Proposal and Evaluation of Pavement Deterioration Prediction Method by Recurrent Neural Network

Tomoyuki Okuda
Graduate School of System Design and Management
Keio University
Kohoku Yokohama, Japan
t.okuda@keio.jp

Kouyu Suzuki
Infrastructure Management Department
Pasco Corporation,
Japan

Naohiko Kohtake
Graduate School of System Design and Management
Keio University,
Japan

***Abstract*— The pavement deterioration prediction model is a basic module of the PMS (Pavement Management System), and its prediction results influence the decision making of pavement administrators. Hence, it is very important to improve prediction accuracy. There is a rutting depth as a major indicator showing the state of pavement used in PMS. In this research, we propose a method to predict rutting depth by introducing a technique to improve prediction accuracy by suppressing over-fitting by dropout and gradient clipping in the recently rapidly developing NN (Neural Network) model. In addition, since pavement survey data are time series data that were inspected at the same place multiple times, we applied the RNN (Recurrent Neural Network) model which can model time series data. The proposed method was applied to rutting depth prediction of periodic survey data of Kawasaki city in Japan from 1987 to 2016. In order to compare prediction accuracy, we predicted three years later using proposed method and MLR (Multiple Linear Regression) which is a typical regression model and MLP (Multi-Layer Perceptron) which is most frequently used among NN models. The RMSE and correlation coefficient R between the prediction result and the measured value were compared. We validated that the prediction ability of RNN is the highest.**

***Keywords*—pavement management system; pavement condition survey; recurrent neural network; neural network; machine learning;**

I. INTRODUCTION

Pavement is one of the most important elements for supporting social infrastructure, and it is always required to maintain efficiently under budget constraints. In order to make pavement maintenance management more efficient, pavement management system (PMS) has been studied and operated conventionally [1].

Prediction of pavement deterioration is a major function of PMS. Efficient repair and rehabilitation plan use the prediction results to formulate and implement future plans and to simulate future state changes in various scenarios. Based on the prediction results, each pavement administrators will make decisions on planning and implementation of maintenance management. Therefore, the prediction accuracy of the pavement deterioration prediction model greatly affects the maintenance and management planning and implementation. Hence, it is very important to improve the prediction accuracy.

However, due to various factors such as construction quality, weather conditions, traffic loading and so on [2], the deterioration process of pavement is very complicated. There is NN (Neural Network) model as a model that can learn such complicated relation. The NN model is suitable for learning the nonlinear and complicated relationship between input variables and output variables[3]. In the conventional NN model, it was difficult to improve prediction performance owing to the problem of over fitting, but in recent years the problem of over fitting has been solved by introducing learning techniques such as dropout [4] and gradient clipping [5]. In addition, since the survey result of the pavement used as the object of deterioration prediction of the pavement is time-series data which regularly inspects the same place, it can be modeled by RNN (Recurrent Neural Network) applying the NN model to the time series prediction.

In this research, we propose a prediction method by RNN model for rutting depth (RD), which is one of main indicators showing the condition of pavement. The proposed method is applied to predict rutting depth of periodic survey result of Kawasaki city in Japan from 1987 to 2016 and the prediction ability has been thoroughly evaluated.

II. REVIEW OF PAVEMENT DETERIORATION PREDICTION MODEL

The pavement deterioration prediction method has various kinds of prediction methods depending on the accuracy of the indicator showing the state of the pavement to be predicted, the input variable used for prediction, preprocessing of the data, the algorithm of the deterioration prediction model and so on. Among them, the deterioration model algorithm can be roughly classified into the following three types.

1) Mechanical Model

The method 1 is a method of calculating the deformation / destruction amount of pavement from finite element method from detailed attribute information such as temperature,

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Young's modulus, aggregate particle size, pavement composition and the like and pavement force due to traffic load [6], [7]. This method is used to study pavement design and materials because it can understand micro change such as deformation of each layer constituting the pavement.

