IECE Transactions on Intelligent Systematics
http://dx.doi.org/10.62762/TIS.2024.136898

RESEARCH ARTICLE

Deep Prediction Network Based on Covariance Intersection Fusion for Sensor Data

Hanchi Ren[1,*], **Yeqing Wang**[2] and **Huijun Ma**[2]

[1] Department of Computer Science, Swansea University, Swansea SA1 8EN, United Kingdom
[2] School of Computer Science and Artificial Intelligence, Beijing Technology and Business University, Beijing 100048, China

Abstract

To predict future trends based on the data from sensors is an important technology for many applications, such as the Internet of Things, smart cities, etc. Based on the predicted results, further decisions and system controls can be made. Raw sensor data sets are often complex non-linear data with noise, which results in the difficulty of accurate prediction. This paper proposes a distributed deep prediction network based on a covariance intersection (CI) fusion algorithm in which the deep learning networks, such as long-term and short-term memory networks (LSTM) and gated recurrent unit networks (GRU) are fused by CI fusion algorithm to effectively develop the performance of prediction. Moreover, the variance is obtained to value the prediction results. The model is validated on the real weather dataset in Beijing. The experiments show that LSTM and GRU have their pros and cons for different data, CI fusion can develop the accuracy of the final predictions, and the entire framework has robust prediction results with a reasonable estimated variance.

Keywords: Deep prediction network, covariance intersection (CI) fusion, sensor data analytics.

Academic Editor:
Weimin Zhang

Submitted: 05 January 2024
Accepted: 19 May 2024
Published: 25 May 2024

Vol. 1, **No.** 1, 2024.
10.62762/TIS.2024.136898

***Corresponding author:**
Hanchi Ren
hanchi.ren@swansea.ac.uk

Citation
Ren, H., Wang, Y., & Ma, H. (2024). Deep Prediction Network Based on Covariance Intersection Fusion for Sensor Data. IECE Transactions on Intelligent Systematics, 1(1), 10–18.

1 Introduction

Time series data exists in many real-world systems, and the analysis and prediction of time series data can provide effective guidance for system control.

For the prediction of time series data, researchers have proposed some solutions. For example, the traditional mathematical equation model Autoregressive Integrated Moving Average model (ARIMA) [1] can only predict stationary time series data and mainly focus on processing stationary noise data. For non-stationary time series data, the modeling process of ARIMA model needs to increase the smoothing step. At the same time, it is difficult to set the correct model order. In addition, for nonlinear data relationships, the ARIMA model is difficult to use. In paper [2], Thissen et al proposed an SVM algorithm, which is of certain modeling ability for nonlinear data with a small amount of noise, but it is difficult to determine its parameters [3].

With the development of sensor technology, the information obtained is more and more abundant, and the data-driven deep learning model has been widely studied and applied. In particular, the recurrent neural network (RNN) [4–6] shows strong modeling capabilities in nonlinear time series data. However, due to the long-term dependence of RNN in capturing data, there are problems such as gradient disappearance and gradient explosion. Improved RNNs such as LSTM [7–9] and GRU [10, 11] have been proposed and applied. LSTM sets three gating units to control the memory and forgetting of time series through cell state. LSTM solves the gradient disappearance and gradient explosion problem of RNN and realizes the long-term dependence of capturing data. GRU has reduced a gating unit based on LSTM, reducing network parameters while maintaining the modeling capabilities comparable to LSTM.

At the same time, papers [12, 13] shows that bidirectional LSTM performs better in periodic time series data, even if it needs to be trained for a longer time. In addition, in the case of multiple input variables, the RNN series network cannot be highly accurate because it cannot take into account the lateral relationship in multiple variables. In papers [14–16], authors combined the convolutional neural network CNN with LSTM, in which CNN extracts the local spatial features of multidimensional data, considering the horizontal relationship of multidimensional time series.

