VOL. 12, NO. 5, MARCH 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

ANALYSIS OF TRANSPORTATION MODE CHOICE USING A COMPARISON OF ARTIFICIAL NEURAL NETWORK AND MULTINOMIAL LOGIT MODELS

Hussain Dhafir Hussain, Ahmed Madha Mohammed, Ali Dawod Salman, Riza Atiq bin O. K. Rahmat and Muhamad Nazri Borhan
Universiti Kebangsaan Malaysia, Faculty of Engineering and Built Environment, Selangor, Malaysia
Ministry of Higher Education and Scientific Research, Al-Mustansiriya University, Iraq
E-Mail: hussaindhafir@siswa.ukm.edu.my

ABSTRACT

The transportation system around the globe is witnessing a dramatic change which possibly generating from the massive increase in the population. This contributed to a legitimate dilemma which is traffic congestion taking into consideration the accompanying problems that raised namely air pollution as well as traffic accidents. Public transportation is substantial and their importance reflects in both economic and social quality of each and every citizen life. Despite these facts, the public means of transportation is still to this day not the people's choice to perform their daily trips, this applies, particularly, to private car users. The candid solution to this problem is to turn people's attention to public transportation system (bus and vanpool) and simulate them to abandon their private cars. This study works on a comparison between two mode choice models, Multinomial logistic regression (MNL) and Artificial neural network (ANN) for the purpose of prediction of the behavioural transportation of mode choice with the purpose of evaluation of the accuracy levels in the predictability in each model. The results show that artificial neural network readily outperformed the multinomial logistic regression in the predictability of mode choice.

Keywords: artificial neural network, multinomial logit, mode choice, public transport.

1. INTRODUCTION

The ever increasing public interest in private cars is the main contributory factors for worsening issues of road congestion. Private means of transportation has been the preferred, reliable, comfortable and time-efficient means of transportation. It has greatly influenced the ever increasing traffic congestion, accidents, jams, and pollution. It was reported victims of car accidents are disproportionately the young and the economically disadvantaged people. There must be a radical resolution to this problem which is to encourage the commuters to ditch their cars and use public means of transportation (car, bus, and vanpool). Belwala [4] stated that the role of public transportation is crucial in our daily bases and highly effective public services are needed.

Logistic regression is a noted classification method in statistical learning and artificial neural network (ANN) considered being a global model that acquired a great deal of popularity lately [15].

Nazri *et al.* [13] elucidate that artificial neural network ANN is a processing technique depending on understanding the human brain as it consists of several layers contain many interconnected elements which are called nodes. Artificial intelligence technique has superb results in various fields of engineering this is due to its ability to deal with complicated issues and an have excellent ability for adaptation with the new data [6]. According to Zulkarnain Hassan *et al.* [18] artificial neural network have the advantage to come up with a relationship between the input and output and it is quite flexible compared to other conceptual models. Another ANN differs from the regression is it is not ought to possess the same terms on the dataset. Artificial neural network also capability to generalize. Adielsson [3] pointed out ANN disadvantage is that the results can be excessively hard to interpret.

The Multinomial logistic (MNL) is a familiar method for analyzing the potential influence of explanatory variables on a category of dependent variables. Multinomial logistic regression utilizes the ultimate likelihood ratio to estimate the probability of the dependent variables, multinomial logistic regression usually used when the dependent variable in which the number of categories is more than two [14].

The fundamental assumptions that create multinomial logit models are:

a) error elements are distributed extreme-value (Gumbel),

b) error elements are similar and independently distributed across alternatives.

c) error elements are identical and independently distributed across individuals/observations.

The most featured assumption in the case of error distribution within the statistical and modelling literature is that error distributions are normal. There are significant reasons based on the backgrounds of theory and practical, for adopting normal distribution in numerous settings. In any case, adopting normal distribution for errors in the choice model does result to multinomial probit model (MNP), and this model contains certain properties that make it difficult to adopt choice model analysis. As for the Gumbel distribution, the reason for selecting is because it poses computation advantages in areas where an emphasis is laid on maximization; it makes it easy to calculate the normal distribution besides producing a choice model based on probability.

