A Multiagent Approach to Modeling Autonomic Road Transport Support Systems

Maksims Fiosins, Bernhard Friedrich, Jana Görmer, Dirk Mattfeld, Jörg P. Müller, and Hugues Tchouankem

Abstract In this chapter, we investigate a multiagent based approach to modeling autonomic features in urban traffic management. We provide a conceptual model of a traffic system comprising traffic participants modeled as locally autonomous agents, which act to optimize their operational and tactical decisions (e.g., route choice), and traffic management center(s) (TMC) which influence the traffic system according to dynamically selected policies. In this chapter, we focus on two autonomic features which emerge from the local decisions and actions of traffic participants and their interaction with the TMC and other vehicles: (1) *Autonomic routing*, in which we study how vehicle agents can individually adapt routing decisions based on local learning capabilities and traffic information communicated truthfully by a traffic management center; and (2) *Autonomic grouping*, i.e., collective decision-making of vehicles, which exchange route information and dynamically form and operate groups to drive in a convoy, thus aiming at higher speed and increased throughput. Communication is based on a (simulated) vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) protocols. Initial experiments are reported using a real-world traffic scenario modeled in the Aimsun software, which is extended by the decision logic of TMC and vehicles. The experiments indicate that autonomic routing and grouping can improve the performance of a traffic management network, even though negative effects such as unstable behavior can be observed in some cases.

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1 Introduction

The need for individual mobility creates ecological and traffic problems in metropolitan areas, which constitute major limiting factors for urban development. The complexity of managing traffic is steadily increasing. At the same time, new technological trends are about to heavily affect traffic management systems and create new challenges and opportunities: Vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication (collectively referred as V2X) enable real-time data exchange and coordination among vehicles and traffic infrastructure. Vehicles themselves become more and more autonomous through advanced assistance functions such as dynamic navigation and adaptive cruise control over speed, distance, and intersection assistants [4] as well as autonomous driving support [19]. Also, the interplay of advanced sensor systems, ubiquitous mobile networks, and large-scale intelligent data processing [12, 15] is about to transport the vision of the Internet of Things to the traffic management domain.

Traditional traffic management systems have largely attempted to reconcile system optimality with user-optimality conditions in a Wardropian sense [10], i.e., under the restricting behavioral assumption that users make decisions (e.g., choose routes) that minimize time and cost; thus, traditional traffic management policies are largely focusing on the part of user optimality that is not in potential conflict to societal traffic management goals; for instance, proposing a shorter or faster route to a driver will mostly be compliant with his preferences, so the driver is likely to follow such proposal. Also, in the past, users often have not been able to assess how traffic control actions affect their own goals, due to the absence of up-to-date information. With this being subject to change, individual traffic participants may be more likely to take decisions that are not the ones intended or predicted by traffic management. Before this background, sustainable cooperative traffic management systems (TMS) will require new models that enable them to interconnect enforcing system-optimal behavior in terms of safety and efficiency while taking the preferences and goals of the users into account, acknowledging that not all aspects of compliance can be enforced and giving users as much as possible degrees of freedom in acting according to their preferences.

In particular, these new dynamic models need to be able to explain and predict interdependencies between top-down control and bottom-up local strategy. In this context, theories and models of autonomic computing [20] come into play.[1]

[1]We refer to the introductory chapter of this book for a discussion of the core terminology and concepts of autonomics and autonomic traffic management.

Autonomic multiagent systems (MAS) [27] extend the notion of autonomicity to loosely coupled, decentralized systems and—as we argue in Sect. 2.1—are a promising modeling approach for autonomic traffic management systems (TMS).

In this chapter, we report on work studying autonomic features of traffic systems by using a multiagent-based model. The conceptual model and a corresponding technical architecture are described in Sect. 2. In Sect. 3, we study how vehicle agents can individually adapt their routing decisions based on local learning capabilities and traffic information communicated truthfully by a traffic management center (TMC).[2] We found that the local ability to adaptively optimize route choice can lead to reduced travel times, thus increasing both societal and local welfare. We call this feature *autonomic routing*, because the routes of vehicles are not centrally or statically determined, but rather the overall behavior of the traffic system emerges as a reaction of the experiences of the vehicles and the current situation without a central control.

In Sect. 4, we report on initial work considering a type of collective decision-making of autonomous vehicles and its influence on traffic performance. Vehicles exchange route information and vehicles with similar routes dynamically form and operate groups which drive in a convoy, thus aiming at higher speed and increased throughput due to reduced safety distances required. We call this feature *autonomic grouping* because vehicle groups are formed locally without a centralized control, leading to dynamic self-configuration of the traffic system without a central locus of control. In particular, we study the question what market penetration rate of autonomic grouping is required to actually lead to emergent (and desirable) autonomic behavior, measuring, e.g., overall travel times and number of stops in our example scenario for different penetration rates.

Before we start with defining the underlying conceptual and technical model of our approach in Sect. 2, we relate this chapter to the topic of autonomics: While we model our traffic system based on *autonomous* agents, the overall *autonomic* behavior of the system emerges from the interaction of these autonomous agents. Putting it differently, it is not the vehicle or the intersection control which are autonomic, but the system as a whole reveals autonomic behavior.

