A Calibration Framework of a Mixed-traffic Signal
Optimization Model by Multi-objective Evolutionary
Approach

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Abstract - Scooter-mixed traffic flow models have been investigated for decades since the motorcycle is one of the
major modes for daily traffic in some Asian countries. But the
 calibration process of most of them are based on a single
performance metric. In this study, a framework for parameter
optimization of the mixed-traffic model with multi-objectives
has been presented and a NSGA-II algorithm is coupled with
the mixed-traffic flow model to find the non-dominated front in
the objective space. An application example has been
presented that illustrates the potential use of the proposed
calibration framework.

Keywords: Mixed Traffic Flow; NSGA-II; Multi-objective
Evolutionary Approach

1 Introduction
1.1 Background
Scooter-vehicle mixed traffic flows is one of the most
important traffic features in some Asian developing countries,
such as China, Taiwan, Malaysia and Vietnam, etc. Due to
scooter’s maneuverability, agility, and low price compared to
passenger car, it has become the primal transportation mode
for commuters, especially in urban areas [7]. But unlike
passenger car that usually moves along a specific lane and
changes lanes only for overtaking or turning purpose, scooters
moves in a rather irregular and erratic manner, which
consequently creates more chaotic to the congested urban
traffic flows. For the purpose of transportation system
planning, design and control, it is critical to gain deep insights
into the motorcycle behaviors and to develop appropriate
traffic flow models. In the last decade, few papers concerning
this topic in theoretical research [2, 3, 8, 9, 11] and some of
them couple the traffic flow model with signal control model
together to optimize signal timing plans [3, 8]. In all of these
studies, the calibration procedure is based on a single
performance metric or calibration criterion [1, 2, 6, 9]. The
tradeoff between different objectives has been ignored.
Therefore in this study, a multi-objective evolutionary
algorithm known as Non-dominated Sorting Genetic Algorithm II (NSGA-II) [4] has been used to establish a
calibration procedure for the mixed-traffic signal optimization
model. Such algorithm employs a population-based approach
to find multiple optimal solutions, or so-called Pareto optimal
solutions.

The paper attempts to develop a calibration framework
to optimize the parameters of a mixed-traffic flow model by
using NSGA-II. The paper is organized as follows. First a
short review to the scooter-mixed traffic flow model is
provided. Then the parameter optimization problem and
calibration framework is proposed. Section 3 describes the
case study site and results of applying the proposed
framework. The final section concludes this paper.

1.2 Scooter-Mixed Traffic Flow Model
The scooter-vehicle mixed traffic flow model used in the
study was developed by [8, 9]. Consider a typical approach
with mixed-traffic flows, the model conceptually divides the
traffic dynamics into the following stages: a) Upstream
arrivals and propagation to the end of queue, b) lane choice
and merge into existing queue, c) discharging process from
the queue. In the first stage, the model calculates the upstream
arrival rate and estimated travel time from the upstream stop-
line to the downstream end-of-queue. Then a lane choice
model, as shown in (3), distributes the arrivals into different
lanes according to each lane’s queue length and saturation
flow rate.

\[
Q'_{\text{out}}[t] = Q_{\text{in}}' [t] \times \frac{\tilde{E}[t] \times \tilde{S} '[t-1]}{\sum_{i \in L_{\text{out}}^m} \tilde{E}[t] \times \tilde{S} ^'[t-1]},
\]

\[
\tilde{E}[t] = \left( \frac{L'[t]}{m^l} \right)^{-1}
\]

\[
\tilde{S} ^'[t-1] = \frac{S'[t-1]}{\sum_{i \in L_{\text{out}}^m} S'[t-1]},
\]

where \(Q'_{\text{in}}[t]\) is the flow rate of type-\(v\) (\(v=1\) is scooters, \(v=2\)
is passenger cars) arriving the end of queue of lane \(l\) during
time step \(t\); \(Q'_{\text{out}}[t]\) is the flow rate of type-\(v\) vehicles
arriving the end of queue during time step \(t\), \(\gamma_{\text{in}},[t]\) is the
turning ratio of type-\(v\) vehicles with movement \(m\); \(L_{\text{out}}^m\) is the
set of lanes available to vehicles with movement \(m\); \(\tilde{E}[t]\) and
\(\tilde{S} '[t-1]\) denote the normalized factor (between 0 and 1) of
queue length and saturation flow rate on lane \(l\), respectively.
If an approach has a scooter-waiting area, the model assumes that the scooters with through movement merge into the waiting area directly if there is space available. Once the waiting area is fully occupied, the scooters will start to queue on available lanes. Let \( Q_{\text{soc}}^\text{new} [t] \) denote the number of scooters merging into the waiting area, then (1) is rewritten as follows:

\[
Q_{\text{soc}}^\text{new} [t] = Q_{\text{soc}}^\text{new} [t] \times \gamma_{\text{soc}1} - Q_{\text{soc}}^\text{new} [t] \times \frac{E [t]}{\sum_{i=1}^{m} E [t] \times S [t-1]}
\]  

