Fleet learning of thermal error compensation in machine tools

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***Abstract*— Thermal error compensation of machine tools promotes sustainable production. The thermal adaptive learning control (TALC) and machine learning approaches are the required enabling principals. Fleet learnings are key resources to develop sustainable machine tool fleets in terms of thermally induced machine tool error. The target is to integrate each machine tool of the fleet in a learning network. Federated learning with a central cloud server and dedicated edge computing on the one hand keeps the independence of each individual machine tool high and on the other hand leverages the learning of the entire fleet. The outlined concept is based on the TALC, combined with a machine agnostic and machine specific characterization and communication. The proposed system is validated with environmental measurements for two machine tools of the same type, one situated at ETH Zurich and the other one at TU Wien.**

Keywords—fleet learning, machine tool, Industry 4.0, thermal error compensation, federated learning

I. Introduction

Thermal error compensation is a rising topic regarding the precision of machine tools (MT) in various environments. Thermal errors have a major influence on the geometrical shape of the finalized workpiece and therefore, also on the overall productivity of the machine tool. Referring to Mayr et al. [1], the behaviour of the thermal machine tool state is described in a thermal model. Blaser et al. [2] introduced a Thermal Adaptive Learning Control (TALC) to build a thermal model by on-machine measurements and uses this information for compensation. The model can handle changes in the environmental temperature and load-dependent changes. This rule-based model parameter adaption is increased over time to long-term robustness with an adaptive input selection, as presented by Zimmermann et al. [3].

A Fleet Learning Architecture (FLA) for driver assistance systems under challenging external conditions is presented by Wirthmüller et al. [4]. The data in such an architecture is collected from the fleet of vehicles and not only from the initial testing vehicle at the beginning of the process. Federated learning allows shared models to be trained from a bigger amount of decentralized systems and doesn't need to be centrally stored, as described by McMahan et al. [5]. This approach for machine learning in a federation of participating peers, together with a central server, is applied for systems, where only the main model is maintained from the centralized server. This paradigm reduces the amount of data that needs to be transferred between the server and each specific client. In machine tools especially client specific, private data produced by the machine tool, are not allowed to be shared with the other clients connected to the network. Federated learning approaches allow a high level of safety and security, which is mandatory for production. For example, it must not be possible to draw conclusions about the machining strategy or the components produced. In addition, people and employees specific data must also be handled in accordance with labour law.

Industry 4.0 promotes the transformation of physical assets to digital representation. Stoop et al. [6] describes that the model and communication architecture of such a representation are distinguished between model specific and model agnostic association. The information of each specific machine on the factory floor needs to be modelled according to this paradigm. Furthermore, the technological requirements must also be able to reflect this issue down to the program language and basic communication layer. Also, the scalability of such an architecture needs to be considered in all parts. This approach is also followed down to the auxiliary units of a machine tool and, referring to Gittler et al. [7], necessary for further studies like condition monitoring of the whole system.

This study aims to enhance the possibilities of thermal error compensation in machine tools with a fleet learning paradigm. The benefits of possible learnings from each machine tool in a whole fleet will leverage the productivity and performance of the entire fleet. This will result in a more economic and ecological production of parts and the operation of the fleet itself.

II. Method

To achieve the interchangeability of model data between machines, the interfaces designed must be powerful, to achieve a maximum of benefit, and of general acceptance in order to connect as many as possible clients to the network. Some TALC and machine specific aspects need to be considered. Initially, the TALC was always be implemented in the machine tools control or an edge device connected to the machine tool and is pre-set for the specific type. Nevertheless, the general approach of the TALC core is machine agnostic.

A. *Thermal Adaptive Learning Control*

The TALC procedure differentiates between an upstream calibration phase, followed by a compensation phase. In the first phase, the errors of the tool centre point (TCP) are determined by processing data from an on-machine measurement cycle. This cycle measures, according to Blaser [8], the deviation at the TCP with the built-in MT touch probe and a reference sphere, interrupting the manufacturing process. The determined relative errors are stored chronologically. Parallel to this, various temperatures sensors on the machine tool and its surrounding as well as machine tool performing data from the control are recorded. Precisely the environment temperature (ENV), the workspace temperature (WS), metal working fluid temperature and the inner cooling circuits temperatures are continuously recorded and stored. Further information like switch on/switch off of the metal working fluid, process interruptions, measurement raw data, etc. are stored additionally on the machine tools own edge devise.

TALC uses an autoregressive model with exogenous inputs (ARX) for prediction and compensation of the TCP-errors. The ARX Model consists of past and present inputs and past system outputs for the calculation of the current prediction, as described by Blaser [8]. The frequency of temperature inputs, although, are much higher than real TCP deviation feedback. The algorithm chose past predictions, together with available temperature measurements and control data, to predict the current deviations.