In addition, different network models have different performances on different data, and even if the neural network has been trained, the prediction variance in different time periods has fluctuations. Moreover, the output of different neural networks is difficult to judge by appropriate standards. It is biased only by using the root mean square error which are often similar resulting in the reliability of the results cannot be accurately measured. To this end, we can use multiple neural networks to model the data to form a distributed network, but this will cause a problem that how to integrate these results after obtaining multiple prediction results. Therefore, the use of effective fusion methods to synthesize the prediction results of different models can ensure the accuracy and stability of the output results. Commonly used fusion strategies are weighted average method [17, 18], nonlinear artificial neural network (ANN) fusion [19], direct addition or addition, and average [20]. For the weighted average method, it faces the difficulty of determining the weight. However, for the method of ANN, although it solves the problem of determining the weight, it also introduces more parameters, which increases the complexity of the model and requires enough data to train the model. At the same time, for the fusion result of ANN, only a series of predicted estimates can be obtained. In the real system, we can't effectively evaluate the correctness of the estimates. In paper [21], the author uses the method of covariance intersection to fuse the features extracted by the neural network and improve the accuracy. The covariance intersection fusion algorithm can not only obtain interpretable suboptimal estimates in multi-source correlation data fusion but also give the variance of each estimated value to evaluate the correctness of the predicted values.

We designed a distributed deep learning network model combining traditional time series data decomposition technology and a fusion scheme. We use three models of LSTM, GRU, and ConvBiLSTM to perform multi-step prediction on the same time series variable respectively, and then use the covariance intersection fusion algorithm to fuse the prediction results of the three models to ensure the accuracy of the prediction results and give predictions. Quantitative evaluation of the results. In implementing the variance required for CI fusion, the step estimation variance for each prediction time step is obtained by overlapping the prediction data. Finally, by estimating the variance of the step size, the covariance intersection algorithm is designed to fuse the prediction results, and the more accurate prediction results are given, and the possible fluctuation range is also displayed.

Niehsen et al. verified that covariance cross-filtering provides a general framework for information fusion because it can produce consistent estimates for any degree of cross-correlation. In paper [21], covariance intersection algorithm was used in neural networks feature level fusion effectively improves the accuracy of the experiment. Hurley et al.[22] extended the covariance crossover to the fusion of any two probability density functions, and gave the minimum of the covariance matrix of the fusion, thus verifying the covariance intersection algorithm in multiple data. In paper [23], the authors compare the covariance intersection algorithm with other fusion algorithms. The interpretability of the CI is verified and the correct minimum estimated variance is given. Li et al. applied the CI algorithm to the field of vehicle positioning. In multiple vehicle cooperative tasks, the different states of different vehicles were estimated and merged using the CI algorithm. In the case of unknown correlation, CI obtained the best agreement. It is estimated that there are clear advantages over other fusion methods. However, although the CI fusion method can obtain better results when the data source has an unknown correlation, the variance of the different data is required to be known in the application. For most sensor data, the variance can be passed. The measurement is estimated, and the variance of the output of the deep network model is not scientifically defined and cannot be used directly.

Based on the above analysis, we can know that in the face of real highly nonlinear data, neither the traditional mathematical equation model nor the data-driven deep network model can obtain the best results. Therefore, the introduction of appropriate time series data decomposition technology. The complexity of the original data can be effectively reduced, and in the case of insufficient data, the effective feature components are more conducive to the training of the model in the deep network model. However, neural networks are also not universal. Different time series variables and different time periods will lead to differences in the prediction performance of neural network networks. or this reason, in the face of the multi-step prediction problem of complex time series data, it is very meaningful to use the appropriate fusion method to synthesize the prediction results of different neural network models to obtain a more stable final prediction result. In the existing linear fusion method, there is a problem that the weight is difficult to determine, and the nonlinear ANN model will increase the complexity of the model. However, the correlation of the output of the neural network is unknown, so the CI fusion method becomes a natural choice. The research shows that the method still has suboptimal consistent estimation for data sources with unknown correlations. Faced with the problem that it is difficult to the variance required by the CI algorithm. When we model the time series to predict certain values in the future, we can simultaneously model some known observations and unknown to-be-predicted values by enlarging the number of prediction steps, that is, in a prediction Multi-step, both obtaining forecasts of observations also includes predictions of future values. In this way, we can estimate the prediction estimation variance for the prediction period, and based on this variance, design the CI fusion algorithm to obtain more accurate results and quantitative evaluation.

