Identification of the optimal time series machine learning algorithm for the prediction of the ground subsidence with TBM machine data

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ABSTRACT: Controlling ground settlement during tunnel excavation in urban areas is a challenging task for contractors even with tight and comprehensive monitoring. In this study, utilizing the settlement monitoring and the sensor data collected during TBM drive, penetration and settlement prediction models are built. We postulated that TBM machine sensors may capture both actions of the machine and the reactions of the ground. Hence the prediction of settlement can be made if an appropriate algorithm is applied. There are a few sequential algorithms such as vanilla LSTM, LSTM with attention, Transformer, and Informer. This paper attempts to identify the optimal algorithm for training sensor data with a sub-workstation equipped in TBM. By comparing the performances of the algorithms, the DALSTM is identified as optimal algorithm for TBM machine data. Furthermore, subsequent analyses are carried out to develop a settlement prediction model, which demonstrates exceptional performance, marking a promising step towards deployment of the proposed method.

Keywords: TBM, Subsidence Prediction, Machine Learning, Time Series, Sensor Data.

1 INTRODUCTION

The use of TBM in tunnel construction has been gradually increasing in recent years in order to meet high demand for infrastructures such as roads, railways, power supply, telecommunication etc., due to global urbanization. TBM machine has several advantages over the traditional tunneling methods in terms of various safety measures, such as closed mode operation which is applying support pressure on the excavation face with slurry or spoils, and instant support of concrete segment lining, etc., which are mitigating the risk of subsidence.

Numerous research has been conducted on the predictions of the settlement during design phases using analytical, empirical, and numerical methods. One of the most widely accepted analytic solutions is that of Peck (1969), which is based on the measurements from various projects, and modified for the application of TBM excavation for metro projects on mixed geological condition (You and Jung, 2019). However, the design stage predictions have limitations in terms of the uncertainty in construction stages, such as the unforeseen ground condition or inadequacy of construction means and methods.

Major causes of subsidence during the TBM operation are constructional issues such as unexpected geological conditions, over-excavation, untreated tail voids, curvature with short radius, and TBM operational issues such as a failure to maintain stable chamber pressure, too high advance rate, uncontrolled muck handling to name a few. Among them, it is known that face pressure and thrust force related factors are considered as governing factors (Kasper and Meschke, 2006).

The geological condition of the project in this study has a uniform but mixed condition which is layers of alluvial soil, weathered soil, weathered rock, soft rock from top to bottom of the tunnel face along the alignment of the project. Previous study shows that machine learning only with geological data, thus without machine data input, has poor performance in the estimation of settlement (Zhang et al., 2020). On the other hand, as settlement is statistically related with thrust force and advance rate, a more accurate estimation of settlement can be obtained.

In this study, using simple statistical methods, such as Pearson correlation, R2 (coefficient of determinations), RMSE etc., ten parameters, which demonstrate good correlation with penetration and related with settlement, are chosen for the prediction of settlement. With chosen parameters, prediction performance of vanilla LSTM, attention-based LSTM, DALSTM, Transformer and Informer are compared to identify the optimal algorithm for the training of machine data. As a result, the DALSTM method shows the best performance to predict the penetration of training and test sets of 10,660,000 fields of TBM machine data. Along with the training, parameters of hidden layers per each ring are taken and supplied together with settlement records of 49 settlement markers for the subsidence prediction model. After weeks of training and testing, the subsidence prediction model is successfully trained and demonstrated exceptional performance for test cases. The data used for this study is obtained from the TBM machine which was operated in closed mode thus only minimal amount of settlement around 10mm.

2 SELECTION OF PARAMETERS FOR MODEL CONSTRUCTION

The number of TBM sensors are more than thousands and even increasing year by year as the TBM machine becomes more advanced. However not every sensor is related to the penetration or the subsidence and it is impossible to incorporate all sensor data into neural network model due to the limitation of resources and computing power in usual construction site as well as extreme difficulty of maintaining the stability of training. Therefore, selection of most relevant parameters is mandatory to construct an efficient model suitable for the available computing power.

