A Hybrid Energy Consumption Model for Industrial Robot Arms using Robot Dynamics and Data-Driven Approach

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***Abstract*— The accurate energy consumption modeling of robot arms is crucial for energy conservation and optimization. Traditionally, parametric dynamics model is used for estimating the robot arm's torque and power consumptions. However, accuracy of parametric dynamics model relies on the dynamic parameters such as inertia, center of mass, friction etc. In practice, these parameters are hard to estimate and optimization usually require extensive identification process. Similarly, a data-driven approach requires large amount of observation data, are computationally inefficient and suffer from occasional inaccuracies. In this study, a hybrid learning approach combining both parametric model and data-driven method is proposed for energy consumption modelling of industrial robot arm in static pose. Parametric model with approximate estimates of the robot arm dynamics is used to simulate the energy consumption and an artificial neural network is used to learn the error between the simulation and the observed results. Halton-sequence sampling is used for collecting the training data with joint angles as input and energy consumption as output. The effectiveness of proposed model is verified using experimental data and the proposed approach achieves significantly lower mean squared error and higher R-square value than the parametric and the data-driven models while only using approximate dynamic parameters for base dynamics model.**

***Index Terms*— Analytical modeling, Artificial Neural Networks, Data-driven modeling, Energy, Hybrid learning, Machine Learning, Robots.**

I. INTRODUCTION

THE sustainable and efficient use of energy resources plays an indispensable role in environmental preservation and financial prudence. By adopting sustainable energy practices, factories and manufacturing sites can significantly reduce their ecological footprint and alleviate the financial burden associated with excessive energy usage. The popularity of robotic systems, such as industrial robotic arms, can be attributed to the desire to reduce reliance on human labor. As a consequence, the energy consumption associated with these robotic technologies has risen rapidly [1] and will continue to rise in future. In order to promote energy conservation and efficiency, there is urgent need for technologies to reduce the energy consumption by the industries and several government sponsored energy efficiency directives [2] and policies [3]–[5] are also encouraging business and corporations to move towards this goal.

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In recent years, several studies are focusing on the optimization of energy usage by industrial robot arms. In [6] various software-based methods for reducing power consumption and optimizing manufacturing processes are discussed including speed and acceleration optimization, dynamic parameter optimization and energy optimal trajectory planning. This study also highlights the importance of energy vs cycle time trade-off and also shows that the robot arms dynamic parameters plays an important role in modeling of energy consumption. Simulation models [7], [8] are popular way for predicting the energy consumption for industrial robot arm's energy reduction. Utilizing a robotic arm's dynamic model, as demonstrated in [9], allows for accurate estimation of energy consumption through on-site parameter identification, thereby facilitating the development of energy-efficient path planning algorithms for industrial robots. In some studies simplified dynamics model is also used to eliminate the complexity of parameter identification. In [10] , the energy-optimal trajectory planning is primarily focused on velocity and acceleration variables, utilizing state-space equations for the analysis. Similarly in [11], a simplified energy consumption computation was employed to identify energy efficient trajectories, utilizing the sum of kinetic and potential energies of the robotic arm links as the primary energy objective. While simplified energy model are practically valid and usable for optimization tasks, a high-fidelity dynamics model of industrial robot arm often result in better energy estimation and thus also improves the energy optimization accuracy. In [12], a high-fidelity dynamics model, incorporating various parameters and constant losses, is utilized for trajectory optimization in the study. Although the optimization results are noteworthy, the modeling and dynamic parameter identification process is considerably time-consuming and susceptible to experimental errors.

High accuracy physical modeling of industrial robot arm's energy usage requires a combination of equation of motion for the mechanical properties of robot and dynamical equation for the gearboxes and motor drives [13]. Generally, torque data is used for parameter identification of robot dynamics but some studies also utilize power data [14], [15] as the target variable. In some cases, temperature effect [16] and gravitational load effect [17] on the energy consumption of industrial robots are also analyzed and taken into account when creating a dynamical model. While most of the studies emphasizes the dynamic motion analysis for energy consumption that incorporates velocity and acceleration parameters [18], [19], there is a scarcity of research focusing specifically on energy consumption during the static pose of industrial robots.

