

Article

A Data-Driven Method for Predicting and Optimizing Industrial Robot Energy Consumption Under Unknown Load Conditions

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Abstract: The growing diversity and number of industrial robots make energy consumption prediction and optimization increasingly essential. Current data-driven approaches, particularly those based on multi-layer perception (MLP), have shown feasibility but typically overlook the variability or unknown nature of load-related parameters in real-world applications. This paper presents a KAN-LSTM model designed to accurately predict energy consumption under unknown load conditions, alongside a particle swarm optimization (PSO) algorithm for minimizing energy use. First, an industrial robot dynamics and energy consumption model is established. Then, the KAN-LSTM model is trained on datasets from the AUBO-E5 robot, with its predictions compared to alternative network models. Finally, PSO is applied to optimize energy consumption. Experimental results indicate that the KAN-LSTM model achieves high prediction accuracy (95.7–97.1%) and offers substantial energy optimization potential (53.1–64.7%). Optimized industrial robots are particularly suitable for tasks such as picking and palletizing in the courier industry, saving operational costs and increasing the sustainability of automated systems in logistics environments.

Keywords: industrial robots; energy consumption prediction; unknown load conditions; KAN-LSTM model; energy consumption optimization



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1. Introduction

In recent years, with population growth and industrialization, global energy consumption is increasing annually and the ecological environment is deteriorating yearly, so how to use resources rationally to save energy and reduce carbon and emissions has become a global issue [1,2]. According to the World Energy Outlook 2023, about 37.8% of the world's energy is consumed by industry. Industrial robots, with their high efficiency and automation characteristics, have become the key equipment to drive the intelligent manufacturing process [3–6]. At the same time, they play an increasingly important role in various production processes in industry and manufacturing, with a significant impact on industrial energy consumption. According to the statistics of World Robotics 2024 published by the International Federation of Robotics, the compound annual growth rate (CAGR) of the number of global industrial robots is about 12% from 2018 to 2023, and the cumulative growth rate of global industrial robots is about 4.3 million units in 2023, which is 10% higher than the previous year. Moreover, a comparative study found that an average normal working industrial robot consumes up to 21,915 kWh of energy per day [7]. It can

be seen that the high-intensity use of industrial robots and the huge energy demand have put great pressure on environmental energy, and the transformation and upgrading of the manufacturing industry has also put more stringent requirements on the energy efficiency of industrial robots. Therefore, reducing the energy consumption of industrial robots is necessary to reduce the overall energy consumption of the industrial sector, and optimizing the energy consumption of industrial robots to improve energy efficiency is also essential to promote energy saving and carbon reduction policies.

However, accurate modeling and prediction of energy consumption is a prerequisite and foundation for optimizing energy consumption. Modeling the energy consumption of industrial robots is not easy because industrial robot systems have multiple components, such as controllers, actuator controllers, and servo motors, which result in different energy consumption characteristics. The commonly used modeling methods are the direct modeling method and the data-driven method. Direct modeling methods are based on kinematics and dynamics to establish the corresponding equations, which usually require the identification of a number of dynamic parameters, including the joints and drive motors, such as mass, center of gravity position, inertia tensor, and friction coefficients, etc. Qiu et al. used the Newton-Euler method to establish a dynamic model for industrial robots and accumulated the mechanical power output from the joints into the total power [8], but the model did not fully consider the key factor of joint friction. Relevant studies show that the energy consumption caused by friction can account for up to 20% of the total energy consumption of industrial robots [9], which should not be underestimated and is crucial for accurate modeling. Han et al. proposed an iterative identification method for dynamic models considering friction models [10]. However, when this model is applied to various types of industrial robots, the identification of key parameters and the construction of the model must be performed again, and the modeling process is complicated and time-consuming.

The data-driven methods avoid the complex modeling process of traditional modeling methods and can accurately and efficiently model the relationship between operating parameters and energy consumption, with the construction of intelligent algorithmic models to approximate the actual energy consumption. Zhang et al. proposed a BP neural network-based energy consumption prediction model [11], which mainly considered the influence of industrial robot operating parameters on energy consumption. In order to speed up the model reconstruction and improve the model generalization, a migration learning-based energy consumption prediction model for industrial robots was proposed [12]. Jiang et al. proposed a deep neural network energy consumption prediction model based on long short-term memory (LSTM), which revealed the nonlinear mapping between joint motion variables and the energy consumption of industrial robots [13]. It is worth mentioning that all the above studies only considered the effects of joint motion variables and operating parameters on the energy consumption of industrial robots, while ignoring the effects of load on the energy consumption of industrial robots.

In industries such as warehousing, logistics, and manufacturing [14], industrial robots are often used in material handling, machining, loading and unloading, logistic palletizing, etc. These tasks require a large amount of energy, with tasks involving multiple movements or lifting heavy objects possibly requiring more energy than static tasks [15]. Lin et al. found that the effect of load on the energy consumption of industrial robots is relatively linear, with each 1 kg increase in payload increasing the energy consumption by at least 4% [16]. Therefore, they proposed an industrial robot energy consumption prediction model based on a batch normalized long short-term memory network (BN-LSTM) and considered the effects of operating parameters and joint torque on the energy consumption of industrial robots under the condition that the load is known. However, most industrial robots do not have the ability to collect joint torque data [17–19], and the collection of joint torque requires the help of a torque sensor, which is more expensive and requires sufficient installation space and is also prone to damage or failure under extreme environments such as high temperature and high pressure. Therefore, it is necessary to rely on other

measurable physical quantities that are recognized in the work of industrial robots. Yao et al. proposed a generalized energy modeling network DM-PLM, which consists of a dynamic model (DM) and a power loss model (PLM) of industrial robots [20], to predict joint torque under bidirectional recurrent neural network (BiRNN) using joint motion variables under known multi-load conditions and to achieve the prediction of the energy consumption of industrial robots under convolutional neural network (CNN) ResNet.

However, the implementation of the above research methods is based on the conditions that the load-related parameters are known and the loads considered in the experimental validation are uniformly distributed, regularly shaped, and mass-standardized metal blocks, while most of the load-related parameters of industrial robots in actual work scenarios are unknown and the material distribution is not uniform, especially in the field of logistics, where the center of mass of the loads is difficult to be artificially measured in real time. Therefore, it is necessary to establish a load prediction model to meet the demand for real-time input of load-related parameters for energy consumption prediction models. Dong et al. found that the actuator torque difference of industrial robots moving along the same trajectory carrying different payloads can be directly described as a function of the inertial parameter of the payload [21]. Xu et al. proposed an improved two-loop dynamic parameter identification method and constructed a double-weighted payload identification model based on the identification results of dynamic parameters [22]. However, for industrial robots with multiple degrees of freedom, due to the strong nonlinearity of its dynamic model, when it is directly used for parameter identification, it will face the problem of large computational volume and low efficiency. Therefore, neural network prediction models based on dynamic models that can reduce the dependence on sample size and improve the efficiency of load identification is an effective method to solve these difficulties.

This paper proposes a KAN-LSTM energy consumption prediction model, combining Kolmogorov-Arnold Networks (KAN) and long short-term memory (LSTM) networks. The model addresses the challenges of load prediction and energy consumption under unknown load conditions. It enables accurate prediction of load-related parameters and energy consumption for industrial robots. The proposed KAN-LSTM energy consumption prediction model has two main components: load prediction phase and power prediction phase. In the load prediction phase, a data-driven method based on KAN is proposed for load prediction. KAN has a learnable activation function and better interpretability characteristics in terms of weights [23]. Therefore, it can effectively reduce the dependence of load prediction on the sample size and realize the use of fewer parameters to achieve efficient prediction results. Meanwhile, it solves the problems of strong nonlinearity and low efficiency of parameter identification in industrial robot dynamics models. In the power prediction phase, since the output results of the load prediction model $\hat{M}(t), \hat{r}_x(t), \hat{r}_y(t), \hat{r}_z(t)$ are time series data, and the LSTM network has the ability to solve the vanishing gradient and capture the long dependence [24], the data-driven method based on the LSTM network is selected to perform the highly nonlinear power prediction, and the total power of industrial robots is integrated to finally obtain the energy consumption prediction results. In addition, this study achieves the online prediction of load-related parameters by setting a fixed pre-motion trajectory for industrial robots and predicts the energy consumption of industrial robots under multiple trajectories using the proposed model, and finally realizes the optimization of energy consumption of industrial robots by the particle swarm optimization algorithm (PSO).

The research in this paper aims to consider the unknown nature of loads and the impact of loads on the energy consumption of industrial robots, to break the limitation of known loads of the existing energy consumption models, to propose a KAN-LSTM energy consumption prediction model, and to compare the proposed prediction model with three previous studies [11,13,16], where the experiments consider loads in the range of 0–5 kg. The main contributions of this paper are as follows:

- (1) The KAN-LSTM energy consumption prediction model is proposed, which takes into account the influence of load on the energy consumption of industrial robots,

realizes the accurate prediction of load, power, and energy consumption of industrial robots under unknown load conditions, and solves the problem that the load-related parameters of industrial robots cannot be directly used as the input parameters of energy consumption prediction models under unknown load conditions.

- (2) Different from previous parameter identification methods, this paper adopts a data-driven method to predict the load-related parameters of industrial robots, constructs a load prediction model based on the KAN network, overcomes the strong nonlinearity of the dynamic model of industrial robots and the inefficiency difficulty of parameter identification, and achieves high-precision prediction of load-related parameters.
- (3) The proposed KAN-LSTM energy consumption prediction model is experimentally validated on an AUBO-E5 industrial robot, and the *MRE* value of energy consumption prediction of KAN-LSTM model is 1.18%, which is reduced by 48.5%, 46.1%, and 28.0% compared with the results of BP network model, LSTM network model, and BN-LSTM network model, respectively. In addition, this paper also achieved complete energy optimization based on the accurate energy prediction model, with the load prediction accuracy reaching 70.9–96.8% and energy consumption prediction accuracy reaching 95.7–97.1%. The energy optimization potential is 53.1–64.7%.

The rest of the paper is structured as follows: Section 2 models the dynamics and energy consumption of industrial robots, respectively. Section 3 proposes a KAN-LSTM energy consumption prediction model and designs a load prediction model for industrial robots based on KAN and a power prediction model based on an LSTM network. Section 4 performs experimental validation and describes the energy consumption optimization method. Finally, Section 5 provides a conclusion and describes future work.

2. Industrial Robot Modeling

2.1. Dynamic Modeling

At present, there are many methods on robot dynamics analysis, mainly the Lagrange (Lagrange) method, Newton–Euler (Newton-Euler) method, Gauss (Gauss) method, Kane (Kane) method, and so on. In this paper, the Newton-Euler method is used to analyze the dynamics of an AUBO-E5 industrial robot. Considering that in the working state of industrial robots, the influence of friction and external forces brought by loads on the driving torque is very important, the final dynamics equation of the AUBO-E5 industrial robot can be described by the second-order nonlinear differential equation as:

$$\tau = H(\dot{q})\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + \tau_m + \tau_f \quad (1)$$

where $q, \dot{q}, \ddot{q} \in R^{n \times 1}$ represent position, velocity, and acceleration vectors of the joint, respectively. $\tau \in R^{n \times 1}$ is the joint driving moment. $H(\dot{q}) \in R^{n \times n}$ is the matrix of inertia. $C(q, \dot{q}) \in R^{n \times 1}$ is adopted to describe the Coriolis and centrifugal torque. $G(q) \in R^{n \times 1}$ is the gravity term. $\tau_m \in R^{n \times 1}$ is the term of external forces due to the load. $\tau_f \in R^{n \times 1}$ is the friction term.

