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XAI-driven digital twin for cobot dynamic error compensation

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Abstract

Process and product fingerprints (FP) have been approved as effective parameters to reveal the principal contributing factors towards functionality in smart manufacturing processes. Though AI-driven methods outperform other approaches for fingerprint extraction, the lack of explainability in its black-box style predictions leads to misconceptions and trust issues among stakeholders. In this study, a novel explainable-AI (XAI) approach is proposed to identify mathematical fingerprint expressions by formulating them as graphs using the QLattice algorithm, inspired by path integral formulation. Here, the Qlattice model identifies explainable and human-comprehensible FP expressions for cobot dynamic error based on accelerometer signal features. The discovered symbolic model is subsequently applied to a digital twin which successfully tracked and compensated for dynamic errors autonomously in real time.

Keywords: Artificial Intelligence; Explainable AI (XAI); Digital Twins; Colloborative Robot; Dynamic Error; Process Fingerprints

1. Introduction

In smart manufacturing, process fingerprints (FP) represent the core contributing process parameters towards the end functionality. By extracting the fundamental correlation between the process parameters and response, the FP approach plays a vital role in enhancing performance and meeting quality compliance [1]. It is aimed toward minimizing the time and cost invested towards the optimization and metrology of manufacturing systems. Also, though not yet widely explored, the FP-driven approach can help real-time systems like digital twins operate much more efficiently due to lesser data-handling requirements. However, the existing methodologies towards FP identification are limited to very few manufacturing processes and are predominantly a manual, tedious and error-prone approach. Consequently, the identified FP often have poor correlations with the desired responses. Lately, machine learning approaches have been introduced to automate the FP extraction from complex datasets with better results than the conventional approaches [2].

The machine learning (ML) approach, however, has a critical shortcoming of being uninterpretable due to its black-box style predictions [3]. The sophisticated computational structure of advanced ML models like ensembles and deep learning has made it impossible to explain the decision-making rationale to the stakeholders, thus raising serious concerns about the trust and transparency of its predictions, especially when used for high-stakes decisions [4]. Though there have been some recent attempts towards developing explainable AI (XAI) models for smart manufacturing, its application domain is largely limited to defect detection. Even in those cases, the interpretability is imparted through post-hoc tools, and the intrinsic (by design) explainability is yet to be addressed [5]. The existing intrinsically explainable models like regression and decision tree models have less accuracy and are not deemed reliable to model complex manufacturing processes.

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Symbolic regression utilizes the computational capability of ML to extract explainable mathematical expressions from a search space of all potential analytical functions [6]. The approach is capable of producing perfectly explainable expressions and when combined with its in-built capacity for dimensionality reduction, it can be a transformational method for process FP generation. Out of the several strategies for symbolic regression, an evolutionary ML approach called Qlattice has reported the best performance in terms of predictive accuracy [7], and dimensionality reduction and is hence used in this study for FP identification.

Collaborative robots (cobots) are being extensively used for various smart manufacturing applications including assembly, material handling, precision machining, inspection and quality control. Precise motion control of cobot end effectors is critical for their performance [8]. However, unanticipated positioning inaccuracies can happen due to the dynamic behaviour of the cobot during its operation. The dynamic error arises due to various factors such as vibration, resonance, noise, deflections, thermal expansion, and other disturbances that affect the flexible elements during the cobot motion [9]. Since most of it happens outside the servo loop, they are difficult to be identified and compensated through in-built encoders. For such complex real-time process control applications, digital twins are widely employed in smart manufacturing. However, to the best of our knowledge, there are not many digital twin systems developed for real-time positioning control, apart from a recent study which uses attitude sensors for cobot error compensation [10].

Based on the literature study, it was understood that positioning inaccuracies due to dynamic error during cobot motion is yet to be investigated and addressed comprehensively. The existing computational models are largely slow, inefficient and uninterpretable, limiting their applications in real-time systems like digital twins. A faster, more explainable and direct method for dynamic error prediction is a critical bottleneck towards developing a capable online error compensation system. The FP approach is limited to a few machining applications till now and is a promising approach towards cobot dynamic error prediction.

