

Article

A New Period-Sequential Index Forecasting Algorithm for Time Series Data

Hongyan Jiang ^{1,2}, Dianjun Fang ^{1,3,*}, Klaus Spicher ^{1,3}, Feng Cheng ⁴  and Boxing Li ¹

¹ School of Mechanical Engineering, Tongji University, Shanghai 201804, China; 1710211@tongji.edu.cn (H.J.); 1733315@tongji.edu.cn (K.S.); 1831418@tongji.edu.cn (B.L.)

² School of Mechatronic and Power Engineering, Jiangsu University of Science and Technology, Zhenjiang 212003, China

³ Company of Sino-German Institute for Intelligent Technologies and PhD Study, Qingdao 266000, China

⁴ School of Mechanical Engineering, Jiangnan University, Wuxi 214122, China; fcheng@jiangnan.edu.cn

* Correspondence: 1733316@tongji.edu.cn; Tel.: +86-186-16521392

Received: 9 October 2019; Accepted: 15 October 2019; Published: 17 October 2019



Abstract: A period-sequential index algorithm with sigma-pi neural network technology, which is called the (SPNN-PSI) method, is proposed for the prediction of time series datasets. Using the SPNN-PSI method, the cumulative electricity output (CEO) dataset, Volkswagen sales (VS) dataset, and electric motors exports (EME) dataset are tested. The results show that, in contrast to the moving average (MA), exponential smoothing (ES), and autoregressive integrated moving average (ARIMA) methods, the proposed SPNN-PSI method shows satisfactory forecasting quality due to lower error, and is more suitable for the prediction of time series datasets. It is also concluded that: There is a trend that the higher the correlation coefficient value of the reference historical datasets, the higher the prediction quality of SPNN-PSI method, and a higher value (>0.4) of correlation coefficient for SPNN-PSI method can help to improve occurrence probability of higher forecasting accuracy, and produce more accurate forecasts for the big datasets.

Keywords: forecasting; time series data; period-sequential index algorithm; neural networks

1. Introduction

In the big data era, a large number of time series data are continuously generated in the network systems, such as stock price, sales volume, production capacity, weather data, ocean engineering, engineering control, and largely in any system of applied science and engineering which involves investigations of time-varying parameters [1–3]. In general, the distribution of time series data changes over time, and is non-stationary [4,5], while some data shows potential periodicity characteristics. Since the 1950s, time series forecasting has received much interest in prediction science.

Continuously growing numbers of new algorithms have been proposed and studied on time series forecasting. Firstly, the exponential smoothing (ES) method [5,6] and the moving average (MA) method [7] are simple and widely used, and performed well in forecasting competitions against more sophisticated approaches. Secondly, the autoregressive integrated moving average (ARIMA) model integrates autoregressive models (AR) and moving average models (MA), and is widely used as a linear time series forecasting method [8,9]. The ARIMA model gives good accuracy in forecasting relatively stationary time series data, but needs a strong assumption that the values of future data are linearly dependent on the values of historical data [10]. Thirdly, the artificial neural network (ANN) [11–13] and adaptive models [14] have also been used to forecast nonlinear time series data, and improve forecasting accuracy in different time scales. It is also possible to hybrid different methods to improve overall forecasting accuracy [15].

However, no traditional forecasting methods can meet all the targets [16–18], while applying heuristic methods are also worth researching [19]. Here, a period-sequential index algorithm with a sigma-pi neural network (SPNN-PSI) is proposed and dedicated to the prediction of time series data. Here a period-sequential index algorithm (PSI) by identifying structures from transformed data, where there are four indexes carrying implicitly structure information usable for forecasting, the period index, sequential index, small period index, and super sequential index, is combined with a sigma-pi neural network algorithm (SPNN) improving the accuracy and robustness of forecasting algorithm. The SPNN-PSI method has a universal application, and a satisfactory prediction quality improved as the correlation coefficient value of the reference historical datasets increased.

2. Theoretical Model

2.1. Period-Sequential Index (PSI) Algorithm

Finding index-values implicitly carrying structure information, a period-sequential index (PSI) algorithm, is proposed to predict the time series data. The index-values cover the complete period, while the period index and sequential index, as well as small period index and super sequential index, are introduced to describe the dataset structure information in vertical and horizontal dimensions, respectively. In this way, for time series data, the following year's dataset can be predicted using only two consecutive years of reference historical datasets. Figure 1 shows the schematic diagram of the PSI algorithm. H_{-2} , H_{-1} denote reference historical periods, i.e., the year before last and last year. H_0 represents the forecasting period. The period for H_{-2} , H_{-1} , and H_0 is uniform, and defined as T in this paper. At historical time of t , $PI(t)$, $SI(t)$, $pi(t)$, and $si(t)$ describe the period index, sequential index, small period index, and super sequential index, respectively.

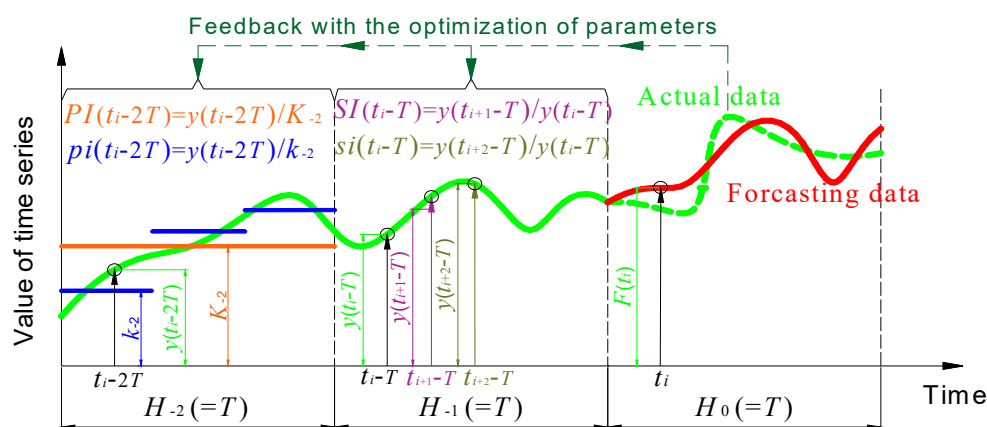


Figure 1. The schematic diagram of the period-sequential index algorithm (PSI) algorithm.