2) Statistical model

The second modeling algorithm type is a method of modeling with several input variables such as traffic load and elapsed years, with observation values representing pavement state as objective variables. Unlike method 1, this method does not use dynamic relationships. Experts formulate the

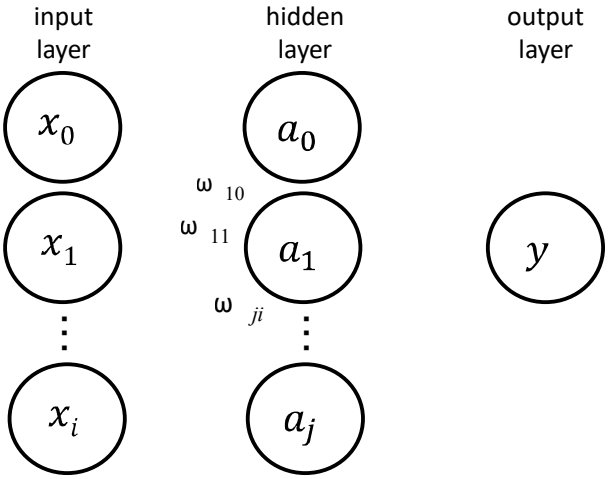


Fig. 1. MLP architecture

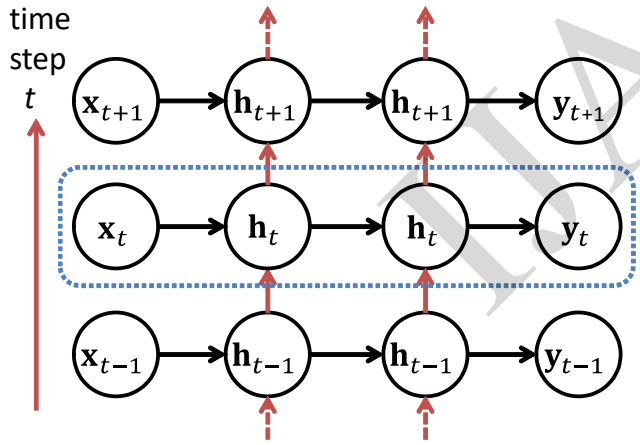


Fig. 2. RNN architecture

relationship between explanatory variables and objective variables, and then determine the parameters of the formulas from the data. Some of the examples of statistical model are: The linear / nonlinear regression model [8], [9], and Markov Chain [10], [11] and Bayesian statistical model [12], [13].

3) Machine learning

The third type differs from second type in that it automatically learns the relationship from the data without explicitly modeling the relationship between the objective variable and the explanatory variable. The most frequently used model of this type is the MLP model [3], [14], [15].

The MLP model is the most basic model of the NN model. On the other hand, in recent years numerous application methods of the NN models have been proposed [16], [17]. With these proposed models, the prediction accuracy higher than the conventional method has been achieved in fields such as image recognition and speech recognition. Since the survey results of the pavement are usually time series data obtained by inspecting the same unit section more than once, degradation prediction by the RNN model adapted to time series prediction is possible among various application methods of the NN model [18].

III. PROPOSED METHOD

NN is a simple model of neurons mimicking nerves of living things, in which a plurality of the neurons is connected. Based on the difference between the output value of the model and the observation data, the model adjusts the value of the weight so that the output value becomes closest to the observation value by using the error back propagation method.

The feature of the pavement deterioration prediction method proposed in this research is to use GRU (Gated Recurrent Unit) which learns faster than LSTM (Long Short-Term Memory) which was used most frequently as RNN model [19]. Moreover, in order to suppress over learning, dropout in the same time [20] and time direction [21] and gradient clipping [5] were applied. Adam was used to improve the efficiency of learning rate setting. Also, it is to use ReLU to deal with gradient elimination problem. In this research, the model was implemented by Chainer [22] .

