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Machine Learning-Based Temporary Traffic Control Cost Analysis

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ABSTRACT

In a design-bid-build infrastructural project, the agency may use a lump-sum, or unit-price for temporary traffic control (TTC) items, while their cost is hard to estimate. This paper presents the research results of developing a machine learning model of the relationship between the TTC items' cost with the project total cost and non-TTC items in infrastructural projects. In detail, 163 infrastructural projects' data were collected for analyzing two research questions: first, the relationship between the TTC items with the project total cost and non-TTC items; second, the relationship between the TTC items' payment option with the project total cost and non-TTC items. The results showed that the proposed feed-forward neural network model outperforms regression methods on classification tasks. It has a 36% accuracy in determining the TTC items' cost as a percentage range of project total cost. Additionally, the proposed model has 94% accuracy in determining the TTC items' payment options, when the information of the project total cost and the major non-TTC items' information are known. With this research, the TTC items' payment option for a new infrastructural project could be confidently decided, and the TTC items' cost could be easily estimated as percentage ranges of the project total cost, which helps project owners and agencies to evaluate the quality of contractors' bids.

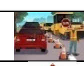
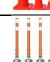
INTRODUCTION

Previous research indicated that the traffic control sign "Road Work Ahead" is effective in reducing passenger cars' and semitrailers' speeding (Bai et al. 2010), and the other temporary traffic control (TTC) methods, such as flaggers, flashers, and pavement liners are helpful in preventing severe crashes in highway work zones (Li and Bai 2008; Li and Bai 2009). TTC is not only important in construction work zone safety for avoiding crashes, it is also beneficial for avoiding project delays and traffic delays.

In public-fund infrastructural projects, the owners' agency may use a lump-sum payment option or unit-price payment option for TTC items. Table 1 lists the most common TTC items in road and bridge construction (Sorel and Henke 2018). These TTC items usually account for a small part of an infrastructural project's total cost, but they are difficult to accurately predicted. A previous study in Canadian highway projects shows the TTC items' cost have no correlation with the project total cost (Anonymous 2016). If the correlation between TTC items' cost, infrastructural project total cost, and non-temporary traffic control (non-TTC) items' cost can be discovered, predicting TTC items' cost for a new infrastructural project will be an easy task for agencies.

In this paper, two research problems were defined, 1) building up the relationship between TTC items' cost with project total cost and non-TTC items; 2) building up the relationship between TTC items' payment options with project total cost and non-TTC items. Solving the 1st problem can provide a standard for the infrastructural project agencies to evaluate the TTC design, plans and bids. Solving the 2nd problem can provide a recommendation for the infrastructural project agencies to decide the TTC items' payment option. Additionally, estimating each TTC items' cost as a percentage of the project total cost may help agencies to evaluate the TTC design, and detect unbalanced bidding behaviors in contractors' biddings. To achieve these research goals, three regression methods and one machine learning method were compared in this paper. The following paper is organized as follows: methodology, results, discussion and conclusion.

Table 1. Temporary Traffic Control Items

Item	Pay Unit	Pictures
Traffic Control	Lump-sum	
Flagging	Man Hour	
Traffic Control Sign	Unit	
Attenuation Device – Type B - __	Each	
Type __ Barricade	Each	
Delineator Drums	Each	
Traffic Cones	Each	
Tubular Markers	Each	
Delineator	Each	
Flexible Delineators	Each	
Stackable Vertical Panels	Each	
Vertical Panels – Back to Back	Each	
Sequencing Arrow Panel – Type __	Each	
Pilot Car	Hour	

Portable Precast Concrete Median Barrier	Linear Foot	
Portable Changeable Message Sign	Each	
Obliteration of Pavement Marking	Square Foot	

METHODOLOGY

Data

In this paper, the data was collected from 163 North Dakota Department of Transportation (NDDOT) funded projects, which were open bid, in 2007; all of which were completed (Jiang et al. 2019). Table 2 lists the collected projects' actual total cost and selected TTC and non-TTC items' actual quantity and actual cost. All selected non-TTC items occur at least 50 times in the 163 projects, such as mobilization, pavement mark, asphalt-cement and emulsions. The selected TTC items include traffic control sign, flagging, barricade, delineator drums in unit-price, and the traffic control in a lump-sum (LS). The data statistic descriptions are shown in Table 2.