The study, therefore, proposes a novel approach to finding the FP expression of dynamic error through a completely explainable data-driven model called Qlattice. The approach is aimed at enabling latency-free dynamic error predictions through significant dimensionality reduction (>75%). Also, here the dynamic error is represented by just the process signatures captured from raw accelerometer data, saving significant computational efforts otherwise required for displacement signal extraction through double integration. Finally, the model is applied to a digital twin for online dynamic error compensation towards improving the positioning accuracy of the cobot end effector.

2. Methodology

2.1. Experimental details

The experimental setup consists of the collaborative robot (COBOT, UR10e), a ball bar test system (Renishaw QC20-W, measurement accuracy of 0.1 µm) to verify the end effector's positioning performance, two triaxial accelerometers (PCB 356B18), a data logger (National Instruments cDAQ-9174), a data card (NI-9234), and a workstation. The overall experimental setup is shown in Fig. 1. One of each accelerometer is positioned at the wrist (closest to the tool centre position (TCP)) and base to accurately record the dynamic deformations with minimal noise. The readings are acquired to the data card through the data logger. Relevant features are extracted from the time and frequency domain using MATLAB 2022a. True positioning data is recorded by RoboDk software during the ball bar test. Ball bar tests are globally accepted standard tests to evaluate the positioning performance and thus have been regarded as 'ground truth' data in this study. The cobot-default positing data from encoders and the Qlattice model predictions are thus compared against the ball-bar results for performance evaluation.

Fig. 1. Experimental setup for cobot motion in a circular path of radii (a) 100 mm (2) 150 mm (3) 300 mm

2.2. QLattice – A novel data-driven algorithm

Symbolic regression is an explainable ML approach which searches the space of all mathematical expressions to identify the optimal equation correlating the input space X and output space Y. Symbolic regression techniques have demonstrated strong performance and generalizability, distinguishing them from alternative graph-based models like decision trees and random forests. As the number of features / independent variables ($x_i \in$ X) increases, the search space will grow exponentially and the exhaustive search becomes infeasible.

A newly developed and extremely capable symbolic regression algorithm called Qlattice is used in this study to extract the fundamental relationship between the cobot's motion signatures and its dynamic errors. Qlattice incorporates graphs that can be interpreted as mathematical formulas, enabling the evaluation of the implications of hypotheses [7]. Unlike conventional approaches that use graph networks and genetic programming to search the expression space, Qlattice models all possible X to Y expressions as spatial path sets [11]. From these infinite paths, the model searches for and selects the expression that best represents the required response, using the loss functions like RMSE.