(2)

Given the average storage space of a scooter waiting area \( \chi \), \( Q_{\text{soc}}^\text{new} [t] \) is calculated by the following:

\[
Q_{\text{soc}}^\text{new} [t] = \min \{ Q_{\text{soc}}^\text{new} [t] \times \gamma_{\text{soc}1} \times \chi - X_{\text{soc}}^\text{new} [t] \times (1 - g_{\text{soc}}^\text{new} [t]) \}
\]  

(3)

where \( X_{soc}^new [t] \) is the number of scooters in the scooter waiting area at time stage \( t \) and \( g_{soc}^new [t] \) is a binary variable representing a green phase for through movement.

The vehicle queues on each lane keep cumulating until the traffic light turns to green. In the discharging process, the model describes how different types of vehicles interact and generates a mixed-traffic discharging rate weighted with the number of each type of vehicles in the queue. The average discharge rate \( S_{c}^d [t] \) is expressed as follows:

\[
S_{c}^d [t] = \frac{\sum \chi_{c}^d [t] \times O_{c} \times h_{soc} \times \chi^{l}}{\sum \chi_{c}^d [t] \times O_{c}}
\]  

(4)

where \( \chi_{c}^d [t] \) is the number of type-\( c \) vehicles in queue on lane \( l \) at time step \( t \); \( O_{c} \) is the occupied space of type-\( c \) vehicles and \( h_{soc} \) is the average discharge headway of type-\( c \) vehicles with movement \( m \). The actual discharging rate for each vehicle type and movement can be calculated as follows:

\[
S_{c}^d [t] = S_{c}^d [t] \times \frac{\chi_{c}^d [t]}{\sum \chi_{c}^d [t]}
\]  

(5)

2 Multi-Objective evolutionary approach for parameter optimization

2.1 Parameter Optimization

The purpose of model calibration can be generally stated as estimation of model parameters so that model simulations and traffic behavior match closely. In the study, the estimation of the parameter values is formulated as a multi-objective optimization problem where two objectives, the absolute errors between the observed and simulated average number of passenger cars and scooters in queue, are considered. The optimization problem is written as follows:

Minimize \( \left( |\bar{x}_{soc} - \bar{x}_{soc}(p)|, |\bar{x}_{pc} - \bar{x}_{pc}(p)| \right) \)  

Subject to \( p_{LB} \leq p \leq p_{UB} \)  

(6)

Where, \( \bar{x}_{soc} \) and \( \bar{x}_{pc} \) denote the observed and estimated average number (of all movements) of scooter in queue, respectively; \( \bar{x}_{soc} \) and \( \bar{x}_{pc} \) are same values of passenger cars. The vector of parameters is represented by \( p \), with a lower bound \( p_{LB} \) and upper bound \( p_{UB} \). The objectives (6) is to minimize the absolute error of average number of scooter in queue and the same of passenger cars. For each approach, the parameter vector has seven elements, including the average discharging headway \( h_{soc} \) for three different movements and two vehicle types and the average storage space of a scooter waiting area \( \chi \). The value of \( p_{LB} \) and \( p_{UB} \) are given according to the field survey data.

2.2 Calibration Framework

The proposed framework of calibration procedure for the mixed-traffic flow model is shown in Fig. 1. The main optimization process is on the left side, which can be any kind of multi-objective evolutionary algorithms (MOEA), i.e., Genetic Algorithm, Particle Swarm, etc. In this study, NSGA-II approach is used. In a sense, these population-based approaches have similar solution structure. At the beginning, a pool of solution candidates are generated and evaluated. Then a procedure of reproduction is revoked and a new generation of solution set is created. This procedure is iterated until the stop conditions are met.

On the other hand, the evaluation procedure is depicted on the right side of Fig. 1. Since the purpose of parameter optimization is to minimize the estimation error, the mixed-traffic model is revoked when a solution is evaluated. The input file of the mixed-traffic model is modified based on the set of parameters represented by the solution being evaluated. Then the model output is analyzed and compared with field survey observations. The differences between estimations and observations are objective values of the solution.


3 Application Example

3.1 Survey Area and Data

The survey field site for this study is a major intersection in Hsinchu County, Taiwan. The data was collected on Oct. 30, 2014 between 05:00 PM and 08:00 PM. The peak-hour demand during 05:35 PM to 06:35 PM is used as the model input, as shown in Table 1. The number of passenger cars and scooters in the queue on each lane were collected in intervals of fifteen seconds. The data was aggregated to the form of average number of vehicles in queue of each movement, as shown in Table 2.