There are two categories of parameters employed in this study, which are related to machine operation with penetration records and subsidence measurements. Parameters related to penetration are chosen based on analyses, such as correlation of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE) shown in equation (1), however mean squared error (MSE) equation, which is the one without square root in RMSE, is omitted due to shortage of space.

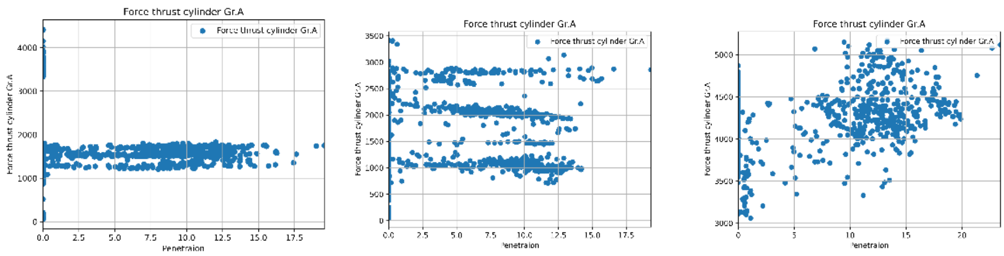
$$R^2 = 1 - \frac{\sum_i^n (y_i - \hat{y}_i)^2}{\sum_i^n (y_i - \bar{y}_i)^2}, MAE = \frac{1}{n}\sum_1^n |y_i - \hat{y}_i|, RMSE = \frac{1}{\mathrm{n}}\sqrt{\sum_{j=1}^n (y_i - \hat{y}_i)^2} \quad (1)$$

Table 1. Correlation of parameters with respect to penetration.

Items	COD(R^2)	MAE	MSE	RMSE
Chainage	-	-	-	-
Penetration	1.0	0.0	0.0	0.0
current pressure real lance	0.033	2.663	8.800	3.900
screw conveyor RPM	0.139	1.960	8.664	3.585
excavation chamber pressure	0.270	2.991	9.066	4.462
torque cutting wheel	0.457	1.640	7.164	2.909
calculated excavated material	9.437	9.508	9.650	9.553
actual excavated material	9.436	9.508	9.650	9.553
stroke thrust cylinder	9.650	9.650	9.650	9.650
thrust force	9.650	9.650	9.650	9.650

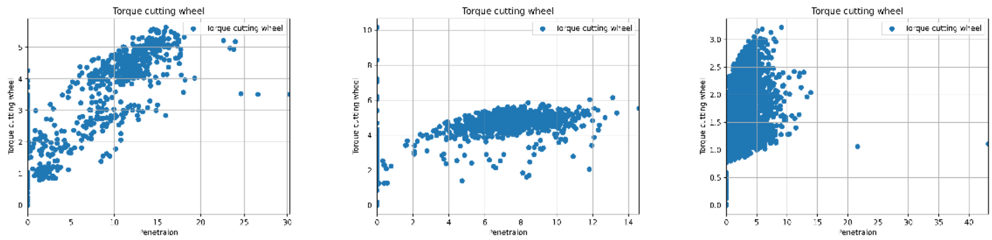
As shown in table (1), four parameters of high correlation with penetration and the rest of four parameters with low correlation were chosen. The latter were selected based on engineering judgement that these four parameters deemed related to subsidence. Chainage, which is the position along the alignment at any given time such as fixed settlement marker position or the location of TBM machine at that moment, showed neither high nor low correlation.

Figure (1) and figure (2) show scatter plots of correlations between penetration vs. thrust force of cylinder A, and penetration vs. torque of cutterhead. Figure (1) shows interesting patterns, i.e., linear correlations in some of ring data and no correlations in some other ring data. One potential explanation is that in the case of figure (1a) or (1b) the operator tried to maintain the thrust force and as the geological condition altered the penetration, whereas the case of figure (1c) the operator actively manipulated the thrust force to achieve target penetration. This may suggest that the geological conditions of each ring were captured as a response to the drive of TBM machine.



(a) ring 03 (b) ring 04 (c) ring 52

Figure 1. Penetration vs Thrust Force of Cylinder A.