Fig. 1 illustrates the conceptual integration of the cloud integration in the TALC process. Machine tool 1 starts at its own time with the initial cloud model provided to each machine in the network from the cloud. This model is used during the first calibration phase. Afterwards, the initial cloud model is updated with machine specific parts and used for the actual compensation, as first machine tool 1 model. If the compensation reaches a threshold, the model is updated another time, to provide the best possible compensation again. At every model update, a set of new parameters are sent to the cloud, in order to enable that other machines can benefit from this information.

For example, if machine tool 2 is later connected to the network, it starts with the new advanced initial cloud model, that already is enhanced using the inputs from MT 1. This procedure is continuously repeated after every model update of each machine connected to the cloud. This procedure ensures the steady enhancements of the TALC model during the whole lifetime of the machine tool fleet.

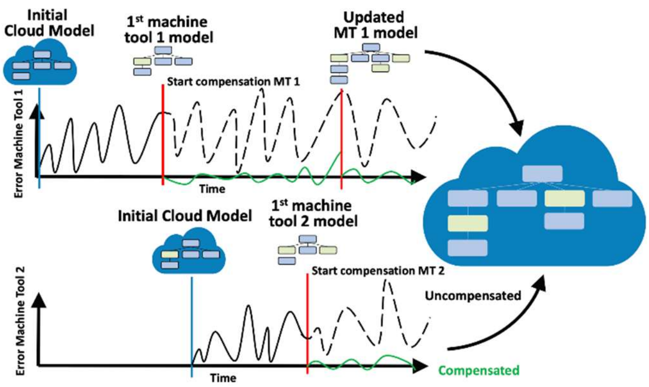

Fig. 1. Conceptual integration of the cloud data in the TALC

B. *Federated Learning*

The approach of Federated Learning (FL) uses a single model, which is shared between the central cloud and the distributed edges. According to Fernandes [9], the FL approach, in combination with Fleet Learning, reduces the required bandwidth of data in each direction and increases the general safety since the model is computed locally. Furthermore, only the model itself is shared with the cloud service and the data is stored and analysed locally, what is important to ensure the safety and secure of manufacturing data. If machine tools exchange data with a network privacy must be ensured. The data must not be usable for drawing conclusions to the manufactured parts or manufacturing strategies. Further on, it must be ensured, that the date could not be used for controlling machine tool users by giving information about e.g. breaks or set-up times.

Using TALC in the cloud this safety and secure level is reached by not exchanging raw data. The TCP error measurements are processed at the edge device describing the change of position and orientation errors of the machine tool as well as axis movement errors. Without knowledge about the previous data exchange, no information to the actual thermal error is possible. Noisy data, like the temperature measurements, are filtered and described by a discrete curve before exchanging. The data sent back to the machine tool, include the determined polynomial order of the thermal error model and the computed model parameters.

Fig. 2 shows a schematic of such a FL which is used for thermal error compensation of the described machine tool. The developed machine tool at the original equipment manufacturer (OEM) is used for the development of an initial TALC model based on the given states during development. The initial model is implemented during serial production of the MT. Each MT of this fleet will send only the model data to the central cloud server and gets the aggregated model data back. This global model, therefore, consists of each learning in every machine tool.

III. IMPLEMENTATION / INTEGRATION

The presented method is implemented on a 5-axis machine tool. One located at ETH Zürich (ZRH) and the other one located at TU Wien (VIE). This type of MT consists of three tool sided linear axes, and a workpiece sided rotary and swivelling axes unit, as illustrated in Fig. 3. The thermal behaviour of this particular machine tool ZRH is investigated by Gebhardt [10]. Both machine tools are of the same type and about ten years old, having different history, with different signs of wear and different MT accessories.

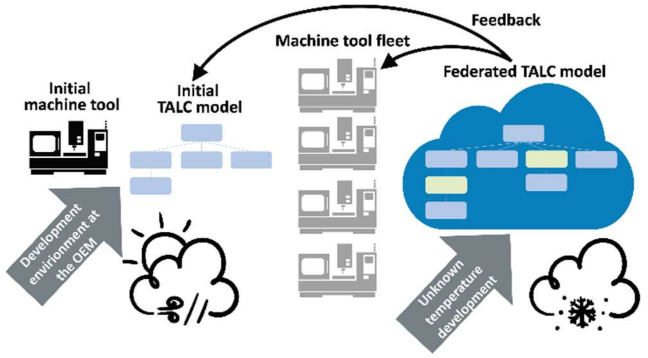

Fig. 2. Schematic of the federated learning with thermal error compensation

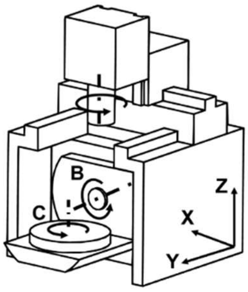

Fig. 3. Schematic of the 5-axis machine tool shown in Blaser et al. [2]

The workshop environment of both machine tools are also very different. In Zurich, for example, the machine is located in a non-air-conditioned workshop, right next to the hall door. While in Vienna, the manufacturing hall in which the machine tool is located is fully air-conditioned. Nevertheless, this aspect adequately represents the real-world conditions of an exemplary machine tool fleet.

