SENSITIVITY ANALYSIS OF SHORT-TERM TRAVEL TIME PREDICTION MODEL'S PARAMETERS

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SUMMARY

This paper discusses the optimization of different parameters of a Short-Term Travel Time Prediction model for better performance using traffic detector data. This travel time prediction model involves a number of parameters which affect the prediction in one way or other. These parameters are temporal size of pattern, spatial weight, temporal weight, search window, number of best matched patterns and prediction horizon. Due to higher dimensionality and large number of possible combinations of these parameters, genetic algorithms are employed for optimization.

INTRODUCTION

This paper discusses optimization of different parameters of a Short-Term Travel Time Prediction model for better performance using traffic detector data. A travel time prediction model based on finding the similar historical traffic instances and then exploring those instances for travel time prediction is developed. The method has already been tested offline on a limited set of data using parameter values based on intuition and was found to be performing quite well.

The benefits of the travel time information provision have been documented in the literature, ranging from spatio-temporal dispersal of traffic and less stressful driving to utilization of alternative modes of travel. The majority of present travel time information systems use instantaneous travel time i.e. summing of travel time information, derived from velocity measurements at different sections of road simultaneously. Instantaneous travel time information requires less computational effort but accuracy decreases with the onset of congestion.

The pattern matching technique used in this research is based on the assumption that traffic scenarios similar to present traffic condition may have occurred before. Present traffic pattern is defined using velocity measurements from traffic detectors along the length of road up to *k* minutes before the present time. Instead of using simple patterns, weighted patterns are used for defining traffic situations. Spatial and temporal weightings are applied in order of importance of the data in affecting the short-term travel time. A database of historical traffic situations is created for searching the closest matched patterns and minimum squared difference is used as indicator of the closest matched patterns from historical database. Instead of selecting one most similar pattern, *N* patterns are selected so that sudden changes in travel time prediction can be avoided.

The research presented in this paper develops a genetic algorithm (GA) for optimizing the parameters of travel time prediction model. Traditional optimization models cannot be employed for this purpose due to large search space and absence of sophisticated functional relationship between the inputs and output.

The objective function for the genetic algorithm is minimization of a comprehensive error measure. Travel time model with optimized parameter set is expected to provide smaller prediction error.

TRAVEL TIME MODEL

The model implemented and evaluated in this research was developed and tested in a previous study [1]. That study indicated that the model is capable of producing travel time predictions with high accuracy. However, the parameters of the model in that study were based on intuition and were not optimized.

In this section, the basic model is presented with a description about the parameters of the model. This model uses the historical and present traffic detector data for finding the nearest neighbours of present traffic pattern from the historical data and it is assumed that nearest neighbours in historical data carry useful information for prediction of present travel time. The method used, is essentially a non-parametric regression method. A simplified flowchart of model is presented in Figure 1.

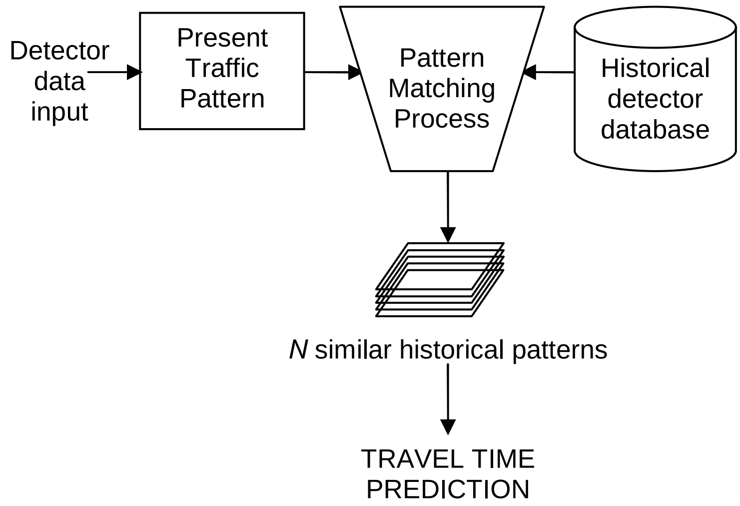

Figure 1: An outline of Travel Time Prediction model

Definition of Traffic Pattern: Detector data for this study consists of speed, flow and lane occupancy. In the previous study [1], it was found that the best traffic pattern for travel time prediction is represented by inverse speed values with speed, lane occupancy and flow as the inferior values in the described order. The traffic pattern is defined on spatial as well as temporal scale. On the spatial scale, traffic pattern includes the whole section of the road for which travel time prediction needs to be made. On the temporal scale, it includes sufficient length of time to define the image of traffic. In previous study [1], it was assumed to be 1 hour.