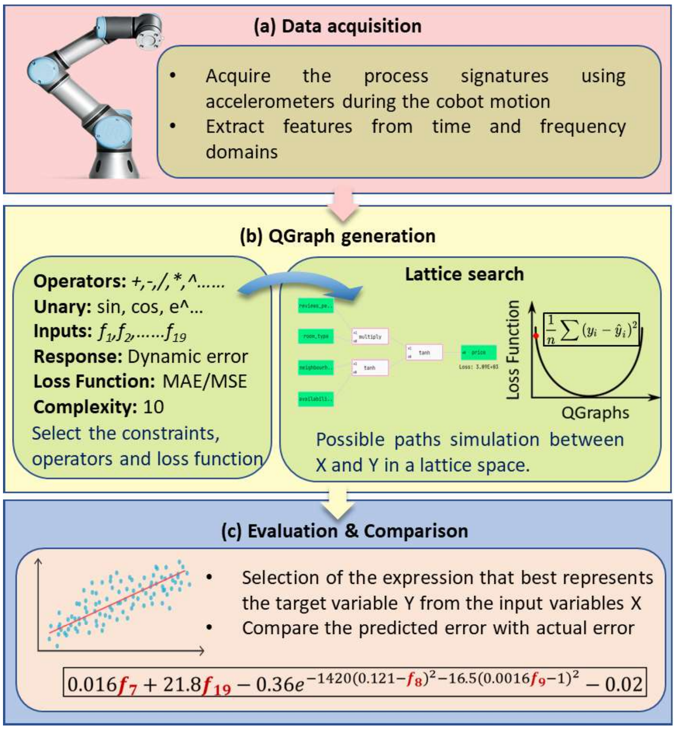

Fig. 2. Overall methodology of Qlattice symbolic regression

To mitigate the computational efforts, Qlattice simulates various paths connecting the inputs x_i with the output Y in a multi-dimensional lattice space inspired by Feynman's path integral formulation. During simulation, the paths which are more likely to map input variables with outputs are formed. New functions are applied on these spatial paths and are further fine-tuned by multiple reinforcements of optimal solutions to improve their accuracy. As the lattice search progresses, several islands of potential solutions evolve independently thereby shrinking the search space. The execution is optimized by representing only a partial subset of Qgraphs at an instance, which is then continuously updated and pruned by eliminating the worst performers based on the loss function [12]. The overall approach and logic are given in Fig. 2. In this study, Qlattice is run based on the Feyn module in Python within a custom-built framework for FP extraction having constrained variables, complexity and computational units.

2.3. Overall approach

The overall methodology of this study is given in Fig. 3 and is described as follows:

- ***Cobot motion:*** The real-time positioning data of the cobot is collected by moving it along circular paths of radii 100 mm, 150 mm and 300 mm (clockwise and counterclockwise) at varying feed rates of 2000, 4000 and 6000 mm/min in the X-Y plane. During the cobot motion, data is acquired from the accelerometer, encoder and ball bar for the x, y, and z axes.
- ***Feature extraction:*** Eight features each are extracted from x and y raw accelerometer signals from time and frequency domains. Time domain features are mean absolute value (MAV), variance, peak amplitude, root mean square (RMS), kurtosis and skewness. Mean frequency and total power are extracted from the frequency domain. The training dataset consists of these extracted features, encoder positioning data, command data, and feed rate. Overall there are 19 features in the input dataset.
- ***Symbolic regression:*** The response of interest is the positioning inaccuracy due to dynamic error. For a circular profile, it is calculated by the average radial deviation of the actual positioning data (extracted from ball-bar positioning data) from its command path. The QLattice approach is executed to find the optimal mathematical FP expression (maximum accuracy and a minimal number of features) that connects the input and output space. The loss function is custom defined as mean squared error, and the number of epochs and maximum complexity is restricted to 10.
- ***Performance evaluation:*** The dynamic error prediction results from the identified mathematical expression are put to comparison against the cobot's default error tracking results from the encoder. In addition, the prediction accuracy is compared against the state-of-the-art explainable and black-box ML models.
- ***Error compensation:*** For real-time error compensation, dynamic errors are computed as soon as the cobot motion commences, based on the extracted features from the sensor data. The resultant dynamic errors are automatically compensated by adjusting the command signal for the remaining path using RoboDk software. The compensated path is compared against the default to evaluate the improvement in positioning accuracy.