Therefore, this paper proposes a distributed multi-step predictive depth network model based on CI fusion and uses LSTM, GRU, and ConvBiLSTM three models as sub-models. Among them, when using ConvBiLSTM, the decomposition method of STL is added to decompose the time series data into three feature components to improve the accuracy. Compared to the existing methods, we use different models for prediction and use CI fusion to obtain the final result after separately obtaining the prediction results. The CI fusion strategy also gives the variance of the predicted values at each moment, and the results are more reasonable and interpretable. This paper mainly has two contributions by following:

1. This paper establishes a general framework for the prediction of complex time series data, which combines the data-driven deep network model and CI fusion strategy to ensure the accuracy and quantitative evaluation of the prediction results.
2. For sensor data, it is often difficult to obtain the variance, so the prediction results of the data-driven deep network model are not easy to evaluate. Therefore, we predict the value of the time at which the observed data has been obtained by expanding the step size backwards and based on this, a covariance fusion strategy is designed. Futhermore, the use of CI fusion variance to give a quantitative evaluation of the prediction results has a more important reference significance in practical applications.

Our highlights are as follows: First, we have established a general distributed network framework for nonlinear complex time series data prediction. By using the covariance intersection fusion scheme, the prediction results of the three models are integrated to ensure the stability of the framework on different data. , improve the prediction accuracy of the neural network, and use the variance to give a quantitative evaluation of the results. Secondly, the estimated variance of one step in multi-step prediction is estimated by the prediction of overlapping data in adjacent modeling steps, and an interpretive CI fusion algorithm is designed based on this variance. The CI fusion algorithm gives the variance of the predicted values that is considered a more reasonable prediction.

The following parts of this paper are organized as follows: Section II presents the existing prediction methods and improvement ideas in the field. Section III introduces the method of this article, as well as the detailed process of each part. Section IV verifies and evaluates the proposed method on the real weather dataset in Beijing through experiments. We draw conclusions and prospection in Section V.

2 Methodology

We have built a generic prediction model, as shown in Figure 1. The three sub-predictors are trained in a supervised learning manner. The input and output of the sub-predictor are historical data from one step and future data from one step, respectively. We can see that the whole model consists of four main components: The three neural network submodels are

GRU, LSTM, and ConvBiLSTM. Among them, when using the ConvBiLSTM model, due to the abstract feature extraction ability of the convolution operation, we use the STL decomposition method to decompose the original data into more efficient three-feature components, and train the predictor based on this data.

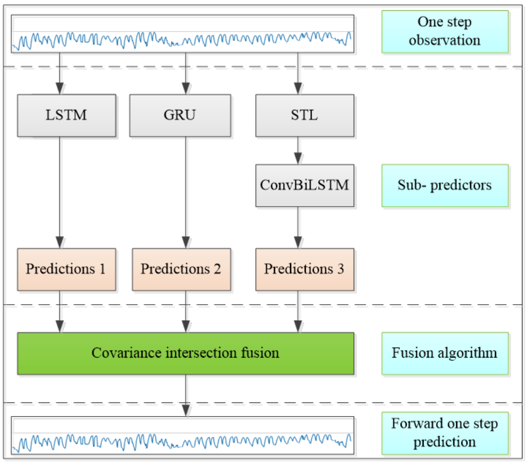


Figure 1. Model framework

Recurrent neural networks (RNNs) maintain a memory based on historical contextual information, which makes them a natural choice for processing sequential data. Long Short-Term Memory network adds cells as the information storage module, which realizes long-term memory of the sequence data, and solves the problem of gradient disappearance and gradient explosion of RNN network.

LSTM uses a gating mechanism to enable the circulatory neural network to not only remember past information but also to selectively forget some unimportant information to model long-term time dependencies. GRU is based on the idea of retaining long-term sequence information. Reduce the problem of gradient disappearance. The principle of GRU is very similar to that of LSTM, which uses gated mechanism to control input, memory and other information to make predictions at the current time step. The GRU has two gate units, a reset gate and an update gate. Intuitively, the reset gate determines how the new input information is combined with the previous memory, and the update gate defines the amount of the previous memory saved to the current time step.

Using the three sub-models to strongly model the nonlinear data ensures the prediction performance of completely different data sources. Finally, using the covariance intersection algorithm for three data sources, the prediction results of the three sub-models are combined to further improve accuracy, at the same time, the covariance intersection algorithm will give a possible range of fluctuations as a quantitative evaluation of the prediction results.

In the CI fusion algorithm, we add some time sensor data obtained to the forward one-step prediction, compare the predicted result of the obtained data with the true value of the moment, and estimate the overall variance of the prediction result in the previous step. Based on the variance, the ci algorithm is designed to fuse the results. Our data format is shown in Figure 2.

