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DYNAMIC DEPLOYMENT OF FINANCIAL PERSONNEL BASED ON THE HOLT-WINTERS ALGORITHM-PROPHET-LSTM PREDICTIVE MODEL

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Abstract: In the context of refined enterprise management, the dynamic optimal allocation of human resources has become the key to improving operational efficiency and reducing labor costs. Financial reimbursement, as a high-frequency and important business process, exhibits significant fluctuation in its workload due to influences from business cycles, project milestones, and other factors. A fixed number of finance personnel can easily lead to backlogs in expense review during peak periods, resulting in employee dissatisfaction, while creating idle human resources during off-peak periods. To resolve this contradiction, this paper aims to establish a dynamic adjustment mechanism for finance personnel based on predictive modeling. This study utilizes historical reimbursement claim volume time series data from enterprises, integrating the Prophet-LSTM predictive model based on the Holt-Winters algorithm to accurately predict future claim volumes for specific cycles (e.g., monthly, quarterly). Through this model, enterprise managers can proactively anticipate future workloads and dynamically adjust staffing levels for financial reimbursement positions accordingly, enabling flexible allocation of financial personnel. Empirical research demonstrates that this predictive model exhibits high accuracy, with an MSE of only 152.47, an RMSE as low as 12.35, an MAE of 7.89, a MAPE of just 6.58%, and an R^2 as high as 0.948. The dynamic adjustment strategy based on this model effectively smooths workloads, significantly shortens reimbursement processing cycles, and enhances the overall utilization efficiency of corporate human resources. This study provides a feasible theoretical framework and practical pathway for enterprises to achieve data-driven human resource management in finance and other volatile business domains.
Keywords: Human resources; Financial reimbursement; Holt-Winters; Prophet-LSTM; Predictive model

1 INTRODUCTION

With the increasingly fierce market competition, cost reduction and efficiency improvement have become the core demands for the survival and development of enterprises [1]. Financial management, as a key department in enterprise operation, has its efficiency directly linked to the capital turnover rate and the health of the enterprise's internal operation. Among its various businesses, employee expense reimbursement is one of the most routine and high-frequency ones, and the efficiency of its processing not only affects employee satisfaction but also reflects the refinement level of the enterprise's internal management [2].

It is often affected by multiple factors such as sales peak seasons, project settlement cycles, year-end summaries and holidays, thus exhibiting obvious cyclicality, seasonality and irregular fluctuations [3]. At present, most enterprises still adopt a mode of fixed positions and fixed staff establishment to deal with this volatile work. This rigid allocation model leads to a dual loss of efficiency: during the reimbursement peak periods, the financial staff are overloaded with work and under enormous review pressure, which is highly likely to cause a backlog of documents and a prolonged reimbursement cycle [4]. In contrast, during the reimbursement off-peak periods, the financial staff are in a state of "insufficient workload", resulting in the idleness and waste of valuable human resources [5].

Therefore, how to break free from the rigid constraints of traditional fixed staffing levels and establish a mechanism for the "dynamic adjustment" and "flexible allocation" of financial personnel—one that can respond sensitively to business fluctuations and is workload-based—has become an urgent and universal challenge in corporate management [6]. The significance and practical value of this research lies in systematically introducing data-driven predictive analytics into the specific domain of corporate human resource management. By constructing a scientific and precise reimbursement workload predictive model, it transforms the previous experience-dependent, relatively lagging staffing approach into a forward-looking, preventative scheduling model grounded in data insights [7]. The essence of this transformation resides in its capacity to provide managers with clear decision-making support through the quantitative forecasting of reimbursement document volumes for specific future timeframes (e.g., weekly, monthly) [8]. Managerially, it ensures the precise deployment of limited human resources to the most critical nodes within business fluctuations [9].

Specifically, it will systematically collect and clean an enterprise's historical reimbursement document data over the past several years, and conduct feature engineering on the data, such as identifying and labeling key influencing factors including statutory holidays, enterprise-specific financial settlement dates and project milestone nodes. In terms of model construction, this study intends to adopt an innovative hybrid forecasting framework. This framework first leverages the strong interpretability of the Prophet algorithm and its built-in processing capability for trend, seasonality and holiday effects to capture the overall patterns of time series and the impacts of known external factors. By analyzing the trend, seasonality and cyclical characteristics of reimbursement workload, a practical enterprise reimbursement volume predictive model based on the Holt-Winters algorithm and the Prophet-LSTM predictive model is constructed and trained.