The Coulomb plus viscous friction model is now commonly used to approximate the actual friction model, so that τ_f can be expressed as:

$$\tau_f = f_v \dot{q} + f_c \operatorname{sgn}(\dot{q}) \quad (2)$$

where f_v, f_c are the coefficient of viscous friction and Coulomb friction coefficient, respectively, and $\operatorname{sgn}(\cdot)$ represents the sign function.

Based on the study [20], τ_m in the kinetic equation can be rewritten as a linear expression:

$$\tau_m = U_m(q, \dot{q}, \ddot{q}) \varphi_m \quad (3)$$

where φ_m is the set of dynamic parameters of the end load and $U_m(q, \dot{q}, \ddot{q})$ is the observation matrix.

For different end loads, the set of dynamic parameters φ_m is:

$$\varphi_m = f_\varphi(M, r) \quad (4)$$

where M is the mass of the load, $r = [r_x, r_y, r_z] \in R^{3 \times 1}$ is the center of gravity of the load, and $f_\varphi(\cdot)$ is the independent variable M, r as a function of the dependent variable φ_m . Therefore, the external force term τ_m due to the load can be expressed as:

$$\tau_m = f_m(q, \dot{q}, \ddot{q}, M, r) \quad (5)$$

where f_m is the functional relationship between the independent variable $q, \dot{q}, \ddot{q}, M, r$ and the dependent variable τ_m .

The equation for the dynamics of the AUBO-E5 industrial robot can be written as:

$$\tau = H(\dot{q})\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + \tau_m(q, \dot{q}, \ddot{q}, M, r) + \tau_f(q, \dot{q}) \quad (6)$$

It can be simplified as follows:

$$\tau = f(q, \dot{q}, \ddot{q}, M, r) \quad (7)$$

Therefore, under the condition of determining $q, \dot{q}, \ddot{q}$, the load-related parameters M, r and joint torque τ are both one-to-one mappings, which allows the prediction of industrial robot load-related parameters by joint torque. However, some industrial robots do not have the ability to read the joint torque in the actual working scenario, and the external torque sensor is expensive. To solve this problem, this paper chooses to replace the joint torque by the industrial robot joint current i in view of the existence of $\tau_n = k_n \cdot i$ relationship between torque and current and finally simplifies the dynamics equation of the AUBO-E5 industrial robot as:

$$(M, r) = f(q, \dot{q}, \ddot{q}, i) \quad (8)$$

2.2. Energy Consumption Modeling

Industrial robots consist of electrical components (motor drivers, microcontrollers for each motor, sensors, and chopper resistors) and electromechanical components (the motors and mechanical brakes) [25], as shown in Figure 1. Therefore, the following equations for determining the electrical power can be proposed:

$$P = P_E + P_B + P_R + P_{M_i} + P_{MD_i} \quad (9)$$

where $P_E, P_B, P_R, P_{M_i}, P_{MD_i}$ are the power of all electronics, braking, chopping resistors, each motor and motor driver, respectively.

For the motor power, P_M can be simply expressed as [26]:

$$P_M = P_{mec} + P_{Cu} + P_{Fe} + P_{add} \quad (10)$$

where P_{mec} is the power of the mechanical system under neglecting the mechanical transmission efficiency, which can be expressed as $P_{mec} = \tau^T \dot{q}$, P_{Cu} and P_{Fe} represent the copper and iron losses, respectively, which are related to the torque of the motor and the rotational speed of the motor, which can be expressed as $P_{Cu} = \varphi_{Cu}(\tau \otimes \tau)$ and $P_{Fe} = \varphi_{Fe}(|\dot{q}|)$, respectively; P_{add} represents the miscellaneous losses and the possible computational errors, which are related to the absolute value of P_M , which can be expressed as $P_{add} = \varphi_{add}(|P_M|)$.

Thus, P_M can be simplified as:

$$P_M = f(q, \dot{q}, \ddot{q}, M, r) \quad (11)$$

The parameters P_E, P_B, P_R are usually considered constant during robot operation and P_{MD_i} is strongly correlated with joint motion parameters [26]. In addition, considering that some of the dynamic operation parameters have a significant impact on the energy

consumption of industrial robots [27], the maximum velocity of industrial robots V_{max} and maximum acceleration of industrial robots A_{max} will also be used as one of the input parameters, and after replacing the energy models of motors, motor drivers, brakes, and electronics, we obtain the following simplified equations:

$$P = P_C + P_{M_i} + P_{MD_i} = f(q, \dot{q}, \ddot{q}, M, r, V_{max}, A_{max}) \quad (12)$$

Furthermore, the energy consumption is the integral of the industrial robot power P over time and can be written as:

$$E = \int P dt \quad (13)$$

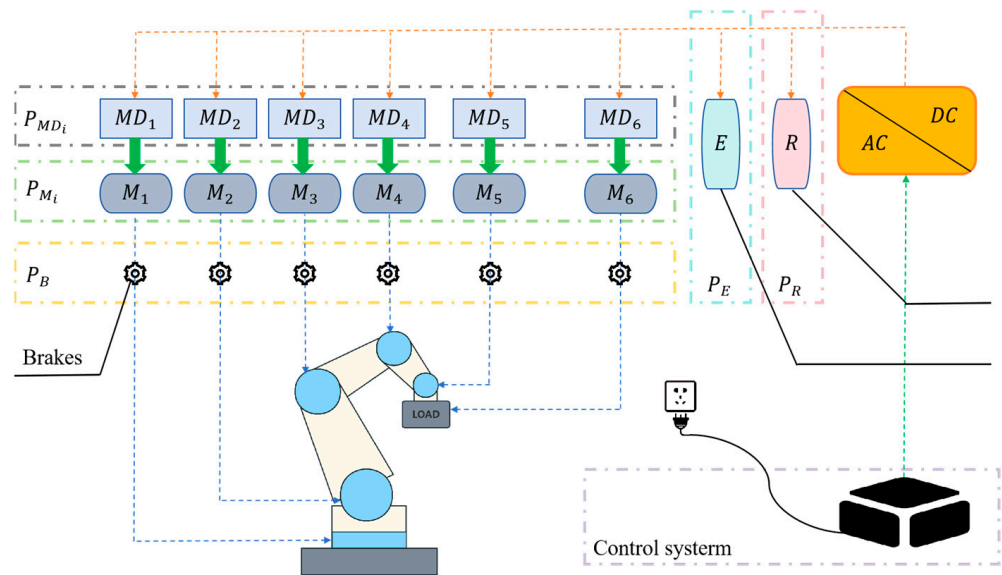


Figure 1. Analysis of energy consumption of industrial robots.

3. Projection Methods

3.1. KAN-LSTM Energy Consumption Prediction Modeling

In order to overcome the limitation that the unknown load cannot be used as the input of the energy prediction model, this paper proposes the KAN-LSTM energy prediction model, which has the input parameter $X_{KAN-LSTM} = [q^T, \dot{q}^T, \ddot{q}^T, i^T, V_m, A_m]^T$ and the output parameter $Y_{KAN-LSTM} = E$ as shown in Figure 2. The proposed energy consumption prediction model includes two parts: load prediction model and power prediction model. Firstly, the unknown load of the industrial robot is predicted by the KAN load prediction model, and its output is used as one of the input parameters of the power prediction model, and then the LSTM power prediction model is used for power prediction, and finally the predicted power is integrated to obtain the total energy consumption.

In the load prediction phase, considering that most of the existing load prediction methods are parameter identification methods with low efficiency and large computation, this paper proposes a load prediction model based on KAN, which relies on the powerful learning ability and adaptability of neural networks to achieve high-precision prediction with greater ease, and achieves reliable online prediction of loads by fixing the pre-movement trajectory in energy consumption optimization experiments. Based on the dynamics modeling and energy consumption modeling in the above Section 2, it is known that the load parameters M, r are strongly correlated with the industrial robot joint angles q_i , joint angular velocities $\dot{q}_i$, joint angular accelerations $\ddot{q}_i$, and joint currents i_i . Therefore, the input parameters of the KAN load prediction model X_{KAN} can be written as:

$$X_{KAN} = [q^T, \dot{q}^T, \ddot{q}^T, i^T]^T \quad (14)$$

The model output parameters are the load-dependent parameters M and r :

$$Y_{KAN} = [M, r_x, r_y, r_z]^T \quad (15)$$

where M is the mass of the load and $r = [r_x, r_y, r_z] \in R^{3 \times 1}$ is the center of gravity of the load.

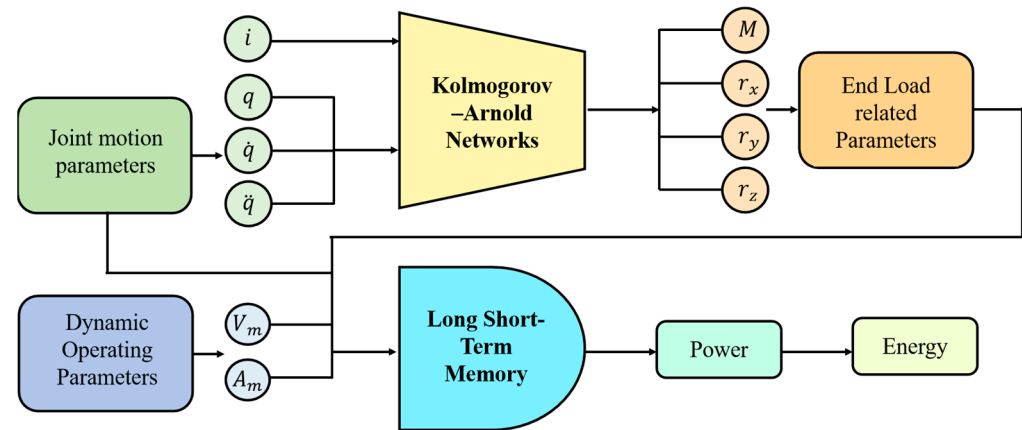


Figure 2. KAN-LSTM energy consumption prediction model.

In the power prediction stage, the results of the load-related parameters predicted by the KAN network will be used as one of the input parameters of the power prediction model. Considering that the results of the load prediction and the parameters collected by the industrial robots are time series data and that the LSTM network has shown excellent prediction ability many times in the research related to the prediction of energy consumption of the industrial robots, a data-driven method based on the LSTM network was finally chosen for highly nonlinear power prediction for industrial robots. Based on the energy consumption modeling in Section 2, the input parameters of the LSTM power prediction model will include industrial robot joint angles q_i , joint angular velocities $\dot{q}_i$, joint angular accelerations $\ddot{q}_i$, the load-dependent parameters M and r , maximum velocity V_{max} , and maximum acceleration A_{max} . Therefore, the input parameters X_{LSTM} of the LSTM power prediction model are:

$$X_{LSTM} = [M, r_x, r_y, r_z, q^T, \dot{q}^T, \ddot{q}^T, V_{max}, A_{max}]^T \quad (16)$$

The model output parameter Y_{LSTM} is the power P , which is finally integrated to obtain the total energy consumption E of the industrial robot as shown in Equation (13).