Table 2. Data Description

Items / Actual Cost and Quantity		**Count**	**Total**	**Mean**
PROJECT Actual Cost		163	126048743.58	773305.18
Non-TTC Item	MOBILIZATION_L SUM Actual Cost	163	6327285.94	38817.71
	PVMT MK PAINTED 4IN LINE_LF Actual Cost	98	889150.95	9072.97
	PVMT MK PAINTED 4IN LINE_LF Actual Quantity	98	16946425.50	172922.71
	SS1H OR CSS1H OR MS1 EMULSIFIE Actual Cost	57	1375037.37	24123.46
	SS1H OR CSS1H OR MS1 EMULSIFIE Actual Quantity	57	752223.14	13196.90
	PG 58-28 ASPHALT CEMENT_TON Actual Cost	54	28292544.66	523936.01
	PG 58-28 ASPHALT CEMENT_TON Actual Quantity	54	72251.63	1337.99

Unit-price TTC Item	TRAFFIC CONTROL SIGN_UNIT Actual Cost	141	396574.89	2812.59
	TRAFFIC CONTROL SIGN_UNIT Actual Quantity	141	236365.00	1676.35
	FLAGGING_MHR Actual Cost	68	726679.00	10686.46
	FLAGGING_MHR Actual Quantity	68	30156.75	443.48
	FLAGGING_MHR %	68	69.79	1.03
	TYPE III BARRICADE_EA Actual Cost	65	74086.19	1139.79
	TYPE III BARRICADE_EA Actual Quantity	65	722.00	11.11
	DELINEATOR DRUMS_EA Actual Cost	54	73801.84	1366.70
	DELINEATOR DRUMS_EA Actual Quantity	54	2836.00	52.52
LS	TRAFFIC CONTROL_L SUM	8	26343.80	3292.98

Variables and Assumptions

As the previous study (Anonymous 2016) indicates, there is no correlation between the TTC items' cost and the project total cost in infrastructural projects. Thus, in this paper, the 1st assumption is that the $Variable\ Y1$ (traffic control sign item cost) has no correlation with the project actual cost $X1$ and selected non-TTC items' actual costs $X2, X3, X5, X7$ and actual quantities $X4, X6, X8$ (see Table 3).

As the $Y1/X1$ (percentage of traffic control sign item cost to project total cost) ranges from 0% to 3.297% in the 163 projects ("0%" was assigned to the project that did not have the traffic control sign item). Figure 1 uses 0.36% as the interval to categorize the $Y1$ into ten classes. Then, ten labels "0", "1", "2", "3", "4", "5", "6", "7", "8" and "9" were assigned to $Y2$, which means that if $Y1/X1$ is [0, 0.36] then $Y2$ is "0". Thus, the 2nd assumption is that $Y2$ has no correlation with the project actual cost $X1$ and selected non-TTC items' actual costs $X2, X3, X5, X7$ and actual quantities $X4$, $X6$, $X8$ (see Table 3).

The 3rd assumption is $Y3$ (actual cost of the traffic control in lump-sum) has no correlation with the project actual cost $X1$ and selected non-TTC items' actual costs $X2, X3, X5, X7$ and actual quantities $X4, X6, X8$ (see Table 3).

Additionally, the 4th assumption is $Y4$ (the payment option of lump-sum or unit-price for TTC items) has no correlation with the project actual cost $X1$ and selected non-TTC items' actual costs $X2, X3, X5, X7$ and actual quantities $X4, X6, X8$ (see Table 3). $Y4$ was assigned "0" to the project with unit-price TTC items and assigned "1" to the project with a lump-sum traffic control item. Table 2 shows 8 of the 163 projects that used the lump-sum option to pay for TTC item.

