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Data-Driven Self-Calibration of Force Sensing for Industrial Robots with Unknown Tool Attachments

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Abstract: Reliable force perception is essential for robots that physically interact with their environment, especially in applications involving manipulation, tool use, teleoperation, and contact-rich tasks. However, force/torque sensors mounted on industrial robots can produce biased measurements when unknown or interchangeable tools are attached to the end-effector. These biases become more difficult to compensate when the tool holder's mass, center of mass, and inertial properties are not precisely known. This study presents a data-driven self-calibration framework for a KUKA KR 600 robot equipped with an ATI Gamma force/torque sensor to compensate force offsets under both quasi-static and dynamic conditions without requiring prior knowledge of tool properties. In the quasi-static case, a third-degree polynomial regression model was trained using end-effector orientation data to estimate gravity-induced offsets. The model achieved a test-set MSE of 0.005 N and a benchmark RMSE of 0.036 N. For dynamic calibration, more than 80,000 motion samples were collected during robot motion. After removing the quasi-static component, the remaining dynamic offset was modeled using polynomial regression and a multilayer perceptron (MLP). The second-degree polynomial model achieved a benchmark RMSE of 0.0458 N, while the MLP achieved a test-set RMSE of 0.041 N. These errors were below the practical accuracy limit of the ATI Gamma sensor, indicating that the proposed method can provide accurate force compensation under both static and dynamic conditions. The results show that the proposed framework improves force perception without manual tool modeling or hardware modification. Overall, by enabling robots to separate tool-induced disturbances from true interaction forces, this method supports more reliable robotic interaction, adaptive manipulation, and future integration into autonomous, haptic, and teleoperated robotic systems.

Keywords: Force sensor self-calibration, autonomous robots, dynamic force compensation, robotic manipulation, polynomial regression, neural networks, force perception, data-driven modeling.

1. Introduction

Accurate force sensing plays a critical role in robotic systems that interact physically with their environment [1]. In contact-rich tasks such as teleoperation, assembly, and robotic-assisted procedures, force feedback helps improve precision, safety, and responsiveness [2]. In these applications, the ability to measure and interpret interaction forces allows the robot to respond more reliably to external conditions and perform tasks with better control [3]. For autonomous and semi-autonomous robots, force sensing is not only a measurement problem but also an important part of perception, since the robot must distinguish true external contact forces from undesirable disturbances caused by its own motion and attached tools [4].

Despite the importance of force measurements, raw force/torque sensor readings are often affected by tool attachments mounted on the robot end-effector. These attachments introduce additional forces due to their mass, mass distribution, and inertial effects during motion caused by linear and angular accelerations [5]. In practical robotic systems, the mass properties of tool holders may be unknown, variable, or difficult to identify accurately, especially when tools are frequently changed, modified, or customized for different tasks. As a result, the force sensor may report offsets that do not represent real interaction forces. This problem becomes more complex under dynamic conditions, where changes in acceleration and orientation continuously affect the measured force signal [6].

Traditional calibration techniques rely on analytical models that require prior knowledge of the tool's physical characteristics, including mass distribution and inertia [7]. These methods can be effective when the tool is fixed and fully characterized. However, they are less practical for robotic systems that use interchangeable or custom-designed end-effectors, where repeated manual calibration can reduce flexibility and increase setup time. Recent studies have explored data-driven calibration methods that use machine learning to estimate and compensate force sensor bias. However, many of these approaches focus mainly on static or quasi-static conditions and do not fully address motion-induced force disturbances. In addition, there is still limited comparison between simple interpretable models and more flexible learning-based models for dynamic force compensation in physical industrial robots [8][9].

For robots operating in real-world applications, the ability to self-calibrate force sensing without detailed tool information can improve reliability and reduce manual setup requirements, especially when tools are changed or used for different manipulation tasks [10]. This is particularly relevant for robotic manipulation and physical interaction tasks, where reliable estimation of contact and interaction forces is important for control and task execution [11]. It is also important in haptic systems and teleoperation, where accurate force feedback directly affects safety, quality, and task performance [3]. A self-calibration framework can help the robot maintain reliable force measurements even when tool properties are unknown or change between tasks. Therefore, data-driven force sensor calibration can be considered an enabling component for adaptive and autonomous robotic behavior.

This paper proposes a data-driven calibration method for the KUKA KR 600 robot equipped with an ATI Gamma IP60 SI-130-10 six-axis force/torque sensor. The proposed method operates under both quasi-static and dynamic conditions without requiring knowledge of the attached tool's physical properties. In the quasi-static case, a third-degree polynomial regression model was trained using the end-effector's orientation (roll, pitch, yaw) to compensate for gravity-induced offsets. For dynamic calibration, a large dataset was collected and evaluated via multiple models using a nine-dimensional input vector (position, orientation, and linear acceleration). Polynomial regression models of varying degrees were compared and showed the second-degree model offered the best trade-off between accuracy and complexity. A multilayer perceptron (MLP) model was also developed for achieving the highest accuracy in dynamic conditions. The results demonstrate that data-driven models can reliably correct sensor errors and enable accurate force estimation without tool-specific calibration. The overall workflow of the proposed calibration framework is shown in Figure 1. The framework includes raw data acquisition, feature extraction, quasi-static calibration, dynamic offset learning, force compensation, and final corrected force estimation.

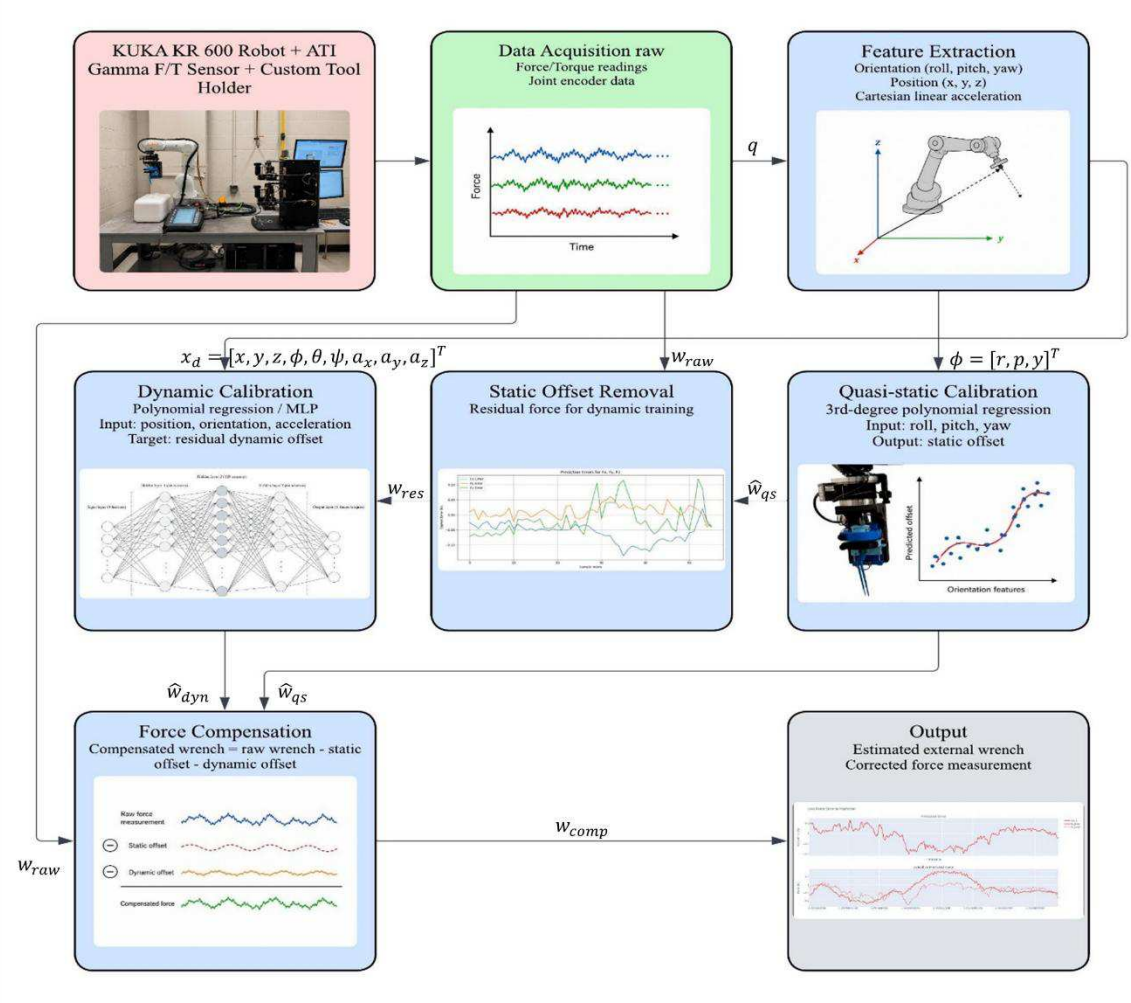


Figure 1. Overview of the proposed data-driven force/torque sensor calibration framework. Raw force/torque readings and robot motion data are used for feature extraction, quasi-static offset estimation, dynamic offset modeling, and final force compensation. The quasi-static model estimates gravity-induced offsets, while the dynamic model estimates the remaining motion-induced offsets after static compensation. The final output is a corrected force measurement obtained without requiring prior knowledge of the attached tool properties.

