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Improved Thermal Behaviour Modeling of Turning Center using AGWO-Optimized xLSTM

Arpita Roy, N. Rino Nelson

Department of Mechanical Engineering

IIITDM Kancheepuram, Tamil Nadu, India

INTRODUCTION & AIM

Introduction:

Thermal deformation is a major source of positioning error in CNC machine tools due to uneven heat generation and complex temperature variations across machine components. The temperature data collected from multiple sensors is nonlinear, noisy, and exhibits strong time-dependent behavior, making accurate prediction challenging.

Traditional modeling approaches fail to capture long-term temporal dependencies effectively. Deep learning models such as xLSTM provide improved capability for handling sequential data, but their performance depends heavily on proper hyperparameter tuning.

Aim:

To develop an accurate thermal error prediction model using xLSTM and improve its performance using Adaptive Grey Wolf Optimization (AGWO).

METHOD

Dataset:

- Three experimental datasets collected from a CNC turning center were combined to form a unified dataset containing a total of **1371 samples**, ensuring sufficient data for training and validation.
- Each sample consists of **15 temperature sensor features**, strategically placed across critical machine components such as bearings, spindle, and structural elements to capture the thermal distribution within the system.
- The target variable is **Diameter Variation**, representing the thermal-induced dimensional error in the machining process, which directly impacts the accuracy and precision of the CNC machine.

Preprocessing:

- Unnecessary and redundant columns were removed, and missing values were handled to ensure a clean and consistent dataset for training the model.
- All input features were normalized using MinMaxScaler so that values lie within a similar range, which helps in improving model convergence and training stability.
- Time-series sequences were created using a sliding window approach with a sequence length of 10, allowing the model to learn temporal patterns in thermal behavior.

Model Architecture:

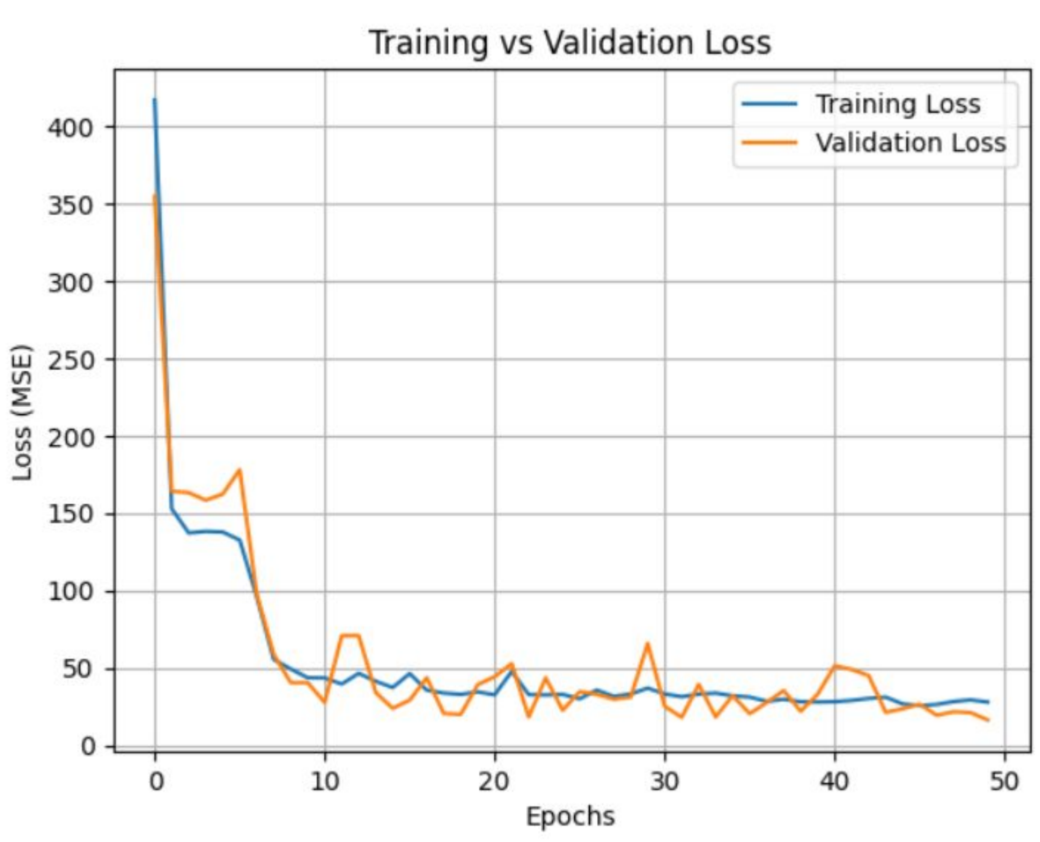
- Multi-layer LSTM (xLSTM structure)
- Dropout layers to prevent overfitting
- Dense layer for feature extraction
- Output layer for regression