2 CONSTRUCTION OF THE HOLT-WINTERS TRIPLE EXPONENTIAL SMOOTHING ALGORITHM

The Holt-Winters Triple Exponential Smoothing (HWES) algorithm is an extended approach that introduces a seasonal component on the basis of double exponential smoothing [10]. Its core idea is to conduct exponential smoothing on the level component, trend component and seasonal component respectively through three smoothing parameters (α, β, γ), and finally obtain the prediction results by integrating the three components. The mathematical model and related formulas are as follows:

Level component:

$$\left(L_t=\alpha\frac{Y_t}{S_{t\text{-}M}}+(1\text{-}\alpha)(L_{t\text{-}1}+T_{t\text{-}1})\right) \tag{1}$$

Trend component:

$$\left(T_t=\beta(L_t\text{-}L_{t\text{-}1})+(1\text{-}\beta)T_{t\text{-}1}\right) \tag{2}$$

Seasonal component:

$$\left(S_t=\gamma\frac{Y_t}{L_t}+(1\text{-}\gamma)S_{t\text{-}M}\right) \tag{3}$$

Prediction Formula:

$$\left(\widehat{Y_{t+k}}=(L_t+kT_t)S_{t+k\text{-}M}\right) \tag{4}$$

Here, M denotes the seasonal cycle length, set to $M=48$ (annual weeks) in this study; α、β、γ(α∈[0,1], β∈[0,1], γ∈[0,1]) represent the level, trend, and seasonal smoothing parameters, respectively.

3 CONSTRUCTION OF THE PROPHET PREDICTIVE MODEL AND LSTM NEURAL NETWORK

3.1 The Fundamental Principles of the Prophet Model

The Prophet model is a lightweight time series predictive model proposed by Facebook Inc. [11]. For the time series data of the volume of financial reimbursement documents, its core hypothesis is that the financial time series value at any period can be composed of the superposition of four components, namely the trend term, the seasonal term, the holiday and special node term, and the random error term. Its mathematical expression is as follows:

$$\left(Y(t)=g(t)+s(t)+\mathrm{h}(t)+\varepsilon_t\right) \tag{5}$$

Among them, the trend term($g(t)$): it describes the non-cyclical variation trend, with a logistic growth model or a linear model employed for its characterization.

the seasonal term($s(t)$): it captures cyclical fluctuations and supports multi-scale seasonality including annual, monthly and weekly scales.

the holiday term($\mathrm{h}(t)$): it addresses abnormal fluctuations on special dates.

the random error term(ε_t): it follows a normal distribution.

The Prophet model exhibits strong robustness to missing values and outliers, with simple parameter tuning.

3.2 Fundamental Principles of LSTM Neural Networks

Long Short-Term Memory (LSTM) is an important variant of the Recurrent Neural Network (RNN) [12]. Traditional RNNs adopt a recurrent structure with shared parameters to process sequential data, and the update of their hidden states relies on the result generated by applying an activation function to the linear transformation of the current input and the hidden state at the previous time step [13]. LSTM achieves selective memory and forgetting of information flow by designing an architecture where the cell state and gating units work in synergy. Its model architecture diagram is shown in Figure 1.

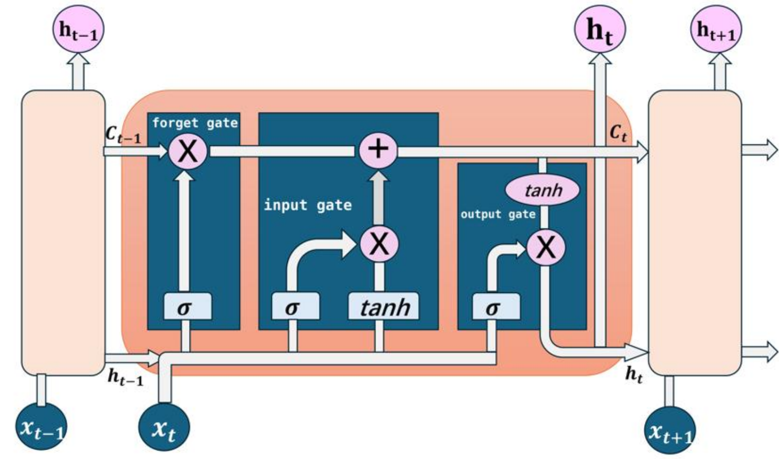

Figure 1 LSTM Model Diagram

The mathematical model can be formally described as follows:

