

Equipment Capacity Prediction in Industrial Automation Scenarios Based on Machine Learning Algorithms

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Abstract. Under the background of intelligent manufacturing, the capacity prediction of industrial automation equipment is of vital importance for production optimization. The traditional management model and conventional machine learning algorithms are unable to cope with the problems such as multi-source coupling of industrial data and noise interference, and have limitations such as inaccurate feature recognition and insufficient generalization. This paper proposes the FVIM-XGBoost algorithm, which optimizes the XGBoost hyperparameters using a four-vector intelligent meta-heuristic optimization algorithm, strengthens the extraction of key features and improves the robustness of the model. This algorithm integrates feature importance optimization and parameter adaptive adjustment, and conducts experimental verification based on real industrial production line data. The results show that its prediction accuracy, error control and generalization ability are superior to many mainstream algorithms, and can provide an efficient and reliable technical solution for the capacity prediction of industrial automation equipment.

Keywords: Industrial automation equipment capacity prediction, FVIM, XGBoost

1. Introduction

The global manufacturing industry is accelerating its transformation to intelligence, and the popularization and application of industrial automation equipment has become the core driving force. With the continuous advancement of intelligent manufacturing policies, the coverage of automated production lines continues to expand, and equipment operation data increases exponentially [1]. At present, the manufacturing industry is generally faced with problems such as low equipment utilization rate, large fluctuation of production capacity, lack of accurate basis for production scheduling, etc. The traditional experience-dependent management mode is difficult to adapt to complex and changeable production scenarios. Accurately predicting the production capacity of automation equipment has become a key link to optimize the production process, improve the efficiency of resource allocation and enhance the market competitiveness of enterprises, and also provides important data support and decision-making basis for industrial intelligent upgrading [2].

Machine learning algorithms have become the core technology to solve industrial forecasting problems with powerful data mining and pattern recognition capabilities [3]. It can automatically

capture nonlinear correlations and potential laws from multi-dimensional data such as equipment running time, temperature, vibration, feeding rate, etc., and break through the limitations of traditional statistical models for modeling complex relationships. In the production capacity prediction of automated equipment, machine learning can efficiently process massive heterogeneous data, quickly build a mapping model between input and output, and realize accurate production capacity prediction. At the same time, the algorithm has the ability of adaptive optimization, which can continue to iterate with the change of production conditions, effectively improve the prediction stability and generalization ability, and provide scientific support for production plan formulation and equipment operation and maintenance arrangement [4].

When the existing mainstream algorithms process industrial data, there are still problems such as inaccurate identification of feature importance and insufficient model generalization ability. As an improved algorithm of gradient boosting tree, XGBoost performs well in structured data prediction, but there is still room for improvement in feature screening and model optimization in the face of complex data with multi-source coupling and noise interference in industrial scenarios [5]. Therefore, this paper proposes FVIM-XGBoost algorithm, which integrates feature importance optimization and model parameter adaptive adjustment strategies, strengthens the ability to extract key production features, optimizes the model training process, effectively improves the accuracy and robustness of automation equipment capacity forecasting, and provides more efficient technical solutions for industrial intelligent forecasting.

2. Data sources

This data set is constructed by collecting real operation monitoring information of industrial automation production line on the spot. The acquisition process covers the continuous operation conditions of multiple automated production equipment, and records many key characteristics such as equipment number, running time, working temperature, vibration amplitude, raw material feeding rate, working voltage, maintenance interval days, operator skill level and product specifications. After the original data is standardized, such as eliminating outliers, standardizing values and completing missing values, 1058 high-quality samples are finally formed. The correlation thermogram of each variable is output, as shown in Figure 1.



Figure 1. The correlation heat map

Output a violin plot of the arguments, as shown in Figure 2.

