantages of wide application range and low cost. There are two main categories of thermal error modeling methods: mechanism models and data-driven models [5]. The theoretical thermal error model, mainly from the thermal deformation mechanism to study, from heat to temperature to thermal deformation of the entire thermal deformation process to study the relationship between the three, to optimize the spindle structure and can achieve the prediction of spindle thermal error, but the model is more complex in the solution process, there is a situation of non-convergence [6]. Data-driven thermal error utilizes a learning mechanism to establish a mapping relationship between surface temperature and spindle thermal error, which does not rely on much a priori knowledge, but rather on easily collected sensor data [7,8]. There is difference in thermal error prediction methods based on machine learning, deep learning and transfer learning as shown in Figure 1. In recent years, due to the increase of relevant thermal error data and the improvement of massively parallel computing capability, the data-driven deep learning based thermal error modeling method has gradually become a research hotspot. Data is a key factor in the adoption of smart compensation. The training and prediction of thermal error models under multiple operating conditions data become a high-dimensional, big data processing problem [9]. Deep learning-based thermal error modeling has achieved significant success, but the two main issues of data distribution and data availability still need to be considered. First, the distributions of training data and test data are assumed to be the same in deep learning models. However, in real-world scenarios, operating conditions such as load and speed can vary greatly depending on the task [10]. Therefore, the distribution of test data and training data is different when collected under different operating conditions. Second, the deep learning model's performance depends largely on the amount of labeled data used to adjust the model weights and biases [11,12]. However, collecting and labeling a large amount of data is a time-consuming and laborious task. The performance of deep learning-based thermal error prediction in general is not guaranteed if the problem of data collection and labeling under different operating conditions cannot be well solved.

Transfer learning improves the performance of target learners in the target domain by transferring knowledge from different but related source domains [13,14]. This reduces the dependence on a large amount of target domain data for constructing the target learner. Transfer learning has become a popular and promising field due to its promising applications [15]. Although there have been some valuable and impressive thermal error modeling applications on transfer learning, these relatively isolated approaches do not provide a complete review of the research progress of transfer learning in thermal error modeling. Due to the rapidly expanding field of transfer learning, a comprehensive review of related research is both necessary and challenging.

This study reviews the applications, opportunities, and challenges of data-driven methods applied to thermal error modeling, focusing on transfer learning methods for thermal error modeling.

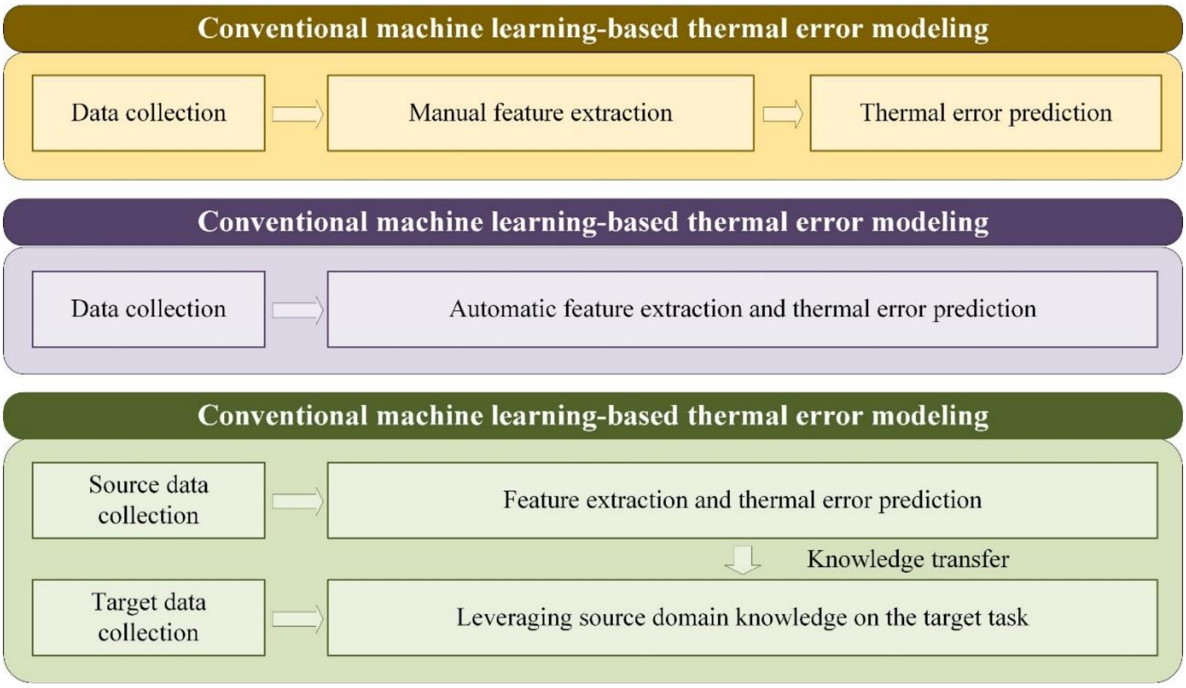

Figure 1. Differences between machine learning-based, deep learning-based, and transfer learning-based thermal error prediction methods.

2. Intelligent compensation system framework

The transition to intelligent machining processes requires the development of intelligent systems for thermal error modeling and compensation. A typical test setup for a five-degree-of-freedom thermal error of a spindle is shown in Figure 2 [16]. The test mandrel is mounted on the spindle, and the fixture that holds the displacement sensor is bolted to the work table. Displacement sensors X1 and X2 are mounted in parallel on one side of the test mandrel and Y1 and Y2 are fixed on the other side of the test mandrel. The angle between X1, Y1 and X2, Y2 is 90°. With this device it is possible to obtain axial thermal errors (Z-direction), two radial thermal errors (X-direction and Y-direction) and two tilt thermal errors.