(a) ring 99 (b) ring 105 (c) ring 119

Figure 2. Penetration vs Torque of Cutting Wheel.

Figure (2) shows the patterns of relationship between penetration and torque of cuttterhead, i.e., various sparsity and gradients. Figure (2a) demonstrates strong correlation between penetration and torque, and figure (2b) shows no or mild correlation, whereas figure (2c) shows low penetration as well as low torque. These trends also suggest that the underlying geological conditions as a reaction to the drive of the TBM machine as well.

3 CANDIDATE ALGORITHMS FOR TBM DATA

The first algorithm applied for this study is vanilla LSTM (Long Short-Term Memory) which is a type of recurrent neural network (RNN) that was first proposed by Hochreiter and Schmidhuber in 1997. LSTM is designed to overcome the problem of vanishing gradients in traditional RNN methods. LSTM has been successfully applied in a wide range of applications, such as speech recognition, natural language processing, and image captioning. Its ability to handle long-term dependencies makes it particularly suitable for tasks that involve sequential data.

The second algorithm is Dual Attention LSTM which is a type of neural network architecture that combines the capabilities of long short-term memory (LSTM) and dual attention mechanisms (Qin et al., 2017). The Dual Attention LSTM uses attention mechanisms to selectively focus on specific features in the input data, enabling the network to extract more relevant information and improve its overall accuracy. It utilizes both spatial and channel attention mechanisms to capture the interdependencies between different regions and channels of the input data. The combination of these allows the Dual Attention LSTM to effectively model complex relationships in the input data and achieve state-of-the-art results in a variety of tasks, such as image classification, and segmentation.

The third algorithm is Transformer which is designed for natural language processing (NLP) tasks (Vaswani et al., 2017). Transformer model is based on the attention mechanism and omission of recurrent network, which allows the network to handle the input parallelly. This mechanism enables the Transformer to capture long-range dependencies in the input sequence more effectively than previous models. Transformer has achieved state-of-the-art performance on a range of NLP tasks, including machine translation, language modeling, and question answering.

The final algorithm is Informer model which is a neural network architecture for time series forecasting (Zhou et al., 2020), extends Transformer model, which was originally designed for natural language processing, to time series forecasting by incorporating techniques such as dilated convolutions and causal attention. One of the key innovations of Informer model is its multi-scale feature representation. Informer model also employs a novel residual connection mechanism that helps to stabilize the training process and improve the model's accuracy.

4 COMPARISON OF THE PERFORMANCES OF ALGORITHMS

Using the parameters chosen in the previous section, the performance of DL algorithms, LSTM, DALSTM, Transformer and Informer, are compared. It was presumed that the best performing algorithm would provide the best feature extraction from the TBM machine data. Figure (3) and figure (4) are some of prediction performances of LSTM and DALSTM. Those of transformer and informer are not impressive and omitted in this paper.

DALSTM shows the best performance of penetration prediction on test sets. The results are contrary to our initial expectation as the more advanced algorithms, Transformer and Informer, would show the better performance. Poor performances of advanced algorithms could be due to an insufficient number of layers and components, reduction of hyper parameters, e.g., d_{model} from 512 to 256, n_{head} from 8 to 6 because of shortage in GPU memory. On the other hand, although the DALSTM model requires fraction of memory, it spends more time for training in return.

The prediction performance indices of algorithms are evaluated using MAE, MSE, RMSE, MAPE. As shown in figure (5) the performance indices of four algorithms is fluctuating, however, in general DALSTM shows the best performance among 4 algorithms, depicted by orange squares, showing minimum errors.

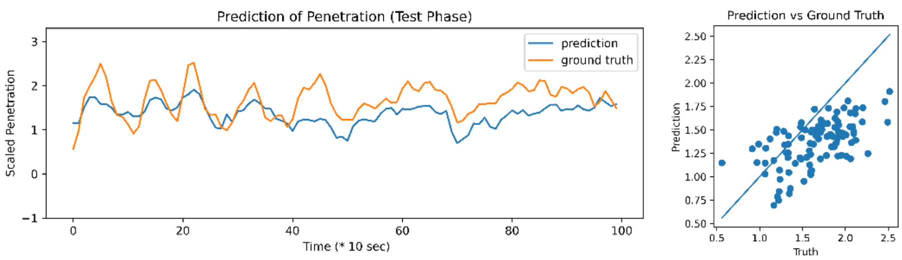


Figure 3. Prediction of penetration using LSTM.