3.2. KAN Load Prediction Modeling

Kolmogorov–Arnold Networks (KAN) is a novel neural network architecture that, unlike traditional multi-layer perceptron (MLP), employs learnable activation functions as edges, where each weight parameter can be replaced by a univariate function. These functions are usually parameterized in the form of spline functions, and the flexibility of the spline allows the neural network to dynamically learn and optimize the activation patterns to adaptively model complex relationships in the data and ultimately minimize the approximation error [28]. The KAN network is inspired by the Kolmogorov–Arnold representation theorem: any multivariate continuous function f can be expressed as a combination of finitely many univariate continuous functions. Formally, a continuous multivariate function $f(x) : [0, 1]^n \rightarrow R$ can be represented by a finite superposition of univariate functions [29]:

$$f(x) = \sum_{i=1}^{2n+1} \varphi_i(\sum_{j=1}^n \varphi_{i,j}(x_j)) \quad (17)$$

where $\varphi_i : \mathbb{R} \rightarrow \mathbb{R}$ and $\varphi_{i,j} : [0, 1] \rightarrow \mathbb{R}$ denote the outer and inner functions, respectively.

A KAN layer can be defined as a matrix consisting of univariate functions $\{\varphi_{i,j}(\cdot)\}$, where $i = 1, \dots, N_{in}$, $j = 1, \dots, N_{out}$, N_{in} , N_{out} denote the number of inputs and outputs, respectively, and $\varphi_{i,j}$ refers to the trainable spline function. Thus, the Kolmogorov–Arnold theorem can be represented as two KAN layers, with the inner function constituting a KAN layer with $N_{in} = n$, $N_{out} = 2n + 1$, and the outer function constituting a KAN layer with $N_{in} = 2n + 1$, $N_{out} = n$. One can use $[n_0, \dots, n_{L-1}]$ to define the structure of a KAN, where L denotes the number of KAN layers, and a generic deeper KAN network can be represented by the composition of L layers:

$$y = \text{KAN}(x) = (\varphi_{L-1} \circ \dots \circ \varphi_0)x \quad (18)$$

where the composite operator $\circ$ indicates that the function matrix φ_L will be composited sequentially, which means that the output of each layer will become the input of the next layer. Thus, the two-layer KAN network can be represented as:

$$y = \text{KAN}(x) = (\varphi_1 \circ \varphi_0)x \quad (19)$$

Based on [29], the activation function $\varphi(x)$ is the sum of the basis function $b(x)$ and the spline function:

$$\varphi(x) = w_b b(x) + w_s \text{spline}(x) \quad (20)$$

Then set:

$$b(x) = \text{silu}(x) = x / (1 + e^{-x}) \quad (21)$$

In most cases, $\text{spline}(x)$ is parametrized as a linear combination of B-splines such that:

$$\text{spline}(x) = \sum_i c_i B_i(x) \quad (22)$$

where c_i s are trainable. In principle w_b and w_s are redundant since it can be absorbed into $b(x)$ and $\text{spline}(x)$. However, we still include these factors (which are by default trainable) to better control the overall magnitude of the activation function.

The structure of the two-layer KAN network designed in this paper is shown in Figure 3, where the input parameter is $X_{KAN} = [q^T, \dot{q}^T, \ddot{q}^T, i^T]^T$ and the output parameter is $Y_{KAN} = [M, r_x, r_y, r_z]^T$.

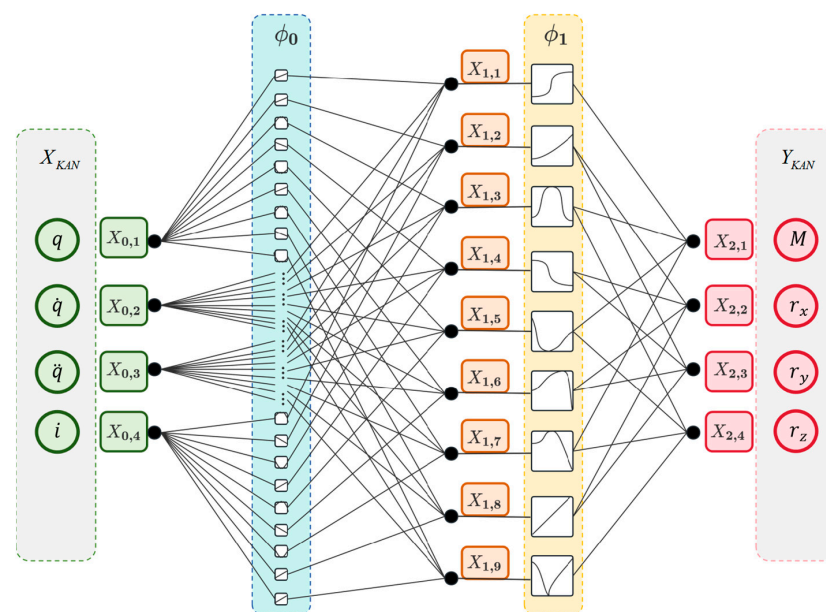


Figure 3. KAN load prediction model structure.

It is worth mentioning that, due to the property of learnable spline function instead of linear weight matrix, the KAN network can still achieve efficient load prediction and significantly improve the accuracy and interpretability of the model when using fewer parameters [29].

3.3. LSTM Power Prediction Modeling

The power of an industrial robot is closely related to its operating parameters. Therefore, a neural network model can be constructed to fit the relationship between power and operating parameters to approximate the real power model of industrial robots. The LSTM network, long short-term memory, is a special variant of recurrent neural network (RNN), which makes up for the problems of gradient vanishing, gradient bursting and insufficient long-term memory capability of RNN networks, and can effectively utilize remote temporal information to solve time-dependent causal sequence prediction problems.

LSTM neural network is a recurrent neural network with LSTM cells as the hidden layer; LSTM cells are the basic units of the LSTM neural network. The structure of LSTM neural network and the structure of LSTM cells are shown in Figure 4. The LSTM cells have three gate structures—the forgetting gate, the input gate, and the output gate—which are a layer of fully connected neural network. The LSTM cells through the gate structure selectively transmit information for the purpose of information storage, extraction, and prediction. Therefore, its computational principle can be expressed as [30]:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (23)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (24)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (25)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (26)$$

$$O_t = \sigma(W_O \cdot [h_{t-1}, x_t] + b_O) \quad (27)$$

$$h_t = O_t * \tanh(C_t) \quad (28)$$

where f_t , i_t , and O_t are the outputs of the forgetting, input, and output gates at time t , respectively. W_f , W_i , W_C , and W_O are the weight coefficients matrices corresponding to each gate, respectively. b_f , b_i , b_C , and b_O are the bias terms corresponding to each gate, respectively. h_t and C_t are the cells at the moments of t , σ , and $\tanh$ output and state, and σ and $\tanh$ are the s-type activation function and hyperbolic tangent activation function, respectively.

The input parameters of this model are $X_{LSTM} = [M, r_x, r_y, r_z, q^T, \dot{q}^T, \ddot{q}^T, V_{max}, A_{max}]^T$, and the output parameter is $Y_{LSTM} = P$. The LSTM network designed in this paper includes four functional modules: Preprocessing layer, Stacked LSTM layer, Fully connected layer, Dropout layer, and Regression output layer. The Preprocessing layer normalizes the input data and extracts a certain percentage of data as the test set by stratified sampling. The remaining data are divided into training and validation sets by k-fold cross-validation method to train the proposed neural network. The Stacked LSTM layer mines the deep rules between the total power and the input variables, while the Fully connected layer is later used to reduce the dimensionality of the Stacked LSTM output data and the Dropout layer is added to prevent overfitting. The Regression output layer is used for the output of the total power curve and denormalization.

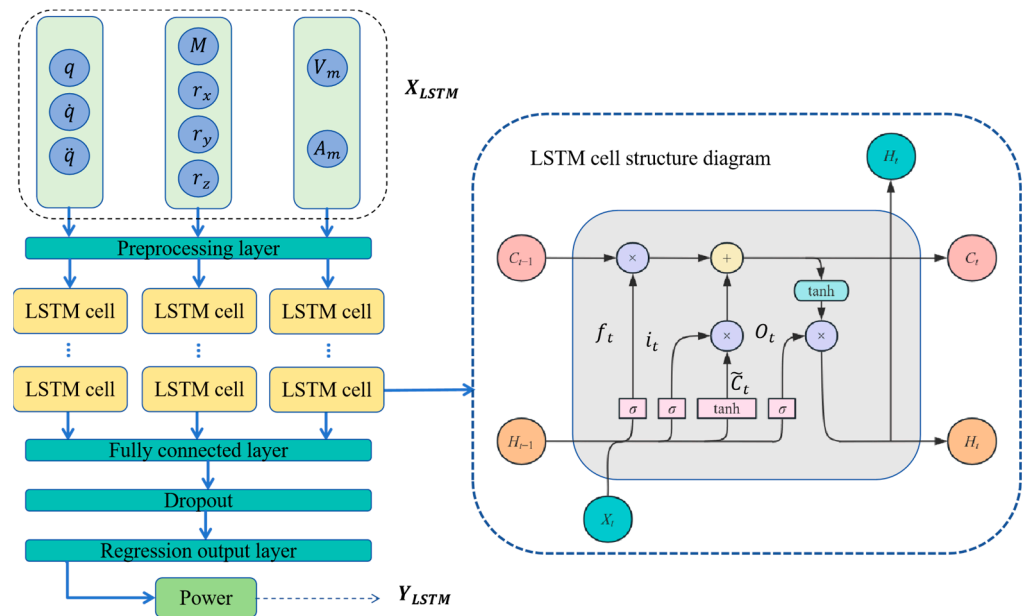


Figure 4. LSTM power prediction model structure.

4. Experiments and Results

4.1. Data Collection

The experiment is carried out on the AUBO-E5 collaborative robot (AUBO Robotics Technology, Beijing, China, Maximum load of 5 kg, Range of motion of 886.5 mm) manufactured by AUBO-E5, and the AUBO-CB-M controller is used to drive the robot, as shown in Figure 5a. In order to ensure the accuracy of the measured energy consumption of the industrial robot, the experiment will be conducted using a NAPUI Digital Power Meter PM9800 (NAPUI Technology, Dongguan, China), and the sockets for the power measured by the power meter will also be used by the robot individually, and the power meter and its wiring will be as shown in Figure 5b. In the experiment, the robot is connected to a computer via Ethernet and the data of the robot are collected in real time via Modbus communication, which has an Intel(R) Xeon(R) Silver 4210R CPU running at 2.4 GHz with 64 GB of RAM. At the same time, the computer uses RS485 communication technology (Electronic Industries Association, Arlington, VA, USA) to collect the power meter data in real time; in order to ensure the synchronization of the experimental data collection, the collection frequency of the industrial robot data and the power meter data is uniformly set to 10 Hz, and all the collected data are stored in the computer in the form of csv.

In the experiment, the motion mode of the industrial robot was set to PTP mode, V_{max} and A_{max} could be selected arbitrarily from 1% to 100% of the corresponding maximum values, and it should be noted that V_{max} and A_{max} were normalized by percentage. The experimental trajectories were automatically generated by the demonstrator based on the multiple path points selected, and the collected data consisted of a total of 13 different load conditions (including no-load conditions), as shown in Table 1. The load mass was in the range of 0 to 5 kg and was placed one by one according to the 3 holes of the designed load-bearing plate, as shown in Figure 6.