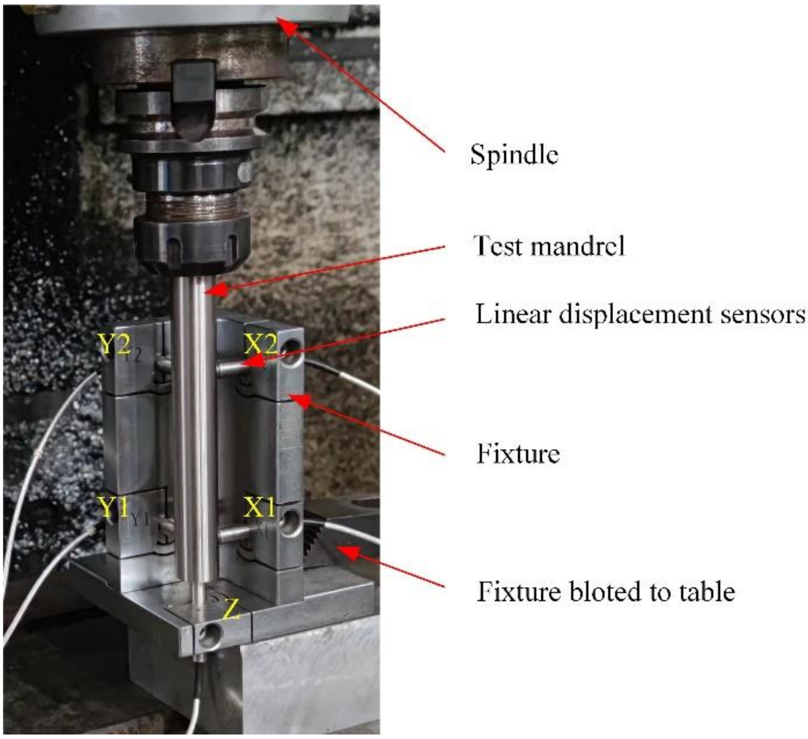

Figure 2. 5-DOF spindle thermal error typical test equipment.

2.1. Sensor selection

In current data-driven thermal error-based modeling, widely used model inputs include temperature, power, current, rotational speed, and cutting force [17]. There are many reasons that affect the selection of a sensor, including machining conditions, the distance between the sensor and the spindle, the difficulty of placing and positioning the sensor, and the presence of cutting fluids or dust [18]. A choice can be made between contact and non-contact sensors depending on actual requirements. The complex structure of data composed using various sensors and machine vision systems makes it challenging to integrate this data [19].

2.2. Thermal error compensation

Error compensation is the process of artificially creating an error to offset the original thermal error of a machine tool. Thermal errors of machine tools can be significantly reduced by thermal error compensation with low cost and flexible application, which can be implemented on machines already in operation [20,21]. For open CNCs, the error compensation algorithm can be written into the main CNC program; for semi-closed commercial CNCs, an external compensator can be used. For most researchers, external compensators are the primary implementation of error compensation. The external compensator reads the position, speed and other information needed for real-time compensation through the communication protocol of the CNC system, and then calculates the compensation amount in real time through the compensator, and writes the compensation amount into the CNC system [22].

3. Transfer learning

3.1. Definitions and notations

Transfer learning is a learning method mainly for problems with only a few or even zero labeled samples in the target domain. As shown in Figure 3, the "knowledge" gained from historical tasks can be transferred to existing tasks through transfer learning, enabling cross-domain knowledge application [23,24]. There are some important definitions of basic concepts of transfer learning presented.

Definition Domain: A domain D is comprised of a feature space X and a marginal probability distribution $P(\boldsymbol{X})$, where $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_n\}$, $\boldsymbol{X} \in X$.

Definition Task: A task T is composed of a label space y and a mapping function $f(x) = Q(y|\boldsymbol{x})$, which represents the conditional probability distribution.

Definition Transfer learning: In transfer learning, with source domain D_s, target domain D_t, source task T_s and target task T_t, knowledge gained from D_s and T_s is used to enhance the learning of $f_t(\boldsymbol{x})$ learning in D_t, where $D_s \neq D_t$, exclusive or $T_s \neq T_t$. $D_s = \{X_s, P(\boldsymbol{X}_s)\}$.