The main symbols used in the proposed calibration framework are summarized in Table 1.

Table 1. Symbols and definitions used in the proposed calibration framework

Symbol	Definition
w_{raw}	Raw force/torque sensor reading measured by the ATI Gamma sensor
q	Robot joint encoder data used to obtain robot kinematic information
$\phi = [\phi, \theta, \psi]^T$	Orientation feature vector used for quasi-static calibration
$\widehat{w}_{qs}$	Estimated quasi-static offset caused mainly by gravity and tool orientation
$\widehat{w}_{dyn}$	Estimated dynamic offset caused by robot motion and acceleration effects
$w_{res} = w_{raw} - \widehat{w}_{qs}$	Residual wrench after quasi-static offset removal, used as the target for dynamic calibration
$x_d = [x, y, z, \phi, \theta, \psi, a_x, a_y, a_z]^T$	Dynamic calibration input vector, including position, orientation, and acceleration
w_{comp}	Final compensated wrench after removing quasi-static and dynamic offsets from the raw sensor reading

The main contributions of this work can be summarized as follows. First, a data-driven quasi-static calibration strategy is proposed to compensate gravity-induced force offsets without requiring prior knowledge of tool mass or center of mass. Second, a dynamic calibration framework is developed to model motion-induced force disturbances using both polynomial regression and deep learning approaches under realistic operating conditions. Third, the proposed method is demonstrated on a physical industrial robot and designed to be scalable to applications involving interchangeable tools and dynamic motion, enabling accurate force estimation with minimal manual intervention.

2. Background and Related Work

Accurate force sensing is critical in robotic applications such as human–robot interaction, teleoperation, and precision assembly. However, external attachments and tool variability often introduce static and dynamic offsets that degrade measurement fidelity. Previous studies have investigated methods to compensate for these effects using analytical, model-based, or learning-based techniques.

Kim et al. [12] proposed a novel 6-axis force/torque (F/T) sensor that autonomously compensates for gravitational offsets caused by attached tools. Their sensor integrates a 9-axis inertial measurement unit (IMU) to estimate the orientation of the sensor and uses capacitance-based sensing to measure forces and torques. To eliminate the need for manual calibration (e.g., entering the tool's weight and center of mass), the authors employed an artificial neural network (ANN) to estimate the F/T offsets directly from the measured F/T data and orientation angles. The proposed autonomous weight compensation (AWC) method demonstrated high accuracy under both trained and untrained test conditions, with force and torque estimation errors remaining below 1.1% of full-scale output (FSO). This work addresses a key limitation in existing F/T sensors by enabling real-time, tool-independent compensation suitable for applications in robotic manipulation and human-robot interaction.

However, their method was limited to static conditions and did not address dynamic effects such as acceleration-induced forces. Moreover, the compensation mechanism required embedding an IMU and an ANN model inside a specially designed sensor, which makes it unsuitable for retrofitting existing commercial force and torque sensors or robots with interchangeable tools. This limitation highlights the need for a data driven and software-based calibration approach, like the one proposed in this study, that can be applied to standard sensors operating under both quasi static and dynamic conditions [12].

Duan et al. [5] developed a fast and robust method for gravity and inertial force compensation in six-axis force/torque (F/T) sensors, addressing challenges in high-speed, high-precision robotic operations. Their approach integrates a custom-designed F/T sensor equipped with an accelerometer to directly capture both gravitational and inertial effects. A trajectory design method based on a finite Fourier series is introduced to excite the robot joints in a representative manner, enabling accurate identification of payload mass, center of gravity, and installation inclination. Using least squares optimization, they identify twelve key parameters including the tool mass, zero offsets, and dynamic loads within 10 seconds. Experimental results show that their method significantly reduces force errors to below 0.5 N and torque errors to below 0.2 Nm, outperforming traditional compensation techniques that typically neglect inertial effects. This work demonstrates an efficient and scalable compensation framework well-suited for industrial applications requiring rapid adaptation to changing payloads and motion profiles.

However, their approach depends on a self-developed sensor with embedded acceleration sensing and requires detailed knowledge of the tool's mass and inertia, making it unsuitable for robots equipped with standard commercial sensors. The identification process also relies on analytical modeling and controlled excitation trajectories, which limit its adaptability to scenarios with unknown or interchangeable tools. In contrast, the proposed method in this study introduces a fully data driven calibration method that compensates both static and dynamic offsets without requiring any prior knowledge of the tool or modifications to the sensor hardware [5].

Yao et al. [13] proposed an integrated compensation method to improve the accuracy of six-axis force/torque sensors used in robotic systems. These sensors are often affected by disturbances such as zero drift, system error, self-gravity, and the gravity of the attached tool, which can significantly degrade measurement accuracy during contact tasks. To address this, the authors developed a two-stage approach: a neural network was trained to estimate the sensor's zero-point (comprising drift, system error, and self-gravity) based on the robot's pose, while the gravitational effects of the tool, including its center of mass, were identified using the least squares method. This separation between sensor and tool allowed for more flexible calibration, particularly useful when tools are replaced in dynamic manufacturing scenarios. The method was validated on a UR10 robot equipped with a tandem six-axis force sensor. Results demonstrated that the proposed method outperformed conventional techniques such as bias compensation with least squares and double least squares approaches. Notably, it reduced mean absolute errors in force estimation to below 0.6 N and achieved a maximum compensation error under 1.5% of full scale, confirming its effectiveness in reducing disturbance forces and enhancing force sensing accuracy.

Osburg et al. [14] proposed a deep learning–based approach to improve static contact wrench estimation in redundant serial robotic manipulators. Using the KUKA LBR iiwa 7 R800 robot, they trained feed-forward neural networks to map joint torque and position data to end-effector contact wrenches, eliminating the need for external force/torque sensors. A large-scale dataset consisting of both simulated (3 million samples) and real-world data (330,000 samples) was generated by applying known weights at the end-effector under various base orientations. To isolate the torques induced by the calibration weights, the authors introduced a data-driven gravity compensation model based on linear regression, which requires no prior knowledge of the robot's inertial parameters. The trained model significantly outperformed the manufacturer's proprietary force estimation model, reducing median force estimation errors by up to 65% and moment errors by over 90%. Additionally, the approach showed robust performance near singular configurations and demonstrated transferability to a different robot model (KUKA LBR iiwa 14 R820) without requiring retraining. This work highlights the potential of neural network models to provide accurate and robust wrench estimation in static scenarios, especially within low-force operational ranges relevant to tasks such as ultrasound imaging.

This study builds upon that direction by introducing a two-stage calibration scheme combining polynomial regression and deep learning for dynamic and static compensation. Unlike prior methods that rely on known mass properties or embedded redesigns, the proposed approach uses measured orientation, position, and acceleration to learn offsets induced by gravity and motion and successfully benchmarks against both static and dynamic conditions.

To provide a clearer comparison of existing force sensor compensation approaches, Table 2 summarizes the key characteristics of prior studies, including sensor type, calibration method, main features, and reported performance.

This comparison highlights the differences between analytical and data-driven strategies and positions the proposed method relative to existing work.