Since the parameter display limitations vary for different types of industrial robots, in order to improve the migration capability of the proposed energy consumption prediction model, the following parameters will be captured in the experiments in this paper: execution time t , end-effector position pos_i , joint angle q_i , joint angular velocity $\dot{q}_i$, joint angular acceleration $\ddot{q}_i$, joint current Maximum velocity V_{max} , Maximum acceleration A_{max} , load M , center of mass r , and real-time power P . The joint angular velocity $\dot{q}_i$ and joint angular acceleration $\ddot{q}_i$ are determined from the joint angle q_i difference $\dot{q}_i = \Delta q_i / \Delta t$ and $\ddot{q}_i = \Delta \dot{q}_i / \Delta t$ are determined, and the center of mass r is the center of gravity matrix of the

load with respect to the center of the robot end flange and is obtained from SolidWorks simulations. The transformation of the industrial robot joint coordinate system to the end-tool coordinate system t is shown in Figure 7, where the coordinate system $\{O_W\}$ denotes the world coordinate system, the coordinate system $\{O_B\}$ denotes the robot base coordinate system, $\{O_F\}$ denotes the robot end-flange center point, and $\{O_T\}$ denotes the center of mass coordinate system of the end-effector.

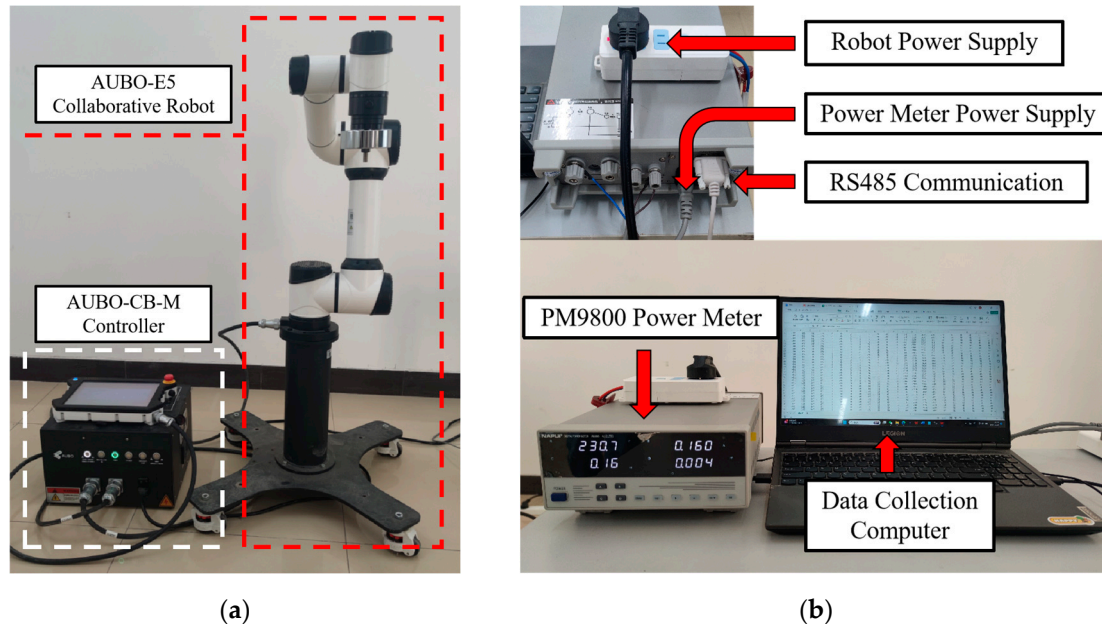


Figure 5. Experimental equipment and configuration. (a) AUBO-E5 collaborative robot; (b) PM9800 power meter and mounting position.

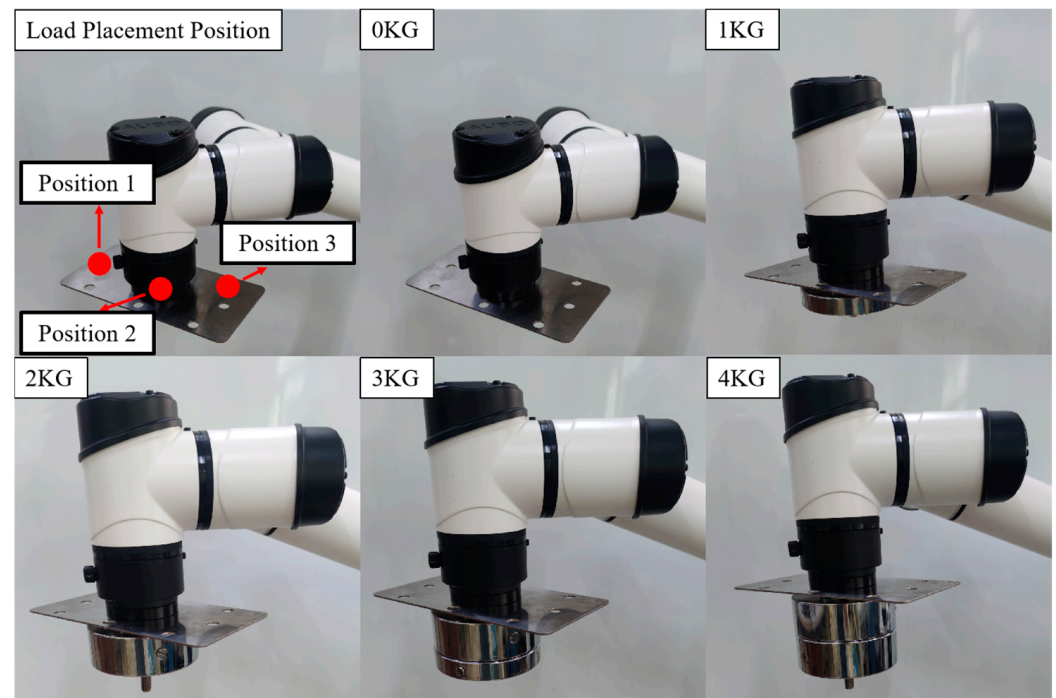
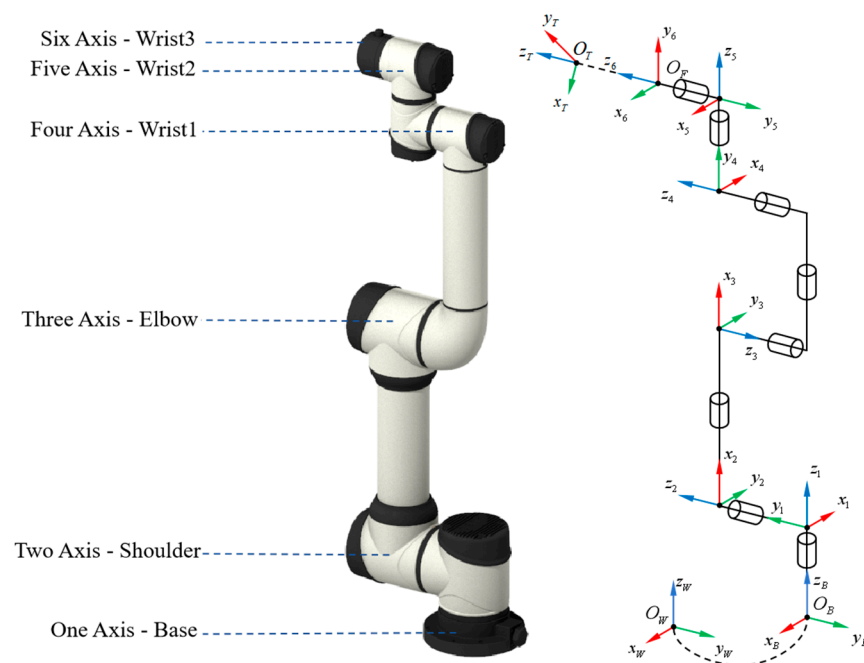


Figure 6. Load experiment installation and configuration.

Table 1. Different load conditions for industrial robot experiments.

Load Condition	Mass (kg)	Center of Gravity (mm)
Load 1	0	[0, 0, 0]
Load 2	1	[−58.612, 0, −8.521]
Load 3	1	[0, 0, −8.563]
Load 4	1	[50.759, 29.306, −8.574]
Load 5	2	[−65.641, 0, −17.171]
Load 6	2	[0, 0, −17.171]
Load 7	2	[56.847, 32.821, −17.171]
Load 8	3	[−68.444, 0, −25.866]
Load 9	3	[0, 0, −25.866]
Load 10	3	[59.275, 34.222, −25.866]
Load 11	4	[−69.961, 0, −34.565]
Load 12	4	[0, 0, −34.565]
Load 13	4	[60.588, 34.98, −34.565]

**Figure 7.** Coordinate system conversion for industrial robot.

It is worth noting that when collecting robot joint information, duplicate data points containing end positions, joint angles, etc. are inevitably generated due to the non-exact synchronization of data collection and robot start or stop operations. Also, protection mechanisms in the robot's operating program, such as short pauses set to protect components, can lead to data duplication. To ensure the validity and applicability of the dataset, it is necessary to eliminate all redundant data with identical joint parameters and preprocess the collected experimental data. In this paper, data preprocessing is implemented in python environment with the following main steps: firstly, missing values were processed by forward padding to ensure data completeness. Second, outliers were detected using the interquartile spacing (IQR) method and removed by upper and lower limits. For duplicate data, de-duplication commands were used for deletion. Finally, the features were scaled to a uniform range by normalization to ensure the convergence and performance of the model. A total of 57,200 valid sample datasets were collected for the final experiments (data sampling rate of 10 Hz).

4.2. Experimental Validation

4.2.1. Experimental Evaluation Criteria

For load prediction, the mean square error (*MSE*) will be used as the loss function of the KAN load prediction model, while the root means square error (*RMSE*) and R^2 will be used to evaluate the prediction results of the load prediction model with the following formulas:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (29)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (30)$$

$$R^2 = 1 - n \times \frac{MSE}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (31)$$

where n is the number of samples, y is the true value of the load-related parameter, $\hat{y}$ is the predicted value of each parameter output by the model, and $\bar{y}$ is the mean value of each related parameter predicted. The *RMSE* is used to express the absolute error between the predicted value and the true value, and its value is positively correlated with the modeling error. The value of R^2 is used to reflect the effect of curve fitting. The closer the value is to 1, the better the curve fitting effect is.

In terms of power prediction, in order to accurately predict the real-time power of the robot during the whole operation process, the mean square error (*MSE*) is used as the loss function of the LSTM power prediction model to calculate the loss of the total energy curve, and the root mean square error (*RMSE*) and the mean absolute error (*MAE*) are used to characterize the prediction error of the LSTM power prediction model. The three metrics are calculated as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (P_i - \hat{P}_i)^2 \quad (32)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - \hat{P}_i)^2} \quad (33)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{P}_i - P_i| \quad (34)$$

where P is the actual measured power value, $\hat{P}$ is the model predicted power value, and n is defined as the number of summation iterations that occurred.