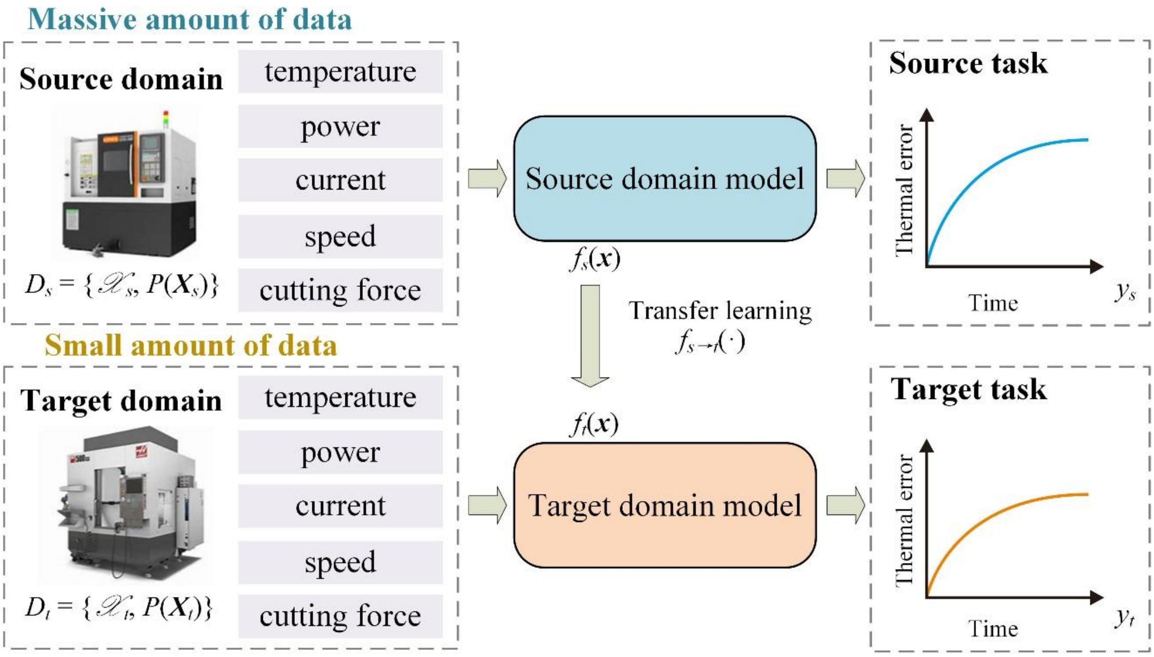

Figure 3. Illustration on transfer learning-based thermal error prediction.

3.2. Types of transfer learning

Data-driven approaches should meet the current needs of the industry in different ways. Manufacturing requirements regarding data-driven approaches include these: dealing with high-dimensional problems; reducing the possible complexity of the results and providing transparent and specific recommendations; adapting to changing environments with reasonable effort and cost; and advancing existing knowledge by learning from the results [25–27]. The internal and interrelationships of the processes involved and the required correlations or causality need to be identified [28]. Deep and transfer learning are two of the most important tools to fulfill the above requirements.

However, existing methods based on machine learning and deep learning are trained and predicted under constant conditions, which often require same distribution among the test data and the training data [29]. However, since machine tools often operate under different conditions, it is difficult for spindles operating under new operating conditions to directly use thermal error prediction models trained under old operating conditions [30]. On the one hand, a large amounts of historical data from past operating condition can't be effectively used [31]. On the other hand, because of the high cost of collecting data under new operating conditions, the general applicability of these methods is undermined [32]. Therefore, it is urgent to have an efficient method to predict thermal errors of spindles under different operating conditions. A single model is developed without the need to collect many labeled data under new conditions.

Based on the learning methods, transfer learning can be divided into the following four broad categories [33]:

(1) Instance-based Transfer Learning: The samples in the source and target domains are transferred by weight reuse. The data samples are repeated for transfer learning depending on certain weight generation rules.

(2) Model-based Transfer Learning: Parameter sharing models for source and target domains are utilized. The source and target domains perform the sharing of parameter information to realize the transfer approach. This transfer approach is used under the assumption that source domain data and target domain data can share certain parameters of the model.

(3) Feature-based Transfer Learning: Source domain and target domain are transformed by features into a same space. One is to convert the features of the source domain and target domain to each other to narrow the gap between the source and target domains. Another is to convert the features of the source domain and target domain into a unified feature space, and then classify and recognize them with traditional machine learning methods.

(4) Relation-based Transfer Learning: Logical network relationships in the source domain are utilized for transfer. The relationship is mainly mined and utilized for analogical transfer.

For relation-based transfer learning, it is necessary to find data in the source domain that is similar to the target domain. The weights of these data are adjusted so that they match the data in the target domain. The advantage of relation-based transfer learning is that the method is simple and easy to implement. The disadvantage is that the selection of weights and the similarity measure depend on experience, and the data distribution of the source domain and the target domain are often different. However, in the field of thermal error of machine tools, due to the diversity of working conditions, the data distribution of the source domain and the target domain are often different. In the field of thermal error prediction, the popular methods are model-based and feature-based methods. The model-based method achieve transfer between different models by tuning and adapting parameters. The feature-based methods map them into the same space where they obey the same probability distribution by transforming the features.

The similarity between the target domain and source domain, along with the amount of data in the target domain, are crucial indicators for choosing appropriate transfer methods [33]. As shown in Figure 4, the transfer learning schemes for thermal error modeling are categorized into four types according to the dataset size and the data similarity between source domain and the target domain. In Scenario I (S1), when the target domain dataset is large and closely resembles the source domain data, the network weights obtained from training on the source domain data can be largely preserved. Building on this, a satisfactory transfer learning thermal error prediction model can be achieved in the target domain by conducting several batches of training with the target domain data. In Scenario II (S2), the target domain data closely resembles the source domain data, making the transfer process similar to S1. However, fewer batches of target domain data are required to achieve a satisfactory transfer learning thermal error prediction algorithm in the target domain. In Scenario III (S3), the target domain dataset is small and has low domain similarity, training the network directly in the target domain makes it challenging to achieve the desired prediction goal. By transferring as many weights as possible from the network trained in the source domain and fine-tuning with a small amount of target domain data, the new network can more easily leverage information from the source domain, thereby increasing the likelihood of achieving the desired prediction goal. In Scenario IV (S4), the domain similarity is low but the target domain dataset is large enough. The use of network weights obtained from the source domain may result in the entire network weights being at a local optimum. A more reasonable approach would be to transfer only the network structure and reinitialize the weights for training.