A. *Cloud Communication*

The communication to the central TALC cloud is distinguished between machine agnostic and machine specific data. Fig. 4 illustrates the general communication setup. On the right side, the proof of concept machine tools from Zurich and Vienna are illustrated. The green parts represent the model parameter communication between the central TALC model and the representative on each machine. The gray parts are the machine specific temperature and error data, which have low information and can be stored optional in the cloud for further analysis.

The connection from the machine tool control to the cloud is realized through a distributed numerical control (DNC) interface on the MT side. This DNC acquires information about the machine status, TCP-error and general process information through the FOCAS 2 protocol from Fanuc. This information is communicated with the edge node represented by a PC, which is running MATLAB and communicating to the ThingSpeak Internet-of-Things (IoT) cloud. Furthermore, the temperature data is also acquired by temperature sensors, which are arranged in a bus network.

The advantage of this edge node setup is in the reliability and security of the proposed approach. The machine tool is still up and running in case of connection loss to the central server. This is an important aspect for the robustness in real world application. Also, the security of sensible data about the workshop condition and NC program are not forced to leave the environment of the MT user, which is a potential and severe security issue.

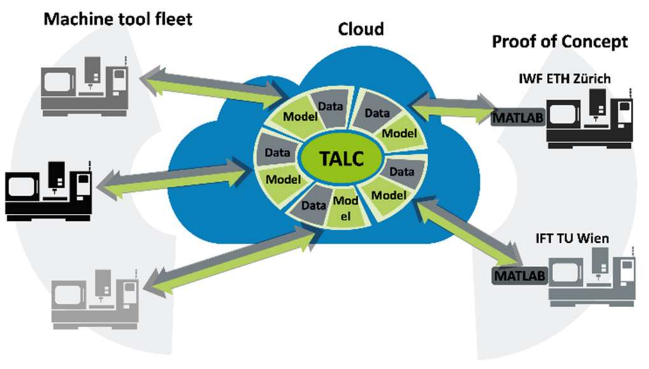

Fig. 4. Cloud communication concept with machine tool specific and machine tool agnostic data according to Stoop et al. [6]

IV. Results

The results of the proposed fleet learning are acquired on the two proof of concept machine tools in Zurich and Vienna.

A. *Environment Test*

The performed environment tests are evaluated for a 70-hour period on the MT in Vienna and for 96-hour in Zurich. The added TCP-errors based on the measurements and temperatures are presented in Fig. 5 for Vienna and Fig. 6 for Zurich. The resulting environment temperatures (ENV) directly shows the difference regarding the air-conditioning in Vienna and the typical daytime cycle in Zurich. The workspace temperature (WS) also indicates the amplitude and phase shifted dependence on the ambient temperature in this no-load test procedure.

The uncompensated relative error, which is based on the measurements and the predicted error, shows a short warm-up period of a few hours and afterwards a strong dependency between the error Y0C and the environment temperature. It is also stated that the error Z0T is always negative in the case of the machine tool in Vienna and mostly positive in the case of Zurich. This result is directly linked with the environment start temperature, which is, in the case of VIE, mostly higher than during the measurement and ZHRs mostly lower. The behaviour is described therefore, as inversely proportional.

B. *Compensation*

The machine tool is compensated with the TALC in the cloud procedure during the described environment test. Fig. 7 shows this compensation based on the model built by the machine itself. The static drift is compensated very well, right from the beginning of the compensation period. Although, there are some peaks, for example, of the error Z0T after 10 hours and the error R0T around 40 hours, which are worse than the relative uncompensated values. The initial model and the following updates are compared to the model built according to the FL schematic.

Fig. 8 presents the thermal error compensated machine tool in Vienna after the first federated model built with the input from the machine tool in Zurich.