We assume that the forecasting value follows the measurement Equation (1),

$$F(t_i) = G(PI(t_i - 2T), PI(t_i - T), SI(t_i - 2T), SI(t_i - T), pi(t_i - 2T), pi(t_i - T), si(t_i - 2T), si(t_i - T)), \quad (1)$$

where $F(t_i)$ is the forecasting value at time of t_i ($i = 1, 2 \dots N$) during H_0 period. N represents the number of model forecasting samples. $PI(t_i - 2T)$, $PI(t_i - T)$, $SI(t_i - 2T)$, $SI(t_i - T)$, $pi(t_i - 2T)$, $pi(t_i - T)$, $si(t_i - 2T)$, and $si(t_i - T)$, as the eight variables in Equation (1), are described as follows:

(1) Period index

The period index indicates the relationship between the reference historical data and the reference value which can be explained through Equations (2) and (3),

$$PI(t_i - 2T) = \frac{y(t_i - 2T)}{K_{-2}}, \quad (2)$$

$$PI(t_i - T) = \frac{y(t_i - T)}{K_{-1}}, \quad (3)$$

where $y(t_i - 2T)$ and $y(t_i - T)$ describe the reference historical data at time of $t_i - 2T$ and $t_i - T$, respectively. K_{-2} and K_{-1} are reference functions of period index. A standard period average is originally set to be a reference function of period index, and where it is defined as a constant.

(2) Sequential Index

The sequential index indicates the relationship between two adjacent reference historical data with the defined time steps. It is calculated through Equations (4) and (5).

$$SI(t_i - 2T) = \frac{y(t_{i+1} - 2T)}{y(t_i - 2T)} \quad (4)$$

$$SI(t_i - T) = \frac{y(t_{i+1} - T)}{y(t_i - T)} \quad (5)$$

(3) Small Period Index

The small period index indicates the relationship between the reference historical data and the reference value, which can be explained through Equations (6) and (7),

$$pi(t_i - 2T) = \frac{y(t_i - 2T)}{k_{-2}}, \quad (6)$$

$$pi(t_i - T) = \frac{y(t_i - T)}{k_{-2}}, \quad (7)$$

where k_{-1} and k_{-2} are reference functions of a small period index. Here a small period (such as three months, because of seasonal factors) average, is originally set to be a reference function of small period index.

(4) Super Sequential Index

The super sequential index indicates the relationship between two interval reference historical data with the defined steps. It is calculated through Equations (8) and (9).

$$si(t_i - 2T) = \frac{y(t_{i+2} - 2T)}{y(t_i - 2T)} \quad (8)$$

$$si(t_i - T) = \frac{y(t_{i+2} - T)}{y(t_i - T)} \quad (9)$$

Therefore, the forecasting value is given by:

$$F(t_i) = c \cdot PI(t_i) \cdot K_0 + d \cdot SI(t_{i-1}) \cdot y(t_{i-1}) + e \cdot pi(t_i) \cdot k_0 + f \cdot si(t_{i-2}) \cdot y(t_{i-2}), \quad (10)$$

where,

$$PI(t_i) = 0.5 \cdot PI(t_i - 2T) + 0.5 \cdot PI(t_i - T) \quad (11)$$

$$SI(t_{i-1}) = 0.5 \cdot SI(t_{i-1} - 2T) + 0.5 \cdot SI(t_{i-1} - T) \quad (12)$$

$$pi(t_i) = 0.5 \cdot pi(t_i - 2T) + 0.5 \cdot pi(t_i - T) \quad (13)$$

$$si(t_{i-2}) = 0.5 \cdot si(t_{i-2} - 2T) + 0.5 \cdot si(t_{i-2} - T) \quad (14)$$

$$K_0 = \gamma_0 \cdot K_{-1} \quad (15)$$

$$k_0 = \gamma_0 \cdot k_{-1} \quad (16)$$

$$\gamma_0 = \sqrt{\frac{\text{median}\{y(t_1 - T), y(t_2 - T) \cdots, y(t_N - T)\}}{\text{median}\{y(t_1 - 2T), y(t_2 - 2T) \cdots, y(t_N - 2T)\}}} \quad (17)$$

where, c, d, e , and f are the weighing factors of forecasting Equation (10). K_0 and k_0 are the correction coefficients for period index and small period index, respectively. γ_0 is planning factor, which is defined by median method in Equation (17).

2.2. SPNN-PSI Method

SPNN has been proposed by Lyutikova [20]. The products of the different linear combinations of the inputs in SPNN are the output of the network. SPNN has simpler structure, less variance, and faster convergence speed. A high SPNN degree determines the function that defines the relationship between output and input to depend on more parameters and to have a more complex structure. This can contribute to better prediction results but can also cause overfitting, which requires more computation time for the training algorithm. In the study, the architecture of SPNN-PSI with degree 4 and 8 inputs is shown in Figure 2, which can reproduce modeling function of Equation (10). As shown in Figure 2, $PI(t_i)$, K_0 , $SI(t_{i-1})$, $y(t_{i-1})$, $pi(t_i)$, k_0 , $si(t_{i-2})$, and $y(t_{i-2})$ are the input parameter of SPNN-PSI; $F(t_i)$ is the predicted output value at time of t_i ; c, d, e , and f are the weight values of network connection.