Using the three sub-models to strongly model the nonlinear data ensures the prediction performance of completely different data sources. Finally, using the covariance intersection algorithm for three data sources, the prediction results of the three sub-models are combined to further improve accuracy, at the same time, the covariance intersection algorithm will give a possible range of fluctuations as a quantitative evaluation of the prediction results.

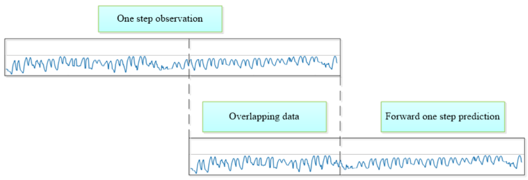


Figure 2. Data format

In the target tracking, in order to avoid errors caused by the influence of information redundancy in the Kalman filter estimation, the covariance information must be maintained, but in a fully distributed system, the cross-covariance information cannot be uniformly maintained. In order to solve the above problems, [24] Julier S et al. proposed a data fusion mechanism that does not require independence assumptions, which can be applied to the covariance cross-fusion algorithm of arbitrary complex distributed systems. We designed a covariance intersection algorithm that uses three sources of information. A general covariance algorithm can fuse multiple sources of information. Suppose multiple information source data is y^m, m represents the number of information sources. The intersection represents the convex combination of covariance, and the covariance intersection algorithm are following:

$$P^{-1} = \omega_1 P_1^{-1} + \omega_2 P_2^{-1} + \ldots + \omega_m P_m^{-1} \quad (1)$$

$$
\begin{aligned}
& P^{-1}y = \omega_1 P_1^{-1} y_1 + \omega_2 P_2^{-1} y_2 + \cdots + \omega_m P_m^{-1} y_m \\
& \text{s.t.} \quad 1)\ \omega_1, \omega_2, \ldots, \omega_m \in [0,1] \\
& \qquad\ \ 2)\ \omega_1 + \omega_2 + \cdots + \omega_m = 1
\end{aligned} \tag{2}
$$

where, ω_m represents the weight of the m data source, P_m represents the variance of the m data source, y represents the fusion result. When using the convex optimization algorithm to get the appropriate weight, you can get the best fusion result.

In our paper, three sub-predictors were chosen, so there are three data sources. The estimated variance of the three sub-predictors is obtained by prediction of repeated data of adjacent step sizes. The values at the same time are predicted by three sub-predictors, and the results are $\hat{y}_n^1$, $\hat{y}_n^2$, $\hat{y}_n^3$, respectively. Where n represents the moment. The estimated variance is P_1, P_2, P_3 which are calculated by formula (3) respectively and covariance P is calculated by formula (4).

$$
\hat{P}_i = \sqrt{\frac{1}{13} \sum_{r=1}^{13} \left(\hat{y}_{24}^{i,r} - \hat{y}_{37}^{r} \right)^2} \tag{3}
$$

$$
P^{-1} = \omega_1 P_1^{-1} + \omega_2 P_2^{-1} + \omega_3 P_3^{-1} \tag{4}
$$

where ω_1, ω_2, ω_3 represent the weights respectively of different predicted values of each model.

$$
\begin{aligned}
\min_{\omega_1, \omega_2, \omega_3} \ & P^{-1} = \omega_1 P_1^{-1} + \omega_2 P_2^{-1} + \omega_3 P_3^{-1} \\
\text{s.t.} \quad & 1)\ \omega_1, \omega_2, \omega_3 \in [0,1] \\
& 2)\ \omega_1 + \omega_2 + \omega_3 = 1
\end{aligned} \tag{5}
$$

We use Sequential Least Squares Programming [25] to optimize P^{-1} under the constraints of ω_1, ω_2, and ω_3, to get the best value for each weight according to formula (5). Then, calculate the result of the fusion according to formula (6).

$$
P^{-1} \hat{y}_n = \omega_1 P_1^{-1} \hat{y}_n^1 + \omega_2 P_2^{-1} \hat{y}_n^2 + \omega_3 P_3^{-1} \hat{y}_n^3 \tag{6}
$$

where $\hat{y}_n$ represents the fusion result at time n.

The flow of our entire algorithm is as follows pseudo code, where the symbol convention is as follows: the agreed symbols of t, T are set to 24, 37 respectively, representing the forward 24 step prediction. y_1 to y_{37} represent 37 real values of historical moments. $\hat{y}_{24}$ to $\hat{y}_{37}$ represent 13 predicted values of historical moments and $\hat{y}_{38}$ to $\hat{y}_{61}$ represent 24 forward predicted values.