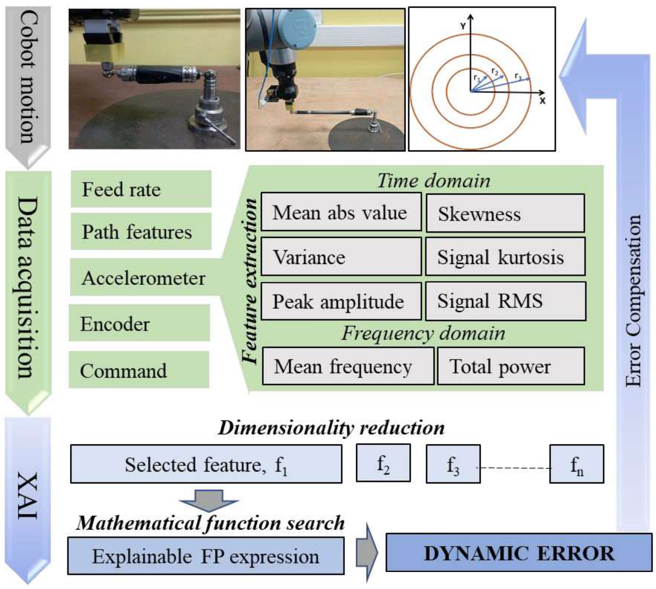

Fig. 3. Qlattice-based error prediction and compensation in a digital twin

3. Results and Discussions

Raw accelerometer signals are processed using MATLAB software after accessing through an NI datalogger during the cobot motion. The input dataset to the Qlattice model includes the features extracted from raw accelerometer signals (X and Y) along with the feed rate, encoder and command path information. Table 1 shows the stages of the mathematical expression search towards its final convergence to the best-performing analytical equation. The final selected model (represented by Epoch No. 10) demonstrates a substantial reduction in the number of features from 19 to 4.

Table 1. Stages of mathematical expression search

Epoch No.	No. of models searched	Time (sec)	No. of variables	Variables of the best solution after each epoch	MSE (10^-5)
1	1018	1	3	Encoder radii, MAV(y), RMS(y)	15.5
2	2120	4	4	Command radii, MAV (x), Variance (y), RMS (x)	1.97
3	3159	8	4	Kurtosis (x), MAV (x), peak amplitude (x), RMS (x)	2
4	4172	12	4	Kurtosis (x), MAV (x), peak amplitude (x), RMS (x)	1.9
5	5182	17	5	Command radii, MAV (x), RMS(y), kurtosis(y),variance (y)	1.39
6	6203	21	5	Skewness (x), kurtosis (y), RMS (y), feed, encoder radii	0.888
7	7227	26	5	Skewness (x), kurtosis (y), RMS (y), feed, encoder radii	0.875
8	8250	33	5	Skewness (x), kurtosis (y), RMS (y), feed, encoder radii	0.868
9	9244	39	4	Skewness (x), MAV (y), power (x), peak amp (x)	0.893
10	10236	45	4	RMS (x), power (y), kurtosis (x), peak amplitude (x)	0.876

Qlattice was run with both mean absolute error (MAE) and mean square errors (MSE) as loss function and the difference in predictive accuracy was observed to be < 1%, with MSE marginally outperforming the former. Also, the complexity of the search space can be customized to a certain maximum. In theory, the more the allowed complexity, the wider is the lattice space and the solutions are likely to be better due to unconstrained search. A maximum permitted complexity of 10 is selected here to guarantee at least a 50 % dimensionality reduction. The best-fitted Qlattice model after 10,236 searches is given in Fig. 4.

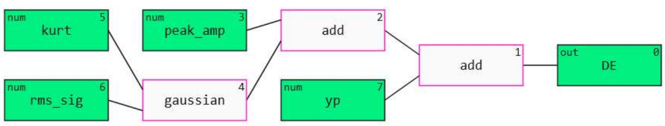

Fig. 4. The best-fitted Qlattice model of Dynamic Error (DE)

The corresponding equation is given below as equation (1).

$$DE = 0.016\boldsymbol{f_7} + 21.8\boldsymbol{f_{19}} - 0.36e^{-1420(0.121-\boldsymbol{f_8})^2-16.5(0.0016\boldsymbol{f_9}-1)^2} - 0.02 \quad (1)$$

Here $\boldsymbol{f_7}$ is the peak amplitude (x), $\boldsymbol{f_{19}}$ is the total power (y), $\boldsymbol{f_8}$ is the RMS (x) and $\boldsymbol{f_9}$ is kurtosis (x). It is interesting to note that the expression contains just the raw accelerometer signals and features from other sources including the encoder data are considered less significant. This implies that the dynamic error could be entirely represented by just the raw accelerometer signal features, thereby eliminating the need for displacement extraction and filter cut-off identification- as performed conventionally. This will contribute towards latency-free real-time positioning error prediction and compensation during the cobot motion. The significance of the selected features towards revealing insights into the process physics behind the occurrence of dynamic errors is discussed later in a separate subsection. The performance of the model in terms of R^2 value is 0.994, RMSE is 0.00291 and MAE is 0.0024. The actual (ball-bar) vs. predicted dynamic error is plotted in Fig. 5.