Table 2. Summary of Related Works on Force Sensor Compensation Methods

Study	Sensor Type & Platform	Compensation Method	Key Features	Results	% FSO (Force)
Kim et al. [12]	Custom 6-axis F/T sensor with 9-axis IMU	ANN-based autonomous weight compensation	Tool-independent, no manual input	Estimation error < 1.1% FSO	< 1.1%
Duan et al. [5]	Custom 6-axis F/T sensor + accelerometer	Least Squares + Fourier trajectory design	Fast (<10s), includes inertial forces	Force error < 0.5 N	0.10%
Yao et al. [13]	UR10 robot + tandem 6-axis F/T sensor	NN (zero drift) + LS (tool gravity)	Separates tool/sensor error, flexible calibration	MAE < 0.6 N; Max error < 1.5% FSO	< 1.5%
Osburg et al. [14]	KUKA LBR iiwa 7 R800 (no external F/T sensor)	Deep NN + Linear Regression	Sensorless, large dataset, model transferable	Force error ↓ 65%; moment ↓ 90%	N/A (no F/T sensor)
The proposed method in this study	ATI GAMMA F/T sensor on KUKA KR 600	Polynomial Regression + MLP (2-stage)	No known mass/inertia; dynamic & static calibration	Quasi-static RMSE = 0.036 N Dynamic RMSE = 0.041 N (MLP) Max error = 0.53 N	0.0072% 0.0082% 0.106%

3. Methodology

To address the challenge of force sensor offset caused by unknown tool attachments, a model-based calibration method is developed for the KUKA KR 600 robot. The actual experimental setup used for data collection is shown in Figure 2(a), including the KUKA KR 600 robot, the ATI Gamma force/torque sensor, a custom-made tool holder attached to the robot end-effector. A close-up view of the ATI Gamma force/torque sensor, the custom-made tool holder, and the attached surgical forceps is shown in Figure 2(b). The tool holder includes roll and actuation mechanisms and represents the type of end-effector attachment that introduces the force offsets addressed in this study. These components are central to the proposed calibration framework, since the unknown tool attachment introduces the force offsets addressed in this study. Traditional calibration procedures often require precise knowledge of the tool's mass properties and center of mass; however, in applications involving interchangeable or custom-designed tool holders, these parameters are difficult to determine consistently. To overcome this, a data-driven approach is adopted that learns the effect of the tool holder from empirical measurements, allowing to isolate and remove its influence from the force sensor readings. Two calibration modes were explored: quasi-static and dynamic.

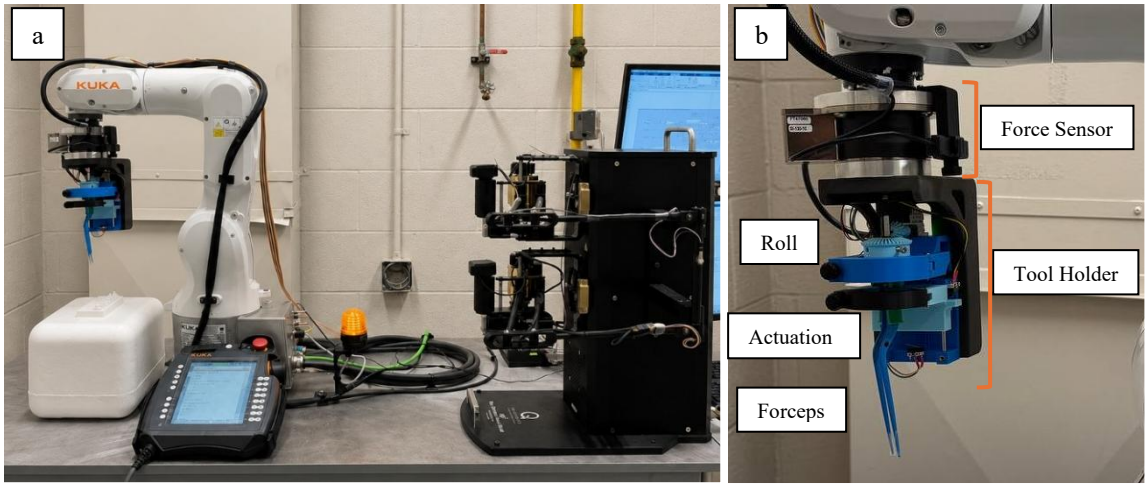


Figure 2. Experimental setup used for force sensor calibration. (a) Full view of the laboratory setup, including the KUKA KR 600 robot and associated hardware. (b) Close-up view of the ATI Gamma force/torque sensor, the custom-made tool holder, and the attached surgical forceps at the robot end-effector. The close-up also indicates the boundary between the force sensor and the tool holder, as well as the roll and actuation components of the tool holder end-effector.

3.1. Quasi-static Calibration

In the quasi-static mode, the end-effector of the robot was sequentially positioned at various orientations and held stationary at each pose for approximately one second to eliminate the influence of acceleration or velocity. The purpose was to isolate the gravitational component of the force acting on the sensor due to the tool holder. We initially conducted two trials to compare input variables:

1. **Joint-angle-based model**: The joint configuration vector $\boldsymbol{q} = [q_1, q_2, \ldots, q_6]$ was used as input to the model.
2. **Orientation-based model**: The roll, pitch, and yaw angles of the end-effector (derived from the robot's forward kinematics) were used as inputs.

In both cases, the corresponding 3-axis force sensor readings (F_x, F_y, F_z) were recorded. A total of 362 data points were collected for training and testing. The dataset was split into 80% for training and 20% for testing. Among the two approaches, the orientation-based model produced significantly better results. A third-degree polynomial regression model was trained using roll, pitch, and yaw as input features. The third-degree polynomial was chosen as it provided sufficient flexibility to model the nonlinear relationship between end-effector orientation and the force offset, without overfitting the relatively small dataset.

To evaluate the model's generalization capability, an independent benchmark dataset consisting of 56 data points was collected. The model was used to predict the expected force readings due to the static influence of the tool holder. These predicted forces were then subtracted from the raw sensor measurements to estimate the net external force.

3.2. Dynamic Calibration

To extend the force sensor calibration beyond static poses, a dynamic model was developed to account for motion-induced offsets that occur during real-time operation of the robot. Data was collected while operating the KUKA KR 600. The robot was moved through a range of random orientations, positions, and velocities to simulate realistic use cases intended for future applications. These movements introduced inertial effects due to acceleration and changing tool orientations, which required compensation.

The dynamic calibration process was performed in two stages. First, the previously trained quasi-static model was applied to the force sensor data to remove the estimated static offset caused by gravity. The residual force, representing inertial and motion-induced components, was treated as the dynamic offset to be modeled.

A nine-dimensional input feature set was constructed consisting of the end-effector's position (*x, y, z*), orientation (roll, pitch, yaw), and Cartesian linear acceleration along each axis. The acceleration components were obtained by numerically differentiating the end-effector position data derived from forward kinematics. As such, they were indirectly derived from the joint encoder values.

Initially, joint-based dynamic features, including angular velocity and angular acceleration ($\dot{\theta}$, $\ddot{\theta}$), were evaluated as candidate inputs since they are directly available from the robot controller. However, models trained using these joint-space variables showed limited correlation with the measured force data and resulted in weaker prediction performance.

Subsequently, Cartesian features derived from the end-effector motion were investigated. In this representation, linear acceleration demonstrated a stronger relationship with force measurements due to its direct connection to inertial effects acting at the end-effector. Velocity terms showed minimal correlation and were therefore excluded from the final model. Based on these observations, Cartesian linear acceleration was selected as an input feature for the dynamic calibration model.

Two modeling approaches were implemented and compared: a polynomial regression model and a multi-layer perceptron (MLP) neural network. Polynomial regression was chosen for its simplicity, interpretability, and effectiveness in approximating nonlinear relationships when the functional form is unknown but smooth [15]. On the other hand, the MLP was selected to capture more complex and high-dimensional nonlinearities that may arise during dynamic robot motion and are difficult to model with explicit functions.