In our view, truly autonomic traffic systems that fully comply with the definition in the introduction of this book still do not exist. In the context of autonomicity, our work is an initial attempt to study how a multiagent-based approach can support adaptive and collective self-organization, self-configuration, and self-optimization, considering two specific features, i.e., routing and grouping. Based on these results, we hope to be able to tackle some of the challenging issues that are required to be solved to support truly autonomic traffic management systems.

[2]By this we mean that the TMC does not communicate information strategically, but to the best of its knowledge.

2 Conceptual Model and Technical Architecture

In this section, we define the basic concepts underlying our approach and discuss our research methodology (Sect. 2.1); in Sect. 2.2, we sketch the corresponding technical architectures based on which the autonomic features described in this chapter were implemented and validated.

2.1 Conceptual System Model

Our conceptual view (and related modeling approach) of next-generation traffic systems is illustrated in Fig. 1. It shows three basic sets of entities: The traffic management (TM), a smart traffic infrastructure, and the traffic participants (in this work we focus on vehicles). *Vehicles* are represented as general self-interested and autonomous software agents [21], whose internal architecture is based on a sense-update-decide-act model and whose informational state, motivations, and capabilities are modeled by a Belief, Desire Intention (BDI) architecture [22]. While the agents aim to meet their goals (or to maximize their utility according to a local utility function, involving, e.g., individual travel times, energy consumption, and speed or route preferences), we assume for the scope of this chapter that vehicles will comply with basic traffic laws and also will not voluntarily violate these types of rules, but act towards their local ends within the boundaries of these rules. We also do not consider changes in traffic management policies and concentrate on the behavior of (autonomous) vehicles given some fixed traffic management regime.

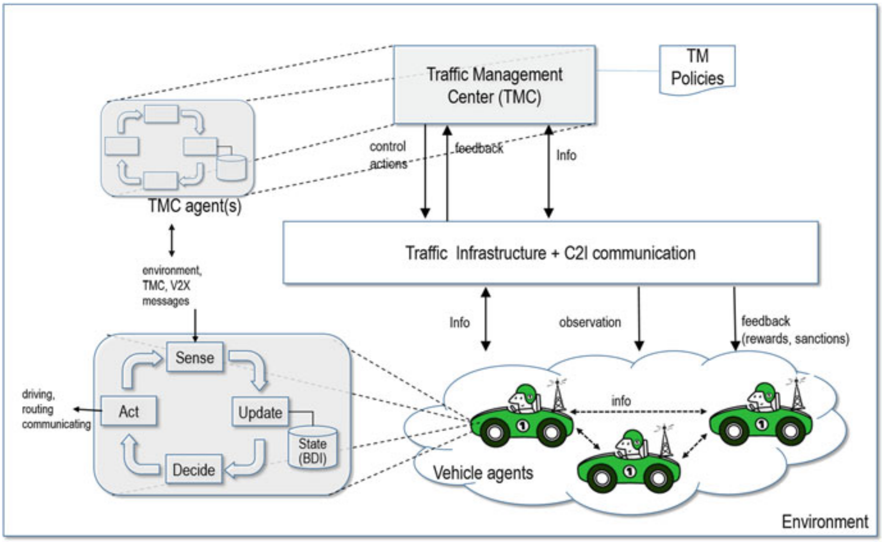

Fig. 1 Conceptual system model

The objective of *traffic management* is to optimize the overall traffic performance, which can be measured by criteria such as overall travel times or distance travelled, fuel consumption, and emissions, but possibly also criteria such as driver satisfaction. Thus, the objectives of traffic management and individual drivers may be partly conflicting. TM can influence the behavior of traffic participants mostly through exerting control (guided by some TM policies) on the traffic infrastructure, even though also direct communication between TM and traffic participants may be possible in some cases. The intelligent *traffic infrastructure* is the third major entity of our overall system. This infrastructure comprises intelligent sensing, light signaling, traffic signs, road side units, V2X communication infrastructure, and other components. It observes the traffic situation and communicates with vehicles and TM.

Another general conceptual approach, labeled *micro-meso-macro approach* (abbreviated M3 in the following), for analyzing and describing complex self-organizing systems has been proposed by Sanderson et al. in [24]. This approach, depicted in Fig. 2, is complementary to our conceptual system model of Fig. 1 in that it refines the architecture by identifying three interacting levels relevant for system modeling and analysis: the micro level, the meso level, and the macro level. At the micro level, we model and analyze individual agent behavior, in our case a vehicle; the meso level describes clusters or groups of micro-level individuals and their local interactions; in our case, meso-level interactions could be cooperative driving maneuvers such as platooning, but also, e.g., interactions between vehicles and light signals for cooperative intersection management [28]. Finally, the macro level represents infrastructure and system-wide, societal goals such as the reduction of overall congestion, the increase of throughput, or the minimization of travel times.