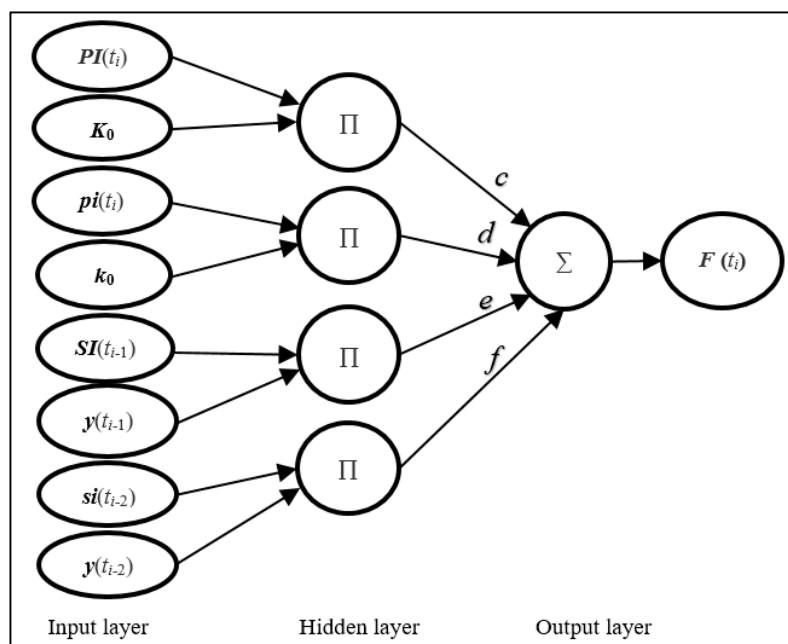


Figure 2. The architecture of the period-sequential index algorithm with sigma-pi neural network (SPNN-PSI).

The input vector z_i is given by

$$z_i = \begin{bmatrix} PI(t_i) \cdot K_0 \\ SI(t_{i-1}) \cdot y(t_{i-1}) \\ pi(t_i) \cdot k_0 \\ si(t_{i-2}) \cdot y(t_{i-2}) \end{bmatrix}. \quad (18)$$

The weight matrix w is defined as follows

$$w = \begin{bmatrix} c & d & e & f \end{bmatrix}. \quad (19)$$

In order to obtain the optimized weight values of c , d , e , and f , the output vector is defined as the observation data $y(t_i - T)$ during H_{-1} period.

$$y_i = y(t_i - T) = w \cdot z_i \quad (20)$$

In this study, multiple inputs and outputs are combined into the following equation:

$$Y = w \cdot Z \quad (21)$$

where Y and Z are a matrix of multiple outputs and matrix of multiple inputs, respectively.

$$Y = [y(t_1)y(t_2) \dots y(t_{i-1})y(t_i - T) \dots y(t_N - T)] \quad (22)$$

$$Z = \begin{bmatrix} PI(t_1) \cdot K_0 & PI(t_2) \cdot K_0 & PI(t_3) \cdot K_0 & \dots & PI(t_i) \cdot K_0 & PI(t_{i+1}) \cdot K_0 & \dots & PI(t_N) \cdot K_0 \\ SI(t_N - T) \cdot y(t_N - T) & SI(t_1) \cdot y(t_1) & SI(t_2) \cdot y(t_2) & \dots & SI(t_{i-1}) \cdot y(t_{i-1}) & SI(t_i) \cdot (\gamma_0 \cdot y(t_i - T)) & \dots & SI(t_{N-1}) \cdot (\gamma_0 \cdot y(t_{N-1} - T)) \\ pi(t_1) \cdot k_0 & pi(t_2) \cdot k_0 & pi(t_3) \cdot k_0 & \dots & pi(t_i) \cdot k_0 & pi(t_{i+1}) \cdot k_0 & \dots & pi(t_N) \cdot k_0 \\ si(t_{N-1} - T) \cdot y(t_{N-1} - T) & si(t_N - T) \cdot y(t_N - T) & si(t_1) \cdot y(t_1) & \dots & si(t_{i-2}) \cdot y(t_{i-2}) & si(t_{i-1}) \cdot y(t_{i-1}) & \dots & si(t_{N-2}) \cdot (\gamma_0 \cdot y(t_{N-2} - T)) \end{bmatrix} \quad (23)$$

Then, based on the measured value Y and input Z , the learning control method of the initial training neural network is used to get the optimal weight matrix w , which is given:

$$w^T = (ZZ^T)^{-1}ZY^T. \quad (24)$$

2.3. Error Evaluation

In order to evaluate the obtained results, the forecasting accuracy was measured with three error indicators, that are the mean absolute percentage error ($MAPE$), the root mean squared error ($RMSE$) and the mean absolute error (MAE) [20,21]. Calculation equations of error indicators are given in the below Equations (25)–(27). In addition, the Pearson correlation coefficient (r) in Equation (28) is also used to quantify the strength and direction of the linear relationship between two sets of data during the reference historical period [22].

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y(t_i) - F(t_i)}{y(t_i)} \right| \times 100\% \quad (25)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y(t_i) - F(t_i))^2}{N}} \quad (26)$$

$$MAE = \frac{\sum_{i=1}^N |y(t_i) - F(t_i)|}{N} \quad (27)$$

$$r = \frac{\sum_{i=1}^N (y(t_i - 2T) - K_{-2}) \cdot (y(t_i - T) - K_{-1})}{\sqrt{\sum_{i=1}^N (y(t_i - 2T) - K_{-2})^2} \cdot \sqrt{\sum_{i=1}^N (y(t_i - T) - K_{-1})^2}} \quad (28)$$

where $y(t_i)$ is the measured value at time of t_i during H_0 ; $F(t_i)$ is the forecasting value at time of t_i during H_0 .