Most of the literatures discussed in this section so far, focuses on analytical modeling of dynamic parameters and their identification for energy usage estimation. In most of the cases, some of the parameters like friction effect, temperature effect and inertia parameters are hard to identify and their accuracy is subjected to experimental setup and boundary conditions. Although using Lagrange method [20] to model the robot dynamics can reduce number of parameter that needs to be identified, the experimental errors and boundary definitions still affect the overall accuracy. There exist the data-driven approach to model the energy [21], however, it requires large amount of data for modeling. Similarly, machine learning methods to model the energy consumption like artificial neural networks (ANN) also follow the big data trend and require large training dataset to achieve reasonable accuracy. Some recent studies, however, have explored the application of a hybrid method known as physics-informed neural network [22], that incorporates the physical model of the system into the machine learning framework thus significantly reducing the data size required for training. Hybrid models, which combine an approximate physical model with an ANN for learning the model errors using a small amount of training data, can achieve higher accuracy than purely physical models, while simultaneously reducing the labor and time required for optimization or fine-tuning of the model [23]. Several studies has shown promising results by using hybrid learning models [24], [25] for various application in different domains.

Drawing from the literature review, this study presents a hybrid energy consumption model for industrial robots, employing hybrid learning that combines an approximate dynamics model with an ANN. The primary focus is on modeling energy consumption in static state of robot arms (in state of no motion), considering joint angles as input variables. A low discrepancy sampling technique is used to collect the robot arm's energy consumption at different poses within a defined workspace. The performance of the physical model's energy estimation is compared to the proposed hybrid method to showcase the proposed models applicability in this domain. The paper is structured as follows: Section II discusses robot arm dynamics; Section III discusses the dynamics properties of robot arm used in this study. Section IV presents the proposed methodology; Section V showcases results and comparisons between methods; and Section VI concludes the study and its findings.

II. DYNAMICS OF INDUSTRIAL ROBOT ARM

The dynamics of an industrial robot arm can be characterized by assigning mass, center of mass and moment of inertia of links together with the friction properties of the actuator drives at each joint. Equations of motion is most common method of determining the joint torques of the robot arm as a function of robot arm dynamics properties and joint angles. For a robot arm with n joints and joint angles $q \in \mathbb{R}^n$, the applied torque by joints $\tau \in \mathbb{R}^n$ can be calculation using equation of rigid body equation of motion [26] as shown in Equation (1):

$$\tau = M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + \tau_f(\dot{q}) \qquad (1)$$

Where, $M(q) \in \mathbb{R}^{n\times n}$ denotes a positive definite mass matrix, $C(q,\dot{q}) \in \mathbb{R}^{n\times n}$ represents the matrix for Coriolis and centrifugal effects, $G(q) \in \mathbb{R}^n$ represents the torque exerted due to gravity effect and $\tau_f(\dot{q})$ is the function representing the frictional torques.

When the robot arm is in static condition (no motion), only gravity term $G(q) \in \mathbb{R}^n$ is considered for calculating the torques applied on robot arm joints. The gravity term of each joint can be calculated as a function of mass of the link, center of mass of the link and joint angle. The equation for computing the gravity term can written as Equation 2:

$$G(q_i) = \sum_{i,j=0}^{n} m_j \cdot g \cdot \left({\partial p_j}/{\partial q_i} \right) \qquad (2)$$

Where m_j is the mass of the link j, g is the gravitational force acting on the link j (-9.81 m/s2), p_j is the position of center of mass of link j, and q_i is the joint angle of joint j. The summation term used in Equation 2 is applied over all links to obtain the gravity term, $G(q) = [G(q_0), G(q_1), \dots, G(q_n)]^T$.

III. THE DYNAMIC PARAMETER ESTIMATION

In this study, a medium payload industrial robot arm, the Yaskawa Motoman MH12, is examined, as depicted in Fig. 1. The robotic arm features a six-axis configuration, comprising 6 links and 6 joints with maximum payload limit of 12 Kg. A three-dimensional (3D) model of the robot arm is employed to estimate dynamic parameters using SolidWorks, a computer-aided design (CAD) software. Each link is assigned a material of gray cast iron, with a density of 7.34 g/cm³. It is crucial to acknowledge that the CAD model provided by the manufacturer is an approximation of the actual robot and does not consider hollow sections, wiring, and tubing regions. Consequently, the calculated center of mass (CoM) and mass properties may not accurately represent the real robot. To address this issue, tubing, wiring, and hollow regions were added to the model based on actual robot measurements, without requiring complete disassembly. After modifying the 3D model of the robot we calculated the CoM and mass properties of the robot using the CAD software as listed in Table I. Despite potential discrepancies, these estimations provide a suitable foundation for constructing a dynamic model that assesses static state energy consumption for the robot arm.