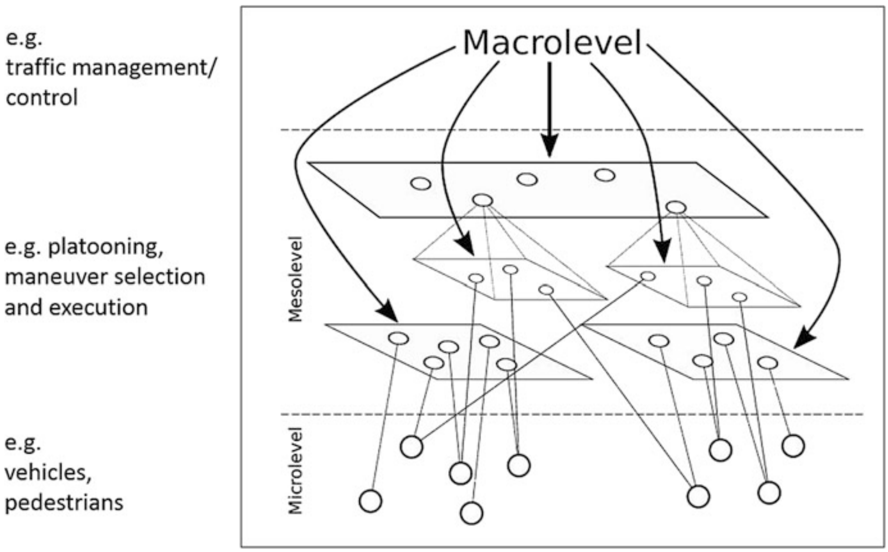

Fig. 2 Sanderson's micro-meso-macro approach [24]

The M3 model also provides a valuable framework for modeling interactions between the processes and systems at and across the three layers. For example, in Sect. 3 we study effects of autonomic behavior at micro and macro level, whereas in Sect. 4, we investigate how autonomic meso-level phenomena impacts the micro and macro level. While M3 is not restricted to multiagent models, the three-level model is well suited as a methodology for describing and analyzing multiagent systems, which can be very naturally described using these levels and their interactions.

Before we outline our conception of and assumptions on these components, we note that the study of self-adaptation and resilience of this overall system, according to the definition of autonomicity underlying this book, can be approached in three differing ways: *A first line of research*, starting from classical traffic control and engineering, would study how TM and infrastructure can cooperate and self-adapt using autonomic features based on static or probabilistic models of traffic participant behavior. *A second line of research* would assume that TM remains static (or predictable using some probabilistic models), while infrastructure and traffic participants reveal collective autonomic behavior; it is this line of research we start from in this chapter.

A third, most challenging line of research, towards which our long-term research is aiming at, will study the complex interactions of autonomic behavior both at TM and traffic participants side, possibly leading to effects such as oscillations or the type of game-theoretic phenomena such as the tragedy of the commons. Following the third line, a major objective (and success criteria) for autonomic behavior is the degree to which it can reliably prevent or dampen these negative effects, degrade gracefully and recover quickly when faced with disturbances (e.g., road blockings), and maximize overall (societal) utility, possibly measured by aggregated individual satisfaction of traffic participants. In such a setting, traffic management (TM) will have direct and indirect instruments at its disposal to influence the behavior of traffic participants. Direct instruments include dynamic signal plans, speed limits, or modifying the direction of lanes. Indirect instruments include incentivizing mechanisms such as (real or virtual) payments made for behavior of traffic participants that complies with the goals of traffic managements (such as certain routes being taken or avoided) and sanctions enforced on traffic participants whose behavior does not comply with traffic management goals; the latter can be implemented, e.g., by dynamic pricing schemes for the usage of traffic infrastructure (such as roads or parking space).

We found the paradigm of autonomous agents and multiagent systems (see [5] for an up-to-date review of agent-based models, methods, and applications in traffic and transport) to be an appropriate conceptual model for studying autonomic traffic management systems, because it supports (1) the notion of autonomy including restricted local states, local preferences, motivations, and capabilities; (2) the notion of communication and coordination; (3) a unified view of human and automated agents (e.g., vehicles operated by human drivers and autonomous vehicles); and (4) models and mechanisms that allow an integrated study of the relationship between individual and collective reasoning and decision-making, including multiagent planning, game-theoretic models (see [30]), auctions and market mechanisms (see, e.g., [16, 31]), and models of computational social choice (see, e.g., [7]).

2.2 The PLANETS Technical Architecture

In this section we describe a technical architecture in which the conceptual model described above has been prototypically implemented. The PLANETS simulation architecture used for the work described in this chapter is based on the Aimsun traffic simulator (see Fig. 3). Aimsun is used as the traffic environment to create realistic traffic demand and vehicle behavior; the vehicles [assumed to be equipped with an on-board unit (OBU)] are modeled as agents using the Jade framework; also the TM is modeled as a separate component which interacts with Aimsun, e.g., by modifying signal plans. Finally, OMNET++ is used as a platform for realistic simulation of wireless V2X communication.

The TM component represents the top-down control of the system. It collects information from vehicles in the form of Floating Car Data (short messages with locations and speeds of the vehicles) as well as from detectors in order to estimate actual vehicle flows in the streets of the network and convert them to the Level of Service (LoS), denoting different degrees of road congestion [23]. Based on the LoS, one of a number of predefined strategies for traffic light control is selected and corresponding information is sent to vehicles. We refer to [18] for a description of the TMC component.