3. Steps of Computation

The flow chart of the optimized network model is shown in Figure 3. The specific steps are as follows:

Step 1: Initialize the reference historical datasets.

Step 2: Training the reference historical two-cycle-years datasets, calculate the parameters Y and Z by solving Equations (22) and (23).

- Step 3: At the time step of t_i , take Y and Z into the Equation (24), and solve it, and get the optimal weight matrix w .
- Step 4: Update the optimal values of c , d , e , and f in Equation (10), solve Equation (10), and get the forecasting value $F(t_i)$.
- Step 5: If the time steps of the stop condition ($t_{i+1} > t_N$) are satisfied, the search stops, and output parameters of $MAPE$, $RMSE$, MAE , and r ; Otherwise, the time step is added, and the procedure returns Step 2.

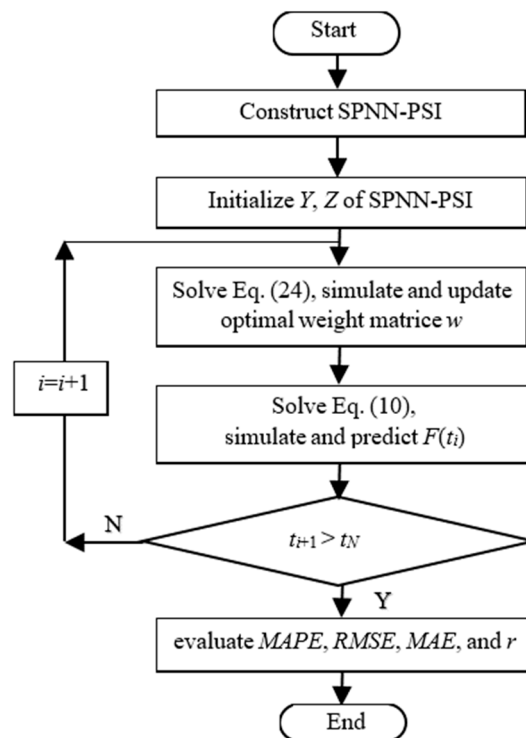


Figure 3. The flow chart of the optimized network model.

4. Results and Discussion

Three groups of actual time series datasets [23–25] are shown in Table 1. In these three samples, two-cycle-years datasets from January 2016 to December 2017 are used as reference historical data to forecast the data of 2018. In order to evaluate the confidence of the period-sequential index algorithm with sigma-pi neural network (SPNN-PSI), the correlation coefficients of datasets for 2016 and 2017 are further computed, and listed in Table 1. Then, a comparison analysis of the prediction value and the real value was implemented by using the SPNN-PSI, MA, ES, and ARIMA methods, so as to show a more direct observation of the prediction.

Table 1. Time series datasets used in the experiments.

Dataset Names	Reference Historical Data		Forecasting Data
	Month/Year	Correlation Coefficient	Month/Year
Electric motors exports (EME) [23] dataset	January 2016–December 2017	0.9388	January 2018–December 2018
Volkswagen sales (VS) dataset [24] dataset	January 2016–December 2017	0.8392	January 2018–December 2018
Cumulative electricity output (CEO) [25] dataset	January 2016–December 2017	1.0000	January 2018–December 2018

4.1. Periodic Recognition and Prediction on Electric Motors Exports (EME) Dataset

For the EME datasets, the electric motors exports in China between January 1995 and June 2019 is used as an example [23] to show the correlation coefficient detection and prediction results. Using the reference historical two-cycle-years dataset from January 2016 to December 2017, the monthly electric motors exports from January to December of 2018 are predicted by using the SPNN-PSI, MA, ES, and ARIMA methods, as shown in Figure 4. It can be seen from Figure 4 that, compared with MA, ES, and ARIMA methods, the SPNN-PSI method demonstrates a better prediction trend with good volatility and following quality.

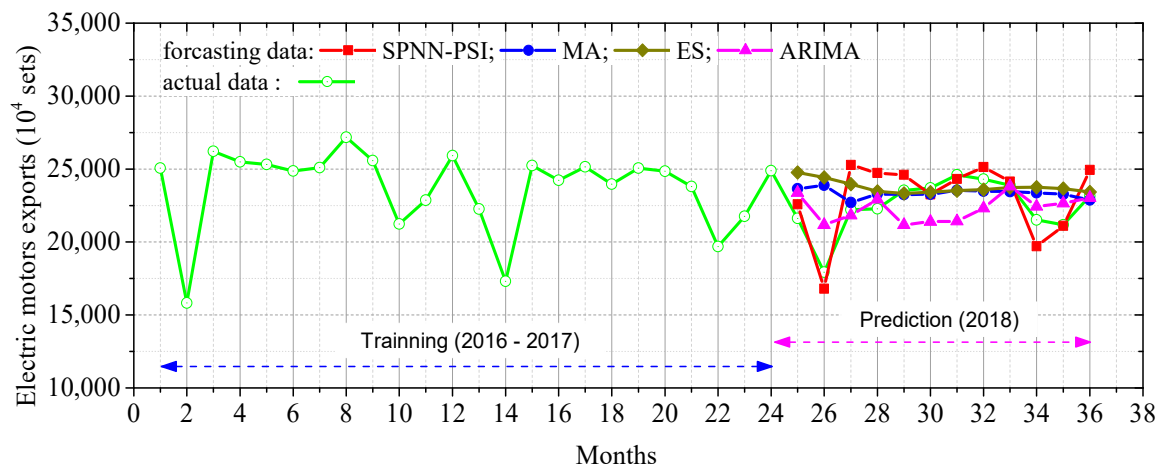


Figure 4. Time series pattern and prediction on the electric motors exports (EME) dataset.

