Forecast of drainage in lowland agricultural area using LSTM deep learning
-Case study in Shintone watershed-

Shuhei IKEDA
Supervisor: Tasuku KATO (TUAT) Claudio Gandolfi (UNIMI)

Ⅰ.Introduction

The effects of global warming include rising sea levels, regional changes in precipitation, more frequent extreme weather events such as heat waves, storms and expansion of desert.[1] Japan is particularly vulnerable to flooding because of its steep geography and humid climate characterized by typhoons. Japan has been coping with the problem of flood control for a long time.[2] Although we have several methods to forecast flooding, they are not quite accurate and credible.[3] Therefore, flood disaster risk mitigation plans should be properly prepared and implemented for mid- long-term future floods considering climate change impact and mitigate flood risk in river basin. Holger et al ANN (Artificial Neural Network) for the forecast of water resource is available in river systems.[4] After for years, another research for urban water supply forecasting was conducted with different way, named Long Short Term Memory network. LSTM is a kind of Artificial Neural Network, which can extract input features and reflect it to regression analysis.

Ⅱ. Objective

In this study, a medium- and long-term flow forecasting system is proposed for management of a drainage pumping station with develop an LSTM deep neural network model to forecast the water volume from the draining station, based on observed data.

Ⅲ. Study area

Shintone river basin is located in South part of Ibaraki prefecture in Kanto region, Japan. Shintone river flows to Kasumigaura Lake which is the second largest lake in Japan, through Agricultural area. it is 2,377(ha) with pipeline allocation system and the irrigation and drainage water are fully controlled by 2 irrigation pumps (Pump1 and Pump2 are for irrigation) and 1 drainage pump (Pump3) because the basin is topographically called lowland flat field and lower elevation than surrounding river.

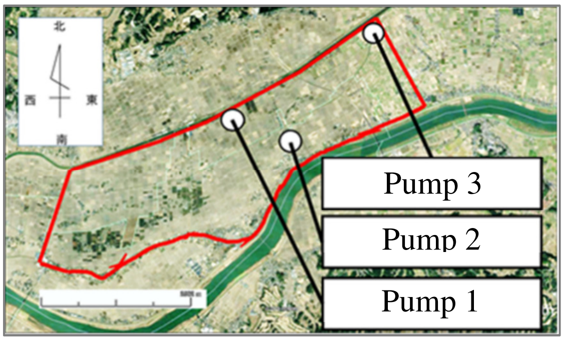

Fig.1 Research site and Pumps location

Ⅳ. Materials and Methods

Dataset during the period 2014-19 used on this research is below.

1. Pump Irrigation and drainage dataset
2. Precipitation (m^3) Temperature (℃), Humidity (%), radiation (MJ/m2)

The dataset of 2014-2018 was supervised into the LSTM, and 2019 dataset was used as forecast simulation. At first, its optimised hyperparameters and input data were extracted by several experiments. Hidden Layers, Learning Rate, Iteration Epochs are 350, 0.02, 15000 respectively. RMSE (Root Mean Square Error) and NSE (Nash-Sutcliffe Efficiency) were adopted to evaluate their simulation quality. RMSE is the standard deviation of the residuals (forecast errors). NSE measures the ability to forecast variables different from the mean and gives the proportion of the initial variance accounted for by the model.

Ⅳ. Result and Discussion

The simulation result of LSTM (LSTM-1)is showed with DNN Feed Forward simulation result and observed data to look at the accuracy and compare the improvement in Fig.2. The huge

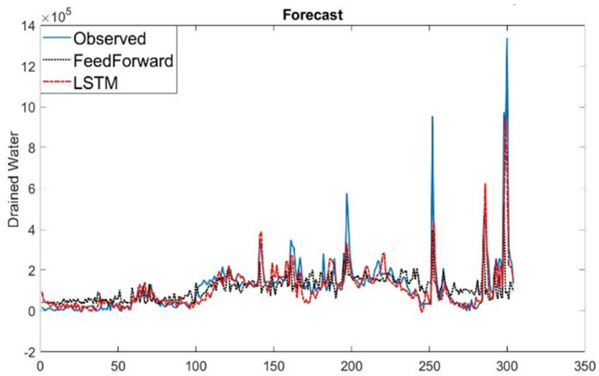

Fig.2 Simulation comparison of LSTM network
DNN Feed Forward

14th/Oct, respectively) by the strong typhoon attacks. The huge error was observed at Day 252, 98-300 (5th/Sep, 12-14th/Oct, respectively) by the strong typhoon attacks. It occurred a flood and larger drainage on study site since record breaking heavy rainfalls. The supervised dataset (2014-2018) used for training, did not include that magnitude rain events although Japan was attacked by several typhoons in the term of different years. Feed Forward deep neural network's RMSE is 115,428 as shown in Table 1. The result is further values than LSTM-1 (76,868). Feedforward does calculate only one direction from Input to Output Layers via Hidden Layers in a row. LSTM however, has a loop circle feature making the network deeper learning. In addition, forget gate, input gate, output gate are existed to judge which supervising data should be suitable to remain for later calculations improved.[5] As a result, the accurate forecast of the maximum drainage water flow value during the typhoon season is difficultly caught up, but even the others hydrological models also are not able to forecast those irregular events because of areas with complex topography and steep slopes. Overall, LSTM-1 obtained a great score on NSE.

Table 1 Model validation

	RMSE(m^3)	NSE
LSTM-1	76868	0.6973
FeedForward	115428	0.3175

Ⅴ. Conclusion

To consider about flooding in the future, we cannot ignore disasters caused by climate change. Thus, this research established a medium- and long-term water flow forecast system with an LSTM deep neural network model. Its results indicated that LSTM performance was better for forecasting water quantity data from past compared to a typical DNN: Feed Forward network. Looking at the forecast results, the forecast using LSTM-1 showed that better forecast than traditional neural network and it is acceptable as a forecast model according to NSE validation, 0.69. Although the forecast simulation was not following the same values as the observed values, all the water fluctuation peaks was followed. LSTM can forecast future discharge directly from actual observation data (Pumps / weather data). That is, soil texture and hydrological data are not required for model construction and forecast. LSTM is an effective forecast method even in areas where maintenance is not possible since it can construct a discharge / runoff forecast model for the relevant block if sufficient past weather data and drainage data are obtained.

To forecast some different output such as water quality through water quantity data, is quite interesting and somehow innovative. It must facilitate our research to proceed another stage. In fact, the system is currently under manual control, we can try to establish a program system automatically involving new observed data to itself, mitigating water flood disaster.

Ⅵ. REFERENCES

[1]Van Aalst et al.(2006), The impacts of climate change on the risk of natural disasters.
[2]Takahasi et al. (2004) Evolution of river management in Japan
[3]Toshiaki et al. (2003) Basic study on the use of a neural network to forecast flooding on the Abukuma river
[4] Holger et al. (2010) Methods used for the development of neural networks for the forecast of water resource variables in river systems:
[5] Gers, F.A.et al.(1999) 'Learning to forget: continual prediction with LSTM'