The vehicle with OBU component implements the basic agent cycle illustrated in Fig. 1 above. Next to basic operational decisions (speed and lane choice), a vehicle agent can make tactical decisions relating to route choice (detailed in Sect. 3) and vehicle group formation (see Sect. 4). Routing decisions are based on the vehicle

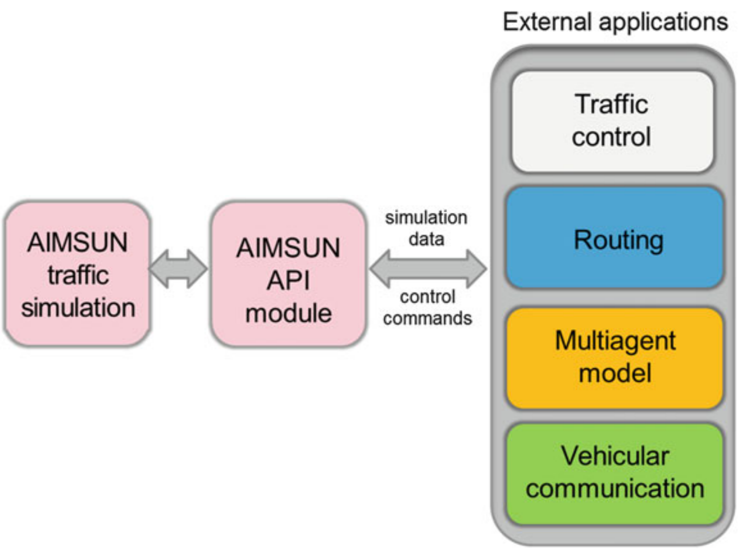

Fig. 3 Technical architecture overview

preferences and information from TMC; grouping decisions are based on V2V information exchange and speed coordination.

The technical architecture of the OBU is modular and extensible and (in the version underlying the work described in this chapter) comprised of the following components (called Apps for easier understandability by non-computer scientists):

- Learning App—updates a model of travel times for different routes based on local history and information provided by the TMC
- Routing App—provides access to external (or vehicle-internal) routing services
- Grouping App—implements group formation protocols and corresponding decisions
- CommBox—provides access to basic V2X (V2I and V2V) communication
- setRoute App—translates the vehicle's tactical plans (route) to corresponding operational actions (e.g., lane choices, turns)

The V2X communication module implements realistic V2X communication, taking influence of buildings into account. It implements V2I communication between OBU and Road Side Units, assumed to be installed in the streets (intersections) as well as V2V communication in the form of broadcast messages sent by OBU and received by other OBUs.

As a main simulation environment for our experiments, we use a road network that models a part of Hanover (Germany) with two parallel and five perpendicular streets (see Fig. 4, left part) and a real exemplary traffic demand profile for a 1 h morning rush hour period. Figure 4 (right part) illustrates the road network model as defined in Aimsun.

In the following two sections, we describe the autonomic features enabling self-organized routing and group formation, which have been realized and evaluated based on the PLANETS architecture.

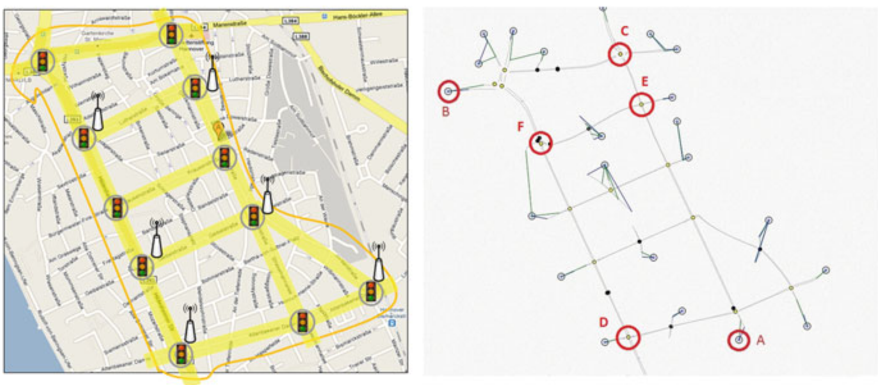

Fig. 4 Simulated traffic network (*left*); representation in Aimsun (*right*)

3 Autonomic Routing

In this section, we study how vehicle agents can individually adapt their routing decisions based on micro-level learning capabilities and traffic information communicated truthfully by a traffic management center (TMC) via some (possibly decentralized) infrastructure (meso level). We call this feature *autonomic routing*, because the routes of vehicles are not centrally or statically determined, but rather the overall behavior of the traffic system emerges as a reaction of the experiences of the vehicles and the current situation without a central control. In Sect. 3.1, we describe the underlying models and methods; Sect. 3.2 describes experimental results carried out to validate the autonomic routing feature.

3.1 Models and Methods

The process of route choice (in the following called *routing*) is performed by the OBU component of the PLANETS architecture; its result can be displayed as a route recommendation to the vehicle driver (or, depending on the scenario, be used to control an autonomous vehicle). As we have seen in Sect. 2.2, each OBU is controlled by an intelligent agent. In this section, we use the term *agents* to denote the intelligent in-vehicle units.

Routing decisions of the agents are based on their individual preferences, derived from their past experience, as well as on current information from the TMC. Individual preferences are modeled through utility functions [11]. We model agent preferences on the level of road segments: each agent has its own opinion about each road segment, based on its previous experience (e.g., related to congestion level or travel time). Road segment preferences may be easily converted to route preferences, used in the routing process. We suppose that agents make routing decisions that maximize their utility values.