Table 2 presents a more visual view of prediction errors of each model. According to the results obtained in Table 2, the corresponding error of *MAPE* is 5.34%, 6.79%, 8.11%, and 6.97% for the PSI, MA, ES, and ARIMA methods, respectively. It also can be noticed that the four errors are within a reasonable range, but the developed SPNN-PSI algorithm is more suitable for the prediction of the EME dataset used in this paper due to lower *MAPE*, *RMSE*, and *MAE*, as compared to the other three prediction methods. In addition, the correlation coefficient of its historical reference data is shown in Table 1. The example shows that the proposed SPNN-PSI algorithm achieves satisfactory accuracy in time series prediction on the EME dataset whose historical reference data has a relatively higher correlation coefficient value of 0.9388.

Table 2. Error indicators of each prediction model on the EME dataset.

Model	Error Indicators		
	<i>MAPE</i> (%)	<i>RMSE</i> (10^4 Sets)	<i>MAE</i> (10^4 Sets)
SPNN-PSI	5.34	1480.06	1179.87
MA	6.79	2062.60	1393.56
ES	8.11	2406.33	1667.28
ARIMA	6.97	1873.41	1535.20

4.2. Periodic Recognition and Prediction on Volkswagen Sales (VS) Dataset

For the VS dataset, the Volkswagen sales in China between January 2007 and June 2019 is used as another example [24] to show the correlation coefficient detection and prediction results. Figure 5 shows the prediction results in 2018 by using the PSI, MA, ES, and ARIMA methods. As shown in Figure 5, between January 2018 and May 2018, the predicted VS using the PSI method can be almost identical with actual VS, comparing to the MA, ES, and ARIMA methods, and a lower *MAPE* of 4.48% is also achieved by Equation (18). Meanwhile, it can be seen that, the trend of the predicted values

between June 2018 and December 2018 is similar to that of the actual values when using PSI method, but the difference between them at each time point is larger than that of using the MA, ES, and ARIMA methods, achieving a value of *MAPE* at 19.36% for the period between June 2018 and December 2018.

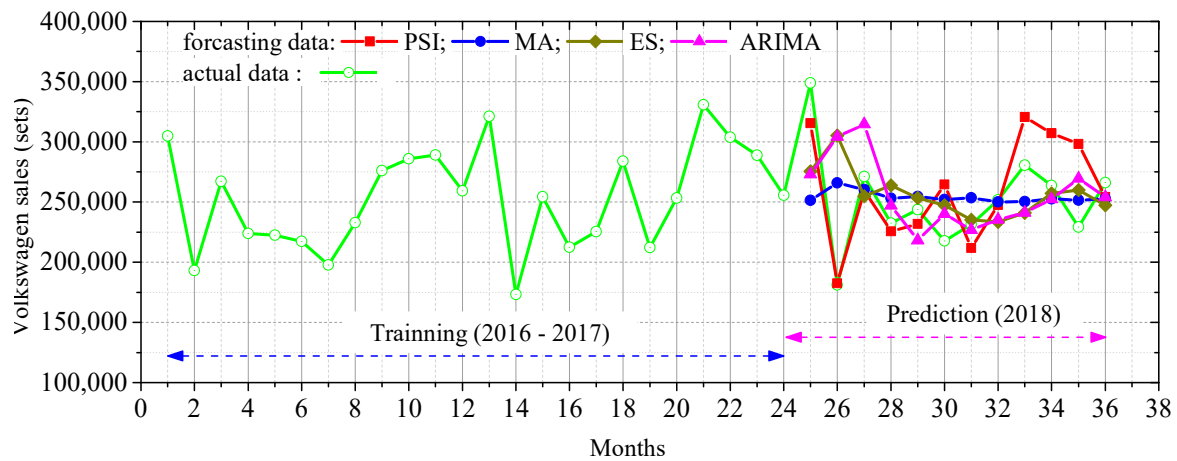


Figure 5. Time series pattern and prediction on the Volkswagen sales (VS) dataset.

To clearly show the correlation coefficient value and the prediction results, we show correlation coefficient detection results from January 2016 to December 2017 (shown in Table 1), and Table 3 presents the further prediction errors of each model. Compared with the EME dataset, the time series dataset of VS has a lower correlation coefficient value ($=0.8392$) of reference historical dataset. However, a higher *MAPE* value of 9.94% for the VS dataset in 2018 can be achieved in Table 3. Therefore, the example shows that the prediction accuracy and quality of the proposed SPNN-PSI algorithm can be decreased due to the decreasing correlation coefficient value of reference historical dataset (shown in Table 1), as compared to that of the EME dataset.

Table 3. Error indicators of each prediction model on the VS dataset.

Prediction Model	Error Indicators		
	<i>MAPE</i> (%)	<i>RMSE</i> (Sets)	<i>MAE</i> (Sets)
SPNN-PSI	9.94	32,148	24,970
MA	12.33	41,610	29,998
ES	14.38	46,810	33,500
ARIMA	15.13	48,211	35,702

To sum up, the *MAPE*, *RMSE*, and *MAE* values by SPNN-PSI method in Table 3 are all lower than that by MA, ES, and ARIMA methods. Thus, the forecasting quality of SPNN-PSI method is better, and the developed SPNN-PSI algorithm is still suitable for the prediction of VS dataset used in this paper.