Pattern matching procedure: The basic aim of the pattern matching procedure is to find the most similar historical pattern(s). Hence, the first task is to create some historical days' database. One way of searching the patterns is to search the whole historical database for the most similar pattern, but this makes the search process computationally intensive. Therefore, by making use of the assumption that traffic patterns are recurrent in nature and adding that these recur on daily basis, we can restrict the search to only that time of the day in the historical database for which prediction is to be made on the prediction day. Traffic patterns of all days in the historical database within a time frame of $\pm x$ minutes of prediction time were searched for closest patterns. The $\pm x$ minutes time frame is used, as the probability is low that traffic situations will recur exactly at the same time as they occurred before. In previous study, x was assumed to be 30 minutes but we need to establish a value which gives a better prediction.

Sum of the squared difference between the prediction time traffic pattern and the historical traffic patterns is used as a criterion for finding similarities between the traffic patterns. The historical traffic pattern having minimum sum of squared difference is regarded as the most similar pattern.

The road section under study is assumed to consist of small links i's each representing a section of road equipped with one traffic detector , where $i=0,1,2,3\ldots n_i$ and similarly time period is divided into slots , $j=0, 5, 10,\ldots\ldots n_j$ as data is in 5 minutes resolution, here n_j is the length of the time window. In this way, the detector data is represented on a temporal and spatial scale. If t is prediction time on prediction day p, then $v(i, t-j, p)$ represents velocity on prediction day p at link i at time $t-j$.

Where,
i=0 refers to the most upstream link;
$i=n_i$ refers to the most downstream link;
j=0 refers to the time slot corresponding to start of pattern on temporal scale; and
$j=n_j$ refers to the time slot at the end of pattern on temporal scale.

Similarly, if $h=1,2,\ldots..n_h$ represents the number of days in historical database and t_s represents the start time of the traffic pattern on historical days then $v(i, t_s\text{-}j, h)$ represents velocity on historical day h at link i at time $t_s\text{-}j$. As the search is performed in $\pm x$ minutes of prediction time t on historical days so $t+x \geq t_s \geq t\text{-}x$ and the final form of the objective function for pattern matching is,

$$\min.of \quad \Delta^2(p,t,h,t_s) = \sum_{i=0}^{n_i}\sum_{j=0}^{n_j} w_s(i).w_t(j)[\frac{1}{v(i,t-j,p)} - \frac{1}{v(i,t_s-j,h)}]^2 \qquad ....[1]$$

As the detector stations are not equi-distant along the length of road, we have proposed a distance weighted inverse speed instead of inverse speed. It has already been assumed that point measurements from the detector stations represent the average traffic conditions on the segment of road from half of the distance to upstream detector to half of the distance to downstream detector. But in this case, the detectors are not equi-distant thus one detector may be representing traffic conditions for a longer length of road than other detector. This causes an unjustifiably equal weight to traffic conditions of different sections. It changes the objective function to this new form,

$$\min.of \quad \Delta^2(p,t,h,t_s) = \sum_{i=0}^{n_i}\sum_{j=0}^{n_j} w_s(i).w_t(j).\frac{L(i)}{L}[\frac{1}{v(i,t-j,p)} - \frac{1}{v(i,t_s-j,h)}]^2 \qquad ....[2]$$

Where, $L(i)$ represents the length of corresponding section and L represents the total length of road for which prediction is to be made.
Where,
$\Delta^2(p,t,h,t_s)$ =sum of squared difference of inverse speed distribution between prediction time t on prediction day p and time t_s on historical day h.

The summation is taken over all study road links i's as well as over the time window j. After calculating sum of the squared differences, n patterns with smallest squared difference i.e. most similar historical patterns to the prediction time pattern are selected.

Travel Time Information and Modification: In this step, travel times, corresponding to selected historical traffic patterns, are extracted from database. It has been found that despite all the care exercised in the selection of most similar patterns; sometimes a few selected patterns have larger travel time differences from rest of the selected patterns. To overcome this problem, Box Plot technique is employed. By using Box Plot technique, outlier travel time values are excluded.