The TMC periodically sends updated information about road segments to the agents. Receiving this information, each agent decides to what extent it trusts this information and correspondingly incorporates it into its preferences. Some agents may simply ignore received information and rely on their own experience, while others may fully accept the received information and use it for making their decisions. So we can model different types of external information acceptance by the agents. These concepts are presented in detail in [13, 14, 18].

Now let us describe the routing process formally. The agent environment is represented as a search graph $G = (V, E)$ (cf. [6, 18]). The vertices V of this graph correspond to road segments; the edges E correspond to turns, which connect these segments. The search graph contains information about allowed turns (not only about roads and intersections). Numerical values (weights) are used to denote the preference values which an agent attributes to a road segment (see Fig. 5).

The planning process of the agent j is based on the individual weights $c_j^{\mathrm{ind}}(t) = \langle c_j^{v,\mathrm{ind}}(t), c_j^{e,\mathrm{ind}}(t)\rangle$, where the weights of the road segments $c_j^{v,\mathrm{ind}}(t) =$

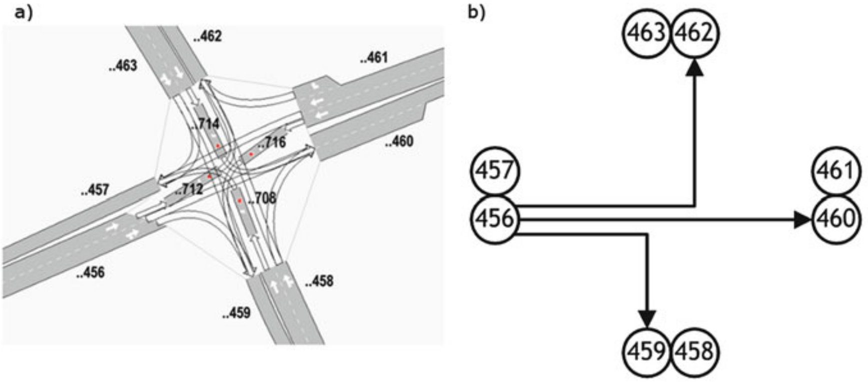

Fig. 5 (**a**) Intersection in Aimsun; (**b**) corresponding search graph

$\{c_{j,1}^{v,\text{ind}}(t), c_{j,2}^{v,\text{ind}}(t), \ldots, c_{j,n_v}^{v,\text{ind}}(t)\}$ correspond to the nodes of the graph and the weights of the turns $c_j^{e,\text{ind}}(t) = \{c_{j,1}^{e,\text{ind}}(t), c_{j,2}^{e,\text{ind}}(t), \ldots, c_{j,n_e}^{e,\text{ind}}(t)\}$ correspond to the edges of the graph at time t.

In order to initialize the weights of an agent, we suppose that there are k initial classes of the agent preferences, each of them representing particular route preferences (this can correspond to inhabitants of the city, guests of the city, transit vehicles, taxis, etc.). For each class i there is a predefined set of the individual weights $\tilde{c}_i^{\text{ind}}$. For each agent entering the network, we assign some class i and initialize its individual weights as $c_j^{\text{ind}}(0) = \tilde{c}_i^{\text{ind}}$.

At time t, each agent receives new information from the TMC in the form of the weights of vertices and edges of the search graph $c^{\text{tmc}}(t)$. As we already mentioned, the agents integrate this new information to their individual weights in different ways. In general, new individual weights depend on old individual weights and new information according to an arbitrary update function U_j, which in general can be different for each vehicle j:

$$c_j^{\text{ind}}(t+1) = U_j(c_j^{\text{ind}}(t), c^{\text{tmc}}(t)). \tag{1}$$

There are different forms of the function U_j in (1). One of the options, used in our simulations, is just a linear combination of individual and received weights:

$$c_{j,i}^{x,\text{ind}}(t+1) = \alpha_j c_{j,i}^{x,\text{ind}}(t) + (1-\alpha_j) c_i^{x,\text{tmc}}(t),$$

where $0 \le \alpha_j \le 1$ represents how much the agent j trusts its own weights, but not received information, $x = \{e, v\}$.

According to the individual weights, the shortest path in the search graph is constructed for the individual agent. As all weights are supposed to be non-negative, we can use Dijkstra's algorithm [9] for construction of the shortest path in the graph. The complexity of the planning algorithm is $O(|V|^2)$.

3.2 Results and Benefits

We perform our experiments using the PLANETS simulator using the Hannover data set (see Sect. 2.2). We track a traffic flow from A to B (cf. Fig. 4, right part). We use three initial classes ($k = 3$) of agents: The agents of the first class initially prefer the right vertical street and so will initially prefer a route A-C-B; the agents of the second class have a preference on the left vertical street and so initially will prefer a route A-D-B. The agents of the third class do not have a special preference on the road segments; they will also initially prefer a route A-D-B because it is of shortest distance. The first two classes do not easily change their routes because they have clearly defined preferences ($\alpha_j = 0.8$); the vehicles of the third class easily change their routing on the base of the information from the TMC ($\alpha_j = 0.1$).