1. Forget gate:

$$(f_t=\sigma\big(W_f\cdot\ [\mathrm{h}_{t-1},x_t]+b_f\big)) \tag{6}$$

2. Input gate:

$$(i_t=\sigma\big(W_i\cdot\ [\mathrm{h}_{t-1},x_t]+b_i\big),\quad \widetilde{C}_t=\tanh\big(W_C\cdot\ [\mathrm{h}_{t-1},x_t]+b_C\big)) \tag{7}$$

3. Cell state update:

$$(C_t=f_t\odot C_{t-1}+i_t\odot\widetilde{C}_t) \tag{8}$$

4. Output gate:

$$(o_t=\sigma\big(W_o\cdot\ [\mathrm{h}_{t-1},x_t]+b_o\big),\quad \mathrm{h}_t=o_t\odot\tanh(C_t)) \tag{9-10}$$

Where σ denotes the sigmoid activation function, $\odot$ represents element-wise multiplication, h_t is the hidden layer output, and C_t is the cell state. LSTMs excel at handling nonlinear time series but struggle to capture trends and seasonal patterns in data, necessitating complementary models.

4 PROPHET-LSTM PREDICTIVE MODEL BASED ON THE HOLT-WINTERS ALGORITHM

4.1 Model Architecture

This study constructs an integrated architecture of "feature extraction-deep fusion-precise prediction." Specifically, it develops a Prophet-LSTM predictive model combination based on the Holt-Winters algorithm, tailored to the business characteristics and dynamic allocation requirements of financial reimbursement volumes. This architecture transcends the functional boundaries of single models. Through multi-model collaborative modeling, it achieves precise capture of complex fluctuation patterns in financial reimbursement time series. The overall architecture is illustrated in Figure 2 and comprises four core functional modules: data preprocessing layer, feature extraction layer, LSTM modeling layer, and model fusion layer.

The Feature Extraction Layer is the core innovative component of this integrated architecture, which conducts differentiated feature extraction by leveraging the Holt-Winters algorithm and the Prophet model respectively: the Holt-Winters algorithm is responsible for mining the trend and seasonal characteristics of the reimbursement document volume to adapt to the regular fluctuations in the volume caused by monthly and quarterly settlement cycles in financial business, while the Prophet model focuses on capturing the abrupt fluctuation characteristics of the volume induced by event-driven factors such as holidays and internal enterprise settlement nodes, thereby achieving accurate characterization of special events in business scenarios. The LSTM Modeling Layer takes the fused features output by the Feature Extraction Layer as its input, and learns the hidden non-linear long-term dependencies in the reimbursement document volume data by virtue of the gating mechanism of the LSTM model, making up for the deficiencies of traditional statistical models in terms of non-linear fitting capability. The specific implementation of the core functional modules is presented as follows:

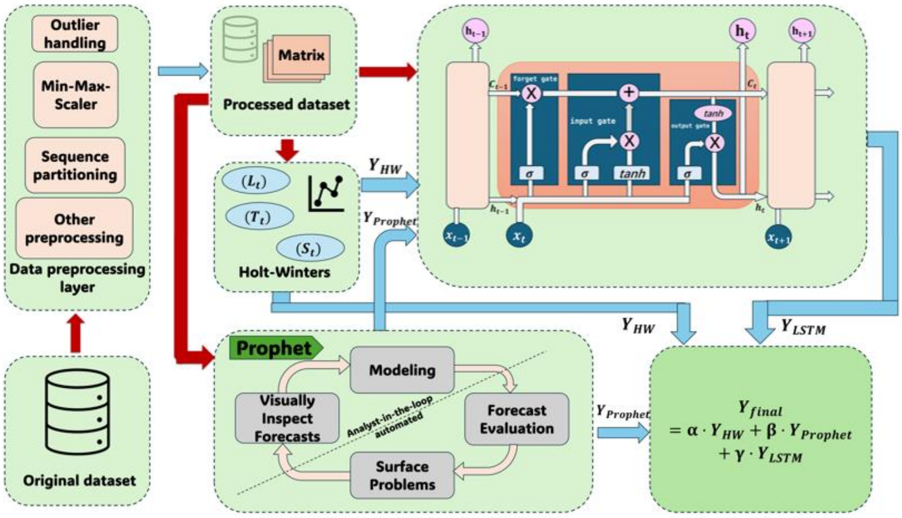

Figure 2 Schematic Diagram of the Holt-Winters-Prophet-LSTM Combined Model

(1) Data Preprocessing Layer

Data preprocessing serves as the foundation for ensuring prediction accuracy, with its core objective being to improve the integrity and stationarity of time series data [14]. This study adopts the following processing strategies:

