



Swarm intelligence algorithms for macroscopic traffic flow model validation with automatic assignment of fundamental diagrams



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ABSTRACT

This paper is concerned with the problem of macroscopic road traffic flow model calibration and verification. Thoroughly validated models are necessary for both control system design and scenario evaluation purposes. Here, the second order traffic flow model METANET was calibrated and verified using real data.

A powerful optimisation problem formulation is proposed for identifying a set of model parameters that makes the model fit to measurements. For the macroscopic traffic flow model validation problem, this set of parameters characterise the aggregate traffic flow features over a road network. In traffic engineering, one of the most important relationships whose parameters need to be determined is the fundamental diagram of traffic, which models the non-linear relationship between vehicular flow and density. Typically, a real network does not exhibit the same traffic flow aggregate behaviour everywhere and different fundamental diagrams are used for covering different network areas. As a result, one of the initial steps of the validation process rests on expert engineering opinion assigning the spatial extension of fundamental diagrams. The proposed optimisation problem formulation allows for automatically determining the number of different fundamental diagrams to be used and their corresponding spatial extension over the road network, simplifying this initial step. Although the optimisation problem suffers from local minima, good solutions which generalise well were obtained.

The design of the system used is highly generic and allows for a number of evolutionary and swarm intelligence algorithms to be used. Two UK sites have been used for testing it. Calibration and verification results are discussed in detail. The resulting models are able to capture the dynamics of traffic flow and replicate shockwave propagation.

A total of ten different algorithms were considered and compared with respect to their ability to converge to a solution, which remains valid for different sets of data. Particle swarm optimisation (PSO) algorithms have proven to be particularly effective and provide the best results both in terms of speed of convergence and solution generalisation. An interesting result reported is that more recently proposed PSO algorithms were outperformed by older variants, both in terms of speed of convergence and model error minimisation.

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1. Introduction and background

Traffic modelling is an essential element of traffic planning and management systems. Traffic models are mainly used for evaluation and system design purposes. Intelligent Transportation Systems (ITS) operating in motorway networks require the use of valid models for tasks like traffic prediction, state and travel time estimation, and real time model based predictive control. Automatic incident systems also make use of such models. Irrespective

of their purpose, models have to be valid for the specific road network they are used for.

This paper is concerned with the problem of macroscopic traffic flow model validation and, hence, microscopic and mesoscopic models are beyond its scope. For a more detailed discussion on modelling approaches, see [1].

Macroscopic models describe the traffic flow as a liquid using aggregate variables. At point x on the road and time t , these are the vehicular density $\rho(x, t)$ (veh/km), mean speed $v(x, t)$ (km/h) and flow (or volume) $q(x, t)$ (veh/h). The macroscopic description of traffic along a motorway was introduced in the seminal papers of Lighthill and Whitham [2] and Richards [3], resulting to the LWR model.

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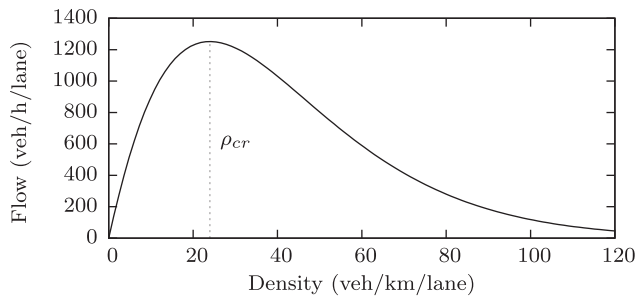


Fig. 1. Example of the fundamental diagram.

The LWR model employs the vehicle conservation equation to calculate densities and flows, which reads

$$\frac{\partial \rho(x, t)}{\partial t} + \frac{\partial q(x, t)}{\partial x} = 0. \quad (1)$$

In order for Eq. (1) to be solved, the relationship between flow and density must be explicitly considered. In the LWR theory it is given in the form

$$q(x, t) = \rho(x, t)V[\rho(x, t)] \quad (2)$$

where $V[\rho(x, t)]$ (km/h) is an equilibrium relationship between density and mean speed, i.e. the so-called fundamental diagram (FD) of traffic. The FD models the traffic flow's tendency to settle to the equilibrium mean speed $V[\rho(x, t)]$ for a given density level $\rho(x, t)$. The typical shape of the density-flow FD, i.e. the way the quantity $(\rho(x, t)V[\rho(x, t)])$ changes with respect to $\rho(x, t)$ is shown in Fig. 1. The FD accounts for the fact that until the critical density ρ_{cr} is observed, the vehicular flow increases with increasing density. The flow is maximised at ρ_{cr} , and when the density increases past that level, the number of vehicles contained per unit of length is such that drivers are forced to slow down, reaching to zero speed at jam density level ρ_{max} . Different functional expressions for the FD have been proposed in the literature, see [4–6].