When simulating this setting, the road segments from C to B quickly become overloaded. Intersection C is overloaded as well, because many vehicles need to turn left there (see Fig. 6, left part). Assume now that as a reaction to the overload of the street C-B and of intersection C, the TMC decides to close the road segment E-C in the direction C. It informs the vehicles by using variable traffic signs as well as by corresponding V2X messages. In this case, our observed flow will prefer a route A-E-F-B. The intersection D will become heavily loaded as well (Fig. 6, right).

The vehicles of the second class will mostly continue to use this intersection. The vehicles of the third class will mostly switch to the route A-E-F-B. As a result, about 70 % of the vehicles of this flow will follow the route A-E-F-B, about 20 % the route A-D-F-B, and other vehicles follow other routes.

Approximately the same changes are made in other flows. The resulting average time required for one vehicle to cross the street network is shown in Fig. 7. The upper line corresponds to the case where the considered routing scheme is not used. In this case the standard routing scheme of Aimsun is used, which selects the shortest route for each vehicle. The lower line corresponds to the case where 100 % of the vehicles use the proposed routing procedure. We notice a macro-level decrease of travel times by about 10 % by applying the autonomic routing scheme.

To conclude, our initial experiments indicate that the local ability to adaptively optimize route choice can lead to reduced travel times, thus increasing both societal and local welfare. Thus, our *autonomous* vehicles/drivers achieve *autonomic* properties. However, we also found in some cases that the local *autonomous* decisions may lead to oscillating behavior in the traffic network, thus not leading to the

Fig. 6 Screenshots of Aimsun simulation: overload at intersections C (*left*) and D (*right*)

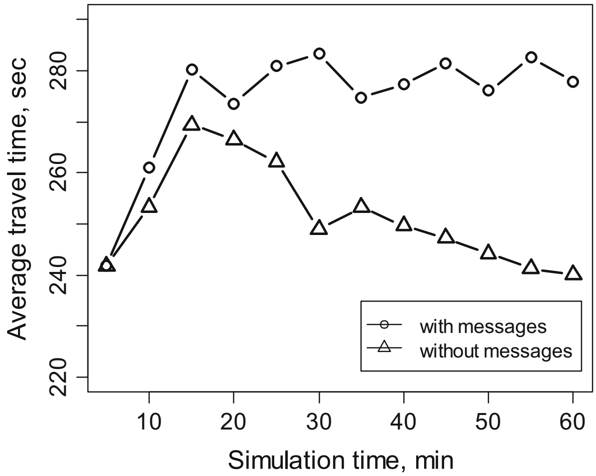

Fig. 7 Travel time without (*above*) and with (*below*) application of the considered routing

desired overall autonomic behavior. So there is a need to more closely study the interaction between TMC policies and local strategies in the future, e.g., by using game-theoretic models [5].

4 Vehicle Group Formation Based on V2V Communication

The autonomic routing showcase discussed in Sect. 3 has shown how autonomic behavior of a traffic system can emerge through local adaptive probabilistic reasoning in combination with information exchange in a multiagent system. In this section we sketch an example of how autonomic behavior can emerge through collective decision-making and acting of autonomous vehicles: In *autonomic grouping*, close-by vehicles exchange route information, and those vehicles with similar routes and preferences dynamically form and operate groups which drive in a platoon [29], thus aiming at higher speed and increased throughput due to smaller safety distances. Group formation is realized by using a multidimensional distance metrics. We call this feature autonomic grouping because vehicle groups are formed locally (at the meso level) without centralized control, leading to dynamic self-configuration of the traffic system on the base of sensing the environment, and TMC/V2X messages individually. The main difference of this work to related research on platooning in automated highway systems [2, 3] is that we consider grouping to occur in the context of urban traffic, which means that vehicles drive with lower speed but dynamics of group formation is much higher with shorter planning horizons. The idea of grouping vehicles also occurs in mesoscopic simulation [8] where a number of vehicles have some common characteristic to save simulation time. In our work, we additionally study how the penetration rate of V2X communication capability influences the macro-level benefit of grouping, measuring, e.g., overall travel times and number of stops in our example scenario (see Fig. 4) for different penetration rates. These results are obtained by using the PLANETS simulator based on Aimsun (see Sect. 2.2). In Sect. 4.1, we describe the underlying models and methods; Sect. 4.2 describes a number of experiments carried out to validate the autonomic vehicle group formation feature.

4.1 Models and Methods

Vehicle group formation is a capability orthogonal to the functionality of routing; it enables a traffic system to adapt speed and lane change decisions in a coordinated fashion aiming to improve traffic flow by minimizing the number of stops and by driving safely with higher speed and less distance in a convoy [17]. Depending on location, destination, routes, and possibly other constraints or preferences, vehicles will consider to form a vehicle group. When driving in a group, speeds and distances can be uniformly agreed and performed; thus several intersections can be crossed by using the green wave, thus avoiding stop times. In our approach, the additional necessary information about the signal plans of the traffic lights will be sent to the members of a group by the Road Side Units (RSU). In these experiments described here, we assume perfect communication between the vehicles. In other work [18], we did investigate group formation with realistic (simulated) communication channels. To avoid the overload of the communication channel, messages are only sent periodically with configurable periods. The data format for the communication is a simplified version of ETSI cooperative awareness messages (CAMs).