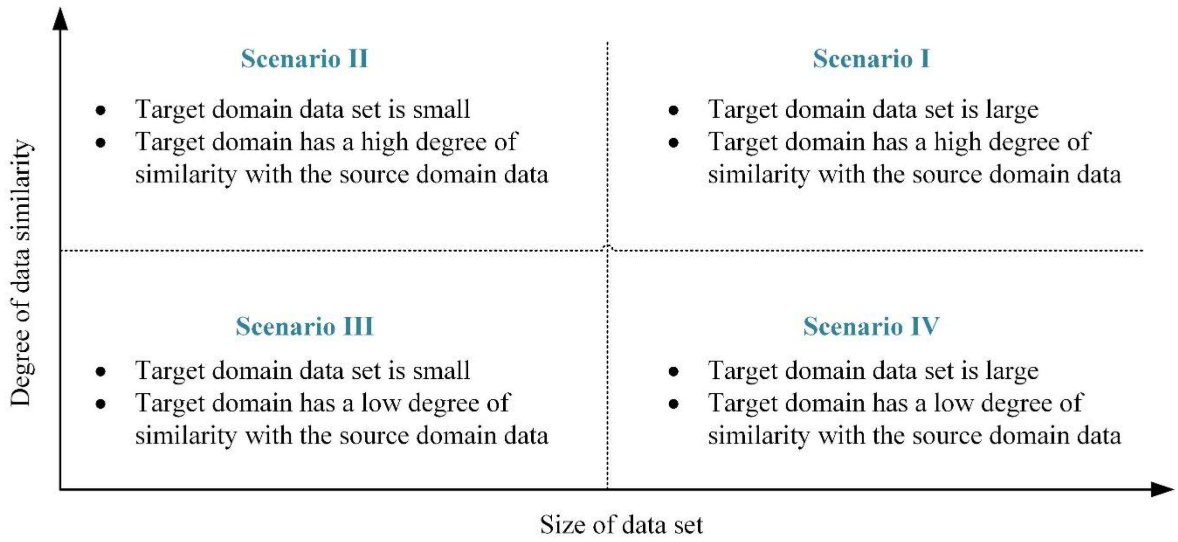

Figure 4. Transfer learning thermal error prediction algorithm scene diagram.

4. Applications of transfer learning in thermal error modeling

In the field of thermal error prediction based on transfer learning, popular approaches are model-based and feature-based approaches. The former realizes the transformation between different models by adjusting and adapting the parameters. Feature-based methods, on the other hand, map the features to the same space by transforming them so that they obey the same probability distribution.

4.1. Thermal error prediction with model-based transfer learning

Transfer learning, although developed in 2009, has only recently been used for feature extraction in thermal error modeling of machine tools. While retaining the data attributes, the features are projected into a low-dimensional potential space to uncover the principal characteristics of different domains under various operating conditions. Model-based transfer between different models is achieved by tuning and adapting the parameters.

Deep learning extracts hierarchical representations of features from raw data, whereas transfer learning offers an effective method for applying learning tasks across different but related datasets. It is important to note that deep transfer learning and multitask learning have different aspects [34]. Deep transfer learning aims to minimize the distributional differences between the source and target domains to enhance the classification accuracy. On the other hand, multi-task learning primarily emphasizes leveraging multiple features from source data during training to enhance the reliability of the metrics. Liu *et al.* [35] proposed the spotted hyena differential optimization algorithm (DSHOA), which utilizes a chaotic initialization strategy, differential variational operator, and nonlinear control factors to optimize the hyperparameters of the DRLSTMN. As shown in Figure 5, the thermal error prediction model is developed for machine tool #1, while a transfer learning model is created for machine tool #2 to improve the model's robustness. It is practical to fine-tune the dense layer of the pre-trained model to transfer the thermal error model from machine tool #1 to machine tool #2 using the transfer learning approach. Afterward, the transfer learning model can be retrained with minimal experimental data on machine tool #2. The parameters of some CNN and LSTM layers were frozen and the corresponding parameters of CNN, LSTM and Dense layers were retrained using the small volume of error data from machine tool #2.

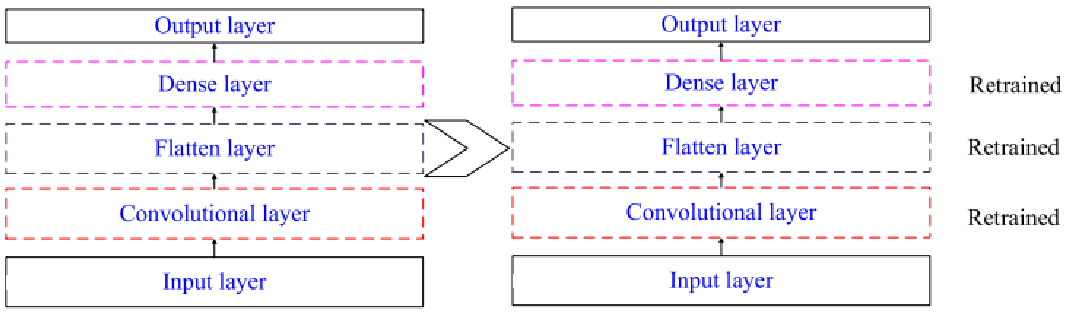

Figure 5. Domain-specific thermal feature alignment based on Gram matrix [35]. Reprinted with permission [36]. Copyright© 2022 Elsevier.

Liu *et al.* [36] proposed a thermal error model for the main axis and c-axis based on a transfer learning model (TLM) of sooty tern optimization (STO)-bilinear temporal convolutional network (BTCN). As shown in Figure 6, the parameters of the well-trained STO-BTCN model are shared and migrated to the model for the new working condition. Two BTCN layers are locked, restricting parameter updates in these layers to further shorten training time. Transfer learning also enhances the model's robustness and generalization capabilities.

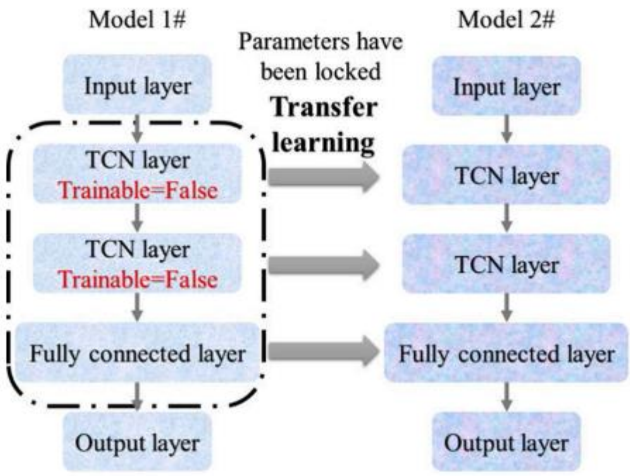

Figure 6. Transfer learning of BTCN [36]. Reprinted with permission [36]. Copyright© 2022 Elsevier.