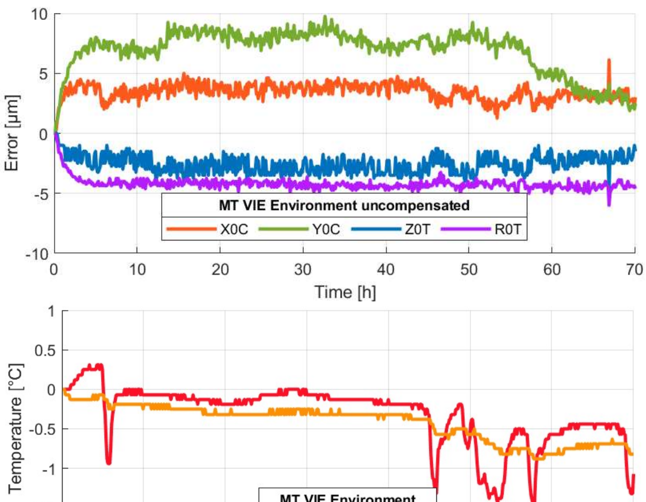

Fig. 5. Machine Tool VIE Environment Variation Error Test

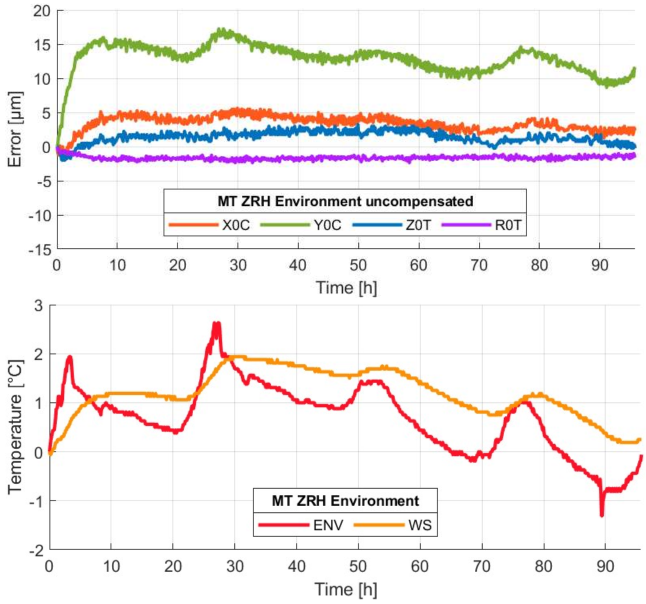

Fig. 6. Machine tool ZRH Environment Variation Error Test

The results are already much more robust compared to the first compensation model. Also, the significant temperature changes between 45 hours and 60 hours are compensated very well and do not make the model drift away for the last 10 hours. Furthermore, the anomaly between 30 – 40 hours of the VIE compensation model is not present. This is due to the learnings regarding the slow temperature changes from the ZRH model. The thermal error in the machine tool is reduced by 67 % in the first case with a single model compensation and by 86 % in the case of the federated learning model.

V. Discussion and Outlook

The presented fleet learning approach for thermal error compensation of machine tools is described in this paper. The thermal stability of machine tools is an important factor to prevent severe production downtime, scrap to enable a sustainable production. Fleet learning is an important and challenging step towards the further development of state-of-the-art algorithm like TALC towards the digital representation. This step also leverages the performance of each machine tool with the intelligence of the whole fleet around the world. The combination and integration of thermal states in the same type of machine tool is characterized using a cloud-based communication model. The proof of concept is illustrated with two real world machine tools and represented with their digital description of the thermal model. This is done without compromising the security and robustness of the implementation on each machine tool. The results are already promising and show a significant reduction of the thermal induced error with the two machines shown.

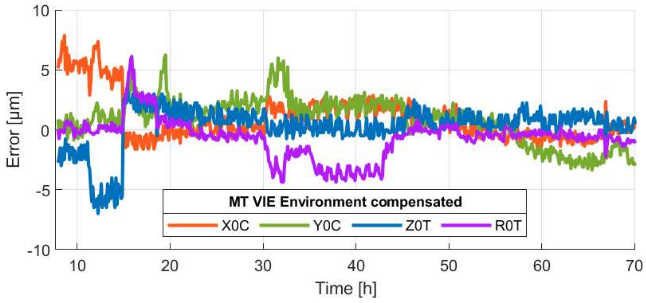

Fig. 7. Machine Tool Vienna real time compensated with their own model

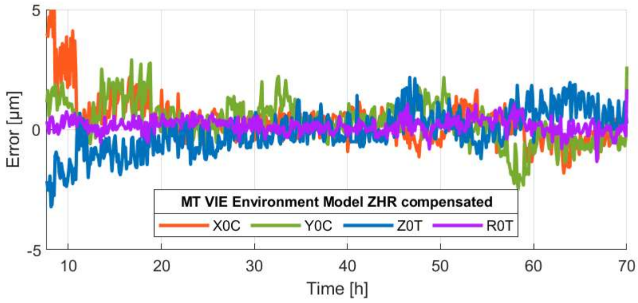

Fig. 8. Machine Tool Vienna simulative compensated with the initial Model from Zurich

Further research should be dedicated to the deployment of the federated learning under various load cases and with numerous of machines. Furthermore, the feature should be implemented in future control and machine tools in terms of Industry 4.0 ready and continuous learning over the whole machine tool lifetime. This step will further accelerate sustainable production and significantly influence the production of the future.

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