Macroscopic Calibration of Microscopic Queue Model Interpretation for Traffic Simulation of Electrical Vehicles *

Hassan Haghighi[1], Maamar El Amine Hamri[1]

Aix Marseille Univ, CNRS, LIS, Marseille, France

{hassan.haghighi, amine.hamri}@lis-lab.fr

Keywords : *traffic model, discrete simulation, calibration, optimization.*

1 Introduction

Modeling & Simulation (M&S) is considered as a useful method in non-reference situations, as opposed to methods based on experimental data. For reliable simulation of the microscopic patterns based on the macroscopic results, our main equations are the macroscopic flow dynamics equation, Lighthill-Whitham-Richards (LWR) [1, 2], the microscopic Gibbs model [3], and the continuity equation for energy [4] where queuing systems rely on discrete event simulation systems. Since these systems operate in an open loop structure and are time-consuming in terms of run time, it is possible to reach a model for microscopic simulation by using the results of the macroscopic system in an inner high-frequency closed loop structure. As a result, using a bidirectional optimization structure, the key parameters of the model can be calibrated.

2 Mathematics model

The objective is to increase the accuracy of the microscopic model by using the macroscopic effects while extracting microscopic patterns from the macroscopic solution. According to the velocity v as a function of traffic density $\rho \in [0, \rho_{max}]$, the flow dynamics is $Q = \min\{V\rho, w(\rho_{max} - \rho)\}$ where the congestion wave speed w is a function of critical density ρ_{cri} and traffic free velocity V as $w = \frac{\rho_{cri} v_{max}}{\rho_{max} - \rho_{cri}}$. Therefore, a simplified continuity LWR model for ρ and charging energy e as the state of the charge (SOC) at time t and location x, as well as a queue model of velocity and location as the Gipps model for n^{th} vehicle $\{n \in \mathbb{N} | n \geq 2\}$, can then be described as follows:

$$\frac{d\rho}{dt} + \frac{dQ}{dx} = 0 \tag{1}$$

$$\frac{de}{dt} = F(v, \Omega, \theta) \tag{2}$$

$$\begin{aligned} v_n(t+\tau) = \min\Bigg\{ & v_n(t) + 2.5 a_n \tau \left(1 - \frac{v_n(t)}{V_n}\right) \sqrt{0.025 + \frac{v_n(t)}{V_n^d}}, \\ & b_n \tau + \sqrt{b_n^2 \tau^2 - b_n \left[2\left(\delta x(t) - s_{n-1}\right) - v_n(t)\tau - \frac{v_{n-1}(t)^2}{\hat{b}}\right]} \Bigg\} \end{aligned} \tag{3}$$

where F as the battery discharge function depends on velocity v, engine shaft rotation Ω, and road ramp angle θ. The Gibbs model is dependent on several parameters, such as reflection time τ, desired maximum acceleration a, safety distance s, maximum desired velocity in traffic free conditions V, which are different for each vehicle based on its conditions and driver's traffic behavior. Let to consider the mentioned parameters as random variables normally distributed with mean μ and standard deviation σ, as $\tau_n \sim \mathcal{N}(\mu_\tau, \sigma_\tau^2)$, $a_n \sim \mathcal{N}(\mu_a, \sigma_a^2)$, $s_n \sim \mathcal{N}(\mu_s, \sigma_s^2)$,

*This work was supported by the French agency ANR under the chair in artificial intelligence MASSALIA.

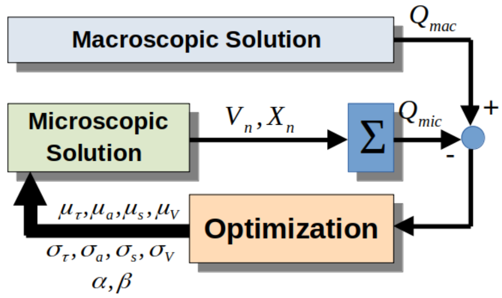

FIG. 1: Optimization diagram

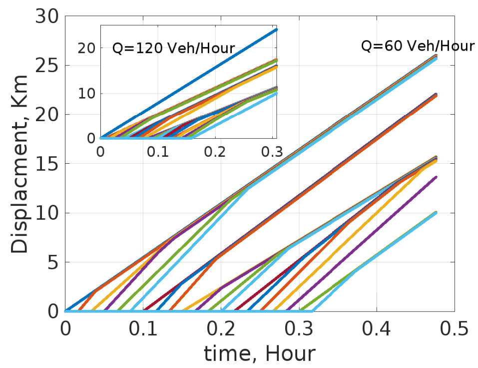

FIG. 2: Gipps queue model for 20 cars with different desired parameters and different flows

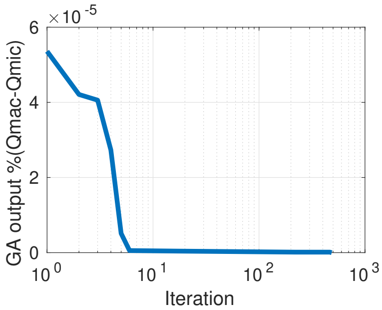

FIG. 3: Genetic algorithm optimization process

Traffic Parameters		GA Parameters	
N of vehicles	20	Initial population	100
Road length,Km	10	N,Generation	51
$(\mu_\tau^*, \sigma_\tau^*), s$	$(0.66, 0)$	N,Iteration	486
$(\mu_a^*, \sigma_a^*), \frac{m}{s^2}$	$(1.58, 0.45)$	Error order	$O(10^{-7})$
$(\mu_s^*, \sigma_s^*), m$	$(6.51, 1.11)$		
$(\mu_V^*, \sigma_V^*), \frac{m}{s}$	$(20.1, 3.21)$		
$(\alpha^*, \beta^*), \frac{m}{s^2}$	$(-0.374, -1.79)$		

TAB. 1 - Optimal output

and $V_n \sim \mathcal{N}(\mu_V, \sigma_V^2)$. Also we can estimate the maximum breaking deceleration $b_n = \alpha a_n$, and frontal vehicle maximum deceleration $\hat{b} = \min\{\beta, \frac{b_n - \beta}{2}\}$. Calibrating these parameters with macroscopic results takes place in the closed loop as shown in Fig. 1, considering the objective to find the optimal values of μ_τ^*, σ_τ^*, μ_a^*, σ_a^*, μ_s^*, σ_s^*, μ_V^*, σ_V^*, α^*, and β^* as following cost function for macroscopic flow Q_{mac} and microscopic flow Q_{mic}.

$$\begin{aligned} J = \min_{\{\mu_\tau, \mu_a, \mu_s, \mu_V, \sigma_\tau, \sigma_a, \sigma_s, \sigma_V, \alpha, \beta\}} & \sum (Q_{mac} - Q_{mic})^2 \\ \text{s.t.} \quad & v_{mac} \leq v, \rho \leq \rho_{max}, (\mu_\tau, \mu_a, \mu_s, \mu_V, \sigma_\tau, \sigma_a, \sigma_s, \sigma_V) > 0 \\ & -2.0 \leq \alpha < 0, -3.0 \leq \beta < 0 \end{aligned} \tag{4}$$

3 Conclusions and simulation results

Microscopic simulation for two types of dynamic flow is shown in Fig. 2 for 20 vehicles. Fig. 3 and Tab. 1 present the optimal values of Calibration. The model and optimization performance show high efficiency in the behavior of output error.

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