Table 3. Variables Description

Variable	Description	Min	Max
Y1	TRAFFIC CONTROL SIGN_UNIT Actual Cost	0	20094.95
Y2	TRAFFIC CONTROL SIGN_UNIT Class Label	0	9
Y3	TRAFFIC CONTROL_L SUM Actual Cost	0	6000
Y4	TRAFFIC CONTROL_L SUM or Not	0	1
X1	PROJECT Actual Cost	9250	10793933.07
X2	MOBILIZATION_L SUM Actual Cost	300	376000
X3	PVMT MK PAINTED 4IN LINE_LF Actual Cost	0	46910.682
X4	PVMT MK PAINTED 4IN LINE_LF Actual Quantity	0	1116921
X5	SS1H OR CSS1H OR MS1 EMULSIFIE Actual Cost	0	132980.544
X6	SS1H OR CSS1H OR MS1 EMULSIFIE Actual Quantity	0	73878.08
X7	PG 58-28 ASPHALT CEMENT_TON Actual Cost	0	1858257.75
X8	PG 58-28 ASPHALT CEMENT_TON Actual Quantity	0	4680.75

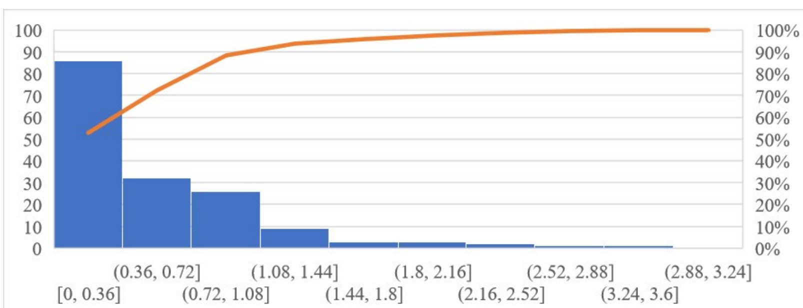


Figure 1. Variable Y1

Correlation Coefficient and Regression Models

In statistics, the Pearson Correlation Coefficient (PCC) is a measure of the linear correlation between two variables (Anonymous 2019). Thus, in this paper, the relationship between the TTC items' cost and the project cost, and the relationship between the payment option and the project cost could be identified with the PPC.

To verify the four research assumptions, the eight continuous variables in Table 3 were used as the independent variables in regression models. As the dependent variables $Y1$ and $Y3$ are continuous variables, using Multi-linear Regression is better. Considering the dependent variable $Y4$ is binary variable, Binary Logistic Regression is better. Additionally, the dependent variable $Y2$ is an ordinal variable with 10 categories, so using Ordinal Logistic Regression is better (Anonymous 2019). Thus, the proposed regression models include:

1) Multi-linear Regression Model,

$$Y1 = b_0 + b_1X1 + b_2X2 + b_3X3 + b_4X4 + b_5X5 + b_6X6 + b_7X7 + b_8X8$$

2) Ordinal Logistic Regression Model,

$$\text{logit}[P(Y2 \le h)] = \ln(\frac{P(Y2 \le h)}{1 - P(Y2 \le h)}) = b_{0h} + b_{1h}X1 + b_{2h}X2 + b_{3h}X3 + b_{4h}X4 + b_{5h}X5 + b_{6h}X6 + b_{7h}X7 + b_{8h}X8$$

3) Multi-linear Regression Model,

$$Y3 = b_0 + b_1X1 + b_2X2 + b_3X3 + b_4X4 + b_5X5 + b_6X6 + b_7X7 + b_8X8$$

4) Binary Logistic Regression Model,

$$\text{logit}[P(Y4 = 1)] = \ln(\frac{P(Y4 = 1)}{1 - P(Y4 = 1)}) = b_0 + b_1X1 + b_2X2 + b_3X3 + b_4X4 + b_5X5 + b_6X6 + b_7X7 + b_8X8$$

Neural Network Model

The artificial neural network is a type of machine learning method that can perform regression tasks and classification tasks. Thus, in this paper, $Keras$ (an open-source neural-network library written in Python capable of running on top of TensorFlow) is used to set up the proposed two-hidden-layers feed-forward neural network (see Figure 2).