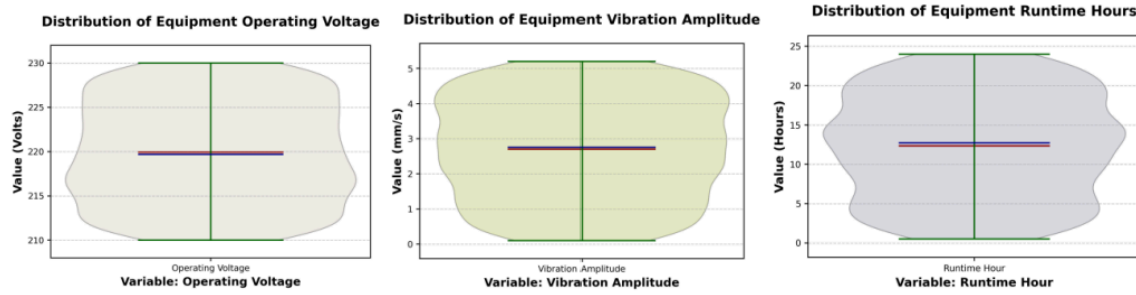


Figure 2. The violin plots

3. Method

3.1. FVIM

FVIM, or Four Vector Intelligent Element Heuristic Optimization Algorithm, is an intelligent search algorithm for global optimization. Its core design revolves around four optimal vectors, and the synergy of these four vectors guides the population to efficiently optimize in the solution space [6]. Firstly, the algorithm initializes the population, sets the upper and lower bounds of parameters for each optimization problem, randomly generates the initial particle position and calculates the fitness, and selects the four vectors with the best fitness in the population as the core guiding vector. The iterative stage is the core of the algorithm, which computes a new average vector based on these four optimal vectors, which fuses the dominance information of the four superior solutions to provide the particles with a better moving direction [7]. The position updating of particles no longer relies on a single optimal solution, but synthesizes the information of four optimal vectors and the new average vector, and realizes the position iteration through a specific motion equation. This multi-vector guidance mechanism greatly improves the global exploration ability of the algorithm, can effectively jump out of the local optimal trap, at the same time, enhance the local development accuracy, and achieve a balance between convergence speed and optimization quality. The network structure of FVIM is shown in Figure 3.

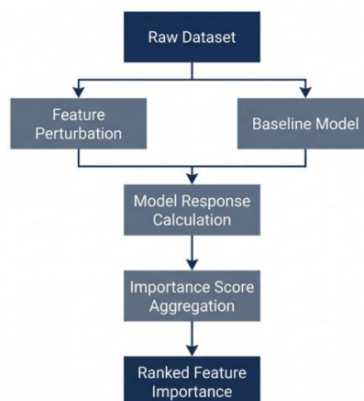


Figure 3. The network structure of FVIM

3.2. XGBoost

XGBoost is an extreme gradient boosting algorithm, which belongs to the advanced version of gradient boosting decision tree. The core is to build a strong prediction model by serially integrating multiple CART decision trees. It follows the idea of additive model of Boosting, and adds a new decision tree in each round of training, which specifically fits the residuals of the prediction results of all previous trees, and gradually reduces the overall loss of the model [8]. The key innovation of the algorithm lies in the second-order Taylor expansion of the objective function, and using the first-order and second-order derivative information of the loss function at the same time. Compared with the traditional GBDT with only the first-order derivative, it can approach the optimal solution more accurately, and the convergence speed and model accuracy are significantly improved. XGBoost explicitly adds a regularization term to the objective function, including the penalty of the number of leaf nodes and the penalty of the sum of squares of leaf weights, strictly controls the complexity of the tree model from the mathematical level, effectively suppresses overfitting, and improves the generalization ability of XGBoost [9]. The greedy algorithm is used to grow tree, and the optimal splitting point is selected by calculating the objective function gain brought by feature splitting. At the same time, it supports engineering optimization such as feature parallel computation and cache optimization, which can efficiently process large-scale sparse data. The network structure of XGBoost is shown in Figure 4.

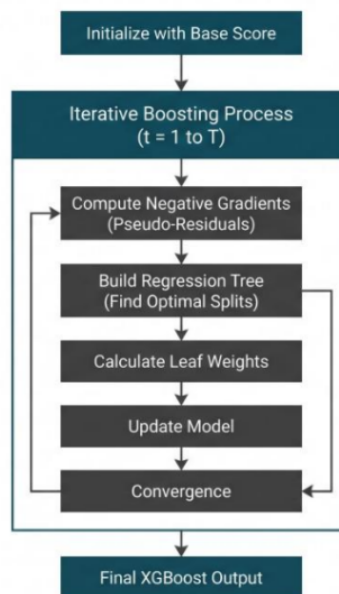


Figure 4. The network structure of XGBoost

3.3. FVIM-XGBoost

FVIM-XGBoost is an improved algorithm that integrates FVIM optimization algorithm with XGBoost model. The core is to optimize the key hyperparameters of XGBoost with the global optimization ability of FVIM and improve the overall performance of the model. The prediction effect of XGBoost highly depends on the reasonable configuration of hyperparameters such as deep regularization parameters of learning rate tree. Traditional grid search or random search is easy to fall into local optimum and inefficient, while the multi-vector guided optimization mechanism of