3 Experiments

3.1 Dataset

The data in our experiments come from the meteorological dataset used in a Global AI Challenge contest in 2018, which focuses on real-world meteorological data observed at a weather station in Beijing, including meteorological factors such as temperature, relative humidity, and wind speed. The data set has high continuity with fewer missing values. Our experiments are based on two variables, temperature and wind speed. These two variables have distinct trends, the temperature changes have obvious periodicity rather than the wind speed has obvious abrupt changes. Data is collected every hour. We selected continuous 200-day data as the data source and filled in the missing values with data from the previous moment of the missing moment. We use 170 days of data as a training set for network models, and the remaining 30 days of data as a test set.

3.2 Experiment setup

The experiment hardware and software environments are set up to run the proposed prediction model. The open source deep learning library Keras, based on TensorFlow, is used to build all learning models. All experiments are performed on a PC with an Intel(R) CORE(TM) CPU i5-4200U 1.60 GHz and 4 GB of memory.

In order to model the deep neural network effectively, a large number of hyper parameters need to be set. In experiments, the default parameters in Keras are used for deep neural network initialization such as weight initialization and Learning rate. Usually, when we use neural networks to build models, the size of the network layer and the number of neurons are not strictly defined. Instead, the complexity of the model structure is determined based on the data. We determine the parameters of each layer of the model through multiple experimental adjustments. In addition, We use the commonly used activation function Tanh as the activation functions of the LSTM, GRU and BP. The convolution layer's activation function is set ReLu. The size and hyper parameter details of each network model are shown in Table 1.

A detailed introduction of the three sub-predictors is as follows.

1. GRU: In this model, the raw data was not processed except for data preprocessing-related operations, and it was used to train the GRU network to build a predictive model.

Table 1. Hyperparameters details for all experiments

Model	Number of layers	size	Experiment setup
GRU	2 GRU	[37], [37]	Batch size: 20 Epochs: 4000
LSTM	2 LSTM	[37], [37]	Batch size: 20 Epochs: 4000
ConvBiLSTM	2 CNN & 1 BiLSTM &1 LSTM & 1 Dense	[3,3], [3,3], [37], [37], [37]	Batch size: 20 Epochs: 4000
BP	3 Dense	[3], [5], [1]	Batch size: 30 Epochs: 100

2. LSTM: Train the network with exactly the same data as the submodel of GRU.
3. ConvBiLSTM: Using the same data as the previous two models as the data source, the three feature components are obtained through the STL decomposition method before the data enters the network. Use this feature component to train this network to get a predictor.

The method proposed in this paper mainly used the fusion idea of distributed network, obtains the prediction results of the same time period through three sub-models, and designs the covariance intersection fusion algorithm at the end, so as to synthesize the results of the three models and obtain the final predictions. The prediction performance of different models was evaluated by comparison with real values. The root mean square error (RMSE) was used to estimate the performance of models. RMSE is frequently used to measure the difference between values predicted by a model and the values actually observed from the environment. A value of 0 indicates that the observed value exactly fits the predicted value. The calculation is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

where $\hat{y}_i$ represents the predicted value, y_i represents the truth value, and n represents the number of test data.

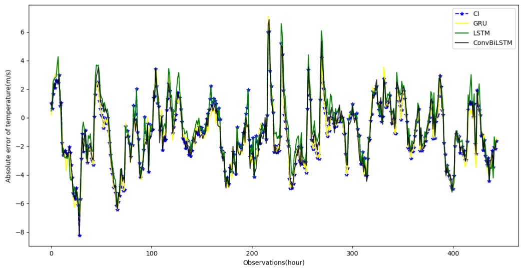
We have designed two experiments. Experiment 1 verifies the effectiveness of the CI fusion algorithm. In the prediction of two variables, the fusion algorithm is improved compared to the sub-predictor. In experiment 2, we used bp fusion to compare with ci results. The results show that the ci fusion algorithm not only gives more accurate prediction values, but also gives a reasonable range of fluctuations, which is more practical.