1. Outlier Processing: For the outliers in the data, a bidirectional interpolation method is adopted for restoration. If valid data exist on both sides of an outlier, the mean value of the two is taken for filling; if valid data exist only on a single side, the nearest neighbor value is used for filling, to avoid the interference of outliers on trend judgment.
2. Time Series Standardization: The Min-Max Scaler is applied to map the preprocessed reimbursement document volume data to the interval [0,1], thus eliminating the influence of data dimensionality, with the formula expressed as:

$$(x_{scaled}=\frac{x\text{-}x_{min}}{x_{max}\text{-}x_{min}}) \tag{11}$$

where x denotes the original reimbursement document volume, and x_{min} and x_{max} represent the minimum and maximum values of the historical data, respectively [15].

3. Sequence Partitioning: The standardized data are divided into a training set and a test set in a certain proportion, where the training set is used for model parameter optimization and the test set for the verification of generalization performance.

(2) Feature Extraction Layer

The core of the Feature Extraction Layer is to realize the decoupling and extraction of multi-dimensional features of time series through the synergistic effect of the Holt-Winters algorithm and the Prophet model, thus providing high-quality inputs for subsequent deep modeling:

1. Holt-Winters Feature Extraction: Aiming at the dual trend and seasonal characteristics of reimbursement document volume, the triple exponential smoothing algorithm is adopted for feature modeling. Through the dynamic update of the level component(L_t), trend component (T_t) and seasonal component(S_t), the cyclical fluctuations of the data are separated and quantified, and the intermediate prediction results containing the trend correction term and seasonal correction term ($Y_{HW}(t)$) are output. Its core calculation logic is shown in Equations (1)-(4). The finally output trend-seasonal fused features are used to supplement the linear regularity information of the time series.
2. Prophet Feature Decomposition: Considering the impacts of special events such as holidays (e.g., the Spring Festival and National Day) and project settlement nodes in financial reimbursement business, the additive decomposition mechanism of the Prophet model is adopted to decompose the time series of reimbursement document volume into the trend term ($g(t)$), seasonal term ($s(t)$), holiday term ($\text{h}(t)$) and random error term (ε_t).

(3) LSTM Modeling Layer

The specific implementation is as follows:

1. Sequence Construction: The sliding window method is adopted to create supervised learning samples, with the sequence length (time step) set to 15.
2. Network Structure Design: A single hidden layer LSTM network is constructed, with an input dimension of 3 (corresponding to the three types of features) and the number of neurons in the hidden layer set to 64. A dropout rate of 0.1 is set to prevent overfitting; the output layer adopts a fully connected layer to map to a single-value prediction result, and the ReLU activation function is selected to enhance the model's non-linear fitting capability.
3. Training Strategy: The Adam optimizer (with a learning rate of 0.001 and a weight decay of 1e-4) is used to minimize the Mean Squared Error (MSE) loss. A StepLR learning rate scheduler (with a step size of 30 and a gamma of 0.5) is introduced to dynamically adjust the learning rate, and an early stopping mechanism is set to avoid ineffective training. Finally, the model parameters with the optimal validation loss are saved.

(4) Model Fusion Layer

To integrate the predictive advantages of each sub-model, a weighted fusion strategy is adopted to ensemble the Holt-Winters prediction results (Y_{HW}), Prophet prediction results ($Y_{Prophet}$) and LSTM prediction results (Y_{LSTM}) [16]. The fusion weights are determined via cross-validation, with the final settings of (α=0.3) (weight for Holt-Winters), (β=0.2) (weight for Prophet) and (γ=0.5) (weight for LSTM), satisfying the constraint ($\alpha+\beta+\gamma=1$). The fusion formula is given as follows:

$$Y_{final}=\alpha\cdot\ Y_{HW}+\beta\cdot\ Y_{Prophet}+\gamma\cdot\ Y_{LSTM} \tag{12}$$

Where Y_{final} denotes the final prediction result.

