 doi:10.20944/preprints202008.0392.v1

An integrated approach to air passenger index prediction: mutual information principle and support vector regression (MI-SVR) blended model

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Featured Application: Results of this work provides an effective reference method for the evaluation of API in airport construction, operation and management ,and the same time, the results of this work provides certain decision-making reference for the general public to choose travel time and transportation mode.

Abstract: Air passenger traffic prediction is crucial for the effective operation of civil aviation airports. Despite some progress in this field, the prediction accuracy and methods need further improvement. This paper proposes an integrated approach to the prediction of air passenger index as follows. Firstly, the air passenger index is defined and classified by the K-means clustering method. Based on the mutual information (MI) principle, the information entropy is used to analyze and select the key influencing factors of air passenger travel. By incorporating the MI principle into the support vector regression (SVR) framework, this paper presents an innovative MI-SVR machine learning model used to predict the air passenger index. Finally, the proposed model is validated by passenger throughput data of the Shanghai Pudong International Airport, China. The experimental results prove the model feasibility and effectiveness by comparing them with conventional methods, such as ARIMA, LSTM, and other machine learning models, outperformed by the MI-SVR model. Besides, it is shown that the prediction effect of each model could be improved by introducing influencing factors based on mutual information. The main findings are considered instrumental to the airport operation and air traffic optimization.

Keywords: airport operation and management; air passenger index(API) prediction; machine learning(ML); mutual information(MI); support vector regression (SVR); K-Means

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1. Introduction

The global 'digital divide" status quo is quickly changing with the progress in artificial intelligence (AI) technologies and their application area expansion. The heart of AI technologies is machine learning (ML), which has branched into shallow and deep learning [1]. Examples of shallow ML models are the support vector machine (SVM) invented by Cortes and Vapnik [2] in 1995, and neural networks (NN). Numerous shallow ML models have been deployed in many research fields, including speech and natural language processing, computer vision, and public opinion mining [3-7]. The linear and nonlinear shallow models have gained impressive results in regression and prediction studies, including the prediction of airport passenger throughput with high accuracy [8-10]. Such linear models as autoregressive integrated moving average (ARIMA) [10] and gray model (GM) [11] have achieved significant predictive results. However, nonlinear models, including the BP-neural network [12], recurrent neural network (RNN) [13], long- and short-term memory network (LSTM) [14-16], and support vector regression (SVR) [17-21] were found to be more robust than linear ones due to their strong fault-tolerance levels.

Current airport passenger throughput prediction literature portrays the predominance of research output from mature western aviation markets. These markets possess high statistical regularity [9,40], and therefore, predictive models used may not generally be appropriate for emerging markets. To overcome the statistical irregularity in developing markets, the mutual information (MI) principle of the probability and information theories, which reflects not only linear but also a nonlinear correlation between variables is used in this study for the airport passenger throughput prediction for the Shanghai Pudong International Airport (PVG), which is a typical international hub airport in mainland China. The superior predictive capacity of blended MI and ML models is discussed in the literature [22, 23]. Using the achievements of prior studies, this paper not only focuses on passenger throughput of civil aviation airports but also processes ancillary data related to passenger throughput, to obtain a comprehensive visual representation of air passenger travel. Based on relevant literature, the current study combines the information theory knowledge with the SVR method and calculates MI to enable the selection of key influencing travel characteristics to build the blended MI-SVR model. The main goal of this blended model development is to achieve a better forecast that accurately guides passengers' choice of travel time, given the selected influencing features of air travel.

ML methods are more and more widely applied to air passenger transportation. In terms of route flow, the gray model is used for route passenger flow prediction [24], while classical neural network models and other blended models are exploited for the hybrid prediction of airport passenger and freight route flows [25]. The regional aviation passenger flow aspect is covered by the neural networks and SVR models [9], which effectively predict the regional aviation market trends of the short- and long-term passenger flow. The effective strategy, which allows a regional aviation company to increase the hub passenger flow influence in the existing route network, was proposed [21]. Air passenger flow characteristics are quite accurately predicted based on the time sequence columns [5,15,16,19] and nonlinear vector autoregressive neural network [9]. In study [26]. the comprehensive gray correlation method was adopted to analyze the factors influencing air passenger volume, identify the main ones, and elaborate the respective multiple regression model. As follows from the above brief survey, the attempts to improve the model prediction accuracy in this field involve either a refinement of a particular single model or blending of several models, to achieve better results.

The MI approach can reflect both linear and nonlinear correlations between variables. The efficiency of feature selection based on MI [22, 27] and ML field [23, 39-40] is well-known. In contrast to the previous studies, this paper analyzes the passenger throughput of a civil aviation airport and processes the passenger throughput as the basic data. Thus, it can directly reflect the travel situation on air passenger flow and provide auxiliary data for the monthly decision-making of civil aviation airport’s operation service. Besides, available methods mostly take into account the accumulated historical data and neglect other related factors that affect the travel of air passengers. Based on the research of other scholars, this paper introduces the knowledge of information entropy and SVR method, selects key influencing factors through the calculation of mutual information to build an ML prediction model, to find a better prediction method for the travel schedule selection by passengers choose and provide the relevant reference basis.