3.3 Results of Case No. 1

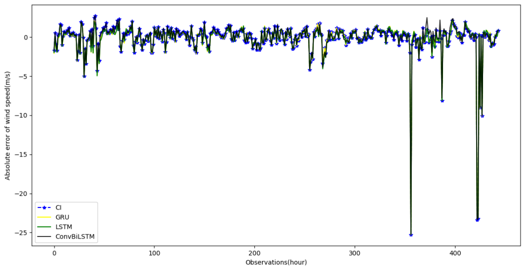
We completed two experiments on a real dataset, each of which included predictions of two meteorological variables, temperature (T) and wind speed (WS). We process the data into pairs of data with overlapping moments, recording 37 moments per day, with 13 observations being historical values and 24 moments being observations for the next day. We use the data from the previous day to predict the trend of the next day, thus building a forward 24 step prediction model. Results of the first experiment are shown in Fig.5 and Figure 3.The prediction results of T and WS are shown in Figs. 5 (a) and (b) respectively. The red line presents the ground truth of T and WS, and the blue line presents fusion results by CI. The green, yellow, and black lines are the predictive results with LSTM, GRU and ConvBiLSTM models, respectively.

Figure 3(a) shows the comparison of the ground truth (real) and the 24-step forward predictive results of two non-stationary time series data obtained by four different models. It can be seen from the figure that it is not feasible to use the single GRU or LSTM model to predict the non-stationary time series data. This is because the trend of different variables is often very different, for example, the temperature has obvious periodicity, and the peak of wind speed is often very large. Although the ConvBiLSTM model combines CNN and BiLSTM to achieve extract features of local spatial dimension and temporal dimension, there is no ideal accuracy on the real data set. The main reason is that the ConvBiLSTM network is relatively large with more parameters, and it is easy to overfit on small data sets.

Figure 3 shows the absolute error of the predictive results and ground truth of non-stationary time series. The blue line represents the fusion results by CI and the green, yellow, black lines are the predictive results with LSTM, GRU and ConvBiLSTM models, respectively. The closer the difference is to the value of 0, the more accurate the predictions.



(a) Temperature predictions absolute error



(b) Wind speed predictions absolute error

Figure 3. Results of two fusion methods

The quantitative results are shown in Table 2, alongside RMSE comparative analysis of four models.

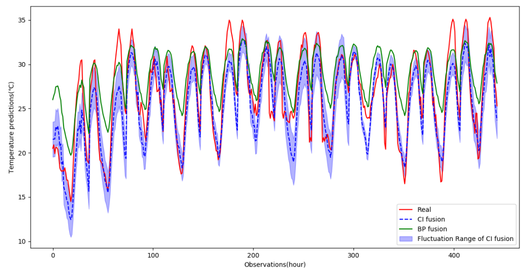
As indicated in Table 2, the smallest RMSE for multi-step forward prediction also reflects our CI fusion method's superior performance. In temperature predictions, compared to the single LSTM, GRU and ConvBiLSTM models, our CI fusion results' RMSE is reduced by 1.3%, 6.2% and 3.7%, respectively. The primary reason for this is that the proposed CI based model can give an improved predicted value even if the correlation between the predicted value and the true value is unknown. At the same time, the CI algorithm comprehensively considers the predicted value and variance information of each data source when merging multiple data sources, thereby increasing the reliability of the results. In addition, in the prediction of wind speed data, the results of the CI fusion method is also slightly improved. This is mainly because the sampling interval of the wind speed is 1 hour and the data is extremely abrupt. Therefore, in multi-step prediction, it is difficult to correctly predict the peak point. Even so, the CI fusion model gives stable and better results than a single predictor such as LSTM and GRU.

Table 2. The RMSE of five results from different models

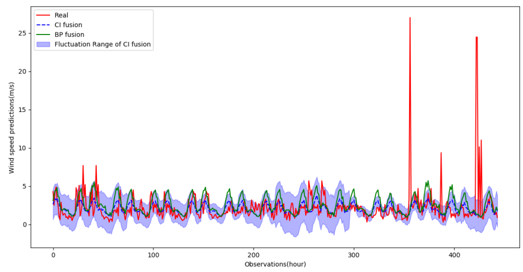
Model	RMSE(T)	RMSE(WS)
ConvBiLSTM	2.4131	2.4843
CI fusion	2.3235	2.4784

3.4 Results of Case No. 2

In the second experiment, we mainly compared the results of the two fusion methods of linear fusion method CI and nonlinear backpropagation neural network (BP). In Section III, we can see that the CI fusion method gives an optimal variance of the results, while the BP fusion algorithm can only give a series of predicted values. Figure 4 shows the prediction results of the two fusion methods. Based on this, we propose a more reasonable evaluation method, which uses the optimal variance of the predicted values to estimate the possible fluctuation range of the predicted values. As can be seen from Figure 4, most of the values in the predicted sequence are within reasonable fluctuations. A few outliers can be understood as noise of data.