In Box Plot technique, the upper bound, U, and lower bound, L, of a data set is calculated using the following formulae.

$$U = Upper\ quartile + 1.5 * Interquartile\ range$$

$$L = Lower\ quartile - 1.5 * Interquartile\ range$$

where
Lower and upper quartiles are the 25th and 75th percentiles, and
Interquartile range is the difference between upper and lower quartiles.
Any point lying above U or below L is regarded as an outlier and is discarded. This technique helps to improve the prediction, especially when the travel time values are uncharacteristically different from other selected values.

Final Prediction: Finally, after exclusion of the outliers, there are n_k patterns out of the historical database for every prediction time, t, on prediction day, p. The final prediction is calculated as:

$$\hat{T}(t,p) = \frac{\sum_{h\in\Omega(t,p)} T(t_s,h)}{n_k} \qquad .....[3]$$

Where:
$\Omega\ (t,\ p)$ represents the set of patterns out of the N best matched patterns that are not the outliers;
$T\ (t_s,\ h)$ is the travel time values extracted from these historical patterns; and
$\hat{T}(t,p)$ represents the final prediction.

MODEL PARAMETERS

In the above described model, it can be seen that there are different parameters involved which were estimated, in a previous implementation [1] of the study, based on intuition. These parameters are

1. Temporal Size of the Pattern: For the temporal size of pattern, a careful analysis is necessary as an insufficient size can cause an incomplete image of the traffic searched in historical database, resulting in poor prediction while large size will require a large computational effort and can also result in poorer prediction as traffic pattern may consist of unnecessary details which are not affecting present travel time. A very practical range for temporal size may be from 10 minutes to 160 minutes. It needs to be investigated that how variation of temporal size affects travel time prediction and what temporal size is optimum.

2. Spatial Weight: It is known that in free flow condition, waves in traffic move in forward direction meaning that upstream data is influencing traffic condition more than the downstream data. However, in the congested condition, waves move in backward direction in the form of shockwaves meaning that downstream data is more important than upstream data. Spatial weights can be applied in order of importance of data in influencing the travel time in order to get a rational traffic pattern. Spatial weight is assumed to vary linearly. Spatial weight function can be represented as follows,

$$w_s(i) = \begin{cases} W_s - \left[(W_s - 1).\dfrac{i}{n_i} \right] & \textit{if higher weight for upstream} \\ 1 + \left[(W_s - 1).\dfrac{i}{n_i} \right] & \textit{if higher weight for downstream} \end{cases} \quad .....[4]$$

   where,

   W_s range from 1 to 8;
   i=0 refers to the most upstream link; and
   i=n_i refers to the most downstream link;

3. Temporal Weight: A very simple assumption is that the traffic present on the road now is more important in influencing travel time than traffic present on the road sometime before. Hence, a temporal weight needs to be applied in order to account for importance of data.

$$w_t(j) = W_t - \left[(W_t - 1).\frac{j}{n_j} \right] \quad .....[5]$$

   where,

   W_t range from 1 to 8;
   j=0 refers to the time slot corresponding to start of pattern on temporal scale; and
   j=n_j refers to the time slot at the end of pattern on temporal scale.

4. Search Window: Traffic patterns are recurrent in nature and usually recur on daily basis but it is very unlikely that traffic patterns will recur exactly at the same time. Thus the proper size of the search window also needs to be investigated. The size of time window may be from ±15 to ±120 minutes. A search window of ±60 minutes means that for a traffic pattern at 9'o clock, a search for similar pattern will be performed on all historical days from 8'o clock to 10'o clock. The optimal size needs to be investigated in order to reduce the computational effort while maintaining a sufficient level of accuracy.

5. Number of Best Matched Patterns: It has been found that using only one best matched pattern for prediction, can result in a sudden jump in travel time while using an average of larger number of patterns helps in a smooth transition. The number of best matched patterns to be used for prediction, needs to be investigated. In this study 5, 10, 15…, 40 best matched patterns are tried for prediction.

GENETIC ALGORITHM

Genetic algorithms (GA) follow the process of natural evolution to search and optimize the functions. They involve the random generation of possible solutions and then to look for the useful information about the fittest solutions to produce subsequent generations of solutions in such a way that fittest solutions get more and more representation. According to [2], they efficiently exploit historical information to speculate on new search points with expected improved performance. GAs differ from other optimization and search procedures in the following ways,

1. They search among a population of points and not a single point.
2. They use objective function information and not the gradient information.
3. Transition rules are probabilistic and not deterministic.
4. Instead of parameters, coding of parameter is used.