In detail, the input layer has eight nodes, which stand for the eight selected $variables\ X1 \sim X8$. The first hidden layer has 40 nodes, with activation function rectified linear unit ($ReLU$) (see Table 4). The second hidden layer has half of the nodes of the first hidden layer with activation $ReLU$. The output layer only has one node with the linear activation ($Linear$).

For the proposed four research assumptions, the $Variables\ Y1, Y2, Y3\ and\ Y4$ will be separately trained and tested in four neural network models.

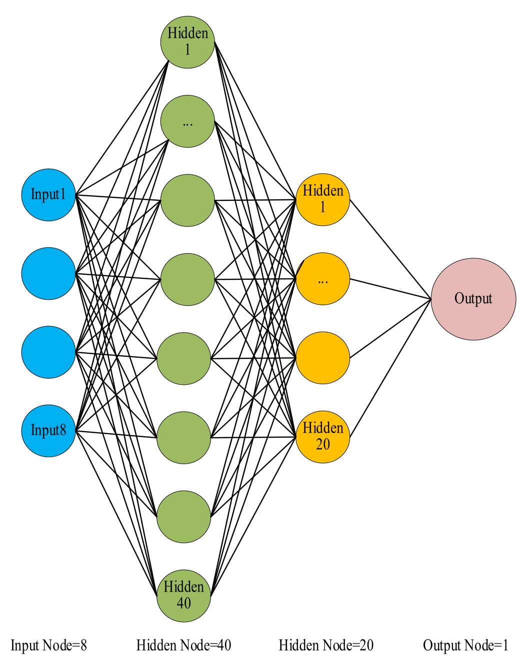
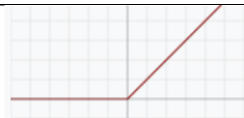
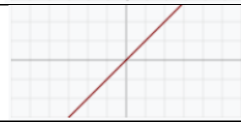


Figure 2. Two-layer feed-forward neural network model architecture

Table 4. Activation Functions

Name	Plot	Equation
ReLU		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$
Linear		$f(x) = x$

RESULTS AND DISCUSSION

Correlation Coefficient

In this paper, the confidence level was set as 95.0%, and the significance level was 0.05.

The Pearson Correlations between $X1$ and $Y1$ to $Y4$ are listed in Table 5. The correlation between $X1$ and $Y1$ is 0.668 (*P-value*<0.05), which means that $Y1$ has a positive relationship with $X1$, and the correlation coefficient is significant. That result is different from the previous research result. The Pearson Correlation of $X1$ and $Y2$ is – 0.210 (*P-value*<0.05), which means that $Y2$ has a negative relationship with $X1$, and the correlation coefficient is significant as well. Thus, the traffic control sign cost has a positive relationship with the project total cost.

The Pearson Correlation of $X1$ and $Y3$ is – 0.054 (*P-value*> 0.05), which means that $Y3$ (traffic control lump-sum cost) has no significant relationship with $X1$ (project total cost), and the same for $Y4$ and $X1$. Thus, the TTC items' payment option has no relationship to the project total cost.

Table 5. Correlations

Sample 1	Sample 2	Correlation	95% CI for ρ	P-Value
Y1	*X1*	0.668	(0.573, 0.745)	0.000
Y2	*X1*	-0.210	(-0.352, -0.058)	0.007
Y3	*X1*	-0.054	(-0.206, 0.101)	0.497
Y4	*X1*	-0.047	(-0.200, 0.107)	0.549

Regression Analysis

Similarly, the confidence level for all intervals was set as 95.0%.

The 1st multi-linear regression equation is $Y1 = 578 + 0.001992\,X1 + 0.00467\,X2 + 0.1008\,X3 + 0.00247\,X4 - 0.0052\,X5 + 0.0301\,X6 - 0.00176\,X7 - 1.05\,X8$, with R_sq=67.57%, $R\_sq(pred)$=60.44%. The $b_2, \ldots, b_8$ have *P-value* >0.05 (see Table 6), which means the non-TTC items $X2, \ldots, X8$ have limited impacts to $Y1$, while the b_1=0.001992 (*P-value*<0.05) confirms that $X1$ has a positive impact to $Y1$. Thus, the 1st assumption is verified to be false. Additionally, the R_sq indicates that the 1st regression model can explain about 68% of the dependent model, and the $R\_sq(pred)$ means this model has 60% accuracy in predicting the $Y1$.