4.3. Periodic Recognition and Prediction on Cumulative Electricity Output (CEO) Dataset

For the CEO dataset, a time series subset of cumulative electricity output in China [25] is used as an example to show the correlation coefficient detection and prediction results. For the large-scale reference historical time series dataset from January 2016 to December 2017, there is an obvious similarity periodicity in the CEO dataset with a length of 12 months (one year), and shows an upward trend from January to December. Based on the detected periodic model from January 2016 to December 2017, we predict the CEO for the next periodic (the whole year of 2018), as shown on the right side of Figure 6. We can see that the predicted values are very close to the actual values when using PSI method, while there are large deviations when using other methods, especially in January 2018.

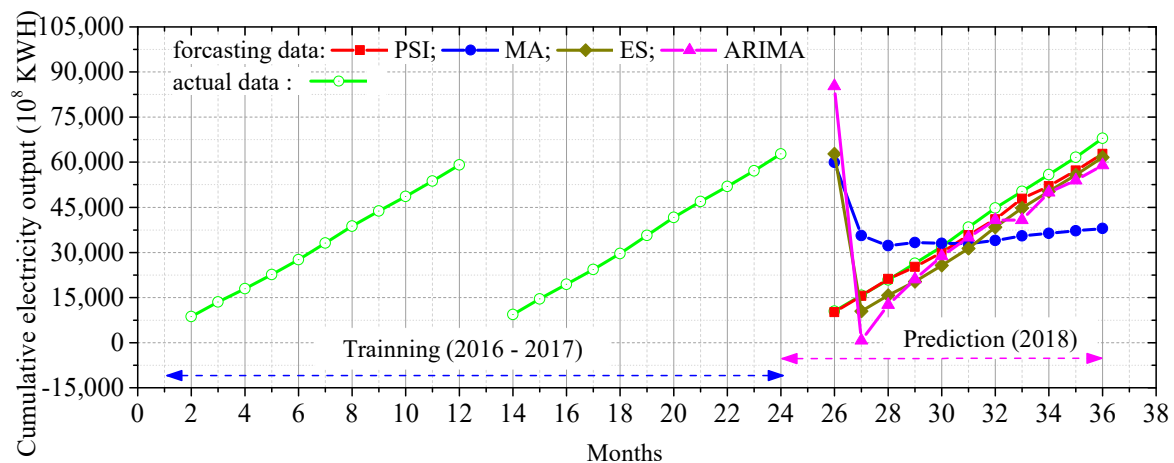


Figure 6. Time series pattern and prediction on cumulative electricity output (CEO) dataset.

Then, we evaluate the forecasting accuracy of the SPNN-PSI method by comparing the actual values and the predicted values, shown in Table 4. Because the correlation coefficient for reference historical dataset achieves a very high value (equal to 1.0, shown in Table 1), the MAPE, RMSE, and MAE by SPNN-PSI method are lower and equal 5.23% , 2912.23×10^8 , and 2374.38 KWH, which indicates a smaller difference between the prediction value and actual value. By contrast, the higher MAPE, RMSE, and MAE by other forecasting methods are also given in Table 4. Their MAPE values are all more than 50% , which indicates a relatively large fluctuation of prediction error.

Table 4. Error indicators of each prediction model on the CEO dataset.

Prediction Model	Error Indicators		
	MAPE (%)	RMSE (10^8 KWH)	MAE (10^8 KWH)
SPNN-PSI	5.23	2912.23	2374.38
MA	79.08	21,870.05	17,608.59
ES	61.14	16,757.26	10,136.89
ARIMA	86.63	23,782.35	13,251.02

In a sum, based on the above error indicators, the proposed SPNN-PSI algorithm achieves very high accuracy and quality in time series prediction on the CEO dataset with its very high correlation coefficient value of 1.0.

4.4. Accuracy Analysis of SPNN-PSI Algorithm

After receiving the forecasting results of the above three groups of time series datasets, the forecasting accuracy (FA) was also calculated by using Equation (29). If the FA is close to 100% and the MAPE is close to 0, the model is considered to have excellent forecasting accuracy. Then, the FA of the VS, EME, and CEO datasets (in Table 1) were further analyzed and shown in Table 5. It can be seen that the FA can increase when the correlation coefficient (r) of the reference historical data increases. Thus, we think that there may be a positive correlation between r and FA.

Table 5. Comparison of forecasting accuracy for the VS, EME, and CEO datasets.

Dataset Names	r	MAPE (%)	FA (%)
VS	0.8392	9.94	90.06
EME	0.9388	5.34	94.66
CEO	1.0000	5.23	94.77

$$FA = 1 - MAPE \quad (29)$$

To further illustrate this correlation between the two, it was applied to the first case of the monthly export volume of specifically chosen 31 different kinds of products from January 1995 to December 2018 [23]. The scatter diagram of FA vs. r is shown in Figure 7a. It can be seen in Figure 7a that, dense point clouds are located in one area surrounded by red lines, while some individual points scatter in the other areas. It is evident that, when using SPNN-PSI method in this paper, the higher value of r ($r > 0.4$) can help to improve occurrence probability of higher value of FA ($FA > 70\%$), and produce more accurate forecasts for the datasets of monthly export volume in the first case. Then, it is further examined empirically by using another case of big data, referring to vibration signal in hydraulic test rig with a sampling frequency of 1 Hz during 132,300 s [26]. This test rig cyclically repeats constant load cycles (duration 60 s) and measures process values. Figure 7b gives the scatter diagram of FA vs. r . It can be seen that Figure 7a,b shows a similar characteristic of scatter distribution, but whether r is positive or not in Figure 7b, the proposed PSI model can predict high values of FA (between 92% and 100%) and produces accurate forecasts of vibration. If we consider r is one dominant factor for forecasting accuracy, in the condition of $r > 0.4$, higher values of $FA > 97\%$ are easier to be applied and predicted using the proposed PSI algorithm.