Working of Genetic Algorithm

Working of Genetic algorithm can be divided into three distinct steps, i.e. formulation of population of solutions, evaluation of each member of population and forming next generation of population by applying genetic operators, namely reproduction, crossover and mutation.

According to pseudo-code adapted from [3], GA works as follows,

```
Initialize the parameters of GA (selection, Pc, Pm, Elitism etc.)
Randomly generate the initial population
While convergence=false
    Calculate the fitness value of each member of the population
    While (number_of_individual <= population_size)
        Select two parents (parent1, parent2) using a selection strategy
        Perform the crossover operation between parent1 and parent2 based on Pc
        Mutate each offspring based on Pm
        Increase counter according to number of offspring
    End While
    Construct the intermediate population with set of offspring
    Construct a new population set using a replacement scheme
End While
Output best individual(s)
```

In the first step, a population of solutions is generated by using pseudorandom number generators where each individual of population represents a feasible solution. Fitness of each individual is calculated. Two parents are selected from the present population according to the selection strategy, usually the individuals having higher fitness have higher probability of selection as parents for the next generation. Crossover operation determines how the parents will mate to produce new offspring and in which manner properties of parents will be shared by the offspring. Mutation operator helps in creating diversity in the population; it usually mutates some property(allele) of offspring based on P_m. After generating the new population, same procedure is repeated until the convergence criterion is met. Convergence criterion, in this case, is the maximum number of generations.

GENETIC MODEL

The Genetic Model used in this study is described in detail in this section.

Objective Function:

As mentioned earlier, genetic algorithm uses the objective function information instead of gradient information. The objective of the present study is to minimize the error in travel time prediction. A comprehensive error measure is formulated which needs to be minimized. Objective function *O(i)* is presented as,

$$Minimize\ O(i) = \frac{1}{R} * MAE * MAPE * \frac{1}{E_5} * \frac{1}{E_{10}} \qquad .....[5]$$

where,

$$R = \frac{\sum_{l=1}^{n} (\hat{T}_l - \hat{T}_{mean})(T_l - T_{mean})}{n\sigma\hat{\sigma}} \qquad ....[6]$$

$$MAE = \frac{1}{n} \sum_{l=1}^{n} \left| \hat{T}_l - T_l \right| \qquad ....[7]$$

$$MAPE = \frac{1}{n}\sum_{l=1}^{n}\frac{\left|\hat{T}_l - T_l\right|}{T_l}\times 100 \quad .....[8]$$

$$E_5 = \frac{\sum_{l=1}^{n} j_l}{n}\times 100 \quad \text{where, } j_l = 1 \text{ if } \left[\frac{\left|\hat{T}_l - T_l\right|}{T_l}\times 100\right] < 5, \text{ else } j_l = 0 \quad ....[9]$$

$$E_{10} = \frac{\sum_{l=1}^{n} k_l}{n}\times 100 \quad \text{where, } k_l = 1 \text{ if } \left[\frac{\left|\hat{T}_l - T_l\right|}{T_l}\times 100\right] < 10, \text{ else } k_l = 0 \quad ....[10]$$

T_l and $\hat{T}_l$ represent the actual travel time and predicted travel time at l^{th} instant respectively. σ and $\hat{\sigma}$ represent the standard deviation for actual and predicted travel time respectively.

Fitness Function:

Genetic algorithms are naturally suitable for maximizing a function and are not able to handle non-negative objective function values. Usually if the objective is to maximize and no non-negative values are going to be encountered for the whole range of parameters, fitness function is assumed to be equal to the objective function. But if the objective is to minimize the problem, then we need to manipulate the objective function to map it to a suitable fitness function which ensures non-negativity as well [2]. In our case, as the non-negativity problem is not present, so we can map the fitness function as,

$$Maximize\ F(i) = \frac{1}{O(i)} \quad ....[11]$$

This can also be written as,

$$Maximize\ F(i) = R * \frac{1}{MAE} * \frac{1}{MAPE} * E_5 * E_{10} \quad .....[12]$$

Coding:

Genetic algorithms cannot operate on the real world parameters directly. First of all, we need to map the real world problem into a coded form on which genetic algorithm can operate. Different types of the coding are possible for genetic algorithms, e.g. binary, numeral, alphabetic or alpha-numeral. Out of these different types, binary is considered as the most efficient in processing the hidden information in the schemata [2]. In this study, binary coding is used. As this study has more than one input parameter, so multi-parameter binary coding is used. Each individual solution is represented by 17 bits. An example individual is 00101010110011011. This example individual represents the five parameters, U_1, U_2, U_3, U_4 and U_5 as explained in the illustration.

