Microscopic traffic flow simulation on highways

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***Abstract*—Traffic flows on a highway were simulated using a microscopic car-following model to describe the evolution of vehicle positions, velocities and accelerations over time - with the aim of understanding root causes for congestion events like bottlenecks in such situations. Studies were also conducted to understand the system's response to various inputs and excitations to determine possible interventions to improve highway performance.**

I. Introduction & Motivations

Traffic congestion is still a major problem affecting road transport around the globe causing a variety of negative impacts that affect local communities and the economy as a whole. Traffic jams and incremental delays result in lost time, productivity and economic output. These include monetary costs arising from increased vehicle operating costs (associated with fuel consumption and maintenance) and crash costs (due to higher likelihood of accidents that are borne directly by individual drivers [1]. Congestion also increases travel time unreliability and driver stress, thus reducing their subjective well-being satisfaction [1]. In addition, to these internal costs, congestion has external costs such as economic losses and higher pollutant emissions. A recent study found that Americans lose an average of 97 hours a year due to congestion, costing them nearly \$87 billion in 2018, equating to $\approx$ \$1,348 per driver [2]. Along with commuters and passengers, congestion negatively affects freight transport as well, with the US trucking industry estimated to lose $\approx$ \$73.5 billion and 1.2 billion hours in productivity annually [3]. Improved, more accurate modelling techniques can help resolve such issues by allowing for better regulation of traffic flows that prevent jams, bottlenecks and congestion, while enhancing road safety. There are broadly two approaches to traffic modelling. Macroscopic (or continuum) models describe the dynamics in terms of aggregate quantities like densities and flows as functions of space and time, typically using partial differential equations. Microscopic models describe the behavior of individual vehicles themselves as discrete entities moving in continuous space [4]. Microscopic techniques include both car-following models (continuous-in-time) as well as cellular automata models. Car-following (or *follow-the-leader*) methods are often preferred for purposes of direct comparison with empirical data, due to the ease of tracking the position and velocity of each car using existing trackers and detectors on road networks [5].

II. Problem formulation

In this study, a microscopic, car-following model is implemented to describe traffic flows on a highway. In this "follow the leader" model, the cars follow one another and thus the velocity and acceleration of each car are determined by the motion of the car in front of it. Initially, a simplified situation is considered that includes only flows in one direction on a single lane. After establishing the fundamental framework, the model can be refined and made more complex to account for multi-lane, bidirectional flows with the possibility of lane changes and merging as well [7]. Furthermore, the preliminary model ignores effects of potential traffic disruptions such as traffic lights, speed limits or speed-breakers, stochastic effects of vehicles slowing down unexpectedly, or cars entering the highway from on-ramps or leaving via exits. The model can later be augmented by including such effects as inputs, sources or excitations to study the system's response. The model implemented here is the intelligent driver model (IDM), which is currently seen as the standard, most popular choice among car-following approaches [5]. The rudimentary IDM method (implemented here) has been found to sometimes produce unreasonable braking behavior and recent studies have suggested adjustments to eliminate this [6]. This could be one potential method to refine the current simulation. Another possible extension is to incorporate multi-look-ahead models where drivers respond to the motion of more than one car ahead. The *nodes* $i = 1, 2 \dots N$ represent individual cars on the road and the nodal quantities associated with each cars are: (1) its absolute position x_i and (2) velocity $v_i = \dot{\vec{x_i}}$. The leading car is considered to be the reference node (indexed as $i = 0$) and is assumed to be traveling at a certain velocity independent of the traffic density. Thus, the position, speed and acceleration of the leader are set by external inputs u to influence the overall traffic conditions and flows behind it. The *branches* represent relationships among nodes or cars, with associated branch quantities being the relative distances and relative velocities between cars. The state vector $\vec{x}$ consists of the positions and velocities of the N cars, excluding the lead car:

$$\vec{x} = [x_1 \; x_2 \; \dots \; x_N \; \vec{v_1} \; \vec{v_2} \dots \; \vec{v_N}]^T \tag{1}$$

Given this definition of the state vector, the state space model is:

$$\begin{aligned} \frac{d\vec{x}}{dt} &= \vec{f}(\vec{x}(t), \vec{p}, \vec{u}(t)) \\ \vec{y}(t) &= \vec{g}(\vec{x}(t), \vec{p}, \vec{u}(t)) = \vec{x} \end{aligned} \tag{2}$$

where $\vec{p}$ represents all the system parameters. $\vec{f}$ is defined by $\dot{\vec{x_i}} = v_i$ and acceleration $\dot{\vec{v_i}} = \vec{a}_i$, which is computed as a continuous, non-linear function [5]:

$$\dot{v_i} = a^i \cdot \left[1 - \left(\frac{v_i}{v_{max}} \right)^{\delta} - \left(\frac{s^*(v_i, \Delta v_i)}{s_i} \right)^2 \right] \tag{3}$$