4.2. Thermal error prediction with feature-based transfer learning

Feature-based transfer maps feature by transforming them into the same space where they obey the same probability distribution. In practice, the modeled machine tool may be different from the actual machine tool for which the thermal error prediction was performed [37]. This means that the differences between different machine tools can affect the thermal error prediction. Fortunately, with the help of migration algorithms, laboratory thermal error prediction models can be translated to the factory floor. Thus, thermal error prediction models are created for factory applications [38]. For this reason, several literatures have proposed transfer learning based thermal error prediction for spindle thermal error prediction between different machine tools.

Li *et al.* [39] use temperature field data from a small number of idle states and many stopped states of a machine tool to predict thermal errors, and propose a domain adaptive module to learn common features for different operating conditions as shown in Figure 7. The two modules share the output from the feature extractor. The convolutional layer in the feature extractor automatically learns the features from the data. A regression model is fitted to the thermal error based on the extracted features. The domain adaptive module learns domain invariant features by concatenating the features extracted by the convolutional layer. The difference between the two domains is estimated by the MMD metric. The formula for MMD is as follows:

$$MMD(\boldsymbol{X}_s, \boldsymbol{X}_t) = \left\| \frac{1}{N_s} \sum_{i=1}^{Ns} \varphi(x_i^s) - \frac{1}{N_t} \sum_{j=1}^{Nt} \varphi(x_j^t) \right\| \tag{1}$$

where N_s and N_t represent the number of samples in the source domain X_s and the target domain X_t, respectively, while $\varphi(\cdot)$ represents the function of the feature extractor and the fully connected layer.

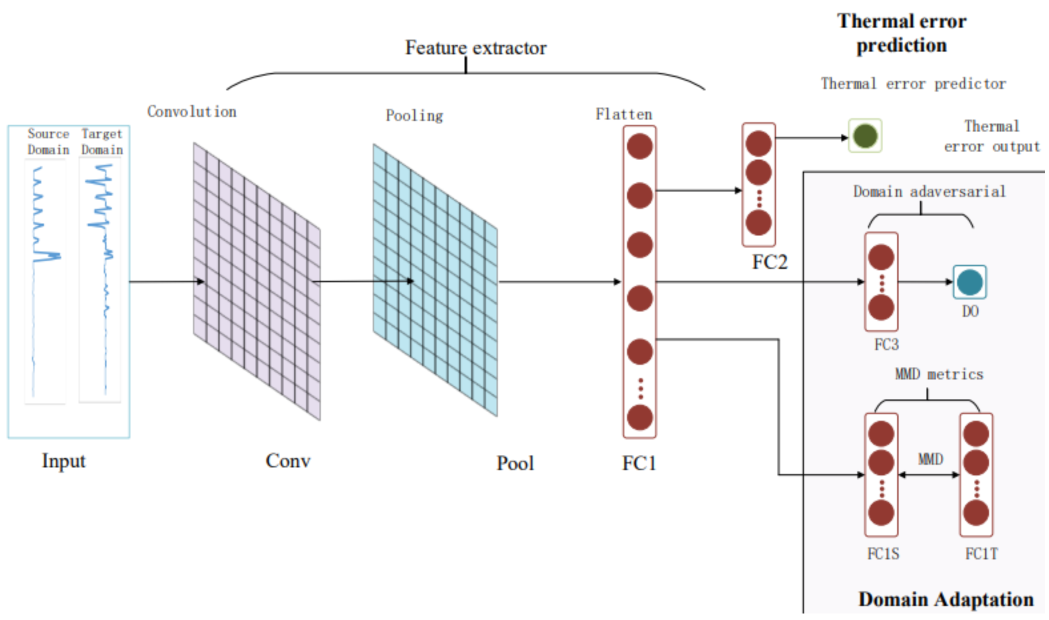

Figure 7. Deep transfer learning with feature-based transfer learning [39].

Due to the scarcity of labeled samples, transfer-domain adaptive methods have been applied to the prediction of thermal errors of machine tools under complex industrial conditions. However, the existing studies are largely based on the assumption that the target distribution is given and unchanging, which violates the fact that the working conditions in real production may change over time. Mao *et al.* [40] proposed a dynamic domain adaptive (SMDDA) thermal error prediction scheme based on subspace metrics in real time. A suitable feature mapping space is constructed to realize the alignment of the regression features. For the thermal feature $\boldsymbol{F}$ with d dimension and regression ground truth $\boldsymbol{Y}$, the parameter ϕ of the linear regression layer $\boldsymbol{Y} = \boldsymbol{F}\phi$ can be estimated by the closed-form solution of ordinary least squares

$$\varphi = (\boldsymbol{F}^{\mathrm{T}}\boldsymbol{F})^{-1}\boldsymbol{F}^{\mathrm{T}}\boldsymbol{Y} \tag{2}$$

where $\boldsymbol{F}^{\mathrm{T}}\boldsymbol{F} \in \mathrm{R}^{d\times d}$ represents the Gram matrix, and $(\cdot)^{-1}$ is an inverse operation.

The feature subspace is constructed in a way that breaks through the limitations of the traditional domain adaptive methods in the thermal error prediction problem. Based on the closed-form least squares solution of linear regression, the pseudo-inverse low-rank property is utilized to align specific subspaces of the inverse Gram matrix, *i.e.*, angle and scale alignment, instead of directly aligning the original feature embeddings. Aligning the angles and scales of features in a specific subspace improves the generalization performance of the transfer learning model while maintaining a high prediction accuracy.

