MODELLING OF TRAVEL BEHAVIOUR OF STUDENTS USING ARTIFICIAL INTELLIGENCE

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Abstract:

Travel demand models are required by transportation planners to predict the travel behaviour of people with different socio-economic characteristics. Travel behaviour of students act as an essential component of travel demand modelling. This behaviour is reflected in the educational activity travel pattern, the timing, sequence and mode of travel of students. Roads in the vicinity of schools are adversely affected during the school opening and closing hours. It enhances the traffic congestion, emission and safety problems around schools. It is necessary to improve the safety of school going children by understanding the present travel behaviour and to develop efficient sustainable traffic management measures to reduce congestion in the vicinity of schools. It is possible only if the travel behaviour of educational activities are studied. This travel behaviour is complex in nature and lot of uncertainty exists. Selection of modelling technique is very important for modelling the complex travel behaviour of students. This leads to the importance of application of artificial intelligence (AI) techniques in this area. AI techniques are highly developed in twenty first century due to the advancements in computer, big data and theoretical understanding. It is proved in the literature that these techniques are suitable for modelling the human behaviour. However, it has not been used in behaviourally oriented activity based modelling. This study is aimed to develop a model system to predict the daily travel behaviour of students using artificial intelligence technique, ANN. These ANN models were then compared with the conventional econometric models developed. It was observed that artificial intelligence models provide better results than econometric models in predicting the activity-travel behaviour of students. These models were further applied to study the variation in activity-travel behaviour, if short term travel-demand management measures like promoting walking for educational activities are implemented. Thus the study established that artificial intelligence can replace the conventional econometric methods for modelling the activity-travel behaviour of students. It can also be used for analysing the impact of short term travel demand management measures.

Keywords: educational activity, ANN, travel demand management, travel behaviour, artificial intelligence, econometric models.

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1. Introduction

Activity-travel behaviour based demand modelling has got wide publicity in the past few decades. This approach views travel behaviour as a demand derived from the necessity to take part in activities. These behavioural models are capable of modelling the time and sequence of activities even though they are complex in nature. Activity-travel behaviour is often investigated by researchers from a variety of standpoints. They separated the compulsory and non-compulsory activities of individuals for developing the activity – travel behaviour model systems. Compulsory / mandatory activities of individuals involve both work and educational activities. Most of the research works are carried out with work/school activity travel-behaviour as a crucial component of travel demand. The econometric model CEMDEP proposed a comprehensive activity generation-allocation scheduling model (Bhatt and Singh 2000, Bhat et al. 2004). It considered 'work/school' as the primary activity of the travel behaviour. Recker et al. (1986) developed STARCHILD (Simulation of Travel /Activity Response to Complex Household Interactive Logistic Decisions), to examine the formation of household travel/activity behaviour. They developed the model with 'planned and unplanned' activities.

Arentze and Timmermans (2000) developed ALBATROSS which is the most comprehensive and operational computational process model. It was a rule-based system which predicts the travel behaviour of mandatory and non-mandatory activities. Work and school activities are considered together as mandatory activities in ALBATROSS. Daily activity participation decisions of individual, which lead to trip chaining, were studied by Wainaina and Richter (2002). FAMOS, (Florida Activity Mobility Simulator), proposed a prism constrained simulation approach where work/school are considered as fixed activities (Pendyala et al. 2005). The rule-based activity scheduler TASHA also takes the same approach for generating work/ school duration (Roorda et al. 2008). Nurul Habib and Miller (2009) developed an econometric modelling framework for activity-agenda formation. The agenda was the collection of different types of activities within a specific time period. This approach dealt with all activity types together in a unified econometric modelling framework. The model ensured the scope for unplanned activities within the time budget. Potoglou

and Arslangulova (2016) identified the factors associated with the travel behaviour of primary and secondary school students on a typical school day in Wales.

Developing countries like India have mixed traffic and the modes used in these countries include bus, train, car, two wheeler and walk/cycle. Hence the mode choice behaviour is more complex in developing countries than in developed countries. Limited studies have been reported in developing countries on activity based travel demand modelling. Bindu et al.(2005, 2006)developed a prototype of time-use diary design which was user friendly, offers fewer burdens on respondent, and ensures good quality and quantity of data. They also presented a tour-based approach of modelling mode choice of the residents of Mumbai city of Maharashtra. The study found that the performance of the mixed logit model is better than Multi Nomial Logit (MNL). Subbarao and Rao (2014) analysed the activity travel behaviour in the context of Mumbai metropolitan region by developing a new activity travel diary. Interactions among households or other members were also facilitated by the newly designed diary. Surekha (2009) developed a micro simulation model for activity travel pattern for Tiruchirappalli City, Tamil Nadu, India. Sreela et al. (2013) studied the shopping activity travel behaviour of workers in Calicut city, one of the major urban centres in Kerala. Manoj and Verma (2013) studied the activity-travel behaviour of non-workers in Bangalore city of India. This study modelled the out-of-home activity participation behaviour of non-workers using a primary activity-travel survey data. Babu et al (2018) explored the travel behaviour of workers and students in Calicut city to model their activity-travel patterns.