FVIM can efficiently traverse the hyperparameter space and quickly locate the global optimal hyperparameter combination [10]. In the process of the algorithm, the hyperparameter optimization problem of XGBoost is transformed into the fitness optimization problem of FVIM firstly, and the evaluation index of the model on the validation set is used as the fitness function of FVIM. FVIM initializes the hyperparameter population, iteratively screens out four optimal hyperparameter combinations, calculates the average vector to guide the population update, and continuously optimizes the hyperparameter configuration. In each iteration, the XGBoost model is trained with the current optimal hyperparameters and the fitness is calculated until the termination condition is satisfied. The XGBoost model trained by the optimal hyperparameters is superior to the traditional parameter adjustment method in terms of fitting accuracy, generalization ability and training efficiency. The network structure of FVIM-XGBoost is shown in Figure 5.

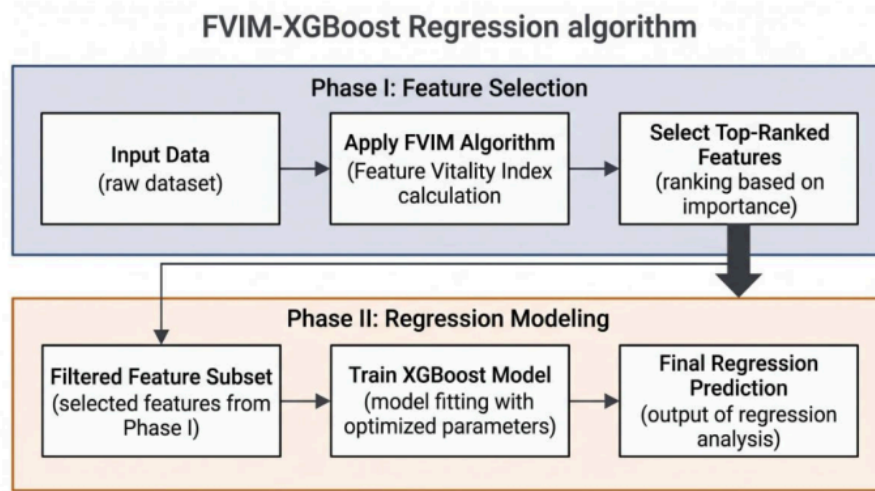


Figure 5. The network structure of FVIM-XGBoost

4. Result

This project optimizes the three key parameters of the XGBoost model based on the FVIM algorithm. Specifically, the lower and upper limits of the maximum number of iterations are set to 10 and 50, the lower and upper limits of the maximum depth of the tree are 1 and 12, the lower and upper limits of the learning rate are 0.01 and 0.30, the population size of the optimization algorithm is set to 30, and the maximum number of iterations is set to 5. At the same time, the model sets the missing value to non-number by default, the sub-sampling ratio is set to 0.9, and the column sampling ratio is set to 1. The objective function uses five-fold cross-validation to calculate the average error rate as the fitness value.

Comparative experiments were performed using a variety of machine learning algorithms, and the results are shown in Table 1.

Table 1. The results of the comparative experiment

Model	MSE	RMSE	MAE	MAPE	R ²
GBDT	572.29	23.923	19.292	6.283	0.923
Decision tree	1636.708	40.456	32.225	10.896	0.79

Table 1. (continued)

ExtraTrees	650.583	25.507	20.289	6.604	0.91
Random forest	869.54	29.488	23.851	7.99	0.883
CatBoost	534.038	23.109	17.886	5.902	0.928
AdaBoost	614.248	24.784	19.506	6.534	0.912
XGBoost	512.138	22.63	18.079	6.208	0.93
BP neural network	834.866	28.894	22.944	7.736	0.889
LightGBM	463.317	21.525	16.936	5.661	0.933
FVIM-XGboost	287.153	16.946	13.685	4.623	0.962

Output the index comparison histogram of each algorithm, as shown in Figure 6.