The rest of this paper is structured as follows. Section 2 clarifies the research topics and methods to address them; section 3 introduces the MI and SVR theory and then presents the blended MI-SVR model. Section 4 analyzes the passenger throughput and weather data of the Shanghai Pudong International Airport (PVG), China, to verify the MI-SVR model's feasibility and effectiveness and assess the PVG air passenger index. Section 5 concludes the paper and discusses future research avenues.

2. Research Tops

The rising demand for civil aviation airports has created enormous operation and management databases that exhibit significant differences between particular airports. Therefore, it is crucial to identify the contextual factors of particular airport’s service capabilities that would facilitate the provision of required support to airports' operations and management and furnish solutions for the public air traffic optimization. This implies the necessity to convert the raw data on passenger throughput to the air passenger index (API), which takes into account the airport's capacity and variability in passenger traffic volumes. The following definitions provide the mathematical representation of API and the level of air passenger index (LAPI).

Air passenger index (API): Setting the value of as the airport passenger throughput per unit period, the API for this period is defined as X_t^*:

$$X_t^* = \frac{X_t - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where $X_{\min}$ and $X_{\max}$ are the minimum and maximum numbers of air passengers per unit time, respectively, while X_t^* varies between 0 and 1.

Level of air passenger index (LAPI): Set $\{p_1, p_2, p_3 \cdots p_t\}$ is the API sequence set of multiple time units. After clustering, the generated cluster $\{N_t\}$ is a collection of data objects. The value is the data element of each cluster after clustering. If the API's unit period is one month, and the airport's monthly API is X_t^*, the level of air passenger index (LAPI) is derived as:

$$N_{X_t^*} = \begin{Bmatrix} 1, p_t \in (0,i) \\ 2, p_t \in (i,j) \\ 3, p_t \in (j,k) \\ \cdots \\ N, p_t \in (\theta,1) \end{Bmatrix} \tag{2}$$

Where p_1, p_2, p_t are time units, while i, j, k, θ are cluster boundary values.

The API and LAPI indexes of civil aviation airports are instrumental in optimizing their operation and management solutions and improving their services. They are incorporated into the blended MI-SVR model elaborated in this study.

3. Related Theory and Model Elaboration

3.1. Mutual Information Theory

The information entropy is a key indicator in the information theory, which was introduced by Shannon in 1948[28] based on the following concept: the more ordered is a system, the smaller is its information entropy and vice versa. Therefore, information entropy can be used to measure the degree of system uncertainty (or degree of ordering) [28-31]. Information entropy can be derived via the following formula:

$$H(X) = -\sum_{i=1}^{n} P(x_i)\log_2 P(x_i) \tag{3}$$

where $P(x_i)$ is the probability of sample x_i, and *n* is the number of samples. It can be seen that the smaller is the occurrence probability of an event, the higher are the information uncertainty and entropy values.

Let the joint probability distribution of the random vector (X,Y) be p_{ij}, then the two-dimensional joint entropy of vector (X,Y) is:

$$H(X,Y) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p_{ij}\log p_{ij} \tag{4}$$

Assuming that the joint probability distributions of X and Y are $p_{i\bullet}$ and $p_{\bullet j}$, respectively, the conditional entropy can be defined as:

$$H(X/Y) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p_{ij}\log\frac{p_{ij}}{p_{\cdot j}}$$
$$H(Y/X) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p_{ij}\log\frac{p_{ij}}{p_{i\cdot}} \tag{5}$$

Thus, MI can be expressed as an entropy value for which the variable X (or Y) is reduced due to the occurrence of the variable Y (or X).

$$\begin{aligned} I(X;Y) &= H(X) - H(X\mid Y) \\ &= H(Y) - H(Y\mid X) \\ &= H(X) + H(Y) - H(X,Y) \end{aligned} \tag{6}$$

By combining formulas (3)-(6), the complete expression of MI can be reduced to the following form:

$$I(X;Y) = \sum_{i,j} p_{ij}\log_2\frac{p_{ij}}{p_{i\cdot}p_{\cdot j}} \tag{7}$$

3.2. Support Vector Regression (SVR)

The support vector regression (SVR) is a widely used ML prediction method, which adopts the principle of minimizing structural risk rather than minimizing empirical risk. This allows one to effectively mitigate numerous problems, such as "dimensional disaster" and traditional pattern recognition [17-19,32-36]. The general linear regression model can be expressed as follows:

$$f(x) = w^T x + b \tag{8}$$

where w is the normal vector of the API input vector, and b is the deviation value. The loss value is zero only when $f(x)$ is exactly the same as the true value. In this study, In the actual air passenger index forecast, it is impossible to predict the exact value of each day accurately. However, the SVR model "softens" the prediction result, allowing a certain error between the predicted and actual values, which is equivalent to forming a prediction error isolation band with a width of 2* ε at the center of the prediction value, falling into the isolation band. If the API value prediction is accurate, the loss is 0, and the API input vector closest to the isolation zone constitutes its "support vector." Noteworthy is that minimizing the loss requires maximizing the sum r of the distances between the two sets of support vectors and the prediction center, which can be achieved by minimizing the Euclidean norm of the normal vector w. Thus, the SVR concept can be expressed as

$$\min\frac{1}{2}w^2 + C\sum_{i=1}^{m} l_{\epsilon}\left(f(x_i) - y_i\right),\quad C > 0 \tag{9}$$

where C is a regularization constant for performing a compromise calculation on the front and the back. The former term (front) indicates that all predicted values fall within the error range, as much as possible in the model structure. The latter (back) applies the ε-insensitive loss function to characterize the fit between the model prediction effect and the actual passenger volume data.