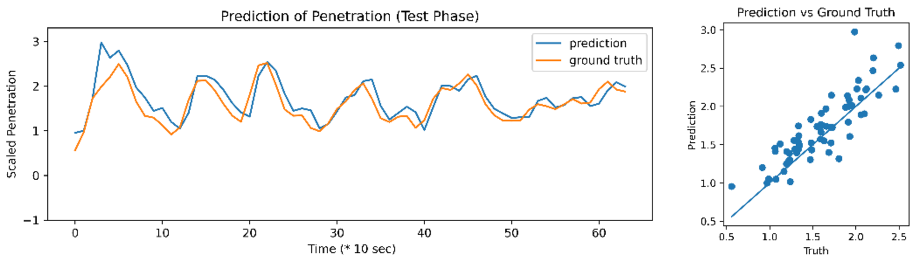
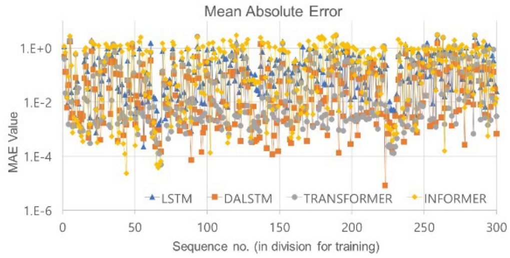
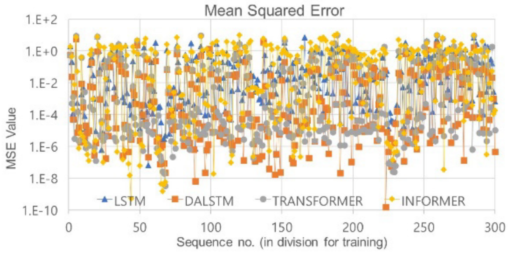
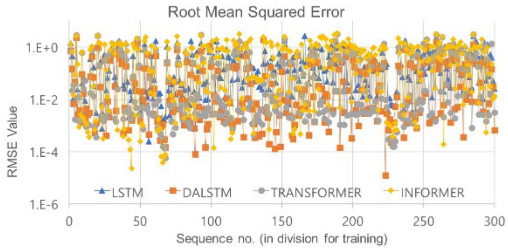


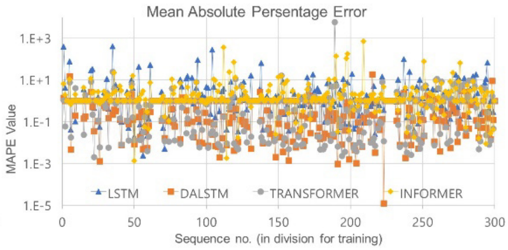
Figure 4. Prediction of penetration using DALSTM.





(a) MAE (b) MSE





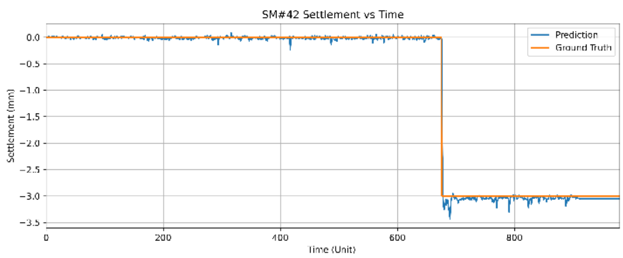
(c) RMSE (d) MAPE

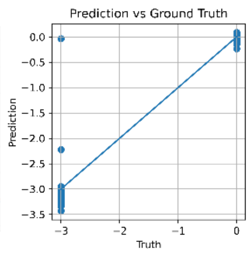
Figure 5. Performance of various methods.