Literature shows that there are so many activity generation model systems for developed countries, in which work and school travel behaviour are modelled together as mandatory activities. Few of the reported studies in developing countries concentrated on school travel behaviour which is the mandatory activity of an individual. Roads in the vicinity of schools are adversely affected during the school opening and closing hours. It enhances the traffic congestion, emission and safety problems around schools. It is necessary to improve the safety of school going children by understanding the present travel behaviour and to develop efficient sustainable traffic management measures to reduce congestion

in the vicinity of schools. This is possible only if the travel behaviour of educational activities are studied. This study is aimed to predict the activity-travel behaviour of students.

The modelling of educational activity-travel behaviour is a complex process that depends on factors such as the traveller's socio-economic characteristics and the relative advantages of each mode as perceived by the user in terms of travel time, cost, comfort, convenience, and safety. This involves lot of uncertainty and hence selection of a modelling technique is very important for the prediction accuracy of the model. Econometric models, which are systems of equations representing probabilities of decision outcomes, are the most popularly adopted method for activity based travel demand modelling. They are based on the theory of probability and statistics, produce probabilities for all possible outcomes, and are typically based on utility maximization assumption. These model systems rely on multinomial logit models, nested logit models, structural equation models, hazard duration models and linear regression models. They do not have any learning and training capability, which is essential for modelling the human behaviour.

Artificial intelligence techniques have been proved to have better learning and training capability and suitable for modelling the human behaviour. Buscema et al. (2009) experimented Artificial Neural Network (ANN) to create diagnostic procedures for eating disorders in human being. The prediction accuracy was reported as 86.94% in this study. Abubakar et al. (2018) proposed and experimented an ANN model for the effect of organizational safety climate and behaviours on workplace injuries. Gibała and Konieczny (2018) applied ANN effectively to predict necessary repairs on ordinary railway switches. Borimnejad et al. (2016) modelled the consumer's behaviour in the Mayadin Management Organization of Tehran for vegetables using ANN and estimated the demand curve and elasticity. Amanatiadis et al. (2014) trained and utilised ANN with the observations on user satisfaction with respect to website attributes. The results indicated that website attributes had impacts on satisfaction, but the relationships found both asymmetry and nonlinearity. Function approximation using ANN was found to be appropriate for estimating relationships providing valuable information about satisfaction's formation. Sharma et al. (2017) attempted to develop SEM and

ANN model to understand and predict the effect of individual characteristics viz; technology experience [TE] and personal innovativeness [PI]) and e-LMS quality determinants on the use of e-LMS by instructors. The ANN model results showed that service quality was the most important predictor of e-learning acceptance followed by SYS-Q, PI, information quality, and TE. Hence it is proved in the literature that ANN is suitable for modelling the human behaviour, however it has not been used in behaviourally oriented activity based modelling. This study is intended to check the suitability of artificial intelligence technique to model the activity-travel behaviour of students. The developed model systems are further applied for analysing the impact of sustainable travel demand management measures.

2. Modelling of travel behaviour of students

Thiruvananthapuram City, which is the capital of Kerala, the southernmost state in India, is selected as the study area. It is a growing city located in the southern region of India. It consists of 100 wards and the total population is 966,856 as per the 2011 census data. An activity travel diary was designed to collect the data by home interview survey. The sample size obtained for the study is 9530 members collected from 2521 households. Student population in the sample was 20.5%, among which, 54% were male. Data of students in the age group 5- 40 were considered for developing the models

Daily educational activity-travel behaviour of students consists of educational activity generation, scheduling of educational activity, involvement in other activities and stopping pattern during travel. Educational activity generation and scheduling part includes models for finding the out-of-home education activities, educational activity duration, educational activity start time, distance travelled, mode and duration of commute for education. Behaviour of students related to other activity include probability to participate in other activities, time of occurrence, mode used, start time and duration of other activities. While commuting for education, the student may stop for other activities and the stopping behaviour includes probability to stop, purpose of stop and duration of stop. Two modelling techniques have been used in this study for modelling the daily activity-travel behaviour of students. i.e: econometric models and artificial neural network models. The models are discussed in the following subsections.