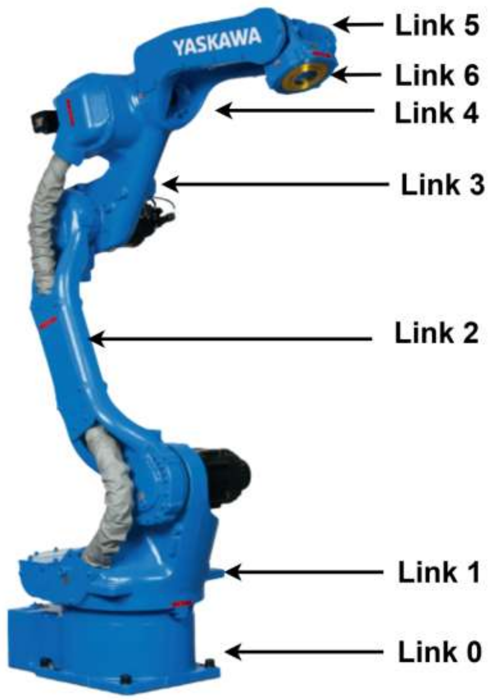

Fig. 1. Robot arm link positions of Yaskawa Motoman MH12.

From Table I, it can be observed that the mass of Link 1 is significantly larger compared to the other links. However, since

Link 1 is perpendicular to the base in its static state, its gravitational forces are primarily transferred vertically to the base, resulting in minimal energy consumption. In contrast, during the robot arm's static operation, the mass properties and CoM locations of Links 2 and 3 play critical roles in determining overall energy consumption. The actuators and motors controlling Links 2 and 3 must generate forces to overcome the gravitational forces acting on them due to their mass and CoM locations. Similarly, Links 4 and 5, although having smaller masses, also contribute to the overall energy consumption of the robot on a smaller scale. This is due to the combined effect of their mass properties and CoM locations, which influence the force requirements for maintaining the robot arm's static equilibrium.

TABLE I
MASS AND CENTER OF MASS PROPERTIES OF MH12

Link	Mass (kg)	Center of Mass, x (m)	Center of Mass, y (m)	Center of Mass, z (m)
0	22.806	-0.050	0.003	0.057
1	44.652	0.035	0.005	-0.188
2	30.939	-0.018	-0.092	0.258
3	10.538	0.089	-0.034	0.120
4	4.9476	-0.224	0.000	0.017
5	2.0965	0.026	-0.015	0.000

IV. METHODOLOGY

In a static pose, the robot arm is motionless, and therefore, the angular velocity is zero. Traditional methods of calculating power or energy, which are typically predicated on motion dynamics, are not directly applicable under these conditions. However, to counteract the effects of gravity and maintain a position, the robot arm must exert opposing torques. This means that even though the arm is not in motion, the servo motors in the joints remain active, leading to power consumption.

The relationship between the motor's torque (τ_m) and the current (I) is described by the Equation 3 [27],

$$\tau_m = K_t \times I \tag{3}$$

Where K_t is the torque constant of the motor. The electrical power (P) consumed by the motor can be calculated as the product of the current (I) and the voltage (V). Substituting I from the Equation 3,

$$P = \tau_m \times \frac{V}{K_t} \tag{4}$$

This Equation 4 describes the power used by the motor in relation to the generated torque, the applied voltage, and the motor's torque constant.

Over time, this power consumption equates to the energy required for the robot arm to maintain a specific pose. This linear estimate provides a bridge between joint torque estimation and energy consumption of different poses. Therefore, the estimated torque value of the robot arm can be used as an effective indicator of its energy consumption in various static poses.

This study uses the absolute sum of applied torques τ as shown in Equation 5 for each joint of the robot arm to represent the energy consumption at any given pose, highlighting the practical considerations that exist even when the robot arm is motionless.

$$\tau = \sum_{i=0}^{n} |G(q_i)| \tag{5}$$

In this research, an industrial robot arm controller, Yaskawa Motoman DX200, is employed, which supports high-speed Ethernet communication using the User Datagram Protocol (UDP) with an average response rate of 50 Hz. This communication protocol enables efficient and real-time data transfer between the robot controller and an external system. To gather the torque data for each joint from the controller, a personal computer is utilized, on which a custom communication software, developed using Python programming language, is implemented. This software facilitates the communication between the robot arm controller and the personal computer, ensuring seamless data transfer and processing.