5 PERFORMANCE OF SUBSIDENCE PREDICION

The last step and the goal of this study is to build a model for the prediction of subsidence along with TBM drives using the results of penetration prediction model of TBM machine data. Due to the small set of data, 80 and 20 percent of data were used for training and testing, thus no validation conducted. Although it is not shown in this paper, numerous training sessions have been conducted with various combinations of training and testing set, and the results show consistent performance.

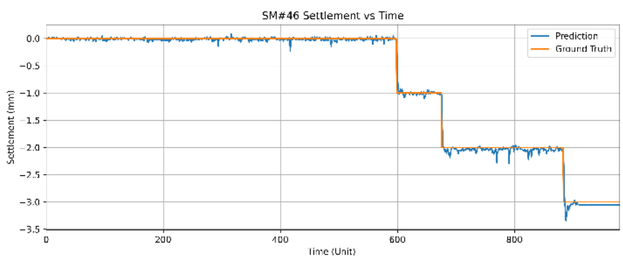
Input data for the subsidence prediction model are daily subsidence records of settlement markers, location of TBM and results of penetration prediction model. Figure (6) to figure (8) show the result of subsidence prediction of three settlement markers, #42, #46 and #49. The results show very good prediction performance for all test and train set. With the supplement of geological information and prediction of settlement during design stage, the performance could be even more enhanced.

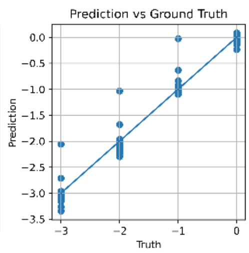




(a) Prediction of subsidence (b) True vs. Prediction

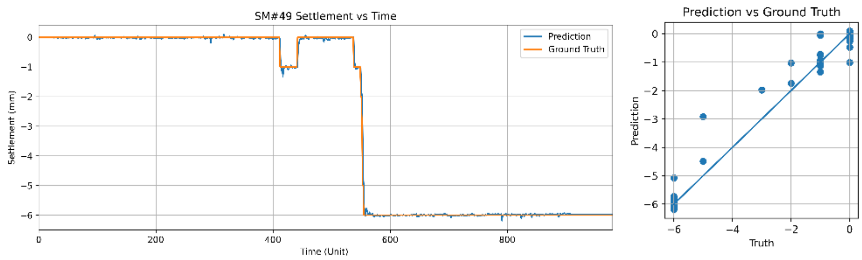
Figure 6. Evaluation of actual subsidence and prediction of #SM42.





(a) Prediction of subsidence (b) True vs. Prediction

Figure 7. Evaluation of actual subsidence and prediction of #SM46.



(a) Prediction of subsidence (b) True vs. Prediction

Figure 8. Evaluation of actual subsidence and prediction of #SM49.

6 CONCLUSION

Despite the intensive monitoring, incidents such as sinkholes due to the construction of tunnels have been continuously occurring globally. In this study, to cope with the difficulty of proper management of subsidence caused by tunnel construction, a neural network model is proposed to predict settlements trained with the large amount of sensor data from TBM machine. Based on the hypothesis, that TBM machine sensors could capture both the actions of the machine and the reactions of the ground, and an appropriate algorithm could learn TBM machine data, models for prediction of penetration and settlement are built along with the selection of parameters and algorithms.

Parameters for a penetration prediction model were chosen, such as current pressure at real lance, RPM of screw conveyor, excavation chamber pressure and torque of cutting wheel, which are showing high correlation with penetration, whereas calculated excavated material, stroke thrust cylinder and thrust force, which are showing low correlation with penetration but potentially relatable to settlement. Using these parameters, four time-series analysis algorithms, i.e., vanilla LSTM, dual attention mechanism LSTM, Transformer, and Informer, applied for training and testing of penetration data. Given the limited resources and capacity of sub-workstation level computers similar to the equipped in TBM machines, it turns out that the best performing algorithm is dual attention LSTM. Subsequent training for subsidence has been conducted with results of training for machine data. Overall, the prediction performance is excellent, and it validates that the approach in this study is feasible, which is an encouraging step towards the deployment of the proposed algorithms.

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