This study illustrates a comparison between artificial neural network ANN and multinomial logistic regression MNL to predict the behavioural transportation of mode choice. Ultimately ANN has a superior result in term of accuracy of prediction.

2. MATERIALS AND METHODS

Given that Baghdad city the capital of Iraq considered to be one of the leading cultural centres in the region, however, because of wars and rapid growth the local authorities are challenged to provided the needed services to the citizens to formulate effective development strategies [1].

A survey was carried out in Baghdad in four substantial and well-known areas with higher percentage of the population and noticeable employment of private cars. The questioner of 700 Iraqi citizens were acquired but only 620 copies were actually consumed in this study (453 main data and 167 validation data).

An increased congestion of roads, pollution, and traffic issues is dreadfully increased due to the increase in utilization of private cars. Based on Eva leidman et al. [8] an estimated 1.2 million people dies from road injuries worldwide which make it the eight cause of death globally. Public transportation system is in desperate need of major changes and developmental plans in order to encourage the commuters to leave their cars and start using public transportation in their day to day bases tripe. According to Gavin *et a*l. [9] Multinomial logistic regression which is a classic statistical method for multi-class pattern recognition problems. The multinomial logit model was formulated. It included demographic and socioeconomic characteristics (age, gender, household, car ownership, driver license, income, education level, travel time, and Distance to destination) specified as the generic variables. In this study, a multinomial logit model is used to understand the commuter's mode choice of car, bus and vanpool.

Artificial neural network is now taking place in developing various travel demands In addition, the enforcement of the ANN's in civil engineering problems of the field of transportation is very widespread [12]. Edara [6] suggested that ANN has the ability to capture complex relationship over other computerized methods. In this study, ANN is used using MATLAB to evaluate the predictability of mode choice (car, bus, and vanpool). When using the application of artificial neural network in MATLAB, the artificial neural network coding (Appendix) is generated which represents the prediction of the model shift.

Figure-1 shows the architecture of three layers Artificial Neural Network: the input layer which represent the variables (Age, gender, level of education, occupation, household size, car ownership, income, distance from home to destination, travel time, driver license, day to destination, distance home to station and cheapest transport) that need to be estimated ,hidden layer (6 hidden layer neurons to achieve higher accuracy) and output layer (three output neurons for car, bus and vanpool) which is illustrated in this study.

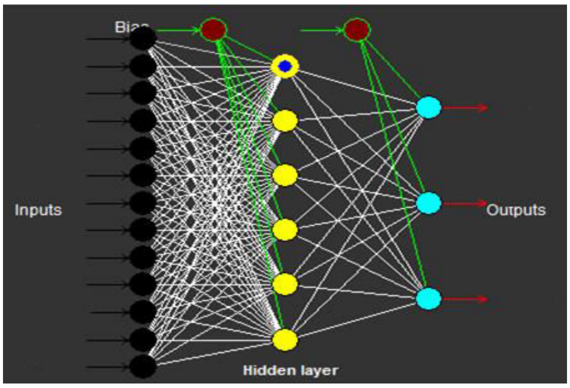

Figure-1. Artificial neural network architecture for car, bus, and vanpool.

A comparison between the Multinomial logistic regression model and ANN model is performed to shed light on which of them will leads in term of accuracy in the predictability of mode choice.

3. RESULTS AND DISCUSSION

3.1 Multinomial Logit Model (MNL)

Multinomial logit model used to model a relationship between polytomous variables and a set of regressor variables. The term multinomial includes a broad sense and variety of models [17].

The Multinomial logit (MNL) is a known method to evaluate the affect of explanatory variables on a category of dependent variables. In the MNL model, it is assumed that travellers possess somewhat unobservable, latent choice or utilities for various kinds of transport mode and they adopt the mode that offers the higher level of utility [16].