3.3. Polynomial Regression Model

Polynomial regression model was trained using the full nine-dimensional input vector, including the end-effector's position, orientation (roll, pitch, yaw), and Cartesian linear acceleration components. The dynamic input vector was defined as:

$$x_d = [x, y, z, \phi, \theta, \psi, a_x, a_y, a_z]^T$$

where x, y, z are the end-effector Cartesian positions, r, p, y are the roll, pitch, and yaw angles, and a_x, a_y, a_z are the Cartesian linear acceleration components. The polynomial model was trained to estimate the dynamic residual wrench after quasi-static offset removal:

$$w_{res} = w_{raw} - \hat{w}_{qs}$$

The estimated dynamic offset was modeled as a polynomial function of the nine-dimensional input vector:

$$\hat{w}_{dyn} = f_{poly}(x_d)$$

For the selected second-degree polynomial model, this function can be written in a general form as

$$\hat{w}_{dyn} = b + Ax_d + {x_d}^T Bx_d$$

Where b represents the bias term, A contains the linear coefficients, and B contains the second-order and interaction coefficients. The final compensated wrench was then obtained by subtracting both the quasi-static and dynamic offsets from the raw sensor measurement:

$$w_{comp} = w_{raw} - \hat{w}_{qs} - \hat{w}_{dyn}$$

To determine the optimal polynomial degree, models of degree one through four were evaluated and compared based on benchmark performance. The second-degree model yielded the best performance and was selected for use in the dynamic calibration process, as it provided a good balance between accuracy and model

complexity. Higher-degree models (e.g., degree three and four) exhibited signs of overfitting, with reduced generalization on the benchmark set.

3.4. MLP Model

To improve model accuracy, a feedforward multilayer perceptron (MLP) was developed that takes the same nine-dimensional input and outputs a six-dimensional vector representing the estimated force components. Feedforward neural networks such as MLPs are widely used for nonlinear regression and system modeling tasks [10][16]. The network architecture consists of three hidden layers with 64, 128, and 64 neurons, respectively. Each hidden layer is followed by a ReLU activation function, batch normalization, and a dropout layer with a dropout probability of 0.2 to improve generalization and mitigate overfitting. The final fully connected linear layer maps to the six output values. In total, the model comprises 18,118 learnable parameters. The architecture of the proposed MLP model is illustrated in Figure 3.

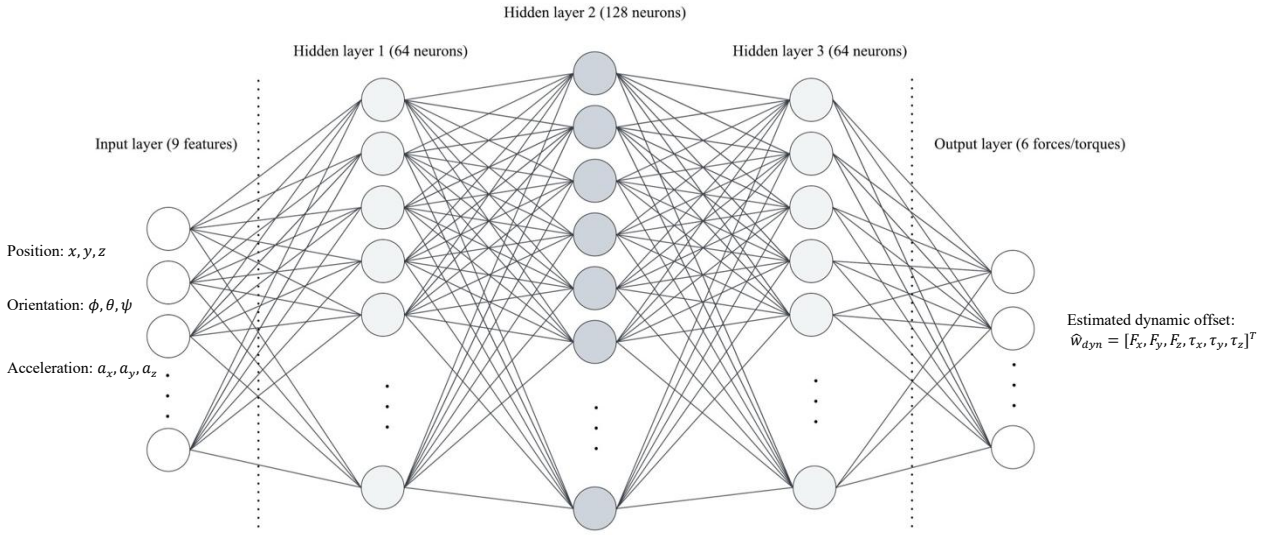


Figure 3. Architecture of the proposed multilayer perceptron (MLP) model for dynamic force estimation. The network takes nine kinematic input features and outputs six force/torque components. Each hidden layer consists of a fully connected layer followed by ReLU activation, batch normalization, and dropout.

The MLP model was trained for 30 epochs using a batch size of 64. The training process employed the Adam optimizer with a fixed learning rate of 0.001 and used mean squared error (MSE) as the loss function. No learning rate scheduler or early stopping mechanism was applied. Dropout was active only during training, and all neurons were used during evaluation.

No explicit feature normalization or scaling was performed; input features such as position, orientation, and acceleration were used in their raw units as obtained from the Simulink model. Despite this, the model converged reliably, likely due to the regularizing effect of batch normalization layers, which normalized intermediate activations during training. Neural networks are not inherently dependent on the absolute magnitude of input features, as feature importance is learned through weight adaptation during training. Moreover, the use of batch normalization mitigates scale imbalance by normalizing intermediate activations, making the model robust to differences in input units and numerical ranges [17].

While the polynomial regression model performed reasonably well, the MLP consistently outperformed it across all evaluation metrics, particularly in capturing highly dynamic behavior. These results support the hypothesis that complex nonlinearities in motion-force relationships are more effectively modeled through deep

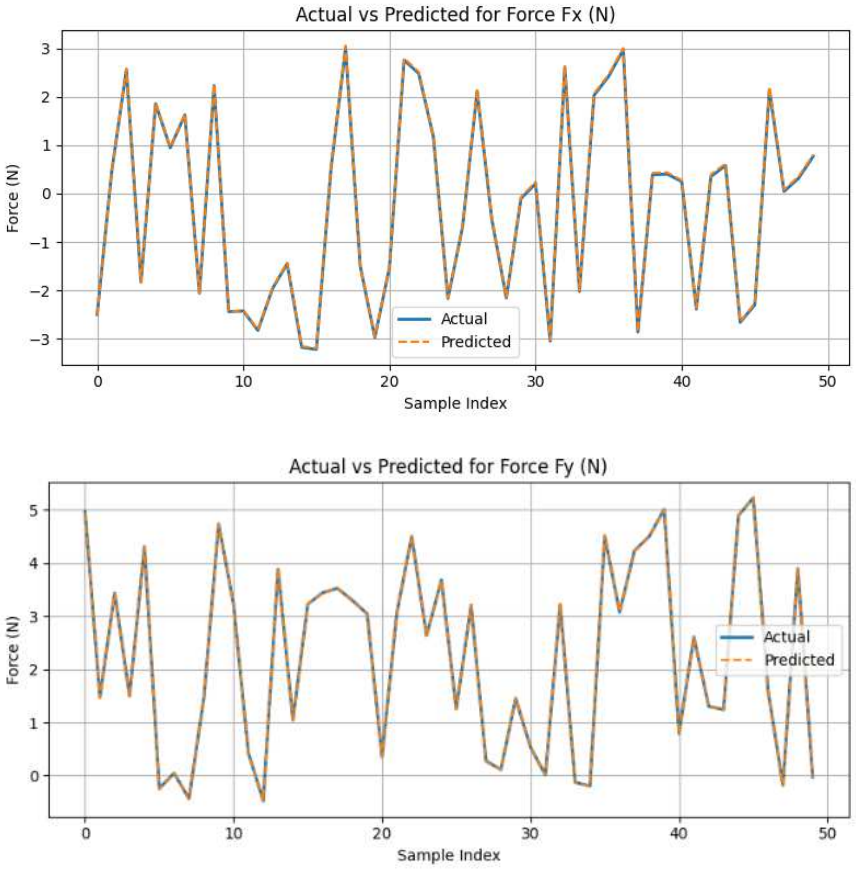
learning approaches. The MLP-based calibration enabled more accurate compensation of motion-induced force distortions during dynamic operation of the robotic system.

