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.

$$Q_v^{l,arr}\left[t\right] = Q_v^{arr}\left[t\right] \times \gamma_{m,v} \times \left[\frac{\tilde{L}^l[t] \times \tilde{S}^l\left[t-1\right]}{\sum_{l \in LG_m} \tilde{L}^l[t] \times \tilde{S}^l\left[t-1\right]} \right], \tag{1}$$

$$\tilde{L}^l[t] = \frac{\left(L^l[t]\right)^{-1}}{\sum_{l \in LG_m} \left(L^l[t]\right)^{-1}} \text{ and } \tilde{S}^l\left[t-1\right] = \frac{S^l\left[t-1\right]}{\sum_{l \in LG_m} S^l\left[t-1\right]},$$

where $Q_v^{l,arr}[t]$ 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; $Q_v^{arr}[t]$ is the flow rate of type-v vehicles arriving the end of queue during time step t, $\gamma_{m,v}[t]$ is the turning ratio of type-v vehicles with movement m; LG_m is the set of lanes available to vehicles with movement m; $\tilde{L}^l[t]$ and $\tilde{S}^l[t-1]$ 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, scooters will start to queue on available lanes. Let $Q^{swa}\left[t\right]$ denote the number of scooters merging into the waiting area, then (1) is rewritten as follows:

$$Q_1^{l,arr}\left[t\right]=(Q_1^{arr}\left[t\right]\times\gamma_{m,1}-Q^{swa}\left[t\right])\times\left[\frac{\tilde{L}^l[t]\times\tilde{S}^l\left[t-1\right]}{\sum_{l\in LG_m}\tilde{L}^l[t]\times\tilde{S}^l\left[t-1\right]}\right] \quad (2)$$

Given the average storage space of a scooter waiting area χ, $Q^{swa}\left[t\right]$ is calculated by the follows:

$$Q_1^{swa}\left[t\right]=\min\left\{Q_1^{arr}\left[t\right]\times\gamma_{thru,1},\chi-X^{swa}\left[t\right]\right\}\times\left(1-g^{thru}\left[t\right]\right) \quad (3)$$

where $X^{swa}\left[t\right]$ is the number of scooters in the scooter waiting area at time stage t and $g^{thru}\left[t\right]$ 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 vehicle interact and generates a mixed-traffic discharging rate weighted with the number of each type of vehicles in the queue. The average discharge rate $S^l[t]$ is expressed as follows:

$$S^l\left[t\right]=\left(\frac{\sum_v X_v^l\left[t\right]\cdot O_v\cdot h_{m,v}}{\sum_v X_v^l\left[t\right]\cdot O_v}\right)^{-1} \quad (4)$$

where $X_v^l\left[t\right]$ is the number of type-v vehicles in queue on lane l at time step t; O_v is the occupied space of type-v vehicles and $h_{m,v}$ is the average discharge headway of type-v vehicles with movement m. The actual discharging rate for each vehicle type and movement can be calculated as follows:

$$S_v^l\left[t\right]=S^l\left[t\right]\times\frac{X_v^l\left[t\right]}{\sum_v X_v^l\left[t\right]} \quad (5)$$

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:

$$\text{Minimize} \quad \left(\left|\bar{x}_{scot}^{obs}-\bar{x}_{scot}^{est}(p)\right|,\left|\bar{x}_{pc}^{obs}-\bar{x}_{pc}^{est}(p)\right|\right) \quad (6)$$

$$\text{Subjected to} \quad p_{LB}\le p\le p_{UB} \quad (7)$$

Where, $\bar{x}_{scot}^{obs}$ and $\bar{x}_{scot}^{est}(p)$ denote the observed and estimated average number (of all movements) of scooter in queue, respectively; $\bar{x}_{pc}^{obs}$ and $\bar{x}_{pc}^{est}(p)$ 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 $h_{m,v}$ for three different movements and two vehicle types and the average storage space of a scooter waiting area χ. The value of p_{LB} and p_{UB} are given according by 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.

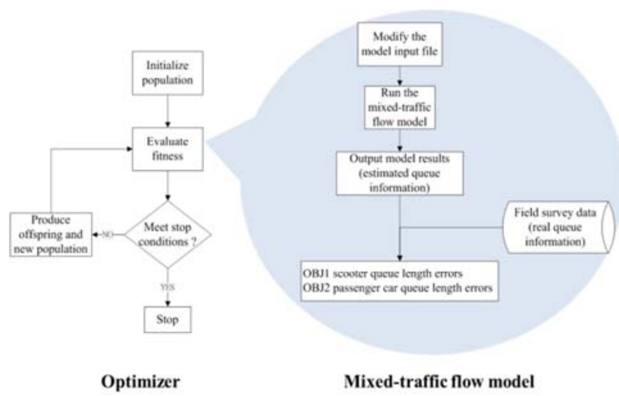

Figure 1 The model calibration framework

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.