Gavin *et al.* [9] stated that MNL provides standard maximum likelihood solution to multiclass pattern recognition problem; it is a common and convenient way for analyzing the potential influence of explanatory variables on a category of dependent variables.

The analysis concentrated on the mode choice decision by people who use the car, bus and vanpool, and the variables that explained their mode choice behaviour. The results on the factors influencing the choice of travel mode for trips are given in Table-1. The coefficients were estimated using the maximum likelihood method.

To test the contribution of the demographic, socioeconomic and mode attribute variables in explaining the mode choice behaviour, the multinomial logit for trips mode choice model was formulated. It included demographic and socioeconomic characteristics.

The Table shows the significant attributes of age, gender, household, car ownership, driver license, income, education level, distance to destination and travel time were all variable are significant levels at ($P \leq 0.05$), while remaining variables are not significant.

The coefficients for Age, car ownership, income, education level, distance to destination and travel time were negative, implying that an increase in them would increase car use.

Table-1. Estimates by the multinomial mode choice model for trips.

						95% Confidence interval for Exp (B)	
Mode of transport	**Independent variable**	**Coefficient**	**df**	**P value (sig.)**	**Exp** (B)	**Lower**	**Upper**
Bus	Intercept	6.719	1	0.000			
	Age	-0.477	1	0.000	0.62	0.513	0.751
	Gender	1.459	1	0.000	4.302	2.032	9.106
	Household	0.607	1	0.049	1.835	0.953	3.531
	Car Ownership	-1.413	1	0.000	0.243	0.14	0.424
	Driver License	1.055	1	0.011	2.873	1.276	6.471
	Income	-0.792	1	0.000	0.453	0.334	0.614
	Education Level	-1.159	1	0.000	0.314	0.196	0.502
	Distance to dest.	-0.285	1	0.023	0.752	0.588	0.961
	Travel Time	-0.657	1	0.000	0.518	0.405	0.663
Vanpool	Intercept	4.886	1	0.001			
	Age	-0.531	1	0.000	0.588	0.494	0.7
	Gender	0.806	1	0.021	2.24	1.129	4.444
	Household	1.01	1	0.001	2.744	1.495	5.039
	Car Ownership	-0.746	1	0.003	0.474	0.291	0.772
	Driver License	1.123	1	0.002	3.074	1.487	6.354
	Income	-0.501	1	0.000	0.606	0.46	0.799
	Education Level	-0.73	1	0.002	0.482	0.307	0.758
	Distance to dest.	-0.518	1	0.000	0.595	0.473	0.75
	Travel Time	-0.536	1	0.000	0.585	0.465	0.736
	No. of observation	453					
	-2 Log likelihood	559.141					
	Chi-square	416.854	18	0.000			
	Cox & Snell's R2	0.602					
	Nagelkerke value	0.680					
	McFadden's value	0.427					

$$P_a = \frac{e^u}{1+e^u} \tag{1}$$

Where;

Pa = probability of private car users shift to public transport (bus and vanpool)

u = utility function for bus/vanpool mode

e = the base of natural logarithms (approximately 2.718).

Classification table was calculated to assess the fit of the model to the data, the mode 48.80% of the bus users, the mode 90.30% of the car users and the mode 69.20% of the vanpool users. The accuracy of prediction was 72.60% (Table-2).

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Table-2. Classification table for mode choice model (n= 453 sample).

Observed	Predicted			
	Car	**Bus**	**Vanpool**	**Percentage correct**
Car	177	14	5	90.30%
Bus	26	62	39	48.80%
Vanpool	12	28	90	69.20%
Overall percentage	47.50%	23.00%	29.60 %	72.60%

Table-3 shows validated mode choice model Classification matrices were calculated to assess the fit of the model to the data. The model correctly classified 91.0% of the car cases, 69.6% of the bus cases and 58.3% of the vanpool cases. The accuracy of prediction was 76.2%.

Table-3. Classification table for validating mode choice model (n= 172 sample).

