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Ann Modeling For Predicting Car Travel Time using Bus As Probe.

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Abstract: ***The critical issue of Intelligent Transportation Systems (ITS) applications is obtaining the near real time information of travel times. This paper proposes a dependable model for predicting car travel time on urban roads in Greater Cairo using buses as probes. The GPS receivers, which are installed on test vehicles and buses, used to collect real travel time data along the urban roads. The travel times of bus and car are compared in order to recognize similarities and differences between the trip profiles of test vehicles and buses. According to the comparison results, the model is developed and validated using Artificial Neural Network (ANN) for estimating car travel time using buses' travel time with acceptable level of accuracy equals 10.53%.***

Keywords* : *ANN, Travel time, urban roads, bus as probe

I. INTRODUCTION

ITS can be defined as transportation systems that applies advanced technologies of electronics, communications, computers and detecting in all kinds of transportation systems in order to improve safety, efficiency and traffic situation through transmitting real-time information. The ITS applications became central for relieving traffic jam. An important element of such schemes is a system to collect, estimate, and spread traffic information to users in real-time. There are many examples of ITS applications such as, Advanced Traveler Information Systems (ATIS), Automatic Vehicle Identification (AVI) and Advanced Traffic Management Systems (ATMS).

Travel time information is a key performance measure for traffic analysts, public agencies, and planners. It is used extensively for network-wide analysis and evaluation. There is a growing interest in techniques for collecting reliable travel time data as well as models and methods that can be used to analyze and disseminate it to end-users (e.g. a traveler) via real-time.

This paper aims to use transit vehicles as probes for collecting travel time information on some urban routes in Greater Cairo. It is important to examine the potential for using buses as probe vehicles for getting average route travel times.

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II. LITERATURE REVIEW

The travel time prediction problem especially on urban roads has been a topic of the research for a long time. The initial motivation for developing these models was for their use in traffic management and certainly the travel time is the most important measure of performance of a transportation system. In recent years, the interest in predicting travel times has increased with the activities related to ITS. A large number of studies is being conducted. Some Studies are used the probe vehicles (these are vehicles equipped with GPS) to estimate travel time. Du (2005) developed a model to estimate the average link travel time for each individual road link in a network by using GPS raw data for, starting from identifying trip ends in continuous data stream, to converting point data to link-by-link data and finally estimating link travel time for the whole road network. The average absolute error for aggregate whole routes was 16.8% which is consistent with the error levels in previous work where relatively more probes were used on smaller portions of overall networks.

Other traffic studies are based on mobile sensors, one of these studies is Hao (2013) who developed the mobile sensor based arterial traffic modeling methods combining proper transportation domain knowledge (such as traffic flow theories or principles) and advanced machine learning and optimization techniques. Domain knowledge described the systematic patterns of arterial traffic flow that should be respected, while learning and optimization techniques were used to reconstruct such patterns from mobile data and estimate parameters of the patterns when needed.

On other hand, various studies have been implemented to examine the validity of using transit vehicles as probes. Cathey and Dailey (2002) defined such a system (transit vehicles as probes) to measure travel time and speed. In addition, Cathey and Dailey (2003) proposed a system to predict travel time and speed using collected data from busses. The results of two above mentioned studies indicated that there was difference between the measured and predicted values of median speed about 12.8 kph.

Tantiyanugulchai and Bertini, (2003) studied the variance in measured travel time and speed of bus as probe to the corresponding values obtained from vehicle equipped by GPS. The results of this study indicated that there was a difference in speed and time between the test vehicle and bus ranging from 3% to 66% according to the number of bus stops.

Chakroborty and Kikuchi (2004) compared the bus travel time (BTT) with automobile travel time (ATT) and suggested a regression model to predict ATT based on BTT. The results showed errors in the predicted model.

Vanajakshi, et al. (2008) presented the background work required for implementing Advanced Public Transportation System (APTS) in Indian traffic conditions using buses as probe vehicles. This study was one of the first approaches to predict travel time under such traffic scenario where GPS data was collected from three consecutive buses traveling in the route corroborating the prediction algorithm based on the Kalman Filter technique, consequently the results are promising.

Pu, et al. (2009) proposed a generic real-time estimation framework and present two case studies in examining the real-time sensitivity of bus probes to non-transit vehicle traffic conditions on signalized urban streets. They concluded that the framework represents a possible logical solution of implementing real-time bus probes by utilizing both historical bus-car speed relationships and real-time bus travel information.