Figure 2 The survey field site

<table>
<thead>
<tr>
<th>Approach</th>
<th>Movement v-type</th>
<th>Left</th>
<th>Through</th>
<th>Right</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (SB)</td>
<td>Scooter</td>
<td>7.0</td>
<td>199.9</td>
<td>23.4</td>
<td>230.3</td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>91.5</td>
<td>520.6</td>
<td>530.8</td>
<td>1142.9</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>98.5</td>
<td>720.5</td>
<td>554.2</td>
<td>1373.2</td>
</tr>
<tr>
<td>2 (WB)</td>
<td>Scooter</td>
<td>90.5</td>
<td>393.5</td>
<td>18.4</td>
<td>502.5</td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>330.3</td>
<td>533.2</td>
<td>38.9</td>
<td>902.4</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>420.8</td>
<td>926.7</td>
<td>57.3</td>
<td>1404.9</td>
</tr>
<tr>
<td>3 (NB)</td>
<td>Scooter</td>
<td>92.5</td>
<td>359.1</td>
<td>115.2</td>
<td>566.8</td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>538.8</td>
<td>484.4</td>
<td>365.6</td>
<td>1517.8</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>631.3</td>
<td>843.5</td>
<td>480.8</td>
<td>2084.6</td>
</tr>
<tr>
<td>4 (EB)</td>
<td>Scooter</td>
<td>22.0</td>
<td>280.6</td>
<td>48.6</td>
<td>351.2</td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>153.9</td>
<td>729.0</td>
<td>236.5</td>
<td>1119.4</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>175.9</td>
<td>1009.6</td>
<td>285.1</td>
<td>1470.6</td>
</tr>
</tbody>
</table>

Table 1 Peak-hour demand (Unit: PCUs)

Table 2 Observed average numbers of vehicles in queue

<table>
<thead>
<tr>
<th>Approach</th>
<th>Movement v-type</th>
<th>Left</th>
<th>Through</th>
<th>Right</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (SB)</td>
<td>Scooter</td>
<td>-</td>
<td>0.102</td>
<td>0.686</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>0.636</td>
<td>7.326</td>
<td>3.203</td>
<td></td>
</tr>
<tr>
<td>2 (WB)</td>
<td>Scooter</td>
<td>-</td>
<td>1.678</td>
<td>4.136</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>2.466</td>
<td>4.008</td>
<td>0.703</td>
<td></td>
</tr>
<tr>
<td>3 (NB)</td>
<td>Scooter</td>
<td>-</td>
<td>0.0254</td>
<td>2.381</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>16.076</td>
<td>11.678</td>
<td>0.737</td>
<td></td>
</tr>
<tr>
<td>4 (EB)</td>
<td>Scooter</td>
<td>-</td>
<td>0.458</td>
<td>1.788</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Passenger Car</td>
<td>1.65</td>
<td>7.076</td>
<td>2.424</td>
<td></td>
</tr>
</tbody>
</table>

3.2 Result and Discussion

The optimized parameters were evaluated by calculating the absolute errors between the observations and model simulation results. The pareto front of each approach is shown in Figure 3-6, respectively. It is obvious that approach 1 does not have tradeoff between two objectives. We may notice that the total demand volume (in Table 2) on the approach is lighter than other approaches and it also has the lowest total scooter volume among all movements. By observing the formulation of lane choice model and discharging model mentioned before, we may notice that different compositions of the mixed traffic, i.e., the number of vehicles in the queue, have great influence on the mixed-traffic saturation flow rate. Since all the scooters that cannot go to the waiting zone will merge into the queue with passenger cars, the parameter has a great deal to do with the mixed-traffic composition. In other words, the approach with higher volume of scooter demand has greater chance of appearance of tradeoff.

Figure 3 The Pareto front of Approach 1
framework. It can be concluded that the proposed calibration framework has potential use in parameter optimization of the mixed-traffic flow model. From the results, the phenomenon of tradeoff between scooter and passenger car errors become obvious when scooter demand rises. Such phenomenon quite coincides with the chaotic nature of mixed-traffic flow in real world.

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5 References

4 Conclusion

In this study, a framework for parameter optimization of the mixed-traffic model with multi-objectives has been presented. In the framework, a NSGA-II algorithm is coupled with the mixed-traffic flow model to find the non-dominated front in the objective space. An application example has been presented that illustrates the use of the proposed calibration framework. It can be concluded that the proposed calibration framework has potential use in parameter optimization of the mixed-traffic flow model. From the results, the phenomenon of tradeoff between scooter and passenger car errors become obvious when scooter demand rises. Such phenomenon quite coincides with the chaotic nature of mixed-traffic flow in real world.