Forecasting product quality using peephole long short-term memory

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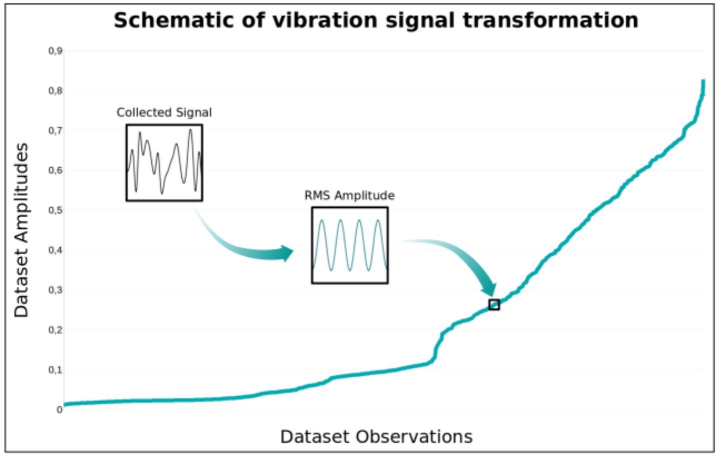
Introduction

Introduction

- Forecasting is essential in manufacturing to **predict the future health of manufacturing systems and plan maintenance activities**.
- Existing studies focus on using process data (**sound, vibration, magnetic**) for predicting system health.

Figure 1: An example of the correlation between vibration data and system health (represent by the increase in vibration amplitudes)



- Limited studies use **product quality data** for forecasting in manufacturing.
- Analyzing product quality data can help identify **patterns, trends, and potential issues in manufacturing processes**.

Challenges in Product Quality Forecasting

Product quality forecasting has several challenges as follows:

- Short-term product quality time series is **nonlinear**, **non-stationary**, and **non-seasonal**.
- **Limited additional information** is available for learning in univariate forecasting compared to multivariate forecasting.
- Forecasting accurately over **a long-time horizon (multi-step ahead)** requires effective methods.

In this study, we propose Peephole Long Short-Term Memory (LSTM)-based Recurrent Neural Networks (RNNs).

- This model can **effectively** forecast product quality data.
- Experiments demonstrate **the superiority** of LSTM-based RNNs over other forecasting methods.

Proposed Model

Feedforward Neural Networks (FNNs)

Feedforward Neural Networks (FNNs): is a neural network architecture in which information goes forward from the input to the output layer.

⇒ **However, when the size of the input increase, we have to change the number of input units.**

Recurrent neural networks (RNNs) have the same elements as FNNs but have additional recurrent connections.

⇒ **These connections help RNN has the flexibility to capture the information of sequence data with different length.**

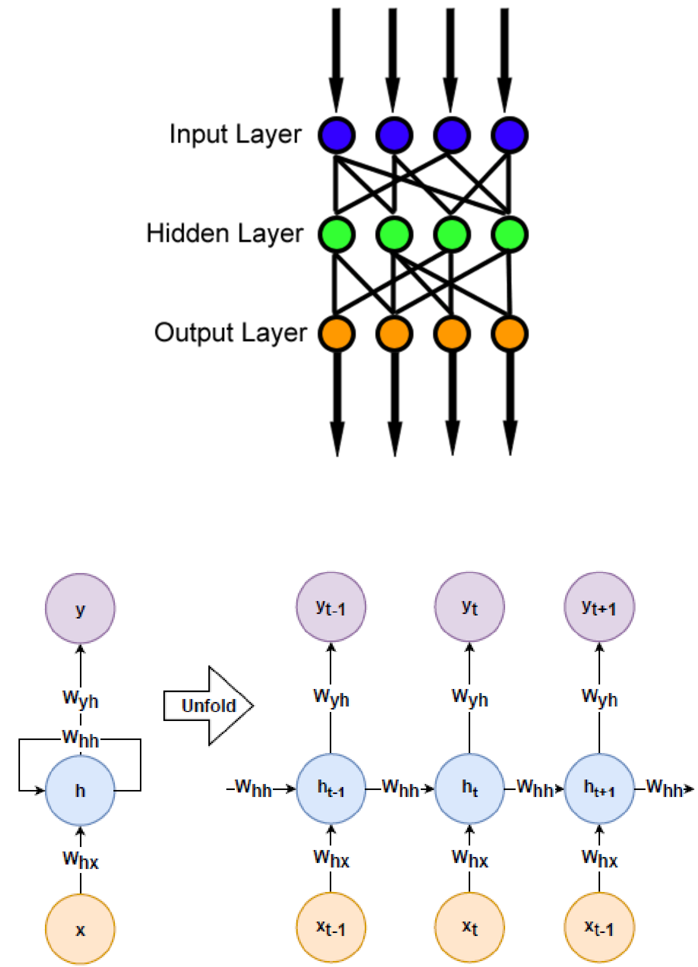


Figure 2: The architecture of FNNs and RNNs

Long-Short-Term Memory (LSTM)

When the length of the input is relatively large, RNNs have a problem with optimization (**gradient vanishing**)

To overcome the vanishing problem, they use the Long-Short-Term Memory (LSTM) cell in RNNs

- The LSTM has additional forget, input, update, and output gates.
- These gates can learn to **memorize long-term and short-term information separably and effectively.**

In order to get better memory utilization, in this study, the peephole connections were added to LSTM.