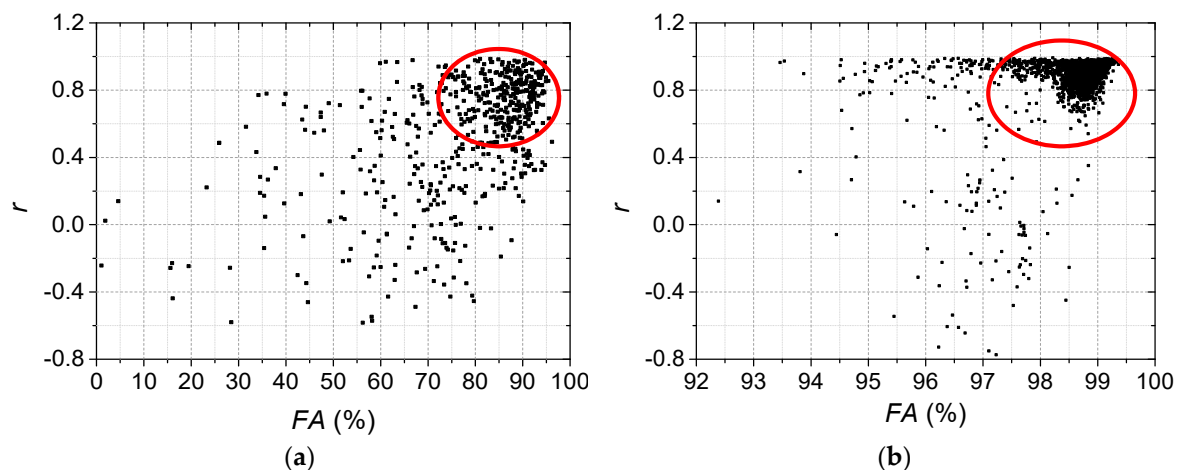


Figure 7. Scatter diagram of forecasting accuracy (FA) vs. correlation coefficient (r). (a) The monthly export volume of specifically chosen 31 different kinds of products from January 1995 to December 2018; (b) the vibration data of hydraulic test rig with a sampling frequency of 1 Hz during 132,300 s.

5. Conclusions

- The SPNN-PSI method with four indexes—the period index, sequential index, small period index, and super sequential index, by finding index-values implicitly carrying usable structure information, combined with a neural network, is initially proposed for predict the time series datasets.
- In contrast to the MA, ES, and ARIMA methods, the proposed SPNN-PSI method shows satisfactory forecasting quality due to lower $MAPE$, $RMSE$, and MAE , and is more suitable for the prediction of time series datasets.
- There is a trend that the higher the correlation coefficient value of the reference historical datasets, the higher the prediction quality of SPNN-PSI method; a higher value (>0.4) of the correlation coefficient for the SPNN-PSI method can help to improve the occurrence probability of higher forecasting accuracy, and produce more accurate forecasts for the big datasets.

Author Contributions: Conceptualization, H.J. and D.F., and K.S.; formal analysis, H.J. and D.F.; investigation, H.J. and D.F.; writing—original draft preparation, H.J. and F.C.; writing—review and editing, H.J., D.F., and B.L.

Funding: The authors gratefully acknowledge the support of key projects for international cooperation in scientific and technological innovation between governments, through grant No. 2017YFE0101600.

Acknowledgments: The authors would like to express their sincere thanks to Klaus Spicher from Sino–German Institute for Intelligent Technologies and PhD Study for his assistance in heuristic prediction method.

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

Abbreviations

c, d, e, f	weighing factors of forecasting equation
FA	forecasting accuracy
$F(t_i)$	forecasting value at time of t_i during H_0 period
$G()$	measurement equation for forecasting value
H_{-2}, H_{-1}	reference historical period
H_0	forecasting period
$-2, -1, 0$	subscripts, and represent during period of H_{-2}, H_{-1}, H_0 , respectively
k_0	correction coefficients for small period index
k_{-1}, k_{-2}	average of measured values during small periods of H_{-1}, H_{-2}
K_0	correction coefficients for period index
K_{-1}, K_{-2}	average of measured values during periods of H_{-1}, H_{-2}
MAE	mean absolute error
MAPE	mean absolute percentage error
N	number of forecasting samples
r	correlation coefficient
RMSE	root mean squared error
$pi(t)$	small period index at time of t
$PI(t)$	period index at time of t
$si(t)$	super sequential index at time of t
$SI(t)$	sequential index at time of t
t	time ($t = t_1 - 2T, t_2 - 2T, \dots, t_N - 2T, t_1 - T, t_2 - T, \dots, t_N - T, t_1, t_2, \dots, t_N$)
T	period for H_{-2}, H_{-1} , and H_0
$y(t)$	measured value at time of t
y_i	output vector
Y	matrix of multiple outputs
w	weight matrix
z_i	input vector
Z	matrix of multiple inputs
γ_0	planning factor