Observed	Predicted			
	Car	**Bus**	**Vanpool**	**Percentage correct**
Car	71	1	6	91.0%
Bus	3	32	11	69.6%
Vanpool	8	12	28	58.3%
Overall percentage	47.7%	26.2%	26.2%	76.2%

3.2 Artificial Neural Network (ANN)

An artificial neural network is an information processing system which is influenced by the human biological nervous system. The most essential part of the artificial neural network is its structure in which the information processing is carried out. It is composed of numerous processing strains called neurons which help in solving the current problem. The neural network has a tremendous advantage which is extraction of patterns that are highly complex to be observed by the human brain or any other computerized mechanism [5].

Figure-2 shows the number of hidden layer neurons applied and so on the model comes to its highest point of accuracy in number (6) and the accuracy levels start to drop after several models as stated by M. Beale *et al.* [11].

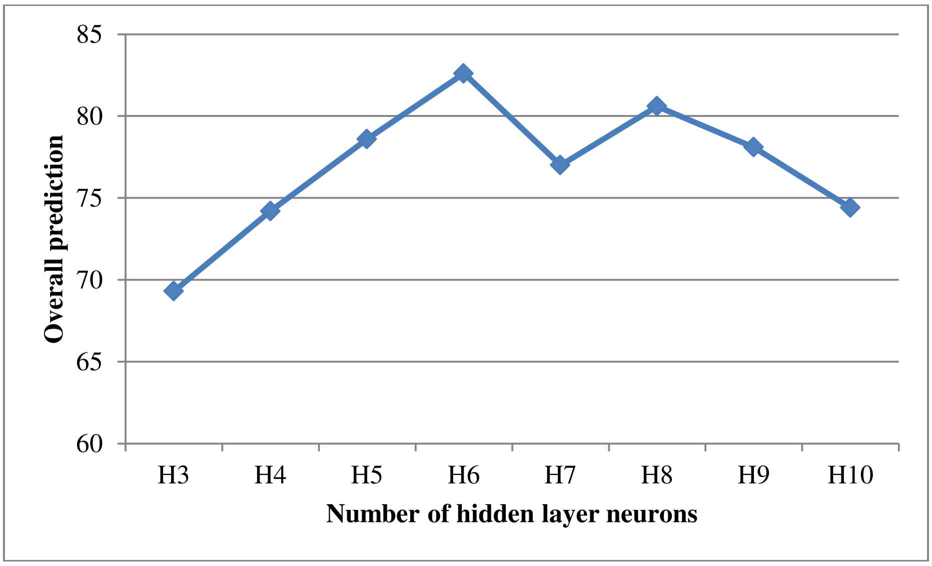

Figure-2. Number of neurons in hidden layer.

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There are three parts of the dataset: the training set, the validation set, and the test set. In this study, 70% of the data for the training set and 15% for each of the validation and test sets was utilized accordingly.

The diagram of the current artificial neural network model has (13) input neuron, (6) hidden layer neurons and (3) output layer neurons as seen below in Figure-3.

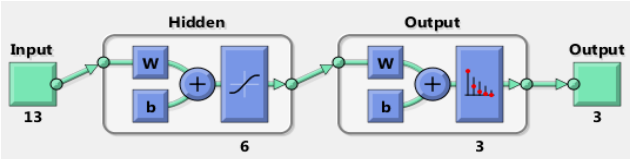

Figure-3. Diagram of the neural network for car, bus, and vanpool.

The efficiency of the neural network which is identified by the ability of suitable prediction of the class of cryptic data and in terms of accuracy the classifier may be calculated.

When using the application of artificial neural network in MATLAB, the artificial neural network coding (Appendix) is generated which represents prediction of model shift

With the employment of confusion matrix the true negative rate, that is, specificity, true positive rate, that is, sensitivity, false positive rate, false negative rate, and accuracy of the network can be measured and the overall execution of the neural network is calculated eventually. Ultimately the confusion matrix of the trained network is fully sufficient for the calculation of the neural network accuracy.