The torque data collection process for this study spans over a duration of 2 seconds, resulting in 100 samples per joint. Once the data is collected, it is processed to compute the average torque value for each joint at a given pose. Utilizing the average value of the torque samples provides a more reliable representation of the joint torque, as it accounts for any fluctuations or inconsistencies in the data due to external factors or system noise. The communication method for data collection is shown in Fig. 2 and the experimental setup in Fig. 3.

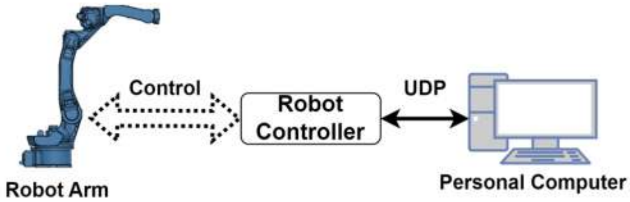

Fig. 2 Schematic diagram of experimental setup for data collection from robot arm.

In order to efficiently sample the workspace of the robot arm, this study employs a low discrepancy sampling method known as the Halton sequence [28]–[30] for the design of experiments. The literatures suggest that low discrepancy sampling methods provide superior space-filling properties in comparison to random sampling, as well as improved convergence results for modeling and optimization tasks. Given that this study utilizes robot arm joint angles as input variables, the upper and lower limits for each joint are defined, as demonstrated in Table II.

Utilizing the Halton sequence, a total of 532 distinct joint angle configurations are generated, taking into account the specified joint limits. It is important to note that some of these limits deviate from the mechanical limits of the robot arm, as they have been adjusted to ensure safety and to prevent collisions between the robot arm and its base, as well as the platform. The resulting x, y, and z-axis positions of the end effector for these joint configurations within the 3D workspace are depicted in Fig. 4.

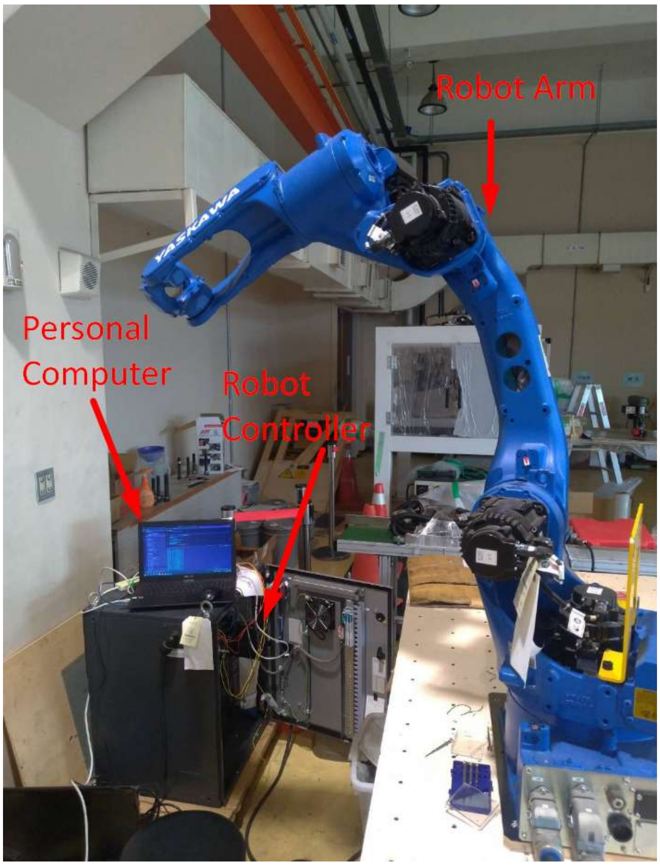

Fig. 3 Experimental setup for data collection from robot arm.

TABLE II
MECHANICAL LIMITS AND LIMITS USED IN DATA COLLECTION EXPERIMENT

Joint	Lower mechanical limits (radians)	Upper mechanical limits (radians)	Lower experiment limits (radians)	Upper experiment limits (radians)
0	-2.9670	2.9670	-1.5708	1.5708
1	-1.5708	2.7052	-0.3491	0.3491
2	-1.4835	2.6179	-1.1355	0
3	-3.4906	3.4096	-2.0944	2.0944
4	-2.6179	2.6179	-1.5708	1.5708
5	-3.1415	3.1415	-3.1415	3.1415

Table II provides information on the mechanical limits of the robot arm's joints and the limits used in the data collection experiment. These limits are essential in determining the range of motion of the robot arm during the data collection process. The lower and upper mechanical limits of each joint are specified in radians, while the lower and upper experiment limits represent the minimum and maximum joint angles explored during the data collection phase.