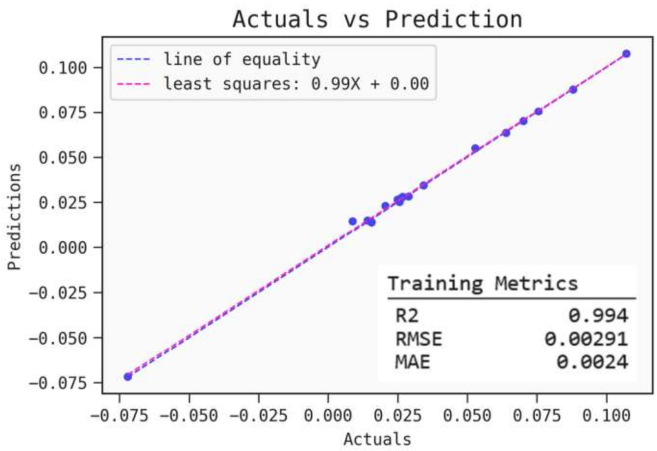

Fig. 5. Qlattice predictions vs. actual dynamic errors during cobot motion

The performance comparison of the Qlattice error predictions with that of cobot positioning data (recorded by an in-built encoder) is presented in Fig. 6. Qlattice predictions are closely matching the true dynamic errors for all the experiments. On average, the Qlattice model predictions deviate from the actual errors by 7.5 %, whereas the positioning errors from encoder data deviate by 65 %. This reinforces the presence of a significant amount of errors due to random vibrations of the flexible elements outside the servo loop which encoders cannot detect. In other terms, the Qlattice model which works on external accelerometer data shows a significant improvement over the cobot defect error tracking by > 50%.

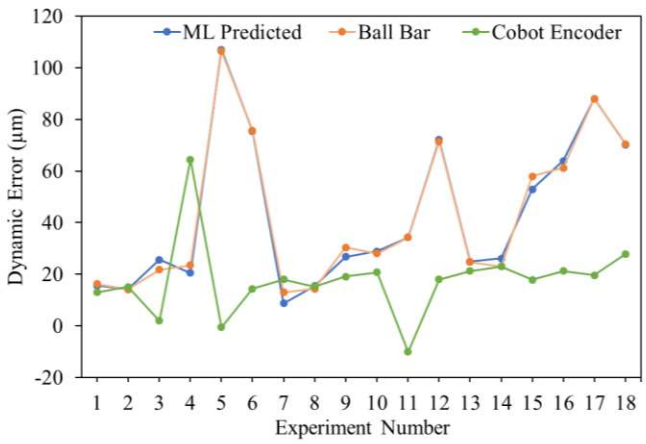

Fig. 6. Performance comparison of Qlattice error predictions with that of the encoder data

