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Multi-Agent Based Vehicular Congestion Management

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Abstract— **In rapidly growing transportation networks, traffic congestion can result from inefficient traffic control infrastructure or ineffective traffic control measures. Existing congestion management techniques in Intelligent Transportation Systems (ITS) have not been very effective due to lack of autonomous and collaborative behavior of the constituent traffic control entities involved in these techniques. Moreover, these entities cannot easily adapt to the traffic dynamics and the traffic control intelligence is mostly centralised making it susceptible to overload and failures. The autonomous and distributed nature of multi-agent systems is well-suited to the transportation domain which is dynamic and geographically distributed. This paper reviews existing congestion management techniques and discusses their limitations. The paper, further, comprehensively surveys multi-agent techniques for congestion management in ITS and describes their advantages over other existing techniques. The paper classifies the multi-agent techniques based on the locus of decision control intelligence and focuses on their suitability of application in congestion management. We conclude with outstanding issues and challenges.**

I. Introduction

INTELLIGENT Transportation Systems (ITS) find applications in almost every transportation domain, from infrastructure planning/management, route planning, vehicle navigation to incidence management, pedestrian safety and congestion management. Congestion management is one of the key applications of ITS. Effective management of traffic congestion will result in even distribution of traffic on arterial roads, reducing travel times, vehicle emissions and probability of road hazards. This together will contribute towards improved environmental and road safety and user satisfaction. Congestion management will enable efficient utilisation of road infrastructure resulting in better operational performance of transport networks.

Intelligent agents are software entities that can undertake autonomous and collaborative actions to offer a system level solution to complex distributed problems [1] such as congestion on transport networks. This paper discusses the benefits of employing multi-agents systems for congestion management. We review the state-of-the-art in existing (non agent based) and multi-agent based techniques for congestion management and discuss the limitations of existing techniques while highlighting the effectiveness of employing multi-agent solutions.

The paper is organised as follows: Section II describes the existing techniques for congestion management and challenges in adopting them. Section III presents a detailed survey of multi-agent techniques and solutions for congestion management. Section IV summarises the multi-agent techniques along with their classification. Section V concludes with directions for future work.

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II. Existing Techniques for Congestion Management

Several congestion management techniques have been identified and reported in the literature. Existing congestion management techniques involve either detection of pre-existing congestion or prediction of possible congestion (and its prevention). Some techniques inform the driver of congested routes while others use this information to provide additional route guidance to prevent stoppages. Table I lists various types of congestion management techniques from the literature along with the challenges in adopting them.

TABLE I
Summary of Existing Congestion Management Techniques

Technique	Challenges
Floating cars (traffic state probes) to capture/relay real-time traffic information for congestion detection [2]	Requires volume of cars for optimum route coverage; involves centralised control; data collection is affected by trip latency [3]
Variable Message Signs (VMS) with road state information for congestion detection/route guidance [4]	Unsuitable for smaller number of vehicles; offers generic travel advice without considering driver preferences.
Ramp Metering for regulating the traffic flow by metering the desired lane for congestion prevention [5]	High installation and maintenance costs depending on the site [5]; increases oscillatory movement of the traffic; has equity issues
Congestion pricing [6] (on busy roads) for traffic flow regulation and decongestion	Affects low income car users; short distance journeys and those living adjacent to cordons
VMS with dynamic lane assignments for congestion avoidance [7]	Involves centralised control and no inter-vehicular communication to deal with conflicting situations
Probe-cars considering historic traffic data for congestion prediction [8]	Does not consider real-time traffic data such as the current road conditions or special events
Time spatial imagery [9] for congestion detection using TV video images	Accuracy depends on lighting and other surrounding environmental factors
Integrated Urban Traffic Control and autonomous navigation systems (route and speed assistance) [10] for congestion avoidance	Offers similar advice without negotiation of possible routes between vehicles which are destined to same location; may lead to congestion shift

A. Limitations of existing congestion management techniques

1) Lack of robustness and autonomy due to centralised control: Techniques such as floating cars and VMS involve central control (for data collection, processing and dissemination) that could be prone to systemic issues such as overloads and failures. Such techniques also limit the possible autonomy of subordinate traffic control entities.