A. MLP Model

The MLP model is a model in which neurons are stacked in multiple layers and is one of the machine learning algorithms that is most used for predicting pavement deterioration. A three-layer MLP model is shown in Figure.1 The state of the neuron is called activity, and the value of the activity a_j of a certain neuron j is obtained by the following equation.

$$a_j = \sum_i \omega_{ji} x_i \qquad (1)$$

Here, x_i is input data in (i = 1,..., n) dimensions, and ω_{ji} is a weight parameter. This a_j was converted by ReLU (Rectified Linear Unit Rectifier)

$$z_j = \mathrm{ReLU}(a_j) \qquad (2)$$

This z_j is the output of neuron j. Here, ReLU(・) is

$$\mathrm{ReLU}(x) = \max(0, x) \qquad (3)$$

By this nonlinear activation function, it is possible to learn the nonlinear relationship between input and output. This calculation is repeated from the input layer to the output layer to obtain the prediction value y.

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B. RNN Model

The architecture of the RNN model is shown in Figure.2. The RNN model is a model in which a connection in the time series direction is added to the MLP model. Processing in the region surrounded by the blue dashed line corresponds to the normal MLP. In addition to the MLP, the RNN has an internal state h_t to transmit information in the time direction. This h_t holds the state of the whole hidden layer and becomes the input to the same hidden layer at the next time (t + 1). By this recurrent connection, information is transferred from (t – 1) internal state h_t to h_{t+1}. Through this connection, we take over all past internal state and determine the current output value y. By doing so, we can model time series data and treat it as a time series prediction model which considers all past time series. There are several types of RNNs. Conventionally LSTM was used more often. However, in recent research GRU was proposed because of its faster learning rate and similar precision compared to LSTM [19].

C. Learning technique of NN models

Over-fitting is known as a problem of lowering prediction accuracy of NN. To avoid this problem, we use dropout [4] and gradient clipping [5]. Dropout forcibly lowers the degree of freedom of the network by invalidating the connection between the layers randomly at the time of learning, and suppresses over fitting. In addition, gradient clipping forces the value of the weight parameter to be below the threshold when the gradient of the network becomes equal to or higher than the set threshold. In addition, Adam [23] which adjusts the learning rate automatically is also used for efficient learning.

It is known that RNN cannot learn well if simply applying dropout to interlayer connections like MLP. Therefore, in this study, we implemented dropouts only within the same time by Stanislaus [20] method which recorded the highest accuracy in some natural language processing tasks. Also, since RNN has a time direction coupling, it is conceivable to apply a dropout in the time direction, apart from the normal dropout for the connection from the input layer to the output layer. In this research, time dropout was applied by variational dropout [21].

D. Data Description

The data used for the verification in this research is survey history data that Kawasaki City conducted a survey of the road surface at about 3-year intervals on major routes. As accuracy evaluation at the time when it was not investigated was impossible, accuracy was evaluated with prediction accuracy after 3 years. The investigation period is 30 years from 1987 to 2016, and one data is recorded for each unit section of 50 m for the route. After calculating the maximum ruffing amount for each traverse profile by the wireline reference method [24], the average value and the maximum value within the unit section are recorded. In addition, the survey target lane is only one lane for each route. We are investigating the lane on the most right side of the descending line as the representative lane. Figure 3 shows the description of data used as model inputs. Measurement interval in the longitudinal direction is 10 m, and data of average value (RDmean) and maximum value (RDmax) per unit section of 50 m are recorded. Therefore, in this research, we constructed an NN model with two outputs, RDmean and RDmax, as shown in the figure 3. In this way, the NN model has a high degree of freedom in selecting input and output variables, and it is also possible to learn the relationship between various input / output variables.

