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MODELING THE EXTERNAL TRUCK ARRIVALS IN CONTAINER TERMINALS BASED ON DBN AND SVM

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Abstract. *Accurately grasping the rules of external truck arrival is the basis to develop the gate plan, yard plan and crane management. To improve the accuracy and rationality of operation plan, a prediction model combining DBN (deep belief net) and SVM (support vector machine) is proposed to predict external truck arrivals. The DBN is used to obtain data characteristics, and the predicted arrivals are obtained through SVM. Comparing this model with other prediction models, numerical results show that DBN obtains data characteristics effectively and model predicts the truck arrivals accurately, which can increase the terminal efficiency and provide a reference to the research of external truck arrivals.*
Keywords: Container terminals, External truck arrivals, Deep belief net, Support vector machine

1. **Introduction.** External trucks are the main transport machine connecting container terminals and hinterland. With the rapid growth of container throughput, the terminal congestion caused by external trucks has become increasingly prominent. The uncertainty of truck arrival leads to re-handling in container yard and reduces the terminal operation efficiency. Taking account of the hugeness, diversity, complexity and volatility of external truck arrivals information, how to effectively extract data features from complex information is an effective way to improve the accuracy of the prediction. The study of external truck arrival is the basis to formulate the operation plan, and the prediction of external truck arrivals can improve the efficiency of terminal operation.

The management of external truck arrival has gained a substantial amount of attention from researchers. To reduce the re-handling work in container yard, the scientific storage strategy has been implemented [1,2]. Chen and Jiang [3] and Phan and Kim [4] solved the terminal congestion caused by external truck arrivals. Recently, studies on the regularity and external truck arrivals have rapidly developed. The models of machine learning are used to predict the external truck arrivals [5-9].

The above papers provide references for the study of the external truck arrivals. However, the traditional model cannot extract the features from data completely, resulting in low prediction precision. In this study, a two-stage model is proposed to predict external truck arrivals. The feature extraction is done by deep belief net (DBN), and the external truck arrival is predicted by support vector machine (SVM). This study can enhance the rationality of operation plan and improve the terminal efficiency. The remainder of the paper is organized as follows. Section 2 provides the prediction model and its algorithm flow. Numerical experiments of prediction model are proposed in Section 3. Conclusions are given in Section 4.

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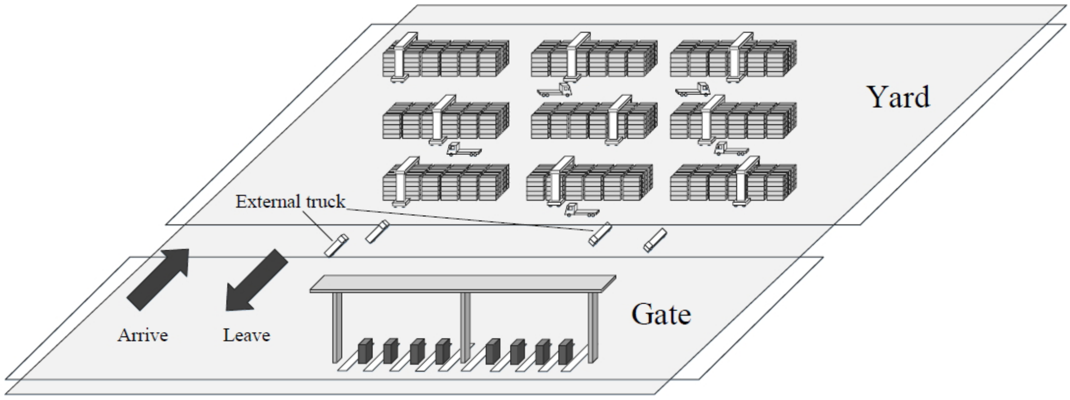


FIGURE 1. The external trucks in container terminals

2. Methodology.

2.1. Problem statement. The external trucks are the main carriers between gate and yard in container terminals, as shown in Figure 1. The regularity of external truck arrival affects the terminal resources allocation and distribution, and it is useful to improve the operation efficiency. Predicting external truck arrivals accurately is important for grasping regularity. Therefore, it is necessary to take an excellent method for external truck arrivals prediction.