2.1. Econometric models

Daily educational activity-travel behaviour model system using econometric modelling technique consists of six models for predicting educational activity generation and scheduling, five models for other activity of students and three models for stop level pattern of students during commute. N-Logit Software was used for developing the econometric models. Binary Logit, Multi Nomial Logit (MNL) and Multiple Linear Regression (MLR) are the econometric models used for modelling the travel behaviour of students. Binary logit models are used for binary choice decision making and Eq. (1) represents the mathematical form of the model.

$$P(Y=1) = \frac{\exp(\beta \cdot X)}{1 + \exp(\beta \cdot X)} \qquad (1)$$

MNL models are used for multi choice decision making and has a mathematical form as shown in Eq. (2). For choice j= 1,2,3…, J

$$\text{Prob}[\text{choice j}] = \frac{\exp(\beta \cdot Xj)}{\sum\limits_{j=1}^{J} \exp(\beta \cdot Xj)} \qquad (2)$$

Multiple linear regression models are used for finding out the duration and it is of the form given in Eq. (3).

$$Y = (\beta \cdot X) + C \qquad (3)$$

Where: β - Coefficient matrix, X - Variable matrix.

2.1.1. Educational activity generation and scheduling

Educational activity generation and scheduling part includes econometric models for finding the out-of-home education activities, educational activity duration, educational activity start time, distance travelled, mode and duration of commute for education. The model coefficients and t- statistics are shown in Table 1. A binary logit model was developed for predicting students with out-of-home activities. Model shows that male, young and unmarried students go for more out-of-home educational activities. The time in minutes a student spends in the educational

institution was modelled by daily educational activity duration. It was modelled as Multiple Linear Regression (MLR). Model shows that under graduate and post graduate students spend more time in educational institution than secondary and higher secondary students, which is normally observed as per the present education system. The educational activity start time of a student is the time(in minutes) of arrival of the student at school/college. To account the variability in start time, it was modelled as MLR.It is observed that if the educational activity duration is more, students reach early in the institution. Under graduate and post graduate students reach the institution early than secondary and higher secondary students. As vehicle ownership increases students are found to reach the institution early.

Distance from home to place of education was also modelled as a MLR. Model shows that the daily distance travelled by under graduate and post graduate students is more than that of secondary and higher secondary students. This may be due to the fact that at lower levels, the students choose institution in the neighbourhood. At higher levels, institutions are limited; hence they are forced to select an institution which is away from the neighbourhood. The students who reach the institution early, travel more compared to others. This is in accordance with the observation that 'under graduate and post graduate students reach the institution early than secondary and higher secondary students' as seen from model for educational activity start time. Daily distance travelled by under graduate and post graduate students is more than that of secondary and higher secondary students as observed in model for daily distance travelled. The mode choice of the commuter for educational activity was modelled as Multi Nomial Logit (MNL). The modes selected are two wheeler, car/van/jeep, bus, train and walk/cycle among which the base mode is selected as walk/cycle. The model shows that male, under graduate and post graduate students and higher age group students prefer two wheelers, which is the normal trend in practice. If the educational institution starts early, there is more probability of choosing two wheeler and car. This is in accordance with the observation 'as vehicle ownership increases students are found to reach the institution early' seen from the model for educational activity start time. It is observed that, if the educational activity starts late, students travel by bus.

Table 1. Econometric Model System for Educational Activity Generation

Model No	Models	Model Form	Constant	Gender	Age Group	Marital Status	Vehicle Owners-hip	Level of Educa-tion	Educatio-nal Activity Duration	Educatio-nal Activity Start Time	Distance to Work Place	Mode of Com-mute
1	Out-of-home Edu-cational Activity	Binary Logit	3.01	-0.49* (-3.02)	-4.12* (-18.54)	2.50* (12.11)						
2	Educatio-nal activity Duration	MLR	376.28					5.81* 3.15)				
3	Educatio-nal activity Start Time	MLR	656.14				2.61* (2.92)	-4.04* (3.68)	0.29* (16.26)			
4	Distance to Place of Education	MLR	14.47					1.91* (6.52)	0.020* (-2.85)	0.02+ (2.56)		
5	Mode of Commute for Educational activity											
	U(TW)	MNL	-1.12	-1.33* (3.5)	1.50* (-3.73)		0.22+ (-2.43)	0.79* (6.95)		-0.003 (6.95)		
	U(Car/van)		3.86	-0.88× (3.94)	-1.03* (-3.54)		0.45+ (-2.43)	0.32		-0.01 (3.37)		
	U(Bus)		3.54	-0.03 (-3.95)	0.28* (-6.55)		0.06 (-1.63)	0.12		0.004× (3.37)		
	U(Train)		3.57	1.19 (1.45)	8.22+ (-1.18)		2.95 (-1.14)	4.85+		0.10+ (1.46)		
6	Commute Duration	MLR	-21.06	3.76* (2.81)				1.52+ (2.07)	-0.04* (-3.05)	0.06+ (2.89)	1.49* (20.42)	2.43* (3.02)