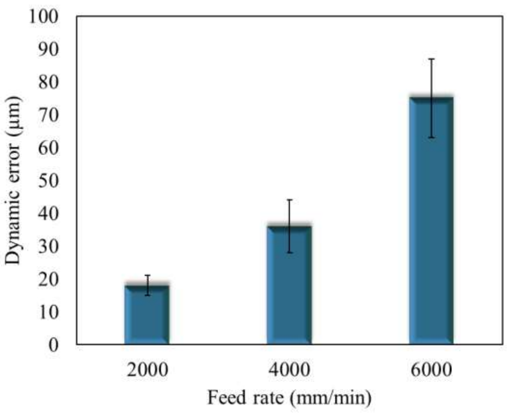

Fig. 7. Variation of dynamic errors with the cobot feed rate

The dynamic errors were observed to be more for higher feed rates, as seen in Fig. 7, which could be attributed to larger vibrations and deflections of flexible elements at higher feeds as compared to low feed rates. A comparison of the predictive performance of QLattice with some of the common explainable (k-nearest neighbours (KNN) and decision tree (DT)) and black-box (artificial neural network (ANN), random forest regression (RFR) and extreme gradient boost (XGB)) ML models are given in Fig. 8. The specifics of each of these models are given in Table 2. Qlattice clearly can match the established black-box ML models in terms of predictive performance, though at a cost of marginally higher training time. Qlattice search took 45 seconds as compared to 13 seconds for the ANN model training. Qlattice is, however, clearly more explainable, accurate and is expected to be computationally faster during real-time predictions. Within explainable models, Qlattice is 15 % more accurate than the DT, a widely used tree-structured ML model.

Table 2. Details of the ML models used for performance comparison

S. No.	Model	Details
1	KNN	Number of neighbors = 2
2	DT	Maximum depth = 2
3	ANN	Network architecture = 19-10-1 Train-test-validation ratio = 70-15-15
4	RFR	Number of estimators = 100
5	XGB	Learning rate = 0.01 Number of estimators = 550 Maximum depth = 3 Evaluation metric = RMSLE
6	QLATTICE	Loss function = MSE Complexity = 10

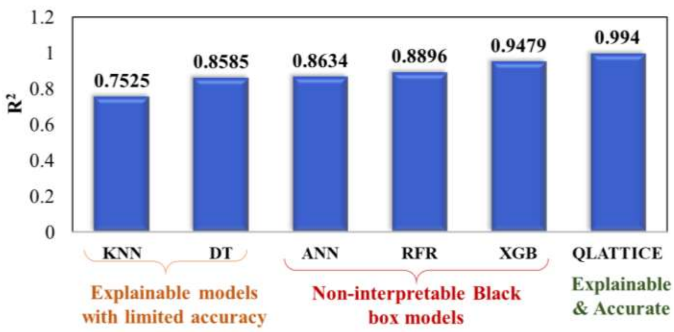

Fig. 8. Comparison of various ML model performances

3.1. Dynamic error compensation

Real-time positioning error prediction and compensation during the cobot motion is of extreme importance from the aspects of accuracy, efficiency, adaptability and safety. Conventional approaches for accurate position tracking of the cobot end effector are computationally intensive and slow, and hence have been deemed unsuitable for real-time error compensation. We propose a novel approach based on the Qlattice dynamic error predictions as given in Fig. 9. Here the command path is split into n-number of adjustable targets, t_i (i=1, 2, 3, … , n). Once the cobot starts its motion, it acquires raw accelerometer signals between targets t_i to t_{i+1}, from which relevant features are extracted. Using this data, the dynamic error is predicted using equation (1) which is then used to reset the subsequent targets by adjusting the motion command through the RoboDk software.

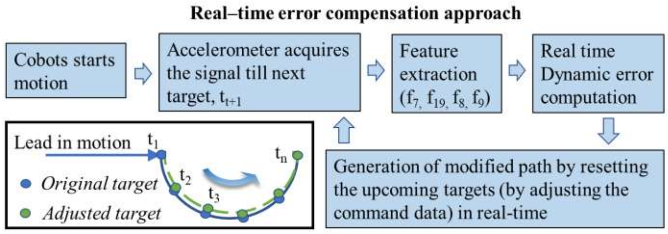

Fig. 9. Digital twin for real-time dynamic error compensation during cobot motion

The approach is validated by considering a 150 mm circular path. Improvement in positioning accuracy is evaluated by comparing the true position data of the cobot end effector before and after online error compensation is seen in Fig. 10 (a) for 2000 mm/min feed rate. It can be observed that the error-compensated ball-bar positioning data is closer to the intended path as compared to default (non-compensated) ball-bar data. The average improvement in positioning accuracy due to error compensation for various feed rates is given in Fig. 10 (b).