Let us consider the example of grouping over a sequence of regulated intersections. Vehicles intend to pass as many successive intersections as possible without stopping, minimizing their individual travel times, whereas an optimal throughput in the network is desired by the centralized traffic management and traffic lights can be regulated accordingly. The idea is to create a motivation for vehicles (at micro level) to join groups (meso level) and act in a coordinated fashion, resulting in reduced overall travel time. In this way, an interaction between macro-level policy and meso-level decentralized grouping is created, which in this example is synergetic, i.e., beneficial for both.

To restrict problems of dynamics and provide enough time for the necessary communication, here we assume that groups in our simulation are (re-)formed at red traffic lights; they then cross the following intersections as a platoon. The first vehicle arriving at the intersection acts as a group leader (first vehicle in the left lane) as illustrated in Fig. 8. It performs a prediction of the traffic state and of the signal plans of subsequent intersections. Depending on the outcome, the leader creates and broadcasts the group plan containing maximal group size, time constraints, and group rules. Each vehicle conducts a relevance check of the received messages; if the goal or partial route fits, it joins the group (dark area in Fig. 8). In detail, vehicles

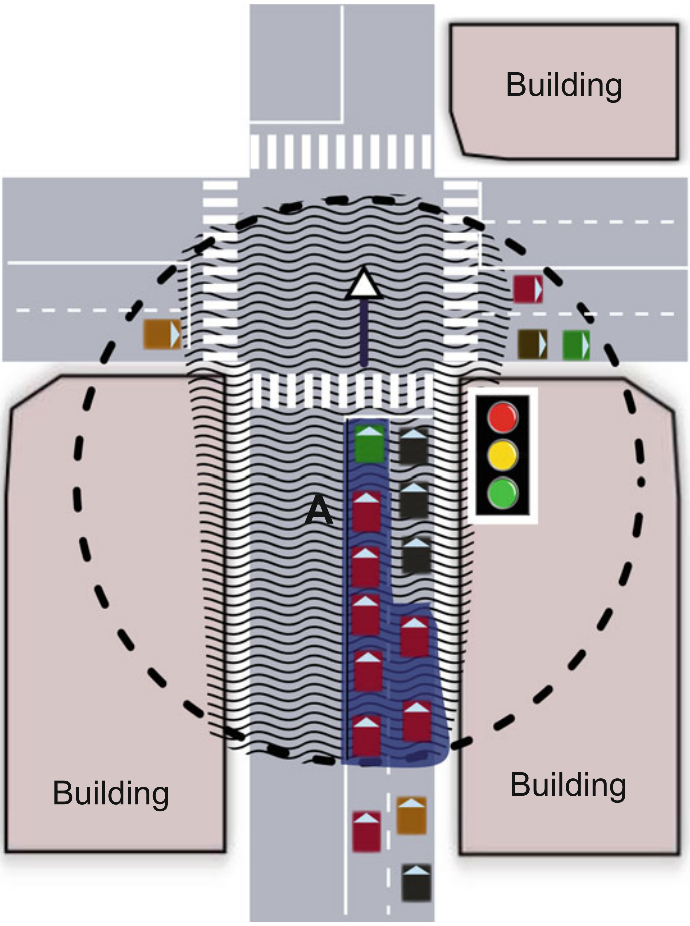

Fig. 8 Communication range of vehicle A computed without (*dashed circular range*) and with consideration of buildings (*shaded area*). Group formation (*dark area*) by a leader (*first vehicle in the left lane*) to pass a green phase

may speed up, slow down, and communicate with other vehicles in order to avoid conflicting situations of slow or blocked vehicles in front; also vehicles may join for coordinated actions. To improve the traffic flow, they can choose lanes and speeds and act dynamically. One benefit of this variant of group formation is simplified control: The group leader makes decisions; other group members contribute to group goals, sharing information and performing local optimization.

The real-time, reliable exchange of information between traffic participants plays an important role to enable autonomic grouping. Moreover, as indicated in Sect. 2.2, a communication model, which includes a complete communication protocol stack, as well as the modeling of the radio propagation channel are essential for application designers—not only for the specification and dimensioning of V2I networks but also for a credible simulation-based investigation of MAS.

Radio propagation models, such as the *Log-Distance Model* or *Two-Ray Ground Reflection Model* are often used for modeling the range of communication in vehicular networks in urban scenarios. In our work [26], we combine a computationally inexpensive radio shadowing model proposed by Sommer et al. [25] with a propagation model which consider the statistic nature of the channel gain amplitude, since the received signal is subject to significant signal fading due to the multipath propagation of radio waves in urban environment. As an illustrative example of the impact of a radio shadowing model on the communication area, Fig. 8 depicts the communication range of vehicle A, which is partially blocked by surrounding buildings (shaded area) and its communication range without consideration of buildings (dashed circle).