References

1. Cao, L.J.; Tay, F.E.H. Support vector machine with adaptive parameters in financial time series forecasting. *IEEE Trans. Neural Netw.* **2003**, *14*, 1506–1518. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Shi, G.; Guo, J.; Huang, W.; Williams, B.M. Modeling seasonal heteroscedasticity in vehicular traffic condition series using a seasonal adjustment approach. *J. Transp. Eng.* **2014**, *140*, 4014012. [\[CrossRef\]](#)
3. Stefanakos, C. Fuzzy time series forecasting of nonstationary wind and wave data. *Ocean Eng.* **2016**, *121*, 1–12. [\[CrossRef\]](#)
4. Yaser, S.A.M.; Atiya, A.F. Introduction to financial forecasting. *Appl. Intell.* **1996**, *6*, 205–213.
5. Dong, Z.; Yang, D.; Reindl, T.; Walsh, W.M. Short-term solar irradiance forecasting using exponential smoothing state space model. *Energy* **2013**, *55*, 1104–1113. [\[CrossRef\]](#)
6. Billah, B.; King, M.L.; Snyder, R.D.; Koehler, A.B. Exponential smoothing model selection for forecasting. *Int. J. Forecast.* **2006**, *22*, 239–247. [\[CrossRef\]](#)
7. Barrow, D.K. Forecasting intraday call arrivals using the seasonal moving average method. *J. Bus. Res.* **2016**, *69*, 6088–6096. [\[CrossRef\]](#)
8. Büyüksahin, U.C.; Ertekin, S. Improving forecasting accuracy of time series data using a new ARIMA-ANN hybrid method and empirical mode decomposition. *Neurocomputing* **2019**, *361*, 151–163. [\[CrossRef\]](#)

9. Wen, X.H.; Feng, Q.; Deo, R.; Wu, M. Two-phase extreme learning machines integrated with the complete ensemble empirical mode decomposition with adaptive noise algorithm for multi-scale runoff prediction problems. *J. Hydrol.* **2019**, *570*, 167–184. [CrossRef]
10. Xie, T.; Zhang, G.; Hou, J.; Xie, J.; Lv, M.; Liu, F. Hybrid forecasting model for non-stationary daily runoff series: A case study in the Han River Basin, China. *J. Hydrol.* **2019**, *577*, 123915. [CrossRef]
11. Voyant, C.; Muselli, M.; Paoli, C.; Nivet, M.L. Optimization of an artificial neural network dedicated to the multivariate forecasting of daily global radiation. *Energy* **2011**, *36*, 348–359. [CrossRef]
12. Mellit, A.; Kalogirou, S.A. Artificial intelligence techniques for photovoltaic applications: A review. *Prog. Energy Combust. Sci.* **2008**, *34*, 574–632. [CrossRef]
13. Linares-Rodríguez, A.; Ruiz-Arias, J.A.; Pozo-Vázquez, D.; Tovar-Pescador, J. Generation of synthetic daily global solar radiation data based on ERA-Interim reanalysis and artificial neural networks. *Energy* **2011**, *36*, 5356–5365. [CrossRef]
14. Mellit, A.; Eleuch, H.; Benghanem, M.; Elaoun, C.; Pavan, A.M. An adaptive model for predicting of global, direct and diffuse hourly solar irradiance. *Energy Convers. Manag.* **2010**, *51*, 771–782. [CrossRef]
15. Mostafavi, E.S.; Ramiyani, S.S.; Sarvar, R.; Moud, H.I.; Mousavi, S.M. A hybrid computational approach to estimate solar global radiation: An empirical evidence from Iran. *Energy* **2013**, *49*, 204–210. [CrossRef]
16. Fang, D.J.; Weng, W.B. Sales Forecasting System for Chinese Tobacco Wholesalers. In Proceedings of the 2nd International Conference on Innovative Computing, Communication, Information Technology, and Ocean Engineering CICC-ITOE201, Macao, China, 5–6 March 2011; Volume 11, pp. 380–386.
17. Yolcu, O.C.; Lam, H.K. A combined robust fuzzy time series method for prediction of time series. *Neurocomputing* **2017**, *247*, 87–101. [CrossRef]
18. Bas, E.; Grosan, C.; Egrioglu, E. High order fuzzy time series method based on pi-sigma neural network. *Eng. Appl. Artif. Intell.* **2018**, *72*, 350–356. [CrossRef]
19. Fang, D.; Zhang, Y.; Spicher, K. Forecasting Accuracy Analysis based on two new heuristical methods and Holt-Winters-Method. In Proceedings of the 2016 IEEE International Conference on Big Data Analysis, Hangzhou, China, 12–14 March 2016; pp. 152–157.
20. Lyutikova, L.A. Sigma-Pi neural networks: Error correction methods. *Procedia Comput. Sci.* **2018**, *145*, 312–318. [CrossRef]
21. Hannan, M.A.; Lipu, M.S.H.; Hussain, A. Neural network approach for estimating state of charge of lithium-ion battery using backtracking search algorithm. *IEEE Access* **2018**, *6*, 10069–10079. [CrossRef]
22. Joshi, B.; Kay, M.; Copper, J.K.; Sproul, A.B. Evaluation of solar irradiance forecasting skills of the Australian Bureau of Meteorology's ACCESS models. *Sol. Energy* **2019**, *188*, 386–402. [CrossRef]
23. HeXun-Macro Data—National Accounts, China Electric Motors Exports Dataset. Available online: <http://mac.hexun.com/Default.shtml?id=A511M> (accessed on 9 October 2019).
24. Owner's Home, Volkswagen Sales (VS) Dataset. Available online: <http://xl.16888.com/b/57411/> (accessed on 9 October 2019).
25. HeXun-Macro Data—Three Major Industries, China Cumulative Electricity Output Dataset. Available online: <http://mac.hexun.com/Default.shtml?id=E210M> (accessed on 9 October 2019).
26. Kaggle-Dataset-Condition Monitoring of Hydraulic Systems, Condition Assessment of a Hydraulic Test Rig Based on Multi Sensor Data. Available online: <https://www.kaggle.com/jjacostupa/condition-monitoring-of-hydraulic-systems> (accessed on 1 April 2018).