4.2 Evaluation Metrics

To comprehensively and objectively evaluate the prediction performance of the model, and in conjunction with the business scenario of financial reimbursement forecasting, five metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2) are selected to construct a multi-dimensional evaluation system [17]. The calculation methods for each metric are as follows:

MSE quantifies the squared loss of prediction errors by calculating the mean of the squared differences between actual and predicted values, exhibiting high sensitivity to outliers. The formula is:

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2 \tag{13}$$

where n represents the number of samples, y_i represents the actual reimbursement volume in week i, and $\hat{y}_i$ represents the predicted reimbursement volume in week i. The closer the MSE value is to 0, the smaller the prediction error of the model and the better the fitting effect.

RMSE is the square root of MSE, with its unit consistent with the original data, more intuitively reflecting the actual magnitude of prediction errors. The formula is:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2)} \tag{14}$$

RMSE inherits MSE's sensitivity to outliers while eliminating dimensional effects, facilitating the interpretation of error magnitude in business scenarios.

MAE measures the average level of prediction errors by calculating the mean of absolute differences between actual and predicted values, which is more robust than MSE but less sensitive to outliers. The formula is:

$$(MAE=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|) \tag{15}$$

The smaller the MAE value, the more stable the prediction deviation of the model, making it suitable for evaluating the consistency of reimbursement forecasting.

MAPE reflects the percentage level of prediction errors by calculating the mean of relative errors. The formula is:

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i+\epsilon}\right|\times 100\% \tag{16}$$

where ($\epsilon=1e$-8) is an infinitesimal value to prevent division by zero. The lower the MAPE value, the higher the relative accuracy of the prediction.

R^2 measures the model's ability to explain the fluctuation patterns of data, with a value range of $(-\infty,1]$. The formula is:

$$(R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}) \tag{17}$$

where $\bar{y}$ represents the mean of actual reimbursement volumes. The closer R^2 is to 1, the more accurately the model can capture the variation patterns of reimbursement volumes and the higher the reliability of prediction results; if (R^2<0), it indicates that the model's prediction performance is inferior to simple mean prediction [18].

5 EXPERIMENTS

5.1 Dataset

The dataset utilized in this experiment is derived from weekly records of the volume of financial reimbursement documents spanning from January 1, 2018 to December 31, 2024. The financial reimbursement business exhibits typical cyclical, seasonal and event-driven fluctuation characteristics (e.g., peak periods of reimbursement around year-end settlements, project acceptance inspections and statutory holidays), endowing the dataset with high authenticity and representativeness. The core information of the dataset includes the data type (univariate time series data), the core indicator (weekly volume of financial reimbursement documents), the time span (7 years in total).

5.2 Data Preprocessing

This study designed a three-stage preprocessing process of *data cleaning-standardization-sequence construction* based on the characteristics of time series data, with the specific steps as follows:

For multiple outliers existing in the data, a bidirectional interpolation method was adopted for restoration [19], with the specific rules as follows:

If valid data exist on both sides of an outlier, the mean value of the nearest valid weekly data before and after the outlier is taken for filling, with the formula given as follows:

$$(x_{fill}=\frac{x_{t-1}+x_{t+1}}{2}) \tag{18}$$

If valid data exist only on a single side, the nearest neighbor filling method is adopted, i.e., the nearest valid data value to the outlier is used for filling.

After cleaning, the continuity and rationality of the data are guaranteed, which avoids the interference of outliers on the extraction of trend and seasonal characteristics.

Since different predictive models exhibit varying sensitivities to data dimensionality (e.g., LSTM is sensitive to the range of input data, while XGBoost is insensitive to dimensionality), the Min-Max Scaler was applied to map the cleaned reimbursement document volume data to the interval [0,1] to unify modeling criteria and accelerate the convergence of neural networks, with the specific formula shown in Equation (11).