In terms of energy consumption prediction, the mean relative error (*MRE*) is used to characterize the prediction error of the KAN-LSTM energy consumption prediction model. The metric is calculated as follows:

$$MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{P}_i - P_i}{P_i} \right| \quad (35)$$

The proposed energy consumption prediction model includes two parts: load prediction model and power prediction model. Algorithm 1 shows the detailed process of parameter optimization based on the KAN-LSTM energy consumption prediction model.

Algorithm 1: Parameter optimization of energy consumption prediction model.

Input: Data set $D = \{(q_i, \dot{q}_i, \ddot{q}_i, i_i, M, r_x, r_y, r_z, V_{max}, A_{max})\}_{i=1}^m$
Divide the data set into D_{kan} and D_{lstm} sets, $D_{kan} = \{(X_{kan}, Y_{kan})\}$, $D_{lstm} = \{(X_{lstm}, Y_{lstm})\}$;
Divide the D_{kan} data set into $D_{k-train}$ and D_{k-test} sets;
Initialize each activation function $\phi(x) = w_b b(x) + w_s spline(x)$, w_b is initialized according to the Xavier initialization, $w_s = 1$, $spline(x) \approx 0$;
while the terminal conditions are not reached, **do**
 for all (X_{kan}, Y_{kan}) in $D_{k-train}$, **do**
 Compute the output $\widehat{Y}_{kan}$ of KAN network to get MSE_{train} ;
 Calculate the gradient of KAN layers;
 Update each spline grids;
 end for
 Generate the MSE_{test} ;
end while
Divide the D_{lstm} data set into $D_{l-train}$ and D_{l-test} sets;
Initialize weights of the LSTM network;
while the terminal conditions are not reached, **do**
 for all (X_{lstm}, Y_{lstm}) in $D_{l-train}$, **do**
 Compute the output $\widehat{Y}_{lstm}$ of LSTM network to get MSE_{train} ;
 Calculate the gradient of LSTM layers;
 Update each weight of the LSTM network;
 end for
 Generate the MSE_{test} ;
end while
Output: Power prediction $\widehat{Y}_{lstm}$

4.2.2. Model Training

The data used in this experiment are the AUBO-E5 data set collected in the first section, from which the part of the data set of input parameters and output parameters required for this experiment is extracted as the data set of this experiment, and it is divided into the training set and the test set according to the ratio of 3:2. Model training was implemented in python 3.9 environment with the PyTorch 2.0 deep learning library. Data preprocessing was implemented in Pandas framework and Numpy framework, data visualization was performed using Matplotlib framework and Seaborn framework, and the program was run in jupyter notebook. The training parameters of the KAN load prediction model and the LSTM power prediction model adapted to the experiments are shown in Tables 2 and 3. The model was iteratively trained for 300 epochs, and the training process of the model is shown in Figure 8, and the fitting results of the load-related parameters and real-time power on the training set are shown in Figures 9 and 10.

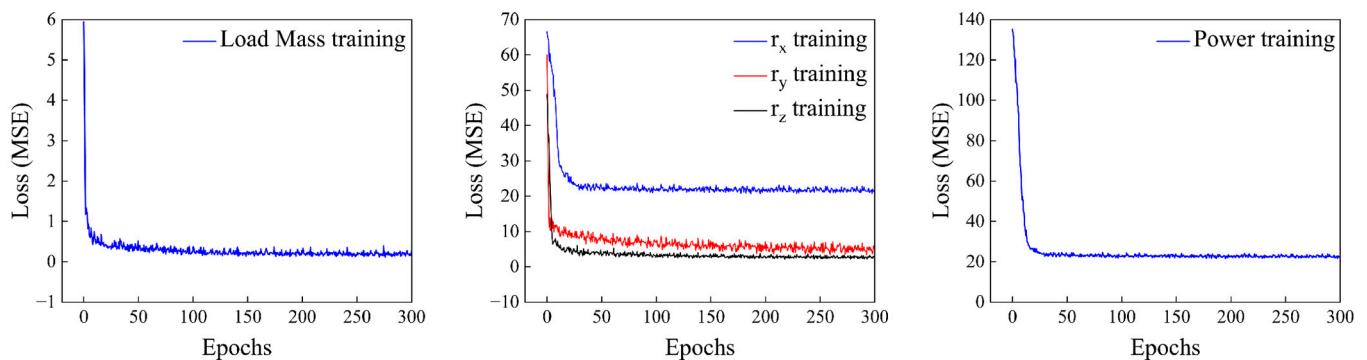


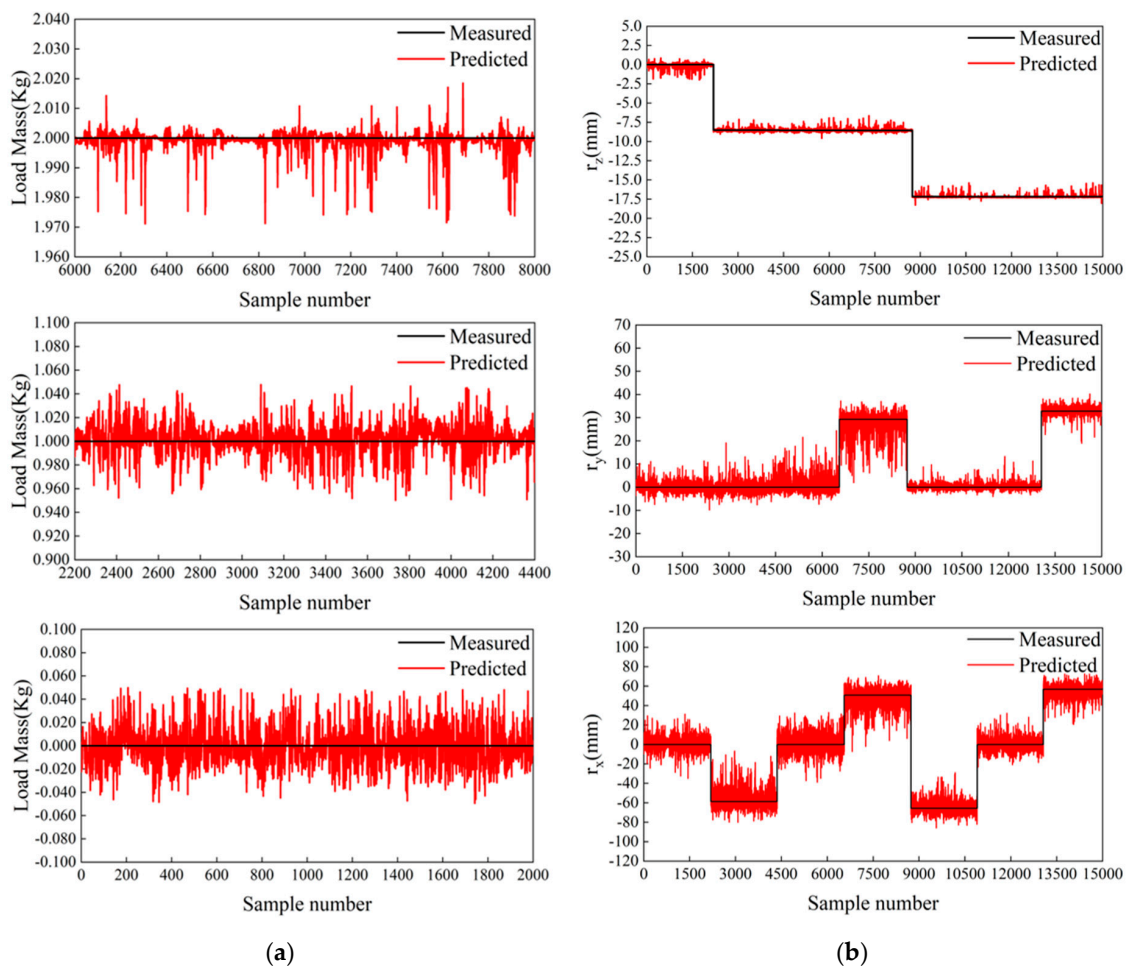
Figure 8. Training process for load prediction model and power prediction model.

Table 2. KAN load prediction model training parameters.

Parameter	Value
Max epochs	300
Width	[4, 9, 4]
Grid size	9
Order of segmented polynomial	3
Noise scale	0.1
Grid eps	0.02
Scale spline trainable	True
Symbolic enabled	True

Table 3. LSTM power prediction model training parameters.

Parameter	Value
Input dimension	30
Learning rate drop factor	0.2
Layers of stacked networks	3
Maximum epoch	300
Number of batch size	32
Learning rate	0.01
Optimizer	Adam

**Figure 9.** Training set adjustment results of the KAN load prediction model (partial data). (a) Training results for the final load Mass M in the range of 0–2 Kg; (b) training results for the x-axis coordinates r_x , y-axis coordinates r_y , and z-axis coordinates r_z of the load center of gravity in the training set.

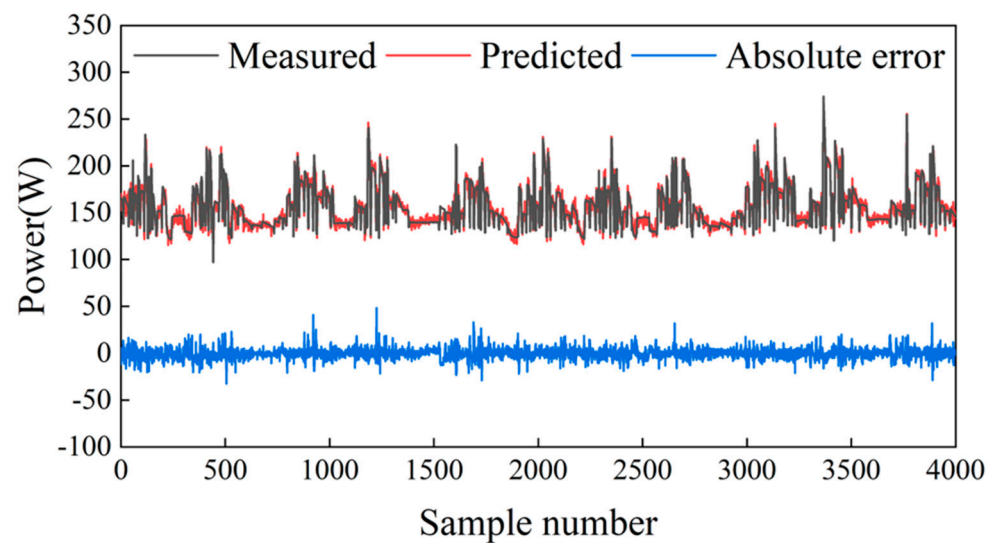


Figure 10. LSTM power prediction model training set fitting results (partial data) with training results and absolute error for the real-time power of the AUBO-E5 industrial robot.

