Augmenting Traffic Signal Control Systems for Urban Road Networks With Connected Vehicles

Craig B. Rafter, *Student Member, IEEE*, Bani Anvari, *Member, IEEE*, Simon Box, and Tom Cherrett

***Abstract*— The increase in traffic volumes in urban areas makes network delay and capacity optimisation challenging. However, the introduction of connected vehicles in intelligent transport systems presents unique opportunities for improving traffic flow and reducing delays in urban areas. This paper proposes a novel traffic signal control algorithm called Multi-mode Adaptive Traffic Signals (MATS) which combines position information from connected vehicles with data obtained from existing inductive loops and signal timing plans in the network to perform decentralised traffic signal control at urban intersections. The MATS algorithm is capable of adapting to scenarios with low numbers of connected vehicles, an area where existing traffic signal control strategies for connected environments are limited. Additionally, a framework for testing connected traffic signal controllers based on a large urban road network in the city of Birmingham (UK) is presented. The MATS algorithm is compared with MOVA on a single intersection, and a calibrated TRANSYT plan on the proposed testing framework. The results show that the MATS algorithm offers reductions in mean delay up to 28% over MOVA, and reductions in mean delay and mean numbers of stops of up to 96% and 33% respectively over TRANSYT, for networks with 0-100% connected vehicle presence. The MATS algorithm is also shown to be robust under non-ideal communication channel conditions, and when heavy traffic demand prevails on the road network.**

***Index Terms*— Intelligent transport systems, connected vehicles, communication systems, traffic signal control, adaptive signal control, V2I.**

I. Introduction

INCREASING traffic volumes in urban areas make network delay and capacity optimisation challenging. The Centre for Economics and Business Research (CEBR) estimated the cost of traffic delays in 2013 for the UK, France, Germany, and the USA as 20.5, 22.5, 33.43, and 124.158 billion dollars respectively (see Table I) and these values are expected to increase significantly over the next 15 years [1]. CEBR defines delay cost as the combination of the direct cost of fuel and time wasted, along with the indirect cost resulting from delays impacting on business efficiency. In 2017, INRIX estimated that traffic congestion cost the combined economies of the UK, Germany, and the USA \$450 billion in lost time and wasted energy [2]. Traffic delays are a significant problem in developed countries.

TABLE I
Country-Level Summary of the Economy-Wide Cost of Transport Delay, and Delay Cost Forecasts Until 2030 (Billions USD) [1]

Country	Delay Cost (Billions USD)				
	2013	**2020**	**2025**	**2030**	**Cumulative**
UK	20.5	25.4	29.2	33.4	479.9
France	22.5	25.4	27.5	29.6	468.7
Germany	33.5	37.3	40.4	43.8	693.3
USA	124.2	151.3	169.7	186.2	2,806.8
Total	**200.7**	**239.4**	**266.8**	**293.0**	**4,448.6**

Connected Vehicles (CV) are those that use wireless communications to share data with other vehicles and infrastructure. CVs present unique opportunities to improve urban traffic management systems' effectiveness at reducing delay. CVs have the advantage over inductive loops in that they do not require intrusive roadworks to be undertaken to install infrastructure, such as inductive loops, to use their data. However, their networking protocols are more complex than those of unconnected vehicles, and they require fleets to contain significant proportions of CVs before their applications become effective. Previous literature does not adequately address the issue of traffic signal delay at CV penetrations below 50%. The current literature also does not properly address the issue of imperfect communication channel conditions and testing traffic signal control algorithms at increasing penetrations of CVs, and in realistic scenarios. This paper proposes a novel traffic signal control algorithm called Multi-mode Adaptive Traffic Signals (MATS) which combines position information from CVs with information collected through existing inductive loops and fixed-time plans to perform decentralised intersection control in urban areas to reduce overall traffic delay. In order to comprehensively test the MATS algorithm, a microsimulation testing framework for traffic signal controllers using CV data is presented. The testing framework is based on a large urban road network in the city of Birmingham (UK). It highlights how traffic signal control algorithms should be evaluated under varying traffic

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Craig B. Rafter, Simon Box, and Tom Cherrett are with the Transportation Research Group, Faculty of Engineering and the Environment, University of Southampton, Southampton SO16 7QF, U.K. (e-mail: c.b.rafter@soton.ac.uk; s.box@soton.ac.uk; t.j.cherrett@soton.ac.uk).