$$l_{\epsilon}(z) = \begin{cases} 0 & \text{if } |z| \le \varepsilon \\ |z| - \varepsilon & \text{otherwise} \end{cases} \tag{10}$$

In the actual API data, a certain value may exceed the normal trend due to external reasons and become an outlier. In this case, the "hard interval" defined above is no longer applicable. Therefore, in the case of serious deviations from the actual value, slack variables ξ_i and ξ_i^* are introduced as "softening" intervals, which reduces the problem formulation to the following form:

$$\min\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i - \xi_i^*) \tag{11}$$
$$s.t.\begin{cases} f(x_i) - y_i \le \varepsilon + \xi_i \\ y_i - f(x_i) \le \varepsilon + \xi_i^* \end{cases} \quad i = 1,2,\ldots,m;\ \xi_i, \xi_i^* \ge 0$$

Using the dual principle and introducing Lagrangian multipliers α_i and α_i^*, the SVR's dual problem can be formulated as in [37]:

 doi:10.20944/preprints202008.0392.v1

$$\max_{\alpha,\alpha^*} \sum_{i=1}^{m} y_i(\alpha_i^* - \alpha_i) - \varepsilon(\alpha_i^* + \alpha_i) - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} y_i(\alpha_i^* - \alpha_i)(\alpha_j^* + \alpha_j)x_i^T x_j \tag{12}$$

$$s.t.\sum_{i=1}^{m}(\alpha_i^* - \alpha_i) = 0, 0 \le \alpha_i^*, \alpha_i \le C$$

When the predicted value of the API falls into the ε-soft zone, α_i and α_i^* can be the non-zero value. Insofar as the predicted value cannot simultaneously fall into two opposite areas, at least one of the parameters α_i or α_i^* is 0. Finally, the SVR regression prediction function [37] can be expressed as:

$$f(x) = \sum_{i=1}^{m}(\alpha_i^* - \alpha_i)x_i^T x + b \tag{13}$$

$$b = y_i + \in - \sum_{j=1}^{m}(\alpha_j - \alpha_j^*)x_j^T x_i \tag{14}$$

For the API time series data with a nonlinear trend, the SVR can map the sample to the high-dimensional space through the nonlinear mapping function $\varphi(x)$, and then replace the inner vector product of the high-dimensional space $\varphi(x_i)\cdot\varphi(x_j)$ with the kernel function $K(x_i, x_j)$.The most commonly used kernel function is the Gaussian radial basis kernel function(RBF) [37], which can be expressed as follows:

$$K(x_i, x_j) = \exp(-\frac{\| x_i - x_j \|^2}{2\sigma^2}) \tag{15}$$

where $gamma$ is the Gaussian radial basis kernel function parameter ($gamma = \frac{1}{2\sigma^2}$) and $\sigma > 0$ is the Gaussian kernel bandwidth.

The RBF function application improves the SVR nonlinear prediction ability. Eventually, the SVR regression function takes the following form [37]:

$$f(x) = \sum_{i=1}^{m}(\alpha_i^* - \alpha_i)K(x, x_i) + b \tag{16}$$

3.3. Model Elaboration

Based on the preliminary data preprocessing, the raw data were converted into the corresponding information entropy value. All data were then normalized to permit the elimination of dimensions in the data unrelated to the API. These dimensions/factors were defined as those with small influence according to the ranking of MI values. Next, the key influencing factors were selected to set the ML model's foundation based on the MI principle and improve the prediction given smaller dimensions. The graphical representation of the MI-SVR model elaboration procedure is given in Figure 1.

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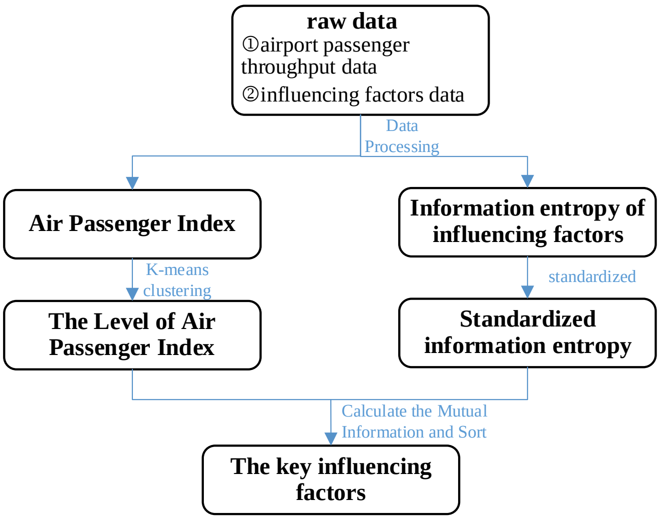
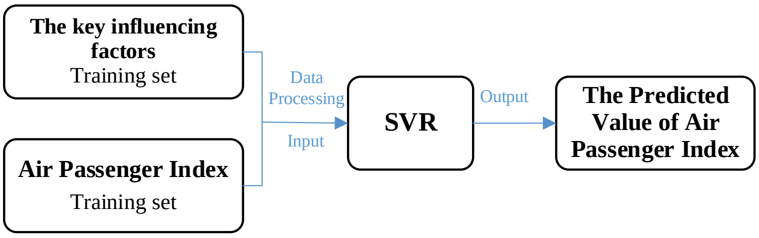


(a) The key influencing factors selected based on mutual information



(b) Blended MI-SVR model application process

Figure 1. MI-SVR model elaboration process and its application to API prediction

The following steps were required for constructing the MI-SVR model for the API prediction.