Variables at 1% level of significance +Variables at 5% level of significance ( ) Values in brackets are t statistics

The commute duration of a student from home to educational institution was modelled as MLR. The fact that commute duration increases with distance to place of education, is justified in this model. As mode of commute changes from walk/ cycle to train, commute duration also increases. The reason may be due to the fact that as distance increases, commuters switch from slower to faster vehicles and due to increase in distance, commute duration will also increase. Male students take less time to commute than female students. The reason is that male students prefer two wheeler and car to commute, which is evident from model for mode choice of commute.

2.1.2. Other Activities of Students

Other activities of students identified are education related, personal business and recreation and shopping, among which shopping has the least share (8%). The models developed for capturing the behaviour of students to participate in other activities are given in Table 2. The choice of an activity was modelled as MNL with base category 'no activity'.

It is seen that students of lower age group have more education related activities than higher age group. Students studying at school/college which starts late, are also found to be more involved in education related activity. It is seen that male students, students with less education duration and high level of education go for personal business and recreation. Male students, students with lower educational activity duration and early start time, carry out shopping activity. Time of occurrence of other activities of students was classified as 'before study' and 'after study'. This was modelled as binary logit with base category 'before study'. Model shows that as educational activity duration increases, other activity occurs before study. If the educational activity starts early, there is more probability for other activity after study. It is also seen that the probability of occurrence of education related activity is more before study and that for personal business and recreation is more after study.

The mode used by students to perform other activity was modelled as MNL. The choices considered are

walk/cycle, two wheeler and car/van/jeep, where walk/cycle was taken as the base mode. It is revealed that higher age group students prefer two wheeler for other activities. As the vehicle ownership increases, there is chance for using car/van/jeep for other activities. There is more probability of using car/van/jeep for shopping activity than education related and recreation. Duration of other activities of students was modelled as MLR. Students spend more time for education related activity than personal business and recreation and shopping. It is observed that duration of activity is more for male students than females. When mode used for the activity changes from walk/cycle to car/van/jeep, duration of activity also increases. Activity duration is observed to be more, if the students participate in other activities after study. Start time of other activity of students or the time spent by the individual at home between the educational activity and other activity was

modelled as MLR. The model given in Table 2 shows that if the duration of commute for education and educational activity duration are more, home stay duration will be less. As the purpose of activity changes from education related to shopping, home stay duration increases.

2.1.3. Stop level Behaviour during School/College-to-Home Travel

While commuting before and/or after education, the students may stop for other activities and the probability of stopping was modelled in this section. The stop level behaviour of students during school/college-to-home travel was only modelled, since the stops during home-to-school/college travel is less than 1%. Coefficients and t-statistics of the models are shown in Table 3. Probability to stop was modelled as binary logit.

Table 2. Econometric Model System for Other Activities of Students

Model No	Models	Model Form	Constant	Gender	Age group	Level of education	Educational activity duration	Educational activity start time	Education related activity	Personal business and recreation activity	
	Probability and purpose of other activities of students										
7	U(Education related)	MNL	4.70	0.29 (1.45)	-1.25+ (-2.50)	-0.04 (-0.17)	-0.002 (-0.98)	0.01* (3.04)			
	U(Personal business and recreation)		-5.62	-2.28* (-5.89)	0.43 (0.94)	0.49+ (2.01)	-0.005* (-2.13)	0.004* (1.13)			
	U(Shopping)		4.52	-1.39* (-2.86)	0.67* (1.07)	0.61 (1.70)	-0.01* (-3.28)	-0.01+ (-2.15)			
8	Time of occurrence of other activities	BL	16.82				-0.01+ (-1.85)	-0.02* (-3.39)	-1.66+ (-1.55)	2.20+ (2.04)	