4. Results

Before presenting the results, the performance of the developed models was evaluated using standard error metrics, including mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE). The evaluation was conducted on both test datasets and independent benchmark datasets to assess generalization and robustness. The performance of the models was analyzed separately under quasi-static and dynamic conditions to understand their effectiveness in compensating gravitational and motion-induced force offsets.

4.1. Quasi-Static Calibration

Under quasi-static conditions, the third-degree polynomial regression model achieved a mean squared error (MSE) of 0.005 on the test set. On the benchmark set, it achieved a mean absolute error (MAE) of 0.021 N and a root mean squared error (RMSE) of 0.036 N. The maximum absolute errors were 0.13 N in the X-direction (0.026% FSO), 0.06 N in the Y-direction (0.012% FSO), and 0.11 N in the Z-direction (0.022% FSO), confirming its effectiveness in compensating for static gravitational offsets. Figure 4 illustrates the force predictions versus ground truth in the X, Y, and Z directions using the third-degree polynomial regression model on the benchmark dataset. The predicted forces closely matched the measured values across all axes, with minimal deviations. Figure 5 show the predicted torque components (*Tx, Ty, Tz*), which also align well with the ground truth under quasi-static conditions.



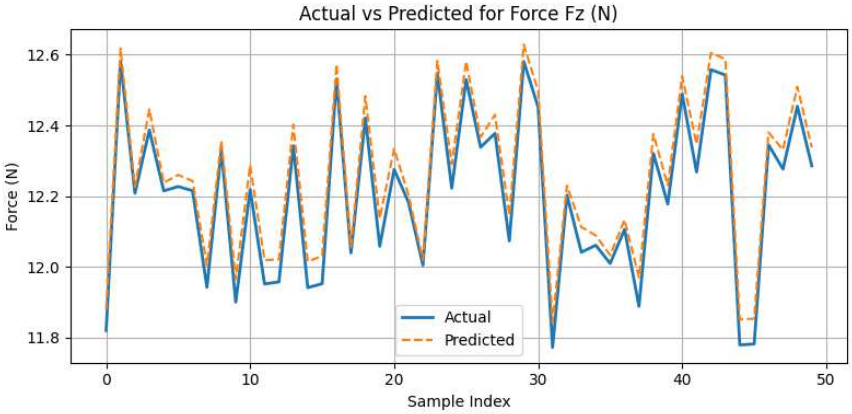
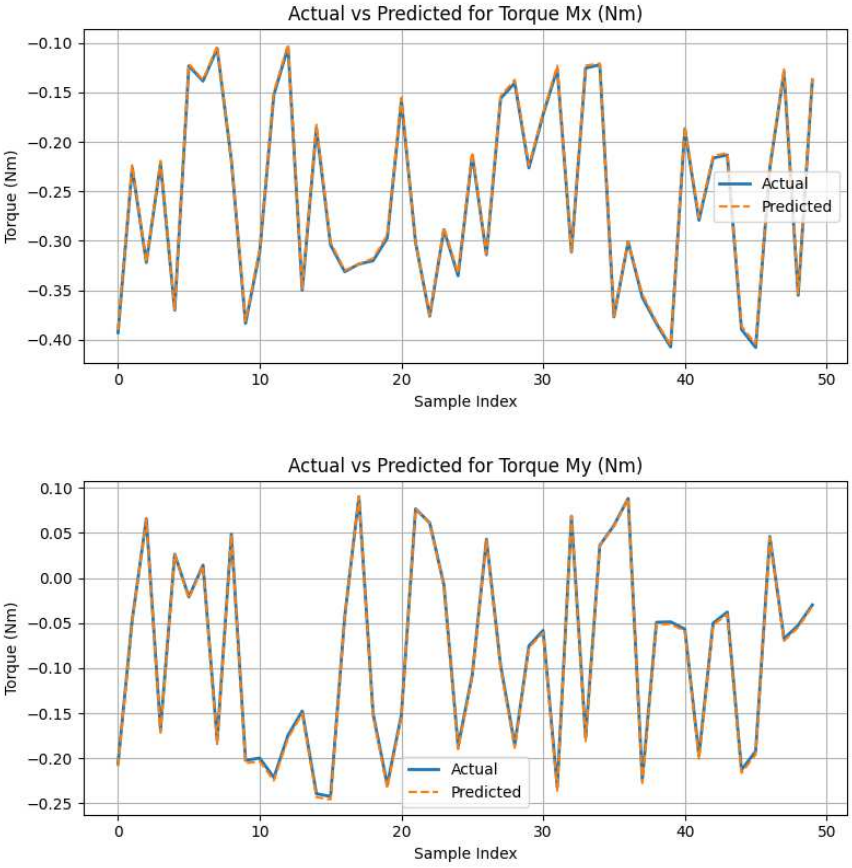


Figure 4. Predicted versus measured force components (F_x, F_y, F_z) using the third-degree polynomial regression model on the benchmark dataset under quasi-static conditions.



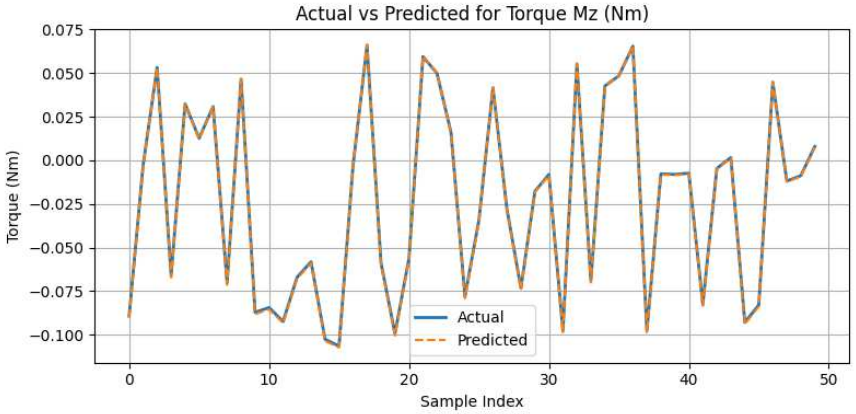


Figure 5. Predicted versus measured torque components ($\boldsymbol{T_x, T_y, T_z}$) using the third-degree polynomial regression model on the benchmark dataset under quasi-static conditions.

Figure 6 presents the signed prediction errors for the force components F_x , F_y , and F_z using the third-degree polynomial regression model on the benchmark dataset. The force prediction errors remain mostly centered around zero, indicating low bias across all three axes. F_y shows greater variability compared to F_x and F_z, but all errors fall within a ±0.6 N range, demonstrating reasonable accuracy under static conditions. This visualization highlights the third-degree model's capability in capturing force trends without significant systematic error.

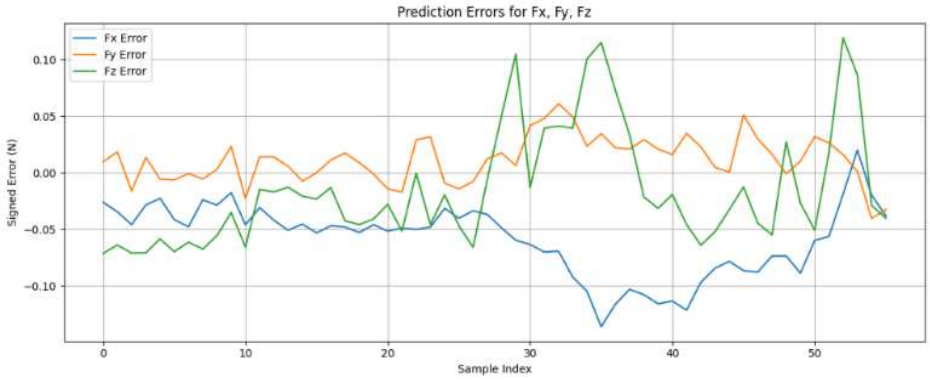


Figure 6. Prediction errors for force components ($\boldsymbol{F_x}$, $\boldsymbol{F_y}$, $\boldsymbol{F_z}$) using the third-degree polynomial regression model on the benchmark dataset, showing low bias and error distribution within ±0.6 N.