Uno, et al. (2009) investigated the using of bus as probe data to measure the variation of travel time on urban roads. The main point, taken into consideration, in this study is the elimination of acceleration, deceleration, and stopping times from the measured bus travel time.

El Esawey and Sayed (2011) used buses as probes for neighbor links travel time estimation. Neighbor links were defined as nearby links that share similar characteristics and are subject to the same traffic conditions within a road network. They proposed a general framework to integrate historical link travel time data and sparse bus travel time data for travel time estimation on a network. Specifically, the purpose was to estimate travel times on links that are not covered by existing sensors, using their travel time relationships with neighbor links. Neighbor links travel time estimation accuracy, using bus probes data, was assessed using the Mean Absolute Percentage Error (MAPE). The value was 15.4% which is an accepted accuracy level in view of the considerable travel time fluctuations in the study area.

Gao, et al. (2013) predicted the next bus arrival time from the real-time data collected from the probe bus fleet by using the Kalman Filter technique. The experimental results showed that this model provides a higher level of veracity and reliability of travel time forecasting in the case of frequently changing traffic conditions.

(Pulugurtha, et al., 2014) examined the relationship between car and bus travel time as most buses operating in urban areas are equipped with AVL units. The role of key influential factors on the ratio between the two travel times was also evaluated and examined to assess the use of buses as probe vehicles.

Elsokkary (2015) proposed two models to estimate travel time on urban roads in Greater Cairo using buses as probes. Travel time data were collected using GPS receivers installed on test vehicles and buses that travel along the same urban routes. The average estimation error of the two models did not exceed 17.6% for each run.

Jaya Krishna Jammula, et al. (2018) developed an ANN and a regression model to compare the predicted travel times with the collected data on a road length of 14 km length by using a probe vehicle equipped by GPS and video camera . Two combinations of ANN models using single hidden layer, different numbers of neurons and epochs have been compared. The travel time of different modes has been compared and the effect of vehicle composition on travel time has been analyzed. The ANN model performs better than the regression model.

In summary, using buses as probe vehicles to predict the average automobile travel times on urban corridors in Cairo is a beneficial idea due to a large number of buses run on the most used arterials (the ones that are of greater importance in terms of average automobile travel time prediction). Generally, they have higher frequencies during peak hour and most buses can be equipped by the transit agency with GPS for predicting the bus arrival time. These characteristics of bus routes and schedules make them ideal as probe vehicles.

III. DATA COLLECTION

A data of 30 trips in main urban roads in Cairo is obtained using Global Positioning System (GPS) device that is equipped in the bus and the automobile as shown in Table (1). High variability was found in the route length where the minimum and maximum lengths were 2 and 16 km, respectively. Such high variability in section length is not recommended by most researchers. Therefore, it was decided to divide the routes into one hundred and three sections, which each section represents one kilometer. The data is examined and analyzed into 103 cases including five attributes as inputs and one output representing the Automobile total travel time (ATT) as shown in Tables (2), (3).