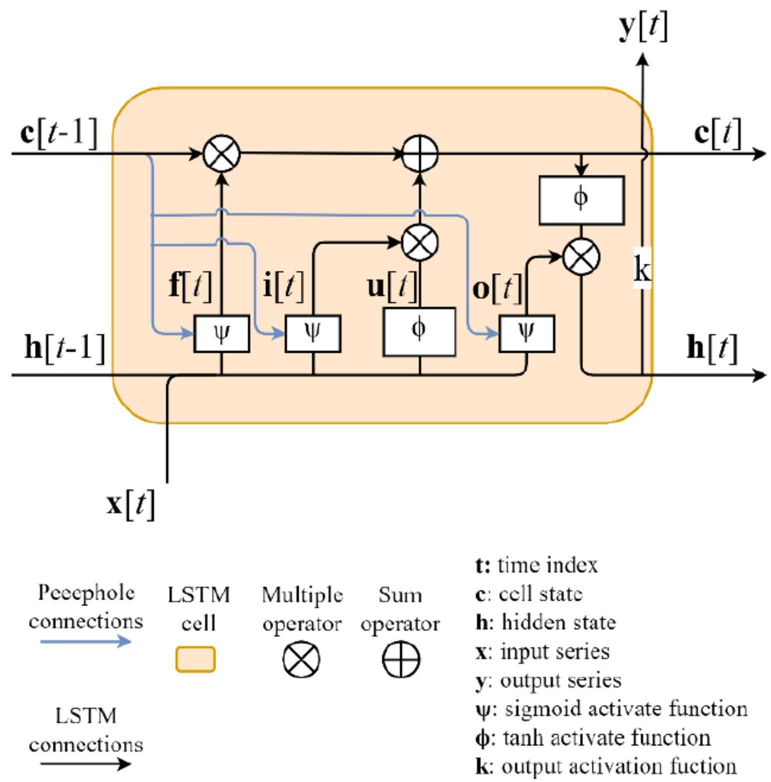


Figure 3: The architecture of peephole LSTM cell

Forecasting Scheme

Forecasting Scheme

To forecasting multiple ahead-of-quality data, we use a "Multi Input Multi Output (MIMO)" strategy

Specifically,

- Given the input time series **s(t) = {s_1, s_2, …, s_{nT}}** with n_T is input length
- LSTM transforms **s(t)** into output time sequences:
    - **Output: y = {y_1,y_2,…,y_H}** with H is the output length