As shown in Figure 8, after 100 epochs, the model test loss is stable, indicating that the model learns the correct laws from the training set. Figure 9 shows the fitting results of load related parameters during the training process of the AUBO-E5 industrial robot, and the specific evaluation metrics are shown in Table 4. The value of R^2 in the KAN network fitting results during the training of load weight is 0.9989, and the value of $RMSE$ is 0.3541. The training fitting results of the load center of gravity in the coordinates of the x-axis show that the KAN network predicts the results with the value of R^2 being 0.9825 and the value of $RMSE$ being 4.5659. The training fitting results of the coordinates of the y-axis show that the KAN network predicts the results with the value of R^2 being 0.9899, and the $RMSE$ value being 1.4456. The training fitting results for the coordinates of the z-axis show that the R^2 value of the KAN network prediction result is 0.9956, and the $RMSE$ value is 1.2414. The experimental results show that the KAN load prediction model is able to stably train and fit the parameters related to the loads of the industrial robots, and it is worth mentioning that this paper incorporates the a priori knowledge of dynamics modeling into the construction of the load prediction model, which improves the interpretability of the model, reduces the possibility of model overfitting, and ensures the modeling accuracy and generalization ability.

Table 4. Evaluation of fitting load results during the training process.

Parameter	R^2	$RMSE$
M	0.9989	0.3541
r_x	0.9825	4.5659
r_y	0.9899	1.4456
r_z	0.9956	1.2414

Figure 10 shows the real-time power fitting results during the training process of the AUBO-E5 industrial robot, and the specific evaluation metrics are shown in Table 5. The results show that the R^2 value of the LSTM network power prediction result is 0.9887, the $RMSE$ value is 5.0211, and the MAE value is 4.7799. The experimental results show that the LSTM power prediction model in the training set has a good performance in real-time power prediction of industrial robots.

Table 5. Evaluation of fitting power results during the training process.

Parameter	R^2	RMSE	MAE
P	0.9887	5.0211	4.7799

4.2.3. Model Prediction Results

To verify the accuracy of the load, power, and energy consumption prediction models proposed in this study, experiments are conducted on the proposed models under unknown load. The model with the smallest prediction error during the training process will be selected for validation. The fitting results of the load-related parameters and the power on the test set are shown in Figures 11 and 12, the evaluation indicators of the prediction results of the load-related parameters are shown in Table 6, and the evaluation indicators of the power prediction results are shown in Table 7. The prediction results of energy consumption of industrial robots under different load conditions are shown in Figure 13, the relative error (RE) comparison graphs of energy consumption prediction under different networks are shown in Figure 14, and the comparison of evaluation parameters are shown in Table 8.

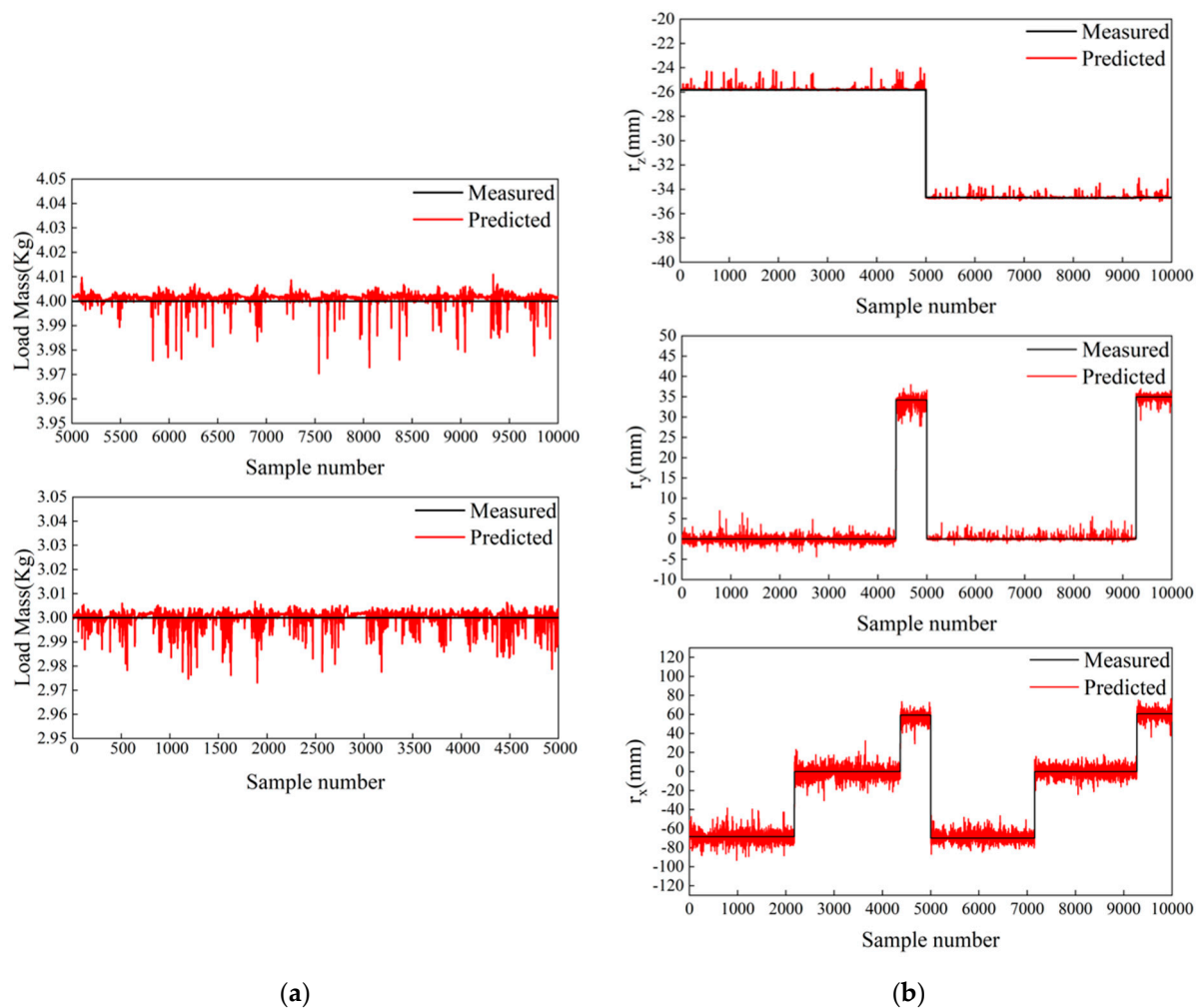


Figure 11. Testing set adjustment results of the KAN load prediction model (partial data). (a) Testing results for the final load Mass M in the range of 3–4 Kg; (b) testing results for the x-axis coordinates r_x , y-axis coordinates r_y , and z-axis coordinates r_z of the load center of gravity in the testing set.

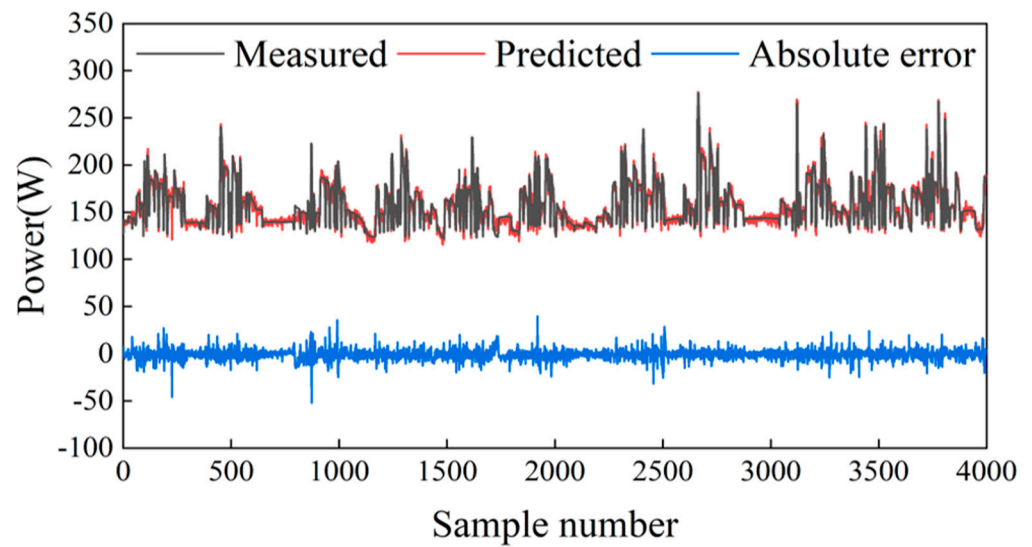


Figure 12. LSTM power prediction model testing set fitting results (partial data), with testing results, absolute error, and relative error line plots for the real-time power of the AUBO-E5 industrial robot.

Table 6. Evaluation of fitting load results during the testing process.

Parameter	R^2	RMSE
M	0.9871	0.4826
r_x	0.9800	5.0646
r_y	0.9892	1.4583
r_z	0.9911	1.4212

Table 7. Evaluation of fitting power results during the testing process.

Parameter	R^2	RMSE	MAE
P	0.9874	6.1062	4.9483

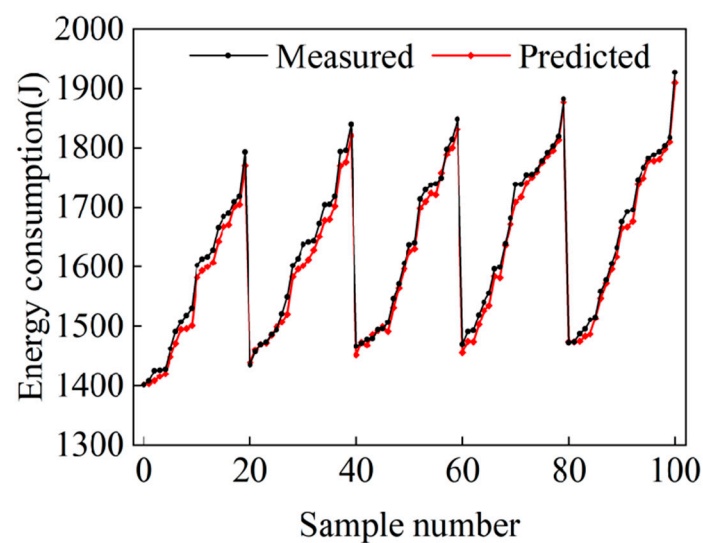


Figure 13. KAN-LSTM energy consumption prediction model fitting results. The test samples 0–20, 20–40, 40–60, 60–80, and 80–100 based on load conditions of 0 kg, 1 kg, 2 kg, 3 kg, and 4 kg, respectively.

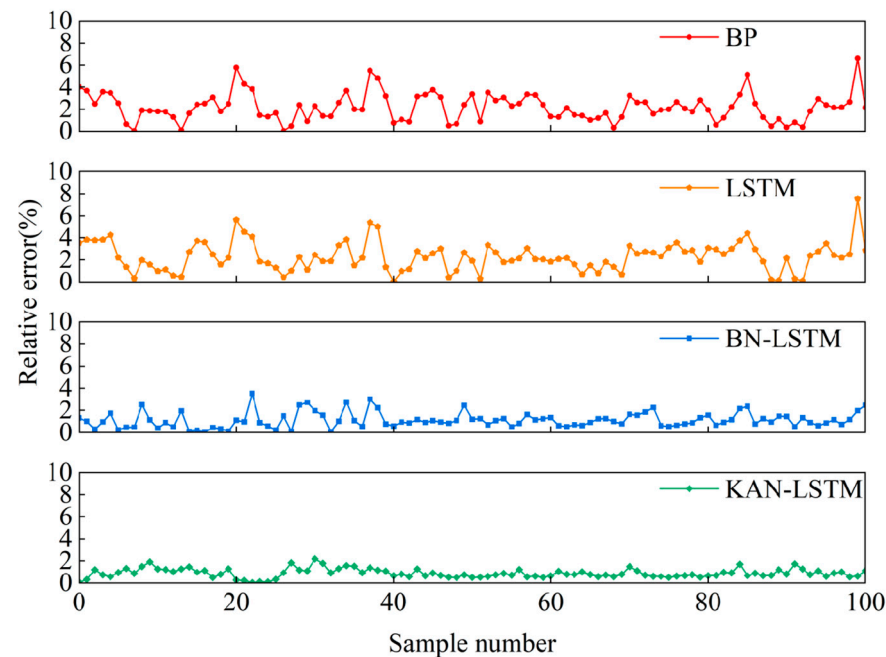


Figure 14. Comparison of relative error results of energy consumption prediction in different network models.