Bani Anvari is with the Centre for Transport Studies, Department of Civil, Environmental and Geomatic Engineering, Faculty of Engineering, University College London, London WC1E 6BT, U.K. (e-mail: b.anvari@ucl.ac.uk).

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demands of mixed-mode traffic, varying levels of CV penetration, and under imperfect communication channel conditions. The MATS algorithm is tested against MOVA using the case study in [3]. In addition, a calibrated TRANSYT [4] plan is used as a benchmark in the testing framework. The MATS algorithm is capable of performing under various levels of connectivity and aims to reduce traffic delay.

The contributions of this paper are as follows:

1) A new traffic signal control algorithm, MATS, is proposed which combines information from existing fixed-time plans and loop detectors, and position data from CVs to perform decentralised control on signalised intersections. The MATS algorithm operates under similar principles to the state-of-the-art MOVA algorithm [5], that is to optimise network capacity for saturated conditions and minimise stops and delays for undersaturated conditions. The MATS algorithm is novel in that it does not require entirely new infrastructure, high penetrations of CVs, or ideal data. Rather, the algorithm can be deployed alongside legacy systems to augment them with data from CVs, even under non-ideal communication channel conditions, an area where existing literature is limited.
2) A testing framework for the microsimulation of traffic signal controllers that use CV data is proposed. The new testing framework overcomes the limitations of existing tests by implementing a large-scale, realistic simulation case study, which accounts for mixed-mode traffic, multiple levels of traffic demand, degraded loop detector coverage, and a full 24-hour simulation period.
3) A communication channel noise characterisation system for the testing framework is proposed. In this paper, non-ideal communication channel conditions are more comprehensively treated than in previous simulation studies. Typically, only channel latency is considered. Here, GPS measurement error and packet loss are also included in the communication channel error model and is shown to have a significant impact on the connected signal control strategy.

Section I-A reviews traffic signal control literature while Section II explains the proposed MATS algorithm. The algorithm is tested using the proposed microsimulation testing framework based on a large-scale urban road network in the city of Birmingham (UK), at varying levels of traffic demand, at CV penetrations from 0-100%, and under imperfect communication channel conditions in Section III. The microsimulation results comparing the MATS algorithm with MOVA, and a calibrated TRANSYT plan on two case studies are presented in Section IV. Finally, the conclusions and avenues for future work are drawn in Section V.

A. Related Work

Effective traffic signal control strategies for urban road networks have been well-studied [6], [7]. There are three approaches to traffic signal control that are currently used: fixed-time, actuated, and adaptive.

Fixed-time traffic control systems create optimised signal-timing plans from historical data and are suitable in areas where traffic remains similar to the calibration state. Fixed-time plans do not adapt to live traffic conditions, so do not perform well where traffic demand varies significantly. The TRAffic Network StudY Tool (TRANSYT) [4], is one of the most widely deployed fixed-time optimisation packages still in modern usage. TRANSYT uses historic flow measurements to generate optimum signal timing plans for both isolated and networked intersections. TRANSYT calculates the optimal signal timings for a given road network model by minimising a performance function consisting of delay, number of stops, and economic factors. TRANSYT has been shown to reduce delay up to 24% over pre-existing signal timing plans in the New England region of the USA [8].

Actuated signal control systems, employ data gathered from roadside sensors such as inductive loops or video cameras to extend the green time of a signal stage between a minimum and maximum limit depending on the current traffic conditions. Microprocessor Optimised Vehicle Actuation (MOVA) [5] is an example of an actuated signal control strategy that uses loop detector data to attempts to minimise delay and stops for the entire intersection. MOVA typically reduces delay at isolated intersections by 13% on average over other actuated systems [9].