0010	1010	110	011	011
U_1	U_2	U_3	U_4	U_5

These five parameters are actually mapped on the real world parameters in the given range and can be decoded based on the corresponding mapping functions.

GA parameters:

GA parameters used in this study are as following,

- <u>Population Size:</u> A population size of 25 is used, which is a small population size. A small population size is used due to the extensive computational effort required. This is compensated to some extent by using a slightly higher probability of mutation to create diversity in population.

- <u>Selection scheme:</u> Roulette Wheel selection is used in this study. According to this selection procedure, each individual in the present population is assigned share in roulette wheel proportional to their fitness and an imaginary ball based on pseudorandom number generator is used to pick the candidate parent for the subsequent generation. In this technique, the individual having higher fitness has higher probability of selection as a parent for next generation.

- Replacement Scheme: In this study, we have used the simple replacement scheme in which offspring replaces their parents. However, one exception is that best solution of present generation is carried over to the next generation as it is, so as not to lose the best solution found so far. This is known as Elitism. Selection of best solution for the subsequent generation does not affect its chances to be selected as a parent.

- Pc, Probability of crossover: In typical GA applications, P_c is usually kept quite high. In this study, a value of 0.90 is used.

- Pm, Probability of mutation: P_m is usually kept quite low but in this study, a value of 0.02 is used. This creates a flare of diversity in population.

- Convergence Criteria: Maximum number of generation is used as convergence criteria. The ideal condition of convergence is when all the individuals in a generation are the same but due to the random nature of genetic algorithms, it is quite difficult to achieve. 20 generations were used in this study.

APPLICATION

Usually the traffic conditions vary during different times of the day from free flow to congestion. Hence if we try to optimize for the whole day, the chosen parameters may be best for one type of traffic condition but not perform very well for other traffic conditions or may perform on average for different traffic conditions. To overcome this problem, we will optimize the parameters of model separately for different times of day. Typically the travel time profile can be divided into four distinct portions depending on the traffic volumes in a 24 hour cycle. These four portions are

1. from mid night to early morning, this is characterized by low volumes of traffic and shorter travel times,
2. from early morning to afternoon, this portion shows start and dissipation of morning commute congestion which is quite typical,
3. from afternoon to evening, this portion represents the evening commute traffic which is quite varying and
4. from evening to midnight, again characterized by low volumes of traffic.

An analysis of historical data shows that free flow conditions persist from midnight to 7’o clock in the morning while the morning peak usually starts building up from 7’o clock and dissipates by 2’o clock in the afternoon. The afternoon congestion is from 2’o clock to 8’o clock and the period from 8’o clock to midnight is free flow period usually. We will try to optimize the parameters of travel time model for the four time regions in a day and optimized travel time model will have time varying parameters.

The days are classified into three categories namely, weekday, Saturday and Sunday while each day is further sub-divided into four portions. Hence, we need to optimize for twelve sets of parameters. But as the free flow condition during the night remain same irrespective of whether it is weekday, Saturday or Sunday hence, we can use the same parameters for free flow regions reducing the required number of parameter sets to 8.

Site Description

The site selected for the optimization and implementation of model is inbound section of route no. 3 of the Tokyo Metropolitan Expressway, i.e. from Yoga to Tanimachi, Figure 2. The length of road is approximately 12km. This road is a part of the network of Tokyo Metropolitan Expressways, which connects many intercity highways to the circular route of Tokyo Metropolitan Expressway. The selected route has two lanes per direction. There are three on ramps and three off ramps between the entry and exit points of the road for which this travel time prediction is made. All the routes of Tokyo Metropolitan Expressway are equipped with ultrasonic detectors which are approximately 300m apart. Historical travel time record shows that travel time on this route varies from 9 minutes in free flow condition to 70 minutes in severe congestion.

