A Systematic Genetic Algorithm Based Framework to Optimize Intelligent Transportation System (ITS) Strategies

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Abstract: Today more and more Intelligent Transportation System (ITS) strategies such as High Occupancy Toll (HOT), ramp metering, variable speed limits, etc., are introduced nationwide to reduce congestion and maintain desired service levels on the freeway. Optimization of all the different parameters in such strategies is vital to manage the traffic effectively. The paper introduces a modeling and optimization framework to calibrate and optimize multiple ITS strategies simultaneously. The framework is capable of estimating the OD matrix, calibrating the model with the experimental data, and conducting system optimization in transportation. The approach can be used to optimize more complex system optimization problems in transportation domain. In this paper, this capability is shown with simulation experiments based on the public data of I-95 Florida. The preliminary results show that the revenue increases with target speed up to a point, after which the revenue drops; the throughput on the HOT lanes increases with decreasing target speed. So, to maximize revenue and throughput together, the optimal parameters exist in the middle of the feasible range. Additionally, when accidents happen, the total throughput can be improved by decreasing the toll rate.

Key words: Intelligent Transportation System, Modeling and Simulation, Genetic Algorithm

1 Introduction

Today more and more Intelligent Transportation System (ITS) strategies are introduced nationwide to reduce congestion and maintain desired service levels on the freeway. Optimization of such ITS strategies independently and simultaneously is a challenge. The managed lanes - High Occupancy Vehicle (HOV) / High Occupancy Toll (HOT), is one such example of ITS strategies. Optimization of all the different parameters in such a strategy is vital to manage the traffic effectively. More importantly, when there are multiple ITS strategies used, optimization of all the parameters in such a system becomes, even though highly desired, a bigger challenge. Some parameters may have a conflicting effect on the outputs of the system. Also, there are multiple objectives such as maximizing throughput, maintaining traffic speeds, maximizing revenue, etc. that need to be addressed. This makes it a difficult problem to tackle.

Today, microscopic traffic simulation models are widely used to capture the dynamics on the freeway. Commercial software tools such as Paramics are helpful to model such systems but they do not provide optimization capability. In some cases, there are tools within the software packages to support one of the steps in the process. For example, Paramics Estimator supports the step of estimating Origin-Destination (OD) matrices. There are several papers proposing different approaches to OD matrix estimation. A genetic algorithm approach is proposed in (Yun and Park 2005, Ma et al. 2005) to compare the performance with Queensod and Newton’s method respectively. Bera et al. (2011) provides a literature
review of different methods for OD matrix estimation. Although there are some very effective ways of estimating OD matrices, this is only one of the steps in calibrating and optimizing a transportation system. It is important to understand the system as a whole to really optimize it. Ozbay et al (2005), Al-Deek et al (2000) develop system models for toll plazas in Paramics. Ender M. (2010), Li et al (2009) develop freeway pricing system models using tolling data. These works describe the system model development step including calibration. However, the studies do not extend to describe how transportation system parameters can be optimized for reduced congestion. In the transportation system shown in Figure 1, it is seen that there are different ITS strategies present with specific algorithms driving it. Each algorithm has its own parameters that need to be set accurately for the system to work correctly. The initial steps of modeling this system, i.e., calibrating it, are absolutely necessary but do not lead to the right values of the parameters in these algorithms. Therefore, it is very important to not only develop a well calibrated model but also to be able to optimize these parameters simultaneously so that a global optimum of the system can be achieved.

![Figure 1: Transportation System with Multiple ITS Strategies](image)

This paper proposes a modeling and optimization framework using Genetic Algorithms and Simplex optimization approach to address the above mentioned challenges. The rest of the paper is organized as follows. In section 2 we overview the GA based calibration and optimization framework for the simulation model of transportation systems. Section 3 presents the application of the framework applying to the I-95 highway, followed by the preliminary simulation results and discussions in section 4. We conclude in section 5 by summarizing the findings and pointing out the potential avenues of future research.