Table (1): Data of 30 Trips

No	Street Name	Direction		Date	Bus Data														Car Data	
					Time	Route Length (meter)	Avg. Speed (Km/h)	TT (GPS) (sec.)	Illegal Stops (Sec.)	Stop Delay (sec.)	Total Stopping Time (sec.)	Acc. delay (sec.)	Dec. delay (sec.)	Stop./ Acc./ Dec. delay (sec.)	FF TT (sec.)	Total delay (sec.)	No. of stops	No. of stations	TT (GPS) (sec.)	Avg. Speed (Km/h)
1	Gezr El-Suez Street	Forward	G1	26-11-12	AM 09:54	7632	19.16	1434	111	101	212	197	420	829	658	976	22	4	1183	21.22
2			G2	26-11-12	10:28 AM	7797	20.61	1362	92	1	93	302	368	762	668	894	12	2	1300	23.79
3		Backward	G1	26-11-12	11:42 AM	10348	21.95	1697	333	141	474	266	258	976	621	1076	21	12	1480	24.27
4			G2	26-11-12	12:19 PM	10638	18.66	2052	297	103	400	325	480	1205	638	1414	17	5	1753	20.85
5	El-Haram Street	Forward	G1	26-11-12	3:15 PM	3472	20.53	609	22	41	63	134	119	316	208	401	11	0	616	18.29
6			G2	26-11-12	3:54 PM	3474	24.82	504	65	5	70	97	77	244	208	296	6	0	512	22.43
7		Backward	G1	26-11-12	4:00 PM	3499	14.25	884	54	130	184	185	201	571	210	674	17	0	858	13.88
8			G2	26-11-12	4:30 PM	3500	16.22	777	41	139	180	154	156	490	210	567	14	0	695	18.13
9	El-Nasr Street	Forward	G1	27-11-12	3:38 PM	9633	25.24	1374	152	237	389	182	124	695	578	796	18	17	1229	28.22
10			G2	27-11-12	4:09 PM	9636	21.43	1619	150	312	462	230	297	988	578	1041	16	0	1579	24.97
11		Backward	G1	27-11-12	5:35 PM	5818	39.16	535	0	38	38	90	51	179	349	186	1	3	542	41.65
12			G2	27-11-12	6:10 PM	5821	25.91	809	89	63	152	152	122	425	349	460	8	7	720	29.11
13	Fesal Street	Backward	G1	28-11-12	6:16 PM	5675	7.43	2751	484	769	1253	274	655	2182	341	2410	62	8	2689	8.84
14			G2	28-11-12	6:44 PM	5673	8.34	2448	230	1104	1334	163	437	1934	340	2108	29	4	2258	9.05
15	Salah Salem Street	Forward	G1	29-11-12	4:18 PM	7016	21.77	1160	116	23	139	241	189	569	421	739	13	3	1048	24.1
16			G2	29-11-12	4:54 PM	7005	19.25	1310	64	58	122	311	256	689	420	890	19	0	1284	17.64
17	El-Haram Street	Backward	G1	2/12/2012	8:42 AM	6717	13.28	1821	189	322	511	259	440	1210	403	1418	49	14	1764	13.11
18			G2	2/12/2012	9:19 AM	6950	17.28	1448	216	184	400	216	316	932	417	1031	20	3	1425	16.16
19	Gameet El-Dewl El-Arabyia Street	Backward	G1	2/12/2012	6:43 PM	2078	11.12	673	24	160	184	106	180	469	125	548	9	3	552	13.55
20			G2	2/12/2012	7:15 PM	1995	16.94	424	60	63	123	75	61	258	120	304	10	0	363	18.49
21	Salah Salem Street	Backward	G1	17-12-12	5:45 PM	8464	11.99	2535	249	826	1075	308	335	1718	507	2028	30	0	2450	12.41
22			G2	17-12-12	6:16 PM	8162	8.86	3318	908	362	1270	313	958	2541	490	2828	73	25	2270	12.94
23	El-Nasr Street	Forward	G1	19-12-12	3:30 PM	15808	17.66	3222	430	443	873	497	632	2001	948	2273	50	10	3143	16.11
24			G2	19-12-12	4:22 PM	15808	14.45	3939	598	1135	1733	360	614	2707	948	2990	46	18	3100	17.16
25		Backward	G1	19-12-12	5:41 PM	16611	11.03	5358	377	2418	2795	585	700	4080	985	4373	64	21	5105	11.57
26			G2	19-12-12	6:29 PM	16612	23.38	2527	297	34	331	499	482	1312	985	1542	31	7	2390	26.32
27	Gameet El-Dewl El-Arabyia Street	Forward	G1	10/1/2013	10:15 AM	1935	21.5	324	46	15	61	55	43	159	116	208	6	5	280	22.38
28			G2		10:45 AM	1969	24.11	294	28	0	28	72	52	152	118	176	3	2	305	21.64
29		Backward	G1	10/1/2013	11:13 AM	1997	20.03	359	66	0	66	92	57	216	120	239	6	1	343	22.26
30			G2		11:47 AM	1970	20.98	338	81	0	81	72	48	201	118	220	4	0	350	19.26

Table (2): Input Attributes

ID	Attributes
X1	Bus Velocity
X2	Stops Delay Time
X3	Bus Acceleration Time
X4	Bus Deceleration Time
X5	Bus Final Time

