An Event-Driven Multi Agent System for Scalable Traffic Optimization

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Abstract. Global demand for mobility will grow from 44 trillion to 122 trillion passenger-kilometres by 2050, and freight demand will triple in that time increasing traffic emissions by 60%. With current innovation and policy measures we are 'on course for a 3.2 °C temperature rise', according to the 2019 UN Emissions Gap Report. Nothing short of revolutionary is required to address this emergency. However, there is hope: shared mobility and widespread adoption of autonomous vehicles could cut CO_2 emissions by 73% and congestion by 24% if managed by appropriate policies. This paper presents a vision and a concept for future distributed management systems for complex multi-modal transport networks that exploit Multi Agent Systems (MAS) to support individual actors based on data collected from heterogeneous sources like vehicles, freight items, infrastructures, Global Positioning Systems (GPS); and simulations of the behaviour of the many different actors involved in the transport system. Event driven approaches are envisioned to react and respond to real-time events efficiently. The main objective is to identify the best optimization strategies to reduce traffic emissions and maximize the use of the public infrastructures and shared mobility. Motivations, expected impacts, and challenges are also discussed.

Keywords: Future mobility · Transport system management · Multi Agent System · Event driven simulation

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1 Introduction

Future mobility systems in Europe will be radically different from today's, requiring radical innovation in response to the environmental crisis, the growing demand for transport, and changes in people's mobility behaviour. The 2011 European Roadmap to a Single European Transport Area [7] issued benchmarks for future mobility systems, including halving the use of conventionally fuelled vehicles by 2030, shifting 30% of road freight over 300 km to other modes, and creating the framework for a European multi-modal transport information, management and payment system. This laid the groundwork for transformative change. Innovation in Mobility as a Service, connected and (semi-)automated transport and optimized traffic shaping is radical in the sense that it will, and should, in every sense of the way, be disruptive. Today, this innovation is in full swing. The 2019 International Transport Forum describes nine policy measures, including congestion charging, parking space reduction, and investment in mobility as a service, and eleven 'potentially disruptive developments', such as autonomous vehicles and shared mobility. The congestion and environmental problems which will arise as the result of dramatic increase in mobility demand cannot be solved solely by in-vehicle technologies or traditional transportation management systems focused on improving the movement of vehicles. Connected or not, human-driven or autonomous, fossil fuel or electric powered—all these vehicles will occupy the road network and will contribute to the congestion almost the same way, hitting the infrastructure capacity limits shortly. The shift from personal vehicles to other modes, especially public and shared transport, is a must and requires demand management systems focused on improving accessibility of mobility for the movement of people and goods.

Unfortunately, many demand management measures, such as congestion pricing, are not welcomed by citizens and are often lost in the political debate due to lack of understanding of the subject matter by all stakeholders, or weak supporting data evidence. Moreover, new mobility services, i.e. ride hailing services or micro mobility services, evolve faster than the legislation and challenge public authorities, decision makers and existing policies. Therefore, there is a need to establish a new paradigm which will allow for participatory, objective, transparent, and inclusive transportation management systems. The 2050 European Energy Roadmap recognises that active citizen participation is 'as critical as technology' in creating flexible and sustainable societies [7]. Smart transport innovation is becoming more 'citizen-focused', but often still interprets participation as a matter of citizens granting access to data about their everyday lives to allow better measures to nudge or enforce behaviour change. Accounting for people's capacity for smooth adoption requires much deeper participation and attention to concerns about the digital ethics of intrusive commercial, surveillance, and security driven exploitation of citizen data [3,13,27]. In this context the proposed methodology takes a novel approach that leverage the shared mobility concept to a new level, shifting the focus from the vehicle to the system and its actors. The city space, the network infrastructure, i.e. roads, parking, curbs etc., and the environment, i.e. air quality and noise levels, are all common goods and shall be accessed and used by the stakeholders on a fair sharing basis [20]. If we use fair sharing as *the objective of the system*, it shall by design give preference to sustainable solutions, i.e. prefer a bus over a personal car or electric vehicle over traditional etc. What we propose in this work is a concept for a distributed, data-driven, intelligent system for future demand and mobility management that cooperates and interact with things, services, and human users in one cyber-physical system. Such a system uses fair sharing as both optimisation objective as well as the objective's enforcement, working at scale to satisfy societies' need for the rapid and radical mobility transformation that is required to address the climate and environmental crisis. The main idea is therefore to co-create systemic innovation with citizens for innovative and inclusive digital travel environments that optimizes the future transport system in a deep, fine-grained, agile, accountable, and ethical manner based on the fair sharing principle.