2) Lack of coordination: The lack of coordination amongst traffic control entities (e.g. uncoordinated traffic signals) prevents global views of traffic state.

3) Lack of adaptivity: Most of the existing techniques cannot adapt dynamically to the changing traffic situation. The information processing and information dissemination time is too high to reflect the real-time traffic situation.

III. Multi-Agents in Congestion Management

A Multi-Agent System (MAS) is a distributed system that consists of a number of autonomous agents, communicating, coordinating, and cooperating with each other in a heterogeneous environment [11]. The transportation environment is non-deterministic (uncertainty of future traffic state), dynamic and distributed in nature. MAS are adaptive (they can reconfigure themselves to accommodate changes), concurrent (they can perform task in parallel), modular and scalable. These characteristics enable MAS to adapt and evolve in such a complex environment. Employing multi-agent systems for congestion management can provide a more robust and flexible solution that can address or overcome the limitations of existing approaches.

This paper classifies the existing MAS approaches into three broad categories depending on the locus of traffic control intelligence: *Infrastructure Based MAS*, *In-vehicle control Based MAS* and *Hybrid MAS* (involving combination of both). The following sections review the work employing these techniques.

A. Infrastructure Based MAS Approach

In the Infrastructure based MAS approach, the core agent software modules incorporated in the roadside infrastructure provide traffic guidance. This approach primarily involves regulation of the traffic flow (e.g. at signals and intersections). Here, the optimisation of traffic signals can result in free flowing traffic with minimum oscillatory (stop-go) movements and stoppages. In this approach, information is exchanged amongst (neighbouring) infrastructure agents to adapt the signal timings and traffic control policies while also offering a global view of the traffic network.

1) Evolutionary Algorithm Based Model

Hoar et al. in [12] propose a MAS-based evolutionary algorithm which draws inspiration from peculiar self-organising behaviour of Ants. This bio-inspired approach models cars as ants and is based on swarm voting and evolutionary search algorithm. In swarm voting, a vehicle votes against a traffic signal which causes idling. The solution (traffic signal timing sequences) continuously evolves where its current fitness quality (optimum timing) is determined by a fitness function. This fitness function is calculated based on the driving time and waiting time. The solution evolves (mutates) based on swarm voting where the votes determine the probabilities by which the traffic lights are mutated. Thus, the evolutionary search algorithm and swarm voting adjusts the timing sequences of the traffic lights for efficient traffic flow. The simulations were carried out with positive results for normal day, rush hour and heavy side-road traffic with varying rate/position of car seeding on simple and complex road networks. The results showed an overall decrease in waiting time of 26% for complex routes.

2) Machine Learning Models

The authors in [13] and [14] describe a Machine Learning approach in which an action taken by the agent is evaluated for its efficiency in terms of reducing the wait time (at signals) or improving speed. Based on this evaluation an agent is given feedback in the form of a reward or penalty. In successive steps the agent gradually learns and maximises the reward resulting in an optimum traffic signal control policy. One such Reinforcement Learning (RL) based approach is described in [13] where Q-Learning algorithm is used for multi-intersection traffic signal scheduling. The results compared Q-Learning algorithm with longest-queue-first (LQF) algorithm. The LQF algorithm performs traffic signal phase selection based on number of vehicles whereas the RL based algorithm uses an additional reward function. When compared with LQF algorithm (and fixed time control strategies) the adaption in RL was seen to result in greater reduction in wait times.

The authors in [14] have proposed the integration of RL agents (based on *Q-Learning algorithm*) with the ramp meter and Variable Message Sign (VMS) infrastructure. This approach simulates work zone traffic for VMS, expressway traffic for Ramp Metering and corridor/expressway for integrated Ramp Metering and VMS infrastructure. The RL agent receives information about the traffic such as speed, volume, and occupancy from the detectors. The RL agent collects road traffic information (e.g. speed, volume, and occupancy) from detectors and selects appropriate control actions such as traffic diversion through VMS, setting metering rate, or a combination of both. When compared with standard ramp metering algorithm ALINEA and base (no control) strategy, the Q-Learning algorithm recorded improvement in travel and stop time under recurrent and non-recurrent congestion scenarios.