Input Variables
Previous RDmean
Previous RDmax
Daily Large car traffic volume
Daily Large car cumulative traffic volume
CBR
Elapsed years after treatment
Number of years elapsed from the previous survey
Road width
Paving thickness
Treatment or not
Structure
Previous treatment method

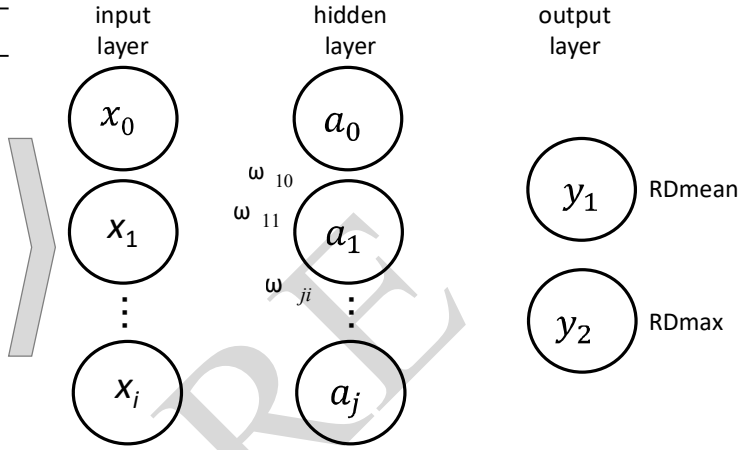


Fig. 3. Proposed model archtechture

Other features related to the used data are shown below.

- Measurement of the rutting depth is carried out by a device that passed the performance confirmation test of the road surface condition automatic measuring device performed by Public Works Research Counter (PWRC). The validation accuracy of the test is ± 3 mm with respect to the observation value using the straight edge.
- Daily large car traffic volume data was derived from the traffic census survey conducted by the Japan Ministry of Land, Infrastructure and Transport Since it is not recorded for each lane, the value simply divided

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Table I: Hyperparameter Of MLP AND GRU

Hyperparameter	MLP	GRU
Learning rate	0.001	0.001
Epoch	200	200
Mini-batch	50	50
Dropout rate	0.1	0.5
Time directional dropout rate	-	0.1
Gradient clipping	don't use	3
Number of hidden layers	2 hidden layer	2 hidden layer
Number of neurons in a hidden layer	15	20

Table II: Result of RMSE and R

	RDmean		RDmax	
	RMSE	R	RMSE	R
MLR	2.190	0.7702	3.710	0.7233
MLP	1.991	0.7949	3.446	0.7438
GRU	1.987	0.8021	3.437	0.7440

by the number of lanes is taken as the traffic volume per lane.

- The repair record is recorded only for repair planned by the road administrator. Therefore, there is no information when substantial repair was done due to occupation work such as sewerage work and local emergency allowance at site judgment. We eliminated this effect as much as possible by removing the outlier described later.
- Nominal scale variables (Treatment or not, Structure, Previous treatment method) are converted to dummy variables, and variables which are of proportional scales are regularized to be 0 on average and 1 in dispersion.
- Since the repair record does not exist, it is difficult to predict and was excluded. In addition, in the section where the inspection is not performed more than twice, there was no second observation value and it was not possible to verify the prediction accuracy, so it was excluded too.

The number of unit sections is 1,764 sections, the total number of data is 6,328, and the number of average time series data per unit section is 3.7.

E. Data splitting for cross validation

In the time series prediction model, 10-Fold cross validation, which divides learning data and validation data into 10 in the time direction, is usually used. However, if we divide it by 10 in the time direction, the RNN model cannot refer to all past time series. Therefore, we used learning data before 2006 and validation data after that. When predicting validation data after 2006, learning data was used as past time series. The number of data before 2006 was 2,865, and the number of validation data after that was 3,463.

F. Multiple Linear Regression Model

For comparison with the above NN model and GRU, MLR (Multiple Linear Regulation) was used. MLR is the most basic model of the regression model. In MLR, it is considered difficult to predict the repair section and the section without repair with the same model, so we used only the data of the section without repair.