Step1: According to the API's definition in section 2, airport passenger throughput data were processed to get the original sequence $\{X_t\}$.

Step2: The influencing factors of API were transformed into information entropy, and then the standardized information entropy was obtained by standardizing (normalizing) the fixed unit length of the converted data.

Step3: According to the mathematical definition of API in section 2, the air passenger throughput data were converted into the API sequence as $\{X_t^*\}$.

Step4: The K-means method was used to cluster API and influencing factors (maximum temperature, minimum temperature, wind force, and wind direction) when forming different clusters.

Step5: The standardized information entropy of each influencing factor, and its MI value with LAPI was calculated.

Step6: According to the characteristics of MI value and the correlation, the factors with high MI values were selected. These factors were introduced into the elaborated MI-SVR model to predict the API.

4. Empirical Analysis

4.1. Numerical Experiments

4.1.1. Data Acquisition and Processing

Using the API definition in Section 2, the raw data was considered representative and suitable for modeling without missing values. First, the data had to be converted into the form consistent

 doi:10.20944/preprints202008.0392.v1

with the constructed model's input dimension. In our case, the original passenger throughput values were converted to API. The dataset used in this paper included the complete raw data on daily passenger throughput, maximum temperature, minimum temperature, weather, wind direction, and wind power for the Shanghai Pudong International Airport (PVG), China, which covered 20 months from January 1, 2017, and August 31, 2018. The weather, wind direction, and wind power data had a textual format, while the temperature data were graded to indicate different temperature levels. The data conversion results are summarized in Table1.

Table 1. Data preprocessing correspondence table and pre-processing raw data from this table

Maximum temperature	Minimum temperature	Wind power	Weather	Wind direction
2-10（cold）	-3-4（Very cold）	Level 1-2	Sunny/Cloudy	No sustained wind direction
11-17（Micro cold）	5-10（cold）	Level 2-3	Cloudy	East Wind
18-25（Moderate）	11-17（Micro cold）	Level 3-4	Light Rain	South Wind
26-32（Micro heat）	18-24（Moderate）	Level 4-5	Shower	West Wind
33-40（heat）	25-31（Micro heat）	Level 5 or higher	Rain	North Wind
			Heavy Rain	Southeast Wind
			Rainstorm	Northeast Wind
				Southwest Wind
				Northwest Wind

For the airport data modeling based on the theory of information entropy, we converted the five categories of data into their corresponding information entropy values. Then, the total passenger throughput data were calculated according to formula (1), and the standardized passenger volume value was classified as the API by the K-means clustering algorithm. The classification results are listed in Table 2. Finally, the MI values of the transfer passenger travel index level and the five key influencing factors were calculated separately. The latter factors controlling the API were the maximum temperature, minimum temperature, wind direction, weather, and wind power. The MI values of these factors in the API are given in Table 3.

Table 2. Using K-means clustering algorithm to classify API , and the API is finally divided into 5 levels.

Level	Travel Index Range	Description
1	0-0.13	Smooth
2	0.13-0.35	Less Smooth
3	0.35-0.52	A little Congestion
4	0.52-0.79	Congestion
5	0.79-1	Severe Congestion

Table 3. MI between influencing factor and the API, and the ranking of the MI values.

Influencing factor	Mutual information value with air passenger index	Rank
Maximum temperature	0.616	1
Minimum temperature	0.534	2
Weather	0.249	4
Wind direction	0.290	3
Wind power	0.136	5

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From the Table 3, it can be concluded that the least impact on the API is wind power. Through statistical analysis of wind factors, it was revealed that the proportion of wind level above level 5 is only 2.3%, while nearly 88% of the data is not higher than level 3 (level 3-4). Therefore, the impact of wind power on the nearly API is relatively small.

4.1.2. Error Analysis Method

To analyze the model prediction results, we used the mean absolute percentage error (MAPE) and root mean square error (RMSE), which can be derived via the following equations:

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n} \frac{\left| y_i - y_i^* \right|}{y_i}}{n} \times 100\% \tag{17}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y_i^*)^2} \tag{18}$$

where y_i and y_i^* are the actual and predicted values, respectively.

4.2. Discussion

4.2.1. Selection of key factors

The RMSE and MAPE values obtained via the MI-SVR model were 0.1030 and 11.44% for the maximum temperature as a single influencing factor. Those for the minimum temperature were 0.1016 and 11.18%, respectively. The minimum temperature effect was found to be slightly higher than that of the maximum one. The analysis also showed that the Pearson correlation coefficient between the maximum and minimum temperatures was 0.581, and a close correlation within the 99% confidence interval was observed.

From Table 3, it can be concluded that wind power had the least impact on the API. The wind power factor's statistical analysis revealed that the share of recorded wind power above level 5 was only 2.3%, while the remaining 88% of the data corresponded to levels 3 and 4. Therefore, the wind power effect on the API was relatively weak.

Given these findings, three key influencing factors, namely the minimum temperature, weather, and wind direction, were selected for incorporation into the forecast of the airline passenger travel index to get more accurate prediction results.