3) Multi-Layered Multi-Agent System Models

In the Multi-Layered Multi-Agent System Models, the traffic control and coordination responsibility is distributed amongst various levels of agents in the hierarchy. The Urban Traffic Control (UTC) technique in [15] consists of Roadside Agents (RSA), Intelligent Traffic Signalling Agent (ITSA) and Authority Agent (supervises and controls several ITSAs). Using the roadside information (collected by RSA) ITSA devises traffic control strategies and estimates the traffic state. ITSAs are capable of resolving conflicts via co-operation and negotiation.

Adaptive and Cooperative Traffic light Agent Model (ACTAM) described in [16], consists of Intelligent Intersection Agent (IIA) capable of data storage and communication (with other IIAs), learning from past/current traffic pattern data and forecasting future traffic states. Based on this data, it devises control strategies to alter traffic state. For vehicle seeding rates of 6 and 30 vehicles/min, it outperformed the fixed sequence traffic signal control with delay time reduction of 33% and 37% respectively.

Other traffic regulation techniques include a decision support system [17] (for intersections) with the capability to resolve conflicts/improve decisions based on traffic feedback data and the agent model in [18] consisting of coordinated traffic control instruments (e.g. ramp meters) for coordinated decision making.

4) Mobile Agent Models

Mobile agents (as self-contained software modules) have the capability to migrate (transfer) to the desired destination in a geographically distributed traffic network and execute in its current (local/migrated) environment. This reduces its dependency on the communication network. Mobile agents can effectively deal with the dynamic traffic environment by executing the most recently updated traffic control. The approach in [19] consists of a City agent, Area agents, Intersection and Ramp agents. The Area Agent does short term forecasting based on traffic data and devises a control strategy for every Intersection and Ramp agent. The City Agent does long term forecasting (based on the traffic status information sent by the Area Agent). The control (mobile) agents consisting of control algorithms are generated by the City agents and dispatched by the Area agent to the lower-level agents for execution.

5) Knowledge Based Models

The knowledge based agent models complement the traffic control systems with more strategic, high-level control methods for route/traffic load estimation, management of conflicting control objectives and selection of congestion management technique [20]. TRYS and TRYS2 described in [20] and [21] aid in traffic analysis and traffic evolution studies. The TRYS approach, with centralised control, considers all the local signal plans and constructs a global signal plan from scratch while TRYS2, with decentralised control, makes incremental adaptations and reuses the previous global plan.

B. In-vehicle Control Based MAS Approach

In the In-vehicle control based approach the core agent software modules are incorporated into the on-board units of the vehicles. These agents perceive the route information obtained from the in-vehicle based sensors/statistical database/road-side infrastructure agents and propose appropriate control measures. For example, the agents provide congestion information coupled with the travel time information or travel speed suggestions and help the driver to avoid a traffic jam and detour to an alternate route. In this approach, the agents coordinate amongst themselves and exchange information via direct or indirect communication.

1) Bio-Inspired Techniques

MAS based techniques such as ant pheromone, honey-bee foraging, fish schooling and bird flocking are inspired from the peculiar features of species (ants, honey-bees, fish, birds), such as self-organisation, finding shortest path to their food sources and using a path trail as a signalling mechanism. These techniques aid in traffic flow forecasting [22], estimation of congested route [23] and [24], traffic organisation with indirect communication [25] and best route selection [26]. Analogous to Ants finding the shortest path between nest and food by depositing a chemical substances (pheromones) of varying intensities, the ant-pheromone technique proposed in [23], involves vehicles depositing digital pheromone (such as speed and acceleration). The pheromones are collected by each of the road segment specific pheromone engines (infrastructure nodes). The navigation component in the vehicle collects this integrated information from the engine to build a dynamically weighted network graph depicting the areas and levels of congestion. The car agent (ant) described in [24] deposits pheromones based on various semantics (speed, braking and inter-vehicular distance) and uploads the traffic-related information to a probe server. Travel time is calculated as a product of pheromone deposition quantity and link length. Shortest route prediction accuracy (calculated as error rates between the predicted and the actual link travel time) using the pheromone technique (0.67) was found to be better than baseline predictions (0.55). Also, the accuracy of multi-semantic pheromone model (0.45) was better than uni-semantic model (0.36).