2 State of the Art and Background

The Multi Agent System, which is proposed in our approach, requires investigations of cause-and-effect relations to understand how "actions" propagate in complex agent systems. Studying the impact of agents' behaviours could reveal measures to assist artificial intelligent (AI) based agents to explore their configuration spaces. These requirements will be addressed through experiments on the interaction of many time-aware AI based agents in simulated complex systems with real data. Existing models of multi-agent reinforcement learning (MARL) [9,16] are the starting point for how AI based agents can be trained together in simulated environments and learn and improve from the interactions with others. Various MARL training set-ups can be explored for our simulation platform including common-pool resources [23] and distributed computational architectures [6], to learn in very large complex systems, and mechanisms such as imitation and hierarchical learning to learn over long time frames [17]. MARL methods for optimising complex multi-actor systems will be supplemented with methods such as evolutionary optimisation [2], fuzzy logic [22], and swarm intelligence [1].

Cloud computing offers the ability to do cross-Cloud training of machine learning models and predictions [18], and the MELODIC[1] platform optimizes the use of Cloud resources for machine learning, including 'edge' devices based on a utility based approach [12]. Also, it uses new Cloud computing models like 'serverless' computing to achieve the highest possible efficiency for the use of resources, especially for demanding computational tasks. Hence, MELODIC allows the system to exploit elastic computing platforms to run scalable simulations in parallel in order to evaluate alternative strategies for selecting the optimal schedule of controls and recommendations that maximize specific key performance indexes of the complex traffic system. In particular, the high-performance capabilities of the computing infrastructure will be exploited using the real-time

[1] https://melodic.cloud/.

monitored data for evaluating any deviation of the current scenario from the predicted scenario. By exploiting Cloud resources, the MAS will have access to practically unlimited scalability of the training and simulation environment, which will enable dynamic, detailed simulations and continuously deliver an understanding of the current state of the traffic system to vehicle agents. The proposed approach will exploit multi agent event-based simulation techniques in real time, to predict the effect of decision making on future evolution of the system [4,10].

3 Concept

The proposed distributed traffic management will be a central part of tomorrow's mobility environment where control must exploit all available data, including the fact that some vehicles are already parts of route optimizing systems, while incorporating information from other participants that are hardly connected at all. The system must minimally disturb the individual mobility experience while achieving the best possible collective flow. This implies that much information must be inferred and deduced from secondary sources. One reasonable assumption is that all participants, including vehicles but also railway networks, fleet logistics, cyclists, scooters, and pedestrians, are connected to a mobile phone network allowing cell size positioning or triangulation. In the near future, 5G will allow more accurate positioning, as will the increased accuracy of new satellite navigation systems like Galileo [11]. This will support more fine-grained situation awareness and allow better guidance of participants equipped with these systems, and indirectly provide information about the traffic situation.

The control system must be fully distributed incorporating many independent actors: the drivers, the vehicles, the crossroads, the city and road authorities, the citizens, and freight items and goods to be transported. Each of these actors will be modelled as one or more software agents pursuing their goals while interacting collaboratively with other agents to ensure the best possible flow for everyone and the best possible use of available road infrastructure. Society and its need for mobility must be understood in order to give a meaning to the concept 'best possible' and to ensure that the road transport remains sustainable for the future.

Further on this basis, a distributed traffic management system consisting of collaborating software control agents can be developed. Each agent, like the ones representing a driver, a car, a crossing, a packet, a device, etc., will preferably be running on the device it represents. For instance, a driver agent will run in the driver's smartphone. Its role will be to guide the driver through the traffic in a collaborative way so that all agents collectively optimize the total traffic flow in real-time. An 'edge' device like the smartphone however, cannot do too heavy computations and the agent cannot communicate too much with its peers. Thus, 'edge' agents must be pre-trained to assess the current state of the system with as little input as possible and provide an optimized output demanding as little processing power as possible. More demanding computations must be done in distributed Cloud computing centres, or even in the core Cloud high performance computing (HPC) centres.

The agents must not just react to real-time measurements of the traffic flow, as their joint response will be lagging behind. The agents must rely on predicted measurements for the foreseeable future and react to the anticipated traffic state. Thus, historical traffic flow data and the derived understanding of mobility patterns and driver objectives will be the basis for training the agents and the predictors for the measurement time series. A data collection architecture is required to allow for the vast amount of information to be stored and provided to the AI algorithms for training and, later, deployment of the agents controlling the system. Additionally, the learning phase of the AI algorithms is to take place in a distributed manner, using mechanisms like federated learning in the training process[2]. Machine and deep learning algorithms have reached the point where situation awareness and deduction are possible with sufficient training data in specific scenarios [15,19]. Furthermore, automated and continuous learning of new scenarios dramatically improves the performance of such systems and their ability to act on unknown critical events. AI algorithms will be used on a broad basis containing a multitude of granular models; being trained to deduce situational awareness for a multitude of specific singular scenarios. This will allow for the distributed training and propagation of learned knowledge to the other learning agents in the network. Specifically, the purpose and aim here is to allow the machine- and deep learning approaches to train on a distributed data set and subsequently bundle and propagate the learned models.