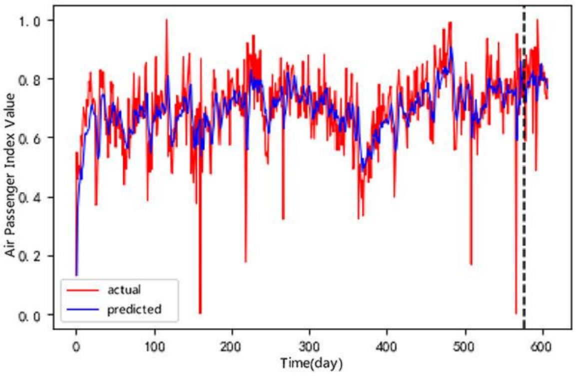
The experimental data used in this study were subdivided into two parts. The first part covered 19 months (577 days) of API data from January 1, 2017, to July 31, 2018, and was applied to the model training. The second part covered the remaining month (August 1-31, 2018) of the dataset and was adopted as a test set for verifying the model fitting effect. The numerical experiments were realized via the Python 3.6 software and produced some noteworthy results. After numerous numerical experiments, it is found that when the specific parameters of the model were set at certain values, the error terms of the overall effect of both the training and test sets reached their minimum values. The model-related parameter settings are listed in Table 4.

Table 4. SVR model parameter setting.

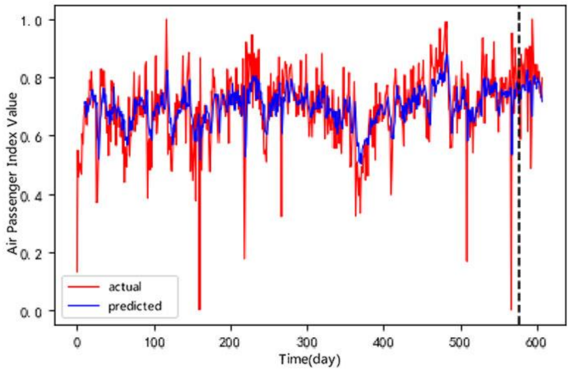
Kernel function	Gamma in kernel function	Penalty parameter C	ε
RBF	0.64	6000	0.1

4.2.2. Comparative Experimental Analysis

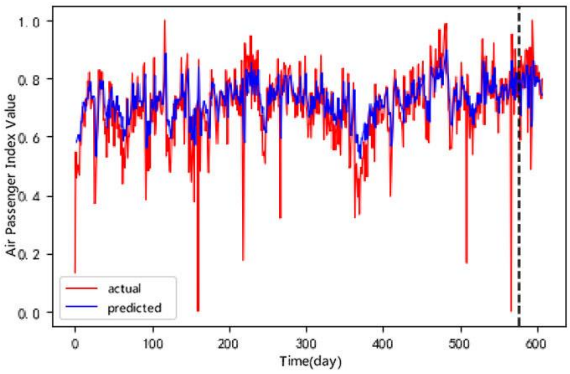
The proposed blended MI-SVR model was tested with the account of influencing factors and without their account (as a single SVR model). For comparison, commonly used LSTM and ARIMA single model, as well as their blended variants, namely the GM(1, 1)-BPNN and SVR-ARIMA models [20, 21], were applied to the training and test datasets. The actual and predicted values of the above six prediction models were calculated, as shown in Figure 2, where the left part of the black dotted line depicts the respective model fitting effect on the training set, and the right part corresponds to the prediction results on the test set. The MI-SVR model outperformed the LSTM and ARIMA single models, which only met the general trend of the data but did not fit well with the higher and lower values. The blended MI-SVR model had a better prediction effect than single models by introducing the conditional entropy of influencing factors.