For instance, joint 0 has lower and upper mechanical limits of -2.9670 and 2.9670 radians, respectively. However, during the experiment, its motion was limited to a range of -1.5708 and 1.5708 radians to ensure safe and controlled operation. Similarly, joint 1 has lower and upper mechanical limits of -1.5708 and 2.7052 radians, respectively. It was constrained within a smaller range of -0.3491 and 0.3491 radians during the experiment because smaller changes in the second joint can cause significant deviations in the end-effector positions. This limitation was put in place to prevent self-collision or collision with other objects in the experimental setup space.

The remaining joints also have specified lower and upper mechanical limits, which vary depending on the joint. For example, joint 2 has a lower mechanical limit of -1.4835 radians and an upper mechanical limit of 2.6179 radians. However, its motion was limited to a range of -1.1355 and 0 radians during the experiment due to safety concerns and to ensure the robot arm's operation remained within the desired workspace.

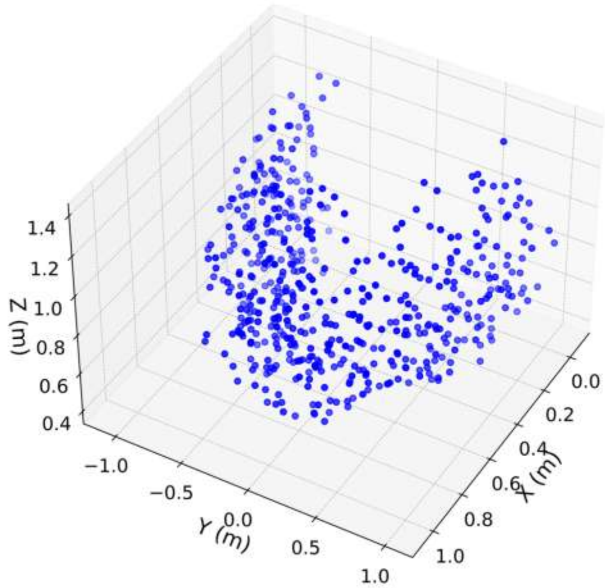

Fig. 4 End-Effector position of robot arm in three dimensional workspace for the joint configurations used in design of experiment.

In order to model the energy consumption of the robot arm for a given joint configuration, this study employs a hybrid machine learning approach. Initially, the applied torque on each joint of the robot arm is calculated using the gravity term, as illustrated in Equation 2. Subsequently, the analytical solution is computed as the absolute sum of torques using Equation 3. These torque values will be utilized for comparative purposes later in the study.

In this study, a hybrid approach is proposed, utilizing ANN, to model the energy consumption of a robotic arm based on joint angles and applied torques, which are due to gravitational effects on each joint. As shown in Figure 5, the proposed approach makes use of a single hidden layer ANN model with 475 neurons. The determination of the number of neurons was accomplished through hyperparameter optimization using the Tree of Parzen Estimators method [31]. This optimization process was conducted using the Hyperopt/Python library [32], which provides an efficient and automated means of searching for the most suitable hyperparameters for the model..

The input variables for the ANN model are comprised of joint angles and gravity-induced torques, resulting in a total of 12 variables (6 for joint angles and 6 for applied torques). The output variable is the absolute sum of torques, as measured from the robot controller for each joint configuration. It should be noted that the model is fed with input joint angles and the estimated joint torques derived from robot dynamics. Therefore, this model is primarily tasked with estimating the error between the measured torque and the estimated torque from the robot dynamics.

For comparison purposes, an ANN model was constructed with one hidden layer, and number of neurons were optimized using the Hyperopt library within a range of 8 to 1000 neurons. The best model configuration was determined to be with a total of 216 neurons in the hidden layer. However, this model was trained to directly predict the total torque. Joint angles were used as the input variables and total joint torques as the output variable in this model. Consequently, this ANN model attempts to establish a data-driven prediction model to directly estimate the total torque values, as is typical in data-driven methodologies.