### 2 A Genetic Algorithm Based Traffic Optimization Framework

The crux of the framework is the traffic simulator and the optimization engine (RHS of Figure 4). In each stage the traffic simulator is used in conjunction with the optimization engine to output the result of that stage. The parameters to be optimized for a particular stage are initially set randomly within the feasible range. The simulation model is batch run to output the simulated metrics. In the Genetic Algorithm (with
Simplex) based optimization engine, the simulated metrics are compared with the desired metrics. This determines the fitness (goodness) of the gene (set of parameter values for that batch run). In the optimization algorithm, genes are evolved towards better solutions; this process is iterated until the optimal gene is found or the maximum iteration times are reached. The candidate solutions i.e., new parameter values found from the optimization engine, are fed back into the simulation model. This process is repeated to get the optimized parameters for that stage. The output of one stage is used as the input for the next stage (LHS of Figure 2). This framework is currently implemented using Paramics (a commercial traffic simulation tool) as the simulator and a computer program written in Java as both the optimization engine and the interface with Paramics.

![Figure 2: GA Based Traffic Optimization Framework – Simulation Combined with Optimization](image)

The three stages of the framework that uses this simulator and optimization engine are described in detail as follows:

**Stage 1 – Origin-Destination (OD) Matrix Estimation:** In this stage, the traffic count and road network is taken as the input and the OD matrix is the output. The OD matrix defines the amount of vehicles traveling from the entries to exits. In general, there are two ways to obtain OD matrix. One approach is survey-based method that tends to be time consuming and labor intensive. The other is an estimation approach based on traffic volume on roads. The latter approach is found to be more efficient and reliable. The goal of this stage is to estimate the OD matrix that minimizes discrepancies between the simulated and the observed link traffic counts. GA is capable of searching a large feasible domain (Yun and Park 2005).

**Stage 2 – Model Calibration:** In this stage, the OD matrix found from the first stage is used as the input and the driver behavior parameters are the output. In order for the simulation model to replicate the freeway traffic flow in a specific area, the parameters that govern the driver behavior must be calibrated (Smith et al. 2008). Some of the driver behavior parameters to be calculated with their ranges include mean target headway, mean reaction time, and time step.

**Stage 3 – Model Optimization:** In this stage, one or multiple ITS strategies present in the system are optimized together. Parameters in the system are found that optimize the set goals with respect to the given constraints. The ITS strategies include congestion pricing algorithm, ramp metering, and variable speed limit etc. The goals include but are not limited to maximizing revenue, maximizing throughputs, minimizing accident rates, etc. The constraints include but are not limited to maintaining the average...
speeds, maintaining the density, etc. The parameters to be estimated include but are not limited to toll rate, toll changing rate, speed limit etc.

3 Application of Framework
This section describes the application of the GA-based framework to calibrate and optimize the HOT lanes system of I-95 based on the public data published on (STEWARD 2012). 8 miles of I-95 Northbound traffic between NW151 Street and NW32 Street in Miami FL is modeled using Paramics. The LHS of Figure 3 shows a segment of I-95 Northbound as an example of a simulation model using Paramics. The RHS of Figure 3 describes the whole road stretch of I-95, where the blue boxes represent loop detectors, and the ramp metering lights and toll gate are highlighted by yellow and red, respectively. Figure 4 describes the HOT lane and GP lane, as well as the detector, and ramp metering.

Figure 3: The Road Map of I-95

Figure 4: Transportation System Comprising of HOT Lanes and Ramp Metering

Pricing Algorithm: The pricing algorithm used here is the dynamic feedback algorithm. The target of the pricing algorithm is to maintain the average speed in HOT as desired. If the average speed is lower than the desired speed, the toll rate is increased to reduce the traffic volume entering the HOT. On the other hand, if the average speed in HOT is higher than the desired, the toll rate is decreased to attract more drivers to enter the HOT. The pricing algorithm is implemented as the plugin in Paramics.

Ramp Metering Algorithm: The ramp metering mechanism has a similar logic to the pricing algorithm. If the speed on the main road is lower than the target value, the ramp metering rate is decreased and vice
versa. Fuzzy logic controller is implemented here for the ramp metering algorithm (Meldrum and Taylor 2000).

**Driver Behavior Model:** Drivers decide whether or not to travel on the HOT lane based on utility functions for HOT and GP lane. Equation (1) and (2) are the utility functions used for HOT and GP respectively.

\[
U_{HOT} = \frac{1}{\alpha TT_{HOT} + TR}
\]

\[
U_{GP} = \frac{1}{\alpha TT_{GP}}
\]

where, \(\alpha\) is the value of time. TR is the toll rate. \(TT_{HOT}\) and \(TT_{GP}\) are the travelling time on HOT and GP lanes respectively. If \(U_{HOT} > U_{GP}\), then drivers choose to enter the HOT lane.