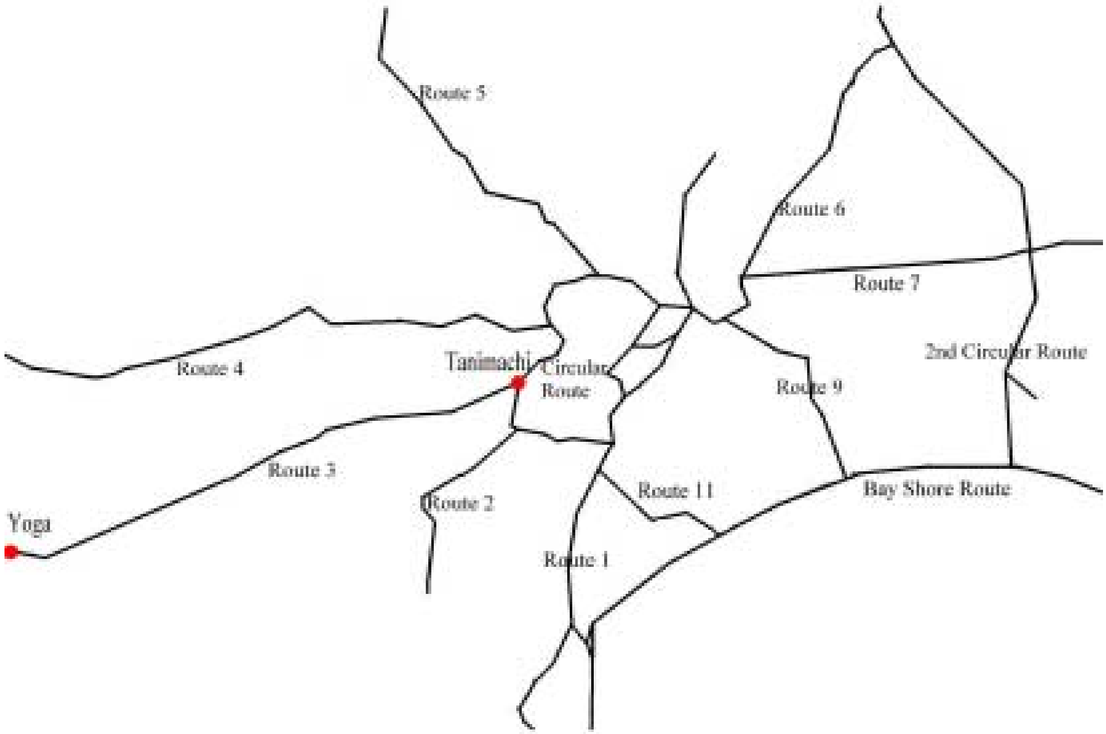

Figure 2: Tokyo Metropolitan Expressway Network

Data

There are 40 detectors on inbound section of route no. 3 of Tokyo metropolitan expressway, i.e. from Yoga to Tanimachi. For this research, detector data from November 1999 to October 2000 was used as historical data. This forms a historical database of one year in total. From preliminary study of the travel time patterns, it has been found that travel time profiles on weekdays are very different from the travel time profiles on the weekends. Further on weekends even travel time profile of Saturdays is totally different from Sundays. Hence, to reduce the computational effort and increase the accuracy of the prediction, only weekdays are searched among the historical database if the prediction day is a weekday and similarly for Saturday and Sunday only corresponding days are searched.

Generally, the quality of data from the detectors is quite good but sometimes at some detector stations, data was found missing due to apparent malfunctioning of the detectors. In this case, missing data was interpolated on spatial as well as on temporal scale.

RESULTS

In calibration section, results of the optimization of travel time model based on genetic algorithm are presented and next in validation section, a comparison of travel time prediction performance with optimized and un-optimized parameters is presented.

Calibration:

Traffic detector data from October 2001 on the above mentioned route is used for calibration. Four weekdays, three Saturdays and three Sundays were selected for calibration. These days are

- Weekdays: Oct.2 (Tue.), Oct.3 (Wed.), Oct.4 (Thu.), Oct.5 (Fri.).
- Saturdays: Oct. 6, Oct. 13, Oct. 20.
- Sundays: Oct. 7, Oct. 14, Oct. 21.

Figure 3 shows the sample performance of GA in finding the better fitness values for the Sundays afternoon parameter optimization. Maximum fitness is the maximum fitness function value for any individual in one generation while average fitness is average of fitness function values for all the individuals in a generation.