Table 6. Coefficients of the Y1 Regression Model

Term	Coef.	SE Coef.	T-Value	P-Value	VIF
Constant	578	185	3.12	0.002	
X1	0.001992	0.000207	9.60	0.000	3.74
X2	0.00467	0.00366	1.28	0.204	1.92
X3	0.1008	0.0818	1.23	0.219	23.02
X4	0.00247	0.00381	0.65	0.517	22.61
X5	-0.0052	0.0299	-0.18	0.861	19.38
X6	0.0301	0.0731	0.41	0.681	31.36
X7	-0.00176	0.00261	-0.67	0.502	49.57
X8	-1.05	1.12	-0.94	0.351	57.86

The 2nd ordinal logistic regression results are listed in Table 7. The $b_1, b_2, b_4, \dots, b_8$ have *P-value* >0.05, which means that the percentage range of traffic control sign cost to project total cost has no correlation with the project total cost and the selected non-TTC items' cost and quantities, except for the non-TTC item's cost $X3$. As b_3= -0.0001909 (*P-value*<0.05), $X3$ has a negative impact in relation to $Y2$. Additionally, applying the multi-linear regression analysis with the variables results in the equation $Y2 = 1.323 + 0.000000X1 + 0.000000X2 + 0.000117X3 - 0.000002X4 - 0.000016X5 + 0.000041X6 + 0.000000X7 - 0.001002X8$, with R_sq=18.71%, $R\_sq(pred)$=6.10% and all $b_1, \dots, b_8$ have the *P-value*>0.05, which means that the percentage range of traffic control sign cost to project total cost has no correlation with the project total cost and selected non-TTC items' cost and quantities. This result is different from the ordinal logistic regression model. But for the ordinal discrete variable $Y2$, the ordinal logistic regression model yields more reasonable results than the multi-linear regression model. Therefore, the 2nd assumption is false.

Table 7. Logistic Regression Table of the Y2 Regression Model

Predictor	Coef.	SE Coef.	Z	P	Odds Ratio	95% CI	
						Lower	Upper
Const(1)	-0.925732	0.237302	-3.90	0.000			
Const(2)	0.954753	0.234848	4.07	0.000			
Const(3)	1.88471	0.280206	6.73	0.000			
Const(4)	3.25795	0.409081	7.96	0.000			
Const(5)	3.50520	0.441871	7.93	0.000			
Const(6)	3.82405	0.490600	7.79	0.000			
Const(7)	4.27256	0.574585	7.44	0.000			
Const(8)	5.72856	1.04718	5.47	0.000			

X1	-0.0000001	0.0000003	-0.29	0.773	1.00	1.00	1.00
X2	-0.0000017	0.0000043	-0.39	0.698	1.00	1.00	1.00
X3	-0.0001909	0.0000914	-2.09	0.037	1.00	1.00	1.00
X4	0.0000052	0.0000042	1.24	0.214	1.00	1.00	1.00
X5	0.0000155	0.0000366	0.42	0.673	1.00	1.00	1.00
X6	-0.0000585	0.0000941	-0.62	0.534	1.00	1.00	1.00
X7	-0.0000004	0.0000037	-0.10	0.917	1.00	1.00	1.00
X8	0.0017148	0.0015896	1.08	0.281	1.00	1.00	1.00

The 3rd multi-linear regression equation is $Y3 = 227.0 + 0.000013X1 - 0.00068X2 - 0.0328X3 + 0.00118X4 + 0.0168X5 - 0.0566\,X6 - 0.00059X7 + 0.517X8$, with R_sq=4.02%, $R\_sq(pred)$=0.00% and all $b_1, \dots, b_8$ have the *P-value*>0.05, thus the lump-sum traffic control cost has no correlation with project total cost and selected non-TTC items' cost and quantities. Therefore, the 3rd assumption is true.