If the infrastructure and demand for mobility of tomorrow would be like it is today, this training would be enough for deploying the agents in a real traffic management system. However, there will be new policies for urban mobility: for instance, a main thoroughfare should be turned into a pedestrian street in the evenings. How can the politicians estimate the effect of such a decision before making the move? Conflicting policy goals easily lead to multi-objective optimization to provide effective multi-modal transport management and recommendations, balancing priorities in different policy indicators. This can include energy, pollutants, etc.; and there will be different scenarios in which the priorities may be different, e.g. disaster management, considering human safety and security. It is therefore proposed that the trained agents will be embedded in a simulator creating a reality where the agents will make decisions and adjust behaviour and the effects of their joint decisions on the traffic flow can be studied. The agents will use reinforcement learning to update their historically trained models during the simulation and as such once the simulation converges to a new stable state, it will be possible to evaluate the effect of the policy decision. If that is as desired by the politicians, then the new policy and regulation can come into effect. In the real word, the modified and re-trained agents can then be deployed to the respective devices of the system actors and thereafter guide the

[2] Federated learning: Collaborative machine learning without centralized training data. https://ai.googleblog.com/2017/04/federated-learning-collaborative.html.

actors optimally based on the new regulations. The operation of the envisioned traffic management system is depicted in Fig. 1.

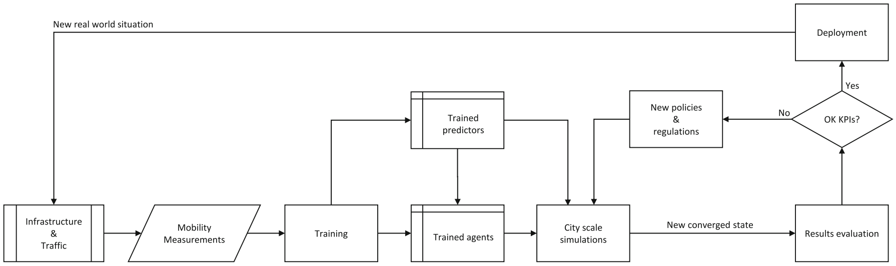

Fig. 1. The operational flow of the proposed traffic management system

Doing embedded simulation where the real software agents are acting will ensure that there will be no difference between simulated behaviour and real-world behaviour. Conducting such simulations at scale is very challenging as simulations today are normally based on simplified models of the reality and it is a research challenge to achieve timely simulations of city-scale systems. The simulation tool is proposed to extend the simulator that is being developed in the GreenCharge[3] project. In particular, the original functionalities, which aim at optimizing the charge schedule of electric vehicles exploiting the capabilities and the decentralized renewable energy sources of a smart neighbourhood, will be complemented to cope with the mobility needs in a future multi-modal network. Parallel simulation must be used to find the best optimization strategies that maximize the key performance indices of the tested policies. Monitored information must be used to measure real values of key performance indexes and to evaluate the deviation between the simulated and actual values, where such comparison is possible.

4 Research Challenges

4.1 Data Quality

Current availability and the quality of data do not allow cities to plan for, and implement, the rapid and systemic mobility transformation that is needed. Regional, national, and international scales of transport emissions, e.g. through tourism and freight, complicate matters further. The data that is available is extremely patchy and of low quality, and not real-time. Even with the addition of data from live services, such as telecommunications mobility data or Google timeline data, or data from active mobility apps such as Strava[4] — even if this

[3] https://www.greencharge2020.eu/.
[4] https://www.strava.com/.

was ethically and legally possible — would not provide sufficiently fine-grained data, because that data, too, is patchy and lacks quality in other ways. For example, Google timeline data collects data from those users who have consented to it, which often excludes the poor, disadvantaged, ethnic minorities, women, children, and the elderly. Moreover, the data is inaccurate, because it does not represent modes of transport accurately, assuming people are on a bus journey when they are out for a jog, for example [5, 24, 25]. With simulated data, accurate, flexible, and live evaluation of systemic mobility dynamics can allow authorities to drive radical innovation in more informed, productive, and sustainable ways.