Model No	Models	Model Form	Constant	Gender	Age group	Educational activity duration	Vehicle ownership	Purpose of activity	Mode for other activity	Time of occurrence	Duration of commute for education
9	Mode used for other activities										
	U(TW)	MNL	-3.46		1.56* (4.12)		0.05 (0.37)	0.18 (0.63)			
	U(car/van/jeep)		-7.84		-0.70 (-0.98)		1.23* (2.62)	1.30* (3.00)			
10	Duration of other activity	MLR	185.26	-15.24* (-2.48)				-38.37* (-10.66)	11.54* (2.97)	13.02+ (3.01)	
11	Start time of other activity	MLR	333.39			-0.74* (-4.47)		29.42+ (1.98)			-1.05* (-3.12)

Variables at 1% level of significance +Variables at 5% level of significance ( ) Values in brackets are t statistics

Table 3. Econometric Model System for Stop during School/College-to-Home Travel

Model No	Models	Model Form	Constant	Level of education	Vehicle owners-hip	Distance to education	Duration of commute for education	Mode of commute for education	Purpose of stop
12	Probability of stop	BL	0.53			-0.45* (-7.58)	-0.22* (-5.67)	-0.10* (-7.47)	
13	Purpose of stop								
	U(Personal business and recreation)	MNL	-0.26	2.40+ (2.52)	-1.16 (-1.58)		-0.01 (-0.90)		
	U(Education related)		8.24	1.46 (1.29)	-3.43 [x] (-1.71)		-0.04+ (-2.20)		
14	Duration of stop	MLR	70.83				-0.35* (-3.73)		35.25* (4.89)

*Variables at 1% level of significance +Variables at 5% level of significance ( ) Values in brackets are t statistics

The model shows that if the distance to education and commute duration is more, there is less probability to stop during school/college-to-home travel. If the mode of commute is bus, the probability to stop is less.

Purposes of stop during school/college-to-home commute are identified as shopping, personal business and recreation, and education related. It was modelled as MNL with base category 'shopping'. It is observed from the model that as the level of education increases, there is more probability for personal business and recreation than shopping. As the commute duration increases, there is less probability for education related activity stop than shopping. Duration of stop during school/college-to-home commute was modelled as MLR. If the travel duration increases, duration of stop is found to be less. Duration of stop is highest for education related activities and least for shopping.

2.2. Artificial neural network models
The econometric models developed in the previous subsection were based on theory of probability and statistics. They do not have any learning and training capability. Hence complex travel behaviour of students are modelled with ANN also, to check whether there is any improvement in the efficiency of the models. ANN is made up of a number of simple, and highly interconnected processing elements, which processes information by its dynamic state response to external inputs. The multi-layer feed-forward network was used in this study. The network was trained using an error back propagation training algorithm. This algorithm adjusts the connection weights according to the back propagated error computed between the observed and the estimated results. This procedure attempts to minimise the error between the desired and the predicted outputs. Four neural networks for modelling the activity-travel behaviour of students are shown in Table 4.

Table 4. ANN Networks for modelling the educational activity behaviour

Sl. No.	Econometric Models	ANN Models
1	Probability of out-of-home educational activity (yes/ no)	Network 1
2	Educational activity duration	
3	Educational activity start time	
4	Distance to place of education	
5	Mode of commute for educational activity	Network 2
6	Duration of commute for educational activity	Network 3
7	Probability and purpose of other activities	
8	Probability of stop during school/college-to-home travel	
9	Purpose of stop during school/college-to-home travel	
10	Time of occurrence of other activities	Network 4
11	Mode used for other activities	
12	Duration of other activities	
13	Start time of other activity	
14	Duration of stop during school/college-to-home travel	

First network deals with educational activity generation and scheduling, second network was developed for mode of commute, third stage for other activity generation and fourth stage network was for other activity scheduling of students. Table 5 presents the input and output variables used for each network. The networks are shown in Figures (Neural Networks for Educational Activity Travel Behaviour Fig. 1a to Fig. 1d). The networks used in this study consisted of four layers: one input layer, two hidden layers and one output layer. The input layer consists of one neuron each for all input variables, two hidden layers consisting of twenty neurons each and the output layer consisting of one neuron each for all output variables. The number of hidden layers and neurons in each layer were selected by trial and error based on the training and testing performance. The number of neurons in the input, output and hidden layers are shown in the networks.