Table (3): Data of 103 Sections

No	X1	X2	X3	X4	X5	ATT
1	23.2	0	10	25.1	60.2	110
2	21.4	25.2	25.3	30.9	59.9	130
3	23	3.6	20	55.5	59.8	174
4	14.2	1.8	16.6	147.4	60.3	274
5	24.5	15.4	18.1	43.9	60	121
6	15.6	0	49.6	73.5	60.2	356
7	23.2	27.3	23.8	13.4	47.1	99
8	35	0	16.4	9.7	60.1	90
9	22.3	8.1	37.6	31	60.1	135
10	34.1	0	27.1	15.2	59.6	88
11	7.4	60.4	76.1	231.4	60	383
12	22.1	0	16.1	66.3	60	152
13	19	0.8	28.6	40.5	60	144
14	32.2	1	12.1	20.5	59.6	129
15	25.8	6.4	20.7	18.7	60.2	104
16	19.4	18.9	32.1	42.8	59.9	184
17	21.9	3	22.6	23.6	60.2	188
18	16.5	13	71.9	30.1	60.1	232
19	12.9	30.2	49.2	79.1	60	265
20	13.1	95.2	35.8	58.1	60.1	288
21	16	0.9	28.3	34	29.8	73
22	22.2	19.4	40.1	24.8	59.9	126
23	12.1	81	48.9	61.2	59.9	260
24	15.8	38.7	36.3	44.4	59.6	208
25	20.2	0	29.2	25.3	30.6	101
26	9.9	140.4	30.4	20.7	59.7	210
27	20	44.7	29.5	22.3	60.1	150

28	17.5	56	22.7	26	59.9	210
29	30.9	1	28	12.5	59.7	131
30	24.8	10.6	36.6	29.3	60.2	108
31	19.1	29.2	29.9	51.9	60.5	143
32	30	0	17.3	12	33	101
33	35.1	0	24.4	11.1	59.7	98
34	24.3	37.7	12.8	18.4	49.1	166
35	26.3	0.6	35.7	16.3	60.4	129
36	33	37.3	7.4	10.4	49.5	139
37	9.2	39.3	55.4	91.1	60.1	356
38	8.4	134.1	67.7	104.5	60.1	586
39	5.3	242.6	44.8	179.6	60	562
40	9.3	121.5	42.1	104.8	60	710
41	11.4	57.2	17.6	32.8	40.2	147
42	7.7	188.4	34.5	74.3	60.1	337
43	13.6	25.6	37.5	102.1	60	301
44	7.2	367.3	22.1	25.6	60.9	1011
45	5.6	384.7	19.6	122	60.1	198
46	5.8	137.7	23.3	84	38.4	165
47	13.4	17.5	59.3	53.6	60.1	172
48	12.1	6.4	67.2	61.3	60.1	218
49	23.7	0	41	20.3	60.1	175
50	27.3	0.7	26	17.1	60	108
51	20.4	0.2	12.9	9.3	60.6	151
52	12.6	30.5	89.9	59.6	60.2	342
53	34	0	18.5	18.8	60	100
54	11	0.6	69.1	88.4	60.1	279
55	18	0	5.3	2.7	59.9	260
56	19.5	40.9	29.2	22.8	60.1	135
57	26.6	3.5	27.1	14.3	59.8	114
58	7.3	77.4	59	178.4	60	288
59	4.2	103.5	32.7	120.7	42.7	1036
60	8.2	95.3	17	62.2	61.2	197
61	32.6	1.3	33.2	7.1	60.3	114
62	15.5	0.8	24.6	39.1	60	259
63	16.5	45.2	42.3	26.3	60.5	136
64	21	22.5	43.6	37.5	59.9	170
65	27.3	9.4	30	20.3	60.1	146
66	5.7	10.8	24.8	20.7	55	610
67	9.3	0	49.7	111.8	62.4	414
68	6.7	303.6	48.7	43.6	60	681
69	10.1	99.6	33.3	65.3	59.8	523
70	5	400	37	39.5	60.1	616
71	10.8	10.2	63.7	59.1	59.8	388
72	2.3	266	52.2	651.5	61.2	456
73	5.9	51.3	71.5	89.4	61.3	539
74	11.4	7	65.2	76.1	60.9	262
75	13.8	15.6	51.7	70.8	61.4	280
76	37.3	0	20.7	5.9	61	110
77	16.3	15.8	49.6	30.8	61.3	163
78	20.5	0.1	46.9	30.2	61.4	193
79	19	23.8	19.3	30.3	61.4	175
80	27.8	0.6	28.4	26.6	61.7	130
81	23.2	8.7	29.4	26	61.5	111
82	14.7	42	56.7	44.3	61.5	150
83	11.5	0	64.2	110.4	63.7	268
84	12.4	0.3	43.7	122.2	59.9	298
85	31.9	0	96.9	0	67	185
86	35.7	10.4	79.6	8.6	61.9	120
87	20.7	15.7	33.9	28.8	60.1	118
88	23.9	1.2	34.5	33.2	59.7	203
89	21.8	0.9	43.6	35.9	59.8	216
90	26.8	1	28	23.4	59.4	116
91	17.2	0	43.7	25	58.8	234
92	36.8	0	24.5	5.6	60.1	109
93	13.1	14.1	70	56.8	60.4	191
94	6.9	168	56.4	117.2	60	785
95	14.8	29.2	34.4	61	60.2	243
96	8.9	68.1	56.8	70.1	60.4	274
97	30	4	23.6	20	60	117
98	14.1	25.4	32.6	40.3	60.1	280
99	20	0.6	31.2	18.5	42	160
100	13.3	88.7	40.8	41.5	59.8	304
101	9.7	29.3	66.1	63.8	62.1	221
102	22.9	11	28.5	17.4	59.6	113
103	31.6	3	28.5	4.3	62.7	111