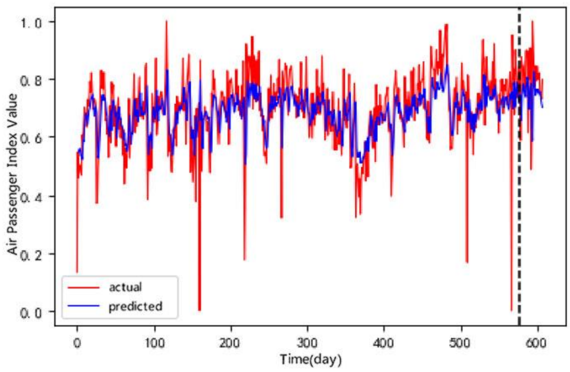
(a) ARIMA



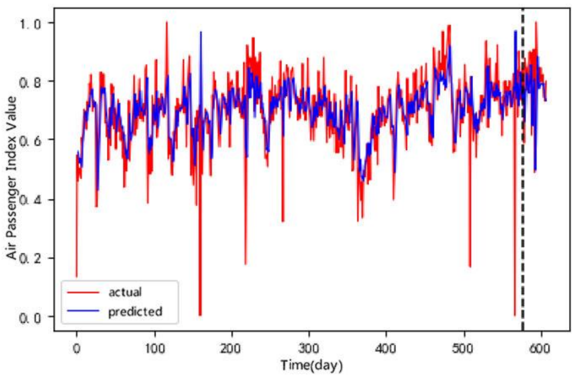
(b) ARIMA + Conditional Entropy



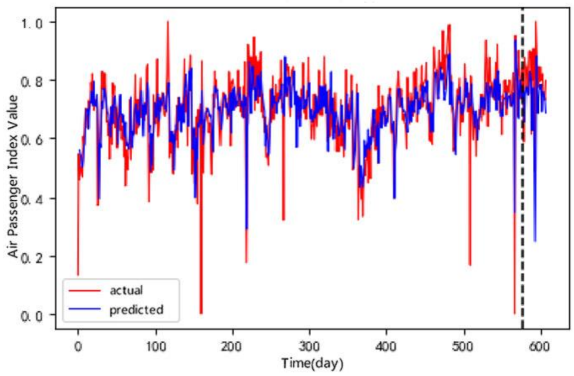
(c) LSTM



(d) LSTM + Conditional Entropy



(e) SVR



(f) SVR + Conditional Entropy

Figure 2. Comparison of actual and predicted values of the different model

The MAPE and RMSE values of the six models calculated via Eqs. (17) and (18), respectively, are listed in Table 5 and Table 6. It is seen that all blended models had a better prediction effect than single ones and others blended variants models, such as GM(1, 1)-BPNN and SVR-ARIMA models.

Table 5. RMSE and MPAE comparison of different models.

Model	RMSE	MAPE
SVR+ influencing factors (MI-SVR)	0.0785	8.04%
LSTM+ influencing factors	0.1053	11.86%
ARIMA+ influencing factors	0.1060	11.66%
SVR	0.1031	11.33%
LSTM	0.1064	12.10%
ARIMA	0.1093	12.09%

Table 6. Comparison with the prediction effect of others blended variants model.

Model	RMSE	MPAE
SVR-ARIMA	0.0981	10.41%
GM(1,1)-BPNN	0.1032	11.45%
MI-SVR	0.0785	8.04%

In summary, since MI is the random event correlation analysis method, the mutual information value can track the existence of a potential relationship. Thus, screening key influencing factors for API prediction based on MI provided the necessary conditions for improving the model's predictive accuracy. After the analysis of each model and the introduction of the highest temperature, the lowest temperature, and the wind direction as influencing factors, the overall prediction effect of each model was significantly improved. It is noteworthy that the MI-SVR model designed in this paper had the best prediction accuracy among other tested single or blended prediction models.

4.2.3. Air Traffic Volume Analysis

The developed MI-SVG model was applied to analyze the API evolution in the Shanghai Pudong International Airport (PVG) during a more extended period, namely 130 months, from January 2008 to October 2018. For brevity's sake, only the most prominent features, which are considered instrumental in guiding operational and managerial decisions, are presented in this study. Figure 3 depicts the LAPI values in each month.

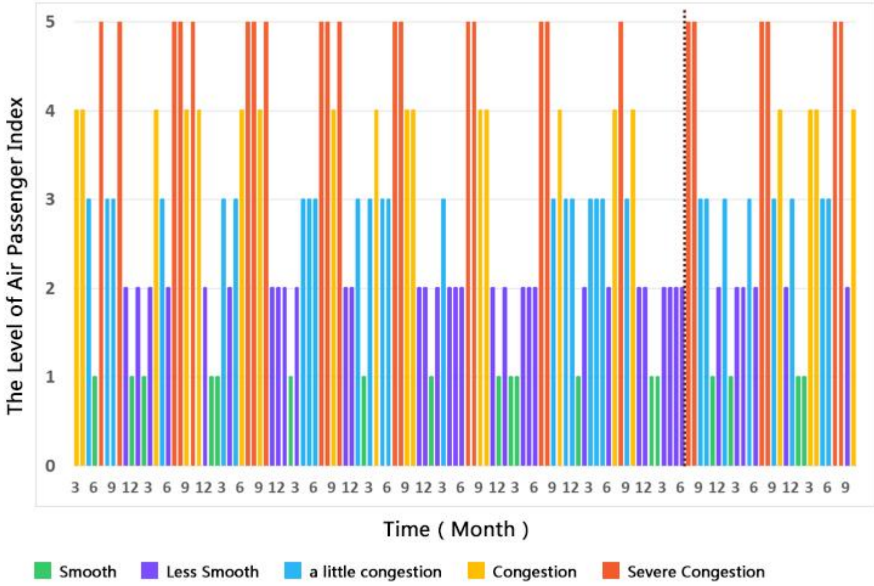


Figure 3. The Level of Air Passenger Index (LAPI) of PVG from January 2008 to October 2018sssss

✓ January and February of each year correspond to the "dead season" of the PVG airport, and their API values are the lowest, which closely correlates with the Chinese New Year festivities. This period can be used by the airport management for performing expansion or upgrade works on its core and ancillary facilities.

- ✓ Fairly stable API values are observed in the period from March to June, November, and December. These months are relatively busy months for major airlines.
- ✓ The busiest period for each year is from July to October. From a global standpoint, this period corresponds to the summer vacation travel period. From a local standpoint, this period is the most lucrative for Shanghai's major tourist attractions.

5. Conclusions and Future Research Avenues

5.1. Conclusions

The current study attempts to deal with the operational and managerial challenges induced by the airport passenger throughput increase. To achieve this objective, the data on airport passenger throughput were converted into the corresponding API and LAPI values. They were evaluated by the K-means clustering method, which indicates the passenger flow at civil aviation airports. The LAPI provides certain decision-making references for the general public to choose travel time and transportation options.