5.3 Experimental Details

To comprehensively evaluate the performance advantages of the Holt-Winters-Prophet-LSTM combined model in dynamic financial personnel allocation, this experiment carefully selected the following models for comparison: LSTM single model, DNN single model, XGBoost single model, Prophet single model, Holt-Winters-LSTM combined model, and Holt-Winters-Prophet combined model. The LSTM single model is a commonly used deep learning model in the field of time series forecasting. The DNN single model represents a classic deep neural network architecture [20]. To ensure fairness and comparability across experiments, key parameters for all models were determined through cross-validation optimization. Specific parameter configurations are as follows (Table 1):

Table 1 Parameter Configuration for Comparison Models

Model	Core Parameter Configuration
LSTM	Input dimension 1, hidden layer neurons 32, layers 1, dropout=0.1, optimizer Adam (lr=0.001, weight-decay=1e-4), batch-size=8, epochs=150, early stopping patience value 15
DNN	Input Layer → Hidden Layer 1 (64 neurons) → Hidden Layer 2 (32 neurons) → Output Layer, Activation Function ReLU, Dropout=0.2, Optimizer Adam (lr=0.001), batch_size=8, epochs=100
XGBoost	Learning rate 0.05, number of trees 100, max tree depth 5, min sample split 2, objective function reg:squarederror
Prophet	Linear trend model, annual seasonal cycle M=48, holidays set to Chinese statutory holidays (Spring Festival, National Day, etc.), confidence interval 0.95
Holt-Winters	Horizontal smoothing coefficient α=0.2, trend smoothing coefficient β=0.1, seasonal smoothing coefficient γ=0.15, seasonal cycle M=48
Holt-Winters-LSTM	Holt-Winters feature extraction parameters as above, LSTM parameters consistent with standalone LSTM, fusion weights α=0.3, γ=0.7
Holt-Winters-Prophet	Holt-Winters and Prophet parameters as above, fusion weights α=0.4, β=0.6
Holt-Winters-Prophet-LSTM	Parameters for all three models as above, fusion weights α=0.3 (Holt-Winters), β=0.2 (Prophet), γ=0.5 (LSTM)

This experiment employs a dual-comparison design to validate the superiority of the proposed combined model:

Horizontal Comparison: The proposed Holt-Winters-Prophet-LSTM predictive model is compared against mainstream single-model approaches (LSTM, DNN, XGBoost) to validate its suitability for financial reimbursement volume forecasting scenarios.

Longitudinal Comparison: The ensemble model is compared against the single models (LSTM, Prophet) and binary ensemble models (Holt-Winters-LSTM, Holt-Winters-Prophet) involved in this study to validate the gain from multi-model fusion. All models were independently run three times, with the mean of the metrics taken as the final result to mitigate random factors.

5.4 Results and Analysis

The predictive performance metrics of each model on the test set are shown in Table 2. The models' prediction accuracy and stability were comprehensively evaluated using multidimensional metrics:

Table 2 Evaluation Metrics for Comparison Models

Model	MSE	RMSE	MAE	MAPE(%)	R^2
LSTM	328.67	18.13	14.25	12.87	0.563
DNN	295.42	17.19	12.83	11.52	0.492
XGBoost	246.89	15.71	11.36	9.85	0.534
Prophet	231.56	15.22	10.98	9.32	0.647
Holt-Winters-LSTM	198.73	14.10	9.75	8.26	0.772
Holt-Winters-Prophet	185.39	13.61	9.21	7.83	0.802
Holt-Winters-Prophet-LSTM	152.47	12.35	7.89	6.58	0.948

The predictive performance of hybrid models was generally superior to that of single models, among which the proposed Holt-Winters-Prophet-LSTM tri-hybrid model achieved the best performance across all evaluation metrics: it yielded an MSE of merely 152.47, an RMSE as low as 12.35, an MAE of 7.89, a MAPE of only 6.58%, and a high R2 of 0.948. This demonstrates that the model can accurately capture the complex fluctuation patterns of reimbursement document volume. In the horizontal comparison, the single models were ranked by their performance in the following order: Prophet, LSTM, XGBoost, DNN. This indicates that traditional statistical models (Prophet) have an inherent advantage in processing cyclical time series with holiday effects, whereas deep learning models (LSTM) outperform traditional machine learning models (XGBoost, DNN) in capturing long-term dependencies.