2.2. External truck arrivals prediction model. To predict the external truck arrivals, this paper combines the advantages of DBN model in data features mining and SVM model in prediction. Due to the complexity of external truck arrival, a two-stage model as shown in Figure 2 is proposed to predict the external truck arrivals of a single ship in each time period. The first stage model is the deep belief network model, and it extracts the features from data and obtains feature vectors. The second stage model predicts the external truck arrivals by SVM.

2.3. Features extraction model based on DBN. The internal features of sample data are extracted based on the first stage model. The DBN model is a deep learning model proposed to ease the inference difficulties of logistic belief networks, which is constructed from a stack of restricted Boltzmann machine (RBM). Figure 3(a) shows the RBM structure, and the lower layer v is visual layer, also called input layer; the upper layer h is hidden layer, also called output layer. The RBM completely forbids the connection of internal nodes, and only allows the nodes connection between visual layer and hidden layer.

The visible layer in RBM corresponds to the input layer, its state can already be observed, and the hidden layer is used to detect features. The energy function is given below:

$$\varepsilon(\mathbf{v}, \mathbf{h}) = -\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} h_i v_j - \sum_{j=1}^{m} a_j v_j - \sum_{i=1}^{n} b_i h_i \tag{1}$$

where w_{ij} represents the weight between the visible node j and the hidden node i, and a_j and b_i are the bias of the visible node and the hidden node.

After determining the parameters, the joint distribution of RBM is obtained by the energy function:

$$p(\mathbf{v}, \mathbf{h}) = \frac{1}{Z} \exp(-\varepsilon(\mathbf{v}, \mathbf{h})) \tag{2}$$

where Z is the partition function to calculate the normalization factor.