Table 5. Input and Output Variables of ANN Models for Students

| ANN Models	Input Variables	Output Variables
Network 1	Gender, age group, level of education, vehicle ownership and marital status	Whether the individual perform out-of-home educational activity, educational activity duration, educational activity start time and distance to place of education
Network 2	Gender, age group, level of education, vehicle ownership, marital status, educational activity duration, educational activity start time and distance to place of education	Mode of commute for educational activity
Network 3	Gender, age group, level of education, vehicle ownership, marital status, educational activity duration, educational activity start time, distance to place of education, mode of commute for educational activity	Duration of commute for educational activity, purpose of other activity, purpose of stop during school/college-to-home travel
Network 4	Gender, age group, level of education, marital status, vehicle ownership, educational activity duration, educational activity start time and distance to place of education, commute mode and duration for educational activity, purpose of other activity, purpose of stop during school/college-to-home travel	Commute mode, time of occurrence and Duration of other activities, duration of stop during commute and duration of home stay between the activities of workers.
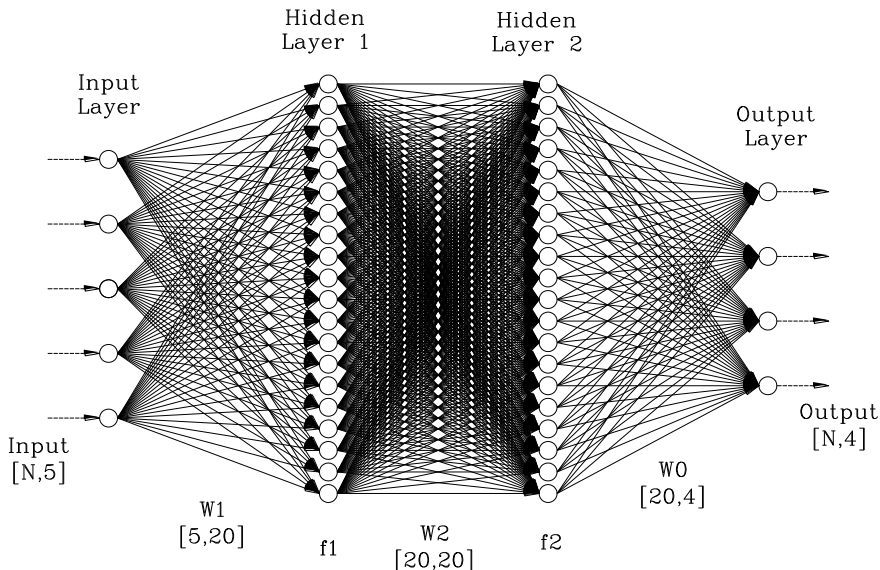
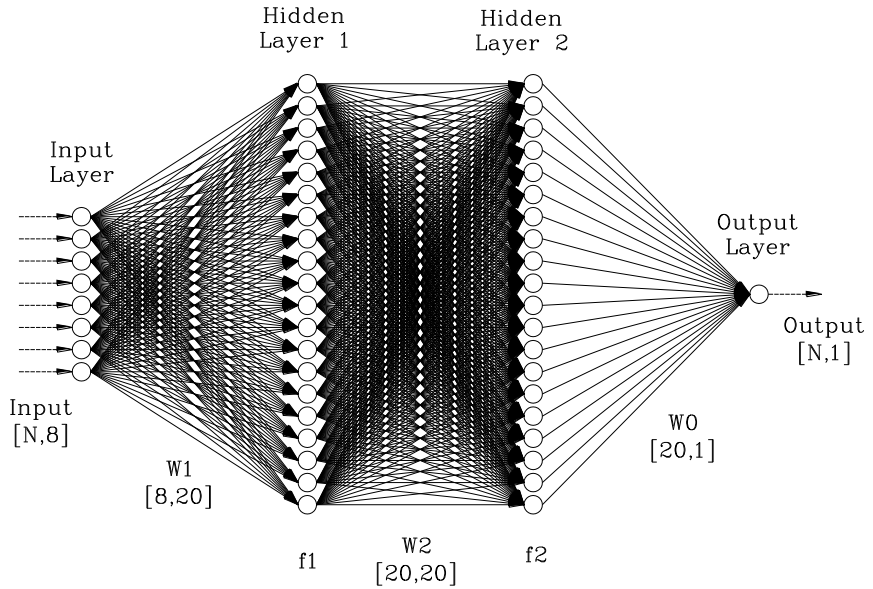Fig. 1a. Network 1 for Educational Activity Generation