4.2 Results and Benefits

To investigate the influence of communication parameters on the effectiveness of the group formation, three input parameters are varied within the simulation setups: transmission power, CAM generation rate, and the ratio of equipped vehicles to the total number of vehicles, i.e., the penetration rate. In order to ensure statistical validity of the results, for all figures in this section, each data point represents the average of ten simulation runs with different random seeds and 1 h simulated time per run. In order to be able to assess the impact of the communication performance related to the traffic efficiency, we focus on the mean travel time (Fig. 9a) as well as the number of stops per vehicle (Fig. 9b) alongside the main road. Figure 9 presents the aforementioned traffic efficiency metrics as a function of the simulation time for different penetration rates. Our measurements indicate no significant improvement

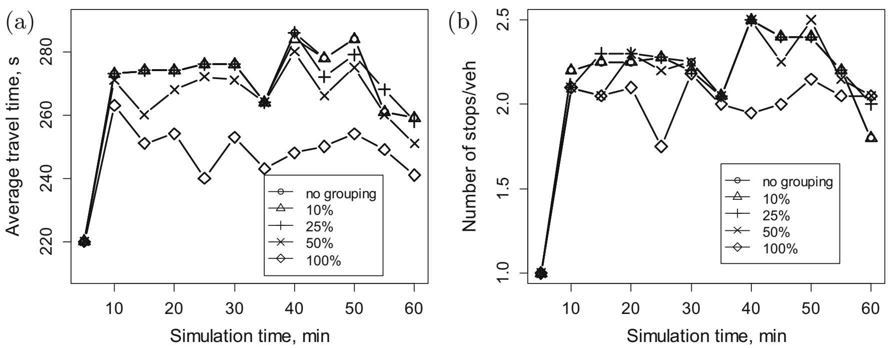

Fig. 9 Mean travel time and mean number of stops per vehicle versus simulation time for different penetration rates. (**a**) Mean travel time. (**b**) Number of stops per vehicle

for penetration rates smaller than 50 %; however, with a 100 % penetration rate, the mean travel time is reduced by up to 14 % and the number of stops per vehicle by up to 20 %.

To summarize, our initial experiments show that in the considered scenario, group formation and coordinated operation of vehicle groups have a positive impact on travel efficiency; it also shows that this overall benefit of self-organized, autonomic grouping behavior strongly depends on the ratio of vehicles that are equipped with the capability of V2X communication and group formation. Also, other experiments (reported in [18]) indicate that the benefit of autonomic grouping depends on the overall traffic density (LoS): Best results can be achieved for dense (but not congested) traffic. In situations of free traffic, too few vehicles are available to form groups, while in a traffic jam, the vehicles are already (involuntarily) grouped, so in these situations grouping does not improve the traffic situation.

5 Conclusion

Cooperative traffic management offers new perspectives to improve traffic safety and traffic flow by means of communication and local optimization. In this context, various new driver assistance systems are under development and partly in an early demonstration stage. However, most of the new cooperative features are designed as individual optimization for the equipped road users and do not necessarily fit a common traffic management plan. In order to overcome this deficiency, this chapter proposes a general conceptual architecture (and an exemplary technical architecture to support it), which allows us to study how aspects of local (autonomous) decision-making can interact with traffic management policies to reveal overall autonomic behavior of a traffic system. In our architecture, strategies are defined as a frame, which provides a flexibility to optimize the individual objectives of the single traffic participants. In this way, traffic planners are allowed to formulate strategies according to the needs of the city's development plan, and cooperative drivers are enabled to optimize their routes and their particular trajectories. Both the general public and the individual driver benefit in this way through the (de-)centralized cooperative traffic management. An analytical description is provided to show how strategies can be formed.

For evaluation purposes, a simulation of the system dynamics, which is able to model the interaction between equipped vehicles and the traffic management system, is necessary. Therefore, as an essential basis for the investigation of various research questions (e.g., concerning the penetration rate of equipped vehicles), the PLANETS simulator was developed. This simulator is based on the commercial traffic simulation software Aimsun and extends Aimsun's capabilities by four external applications, i.e., an external traffic control method, a routing module, a multiagent model, and a communication model (V2X).

Two major shortcomings of the current technical architecture are its limited scalability (due to the choice of Jade, where each agent is represented as a thread) and the fact that Aimsun is a commercial platform with limited access. For this reason, we are currently working on a new architectural approach, using the SUMO simulation platform in order to model the traffic environment, a more lightweight agent model (we are working on a lightweight implementation of the AgentSpeak language), and a more scalable integration approach, which allows for easy parallelization. An initial description of this approach is provided in [1].

Since the real-time exchange of information plays a critical role in MAS, a communication model was developed, which takes into account the frequency-selective and time-variant character of the radio-channel caused by shadowing, reflections, and scattering particularly in urban environments. Simulation shows that communication bottlenecks limit vehicle cooperation possibilities (e.g., multiple group information, cooperative routing, etc.), and broadcast should be used instead of two-sided communication. Cooperative traffic needs more data available for negotiation, and the communication limitations should be taken into account.

In the considered scenario, the routing process is considered to be individual—vehicles do not cooperate in their routing decisions. In our future research we are going to demonstrate how the routing process can be improved by direct exchange of routing preferences between vehicles, which will allow to avoid situations where all the vehicles select an optimal route, making it not optimal. In future, we are going to demonstrate how the groups of heterogeneous vehicles can be formed as well as make group formation and management more decentralized—at the present scenario the group leader was necessary.

Finally, it must be noted that the two autonomic techniques (routing and grouping) described in this chapter have so far been investigated in isolation; they are presented as two possible features of an autonomic traffic system, which have been devised by using the multiagent systems paradigm. Studying how they could be systematically integrated and combined and how this may impact traffic performance is a subject of future research.

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