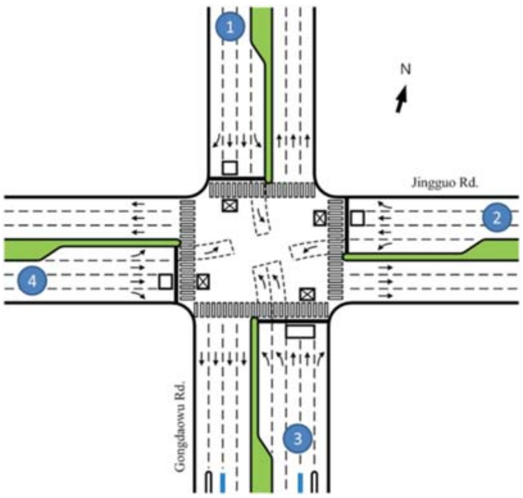

Figure 2 The survey field site

Table 1 Peak-hour demand (Unit: PCUs)

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

Table 2 Observed average numbers of vehicles in queue

Approach	movement / v-type	Left	Through	Right
1 (SB)	Scooter	-	0.102	0.686
	Passenger Car	0.636	7.326	3.203
2 (WB)	Scooter	-	1.678	4.136
	Passenger Car	2.466	4.008	0.703
3 (NB)	Scooter	-	0.0254	2.381
	Passenger Car	16.076	11.678	0.737
4 (EB)	Scooter	-	0.458	1.788
	Passenger Car	1.65	7.076	2.424

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.

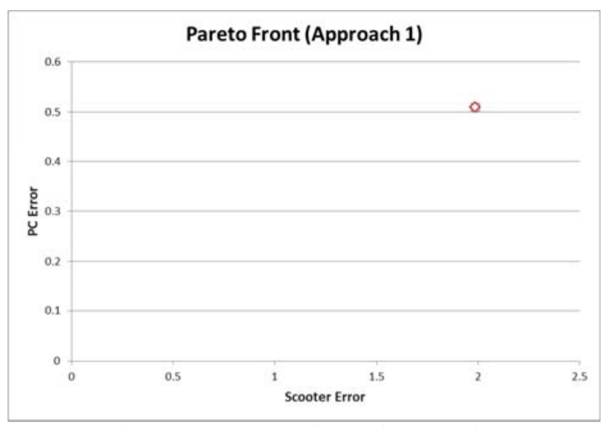

Figure 3 The Pareto front of Approach 1

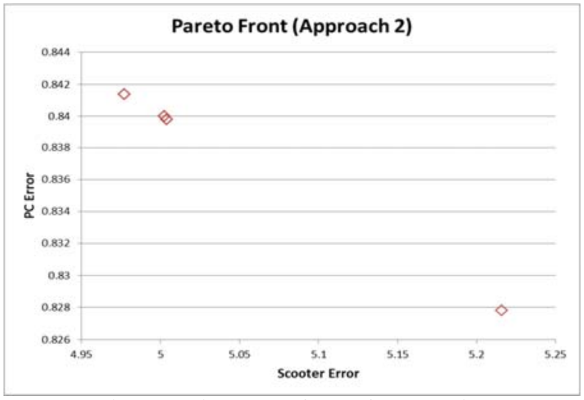

Figure 4 The Pareto front of Approach 2

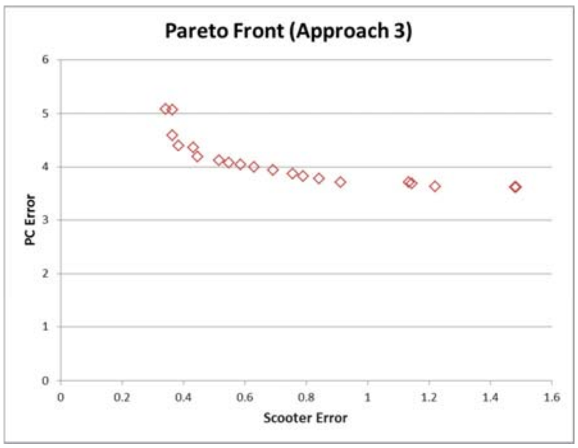

Figure 5 The Pareto front of Approach 3

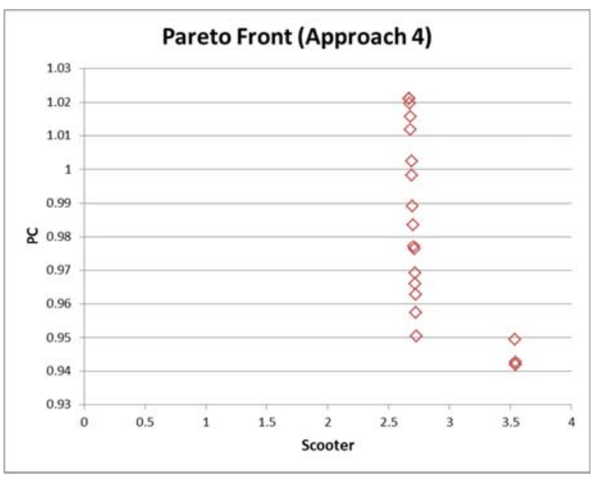

Figure 6 The Pareto front of Approach 4

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.

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