IV. EVALUATION AND DISCUSSION OF APPLICATION RESULT

A. Learning Hyperparameters

For the simplicity, the number of hidden layers is two layers, and the number of neurons in the hidden layer is the same for two hidden layers. For each model of MLP and GRU, cross validation was performed under the conditions of 5 or 7 or 15 or 20 neurons in the hidden layer, drops 0.1, 0.3, 0.5, gradient clipping 1, 3 or none. Among them, the following evaluation was conducted using the model with the lowest RMSE of the verification data in each of MLP and GRU. Table I shows the set values of hyper parameter determined by this.

B. Evaluation of predicting performance

In order to evaluate the prediction performance, RMSE and correlation coefficient R value were obtained. Let RD_k^{pred} k=(1,…,K) be the predicted value and RD_k^{act} is the observation value, then RMSE is

$$\mathrm{RMSE} = \frac{1}{K}\sum_{k}^{K}(\mathrm{RD}_k^{act} - \mathrm{RD}_k^{pred})^2 \tag{7}$$

Correlation coefficient R is

$$\mathrm{R} = \frac{\mathrm{COV}(\mathrm{RD}_k^{act}, \mathrm{RD}_k^{pred})}{\sigma(\mathrm{RD}_k^{act})\sigma(\mathrm{RD}_k^{pred})} \tag{8}$$

where

$$\mathrm{COV}(\mathrm{RD}_k^{act}, \mathrm{RD}_k^{pred}) = \sum_{k}^{K}(\mathrm{RD}_k^{act} - \overline{\mathrm{RD}_k^{act}})(\mathrm{RD}_k^{pred} - \overline{\mathrm{RD}_k^{pred}}) \tag{9}$$

$$\sigma(\mathrm{RD}_k^{act}) = \sum_{k}^{K}(\mathrm{RD}_k^{act} - \overline{\mathrm{RD}_k^{act}})^2 \tag{10}$$

$$\sigma(\mathrm{RD}_k^{pred}) = \sum_{k}^{K}(\mathrm{RD}_k^{pred} - \overline{\mathrm{RD}_k^{pred}})^2 \tag{11}$$

Since RMSE represents the average prediction error value, the smaller the value, the smaller the error is. On the other hand, larger the R value, the better agreement between the predicted value and the observed value. Table II shows the validation results of RMSE and R for RDmean and RDmax in each model. RMSE decreases in the order of MLR> MLP> GRU. The correlation coefficient R shows that the higher the value, the higher the prediction performance. Therefore, it can be said that GRU has the highest prediction performance. Compared with MLR, GRU decreased by about 10% RMSE, but MLP and GRU did not differ greatly.