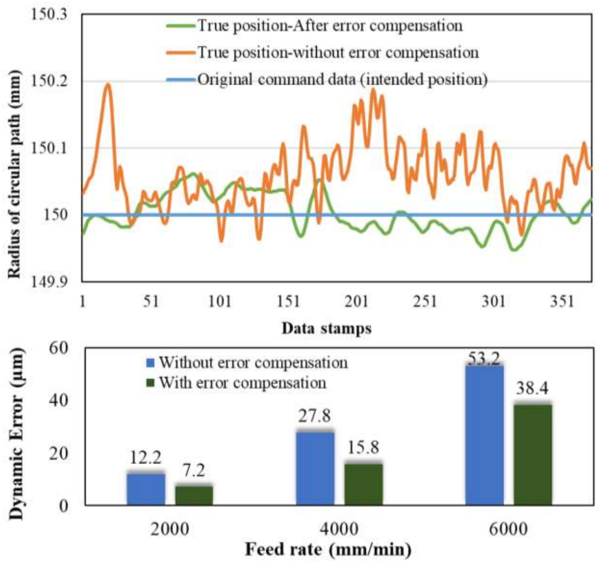

Fig. 10. (a) Ball-bar data showing the effect of real-time error compensation (b) Effect of error compensation at various feed rates

3.2. Insights into the process physics behind dynamic errors

The Qlattice model reveals the most significant accelerometer signal features that influence the dynamic error as kurtosis, signal RMS value, signal power and peak amplitude. Also, since the identified model is a symbolic equation, the type of relationship between the features and dynamic error is easy to comprehend, unlike the opaque deep learning models. Power and peak amplitude has a direct proportionality with dynamic error, while RMS and kurtosis are having a Gaussian relationship.

Useful insights into the process physics behind dynamic errors can be drawn based on these contributing features. High kurtosis values suggest more high-frequency content and transient events, which may cause dynamic errors due to unexpected movements like shocks. RMS reflects the level of vibration or motion, while power measures the distribution of energy across different frequency bands, indicating errors due to resonance effects or external disturbances with specific frequency content.

That being said, it is interestingly observed that, among the features selected, the peak amplitude, RMS and kurtosis are from the x-accelerometer signals, whereas power is from the y-signal. The reasons behind separate feature selection from the x and y signal call for further investigation.

4. Conclusions

Given the growing need for completely interpretable systems in smart manufacturing towards enhancing the trust and transparency of ML model predictions, the study proposes a XAI approach towards cobot dynamic error prediction and compensation. The study combines interpretable ML algorithms, dimensionality reduction and signal processing to detect and compensate for cobot dynamic errors caused by various factors including vibrations and resonance of flexible members. Here, the mathematical expression for process FP, which contains the core contributing features towards dynamic errors is extracted through a data-driven explainable model- Qlattice, inspired by Feynman's path integral formula. In addition, the study successfully applied the discovered symbolic model to a digital twin for online prediction and compensation of dynamic errors autonomously. Finally, being completely interpretable, the approach makes it possible to throw useful insights to unravel the process physics contributing towards the dynamic errors.

The proposed approach is completely transparent, providing users with a clear understanding of the cobot positioning errors, which can enhance trust and safety in human-robot collaborations. It is easy to implement and can be integrated into existing cobot systems without significant modifications. Since the dynamic errors are represented using just the raw accelerometer signal features, it is significantly more efficient than the traditional position-tracking approach of signal filtering followed by displacement extraction. The reduced computational steps and dimensionality reduction account for much faster error computation and could thus be transformational in driving the real-time error compensation models like digital twins. Furthermore, the proposed approach is scalable, allowing for multiple cobots to be monitored and controlled simultaneously.

The initial results are very promising and with further refinement, the approach has enough potential to significantly enhance the reliability and performance of cobots in various industrial applications within manufacturing, logistics, and healthcare. Future research can be done to further improve the robustness of the approach by validating its effectiveness for more complicated paths.

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