As shown in Figure 8, Wang *et al.* [37] proposed a fast transfer learning-based modeling method for obtaining the power consumption model of a target machine tool. After deriving the power consumption model of the source machine tool through detailed experiments, this method requires only a small number of experiments to obtain the power consumption model of the target machine tool. It significantly enhances modeling efficiency and has been experimentally validated on various machine tools.

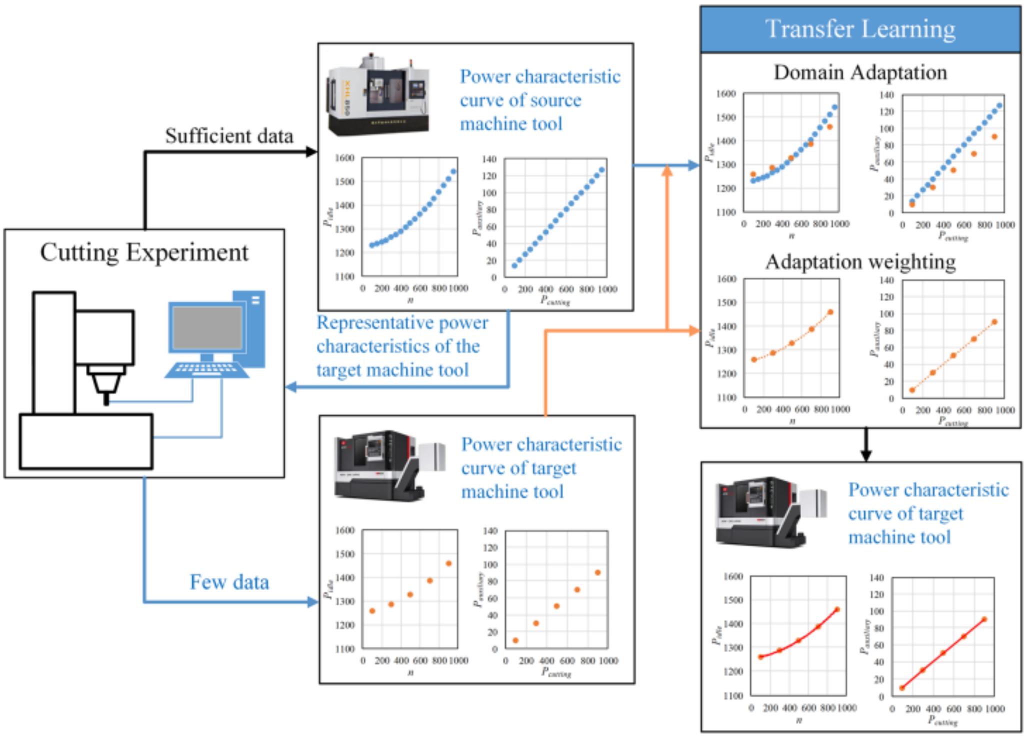

Figure 8. Transfer learning for predicting the power consumption of machine tools [37]. Reprinted with permission [37]. Copyright© 2024 Springer Nature.

Ma *et al.* [41] proposed a multicore joint maximum mean difference (MKJMMD) measure to minimize the distributional differences between the source and target domains. As shown in Figure 9, this approach enables a prediction model initially built on the source domain to adaptively and effectively predict outcomes in the target domain. The effectiveness of the proposed method is validated against other comparative methods by 12 transmission tasks with four operating condition data sets in the target domain where thermal error data are not available. The results demonstrate that the method addresses the challenge of having no labeled thermal error samples and outperforms other methods. A linear combination of multiple kernel functions is used to compute the MK-JMMD metric. This approach enables the model to capture various aspects of the data distribution and facilitates a more comprehensive alignment between the source domain and target domain. The source and target domains are mapped into the reproducing kernel Hilbert space (RKHS) using kernel functions in the JMMD metric. The joint probability distribution of the adaptive layers of the network is then aligned.