The 4th binary logistic regression equation is $P(Y2 \leq h) = \exp(Y')\,/(1 + \exp(Y')$, $Y' = -1.328 - 0.000004\,X1 - 0.000021\,X2 - 0.000497\,X3 + 0.000021\,X4 - 0.01\,X5 - 0.0\,X6 - 0.000001\,X7 + 0.00554\,X8$,with R_sq =30.72%, $R\_sq(pred)$ =18.19% and all $b_1, \dots, b_8$ have the *P-value*>0.05, thus the TTC items' payment option has no correlation with the project total cost and selected non-TTC items' cost and quantities. Additionally, applying the multi-linear regression model to the variables yields $Y4 = 0.0651 + 0.00X1 - 0.00X2 - 0.000010X3 + 0.00X4 + 0.000006X5 - 0.000021X6 - 0.00X7 + 0.000145X8$, with R_sq=5.78%, $R\_sq(pred)$=0.00% and the $b_1, \dots, b_5, b_7$ and $b_8$have the *P-value*>0.05, while b_6 has the *P-value*<0.05 (see Table 8). Thus, the TTC item's payment option is affected by non-TTC item's quantity $X6$. However, this multi-linear regression model is unable to predict $Y4$. Therefore, the 4th assumption is true.

Table 8. Coefficients of the Y4 Regression Equation

Term	Coef.	SE Coef.	T-Value	P-Value	VIF
Constant	0.0651	0.0244	2.67	0.009	
X1	0.000000	0.000000	0.18	0.860	3.74
X2	-0.000000	0.000000	-0.38	0.706	1.92
X3	-0.000010	0.000011	-0.97	0.333	23.02
X4	0.000000	0.000001	0.79	0.429	22.61
X5	0.000006	0.000004	1.55	0.124	19.38
X6	-0.000021	0.000010	-2.16	0.032	31.36
X7	-0.000000	0.000000	-0.28	0.780	49.57
X8	0.000145	0.000147	0.99	0.325	57.86

Feed-forward Neural Network

When training the proposed feed-forward neural network model (see Figure 2), 80% of the 163 projects' data were randomly selected to be used for training the model, and the remaining 20% of the data were used to test the model. The model was set up to train 200 epochs with batch size 20 (16 data used for training and 4 data for testing in each epoch).

Figure 3 shows the 1st neural network model (input $X1, \ldots, X8$, output $Y1$) training and testing results during the 200 epochs. The model prediction accuracy is 0.0 %, because the prediction is only correct when the predicted $Y1$ exactly equals the ground truth $Y1$. Similarly, Figure 5 shows the 3rd neural network model (input $X1, \ldots, X8$, output $Y3$) training and testing results during the 200 epochs. The $Y3$ predicting accuracy is 0.0%, as well. Therefore, the proposed feed-forward neural network model has difficulty predicting the exact value of continuous variables.

Figure 4 shows the 2nd neural network model (input $X1, \ldots, X8$, output $Y2$) training and testing results during the 200 epochs. The predicting accuracy is 36.36%, which means when inputting the project total cost and non-TTC items' information into the model, it can give an accurate result for $Y2$ (percentage range of the traffic control sign cost to the project total cost) 36% of the time. This number is higher than the 1st network model (0.0%) and the 2nd multi-linear regression model (6.10%). The $R\_sq(pred)$ for the ordinal logistic regression model is unknown.

Additionally, Figure 6 shows the 4th neural network model (input $X1, \ldots, X8$, output $Y4$) training and testing results during the 200 epochs. The predicting accuracy is 93.94%, which means when inputting the project total cost and non-TTC items' information into the model, it can give an accurate result for $Y4$ (TTC items' payment option, either a lump-sum or unit-price) 94% of the time. This number is higher than the 3rd network model (0.0%) and the 4th binary logistic regression model (18.19%). Therefore, the proposed feed-forward neural network model has a good performance in classification tasks, especially in 0-1 tasks.