(a) Fusion results of T predictions



(b) Fusion results of WS predictions

Figure 4. Results of two fusion methods

The root mean square error of the two fusion algorithms is shown in Table 3. As can be seen from Table 3, the CI fusion algorithm is improved by 11% when predicting temperature. 21.9

4 Conclusion

This paper mainly establishes a general multi-step prediction network framework for complex sensor timing data. Firstly, three sub-models of LSTM,

Table 3. The RMSE of BP and CI fusion algorithm

Model	RMSE(T)	RMSE(WS)
ConvBiLSTM	2.4131	2.4843
CI fusion	2.3235	2.4784

GRU, ConvBiLSTM are used to model the same data in time synchronization. In the sub-predictor ConvBiLSTM, the original data is decomposed into simple sub-sequences by using STL decomposition technology to reduce the influence of noise on network training, and then the combined convolution and BiLSTM network is established to extract the features on the two dimensions of the horizontal and time stamps for the multi-feature components. By designing the CI fusion algorithm, the results of the three sub-models are combined to obtain better prediction accurate. This not only ensures the accuracy of different variables, but also gives a reasonable quantitative evaluation method. The three sub-models have different performances in different variables and different prediction periods. For this reason, we use CI methods to synthesize different prediction results to ensure the accuracy of the framework. In the CI fusion module, we calculate the step size estimation variance by overlapping data, and finally obtain more accurate prediction results and range of variation, which can explain the prediction result comprehensively instead of the evaluation with only prediction values.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgement

This work was supported in part by the National Natural Science Foundation of China No. 62173002.

References

[1] Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50, 159-175.[CrossRef]

[2] Thissen, U. V. B. R., Van Brakel, R., De Weijer, A. P., Melssen, W. J., & Buydens, L. M. C. (2003). Using support vector machines for time series prediction. *Chemometrics and intelligent laboratory systems*, 69(1-2), 35-49.[CrossRef]

[3] Tay, F. E., & Cao, L. (2001). Application of support vector machines in financial time series forecasting. *omega*, 29(4), 309-317.[CrossRef]

[4] Mikolov, T., Karafiát, M., Burget, L., Cernocký, J., & Khudanpur, S. (2010, September). Recurrent neural network based language model. In Interspeech (Vol. 2, No. 3, pp. 1045-1048).[CrossRef]

[5] Mikolov, T., Kombrink, S., Burget, L., Černocký, J., & Khudanpur, S. (2011, May). Extensions of recurrent neural network language model. In *2011 IEEE international conference on acoustics, speech and signal processing (ICASSP)* (pp. 5528-5531). IEEE.[CrossRef]

[6] Connor, J. T., Martin, R. D., & Atlas, L. E. (1994). Recurrent neural networks and robust time series prediction. *IEEE transactions on neural networks*, 5(2), 240-254.[CrossRef]

[7] Gers, F. A., Schmidhuber, J., & Cummins, F. (2000). Learning to forget: Continual prediction with LSTM. *Neural computation*, 12(10), 2451-2471.[CrossRef]

[8] Fu, R., Zhang, Z., & Li, L. (2016, November). Using LSTM and GRU neural network methods for traffic flow prediction. In *2016 31st Youth academic annual conference of Chinese association of automation (YAC)* (pp. 324-328). IEEE.[CrossRef]

[9] Malhotra, P., Vig, L., Shroff, G., & Agarwal, P. (2015, April). Long Short Term Memory Networks for Anomaly Detection in Time Series. In Esann (Vol. 2015, p. 89).[CrossRef]

[10] Che, Z., Purushotham, S., Cho, K., Sontag, D., & Liu, Y. (2018). Recurrent neural networks for multivariate time series with missing values. *Scientific reports*, 8(1), 6085.[CrossRef]

[11] Yao, S., Hu, S., Zhao, Y., Zhang, A., & Abdelzaher, T. (2017, April). Deepsense: A unified deep learning framework for time-series mobile sensing data processing. In *Proceedings of the 26th international conference on world wide web* (pp. 351-360).[CrossRef]