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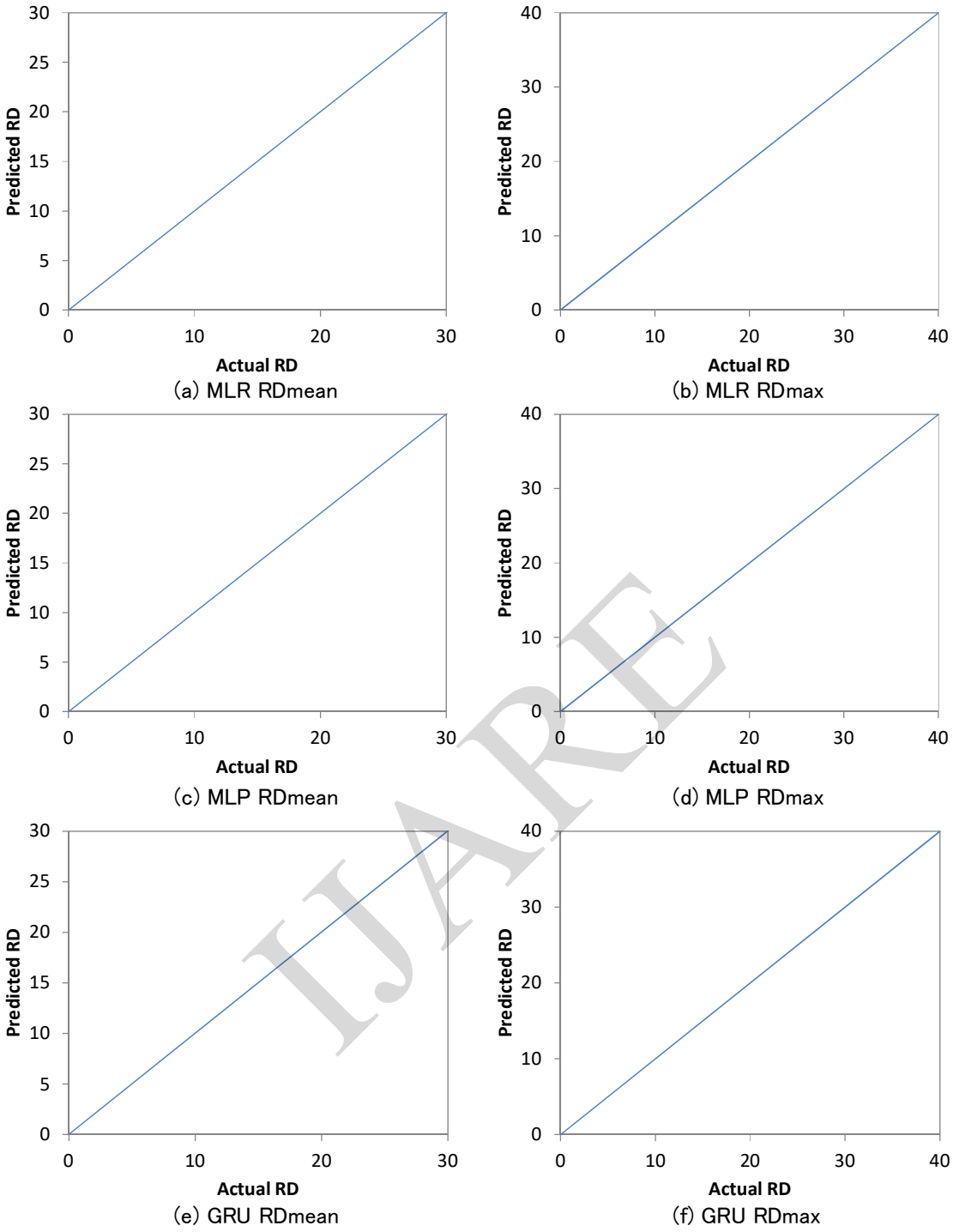


Fig. 4. Relations between actual and predicted rutting depth

C. Correlation of Predicted and Actual Rutting Depth

For each model of MLR, MLP, GRU, the relationship between the observed value and the predicted value of the section without the repair of the validation data is shown in the Figure 4. If there is a plot on the blue line, it means that the observed value and the predicted value are in agreement. Both plots are somewhat widely distributed from blue line. As stated above, the precision of the rutting depth measuring device is prescribed to be within ± 3 mm, and if it actually varies, it is difficult to eliminate the measurement error. Therefore, there is a variation of about 3 mm from the top of blue line, which is considered to be a barrier to reduce RMSE. There are slight differences in MLR, MLP and GRU. As we can see from the figure, GRU with high prediction performance succeeds in predicting a smaller value compared to MLR and MLP.

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Since the MLP model learns the relationship between input variables and output flexibly, it is suitable for learning the relationship between complex input variables and output variables. In this research, it was found that by introducing GRU with connection in the time series direction, which is an application of MLP model, prediction accuracy can be improved more than MLP which was used more frequently as NN model for pavement deterioration prediction.

V. CONCLUSION

Efficient maintenance management by PMS The prediction accuracy by the pavement degradation prediction model has a direct influence on the support of the plan and the decision of the road administrators. Therefore, the prediction accuracy of the deterioration prediction model is important. In this research, we propose a prediction method introducing an RNN model that can model time series data among NN models which have developed rapidly in recent years. The RNN model was found to have higher prediction accuracy than the conventional linear multiple regression and NN model.

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