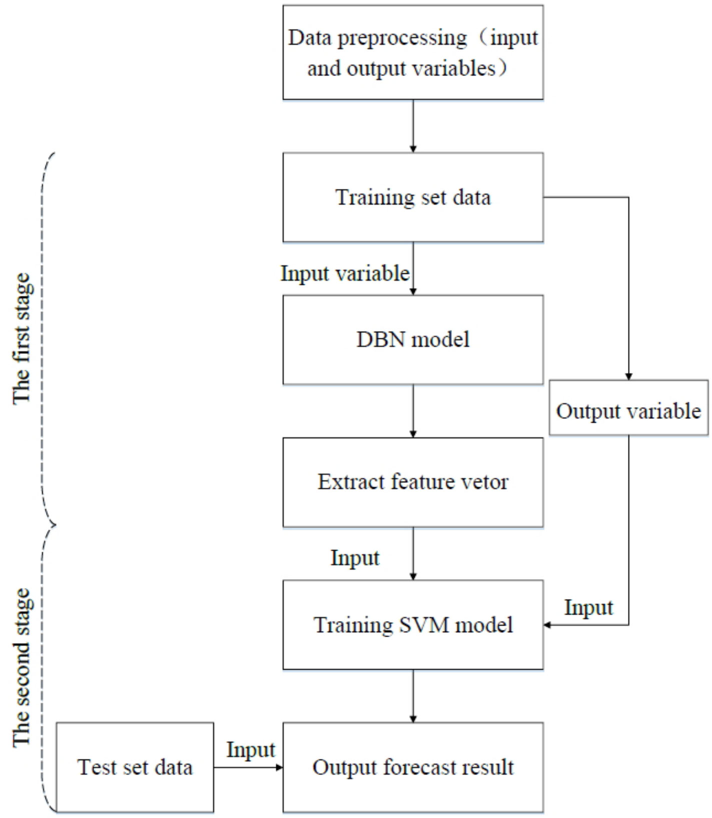
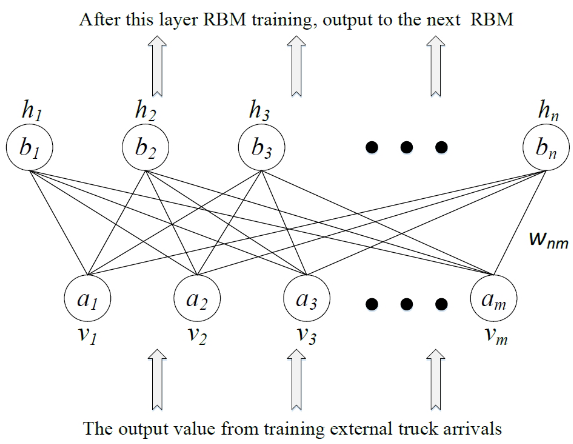
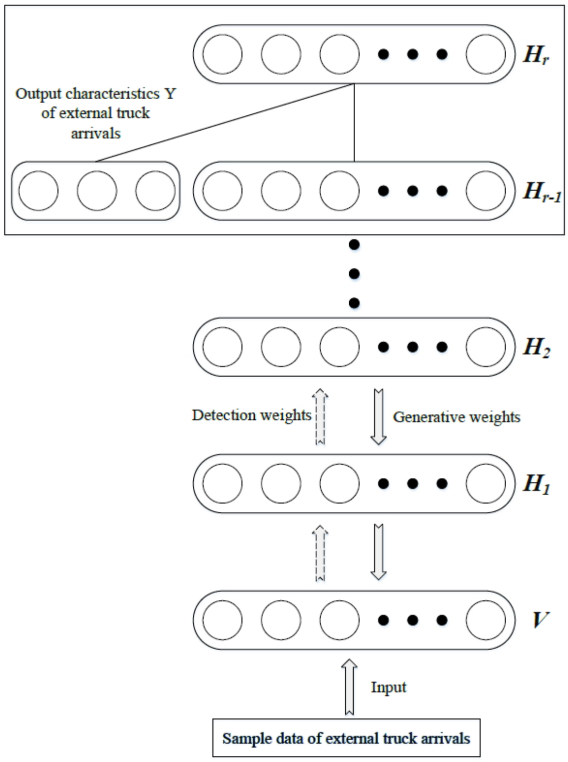


FIGURE 2. The structure of external truck arrivals prediction



(a) Restricted boltzmann machines



(b) Deep belief net

FIGURE 3. The DBN model

All $p(x, h)$ of upper node x are summed to get the node occurrence probability:

$$p(x) = \sum_h \frac{1}{Z} \exp(-\varepsilon(x, h)) \tag{3}$$

When the $p(x)$ is maximum and the energy is minimum, the system reaches the most stable state.

As shown in Figure 3(b), the complete DBN model is formed through the stacking of multi-layer RBM, and the output of each RBM layer is the input of the next RBM layer. First, use the recognition weight to initialize the generative weight, and all parameters are tuned by network training. The input data is encoded and decoded based on unsupervised learning. By comparing the decoded result with the original data, this paper adjusts its own parameters and looks for the new features. The acquired features are new input variables, which predicts the external truck arrivals combined with SVM model.

The algorithm steps of DBN model are as follows.

Step 1. Data processing. The original data is sorted and normalized, and the data set is divided into two parts as training set and test set.

Step 2. Parameter initialization. Initialize the parameter matrix, the learning rate alpha, the momentum and the weights of each layer.

Step 3. Data training. Input the training set data to train the first RBM layer, whose visual layer is $\mathbf{V}$ and hidden layer is $\mathbf{H_1}$.