4.2. Dynamic Calibration

Dynamic calibration focuses on compensating force offsets that arise from motion-related effects such as acceleration and changes in orientation. Unlike the quasi-static condition, where gravitational effects dominate, dynamic conditions introduce additional nonlinearities that are difficult to model analytically. To address these challenges, two data-driven models were developed and evaluated: a polynomial regression model and a multilayer perceptron (MLP). The following sections present their development, performance metrics, and comparative results [6][5].

4.2.1 Polynomial Regression

In dynamic calibration, the second-degree polynomial model was trained using 80% of the dataset and evaluated on the remaining 20%. It achieved an MAE of 0.027 N and RMSE of 0.053 N on the test set, and an MAE of 0.021 N and RMSE of 0.045 N on the benchmark set. Maximum absolute errors were 0.42 N (X), 0.40

N (Y), and 0.26 N (Z), with a total magnitude error of 0.54 N (0.108% FSO). While the model performed reasonably well, its limited capacity to represent highly nonlinear dynamics may have constrained its ability to match the performance of the MLP model in dynamic scenarios. This fact justifies the use of MLP to further improve the accuracy of the force estimation.

Figure 7 present the predicted versus actual force values using the second-degree polynomial model in the X, Y, and Z directions. While the model performed reasonably well in capturing general trends, small deviations were observed, particularly during rapid motion changes. Figure 8 summarizes the corresponding axis-wise errors.

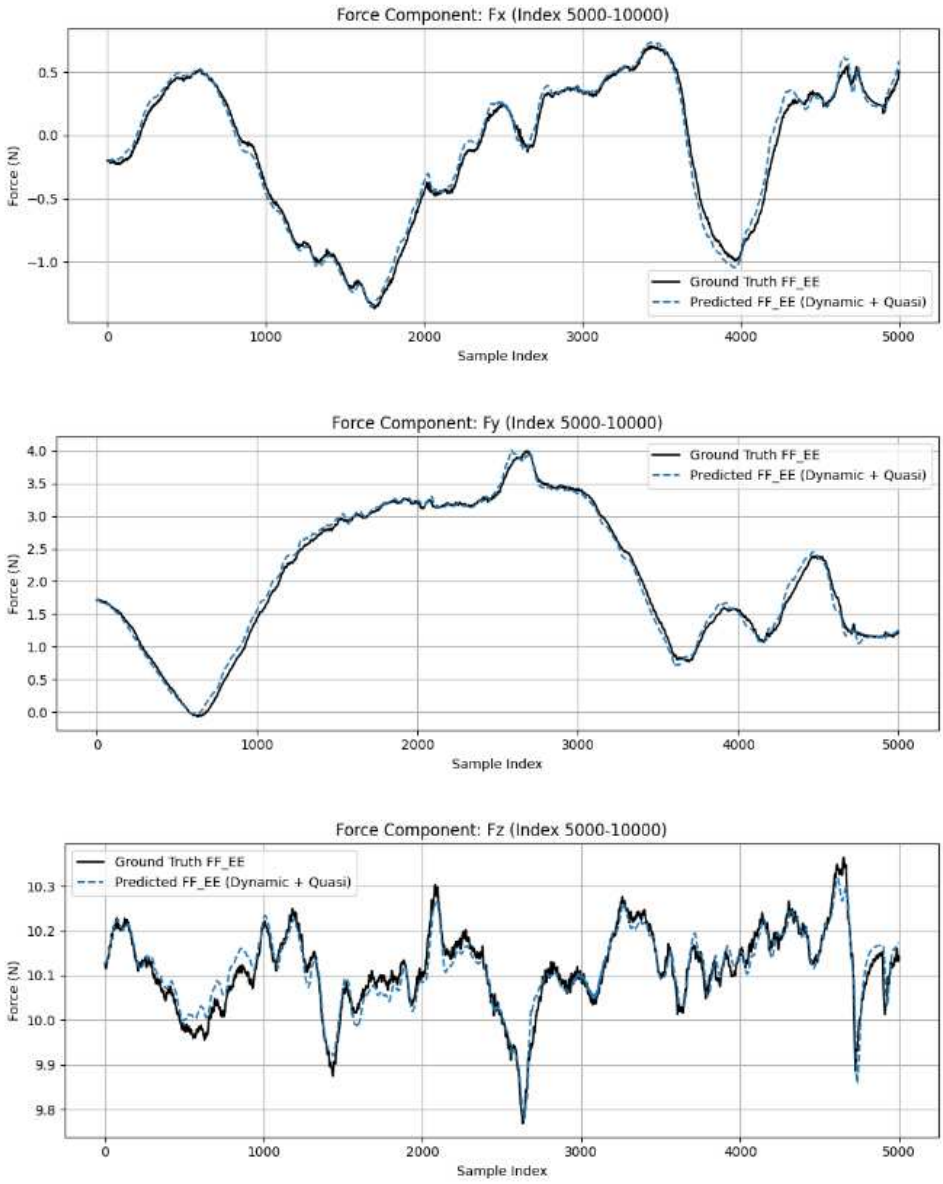


Figure 7. Predicted versus measured force components ($\boldsymbol{F_x}$, $\boldsymbol{F_y}$, $\boldsymbol{F_z}$) using the second-degree polynomial regression model on the benchmark dataset under dynamic conditions.

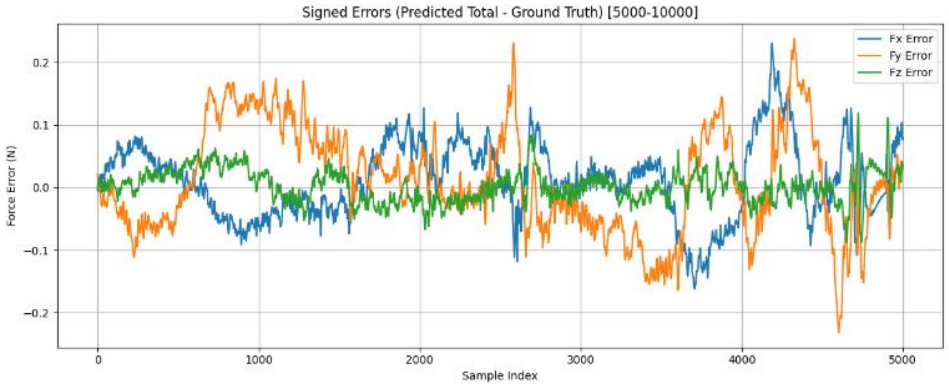


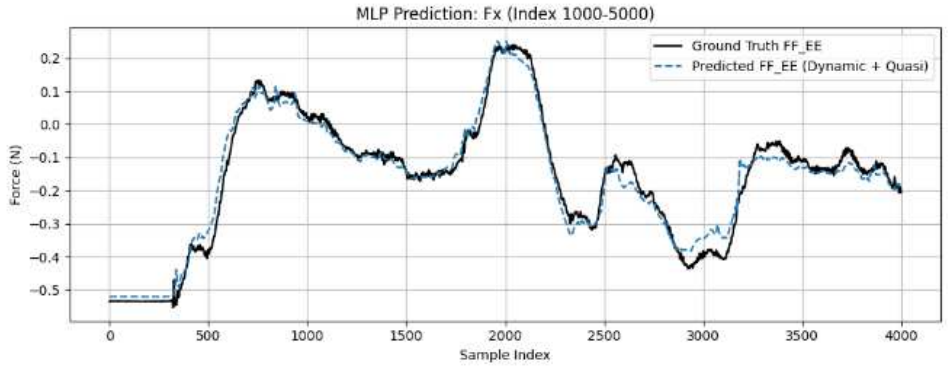
Figure 8. Axis-wise force prediction errors for the second-degree polynomial regression model under dynamic conditions.

4.2.2 Multi-layered Perceptron

The MLP model achieved the best test-set performance, while the second-degree polynomial model showed slightly lower benchmark RMSE. On the test set, it achieved an MAE of 0.021 N and RMSE of 0.041 N. On the benchmark set, the MAE was 0.026 N and RMSE was 0.049 N. The maximum total force magnitude error was 0.53 N (0.106% FSO), with directional maxima of 0.44 N (X), 0.41 N (Y), and 0.26 N (Z). These results demonstrate that the MLP model more effectively captures the nonlinear dynamics associated with motion-induced force offsets.