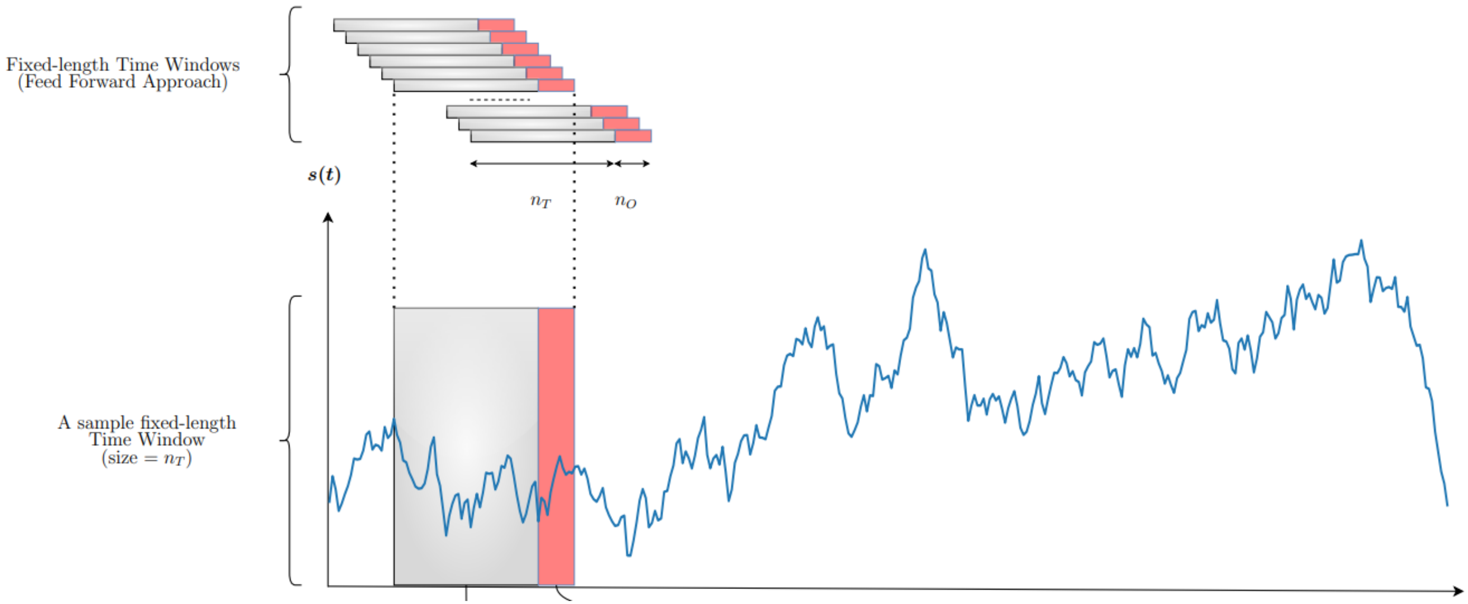


Figure 4: Forecasting scheme

Experiment Result

Experimental Results

We evaluate the model's performance based on 3 metrics:

- root mean square error (RMSE)
- mean absolute percentage error (MAPE),
- and R2 score

Given the forecasting result $\hat{\mathbf{y}} = \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_H\}$ and the actual value $\mathbf{y} = \{y_1, y_2, \ldots, y_H\}$

$$RMSE = \sqrt{\frac{1}{H}\sum_{1}^{H}(y_i - \hat{y}_i)^2}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2},$$

$$MAPE = \frac{100\%}{H}\sum_{1}^{H}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

We compare **peephole LSTM** with 3 baseline methods:

- Support vector regression
- SARIMA
- Convolutional neural network

Forecasting in Airline Passenger dataset

To demonstrate the generalize, we apply our model to a public dataset “Airline Passenger”.
We use a forecasting horizon equal to 12 (H = 12)

Table 1. Forecasting RMSE, MAPE, and R2 score for the Airline Passenger Data Set

Forecasting method	RMSE	MAPE	R2
SVR	0.1565	0.1749	0.0970
SARIMA	0.1393	0.1703	0.0499
CNN	0.1659	0.1921	**0.5184**
LSTM	**0.1059**	**0.1509**	0.4508

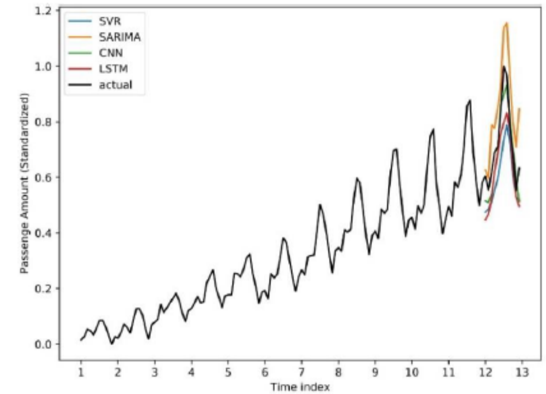


Figure 3. Comparison of the results for the international airline passenger data set both within and outside of the sample

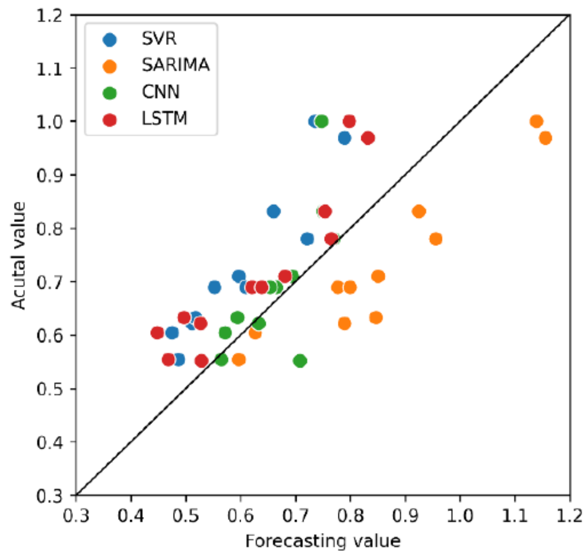


Figure 5. Predicted and actual value of the forecasting methods for international airline passenger data set.