The BeeJamA algorithm proposed in [27] for traffic jam avoidance is based on the analogy of honey-bee foraging wherein the road network is related to a honeycomb model of two layers, net and area layer. The area layer (edges represent roads and nodes represent intersections) is a detailed view of net layer (nodes represent areas and edges represent roads connecting neighboring areas). These layers are divided into foraging zones made up of nodes. The honey bees are sent out to the neighbouring nodes at regular intervals to constantly update the routing information (travel time information). Simulation results confirmed that the average travel time and traffic density (monitored for about 200 seconds) was less with BeeJamA algorithm as compared to Dijkstra's shortest path algorithm. Moreover, non-compliant drivers do not affect the system performance. However, the honey bee behaviour approach might not be feasible for long distance routes.

Some of the other techniques include Ant Based Control algorithm [22] to predict the travel time along with the future traffic load using current/historical data and vehicle guidance algorithm proposed in [26] for best path selection using dynamic and globally coordinated information. In the bird flocking based approach proposed in [25] the vehicles form groups (flocks) to cover the common distance which in turn gives them a bonus (speeding factor) for travelling together. This coordination in turn helps in effective regulation of traffic flow.

2) Driver Behaviour based Models

The driver behaviour models described in [28], [29] and

[30] suggest that drivers choose their route not only based on the travel guidance information but also based on their cognition. These approaches consider driver preferences or driver satisfaction level for route planning. The driver behavior model framework described in [28], consists of the Perception Unit, Emotions Unit, Decision-Making Unit (DMU) and Decision Implementation Unit (DIU). The Perception Unit perceives the environment (speed of the neighbouring vehicle, average speed, etc.) and converts it into fuzzy input. The Emotions Unit uses this input, past history and model demeanor to evaluate the status of driver's satisfaction level. The DMU analyses the environment and makes decisions based on this status to improve the driver's level of satisfaction. The DIU implements the resulting decision at the operational level.

The work in [30] simulates various scenarios with varying driver feedback/conformance, real-time information provisioning and driver's ability to observe the local traffic conditions. The real-time information feedback is provided by Advanced Traveller Information System or the local traffic conditions as perceived by the driver. The simulations recorded decrease in travel time with increase in the feedback. The approach in [29] combines social behaviour of agents with BDI model for realistic decision-making wherein rational decisions are combined with driver's choice of route and mental state. It can thus be inferred that the driver behaviour models if combined with the other multi-agent techniques will be more effective, as in addition to the intelligent algorithms they will also model the driver behavior for more realistic prediction.

3) Decision Tree Based Induction Techniques

The authors in [31] and [32] propose the use of decision trees for traffic state prediction. A node in a decision tree evaluates an attribute in the data set to determine the path to be followed. *Context Aware* congestion estimation approach in [31] makes use of historic and real-time context attributes (such as day of the week and time of the day) and decision trees (J48/JRip) to predict the traffic state. In case of absence of (stationary/mobile) sensors, this technique uses historical information to predict traffic state. The simulation results revealed that the prediction accuracy increased with the number of context attributes. For instance, applying both *day* and *time* context attributes resulted in over 80% accuracy when compared with applying just the *day* context attribute.

The decision tree based AQ21 induction system described in [32] aids in traffic prediction by considering environmental data and driver's degree of awareness of this data.