Step 4. Parameter tuning. For r-layers DBN structure, if $1 < i \le r - 1$, $\mathbf{H_{i-1}}$ is regarded as visible layer and $\mathbf{H_i}$ is used as hidden layer in the i-th RBM, and train the RBM layer by layer. If $i = r$, the final output data Y and $\mathbf{H_{r-1}}$ are regarded as the visible layer, and $\mathbf{H_r}$ is regarded as the hidden layer. The parameters w, a, b are tuned according to the learning rate and momentum.

Step 5. Features output. The data features vectors obtained from Step 4 are input into the second stage SVM model to build the prediction model.

2.4. **Prediction model based on SVM.** The data features extracted from first stage model are input into the second stage SVM model. As shown in Figure 4, the output variable is input into the SVM prediction model to obtain the external truck arrivals. The SVM model takes the minimum confidence range as the optimization target and the training error as the constraint condition. The actual error is minimized by selecting the function subset and its discriminant functions.

The SVM model does not require a specific function expression, which learns the internal relationship between the input variables and the output variables. In the complex external truck arrival system, the trained SVM model can effectively capture the intrinsic relationship between input variables and output variables.

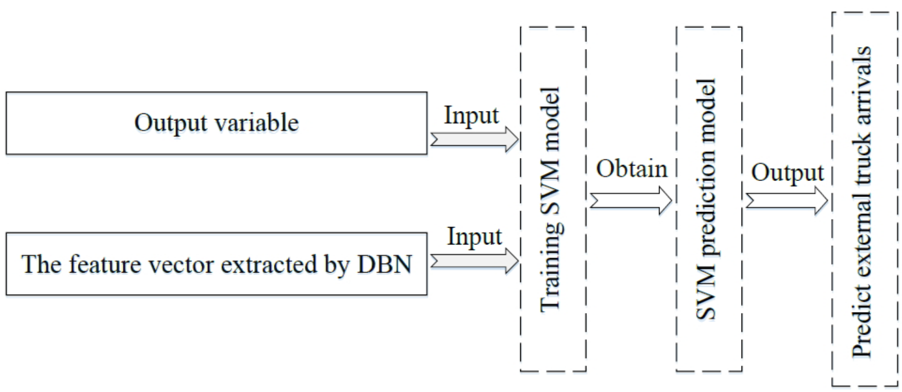


FIGURE 4. The prediction model of support vector machine

The feature vectors extracted by DBN model are input into SVM model, and the algorithm steps are as follows.

Step 1. Kernel function. This paper chooses Gaussian radial basis function as the kernel function:

$$K(x_i, x_j) = \exp\left(\|x_i - x_j\|^2 / \sigma^2\right) \tag{4}$$

Step 2. Regression function. The predicted results are output through constructing the regression function:

$$f(x) = \sum_{i=1}^{n} (a_i - a_i^*) K(x_i, x_j) + b \tag{5}$$

where a_i and a_i^* are LaGrange multiplier, x_i is the i-th sample of n samples, and b is the computed average of all standard support vectors.

Step 3. The method of grid search and cross-validation is used to select the optimal parameters, such as penalty parameter C, nuclear parameter σ and accuracy ε based on data training.

Step 4. Prediction. Combined with the sample data and the output feature vectors of DBN model, the results of external truck arrivals are obtained.

3. **Numerical Experiments.** The external truck arrivals data in Jinzhou Port is used for numerical experiments. Collect the external truck arrivals data from January 7 to January 14, 2015, and obtain the corresponding data of 12 ships. After determining the input and output variables, this paper divides the data of 12 ships into two parts. One part contains the data of 10 ships as the training set, and the other part contains the data of 2 ships as the test set.

3.1. **Influencing factors analysis.** The regularity of external truck arrivals is complicate, and it is the result of various random factors. The actual situation of the terminals needs to be considered. Based on the statistics and other methods, this paper analyzes the regularity of external truck arrival and its influencing factors in Jinzhou Port.