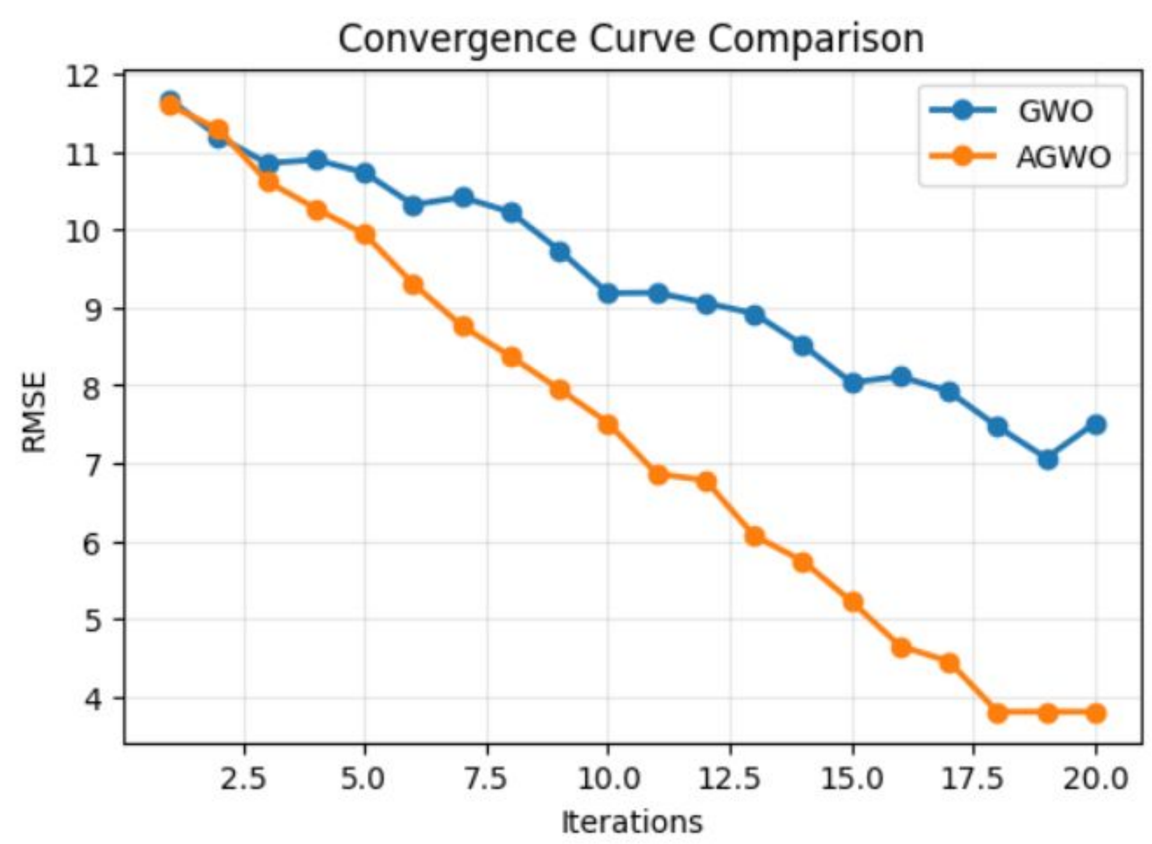
Optimization (AGWO):