As seen in Figure-4, results of the predictability of car, bus, and vanpool exhibit an accuracy of 82.6%. Green blocks show the number and percentage class samples in the data set, red blocks show misclassification, and gray blocks show total classification percentage for each false positive \ false negative.

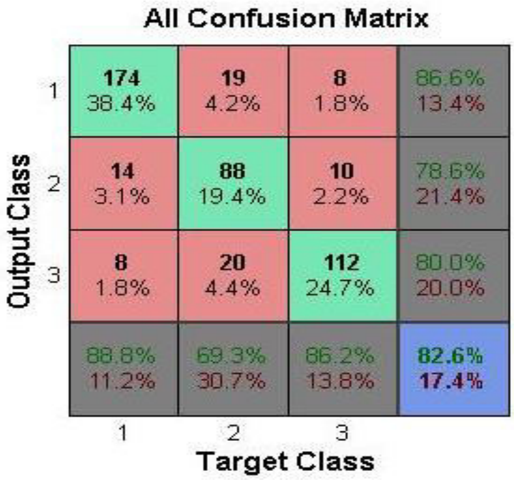

Figure-4. Predictability confusion matrix of car, bus and vanpool.

The results of validation of car, bus and vanpool exhibit an accuracy of 80.9 %, green blocks show the number and percentage of correct classification, red blocks show misclassification, and gray blocks show total classification percentage for each false positive \ false negative as shown in Figure-5.

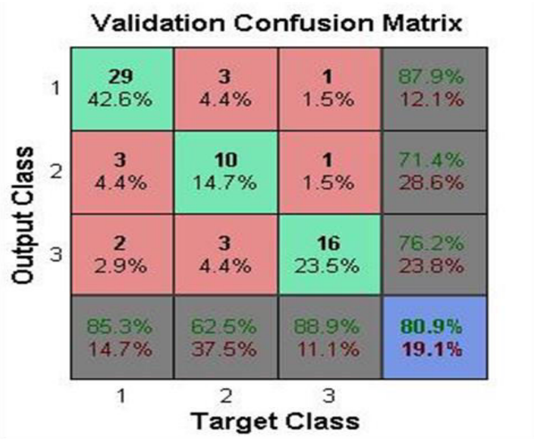

Figure-5. Validation confusion matrix of car, bus, and vanpool.

The quality of classifiers should be calculated properly and the receiver operating characteristic is used primarily for that reason. ROC is usually enforced threshold values across the interval [0, 1] to outputs for every class of a classifier and plot the ROC for each output class. Based on Abhay & Pranav [2] whenever more every curve embraces the left and top border of the plot, the superior the classifier will be.

Figure-6 shows a more precise vision of all various situations i.e. training, validation, testing, and ROC. The position of the curve is considered to be the main indicator of the accuracy of the results in which it comes in contact with the left and the top border of the plot. In this case, the plotroc shows that the classification of the car, bus and vanpool is considered to be fairly accurate.

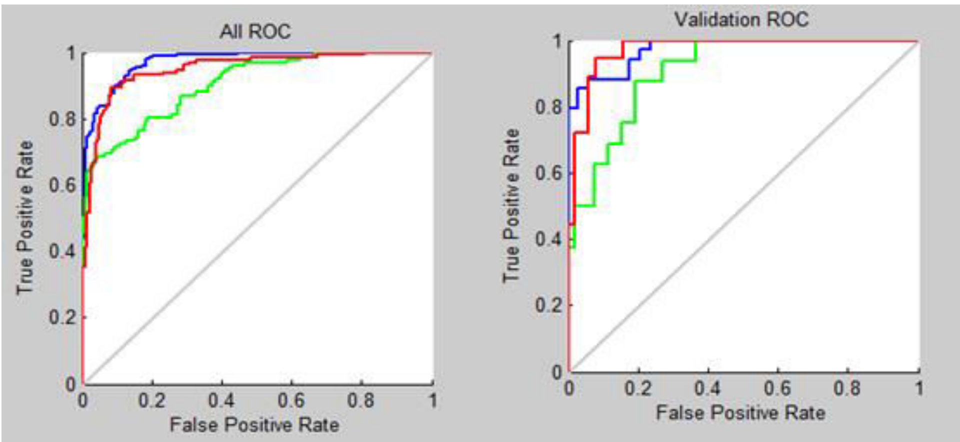

Figure-6. ROC plot of car, bus, and vanpool.