where v_i is the velocity of car i, s_i is the net gap or bumper-to-bumper distance of car i to its leading vehicle $i-1$:

$$s_i = x_{i-1} - x_i - l_i \tag{4}$$

where l_i is the length of each vehicle. Δv_i is the approaching rate (relative velocity) of vehicle i to its leader:

$$\Delta v_i(t) = v_i(t) - v_{i-1}(t) \tag{5}$$

Thus, equations 4 and 5 can be interpreted as constitutive equations linking nodal to branch quantities. The deceleration term in equation 3 depends on the 'desired minimum gap' s^*, which varies dynamically with velocity and approach rate:

$$s^*(v_i, \Delta v_i) = s_0 + T v_i + \frac{v_i \Delta v_i}{2\sqrt{ab}} \tag{6}$$

The above formulation assumes that all vehicles considered to be identical. If this is not true, separate values for the parameters s_0^i, v_0^i, T^i, a^i and b^i need to be used for each car. Here, a is the maximum acceleration, b is the desired comfortable deceleration, v_{max} is the desired maximum velocity, s_0 is the desired stopping or jam distance and T is the desired time gap (or safe time headway). The time gap can be interpreted as a measure of the finite reaction time of drivers to respond to changes from equilibrium traffic flow. Initial parameter values were obtained from literature [5], [6] and are listed in table I below.

Parameter	Typical value	Parameter	Typical value
v_{max}	120 km/h	δ	4
T	1.6 s	s_0	2 m
a	0.73 m/s^2	l	3 m
b	1.67 m/s^2		

TABLE I: Parameter values used in the IDM model.

The inputs are currently the lead car's position and velocity i.e. $\vec{u} = [x_0 \ v_0]^T$. Thus, these only affect the acceleration equation 3 of car index 1 that's directly behind it. The output quantities of interest are the time-varying positions $x_i(t)$ and speed profiles $v_i(t)$ of all remaining cars on the highway i.e $\vec{y}(t) = \vec{x(t)}$ in equation 2, and observing how these respond to changes in lead car behavior. Given speeds, the accelerations of each car can also be computed readily as a function of time.

III. Fundamental Numerical Methods

The model is simulated primarily using finite-difference, time-domain integration to solve the nonlinear ordinary differential equations. These include experimenting with both explicit methods like forward Euler as well as implicit techniques like backward Euler and trapezoidal integration. A multidimensional Newton method will also be implemented to solve the nonlinear equation $\vec{f}(\vec{x}, \vec{p}, \vec{u}) = \vec{0}$ for steady state analysis of the system. Due to the Jacobian being close to singular at steady state, continuation schemes and homotopy methods will also be explore to improve the convergence of the Newton solver. The nonlinear Newton solver will also be implemented using a matrix-free method where the Jacobian is approximated by finite differences using the iterative solver GMRES, since the Jacobian matrix obtained is not symmetric.

IV. The Technical Challenge

The nonlinear system formulated here is observed to very stiff and also sensitive to small changes in parameters and inputs. Thus, while simulating the dynamic response of the system, a comparison will be performed of explicit techniques with fixed time-steps versus implicit methods with adaptive time-stepping to allow some tradeoff between accuracy for increased speed.

V. Results

The results will present graphs displaying the positions, velocities and accelerations of cars on the highway as a function of time. For smaller-scale problems with relatively few number of cars, these curves will likely be included for each of the individual cars. However, for large problems, only aggregated results like average velocities over time will be presented. Temporal analysis of such averaged quantities will be conducted to detect congestion events (e.g. drops in average speed) and spatial analysis (using car positions) will help determine which sections of the road are congested. The response of the system to a few different inputs (i.e. leader car behaviours) and shocks or excitations (e.g. accidents, inlet and exit ramps, speed limits etc.) will be recorded to understand how these influence highway performance and decide which traffic interventions help avoid or relieve congestion. The efficiency and practicality of the simulation techniques will also be demonstrated by showing how runtime and memory requirements scale with problem size

VI. Ethics

Better traffic modelling and simulation could also potentially impact certain stakeholders negatively. Microscopic, car-following methods in particular entail privacy concerns [9] since these require empirical data at the car-level to calibrate parameters. Such accurate predictions of driver behaviour may be used by private or public agencies (including governments) to exploit drivers and commuters. For instance, the data on driving patterns could be used to design predatory policies for congestion charges, dynamic toll pricing and/or setting variable speed limits on highways designed to excessively fine or charge commuters. The system could also be vulnerable to cyber-attacks where external agents with knowledge of the internal model parameters could artificially manipulate traffic conditions in certain areas in an adverse manner. This may also be achieved by certain drivers with greater access to information, who can locally influence traffic flows behind them to serve their own interests, raising issues of equity. Furthermore, the accuracy of simulations is a critical concern to ensure safety and reliability of traffic management strategies, especially with increased penetration of autonomous vehicles.

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