IV. ANN MODEL DEVELOPMENT

Artificial Neural networks (ANN) models consist of processing units arranged between a set of successive layers and connected by a system of weights as shown in Figure (1). ANN models have the ability of detecting the approximate mapping between a set inputs and outputs. In this study, the model is built using NeuroSolutions Software [V6.03] through five main steps.

A. Database Sets

The data is divided into Learning set, Verification set and Validation set. Both of learning and verification sets are used during the network processing with different job. The learning set is used to conclude the relationship between input parameters and outputs. The verification set is used to monitor the error performance during the network learning. The validation set is used to ensure the generalization behaviour of developed model. Having a database of 103 cases; it is decided to use about 75% (76 cases) of database for learning, 15% (15 cases) for verification and 10% (12 cases) for validation.

B. Network Architecture

A supervised feed-forward neural network employing Tanh Function as an activation function is considered a reliable network to be utilized. The network consists of three successive layers as shown in Figure (1). An input layer includes five nodes representing the model input parameters. One hidden layer consists 46 nodes. An output buffer consists of one node representing the automobile travel time in seconds.

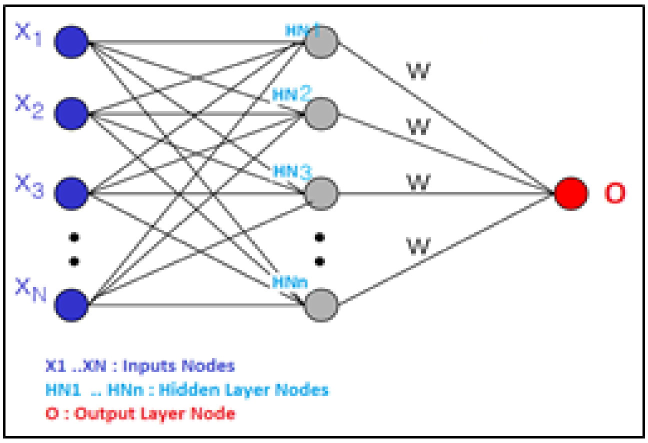


Figure (1): Network Layers

C. Network Learning

Network learning refers to the iterative process involving presentation of learning set to the network (Salem, 2008). The network assessment of results is based on the Mean Absolute Error (MAE) that represents the overall average error of the set and calculated as shown in Equation (1).

$$MAER = 100 * \frac{1}{n} \sum_{i=1}^{n} \left| \left(\frac{\text{Actual TTc} - \text{Predicted TTc}}{\text{Actual TTc}} \right) \right| \quad \textbf{Eq. (1)}$$

Figure (2) presents a detailed view of the 76 cases regarding to the learning set with MAE equals to 10.16% which is considered acceptable error.