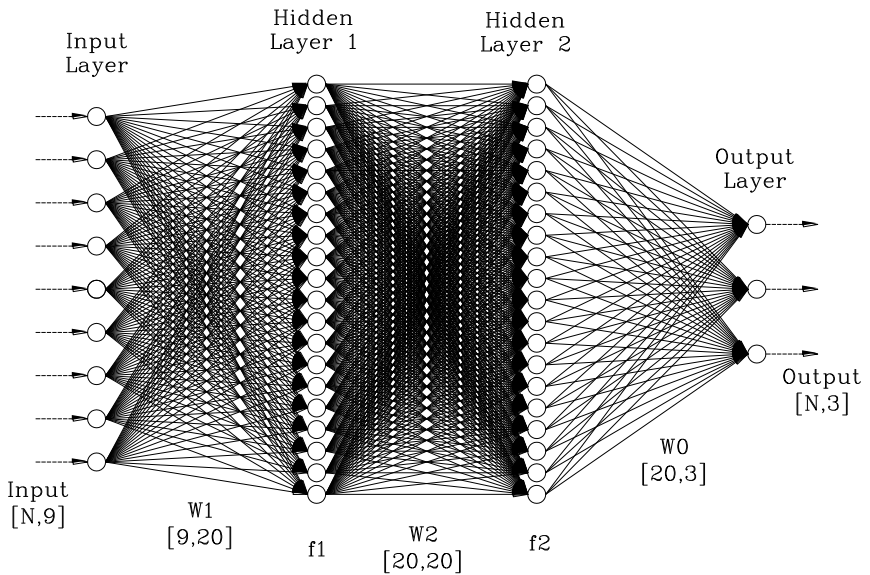Fig.1b. Network 2 for Mode of Educational Activity

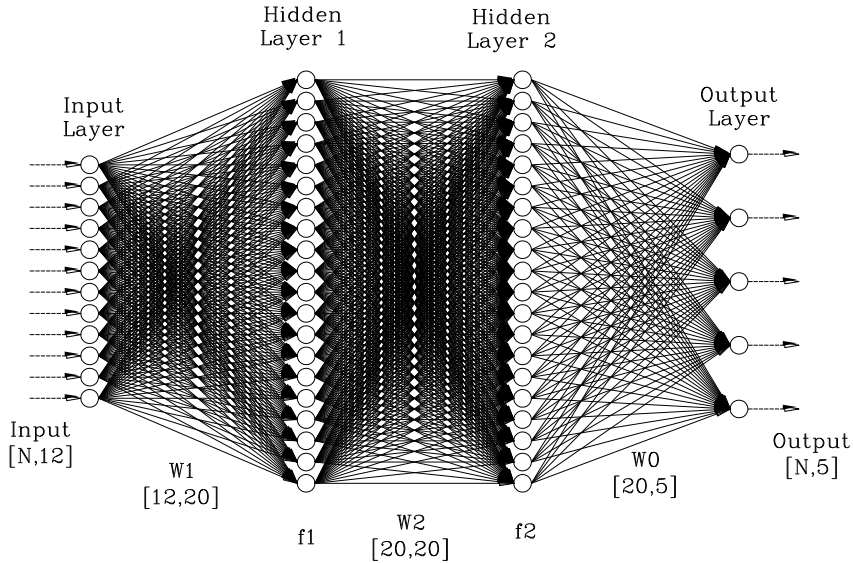Fig. 1c. Network 3 for Educational Activity Scheduling

Fig. 1d. Network 4 for Other Activity of Students

2.3. Validation of the models

Econometric models and neural network models discussed in the previous sections were validated with 20% of the collected data. The actual/collected data was given as input to each of the model for workers. Each of the output was compared with the actual/collected data and RRMSE was found out.

Empty cells are given for continuous variables. RRMSE was calculated for these variables with predicted value and actual value. Prediction accuracies of all the models are given in Table 6. Validation results reveal that ANN models show better accuracy than econometric models.

Table 6. Validation results

Response Variables	Econometric Models			ANN Networks			
	Truly Predicted	Wrongly Predicted	Error (%)	Truly Predicted	Wrongly Predicted	Error (%)	Decrease in Error (%)
Out home Educational activity (Yes/ No)	370	20	5.13	386	4	1.03	4.10
Daily Educational duration	-	-	18.14	-	-	13.99	4.15
Daily Educational Start time	-	-	23.09	-	-	6.72	16.37
Distance to the Education place	-	-	33.03	-	-	11.8	21.23
Mode of Commute before Educational Activity	283	99	25.92	342	40	10.47	15.45
Mode of Commute after Educational Activity	328	54	14.14	356	26	6.81	7.33
Duration of commute before Educational Activity	-	-	20.42	-	-	40	10.47
Duration of commute after Educational Activity	-	-	12.83	-	-	8.64	4.19

The prediction errors of econometric models varied from 5% to 33% and that of ANN models varied from 1% to 14% only. ANN models were able to predict the daily activity-travel pattern of students with accuracy ranging from 86% to 99%. The decrease in percentage error ranges from 4% to 21%, when econometric models are replaced with ANN models. This shows that level of prediction of artificial intelligence is better than econometric models to predict the activity-travel behaviour of students. This can be attributed to the training and learning capability of ANN.