4) Intervehicular Communication Techniques

The IntelliD agent based approach in [33] demonstrates the effect of a single intelligent car over the single lane traffic. It involves inter-vehicular wireless communication wherein the intelligent car adjusts its speed as per the surrounding vehicles. Simulations were carried out with varied number of cars and with/without the intelligent car. The simulations revealed reduction in oscillatory movement of the traffic and also an increase in the mean speed, thereby demonstrating the potential to reduce traffic jams.

C. Hybrid MAS Based Approach

In this approach the core agent software control logic is incorporated inside the vehicle (on-board unit) as well as in the road infrastructure unit, where both possess the intelligence to formulate traffic control policies and are actively involved in traffic management.

1) Bio-Inspired Techniques

In the *Delegate* MAS technique [34], the vehicle agents generate exploration ants (agents) to traverse the virtual road network and gather information on the routes. The vehicle agent then chooses a particular route which satisfies the driver preference to either minimise travel distance or wait time or both. The intention ants not only convey to the intersection agent the time a vehicle would require for arriving at that intersection but also get the queuing time information and accordingly make a booking for the vehicle at the intersection. In this approach, the control is distributed between the vehicle agent which chooses the initial route, and the infrastructure agents which performs smart processing and predicts the queuing time (based on the future load). Simulations revealed promising results for condition where equal preference was given to reduction in travel distance and wait time. However, with greater number of non-equipped vehicles, the bookings might not hold good.

2) Multi-Layered MAS Approach

Braess Paradox arises due to common traffic information used for guiding the vehicles and lack of communication and coordination between the vehicles and central infrastructure. The solution to Braess Paradox proposed in [35] consists of Traffic Management Center (TMC) agent, Traffic Guidance Center (TGC) agent and the In-vehicle information System (IVIS) agent. The TMC agent offers a system optimum (SO) solution for optimum use of the road network (even distribution of vehicles on different routes by offering different guidance routes). The IVIS computes a user optimum (UO) route based on the driver's preferences and conveys it to the TGC agent. The TGC agent coordinates between the IVIS and the TMC to ensure that route choice and capacity allocation satisfies SO and UO. The simulation results showed reduction in the degree of saturation with this approach (post-coordination) and recorded an increase in the driver satisfaction by 2%. However, the SO solution in this approach is obtained using a centralised control system which is prone to failures.

3) Fuzzy Logic Based MAS Technique

The Road Supervision based on Fuzzy Multi-Agent System (RoSFuzMAS) approach in [36] consists of a City Agent, Road-side Agent (RSA) and Intelligent Vehicle Agent (IVA) and uses a hierarchical fuzzy inference engine for optimal route computation. The RSA computes the Path Flux Index (PFI) based on the traffic index of each route and the route length. The fuzzy control model gives the route choice based on the route preference computation (weak/strong) and fuzzy representation of PFI. The route preference is based on various criteria such as roadwork information and time of day. The simulations revealed that RoSFuzMAS equipped vehicles achieved better network management as compared to the non-equipped vehicles in choosing the optimal route by accounting for environmental factors, vehicle states and driver preferences.

IV. Summary of MAS Approaches

Fig.1 depicts a classification of MAS approaches (leaf nodes contain reference numbers of the citations). The paper classifies the literature on multi-agent based congestion management techniques into *Infrastructure based MAS*, *In-vehicle Control based MAS* and *Hybrid MAS* approaches.

Infrastructure-based MAS possess a global view of traffic and can coordinate and negotiate the traffic control policies. It is evident from the simulation results that Infrastructure based MAS outperform the existing techniques in terms of improvement in travel time and reduction in wait time. However, these systems are delay-prone (being stationary), they involve centralised coordination and do not consider driver preferences. An Infrastructure-based Mobile Agents solution has been proposed which can overcome the communication network latency; however, it may involve security risks due to possible malicious code in the migrated agent software.

In-vehicle control based MAS can have micro-level (speed/lane change) control over the vehicles, involve distributed intelligence and take into consideration the driver preferences. Simulation results show that In-vehicle Control based MAS techniques outperform the existing algorithms (e.g. A* and Dijkstra). They can more accurately forecast congestion, predict the travel time/driver behaviour and evaluate the shortest route. However, they do not possess a global view of traffic state (unless they communicate with a roadside unit or a centralised server). Moreover, their performance is affected by non-conforming drivers. In-vehicle control based bio-inspired approaches are promising and possess relatively high congestion prediction capability. They could be further enhanced with improved learning and negotiation mechanisms (e.g. to deal with congestion shifts).