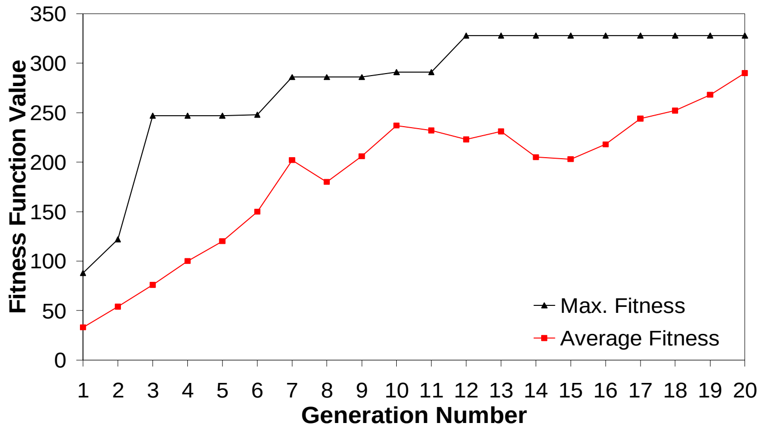

Figure 3: GA Performance for Sunday afternoon parameter set

In Table 1, optimized parameters of travel time prediction model for three classes of the days and different times of the day are shown. The results presented in Table 1 reveal that a larger temporal size of the traffic pattern is not required. The temporal size of the pattern in free flow condition is 10 minutes which means only two data points as detector data is in 5 minutes resolution. In heavy congestion, it goes up to 30 minutes. Another observation is that in free flow condition, higher spatial weight for the upstream traffic and lower for the downstream traffic while during congestion, higher weight for downstream and lower weight for upstream traffic data is needed. Higher weight indicates importance of traffic condition in defining the traffic pattern. This can be explained by the fact that in free flow condition, traffic waves move in the forward direction while in congested condition traffic waves move in backward direction in the form of shockwaves. Temporal weight of greater than one indicates that the traffic present on the road now is more important than traffic present before, in defining the traffic pattern for travel time prediction. Parameter values used in the previous study [1] are also shown in Table 1. These old parameter values will be used for comparison purposes.

TIME OF DAY	SIZE OF TRAFFIC PATTERN(min.)	W_s		W_t	SEARCH WINDOW (min.)	NO. OF BEST PATTERNS USED
		u/s	d/s			
WEEKDAYS						
0:00-7:00	10	2	1	7	±15	25
7:00-2:00	10	1	8	2	±60	40
2:00-8:00	20	1	4	1	±75	15
8:00-0:00	10	5	1	3	±75	25
SATURDAYS						
0:00-7:00	10	2	1	7	±15	25
7:00-2:00	20	1	6	1	±120	10
2:00-8:00	30	1	2	2	±90	10
8:00-0:00	10	5	1	3	±75	25
SUNDAYS						
0:00-7:00	10	2	1	7	±15	25
7:00-2:00	10	1	1	2	±120	5
2:00-8:00	10	1	8	4	±120	10
8:00-0:00	10	5	1	3	±75	25
OLD PARAMETERS						
WHOLE DAY	60	1	1	1	±30	10

Table 1: Optimized and unoptimized parameters of Travel Time Model

Validation:

Traffic detector data from November 2001 on the route no. 3 of Tokyo Metropolitan Expressway is used for calibration. Though the prediction was performed for all the days in November 2001, here only four days results are presented due to space limitations. The test days for validation are

- Weekday: Nov.15, 2001(Thu.) & Nov. 16, 2001(Fri.).

- <u>Saturday:</u> Nov.17, 2001.
- <u>Sunday:</u> Nov.18, 2001.

Figure 4, Figure 5, Figure 6 and Figure 7 shows the travel time prediction results along with the actual travel time, the figures clearly indicate very good travel time prediction.

For comparison purposes, statistical evaluations of travel time prediction results using new parameters and old parameters is also shown in Table 2. In Table 2, E_5 and E_{10} show percentage of predictions having error less than ±5% and ±10% respectively, while P_5 shows the percentage of predictions having an error less than 5 minutes. Results shown in Table 2 clearly indicate better performance by using the optimized parameters.