1) Container loading volume. The container loading volume of the ship determines the total external truck arrivals, and there are obvious differences in the regularity of external truck arrival for different ships. According to the data of Jinzhou Port, for the ships with a load of less than 100, external trucks mostly arrive at the terminal within 3-4 days, and their arrivals are relatively concentrated; for the ships with a load of more than 100, external trucks arrive within 3-5 days, and with the increase of loading volume, the external truck arrivals become more dispersed and have a trend of early arrival. Therefore, the container loading volume is an important factor affecting the external truck arrivals.

2) Time division. Affected by subjective and objective factors, the external truck arrival time is complexity and specificity. Analyze the regularity of daily external truck arrivals, and divide a day into 8 periods (each 3 hours as a period). Most containers in Jinzhou Port are domestic trade containers, and the external truck with export container can enter terminal at any time during a cycle. Figure 5 shows the distribution of external truck arrivals in Jinzhou Port, and there are fewer arrivals in the morning, a gradual increase in the afternoon and a slight decrease in the night.

3) Other factors. In addition to the container loading volume and time division, there are other factors that influence the external truck arrivals, for example, ship arrival time (day of the week), waiting days after external truck arrival and weather. And the impact of various factors on the external truck arrivals is different.

According to the research and analysis of Jinzhou Port data, the factors with huge impact are selected. The factors are as follows: the container loading volume, time period of external truck arrival, weather, ship arrival time (day of the week), waiting days after external truck arrival, external truck arrival time (day of the week). The parameters and variables are defined as follows.

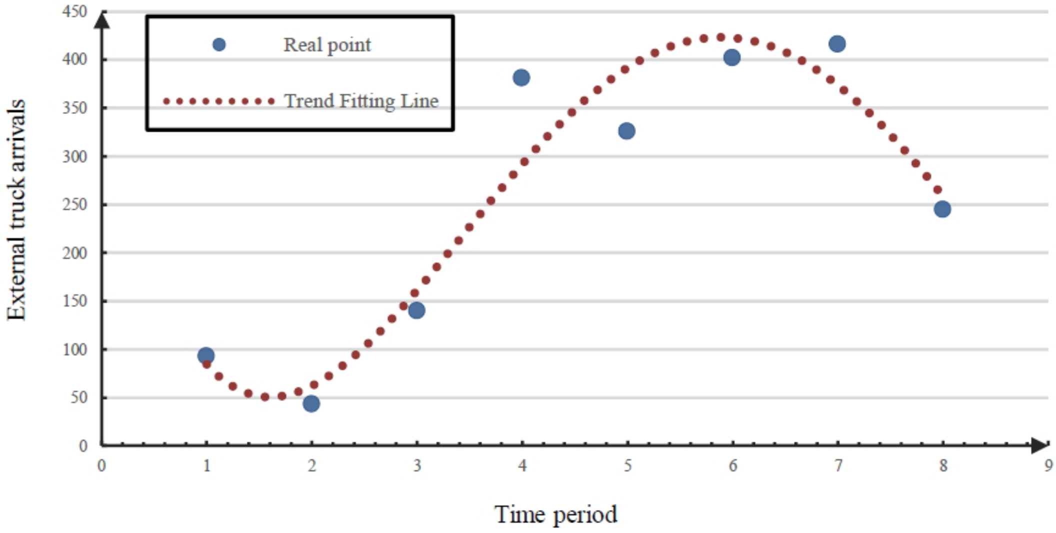


FIGURE 5. The time period of external truck arrivals in Jinzhou Port

M is the set of ships, ship $t \in M$; W is the set of waiting days after external truck arrival, day $i \in W$, and the range of i is 0 to 6; H is the time period set of external truck arrival, time period $j \in H$, and the range is 1 to 8; Z_{ij}^t is the weather of the j-th time period for ship t, the grade is classified according to the degree of badness, 0 means the excellent weather and 10 means the extreme bad weather, $0 < Z_{ij}^t < 10$; R_i^t is the day of a week that ship t has i days to loading, $1 < R_i^t < 7$; E^t is the day of a week that ship t arrives, $1 < E^t < 7$; S^t is the container loading volume of ship t.