3. Application of the ANN models for sustainable transportation planning

The efficiency of any transportation system is primarily assessed in terms of traffic congestion and safety. This depends on the traffic volume, its composition and road capacity. Enhancement of road capacity is a long term management measure and often not feasible. Hence nowadays policy makers rely on short term demand management policies. The study also intended to check the suitability of the developed artificial intelligence to analyse the effect of short term travel demand management measures. The effect of promoting sustainable mode of travel for educational activity is analysed. Cycling/Walking to school is a sustainable means of transportation and it is a good chance to implant a regular physical activity in students' daily routines. ANN models developed in the study were used to analyse the effect of sustainable transportation planning viz; promoting walk as mode for educational activity.

If walking is promoted for educational activity up to 2 km, the resulting impact in other modal shares is studied. It was obtained from the study that walk share of school going students without any TDM measure is 3.0%. It was also found that if walking is promoted upto 2km for all the school going students, the walk share for school going activity would be increased to 13.0%. Figure2 shows the resulting share of different modes. It is revealed that when walk share increases from 3.0% to 13.0%, bus share decreases from 54.9% to 47.9%, two wheeler share decreases from 30.0% to 28.2% and car share decreases from 10.9% to 9.6%.

4. Conclusion

Travel demand models are used to replicate the real world transportation system and to predict the future travel demand. A behavioural oriented approach in travel demand analysis is provided by activity based travel demand modelling and it provides a better understanding of the travel behaviour of an individual. The present study has made an attempt to introduce artificial intelligence in the modelling of daily educational activity – travel behaviour. Artificial Neural Network models were developed in this study and it was compared with the conventional econometric models. Results showed that ANN models are able to predict the educational activity-travel behaviour with better accuracy than econometric models. The decrease in percentage error ranges from 4% to 21%, when econometric models are replaced with ANN models.
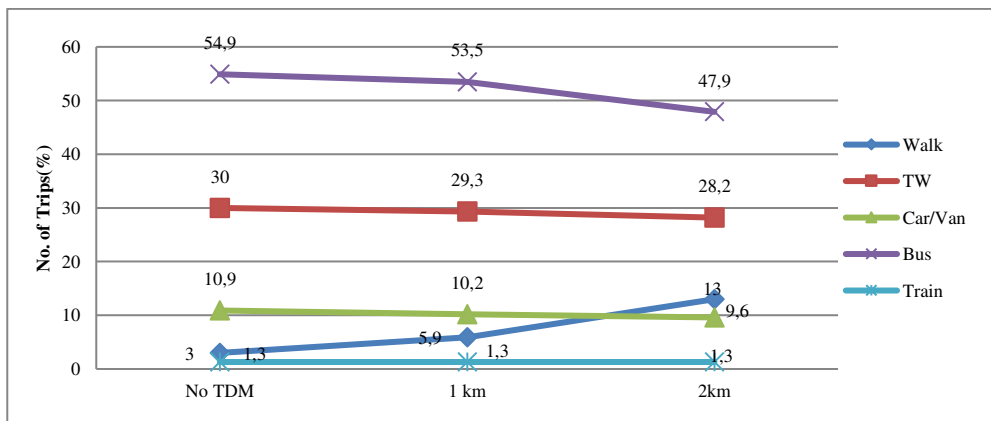

Fig. 2. Modal Share after Shift to Walking

However ANN models do not have a statistical check and model transferability is tedious compared to econometric models. These ANN models were later used for analysing the effect of sustainable travel demand management measure like promoting walking for students. The study revealed that if walking is promoted for educational trips for 1km to 2 km, walk share increases from 3.0% to 13%, bus share decreases from 54.9% to 47.9%, two wheeler share decreases from 30.0% to 28.2% and car share decreases from 10.9% to 9.6%. Similar to the above, different policy options can be tried to obtain a feasible solution to reduce congestion in the school vicinity. Policy or decision makers can use the findings of this study for making appropriate steps for promoting walking for educational activities. It can also be used for designing walkways to improve the safety of school children and to promote sustainable transportation. Hence it was proved in the study that artificial intelligence can effectively be used for modelling the educational activity-travel behaviour than conventional methods. It was also established in the study that the resulting models can be applied for analysing the impact of short term travel demand management measures, which will give more realistic results than conventional models.

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