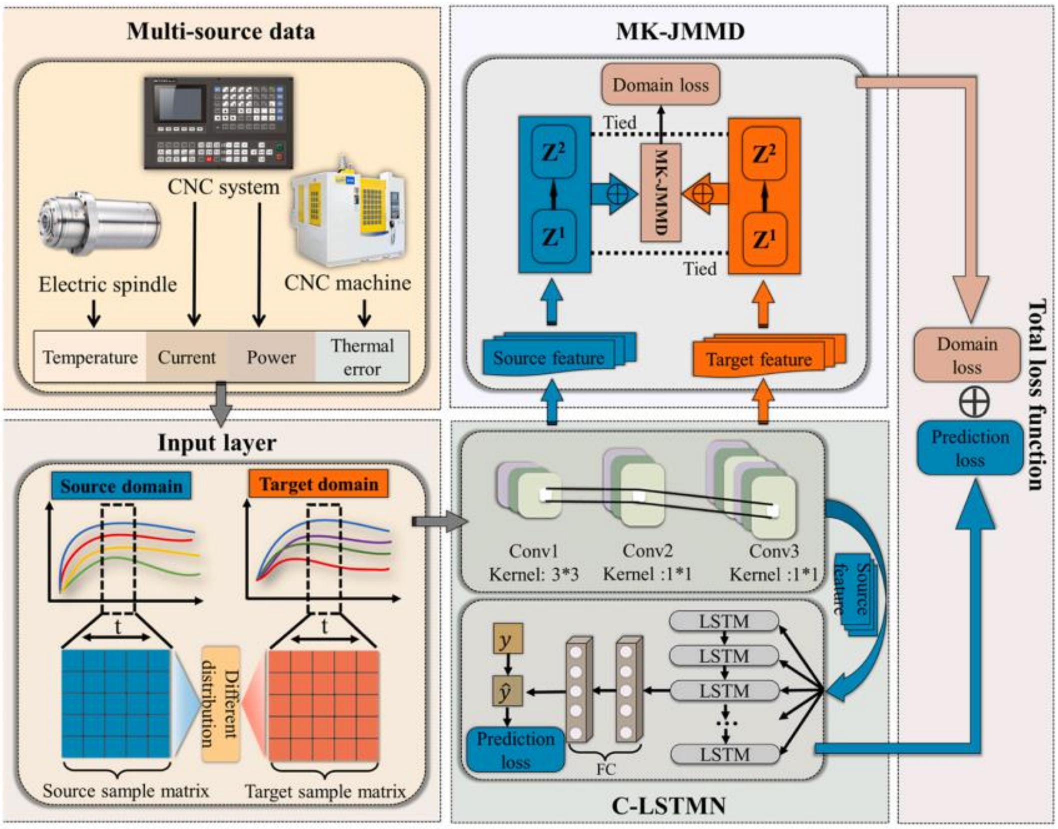

Figure 9. The framework of the proposed DJDAN [41]. Reprinted with permission [41]. Copyright© 2024 Elsevier.

5. Conclusions

An overview of the development of transfer learning-based thermal error in machine tools is summarized in this paper. Data-driven thermal error modeling methods are drawing a great deal of attention in both academia and industry. Many transfer learning algorithms have been applied to thermal error prediction, fault diagnosis, condition monitoring, and lifetime prediction of machine tools. Based on these results, transfer learning has become a hot research topic in the field of thermal error modeling. Feature-based transfer learning techniques and model-based transfer learning techniques have been widely used for thermal error prediction in machine tools. A detailed systematic guide is provided for researchers and practitioners who are about to start or expand their work on thermal error prediction by addressing the entire lifecycle of transfer learning, including data selection, data transformation, and model selection from transfer learning. Common transfer learning methods are presented and discussed, providing researchers and practitioners with options for appropriate data selection and transformation. Different transfer learning architectures are developed for different applications. Some requirements and recent advances in deep transfer learning are presented. Although the effectiveness of these methods has not been thoroughly assessed, transfer learning remains at the academic forefront of thermal error prediction. Further research is needed for spindle speeds and actual cutting conditions for different speed spectra.

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Conflicts of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' contribution

Yue Zheng: Investigation, Writing-original draft. Guoqiang Fu: Conceptualization, Supervision. Sen Mu: Investigation, Writing-review & editing. Sipei Zhu: Supervision, Writing-review & editing. Kunlong Lin: Supervision, Writing-review & editing. Long Yang: Supervision, Writing-review & editing.

References

[1] Jia GJ, Zhang X, Shen YJ, Huang ND. Intermittent multivariate time series spindle thermal error prediction under wide environmental temperature ranges and diverse scenario conditions. *Int. J. Adv. Manuf. Technol.* 2024, 132:4625–4643.

[2] Tian Y, Pan GY. An unsupervised regularization and dropout based deep neural network and its application for thermal error prediction. *Appl. Sci.* 2020, 10(8):2870.

[3] Wu CY, Xiang ST, Xiang WS. Spindle thermal error prediction approach based on thermal infrared images: a deep learning method. *J. Manuf. Syst.* 2021, 59:67–80.

[4] Makoto F, Koichiro N, Naruhiro I, Masahiko M, Soichi I. Adaptive thermal displacement compensation method based on deep learning. *CIRP Ann. Manuf. Technol.* 2019, 25:22–25.

[5] Li Y, Yu ML, Bai YM, Hou ZY, Wu WW. A review of thermal error modeling methods for machine tools. *Appl. Sci.* 2021, 11(11):5216.

[6] Li ZL, Zhu WM, Zhu B, Wang BD, Wang QH, *et al.* Simulation analysis model of high-speed motorized spindle structure based on thermal load optimization. *Case Stud. Therm. Eng.* 2023, 44:102871.

[7] Shi H, Zhang B, Mei X, Wang H, Zhao F, *et al.* Thermal error modelling and compensation of CNC lathe feed system based on positioning error measurement and decoupling. *Measurement* 2024, 231:114633.

[8] Liang YC, Li WD, Lou P, Hu JM. Thermal error prediction for heavy-duty CNC machines enabled by long short-term memory networks and fog-cloud architecture. *J. Manuf. Syst.* 2022, 62:950–963.

[9] Fabian S, Josef M, Clemens S, Petr Ka, Friedrich B, *et al.* Cloud-based thermal error compensation with a federated learning approach. *Precis. Eng.* 2023, 79:135–145.

[10] Li TJ, Sun TY, Zhang YM, Cui SY, Zhao CY. Dynamic memory intelligent algorithm used for prediction of thermal error reliability of ball screw system. *Appl. Soft. Comput.* 2022, 125:109183.

[11] Li PW, Lou P, Yan JW, Liu NY. The thermal error modeling with deep transfer learning, *J. Phys. Conf. Ser.* 2020, 1576:012003.

[12] Mori M, Mizuguchi H, Fujishima M, Ido Y, Mingkai N, *et al.* Design optimization and development of CNC lathe headstock to minimize thermal deformation. *CIRP Ann.* 2009, 58(1):331–334.

[13] Ye Z, Yu JB. State-of-health estimation for lithium-ion batteries using domain adversarial transfer learning. *IEEE Trans. Power Electr.* 2022, 37(3):3528–3543.

[14] Xia M, Shao HD, Williams D, Lu S, Shu L, *et al.* Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning. *Reliab. Eng. Sys. Saf.* 2021, 215:107938.

[15] Xiao YM, Shao HD, Han SY, Huo ZQ, Wan JF. Novel joint transfer network for unsupervised bearing fault diagnosis from simulation domain to experimental domain. *IEEE ASME Trans. Mechatron.* 2022, 27(6):5254–5263.