Hybrid MAS involve not only globally coordinated travel suggestions but also consider driver preferences while making routing decisions. Simulation results showed that Hybrid MAS outperform the existing techniques in terms of reduction in wait time, coordination, driver satisfaction and optimal route calculation.

V. Conclusion

The transportation environment is highly dynamic, indeterministic and distributed in nature. Limitations of existing non multi-agent based congestion management techniques include lack of robustness, coordination and adaptivity which predominantly stem from factors such as lack of communication (between elements of traffic control system) and reliance on centralised control. This limits the capability of existing systems to act autonomously and

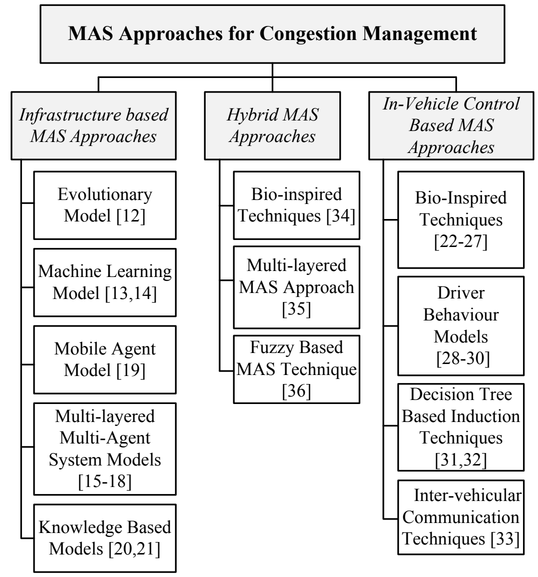

Fig. 1. A Classification of the MAS Based Approaches

respond to the fast changing traffic conditions. Multi-agent systems which are distributed in nature can autonomously act on the traffic information, dynamically adapt to the changes in the traffic flow and also improve on the proposed control actions in real time. This makes MAS inherently well suited to address or overcome the limitations of existing congestion management approaches and provide a more robust solution.

From the presented survey of relevant MAS based approaches, the hybrid MAS based approach emerges as the most effective approach. This approach combines the features of Infrastructure and In-vehicle control based MAS while counteracting many limitations. With the decision control intelligence distributed between the vehicle and infrastructure units, individual driver preferences, journey and destination information can be taken into consideration while still possessing a global view of the traffic state. In order to cope with the traffic dynamics, quick establishment of connections and rapid data exchanges, hybrid MAS could be enhanced with inter-vehicular communication capability using emerging wireless communication technologies such as Dedicated Short Range Communication (DSRC). This will allow Vehicle-to-Vehicle and Vehicle-to-Infrastructure communication enabling inter-agent coordination and collaboration. This can also facilitate rapid optimisation of travel routes by negotiation of conflicting travel advisories in real-time. Hence such enhanced MAS have the potential to effectively alleviate congestion in real-world traffic scenarios. However, the application of agent technology in transportation domain is still evolving and work in this area has been limited to theoretical research with actual on-field deployments being very few.

This literature survey brings out certain open issues and challenges in various MAS techniques to be addressed in future work:

- *need for learning mechanisms to predict possible driver non-conformance,*

- *need for individual preference considerations for Infrastructure based MAS approaches,*
- *need to reduce reliance on central coordination in multi-layered MAS techniques,*
- *need for intelligent algorithms in agent equipped vehicles to minimise the effect of non-equipped vehicles on performance of MAS techniques,*
- *driver behaviour based models should consider other contextual attributes (e.g. speed) for decision-making,*
- *need for enhanced negotiation strategies in case of conflicting traffic control decisions and*
- *need for robust techniques to handle failures that might arise due to delay-prone and intermittent data exchanges.*

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