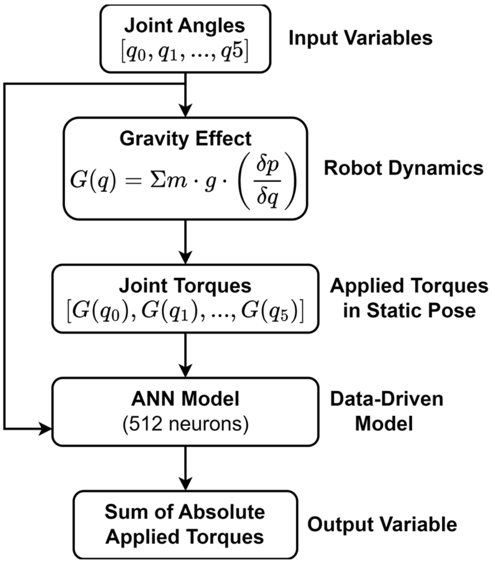

Fig. 5 Schematic representation of the hybrid learning approach for modeling energy consumption in an industrial robot arm by combining robot dynamics and ANN.

The dataset used for this study is divided into two parts: 80% is utilized for training, and the remaining 20% is designated for testing purposes.

During the training process, both the ANN and the hybrid model's ANN are optimized using the ADAM stochastic optimization algorithm [33], a well-regarded algorithm frequently employed in machine learning for the optimization of deep learning models. The sigmoid activation function, a commonly used activation function for hidden layers in ANNs, is utilized for the ANN neurons. The TensorFlow library, an extensively used open-source software library for machine learning, is employed to develop the ANN model. Furthermore, the model is implemented and optimized using the Python programming language, a popular choice for data analysis and machine learning due to its simplicity and comprehensive libraries.

V. RESULTS

To compare the performance of torque estimation between the robot dynamics approach, ANN model and the hybrid learning method, this study employs three evaluation metrics: Root Mean Squared Error (RMSE) as presented in Equation 4, Coefficient of Determination (R^2) as depicted in Equation 5, and Mean Absolute Percentage Error (MAPE) as illustrated in Equation 6. The accuracy of the two approaches is assessed using the MAPE metric, as outlined in Equation 7. In the equations below, $\hat{y}$ represents the predicted value, y is the actual/measured value and n is the total number of samples used for testing (132 in this case). By examining these metrics, the study aims to provide a comprehensive analysis of the effectiveness and robustness of each method in estimating torque values for the robot arm.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=0}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n}(y_i - \bar{y}_i)^2} \tag{5}$$

$$MAPE = \frac{\sum_{i=0}^{n}|y_i - \hat{y}_i|}{n} \times 100 \tag{6}$$

$$Accuracy = 100 - MAPE \tag{7}$$

The comparative results, summarized in Table III, convincingly illustrate that the hybrid approach, which merges robot dynamics and an ANN model, surpasses the standalone robot dynamics model in the task of estimating total torque. This superiority is evidenced by a significant reduction in the RMSE by a factor of 2.22, which brings down the error from 29.31 Nm (for the robot dynamics model) to 13.19 Nm. Furthermore, when employing the hybrid approach, there is a reduction in the MAPE by over 10% as compared to the robot dynamics model.

Conversely, the ANN model, trained on identical data and with the optimized hyperparameters, was unable to accurately correlate the robot torque output with the input robot joint angles. As a result, it underperformed compared to both the dynamic and hybrid models. This weaker performance of the ANN model can be primarily attributed to the limited size of the training dataset.

TABLE III
COMPARISON OF ROBOT DYNAMICS AND PROPOSED HYBRID APPROACH FOR ESTIMATING TOTAL TORQUE

Metrics	Robot Dynamics	ANN	Hybrid Approach
RMSE	29.31 Nm	30.19 Nm	13.19 Nm
R^2	0.687	0.663	0.936
MAPE	15.783 %	16.671%	4.271%
Accuracy	84.217%	83.329 %	95.729%

In addition to improvements in RMSE and MAPE, the hybrid approach also shows an increase in the R^2 value. With a R^2 value of 0.936 for the hybrid approach, it substantially outperforms the robot dynamics model which registers an R^2 value of 0.687. This highlights that the hybrid approach is able to account for approximately 93.6% of the variance in the data, as opposed to the 68.7% explained by the robot dynamics model alone. It is noteworthy that, while the standalone ANN model reached a reasonable accuracy of 83.329%, its R^2 value of 0.663 indicates that it could only explain 66.3% of the variance in the data, suggesting a less precise mapping of the predicted data to the measured data. Despite the limited data, the standalone ANN model approached the accuracy of the robot dynamics model. However, the hybrid approach, which integrates the robot dynamics model and ANN model, outperformed both models in terms of accuracy and R^2 value.