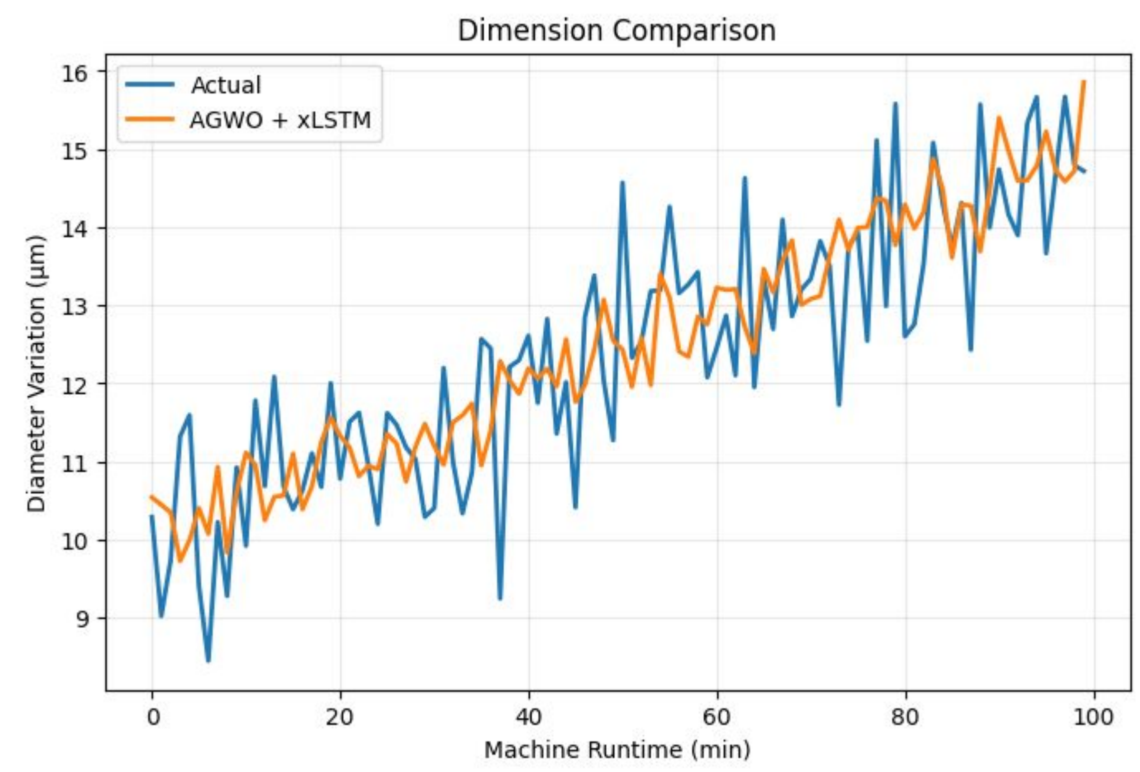
- Hyperparameters optimized:
  - Learning rate
  - Number of LSTM units
  - Dropout rate
  - Sequence length
  - Dense layer size

RESULTS & DISCUSSION

- The baseline xLSTM model achieved an RMSE of **5.57**, which improved to **5.19** after refining the model architecture and training strategy. Further hyperparameter tuning reduced the RMSE to **4.69**, showing a clear improvement in prediction accuracy.
- With the application of AGWO-based optimization, the model performance improved further, achieving an RMSE of approximately **4.0**, indicating effective optimization of hyperparameters.
- The variation of diameter with respect to machine runtime shows that the predicted values closely follow the overall trend of the actual thermal deformation. This demonstrates that the model successfully captures the temporal behavior of thermal errors.
- Minor deviations are observed during sudden fluctuations due to noise and dynamic thermal effects, but the overall alignment between actual and predicted values remains strong.
- The results highlight that combining deep learning with optimization techniques improves model accuracy, convergence behavior, and reliability for thermal error prediction in CNC machining.
  The training and validation loss curves show a steady decrease over epochs, indicating effective learning of the model.
- The validation loss follows a similar trend to the training loss, suggesting that the model generalizes well and does not suffer from significant overfitting.
- The convergence of both curves demonstrates stable training behavior and proper selection of model parameters.
- Early stopping helps prevent overfitting by retaining the best model weights during training.







CONCLUSIONS

- The xLSTM model effectively captures the thermal behavior of the CNC system and provides accurate prediction of thermal error.
- Model tuning improves performance, reducing RMSE from **5.57 to 4.69**, with further improvement achieved using AGWO optimization and brought down the RMSE to be around **4.**
- AGWO enhances convergence and achieves lower prediction error compared to conventional methods.
- The predicted results closely follow the actual trend, demonstrating effective learning of temporal patterns.
- Overall, the approach provides a reliable solution for thermal error prediction in CNC machining.

FUTURE WORK/ REFERENCES/ACKNOWLEDGMENT

Future Work

- Increase AGWO iterations to achieve better convergence and further reduce prediction error.
- Compare performance with other optimization techniques such as Particle Swarm Optimization and Genetic Algorithm.
- Extend the model for real-time thermal error compensation in CNC machines.
- Explore hybrid deep learning models and additional sensor data for improved accuracy.

References:

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