[12] Osogami, T., Kajino, H., & Sekiyama, T. (2017, July). Bidirectional learning for time-series models with hidden units. In *International Conference on Machine Learning* (pp. 2711-2720). PMLR.[CrossRef]

[13] Wu, Y., & Tan, H. (2016). Short-term traffic flow forecasting with spatial-temporal correlation in a hybrid deep learning framework. *arXiv preprint* arXiv:1612.01022.[CrossRef]

[14] Liu, Y., Zheng, H., Feng, X., & Chen, Z. (2017, October). Short-term traffic flow prediction with Conv-LSTM. In *2017 9th international conference on wireless communications and signal processing (WCSP)* (pp. 1-6). IEEE.[CrossRef]

[15] Du, S., Li, T., Yang, Y., & Horng, S. J. (2019). Deep air quality forecasting using hybrid deep learning framework. *IEEE Transactions on Knowledge and Data Engineering*, 33(6), 2412-2424.[CrossRef]

[16] Kim, S., Hong, S., Joh, M., & Song, S. K. (2017). Deeprain: Convlstm network for precipitation prediction using multichannel radar data. *arXiv preprint* arXiv:1711.02316.[CrossRef]

[17] Garcia, F., Mirbach, B., Ottersten, B., Grandidier, F., & Cuesta, A. (2010, September). Pixel weighted

average strategy for depth sensor data fusion. In *2010 IEEE International Conference on Image Processing (pp. 2805-2808)*. IEEE.[CrossRef]

[18] Rojo, J., Rivero, R., Romero-Morte, J., Fernández-González, F., & Pérez-Badia, R. (2017). Modeling pollen time series using seasonal-trend decomposition procedure based on LOESS smoothing. *International journal of biometeorology*, 61, 335-348.[CrossRef]

[19] Li, S., Kwok, J. T., & Wang, Y. (2002). Multifocus image fusion using artificial neural networks. *Pattern recognition letters*, 23(8), 985-997.[CrossRef]

[20] Qiu, X., Ren, Y., Suganthan, P. N., & Amaratunga, G. A. (2017). Empirical mode decomposition based ensemble deep learning for load demand time series forecasting. *Applied soft computing*, 54, 246-255.[CrossRef]

[21] Pu, L., Feng, X., & Hou, Z. (2019, May). Covariance intersection fusion for visual tracking with hierarchical features. In *Tenth International Conference on Graphics and Image Processing* (ICGIP 2018) (Vol. 11069, pp. 1158-1166). SPIE.[CrossRef]

[22] Niehsen, W. (2002, July). Information fusion based on fast covariance intersection filtering. In *Proceedings of the Fifth International Conference on Information Fusion*. FUSION 2002.(IEEE Cat. No. 02EX5997) (Vol. 2, pp. 901-904). IEEE.[CrossRef]

[23] Hurley, M. B. (2002, July). An information theoretic justification for covariance intersection and its generalization. In *Proceedings of the fifth international conference on Information Fusion*. FUSION 2002.(IEEE Cat. No. 02EX5997) (Vol. 1, pp. 505-511). IEEE.[CrossRef]

[24] Julier, S., & Uhlmann, J. K. (2017). General decentralized data fusion with covariance intersection. In *Handbook of multisensor data fusion* (pp. 339-364). CRC Press.[CrossRef]

[25] Gupta, M., & Gupta, B. (2018, August). An ensemble model for breast cancer prediction using sequential least squares programming method (slsqp). In *2018 eleventh international conference on contemporary computing (IC3)* (pp. 1-3). IEEE.[CrossRef]

Hanchi Ren graduated from Swansea University in 2023 with a PhD's degree in Computer Science. His research focuses on Computer Vision, Privacy Preservation, Machine Learning, Deep Learning. (Email: hanchi.ren@swansea.ac.uk)

Yeqing Wang graduated from Beijing Technology and Business University in 2022 with a Bachelor's degree in Automation. He is currently a graduate student in Control Theory and Control Engineering at the same university. His research interests include pattern recognition and prediction, deep Learning, and related fields. (Email: wangyeqing@st.btbu.edu.cn)

Huijun Ma graduated from Changchun Institute of Optics and Mechanics with a master's degree in atomic and molecular physics in 2010. She is currently an on-the-job doctoral student in systems science at Beijing Technology and Business University. Research directions include complex system modeling, pattern recognition and information fusion, machine learning, etc. (Email: mahuijun@th.btbu.edu.cn)