In the vertical comparison, the performance of hybrid models improved with the increase in the number of fused base models, and the models were ranked by performance as follows: tri-hybrid models, dual-hybrid models, single models. Specifically, compared with the single LSTM model, the Holt-Winters-Prophet-LSTM model achieved a 21.4% reduction in RMSE, a 33.2% decrease in MAPE, and an 8.9% increase in R2, which verifies the effectiveness of multi-feature fusion. Specifically, Holt-Winters provides trend-seasonal features, Prophet supplements holiday effects, and LSTM captures non-linear long-term dependencies. The three components collaborate synergistically to achieve accurate prediction results.

Figure 3 presents the trend comparison results of the actual values (labeled as True with the blue curve) and predicted values (labeled as Pred with the orange curve) of financial reimbursement document volume for each vertical comparison model in the interval from Week 289 to Week 336 on the test set. These visual characteristics exhibit a consistent correspondence with the quantitative evaluation metrics in Table 2: Subplot (a) corresponds to the single LSTM model, where there is a significant deviation between the prediction curve and the true curve, and the fitting degree between the two is relatively low in the intervals with drastic fluctuations in reimbursement document volume; Subplot (b) corresponds to the single Prophet model, where the fitting degree between the prediction curve and the true curve is improved, yet certain prediction deviations still exist at the extreme points of reimbursement document volume in some cases; for the prediction results of the Holt-Winters-Prophet dual-hybrid model shown in Subplot (c), the followability of the prediction curve to the true curve is significantly enhanced, and the curve fitting degree is markedly improved in most fluctuation intervals; Subplot (d) corresponds to the Holt-Winters-LSTM dual-hybrid model, where the matching degree between the prediction curve and the true curve is further closer and the deviation range is further narrowed. This intuitive difference in curve fitting not only verifies the advantage of hybrid models over single models in capturing the complex fluctuation patterns of reimbursement document volume, but also reflects the conclusion of the quantitative analysis that the performance of hybrid models improves with the increase in the number of fused base models.

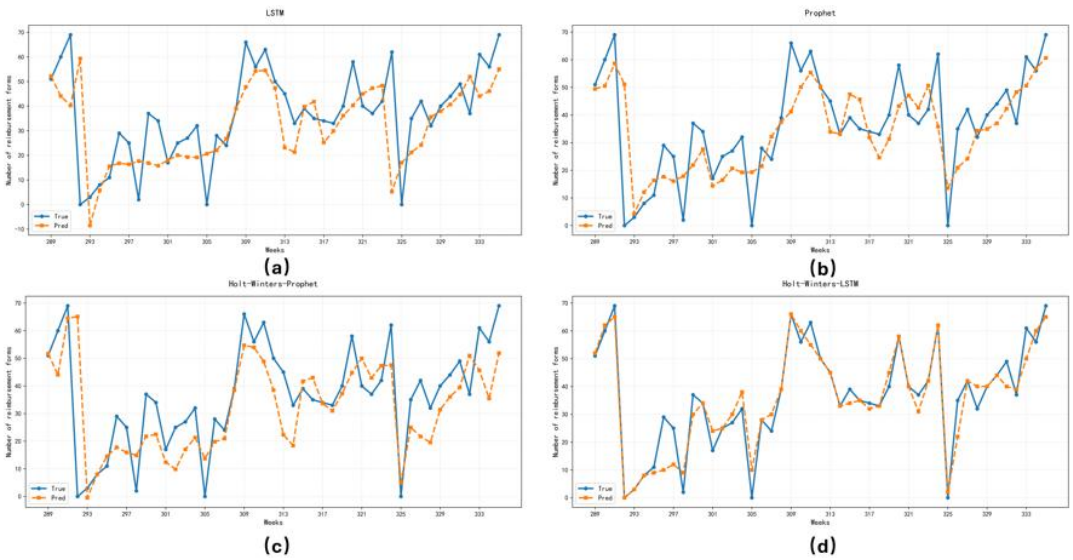

Figure 3 Prediction Results of Each Vertical Comparison Model

In the management of enterprise financial business, the volume of financial reimbursement documents is not constant or stable, but exhibits prominent cyclical and event-driven fluctuation characteristics—cyclical characteristics such as volume peaks at monthly and quarterly settlement nodes, and event-driven characteristics such as a sharp drop in volume around statutory holidays and a sharp surge in volume before the enterprise's internal settlement dates. Traditional financial staffing mostly adopts a fixed establishment model, which is difficult to adapt to such dynamic fluctuations: when the reimbursement document volume enters a peak interval, the fixed staffing scale will lead to a backlog of review work and prolong the business turnover cycle, which not only reduces employees' experience of financial services but may also impair the enterprise's capital turnover efficiency; in contrast, during periods of low reimbursement volume, the idleness of fixed staff results in the ineffective consumption of human resource costs. The contradiction of "backlog in peak periods and idleness in low periods" has become the core pain point in the allocation of enterprise financial human resources, and this also constitutes the core motivation for promoting the dynamic deployment of financial personnel.