Figure 9 show the force predictions using the MLP model, which aligned more closely with the ground truth in all directions compared to the polynomial model. Figure 10 presents the corresponding force prediction errors across the three axes.

Overall, both models showed reliable performance, with the MLP offering improved robustness for dynamic tasks, making it suitable for real-time force compensation in robotic applications with variable tool attachments and rapid movements.



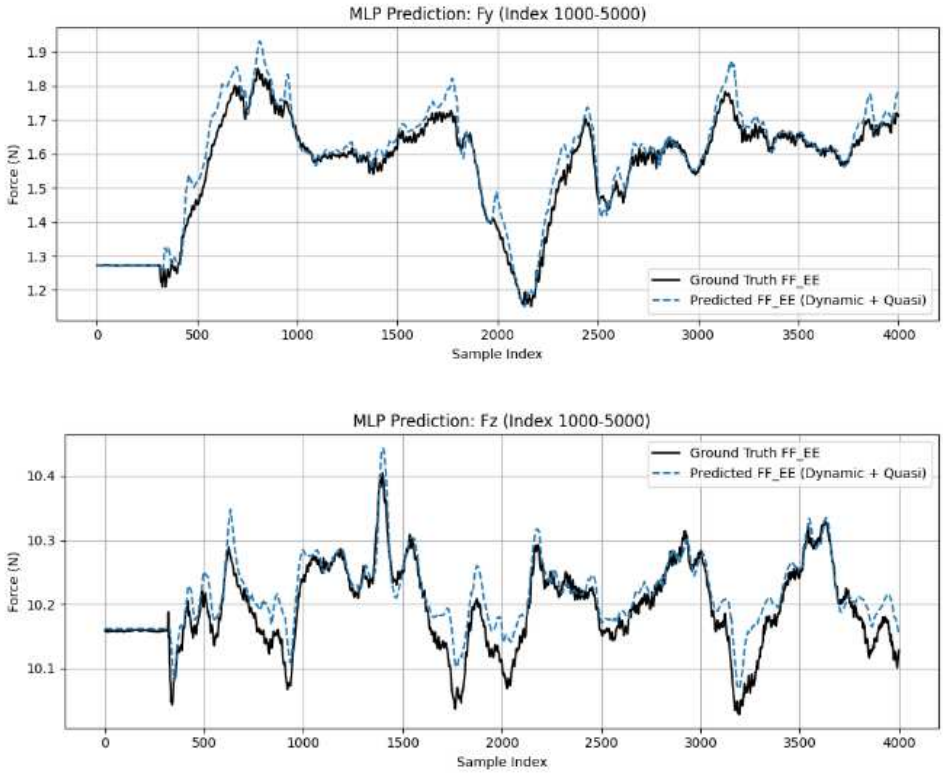


Figure 9. Predicted versus measured force components (F_x , F_y , F_z) using the MLP model on the benchmark dataset under dynamic conditions.

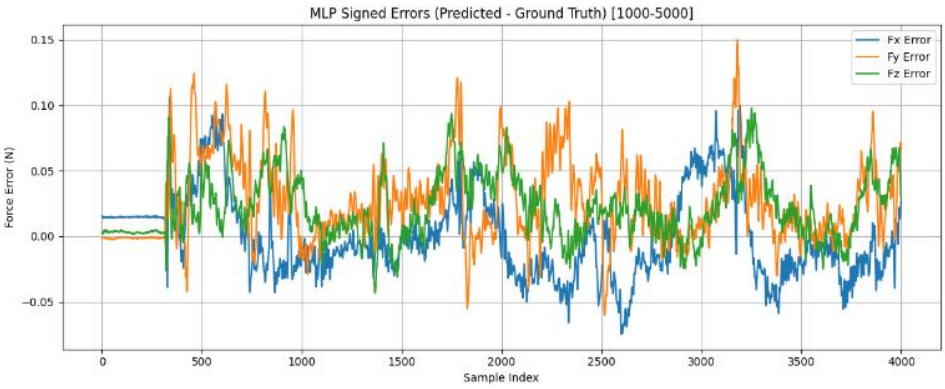


Figure 10**.** Axis-wise force prediction errors for the MLP model under dynamic conditions.

4.3. Correlation Analysis

Correlation analysis was performed to examine the relationship between the selected kinematic features and the measured force/torque sensor readings. The correlation coefficient ranges from −1 to +1. A value close to +1 indicates a strong positive linear relationship, meaning that both variables tend to increase together. A value close to −1 indicates a strong negative linear relationship, meaning that one variable tends to decrease as the other increases. A value close to zero indicates a weak linear relationship. The diagonal values of 1.000 in the correlation matrix represent the correlation of each variable with itself and therefore indicate perfect self-correlation, not model accuracy.

Figure 11 presents a 6 × 6 correlation matrix including the three Cartesian acceleration components (a_x, a_y, a_z) and the three measured force components (F_x , F_y , F_z). Most off-diagonal correlation values are close to zero, indicating that there is no strong direct linear relationship between individual acceleration components and individual force components. This result is expected because the dynamic force offset is influenced by the combined effects of robot position, orientation, tool geometry, and acceleration, rather than by acceleration alone. Therefore, the low pairwise correlations do not exclude the importance of acceleration; instead, they suggest that the relationship between motion and force offset is multivariable and possibly nonlinear.

Figure 12 presents the full correlation matrix of the input features and measured force/torque components. Compared with Figure 11, this matrix provides a broader view of how position, orientation, acceleration, and sensor outputs are related. Although some individual correlations are weak, the dynamic calibration problem depends on the combined contribution of multiple features. This supports the use of polynomial regression and MLP models, which can learn multivariable relationships beyond simple one-to-one linear correlations.

Overall, the correlation analysis shows that simple pairwise linear relationships are not sufficient to explain the dynamic force offsets. This supports the need for a data-driven multivariable model using the full nine-dimensional input vector rather than relying on one acceleration or pose variable alone.

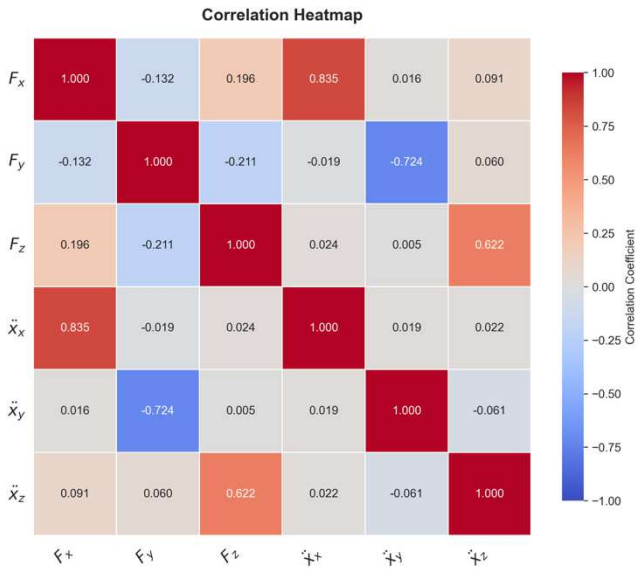


Figure 11. Correlation matrix between the three Cartesian acceleration components $(\boldsymbol{a_x, a_y, a_z})$ and the three measured force components ($\boldsymbol{F_x}$, $\boldsymbol{F_y}$, $\boldsymbol{F_z}$). The diagonal values of 1.000 indicate perfect self-correlation, while the off-diagonal values show the linear relationships and cross-axis coupling between acceleration and force components.