3.2. **Predicted results analysis.** The data features extracted from DBN model are input into the SVM model, and the SVM parameters are obtained by cross-validation and grid search method. The parameter C is 1024, σ is 8, ε is 1.0, and the predicted results are shown in Figure 6.

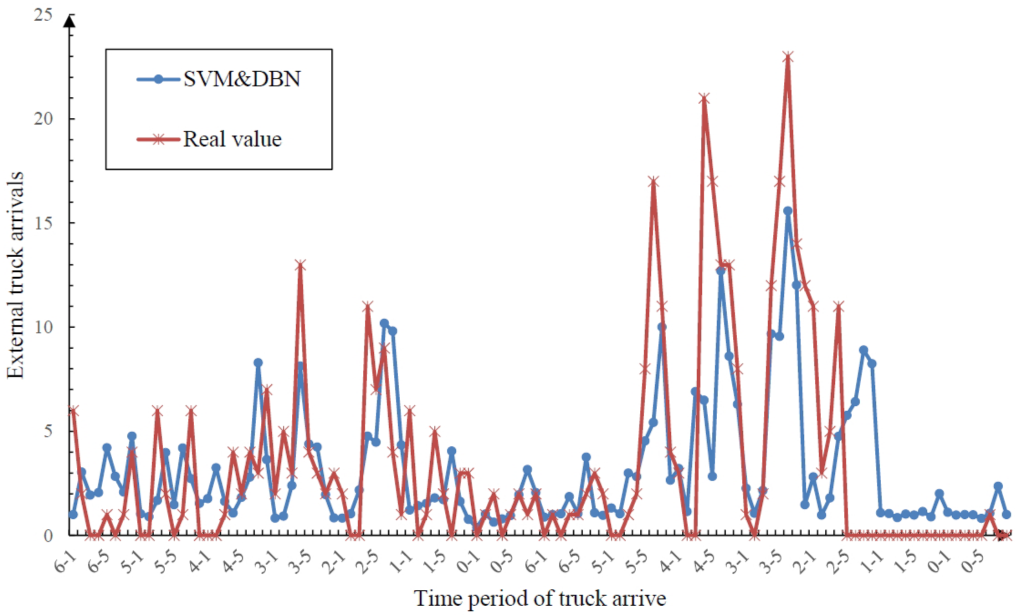


FIGURE 6. The predicted results of DBN&SVM model

1) Error analysis. The MAE (mean absolute error) is calculated to analyze the prediction error:

$$MAE = \sum_{i=1}^{n} \frac{|reality - prediction|}{n} \tag{6}$$

where n represents the total number of periods. The MAE shows the error of the predicted results. The small MAE indicates the accurate and reliable model.

The MAE is 2.56 predicted by the DBN&SVM model. The prediction curve and the real value curve fit well, and the predicted results have high accuracy.

2) Sensitivity analysis. In the proposed prediction model, different factors have different impacts on the results. To clear the impact of factors changes on the results, the Monte Carlo simulation method is taken for sensitivity analysis.

The steps are as follows: firstly, randomly select a sample from the external truck arrivals data, and set $n = 1$; set the step size to 0.1 because the data has been normalized; change one of the samples' factors by 0.1 and find new predicted results based on the changed sample; set $n = n + 1$, go back to the initial step and continue iterating until n reaches the maximum number. Find the corresponding sensitivity R of the factor.

$$R = \frac{1}{N} \sum_{n=1}^{N} \frac{|new\ value - old\ value|}{old\ value} \times 100\% \tag{7}$$

As shown in Table 1, the sensitivity analysis is processed for the container loading volume F_1, waiting days after external truck arrival F_2, time period of external truck arrival F_3, weather F_4, external truck arrival time (day of the week) F_5, and ship arrival time (day of the week) F_6. The factors that have the greatest impact on the results are waiting days after external truck arrival and time period of external truck arrival, and the least influential factors are external truck arrival time and ship arrival time.