Adaptive signal controllers use data from infrastructure in real-time to optimise an objective function to reduce traffic delays and congestion. Adaptive strategies can work with both isolated (decentralised) intersections, and with groups of signal controllers to reduce traffic delays. Currently used adaptive signal controllers include: SCOOT [10], SCATS [11] and InSync [12]. In the UK, SCOOT has been shown to reduce traffic delays by 12% on average, but up to 33% compared with TRANSYT, and 26% on average but up to 48% compared with an isolated vehicle actuation scheme [13].

There has been a great deal of success in reducing delays with adaptive traffic signal control strategies that use data from infrastructure to best respond to varying traffic demand on the road network. The introduction of CVs and the concept of Connected Intelligent Transport Systems (C-ITS) present exciting opportunities for innovation in traffic signal control. CV systems are inherently well suited to mitigate delay, as CVs are an abundant source of data for Adaptive Traffic Signal Control Systems (ATSCS). ATSCSs are more beneficial than traditional traffic control strategies at reducing traffic delay [14], especially in urban areas with fluctuating traffic demands. This paper focuses on using data sent from CVs to infrastructure to improve decentralised adaptive traffic signal control in urban areas.

Recent research has developed traffic signal controllers for C-ITS environments (see [15] and [16] for reviews) which assume perfect communication between vehicles and infrastructure, or require all of the vehicles in the network to be connected as in the slot-based reservation system of Fajardo *et al.* [17]. As CVs are only anticipated to be introduced into the road network from 2020 onward, it will take time for the vehicle fleet to become fully connected [18], and hence there is a need to develop signal control strategies that support this transition period. Other traffic signal controllers for CVs rely entirely on CV data, with limited consideration for unconnected vehicles such as in forecast based departure strategy optimisation [19]. More recent traffic signal control algorithms have begun to consider both connected and unconnected data sources. Beak *et al.* [20] used stop bar detectors to supplement an adaptive phase optimisation strategy using CV data at CV penetrations as low as 25% using a perfect communication system. Ilgin Guler *et al.* [21] proposed an algorithm to enumerate and optimise discharge sequences to reduce delay and tested it at CV penetrations from 0-100%. However, they only test an intersection with two one-way streets at two demand levels, and with perfect communications. Yang *et al.* [22], went further to incorporate loop detectors and trajectory data into their signal control optimisation strategy where varying levels of CV penetration and GPS errors were considered, across a single intersection at two static demand levels. Common limitations in both the algorithms and testing frameworks from these studies were: 1) only cars were simulated, 2) the road network size was small (4 intersections on average), 3) CV data were perfect or only had one source of error, 4) the parameter space was limited, and 5) the impacts of roadside and connected infrastructure degradation are ignored.

The research gaps identified in the literature are addressed in this paper in two ways: 1) the MATS control algorithm that has been developed, and 2) a realistic testing framework for comprehensively testing traffic signal control strategies for connected environments. The MATS algorithm addresses the issue of reducing delay at existing traffic signal control sites in environments with increasing numbers of CVs and where existing infrastructure is degraded. The MATS algorithm does this in a novel way that combines 3 data sources (fixed-time plans, loop detectors, and CVs) rather than two, as is typical in the literature. This paper completes the concepts introduced in [23], [24] by modifying the algorithm to be robust in real-world networks, addressing mode-switching issues, and performing simulations under a comprehensive testing framework. The proposed microsimulation testing framework is unique in that it combines data from the Birmingham and West Midlands traffic data portal [25] with OpenStreetMap (OSM) data [26] to create a large-scale, current, and realistic simulation case study. The testing framework overcomes the limitations identified in the literature by allowing traffic signal control algorithms to be tested with increasing levels of CV penetration, mixed-mode traffic, and multiple traffic demands over a 24-hour period. Furthermore, the three main issues that create imperfect communication channel conditions (GPS measurement error, channel latency, and packet loss) are addressed, which has been lacking in the literature.

II. The Multi-Mode Adaptive Traffic Signals Control Algorithm

A. Concept

The MATS algorithm builds upon the principles for managing oversaturated and undersaturated flows from the state-of-the-art vehicle actuated control algorithm – MOVA [5], and extends those principles with blocking back detection and queue length estimation using CV data. Similar to MOVA, the MATS algorithm reduces delays in undersaturated conditions, and increases capacity in saturated conditions. In addition, the MATS algorithm uses speed, position, and heading data from CVs in combination with fixed-time plans and data from inductive loop sensors to actuate signal timings, to detect blocking back, and to estimate queue lengths.