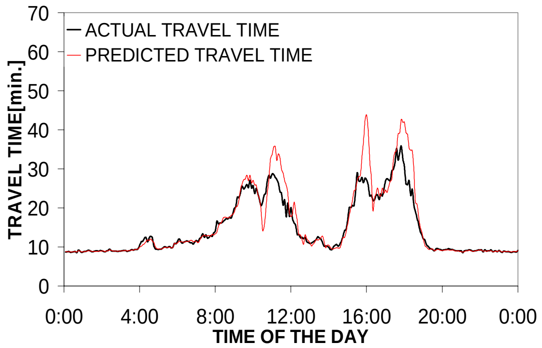

Figure 4:Travel Time Profile for Nov. 15, 2001

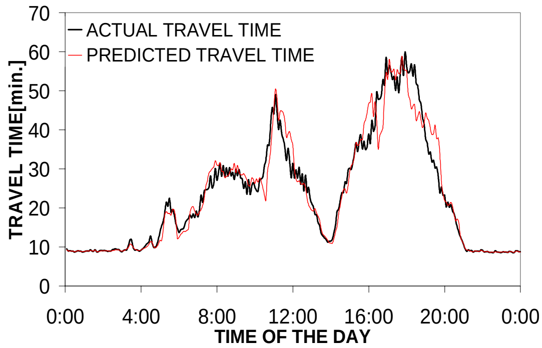

Figure 5:Travel Time Profile for Nov. 16, 2001

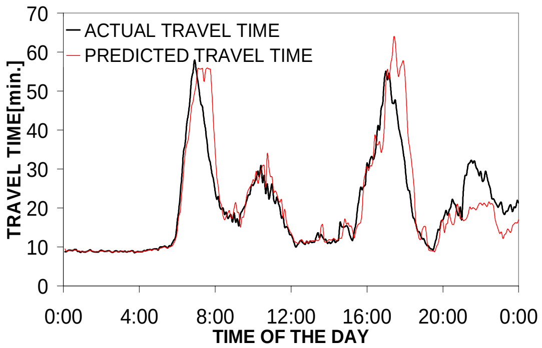

Figure 6:Travel Time Profile for Nov. 17, 2001

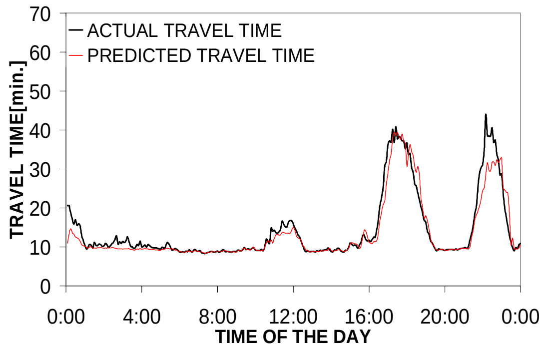

Figure 7:Travel Time Profile for Nov. 18, 2001

Statistics	November 15, 2001		November 16, 2001		November 17, 2001		November 18, 2001	
	New Parameters	Old Parameters	New Parameters	Old Parameters	New Parameters	Old Parameters	New Parameters	Old Parameters
Correlation Coefficient	0.953	0.914	0.971	0.946	0.9	0.738	0.955	0.907
MAE[min.]	1.5	1.8	2.1	3	3.5	6.3	1.5	2.2
MAPE[%]	6.9	9.5	7.1	10.9	13.7	28.7	7.9	12.9
E_5[%]	63.9	57.6	53.8	41	40.3	26.4	54.2	39.6
E_{10}[%]	81.3	72.9	74	60.4	56.9	36.5	72.6	58
P_5[%]	91	87.8	86.5	79.2	74.7	54.9	91.7	86.1

Table 2: Performance comparison of Travel Time Model using old and new parameters

CONCLUSIONS

The results of the present study clearly indicate that pattern matching technique has a good potential for travel time prediction. The use of GA in the optimization of parameters helps in improving the performance of Travel Time prediction model by approximately 5-10%.

The important findings from the application of genetic algorithms for the optimization of parameters are that a bigger traffic pattern is not required for defining the traffic pattern, a small pattern size of 10 minutes, which means two values of recent detector data, as data is at 5 minute resolution, in free flow and a pattern size of 30 minutes, which means six values of recent detector data, in congestion are enough for defining the traffic pattern. This study has shown that higher weight should be given to the most recent traffic data in the patterns. A higher spatial weight for upstream data in free flow condition and for downstream data in congested condition indicates that upstream traffic affects the travel time in free flow while downstream traffic affects the travel time in congested conditions.

In this study, we have used a small population size for implementation of GA due to the intensive computational effort required. It is recommended that further studies should be conducted to optimize the parameters by using a larger population size and larger number of generations.

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