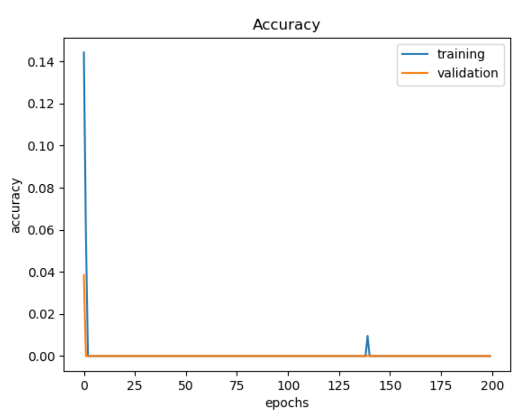


Figure 3. Input X1~X8 and output Y1

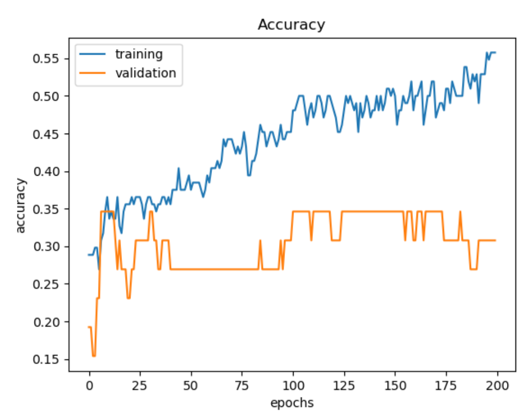
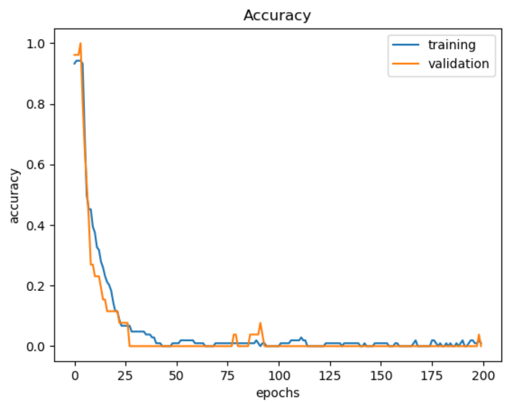


Figure 4. Input X1~X8 and output Y2



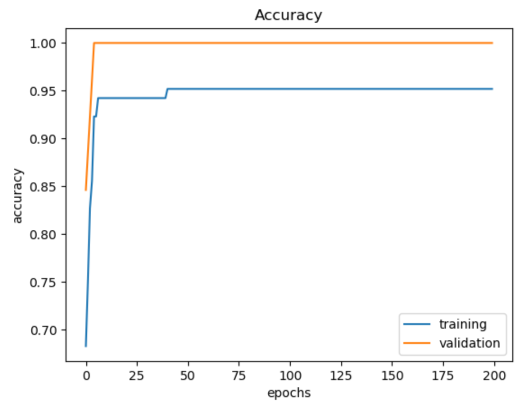


Figure 5. Input X1~X8 and output Y3 **Figure 6. Input X1~X8 and output Y4**

CONCLUSION

This paper compares the multi-linear regression method, ordinal logistic regression method, binary logistic regression method and feed-forward neural network method in predicting the temporary traffic control cost with 163 NDDOT project datasets. The research results show that a) unit-price TTC items, such as the traffic control sign, have a positive relationship with the project total cost, while the lump-sum TTC item's cost has no correlation with the project total cost and the non-TTC items; b) the TTC items' payment option, either lump-sum or unit-price, has no correlation to the project total cost and non-TTC items; c) the multi-linear regression method has the advantage in predicting continuous variables, while the feed-forward neural network has the advantage in predicting discrete variables compared with the ordinal logistic regression method and binary logistic regression method.

The proposed feed-forward neural network only contains eight input nodes, further research may extend the number of nodes by adding more non-TTC items to increase the model's accuracy. Because the authors have tried different combinations of epoch and batch size to enhance the prediction accuracy of $Y2$ (percentage range of the traffic control sign cost to the project total cost), the accuracy is limited to 45 %.

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