Aiming at the prediction of API in civil aviation airports, this paper proposes a blended MI-SVR model, takes account of the key influencing factors for improving the prediction results. Influencing factors selected in this study includes minimum temperature, weather conditions, and wind direction. By way of experimental simulation, the model was verified on the daily passenger throughput data of PVG. The prediction results of the proposed MI-SVR model were compared with those of such popular ML prediction models, such as LSTM, ARIMA, SVR-ARIMA, and GM(1,1)-BPNN models. The main findings of the comparison results are as follows:

(1) The results provided by the proposed model outperform other tested single or blended models by the overall prediction accuracy;

(2) The MI-based influencing factors of API prediction are scientifically viable;

(3) In contrast to single (LSTM and ARIMA) models and blended (SVR-ARIMA and GM(1,1)-BPNN) models, the proposed MI-SVR model achieved relatively better prediction results;

(4) The LAPI evolution at PVG conforms to the rising annual population patterns.

Finally, the MI-SVR model provides an effective reference method for evaluating API in airport construction, operation, and management. For example, the maintenance schedule of airport facilities and equipment, ground service, and aircraft allocation can be optimized with API. This will relieve both airport operators and managers, as well as passengers, of possible performance deterioration.

5.2. Future Research Avenues

In the follow-up studies, more data would be collected and processed to establish a dynamic air trip prediction model. Besides, more datasets, such as high-speed trains network, highway network, air traffic control, and origin-destination demand, will be incorporated into the methodological framework. Furthermore, we plan to investigate the applicability of this methodology to datasets of other civil airports. We also encourage other researchers to explore these directions for civil aviation development.

Author Contributions: Conceptualization and Formal analysis, H.X.; Writing—discussion of the original draft ,H.X. and H.J.; Data curation, Y.Y.; Methodology, C.F.; redrafting and editing, C.A. and X.F..

Funding: This research was funded by the National Natural Science Foundation of China (Grant No. 71774111), and the Key fund projects of Shanghai Municipal Education Commission for scientific research and innovation (Grant No. 14ZZ131)

Acknowledgments: We thank the editors and any reviewers for their helpful comments.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Gu, S.; Zeng, W.; Jia, Y.; Yan, Zh. Intelligent Tennis Robot Based on a Deep Neural Network. *Appl. Sci*. **2019**, *9*, 3746.
2. Cortes C.; Vapnik V. Support-vector networks. *Machine Learning*. **1995**, *20*, 273-297.
3. Hu, P., Lu, Z.X.; Zhang, Y. Q.; Liu, S. L.; Dang, X. M. A New Modeling Method of Angle Measurement for Intelligent Ball Joint Based on BP-RBF Algorithm. *Appl. Sci*. **2019**, *9*, 2850.
4. Y. Zou.; G. Zhang.; L. A. Liu. Research on image steganography analysis based on deep learning. *Journal of Visual Communication and Image Representation*. **2019**, *60*, 266-275.
5. Hyojoo Son.; Changwan Kim. A Deep Learning Approach to Forecasting Monthly Demand for Residential–Sector Electricity. *Sustainability*. **2020**, *12*, 3103.
6. Chen, L. J.; Chen, P. P.; Z. J. Lin. Artificial intelligence in education: a review. *IEEE Access*. **2020**, *8*, 75264-75278.
7. J. Y. Guo.; Z. Xie.; Y. Qin.; L. M. Jia, et al. Short-Term Abnormal Passenger Flow Prediction Based on the Fusion of SVR and LSTM. *IEEE Access*. **2019**, *7*, 42946-42955.
8. X. J. Feng.; Wei X.; Y. L. Huang. Predicting the Airport Passenger Throughput Based on a Support Vector Regression Mode. *Computer Engineering*. ***2005***, *31*, 172-173.
9. S. L. Sun.; H. X. Lu.; Kwok-Leung Tsui, et al. Nonlinear vector auto-regression neural network for forecasting air passenger flow. *Journal of Air Transport Management*., **2019**, *78*, 54-62.
10. L. Zhang.; S. F. Yan. Comparison of Holt- Winters and ARIMA Methods for Forecasting Charge of China Airline Passengers. *Shanghai University of Engineering Science*. **2006**, 20, 280-283,.
11. Yao Y B.; Gao H. Gray model G M(l, 2) Application in airport passenger throughput pre-side. *Journal of Civil Aviation Flight University of China*. **2006**, *17*, 12-16.
12. Jiao P P. Forecasting Method and Its Mechanism of Impacts on Airport Passenger Throughput. *Transportation Systems Engineering and Information Technology*. **2005**, *1*, 107-110.
13. Alex Graves, and Jürgen Schmidhuber, "Framewise phoneme classification with bidirectional LSTM and other neural network architectures," *Neural Networks*. **2005**, *18*, 602-610.
14. Klaus Greff.; Rupesh Kumar Srivastava.; Jan Koutnik; et al. LSTM: A Search space odyssey. *IEEE Transactions on Neural Networks and Learning Systems*. **2017**, *28*, 2222–2232.
15. W. Kong.; Z. Y. Dong.; Jia Y. Dong, *et al*. Short-Term Residential Load Forecasting based on LSTM Recurrent Neural Network. *IEEE Transactions on Smart Grid*. **2019**, *10*, 841- 851.
16. F.L. Yi.; C. Han. Prediction for Tourism Flow based on LSTM Neural Network. *Procedia Computer Science*. **2018**, *129*, 277-283.
17. P. Li.; Z. W. Ni.; X. H. Zhu; *et al*. Air pollution index prediction model of support vector machine based on Fractal manifold learning," *Systems Science and Mathematics*. **2018**, *38*, 1296-1306.
18. H. Sun.; P. R. Yang.; J. H. Cheng. Energy demand prediction model based on Matlab support vector regression machine. *Systems engineering theory and practice*. **2011**, *31*, 2001-2007.
19. Y. X. Sun.; C. F. Shao.; X. Ji; *et al*. Time series prediction of traffic accidents based on ARIMA and information granulation SVR combination model. *Journal of Tsinghua University (natural science edition)*. **2014**, *3*, 348-353.
20. C. Y. Liang.; Y. C. Ma.; R. Chen; *et al*. Prediction of daily tourism demand based on SVR- ARIMA combination model. *Journal of management engineering*. **2015**, *29*, 122-127.
21. Qu, T. Application of combination model in airport passenger throughput prediction. *Computer simulation*., **2012**, *4*, 108-111.
22. Sadia Sharmin.; Mohammad Shoyaib.; Amin AhsanAli, *et al*. Simultaneous feature selection and discretization based on mutual information. *Pattern Recognition*. **2019**, *91*, 162-174.
23. K.R.Chernyshov. An Information Theoretic Approach to Constructing Machine Learning Criteria. *IFAC Proceedings Volumes*. **2013**, *46*, 269-274.
24. Xia, L.; Jie, Y.; C. Lei; *et al*. Prediction for Air Route Passenger Flow Based on a Grey Prediction Model. *International Conference on Cyber-enabled Distributed Computing & Knowledge Discovery IEEE*, Chengdu, China, **2016**.
25. Ratna Sulistyowati.; Suhartono.; Heri Kuswanto.; *et al*. Hybrid forecasting model to Predict air passenger and cargo in Indonesia. *International Conference on Information and Communications Technology (ICOIACT). IEEE*., Zhengzhou, China, **2018**, pp.442-447.