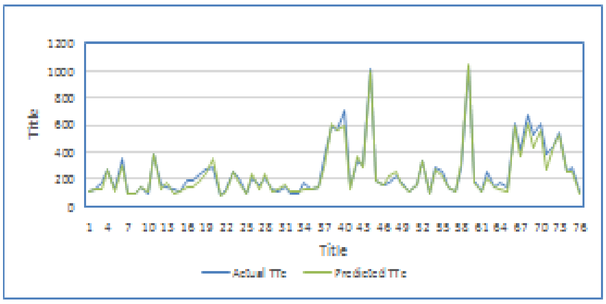


Figure (2): Learning Set Results

D. Network Verification

Network verification refers to the corrective process of network performance based on the results of evaluation data-set. It is a fundamental issue after the learning phase. As, if the learning and verification results are reliable, then the network is ready to be validated. Figure (3) presents a detailed view of the 15 cases regarding to the verification set with MAE equals to 9.88% which is considered acceptable error.\

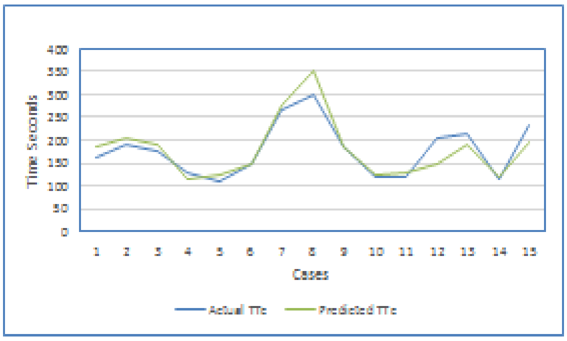


Figure (3): Verification Set Results

E. Network validation

An essential aspect in developing an estimation model is to examine its accuracy and validity (Salem, 2008). In this study, a validation set of 12 cases is used to measure the validity for the verified network. The assessment of validation data-set is also based on MAE. Figure (4) presents a detailed log of the cases regarding to the validation set with MAE equals to 11.55% which is considered acceptable error.

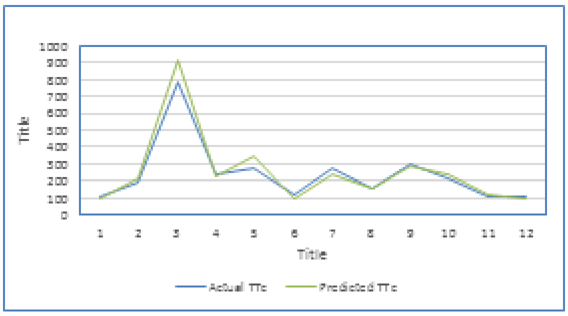
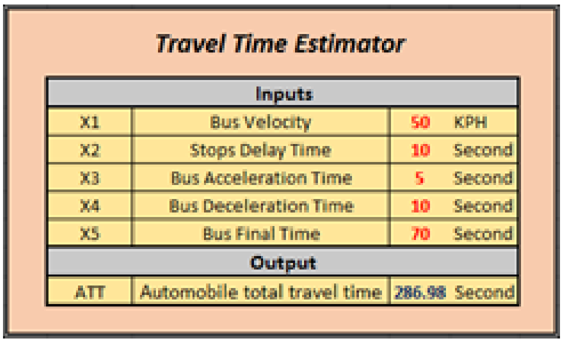


Figure (4): Validation Set Results

V.GRAPHICAL USER INTERFACE (GUI) MODULE

A visual basic application (VBA) module in Excel 20130 is programed for model. The module simplifies the implementation and the use of model in a user-friendly interface. It accepts inputs from user and estimate the Automobile total travel time as shown in Figure (5). The module can be updated to be usable in different roads by adding new section to the available database and re-optimizing the network.



Travel Time Estimator

Inputs			
X1	Bus Velocity	50	KPH
X2	Stops Delay Time	10	Second
X3	Bus Acceleration Time	5	Second
X4	Bus Deceleration Time	10	Second
X5	Bus Final Time	70	Second
Output			
ATT	Automobile total travel time	286.98	Second

Figure (5): GUI Module

VI. CONCLUSIONS

Travel time information is the most important element in ITS applications. In the past, inductance loops, cameras and other sensors have been used to obtain travel time data. This research suggests the use of transit vehicles as probes to collect travel time data on some urban roads in Cairo. This purpose is achieved by comparing the bus travel time with that of an automobile of the same link. This is collected by equipping GPS data loggers in each one, and suggesting an Artificial neural network model developed by using NeuroSolutions Software [V6.03] to predict the automobile travel time based on the travel time of the bus with acceptable level of accuracy that can be applied to real-life traffic problems, such as: congestion management. The model is provided dependable predictions with weighted average error equals 10.53% and considered a valid model to be used in real life applications. As practical aspect, a GUI module is built based on the model to facilitate and automate the process of estimating the (ATT).

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