Table 8. Comparison of evaluation metrics of test set energy consumption prediction results under different networks.

Network	Min RE (%)	Max RE (%)	MRE (%)
BN-LSTM	0.0082	3.5306	1.64
LSTM	0.0204	6.5853	2.19
BP	0.0254	7.5334	2.29
KAN-LSTM	0.0028	2.1813	1.18

Figure 11 shows the prediction results of the load-related parameters of the AUBO-E5 industrial robot in the test set with the specific evaluation metrics shown in Table 6. For the prediction of the load weight, the KAN network fitting result shows that the R^2 value of 0.9871 and the $RMSE$ value of 0.4826. The prediction result of the center of gravity of the load in the x-axis coordinates shows that the R^2 value is 0.9800 and the $RMSE$ value is 5.0646. The prediction result for the y-axis coordinates shows that the R^2 value is 0.9892 and the $RMSE$ value is 1.4583. The prediction results in z-axis coordinates show that the R^2 value of the KAN network prediction result is 0.9911 and the $RMSE$ value is 1.4212. The experimental results show that the KAN load prediction model can stably achieve efficient and accurate prediction of the unknown load-related parameters, which also lays a solid foundation for the accurate prediction of the KAN-LSTM energy consumption prediction model.

Figure 12 shows the real-time power prediction results of the AUBO-E5 industrial robot in the test set, with specific evaluation metrics shown in Table 7. The results show that the R^2 value of the LSTM network power prediction results is 0.9894, the $RMSE$ value is 6.1062, and the MAE value is 4.9483. Figure 13 shows the prediction results of energy consumption of industrial robots under different load conditions. It can be seen that the energy consumption of industrial robots increases as the load increases. The experiment compares the energy consumption prediction with the BP network model, LSTM network model, and BN-LSTM network model to verify the superiority of the KAN-LSTM energy consumption prediction model, and the comparison graph of prediction results is shown in Figure 14, and the specific evaluation indexes are shown in Table 8.

Among the four different energy consumption prediction models, including BP network, LSTM network, BN-LSTM network, and KAN-LSTM network, the KAN-LSTM network provides the experimental results with the smallest relative error in prediction and the prediction curves that are most consistent with the true values. The other three models have MRE values ranging from 1.64% to 2.29%; unlike them, the proposed KAN-LSTM energy consumption prediction model has a higher prediction accuracy than all the other models, with an MRE value of 1.18%. Notably, the energy consumption prediction errors of the other three networks under loaded (except 0 kg) conditions fluctuate more than under 0 kg conditions, with poorer prediction accuracy and stability. In contrast, the proposed model can utilize the load prediction model to predict the unknown load parameters in advance and take the influence of the unknown load into account when predicting the energy consumption, which ultimately achieves a higher accuracy of energy consumption prediction. It can be seen that the energy consumption prediction model based on the KAN-LSTM network used in this paper is more efficient and accurate than the other three network models, which confirms the superiority of the proposed energy consumption prediction model.

4.3. Energy Consumption Optimization

An accurate energy consumption prediction model is the prerequisite and foundation for energy consumption optimization. A coherent industrial robot task usually consists of multiple target displacements, and the trajectory traveled by each displacement is related to the operational parameters: different maximal velocity V_{max} , maximal acceleration A_{max} , end-load mass M , and load center of gravity r can generate different work trajectories. Different trajectories consume different amounts of energy, and the particle swarm optimization (PSO) algorithm can be used to solve the minimum value of energy consumption and optimize the energy consumption of industrial robots since the PSO algorithm has powerful global search capability, better adaptability, and no need for gradient information. Compared with Genetic Algorithm (GA) and Simulated Annealing (SA), the PSO algorithm has more concise operation and faster convergence speed, and it can deal with multi-objective optimization problems, so the PSO algorithm is chosen as the optimization method in this paper. The flow chart of PSO optimization energy consumption is shown in Figure 15.

The method for optimizing the energy consumption of an industrial robot is shown in Figure 16. Since V_{max} , A_{max} , M , and r are operational parameters, the load-related parameters should be predicted using the KAN load prediction model before simulating the motion trajectory. Considering that the input of this model includes joint currents, the industrial robot is set to perform a small period of pre-movement with a fixed trajectory during the task initiation phase, as shown in Figure 17. All the data corresponding to the period of fixed trajectory activity are collected by the industrial robot system in real time and input into the load prediction model to predict the load-related parameters. The output parameters of the KAN load prediction model are passed through the average pooling filter to obtain the final load prediction results. After setting M and r , a variety of trajectory parameters are obtained by setting different combinations of V_{max} and A_{max} (all in the range of 1–100%, only integers can be set), and using simulation software such as AUBO Robot Studio v0.29, Rviz 2, and other simulation software to perform path simulation, where each combination of V_{max} and A_{max} has a corresponding trajectory parameter. Therefore, these simulation parameters are imported into the energy consumption prediction model to obtain different energy consumption prediction values corresponding to the multiple trajectories that can be selected for the working phase. Finally, the PSO algorithm is used to obtain the trajectory that consumes the least amount of energy to complete the task, as well as the operation parameters corresponding to the trajectory.

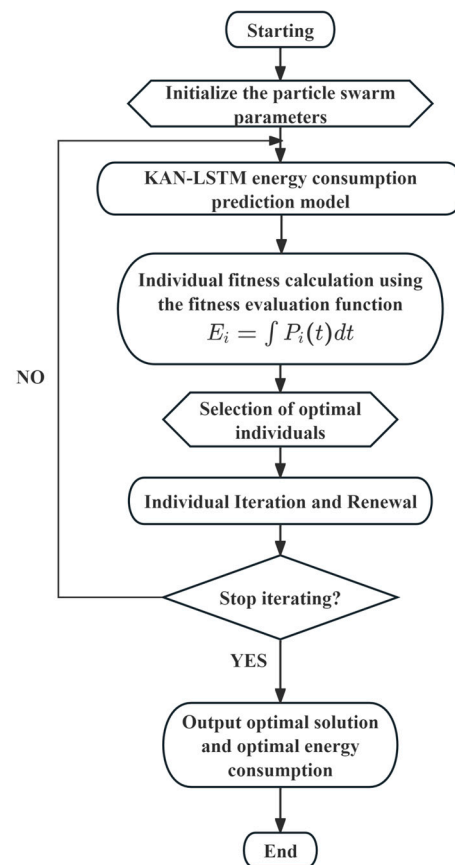


Figure 15. Flowchart of PSO optimization energy consumption.

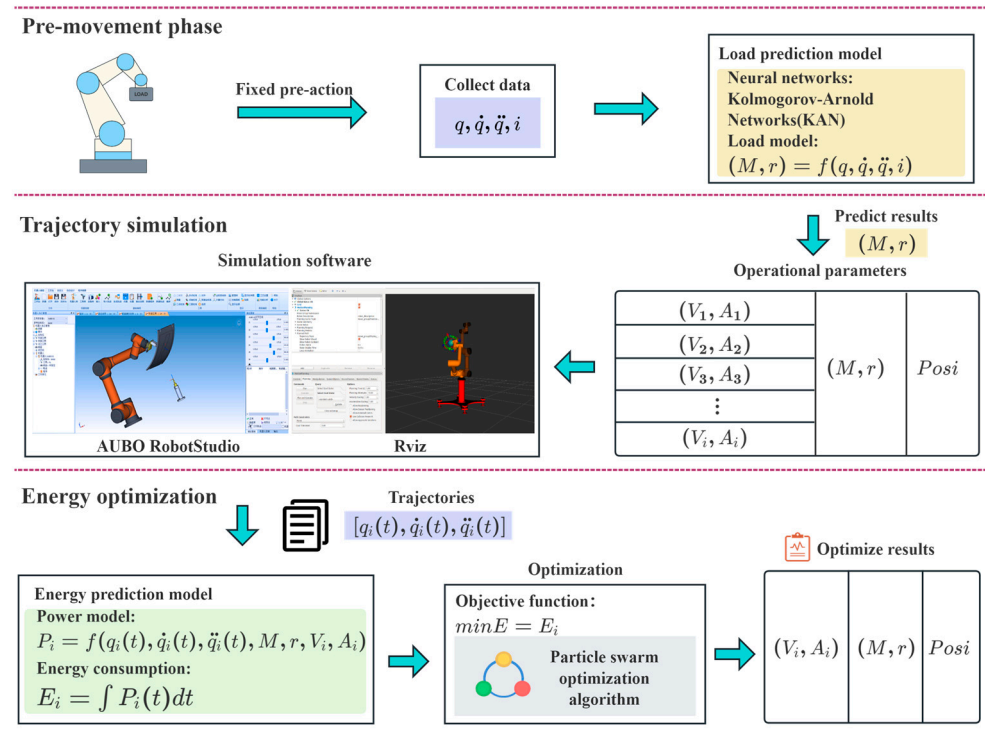


Figure 16. Energy consumption optimization method for industrial robot.

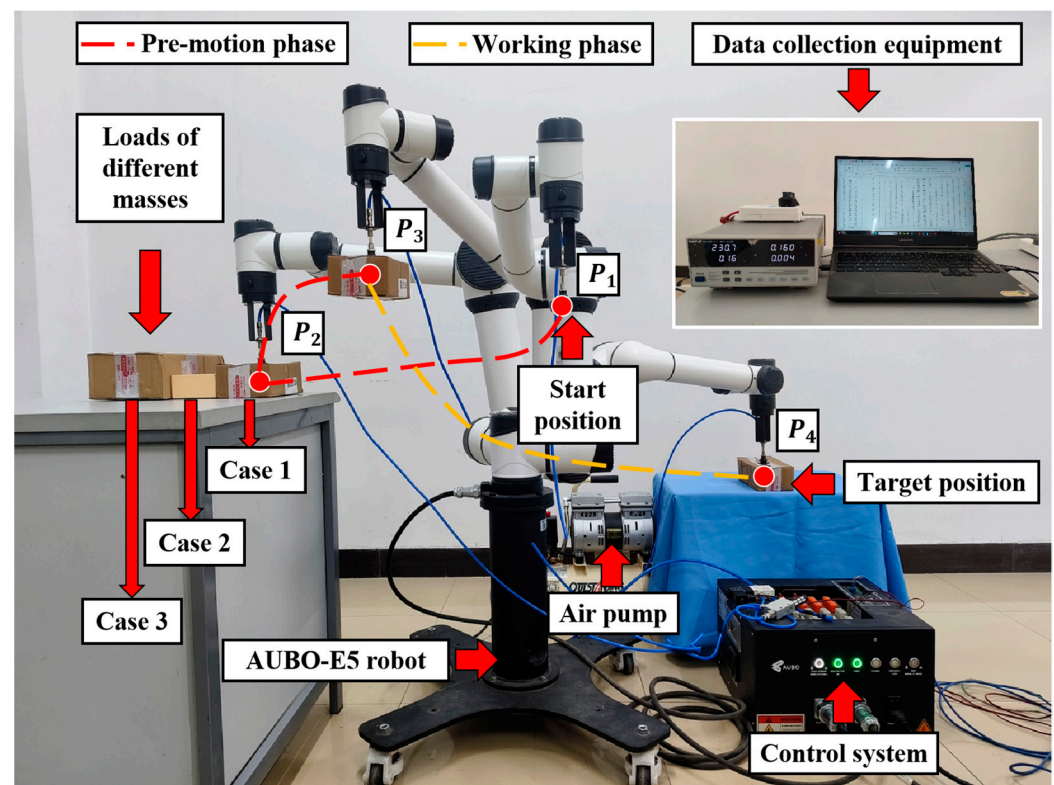


Figure 17. Experimental configuration for energy consumption optimization of industrial robot.