 doi:10.20944/preprints202008.0392.v1

26. Li, J.; Yao, X. F.; Liu Y H, *et al.* Thermo-viscoelastic Analysis of the Integrated T-shaped Composite Structures. *Composites Science and Technology*. **2010**, *70*, 1497-1503.
27. C E Shannon. A Mathematical theory of communication. *The Bell System Technical Journal*. **1948**, pp. 379-423.
28. Fan, X. L.; Feng, H. H.; Ma, Y. Principal Component Analysis Feature Selection Algorithms Based on Mutual Information. *Control and Decision-making*., **2013**, *28*, 915-919.
29. Liang, J. Y.; Feng, C. J.; Song, P. Summary of Big Data Relevance Analysis. *Journal of Computer Science*., **2016**, *1*, 1-18.
30. Wang, Y. Research on Machine Learning Method Based on Mutual Information and Prior Information. Ph.D. dissertation, Graduate School of Chinese Academy of Sciences (Institute of Automation), Beijing, China, **2008**.
31. Zhang, C. T.; Ma, Q. L.; Peng, H. Prediction of chaotic time series based on information entropy optimization for phase space reconstruction parameters. *Journal of Physics*. **2016**, *59*, 7623-7629.
32. Tao, D. W.; Ma, Q.; Li, S. L.; Xie, Zh. N.; Lin, D. X. *et al.* Support Vector Regression for the Relationships between Ground Motion Parameters and Macro seismic Intensity in the Sichuan–Yunnan Region. *Appl. Sci.* **2020**, *10*, 3086.
33. Xu, Y. Research on prediction algorithm of abnormal trend of spacecraft in-orbit state based on machine learning method" M.S. thesis, University of Electronic Science and Technology, Chengdu, China, **2017**.
34. Steven Farber.; Benjamin Ritter.; Fu, L.W. Space–time mismatch between transit service and observed travel patterns in the Wasatch Front, Utah: A social equity perspective. *Travel Behaviour and Society*. **2016**, *4*, 40-48.
35. Hao, X. F.; Liu, L. Railway travel information transfer index model based on travel behavior. *Journal of Transportation Engineering*. **2008**, *6*, 99-103.
36. J. García Nieto.; E.F. Combarro.; J.J. Del Coz Díaz, *et al.* A SVM-based regression model to study the air quality at local scale in Oviedo urban area (Northern Spain): A case study. *Applied Mathematics & Computation*. **2013**, *219*, 8923-8937.
37. Zhou, Z. H. *Machine Learning*, Tsinghua University Press, China: Beijing, **2016**, pp. 121-135.
38. Biljana Petrevska. Predicting tourism demand by ARIMA models. *Economic Research-Ekonomska Istrazivanja*. **2017**, *30*, 939-950.
39. Wu, W. W.; Zhang, H. Y.; Feng, T.; Frank, Witlox. A Network Modelling Approach to Flight Delay Propagation: Some Empirical Evidence from China. *Sustainability*. **2019**, *11*, 4408.
40. Sun, S. L.; Wei, Y. J.; Kwok-Leung Tsui. *et al.* Forecasting tourist arrivals with machine learning and internet search index. *Tourism Management*. **2019**, *70*, 1-10.