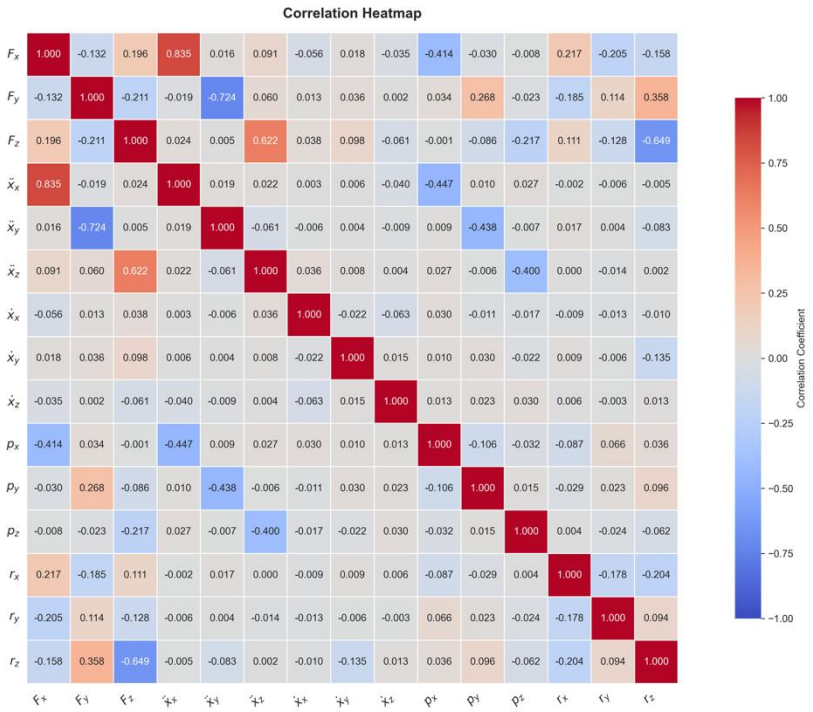


Figure 12. Full correlation matrix of the selected kinematic features and force/torque measurements. The matrix shows the degree of linear relationship among position, orientation, acceleration, and sensor outputs, highlighting feature coupling and multicollinearity in the dynamic calibration dataset.

5. Discussion

The results demonstrate the effectiveness of the proposed data-driven self-calibration approach for both quasi-static and dynamic conditions. In the quasi-static case, the orientation-based polynomial regression model accurately estimated the gravitational offset introduced by the tool holder, achieving errors well below 0.03% FSO. These values are significantly lower than those reported in earlier works such as Kim et al. [9] (≤1.1% FSO) and Yao et al. [10] (≤1.5% FSO), indicating that the proposed method provides a highly accurate static calibration without requiring prior knowledge of the tool's mass or center of mass. This advantage is critical for scenarios involving frequent tool changes or custom tool holders, where recalibration using conventional approaches would be impractical.

For dynamic calibration, both the polynomial regression and MLP models benefited from subtracting the quasi-static offset as a preprocessing step, which effectively isolated motion-induced disturbances. While the second-degree polynomial model offered a good trade-off between accuracy and model complexity, it showed limitations in capturing rapid, nonlinear transients, particularly in the Z-axis where inertial effects are more pronounced. This is consistent with findings in Duan et al. [4], where neglecting complex inertial interactions can limit compensation performance.

The MLP model achieved the best test-set performance, while the second-degree polynomial model showed slightly lower benchmark RMSE. In terms of total force magnitude error, both models performed very closely, with 0.108% FSO for the polynomial model and 0.106% FSO for the MLP model. Although this improvement is small numerically, the MLP may still be useful in tasks where nonlinear transient behavior and instantaneous force accuracy affect contact perception, force feedback, or control response. In contrast, the polynomial model offers a simpler and more interpretable solution with comparable accuracy. This is especially relevant in teleoperation, haptic systems, precision assembly, and robotic-assisted procedures, where both the magnitude and consistency of force estimation are important for safety and task success.

To estimate the force sensor noise, two complementary analyses were performed. The standard deviation of the residuals from the quasi-static calibration provided a noise estimate of approximately 0.21 N along the Z-axis. In addition, near-stationary segments from dynamic experiments were identified based on low acceleration magnitude, yielding a comparable noise estimate of approximately 0.3 N. These values exceed the reported RMSE of the calibrated force estimates, indicating that the proposed method operates close to the sensor noise floor.

The correlation analysis further supports the inclusion of acceleration and orientation data as model inputs. Strong feature interdependence suggests that force prediction in dynamic environments is inherently multivariate, making deep learning architectures like the MLP particularly suited for such tasks. The robustness of the MLP model to raw, unfiltered inputs also implies potential for deployment in real-time control loops without heavy preprocessing, which reduces system latency, a key factor in human-in-the-loop applications.

From the perspective of autonomous robotic systems, the proposed method can be viewed as a force perception layer that improves the robot's ability to interpret physical interaction. During manipulation tasks, the robot must distinguish true external contact forces from internal offsets caused by gravity, motion, and attached tools. If these offsets are not compensated, the robot may misinterpret tool-induced forces as environmental contact, which can affect contact detection, force control, and task reliability. By compensating these offsets without manual tool modeling or hardware modification, the proposed framework supports more reliable force sensing in robotic systems that operate with unknown or changing end-effectors.

This capability is also relevant to teleoperation and haptic applications, where inaccurate force measurements can affect the operator's perception of contact and reduce control accuracy. In such systems, reliable force feedback depends not only on the sensor hardware but also on the ability to remove non-contact disturbances from the measured signal. Therefore, the proposed calibration framework can support safer and more consistent physical interaction in future closed-loop robotic experiments.

A limitation of the present study is that the calibrated force estimates were evaluated mainly at the sensing level rather than through a complete closed-loop manipulation task. Although the results show strong compensation performance under both quasi-static and dynamic robot motion, the effect of the proposed method on contact detection, force control, and task performance still needs to be evaluated directly. Future work should integrate the calibrated force estimates into real-time control experiments and assess their impact during contact-rich robotic manipulation.

Overall, the results highlight three main contributions of this work. First, the proposed quasi-static calibration strategy achieves sub-0.03% FSO accuracy without requiring tool-specific parameters. Second, the dynamic compensation framework models motion-induced force disturbances using both polynomial regression and neural network approaches under realistic robot motion conditions. Third, the method is demonstrated on a physical industrial robot and provides a scalable self-calibration strategy for improving force perception in systems involving interchangeable tools, dynamic motion, and minimal manual intervention.

6. Conclusion

In conclusion, this study presents a data-driven calibration framework for eliminating force sensor offsets in robotic systems with unknown or interchangeable tool attachments. By leveraging a combination of quasi-static and dynamic modeling strategies, robust polynomial regression and MLP-based models were developed to estimate and compensate for static gravitational and dynamic motion-induced forces.

Under quasi-static conditions, a third-degree polynomial model using end-effector orientation achieved a benchmark RMSE of 0.036 N, with maximum errors under 0.13 N across all directions. For dynamic scenarios, the second-degree polynomial model yielded an RMSE of 0.045 N on the benchmark dataset, while the MLP model achieved the highest accuracy, with a test-set RMSE of 0.041 N and benchmark RMSE of 0.049 N. The maximum error in total force magnitude across all models remained below 0.56 N, demonstrating reliable prediction across a wide range of motion profiles.

The main contribution of this study is the development and experimental validation of a two-stage, data-driven force perception framework that compensates for both gravity-induced and motion-induced force offsets without requiring prior knowledge of tool mass, center of mass, or inertial properties. By enabling the robot to distinguish tool-induced disturbances from true external interaction forces, the proposed method supports more reliable physical interaction in robotic systems operating with customized or interchangeable end-effectors. This makes the framework practical for robots operating with customized or interchangeable end-effectors in dynamic manipulation tasks.

The ability to maintain high prediction accuracy without requiring explicit knowledge of tool mass or inertia highlights the practicality and scalability of the proposed approach. In particular, the MLP model's ability to learn complex nonlinear relationships makes it well-suited for dynamic applications where classical analytical models may fall short. These results contribute to improving real-time force estimation in robotic systems, facilitating safer and more precise control in teleoperation, industrial automation, and robotic-assisted surgery. More importantly, the proposed framework addresses a key limitation in existing calibration methods by enabling accurate force estimation without requiring prior knowledge of tool properties or hardware modifications, advancing the practicality of data-driven force sensing in real-world robotic applications.

Future work could investigate hybrid modeling strategies that combine the interpretability of low-order polynomials with the adaptability of neural networks, potentially offering the best of both approaches. Additionally, extending the method to torque compensation in high-load conditions could broaden applicability to more demanding industrial and surgical contexts. Finally, integrating the models into closed-loop control experiments will help assess their real-world performance and stability during prolonged operations. This work demonstrates the feasibility of reliable data-driven force calibration for industrial robotic systems operating in realistic dynamic environments.

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