The specific configuration of the energy optimization validation experiment is shown in Figure 17, where the overall path is divided into the P_1 – P_3 pre-motion phase and the P_3 – P_4 working phase, and the load cases are divided into three types. Using the real-time data collected in the pre-motion phase, the unknown load parameters are predicted by the load prediction part of the proposed KAN-LSTM energy consumption prediction model, and the results obtained for Case 1 as an example are shown in Figure 18, specific predictions are shown in Table 9. After setting the load-related parameters obtained from the prediction model, the working trajectories under different motion parameters are simulated using the simulation software, and the energy consumption distribution plots corresponding to multiple trajectories under different loads are obtained by the proposed energy consumption prediction model, as shown in Figure 19. Finally, the energy consumption is optimized using the PSO algorithm. The particle swarm size in PSO algorithm is 100, the maximum generation is 300, the learning factor corresponding to the individual is set to 1.5, the learning factor corresponding to the global is set to 1.5, and the inertia coefficient is set to 0.6. The optimization process is shown in Figure 20, and the final optimization results are shown in Table 10.

Table 9. Load prediction results in Case 1 from energy optimization experiments.

Parameter	Predicted Output	Measured	Prediction Accuracy (%)
M (Kg)	2.081	2.150	96.8%
r_x (mm)	11.173	9.624	83.9%
r_y (mm)	0.214	0.302	70.9%
r_z (mm)	56.264	58.426	96.3%

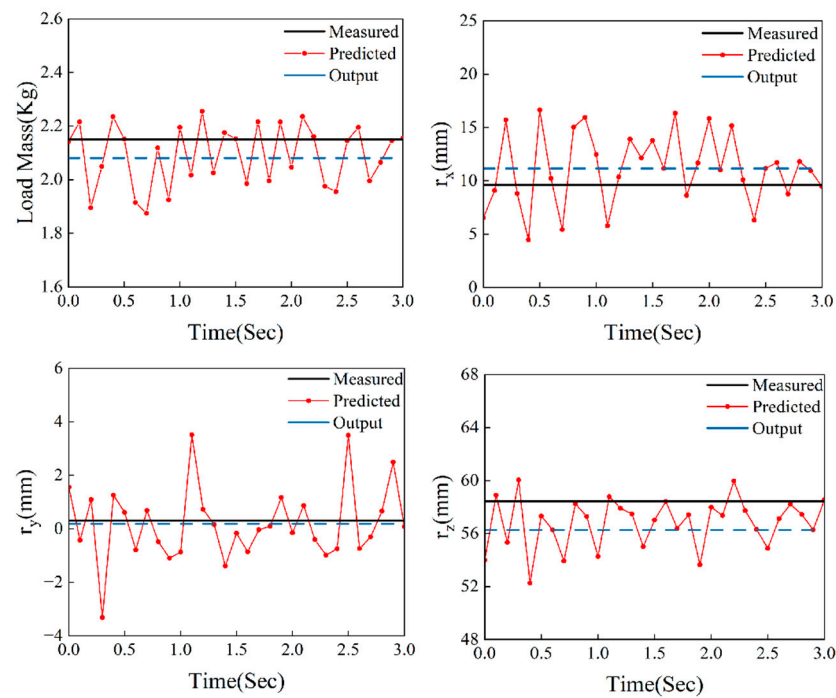


Figure 18. The prediction results obtained by the KAN load prediction model in Case 1 depending on the data collected during the pre-motion phase.

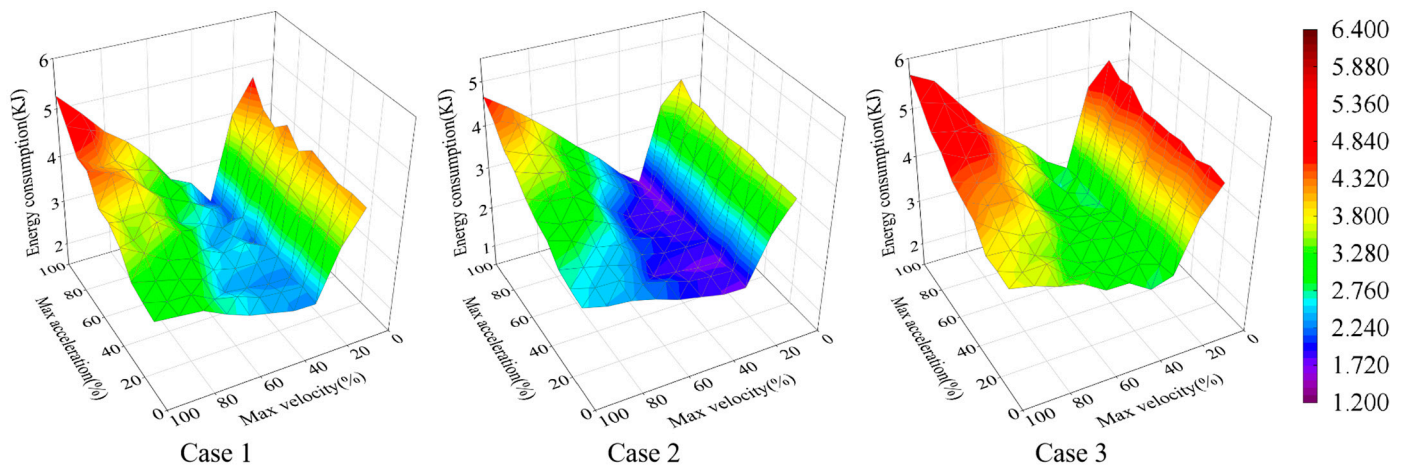


Figure 19. Distribution of energy consumption predictions for trajectories corresponding to different operating parameters in Case 1–3.

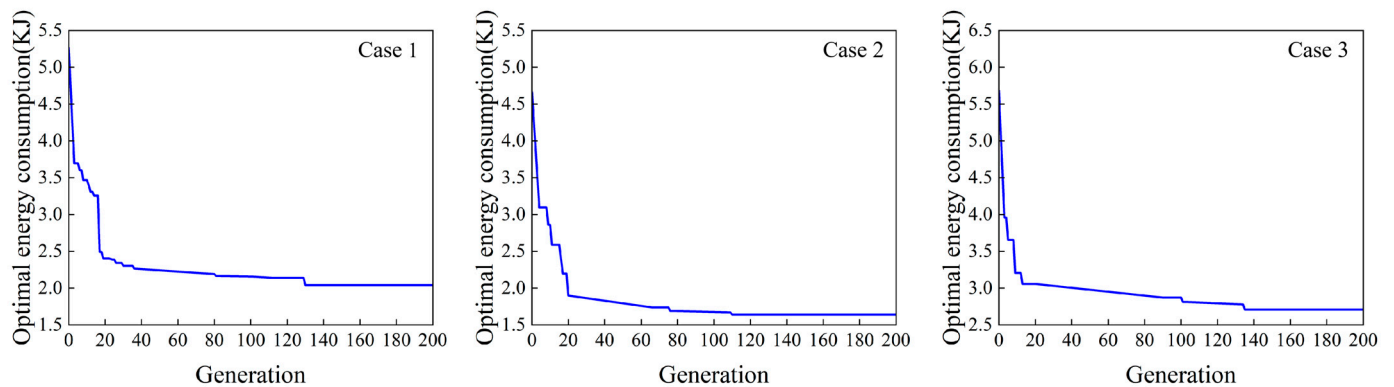


Figure 20. Diagram of the energy consumption optimization process in Case 1–3.

Table 10. Results of energy consumption optimization.

Case Type	Data Type	E_{max}	E_{min}	ΔE	Prediction Accuracy (%)
Case 1	Measured KAN-LSTM + PSO	5.51 KJ	2.13 KJ	61.3%	95.7%
		5.26 KJ	2.04 KJ	61.2%	
Case 2	Measured KAN-LSTM + PSO	4.81 KJ	1.70 KJ	64.7%	96.7%
		4.66 KJ	1.64 KJ	64.8%	
Case 3	Measured KAN-LSTM + PSO	5.89 KJ	2.76 KJ	53.1%	97.1%
		5.68 KJ	2.70 KJ	52.5%	

The results show that the proposed KAN-LSTM model provides a highly accurate model basis for the energy consumption optimization process, with the prediction accuracy of 70.9–96.8% for the unknown load-related parameters, and the prediction accuracy of 95.7–97.1% for the energy consumption, which further verifies the validity and practicability of the model. In addition, the energy optimization potential of this system is 53.1–64.7%, which has a significant optimization effect. Notably, the experimental results in Table 8 can be compared with those in Table 10 to indicate the extent to which the errors of the load prediction model affect the subsequent prediction of energy consumption. The average accuracy of energy consumption prediction for the known load case is 98.82%, while the average accuracy of energy consumption prediction including the load prediction error is 96.5%. Therefore, it can be concluded that the error of the load prediction model does not have a significant effect on the results of the energy prediction model.

5. Conclusions

This paper proposes a KAN-LSTM network-based industrial robot energy consumption modeling method to achieve accurate prediction of industrial robot load parameters and energy consumption under unknown load conditions. The predictive ability of the proposed energy consumption prediction model is experimentally verified on the AUBO-E5 collaborative robot under the multi-load condition, with the MRE value of 1.18%. Compared with the results of the BP network model, the LSTM network model, and the BN-LSTM network model, the values of the MRE are reduced by 48.5%, 46.1%, and 28.0%. In addition, this paper also achieved complete energy optimization based on the accurate energy prediction model, with the load prediction accuracy reaching 70.9–96.8% and energy consumption prediction accuracy reaching 95.7–97.1%. The energy optimization potential of 53.1–64.7%. Optimized industrial robots enable more accurate energy management in variable operating environments, reducing energy waste and lowering operating costs. In the courier industry, based on accurate load prediction, industrial robots can flexibly adapt to different workloads, improve the accuracy and stability of task processing, and also improve the overall sustainability and economic efficiency of the system by reducing energy consumption, thus promoting the widespread application and development of automated logistics technology.

In the future, more factors that affect the energy consumption of industrial robots, such as operating temperature, more complex motion patterns, and overall factory energy optimization, will be considered, and the research will focus on improving the migration capability of the model.

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