[16] Liu HY, Deng HG, Feng XY, Liu YD, Li YF, *et al.* Data-driven thermal error modeling based on a novel method of temperature measuring point selection. *Int. J. Adv. Manuf. Technol.* 2024, 131(3):1823–1848.

[17] Kuo PH, Tu TL, Chen YW, Jywe WY, Yau HT. Thermal displacement prediction model with a structural optimized transfer learning technique. *Case Stud. Therm. Eng.* 2023, 49:103323.

[18] Zhu MR, Yang Y, Feng XB, Du CZ, Yang JG. Robust modeling method for thermal error of CNC machine tools based on random forest algorithm. *J. Intell. Manuf.* 2022, 34(3):2013–2026.

[19] Tan F, Deng CY, Xiao H, Luo JF, Zhao S. A wrapper approach-based key temperature point selection and thermal error modeling method. *Int. J. Adv. Manuf. Technol.* 2019, 106:907–920.

[20] Zhang L, Ma C, Liu JL, Totis G, Weng SB. Multi-layer parallel-perceptual-fusion spatiotemporal graph convolutional network for cross-domain, poor thermal information prediction in cloud-edge control services. *Adv. Eng. Inform.* 2024, 59:102358.

[21] Soori M, Arezoo B. Dimensional, geometrical, thermal and tool deflection errors compensation in 5-Axis CNC milling operations. *Aust. J. Mech. Eng.* 2023:1–15.

[22] Li Y, Zhao WH, Lan SH, Ni J, Wu WW, *et al.* A review on spindle thermal error compensation in machine tools. *Int. J. Mach. Tool Manu.* 2015, 95:20–38.

[23] Zhuang FZ, Qi ZY, Duan KY, Xi DB, Zhu YC, *et al.* A comprehensive survey on transfer learning. *Proc. IEEE.* 2021, 109(1):43–76.

[24] Subramaniam V, Dbouk T, Harion JL. Topology optimization of conductive heat transfer devices: an experimental investigation. *Appl. Therm. Eng.* 2018, 131:390–411.

[25] Li C, Zhang SH, Qin Y, Estupinan E. A systematic review of deep transfer learning for machinery fault diagnosis. *Neurocomputing* 2020, 407:121–135.

[26] Lei MH, Jiang GD, Yang J, Mei XS, Xia P, *et al.* Improvement of the regression model for spindle thermal elongation by a boosting-based outliers detection approach. *Int. J. Adv. Manuf. Technol.* 2018, 99:1389–1403.

[27] Miao E, Gong Y, Xu Z, Zhou X. Comparative analysis of thermal error compensation model robustness of CNC machine tools. *J Mech Eng.* 2015, 51(7):130–135.

[28] Zhao ZY, Huang ND, Shen YJ, Jia GJ, Zhang X, *et al.* Modeling and prediction of full-term thermal error in linear axis of machine tools based on MSTGCN-A. *Int. J. Adv. Manuf. Technol.* 2024, 130(9):4805–4819.

[29] Michaleris P. Modeling metal deposition in heat transfer analyses of additive manufacturing processes. *Finite Elem. Anal. Des.* 2014, 86:51–60.

[30] Wang X, Wang TY, Ming AB, Zhang W, Li AH, *et al.* Cross-operating condition degradation knowledge learning for remaining useful life estimation of bearings. *IEEE Trans. Instrum. Meas.* 2021, 70:1–11.

[31] Kang CM, Zhao CY, Zhang JQ. Thermal behavior analysis and experimental study on the vertical machining center spindle. *Trans. Can. Soc. Mech. Eng.* 2020, 44(3):344–351.

[32] Kuo PH, Lee CH, Yau HT. Stacking ensemble transfer learning based thermal displacement prediction system. *Int. J. Optomechatron.* 2023, 17(1):2225573.

[33] Sun FS, Cao BH, Fan MB, Ye B, Pan JP. Physics-constrained transfer learning for self-assessment of terahertz thickness measurement of thermal barrier coatings. *IEEE Trans. Ind. Inform.* 2024, 20(9):11045–11056

[34] Sun C, Ma M, Zhao ZB, Tian SH, Yan RQ, *et al.* Deep transfer learning based on sparse autoencoder for remaining useful life prediction of tool in manufacturing. *IEEE Trans. Ind. Inform.* 2019, 15(4):2416–2425.

[35] Liu JL, Ma C, Gui HQ, Wang SL. Transfer learning-based thermal error prediction and control with deep residual LSTM network. *Knowl. Based Syst.* 2022, 237:107704.

[36] Liu JL, Ma C, Gui HQ, Li MY. Geometric-thermal error control system for gear profile grinding machine. *Adv. Eng. Inform.* 2022, 52:101618.

[37] Wang Q, Chen X, Chen M, He YF, Guo H. A rapid modelling method for machine tool power consumption using transfer learning. *Int. J. Adv. Manuf. Technol.* 2024, 131(3):1551–1566.

[38] Liu SG, Yang ZQ, Wei Q, Chen YS, Liu LB. Thermal Error Model of Linear Motor Feed System Based on Bayesian Neural Network. *IEEE Access* 2021, 9:112561–112572.

[39] Li PW, Lou P, Yan JW, Liu NY. The Thermal error modeling with deep transfer learning. *J. Phys. Conf. Ser.* 2020, 1576:012003.

[40] Mao HY, Liu ZY, Qiu C, Liu H, Sun JC, *et al.* Subspace metric-based transfer learning for spindle thermal error prediction under time-varying conditions. *IEEE Trans. Instrum. Meas.* 2024, 73:1–11.

[41] Ma S, Leng JW, Chen ZY, Li B, Zhang D, *et al.* A novel adaptive deep transfer learning method towards thermal error modeling of electric spindles under variable conditions. *J. Manuf. Syst.* 2024, 74:112–128.