Typically, a space and time discretised version of Eq. (1), along with the FD constitute the basic elements of a first order macroscopic traffic flow model [2,3,7–11].

Payne-type second order models result from coupling (1) with an empirical equation governing the mean speed $v(x, t)$ dynamics [12]; this equation has the form

$$\frac{\partial v(x, t)}{\partial t} + v(x, t) \frac{\partial v(x, t)}{\partial x} + \frac{1}{\rho(x, t)} \frac{\partial P(x, t)}{\partial x} = \frac{1}{\tau} \{V[\rho(x, t)] - v(x, t)\} \quad (3)$$

where τ is a relaxation constant and $P(x, t)$ a pressure term, which gives rise to a range of different models [13].

Irrespective of the model's order, a number of parameters characterising the aggregate driver-vehicle-infrastructure behaviour are used. For any practical purpose the values assigned to them are based on real data collected from the road network. Using data sets of traffic counts and vehicle speeds, typically obtained by means of inductive loop detectors embedded in the motorway, a rigorous model validation procedure needs to take place, for identifying an optimal set of parameters [14]. The validation process consists of two parts, model calibration and model verification.

The calibration phase aims at determining an optimal set of model parameters that minimises the error for a specific data set. Verification is then performed to corroborate the model's accuracy using a different set of data, not used during calibration. Model validation is a difficult procedure due to the sensitivity and the non-linear nature of the traffic flow process. Furthermore, the resulting optimisation problem has numerous local minima [15].

Here, the second order model *Modèle d'Écoulement de Trafic sur Autoroute (META)* [16] as well as its extension to networks, *META-NETworks (METANET)* [17], is used as a modelling tool. The METANET simulator and its predecessors have been successfully validated for networks of various sizes. A more extensive model validation exercise for the META model was conducted for the Paris ring road in [18]. The validation of the large scale network of the Amsterdam peripheral network is described in [16]. For the modelling of the Paris and Amsterdam sites, the deterministic search algorithm of Box [19] was used. A simplex based algorithm was used by Ngoduy et al. [20] to validate various numerical schemes.

In [21] a method calculating the model parameters by comparing the congestion pattern of the data and model output aiming at avoiding incorrect data forms, was used. A cross entropy method is used in [15] to validate the model used in [21] for a 10km section of a UK highway. A comparative study of the first order Cell Transmission Model (CTM) [7,8] and METANET for a motorway in Greece based on the Nelder–Mead algorithm [22] is provided in [23]. The use of a genetic algorithm to validate METANET on a simple site in the UK is reported in [24]. In [25] a METANET model parameter identification algorithm is discussed using data from a 4.65 km stretch of a California highway; the original expression used for FD in METANET is replaced with a two-regime model and the resulting optimisation problem is solved using a sequential quadratic programming algorithm.

Motivated by the requirements generated for designing autonomous traffic management systems, i.e. systems that exhibit self-* (e.g. self-optimising, self-healing, self-configuring and so forth) properties, the model validation problem's scope was extended to automate elements that traditionally are based on engineering expert opinion [26]. This is one of this paper's contributions. The proposed problem formulation is able to replace expert engineering opinion and judgement by automatically selecting the spatial extension of the application of a FD along with its parameters. This extra requirement increases the problem complexity but removes the need for prior expert knowledge about congestion patterns. Bottleneck identification as used in [27,28] or choosing an arbitrary (based on educated opinion) point for a change in the FD parameter set [16] is not explicitly required. These are left to the optimisation algorithm to deal with, aiming at avoiding over-parametrisation as well. Within this setting, this paper aims at providing the details of mainly particle swarm optimisation (PSO) performance when used for the METANET model validation problem.

In this manner many different categories of algorithms have been applied to various engineering problems. An application of differential evolution to constrained combinatorial problems is shown in [29]. A multi-objective genetic algorithm has been used to optimise electrical drives [30]. A gravitational search is conducted to optimise a fuzzy servo controller in [31]. Particle swarm optimisation has been used for reservoir optimisation [32], and hydrothermal scheduling [33].

In this paper three classes of algorithms are evaluated, particle swarm optimisation (PSO), genetic algorithm (GA) and Cuckoo Search (CS). The emphasis of this paper is on the particle swarm optimisation and a variety of PSOs are used. The GA used is a simple one and is included as a baseline. The CS algorithm is included because it has been shown to outperform PSO for some problems [34,35].

The suggested system has been applied to two UK sites that have their own congestion patterns. The data were obtained from the Highways Agency owned system Motorway Incident Detection and Automated Signalling (MIDAS).

The rest of this paper is organised as follows. Section 2 provides an overview of the METANET model. Section 3 provides the optimisation problem formulation. Section 4 provides the used site descriptions. Section 5 is concerned with the details of the

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