4.2 Collaborative Multi-agent Control

Intelligent agents in complex systems-of-systems are individual entities, but they also interact with each other. These agents will need to counteract or mitigate the actions made by others in the system and this situation is extremely hard to model at scale. Given that each agent will pursue its own goals and objectives, it is a self-optimizing mathematical program: each agent will always try to find the state that optimally satisfies its goals given the current context dependent constraints for its operation; however, the actions of other agents will influence these constraints. Reciprocally, responses to changing constraints may again influence other agents over time. It is difficult to predict how globally imposed policies will affect the stability and performance of such a system.

The challenge here is to try to understand how constraints and global policies affect the performance of agents in such a distributed constraint optimization problem [8]. Coordination is a known problem in multi-agent systems [14] and the approach taken here is based on *deep* reinforcement learning [26]. Cause-and-effect relations must be investigated to understand how "actions" propagate in such systems. Studying the impact of "out-of-the-rules" behaviours, shock-waves that push the whole agent system out of its stable state, could reveal measures to assist deep reinforcement learning based agents to explore their full configuration spaces. We seek to understand such processes in the context of time, both forwards, predicting the results of interventions and backwards in explaining the emergence of unexpected behaviours. This could help identify attractors towards stable and performing behaviour. Understanding such processes would point to new measures to optimise for high performance.

4.3 Data Acquisition and Prediction

Given the fact that, today, nearly everyone has a mobile phone everywhere they go, anonymous connection data from mobile operators can bring a representative picture about real mobility in a city or in entire metropolitan region. Given the widespread use, there is less age, gender, ethnicity, or other social group exclusion bias. However, due to the anonymous nature of the data it is not possible extract information about social groups. Also, the source data from telecommunications operators has certain time-space granularity limits given by the size of the cells and time density of probing. Still, using advanced big data analytical techniques, a representative aggregated model of mobility for the entire metropolitan region composed of series of trips may be generated. Long term observation of the origin-destination matrix allows to extract typical behaviour of travel flows and the deviations from the typical patterns.

Using the agent modelling with agents being calibrated for current mobility practices and where static agents represent current human mobility practices for identifying current modal split, or dynamically, where conditional definition of preferences of interconnected agents represent the people of the future using the proposed Multi Agent System, the connection data from mobile operators will give a structured data framework within which a Multi Agent System may search for potential individual mobility optimizations. The system must be able to collect information from various sources, such as vehicles, networks, positioning systems, management platforms, humans, etc. In-vehicle systems will utilise various sensors and transportation service providers e.g. public authorities, may publish static information, i.e. service schedule, and, if available, dynamic data, i.e. live positioning, about their services and fleets via open application programming interfaces (APIs). To that end, specific connectors must be developed to be able to deal with distributed communications, standardised and non-standardised data sources, and transform them into interoperable information and instructions following cross-domain accepted standards, e.g. SAREF4CITY[5] ontology using the NGSI-LD API of the FIWARE[6] architecture. Once the information is standardised, it must be stored in polyglot repositories, that is, specialised data storage systems as relational, time series, graphs, documents, depending on the final usage, and allow for demand and event prediction as well as scenario simulation and optimisation.

4.4 System Simulations

A MAS represents an effective modelling alternative, compared to analytical modelling, for simulating complex real-world or virtual systems which could be decomposed in interacting individuals [21]. The goal is to emulate the software platform in a simulated environment in order to exploit discrete events-based simulation for accelerating the execution of the MAS, dropping the waiting time between subsequent events. This approach will allow us to introduce, on one side, diversity in scalable scenarios and parallel or multiple simulations and, on the other side, to model likely reactions when the predictive control is enforced in simulation.

5 Conclusion

The proposed *fair sharing paradigm* promotes and accelerates the transition to sustainable mobility. The fair sharing paradigm could promote clean and shared

[5] https://ec.europa.eu/digital-single-market/en/news/saref4city-validation-workshop.

[6] https://www.fiware.org/.

mobility services though substantially reducing road network occupancy, jams, bottlenecks, and pollutant emissions.

The global optimisation that can be achieved by the envisioned system, the exchange of information between the actors and global context awareness will support integration of different transport modes. Route calculation algorithms consider, and try to avoid, predicted traffic situations or crowded areas, routes, or infrastructures, i.e. train stations, airports, etc. The MAS algorithms can consider different parameters and constraints, including pollutant emissions; and by using various data sources, safety related events can be detected as well as or predicted as safety hazards, i.e. 'black-spots', allowing the optimization of the routes to consider such information and advising the users about possible dangers and suggest re-routing. New mobility services can be built on top of this integrated ecosystem, which offers new knowledge for different stakeholders like transport authorities and agencies, citizens, local retail, and future autonomous vehicles.

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