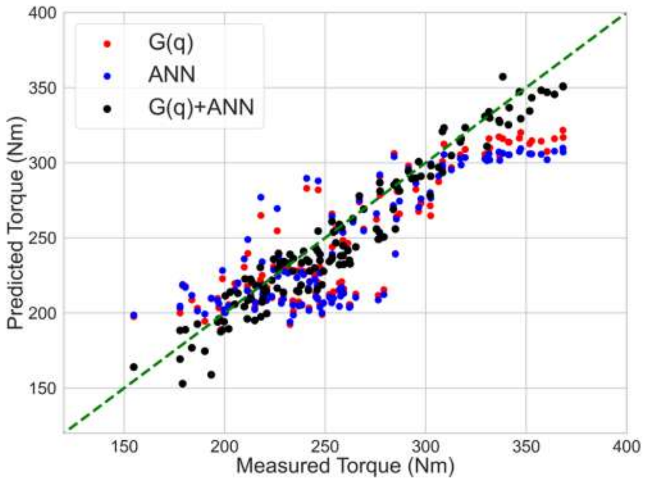

Fig. 6 Scatter plot illustrating the comparison between the total torque output from the robot dynamics (gravity term) and the hybrid learning approach.

In Figure 6, the scatter plot presents a clear visual comparison among the three estimation approaches – the robot dynamics model, the ANN, and the hybrid approach – in relation to the measured or actual total torque data. The data points representing the hybrid approach are observed to cluster tightly along the diagonal (45°) line, indicative of a strong correlation between the predicted and measured total torques. This close alignment highlights the enhanced accuracy and reliability of the hybrid approach in estimating total torque values.

Conversely, the data points corresponding to the robot dynamics model are noticeably scattered and display a weaker correlation with the measured total torques. This spread reflects the limitations of solely using the robot dynamics model to capture the complex behavior of the system, resulting in less accurate and less reliable torque estimations. The ANN model displays the highest dispersion of data points, which further suggests that the model was unable to converge due to the constraints of a limited dataset.

The enhanced performance of the hybrid approach can be attributed to the synergistic combination of the robot dynamics model, which offers a fundamental understanding of the physical behavior of the system, and the ANN model, which effectively captures the nonlinear relationships within the data. Consequently, the hybrid approach emerges as a superior method for estimating total torque in industrial robot applications, with the potential to significantly improve the efficiency, effectiveness, and overall performance of these robotic systems.

Although it could be argued that the accuracy of the robot dynamics model can be improved by employing parameter identification methods, this study demonstrates that the proposed method can achieve superior results using a relatively small dataset of only 532 samples. Furthermore, the proposed method offers several practical advantages, including ease of implementation, reduced time consumption, and the elimination of any need for special modifications to the robot arm or its controller. Notably, the entire estimation process can be completed in under an hour, emphasizing the efficiency of the hybrid approach. Thus, the hybrid approach presents a valuable and efficient solution for total torque estimation in industrial robot applications.

VI. Conclusion

This study effectively showcases the potential of a hybrid learning approach, integrating a parametric robot dynamics model with an ANN model, to accurately estimate total torque in static poses as an indicator of energy consumption, as shown in Equation 3 and 4, particularly within industrial robot applications. The hybrid approach outperforms the robot dynamics model and ANN model alone, achieving significantly lower RMSE and higher R^2 values, and thereby offering a more reliable and precise method for energy consumption modeling. This method proves to be efficient, easy to implement, and does not require extensive parameter identification, or any modifications to the robot arm or controller. The proposed hybrid approach holds significant potential for improving the overall efficiency, effectiveness, and performance of industrial robotic systems.

Moving forward, this study aims to extend the research by investigating the application of the hybrid approach for estimating robot energy consumption during motion (dynamic torque). Additionally, the exploration of payload effects on the model's efficiency will be considered, providing a comprehensive understanding of the hybrid approach's potential in diverse industrial robot applications. This future research direction seeks to further enhance the practicality and adaptability of the hybrid method in addressing the complexities of real-world robotic systems.

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