TABLE 1. The results of sensitivity analysis

Factors	F_1	F_2	F_3	F_4	F_5	F_6
R (100%)	11.5	15.3	17.2	9.6	5.1	4.8

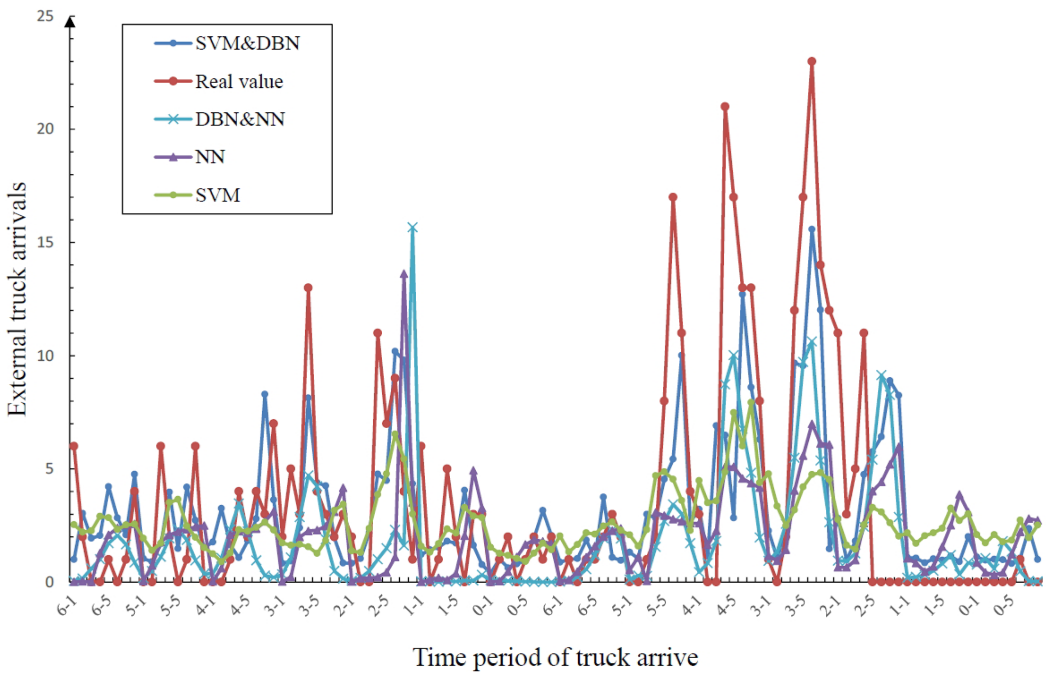


FIGURE 7. The prediction results of four models

3) Comparison with other methods. To evaluate the superiority of predicted model, three models of NN, SVM, and DBN&NN are selected for comparison with DBN&SVM model. The predicted results are shown in Figure 7.

Intuitively, the DBN&SVM model is better than the other three models and has a higher fit. The calculated results show that the MAE values of NN, SVM and DBN&NN are 2.99, 2.93 and 2.87, respectively. The MAE values of three models are larger than that of DBN&SVM model. Therefore, the proposed method has the highest prediction accuracy and the best effect.

4. **Conclusions.** The external truck arrival has attracted increasing amounts of attention from container terminals. The prediction with high precision is the premise to make yard and crane operation plans. To predict the external truck arrivals in container terminals, a two-stage prediction model based on DBN and SVM is proposed. Combining the advantage of DBN in mining data features and SVM in predicting, the predicted results are obtained with the sample data in Jinzhou Port. Comparing this method with other machine learning algorithms, the results show that the proposed DBN&SVM model has higher accuracy and better effect, which provides a new idea for the study of the external truck arrivals. The further research can consider more factors such as container types and traffic network to improve the prediction accuracy.

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