A comparison between ANN models with standard statistical models such as Multinomial logistic regression is considered to be a key element in the development procedure. In case that the results elucidate that using a non-linear model, such as the ANN, is quite restricted; in this case, a less complex method is desirable. Logistic regression characterizes with a useful feature in which of being fully explainable and utilized to provide feedback to the user. Green et al. [10] elucidate that it is crucial to use more than a single measure of performance; an acceptable performance can be measured in different ways.

This study compares two mode choice models whereby ANN and MNL are applied and assessed to predict mode choice of transportation of car, bus and vanpool. Table-4 shows Artificial Neural Network clearly outperformed the Multinomial logit in both predictability wise and validation wise. In the estimation of car, bus, and vanpool the predictability were 72.60% for the multinomial logit model while ANN model were 82.6%. The validation results of multinomial logit model were 76.2% as for the ANN model the results were 80.9%. This is lucid evidence that ANN results are superior to logit models in predictability and validation aspects.

Eftekhar *et al*, [7] accentuate an additional benefit of the ANN model is allowing modulation that is measured as a great sum of variables and using unique approaches that use lesser assumptions that need verification before constructing the models.

Table-4. Comparison model for predictability of mode choice.

Mode	**Prediction (%)**		
	Data set	**Multinomial logit model**	**ANN model**
Car, Bus & Vanpool	Actual data	72.60%	82.6%
	Validation data	76.2%.	80.9%

CONCLUSIONS

The utilization of the artificial neural networks (ANN) and Multinomial logit (MNL) are common for classification purposes. The application of the data to the artificial neural network and Multinomial logit analysis revealed that the predictive ability of the artificial neural network model is similar to the Multinomial logit model. An algorithm is constructed based on artificial neural network (ANN) using MATLAB to investigate transportation features with the intention of recognizing the mode selected for predictability between personal cars and public transportations namely the bus and vanpool.

Obviously, in both terms of predictability and validation, artificial neural network exceeded the Multinomial logit results. For the evaluation of car, bus, and vanpool, MNL model predictability is 72.60% and 82.6% for the ANN model. For validating purpose, MNL model is 76.2% and 80.9% for ANN model.

In conclusion, the most precise predictability outcomes between artificial neural network (ANN) model and Multinomial logit model are demonstrated and it is revealed that the artificial neural network (ANN) model has the capability in predicting mode choice precisely compared to Multinomial logit model.

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APPENDIX

Artificial neural network for car, bus and vanpool model shift

- **Genfunction with cell array support**

function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Generated by Neural Network Toolbox function genFunction, 21-Nov-2016 18:06:03.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
% X = 1xTS cell, 1 inputs over TS timsteps
% Each X{1,ts} = 13xQ matrix, input #1 at timestep ts.
%
% and returns:
% Y = 1xTS cell of 1 outputs over TS timesteps.
% Each Y{1,ts} = 3xQ matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1_xoffset = [1;1;1;0;1;1;1;1;1;1;1;1;1];
x1_step1_gain =
[0.285714285714286;2;1;0.666666666666667;2;1;0.5;0.666666666666667;0.5;0.333333333333333;0.4;0.3333333333333
33;1];
x1_step1_ymin = -1;