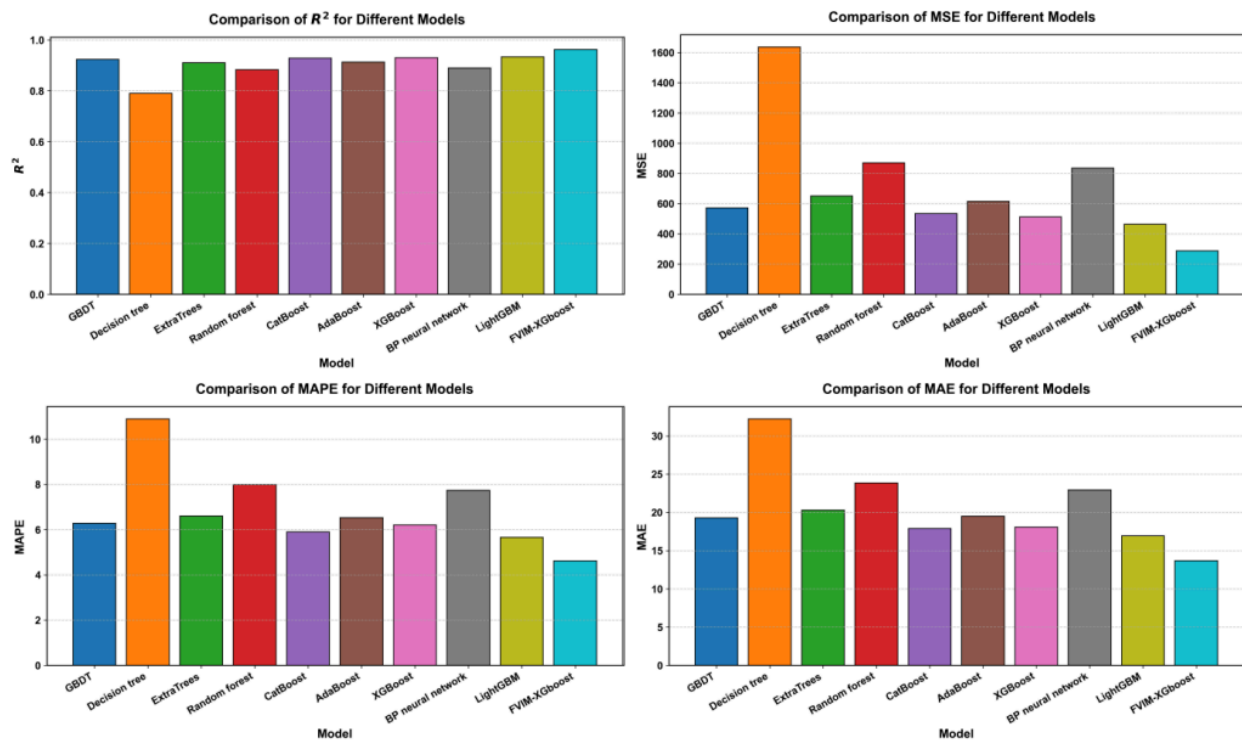


Figure 6. The comparison results of each index of each FVIM-XGboost test set

The FVIM-XGboost regression algorithm proposed in this paper is significantly better than GBDT, Decision Tree, ExtraTrees, Random Forest, CatBoost, AdaBoost, XGBoost, BP neural network and LightGBM in various regression evaluation indexes. Its MSE, RMSE, MAE and MAPE are the lowest values among all models, and R^2 reaches the highest 0.962, which fully reflects the obvious advantages of this algorithm in reducing prediction errors, improving fitting accuracy and generalization ability. Compared with traditional ensemble learning and neural network models, it has better error control and better data fitting effect, and its overall regression performance ranks first among all participating algorithms.

5. Conclusion

The global manufacturing industry is transforming to intelligence, and the widespread application of industrial automation equipment brings massive operation data. Traditional empirical management leads to low equipment utilization rate, large capacity fluctuation and lack of basis for production scheduling. Accurate capacity forecast has become the key to industrial upgrading. Although machine learning can handle complex data, conventional algorithms still have shortcomings in feature screening and generalization performance. In this paper, the FVIM XGBoost model is constructed to improve the parameter configuration and feature learning ability of XGBoost through global optimization mechanism, and effectively adapt to the complex data characteristics of industrial scenarios. Experimental results show that the proposed algorithm is ahead of GBDT, Decision Tree, Random Forest, CatBoost, LightGBM and original XGBoost in terms of prediction accuracy, error level and fitting effect. This research improves the stability and accuracy of capacity forecasting, provides scientific support for production plan formulation and equipment operation and maintenance scheduling, helps to optimize production resource allocation, improves equipment utilization, promotes the intelligent and efficient development of manufacturing industry, and has important practical value for the application of industrial intelligent forecasting technology.

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