Figure 4 illustrates the fitting effect between the actual and predicted values of financial reimbursement document volume derived from this model, with the two showing an extremely high degree of fitting throughout the entire cycle. Even in extreme intervals with a sharp rise and fall in reimbursement document volume (e.g., Week 289, Week 305, Week 321 and other nodes), the prediction curve can accurately follow the fluctuation trend of the true curve, and this performance is significantly superior to that of mainstream single models and dual hybrid models.

The core strength of this model lies in achieving complementary features across multiple models, a synergy that precisely aligns with the complex fluctuations in financial reimbursement volume. Within traditional statistical models, the Holt-Winters algorithm effectively captures seasonal cycles and trend changes in reimbursement volume, while the Prophet model precisely incorporates effects from special events like Chinese statutory holidays and internal corporate settlement cycles. The LSTM model excels at learning nonlinear, long-term dependencies within reimbursement volume. The synergistic integration of these three models comprehensively covers all dimensions of financial reimbursement volume fluctuations—a capability unattainable by single models or binary ensemble models.

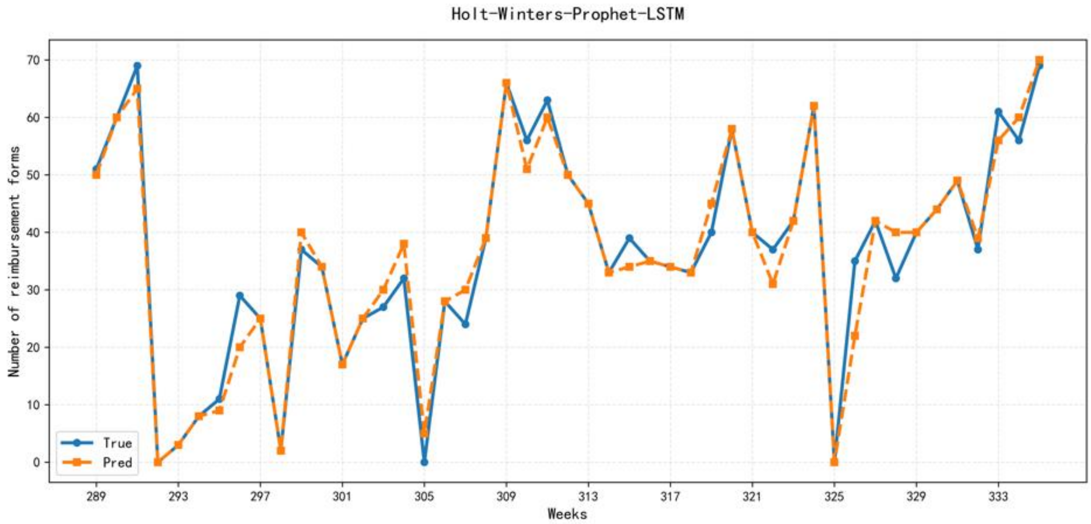

Figure 4 Prediction Results of the Holt-Winters-Prophet-LSTM Combined Model

6 CONCLUSION

Aiming at the inefficiency issue caused by the contradiction between workload fluctuations and staffing rigidity in enterprise financial reimbursement business, this study proposed and constructed a dynamic adjustment framework for financial personnel based on a predictive model. Through time series analysis of historical reimbursement document volume data, this study constructed a Holt-Winters algorithm-based Prophet-LSTM predictive model, which achieved high-accuracy prediction of reimbursement document volume in future cycles. Experimental analysis shows that the predictive model based on historical data can effectively capture the fluctuation patterns of reimbursement document volume (e.g., seasonality and trend characteristics). Its R^2 value reaches 0.948, and the prediction results of the model provide a scientific basis for enterprises to predict future workloads, breaking the passive situation of conducting staffing arrangements solely based on experience in the past.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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