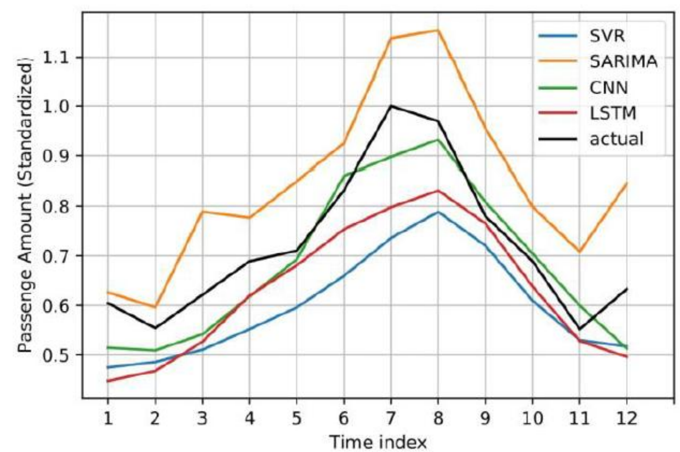


Figure 4. Comparison of forecasting performance for the international airline passenger data set.

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Forecasting in Quality Dataset

We utilized 720 observations of product quality data to predict future quality over a 24-step horizon (H = 24). The result is shown as flowing:

Table 2. RMSE, MAPE, and R2 score results for the Product Quality Data Set

Forecasting method	RMSE	MAPE	R2
SVR	0.1660	0.2220	0.2650
SARIMA	0.1918	0.3550	0.1227
CNN	0.1509	**0.1820**	**0.4640**
LSTM	**0.1280**	0.2320	0.2261

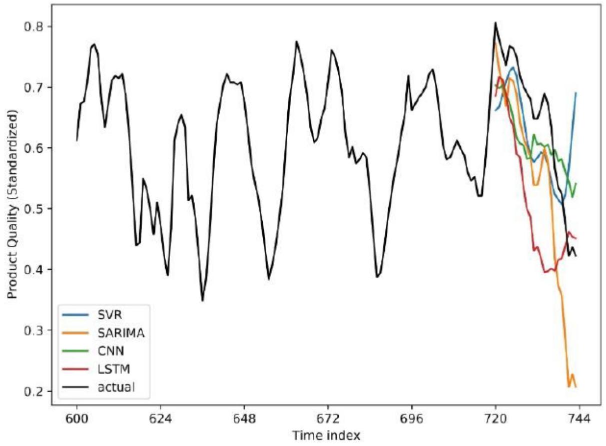

Figure 6. Comparison of in-sample and out-of-sample performance for the product quality dataset

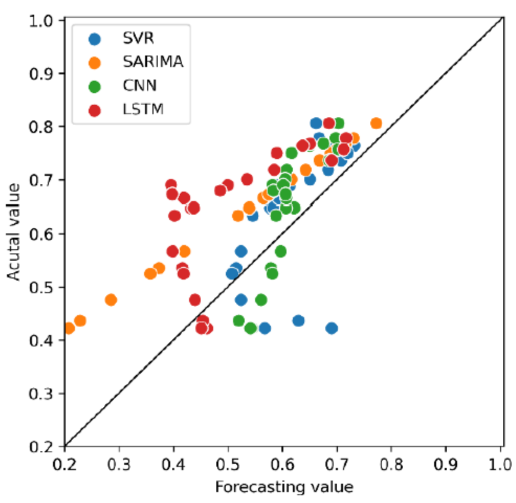

Figure 8. Predicted and actual value of the forecasting methods for international airline passenger data set.

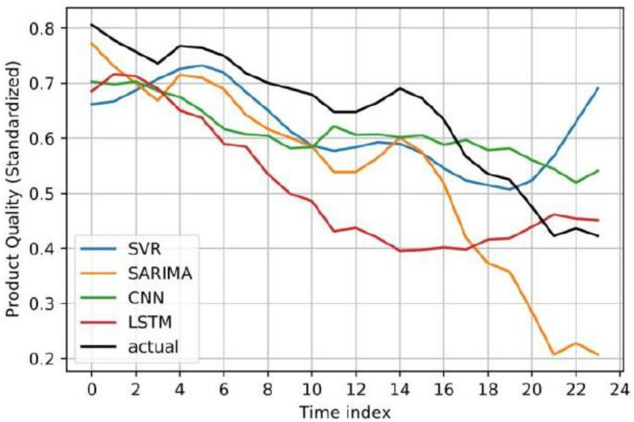

Figure 7. Comparison of forecasting results for the product quality data set.

Conclusion

Conclusion

In summary, this study recommends using **LSTM-based RNN for accurate short-term product quality forecasting** by leveraging long-term dependencies in time series data.

The proposed method **outperforms traditional forecasting techniques** in predicting complex and non-stationary product quality patterns, as demonstrated through tests on **benchmark airline passenger data** and **a comprehensive roasting process dataset**.

Questions and Discussion