% Layer 1
b1 = [-2.2092442938302885;0.75705537327539174;1.0980944634891752;-
0.70778898590902739;0.3390334469826819;-1.7938025687661654];
IW1_1 = [1.8963410516314672 1.6867465373749835 -2.1226341568827487 -0.90298250429925386
0.071710154085210948 1.3758685812761899 -0.16124547062250325 -0.63897208398987737 -1.2576064396116631 -
0.72929777541289531 1.0251475869722948 -0.47448510479449674 -0.33434108371682225;-1.870417986107108 -
0.50356516659482509 0.53071238218172656 -0.34595309800121549 -0.29350691644512766 -0.2887917811835225
0.022863348793722808 -0.38986593306275474 1.6720739051297218 -0.84189086513623079 -1.53574518522409 -
0.10029642850936227 0.053207024767946663;-0.22088777320966607 -0.15875355596934487 -0.96489132748772943 -
0.41511153989688837 0.1506550210949803 -1.1038606188800224 1.7035372994881557 0.62404205564101456 -
0.33124613460298957 1.0216969000732206 0.51686548323182302 1.8622457684088145 1.1879964612175391;-
0.10741754231563946 0.13010452195440014 0.3153093634783819 -1.2773341574250403 -0.55307038828657729 -
1.361324258604216 -1.6369068629342831 -0.51715742834331013 -0.20438321038542343 0.40564850979989336
1.3708837247438659 -0.45124015510831478 1.0225684220164233;-1.0797018186565024 0.48755227733682388
0.22925884871480584 -1.6883932927858758 1.2769224477365948 -0.057760344865615647 0.38891332896093267 -
0.46268758893907458 -0.89464312962280002 0.91788330580830246 -0.93659603943146086 0.23261300537469504
0.64771066477038131;-0.53740791334411608 0.47009453794557121 1.3278461364985052 0.77030047518316036 -
0.31696431260715424 1.127583609353777 -0.16652656310117209 0.027916080772702183 -0.11105338062994535
0.083608621882059836 0.20927635363869082 -0.91127296581600215 0.72913585395156699];

% Layer 2
b2 = [-0.29742321544928096;-0.63098388102945524;-0.77498188399723444];
LW2_1 = [-0.82462120160470787 -2.0910587591954157 1.7302572098898603 -0.68584025472948629 -
2.0199374215572932 -0.84980363556861682;-1.1428142106248986 -0.7655910251352912 -0.81371836247845453 -
0.3446039031978847 0.33753029630980613 0.35292594904710173;2.4996667249378639 2.2655757346858225 -
0.059194185163193414 1.6153468806594327 0.83827243101135251 0.069034669930104958];
% ===== SIMULATION ========

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```
% Format Input Arguments
isCellX = iscell(X);
if ~isCellX, X = {X}; end;

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
Q = size(X{1},2); % samples/series
else
Q = 0;
end

% Allocate outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

% Input 1
Xp1 = mapminmax_apply(X{1,ts},x1_step1_gain,x1_step1_xoffset,x1_step1_ymin);

% Layer 1
a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

% Layer 2
a2 = softmax_apply(repmat(b2,1,Q) + LW2_1*a1);

% Output 1
Y{1,ts} = a2;
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
 if ~isCellX, Y = cell2mat(Y); end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings_gain,settings_xoffset,settings_ymin)
y = bsxfun(@minus,x,settings_xoffset);
y = bsxfun(@times,y,settings_gain);
y = bsxfun(@plus,y,settings_ymin);
end

% Competitive soft transfer function
function a = softmax_apply(n)
nmax = max(n,[],1);
n = bsxfun(@minus,n,nmax);
numer = exp(n);
denom = sum(numer,1);
denom(denom == 0) = 1;
a = bsxfun(@rdivide,numer,denom);
end

% Sigmoid symmetric transfer function
function a = tansig_apply(n)
```

VOL. 12, NO. 5, MARCH 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

a = 2 ./ (1 + exp(-2*n)) - 1;
end

- **Genfunction with no cell array support**

```
function [y1] = myNeuralNetworkFunction(x1)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Generated by Neural Network Toolbox function genFunction, 21-Nov-2016 18:13:17.
%
% [y1] = myNeuralNetworkFunction(x1) takes these arguments:
%   x = 13xQ matrix, input #1
% and returns:
%   y = 3xQ matrix, output #1
% where Q is the number of samples.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1_xoffset = [1;1;1;0;1;1;1;1;1;1;1;1;1];
x1_step1_gain =
[0.285714285714286;2;1;0.666666666666667;2;1;0.5;0.666666666666667;0.5;0.333333333
333333;0.4;0.333333333333333;1];
x1_step1_ymin = -1;