The following describes the three stages of the GA-based framework to calibrate and optimize the simulation model of I-95.

### 3.1 OD Matrix Estimation

In this section, we use the GA-based framework to estimate the OD matrix. The goal is that the simulated metrics for each detector match their observed values in the field. This helps making the simulation model as close to the real world as possible. There are 8 locations where detectors are installed along I-95. The column “Observed Values” in Error! Reference source not found. lists all the detectors’ traffic volume on Oct. 7 2009 from 4:00 PM to 5:00 PM.

The OD matrix defines the number of vehicles traveling from the source/origins to the destinations. Along with I-95 NB there are totally 21 entries/exits that are called “zone” in Paramics. So, there are up to \(21 \times 20 = 420\) pairs of origin/destination zones. Each cell in Table 1 represents the demand between each pair of origin/destination zones. The initial OD matrix is generated using Paramics Estimator.

<table>
<thead>
<tr>
<th>From\To</th>
<th>Zone 1</th>
<th>Zone 2</th>
<th>......</th>
<th>Zone 21</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone 1</td>
<td>0</td>
<td>20</td>
<td>......</td>
<td>19</td>
</tr>
<tr>
<td>Zone 2</td>
<td>129</td>
<td>0</td>
<td>......</td>
<td>15</td>
</tr>
<tr>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
<td>......</td>
</tr>
<tr>
<td>Zone 21</td>
<td>11</td>
<td>52</td>
<td>......</td>
<td>0</td>
</tr>
</tbody>
</table>

All non-zero values from the Paramics output are combined in a string as genes shown in Figure 5, which change and evolve in the GA.

![Figure 5: Example of Gene](image)
For each gene, its fitness is computed as in Equation (3).

\[
\frac{1}{\sqrt{\sum_{i=1}^{n}(x_i - X_i)^2}}
\]  

(3)

where, \(x_i\) is the simulated value for the \(i\)th detector, and \(X_i\) is the observed value for the \(i\)th detector. Since there are totally 8 detectors, \(n\) is equal to 8.

After running the GA-based platform, we get the best OD matrix with simulated outputs (before calibration) compared to observed outputs, as shown in Table 2. Based on the comparison, we can see that the GA-based platform is effective in estimating the OD matrix.

### 3.2 Calibration

During the calibration, the mean target headway, the mean reaction time, and the time step are tuned so that the simulated outputs are close to the observed values. The optimal values for these three parameters are 0.812, 0.269, and 4 respectively, which are different from the default values 1, 1, and 2. After calibration, the simulated outputs are recorded in Table 2.

Table 2 Comparison of Observed to Simulated Values after Calibration

<table>
<thead>
<tr>
<th>Detector</th>
<th>Observed Values</th>
<th>Simulated Values Before Calibration</th>
<th>Simulated Values After Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>600291</td>
<td>3431</td>
<td>3378</td>
<td>3388</td>
</tr>
<tr>
<td>600471</td>
<td>6432</td>
<td>5179</td>
<td>6381</td>
</tr>
<tr>
<td>600521</td>
<td>6149</td>
<td>5217</td>
<td>6109</td>
</tr>
<tr>
<td>600621</td>
<td>6451</td>
<td>5555</td>
<td>6432</td>
</tr>
<tr>
<td>600711</td>
<td>7004</td>
<td>6152</td>
<td>6989</td>
</tr>
<tr>
<td>600791</td>
<td>5720</td>
<td>5054</td>
<td>5758</td>
</tr>
<tr>
<td>600921</td>
<td>7931</td>
<td>7018</td>
<td>7904</td>
</tr>
<tr>
<td>690471</td>
<td>2491</td>
<td>2487</td>
<td>2496</td>
</tr>
</tbody>
</table>

### 3.3 Optimization

In order to reduce the traffic congestion and improve the throughput, multiple ITS strategies have been introduced, e.g., the congestion pricing algorithm, the ramp metering mechanism, the variable speed limit policy, etc. Although there has been research done for each single strategy, limited work has been conducted about how they work together. The GA-based framework introduced here is capable of investigating how multiple congestion prevention strategies affect each other. Without loss of generality, we use the GA-based platform to maximize the revenue obtained from toll charged for HOT lane and maximize the throughput, under the situation that pricing algorithm and the ramp metering mechanism take effect simultaneously. The same steps could be applied when the goal is to maximize the throughput in the HOT lanes or any other variables of interest.
4 Preliminary Results
The target speed on HOT ranges from 55 mile/hr to 60 mile/hr, and the ramp metering rate changes from 10 vehicles/min to 50 vehicles/min. Different scenarios are run to understand and optimize the transportation system. The scenarios are as follows:

4.1 Managed Lanes – Sensitivity to Pricing Parameters
In this scenario, the sensitivity of the parameters in the managed lanes is studied with no ramp metering. The two parameters that are varied is the tolerance of the speed and the target speed on the HOT lanes. The tolerance of the speed is the range within which the toll rate does not change. For example, if the tolerance is 2 mph and the average speed on the HOT lanes is 55 mph, then the toll rate for entry to HOT lanes would not change within 53 and 57 mph range of the HOT lanes.

![Graph showing Throughput and Revenue Sensitivity to Managed Lanes Parameters](image)

Figure 6: Throughput and Revenue Sensitivity to Managed Lanes Parameters

The outputs in the plots of Figure 6 are throughput and revenue respectively. It is observed that the higher target speed makes it harder for the actual speed to reach the target. The toll has to be increased to decrease the traffic flow up to a value, after which no vehicles enter HOT so that the throughput is decreased to 0. The revenue increases with the tolerance of target speed, because the smaller tolerance results in the larger oscillation of tolls and traffic, which has negative affect on revenue.

4.2 Managed lanes and Ramp Metering Optimization
In this scenario, the sensitivity and optimization of the parameters in the managed lanes as well as ramp metering is studied. The two parameters that are varied is the ramp metering rate and the target speed on the HOT lanes. The ramp metering rate is the number of vehicles that are allowed on the GP lanes per minute.

Figure 7 shows how revenue and throughput change along with target speed on HOT and ramp metering rate. It is observed that at very high target speeds on HOT lanes, high tolls and less vehicles are present. At very low target speeds, low tolls & more vehicles are present. Optimum point for revenue is in between (RHS of Figure 7). It is also seen that the throughput of HOT lanes increases with ramp metering rate (LHS of Figure 7). The underlying reason is that the higher ramp metering rate results in more vehicles on the GP, which in turn drives more vehicles to enter the HOT. The throughput of HOT lanes decreases with the target speed increasing, because the higher target speed leads to the higher toll rate, which in turn reduces the number of vehicles entering the HOT lanes.
The system is further optimized using the GA framework in Section 2 to find the parameters that will maximize throughput along with desired levels of revenue. If the target speed on HOT lanes is set at 59 mph and ramp metering rate with [Lower-bound Upper-bound] as [30 40] for all meters, the throughput is maximized and revenue is $6700/hr. If ramp metering parameters can be optimized individually, revenue increases to $7200/hr with [LB UB] as [5 24] [37 49] [49 50] and [34 36] and target speed as 57mph. Thus, with control of key parameters, multiple objectives in different ITS strategies can be balanced together using the framework.

### 4.3 Pareto Analysis of Managed Lanes and Ramp Metering

In this scenario, Design of Experiments analysis is performed on the simulation model. Different parameters including the ones considered above are used as inputs in the model and throughput and revenue are considered as output in the model. High R² value is obtained after regression.

It is found in Figure 8 that pricing and ramp metering parameters explain most of the variations in the outputs – throughput & revenue. It is also important to note that the interactions between pricing and ramp metering parameters have the most effect on the outputs. This validates our choice of the parameters that are varied in different scenarios. It also emphasizes the need of a system level optimization that considers different parameters together in the system.

### 5 Conclusions

The paper proposes a GA-based framework that is used to optimize multiple ITS strategies simultaneously. The framework is capable of estimating the OD matrix, calibrating the model with the
experimental data, and conducting system optimization in transportation. This capability is shown with simulation experiments based on the public data of I-95 (STEWARD 2012). The GA combined with the simplex approach used here has been proved to have higher performance than the classical GA in the transportation related research area. This approach can be used to optimize more complex system optimization problems in transportation domain. The experimental results show that the interaction between pricing and ramp metering algorithm has the most significant effect on the throughput and revenue. Additionally, the revenue increases with the target speed on HOT up to a level, beyond which the revenue drops. On the contrary, the throughput decreases with the target speed on HOT. So, there is an optimal target speed existing in the middle to balance the revenue and throughput.

References