% Layer 1
b1 = [-2.2092442938302885; 0.75705537327539174;1.0980944634891752;-
0.70778898590902739;0.3390334469826819;-1.7938025687661654];
IW1_1 = [1.8963410516314672 1.6867465373749835 -2.1226341568827487 -
0.90298250429925386 0.071710154085210948 1.3758685812761899 -0.16124547062250325 -
0.63897208398987737 -1.2576064396116631 -0.72929777541289531 1.0251475869722948 -
0.47448510479449674 -0.33434108371682225;-1.870417986107108 -0.50356516659482509
0.53071238218172656 -0.34595309800121549 -0.29350691644512766 -0.2887917811835225
0.022863348793722808 -0.38986593306275474 1.6720739051297218 -0.84189086513623079
-1.53574518522409 -0.10029642850936227 0.053207024767946663;-0.22088777320966607 -
0.15875355596934487 -0.96489132748772943 -0.41511153989688837 0.1506550210949803 -
1.1038606188800224 1.7035372994881557 0.62404205564101456 -0.33124613460298957
1.0216969000732206 0.51686548323182302 1.8622457684088145 1.1879964612175391;-
0.10741754231563946 0.13010452195440014 0.3153093634783819 -1.2773341574250403 -
0.55307038828657729 -1.361324258604216 -1.6369068629342831 -0.51715742834331013 -
0.20438321038542343 0.40564850979989336 1.3708837247438659 -0.45124015510831478
1.0225684220164233;-1.0797018186565024 0.48755227733682388 0.22925884871480584 -
1.6883932927858758 1.2769224477365948 -0.057760344865615647 0.38891332896093267 -
0.46268758893907458 -0.89464312962280002 0.91788330580830246 -0.93659603943146086
0.23261300537469504 0.64771066477038131;-0.53740791334411608 0.47009453794557121
1.3278461364985052 0.77030047518316036 -0.31696431260715424 1.127583609353777 -
0.16652656310117209 0.027916080772702183 -0.11105338062994535 0.083608621882059836
0.20927635363869082 -0.91127296581600215 0.72913585395156699];

% Layer 2
b2 = [-0.29742321544928096;-0.63098388102945524;-0.77498188399723444];
LW2_1 = [-0.82462120160470787 -2.0910587591954157 1.7302572098898603 -
0.68584025472948629 -2.0199374215572932 -0.84980363556861682;-1.1428142106248986 -
0.7655910251352912 -0.81371836247845453 -0.3446039031978847 0.33753029630980613
0.35292594904710173;2.4996667249378639 2.2655757346858225 -0.059194185163193414
1.6153468806594327 0.83827243101135251 0.069034669930104958];
% ===== SIMULATION ========
% Dimensions
```

```
Q = size(x1,2); % samples

% Input 1
xp1 = mapminmax_apply(x1,x1_step1_gain,x1_step1_xoffset,x1_step1_ymin);

% Layer 1
a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*xp1);

% Layer 2
a2 = softmax_apply(repmat(b2,1,Q) + LW2_1*a1);

% Output 1
y1 = a2;
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings_gain,settings_xoffset,settings_ymin)
y = bsxfun(@minus,x,settings_xoffset);
y = bsxfun(@times,y,settings_gain);
y = bsxfun(@plus,y,settings_ymin);
end

% Competitive Soft Transfer Function
function a = softmax_apply(n)
nmax = max(n,[],1);
n = bsxfun(@minus,n,nmax);
numer = exp(n);
denom = sum(numer,1);
denom(denom == 0) = 1;
a = bsxfun(@rdivide,numer,denom);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n)
a = 2 ./ (1 + exp(-2*n)) - 1;
end
```