The MATS algorithm bridges the gap between existing and future technologies for traffic management by offering multiple modes of operation based on what sources of data are available. At its lowest level of operation, it operates a fixed-time plan in the absence of data from CVs or roadside infrastructure. As data from loop detectors and CVs becomes available, the MATS algorithm adapts its mode of operation to actuate signal timings using the gathered data. Furthermore, it can respond to traffic demand in real-time and preserves driver privacy as it does not require individual drivers to be tracked through the network. Also, it builds on established traffic management techniques and uses optimisation/heuristic procedures that are clearly defined, making the algorithm intuitive for transport planners to deploy. To increase capacity and reduce delays in the network, the MATS algorithm maintains a cyclic stage pattern and reduces the load on the downstream intersection rather than modifying its stage to serve stages with high demand (i.e. in back-pressure routing). By synthesising fixed-time plans, loop detector data, and CV data into a single algorithm, delays and stops are minimised for road users.

In the following subsections, data acquisition and intersection control in the MATS algorithm are detailed. Data acquisition considers the management of available data from connected sources. Intersection control considers integrating the gathered data into traffic signal control and timing decisions.

B. Vehicle Data Acquisition

Vehicle data acquisition determines which data originate from vehicles in the junction's control region, determining the queue length on routes that are not inactive, and the locations and speeds of the vehicles on the active lanes. A junctions' control region is the area surrounding the junction in which wireless communications are possible. If another junction exists inside the control region, the boundary is cropped to the conflicting junction's nearest stop line. The boundary reduction covers the widest possible control region while allowing data from vehicles associated with other junctions to be ignored. The junction controller receives data from all vehicles inside its control region, ignoring those that are not.

The junction controller monitors time-dependent data regarding the vehicles' positions, headings, and speeds. The junction controller has knowledge of its own layout/map and can determine the headings that correspond to an approach on each of its lanes. Vehicles in range of the junction and travelling with headings matching one of the known approaches ($\pm$ a tolerance to allow for GPS positioning error) are considered to be approaching the junction.

C. Intersection Control

1) Initial Stage Time: The initial stage time is defined based on the length of the queue in inactive lanes. Control strategies frequently use queue length estimates as a parameter, and as a quantity that is desirable to minimise [19]. Queue lengths are determined from the distance of the furthest queuing vehicle from the intersection. A vehicle is considered to be queuing if its speed is less than 0.01 m/s (inferring that vehicles travelling so slowly are at or approaching the end of the queue). The queue clearance time for a lane is given by:

$$t_{\text{clear,queue}} = \frac{l_{\text{queue}}}{l_{\text{queue,max}}} \times t_{\text{green,max}} \tag{1}$$

where $t_{\text{clear,queue}}$ is the queue clearance time, l_{queue} is the queue length, $t_{\text{green,max}}$ is the maximum green time a stage can have, and $l_{\text{queue,max}}$ is the maximum length a queue may have. Setting the queue clearance time in this way means that as the queue length tends towards the maximum range of the communication system, the initial green time tends towards the maximum green time. The queue clearance calculation is unique in that, neglects the start-up loss time that drivers need to react and accelerate. The reason start-up loss is neglected is that the stage time is extended by the presence of the connected vehicle at the tail of the queue if it has not crossed the stop line. This allows the preliminary green time to be automatically corrected if the queue clears slower than expected. In comparison, the MOVA algorithm uses a queue length estimated from vehicle counts over its detectors, so the locations of each inductive loop restrict its estimation.

2) Blocking-Back Detection: Blocking-back occurs at neighbouring intersections where queues of vehicles at a downstream intersection are long enough to obstruct subsequent vehicles from joining the queue. Blocking-back can cause gridlock if traffic cannot proceed in any direction [27], and is typically alleviated through signal coordination. For example, the SCOOT algorithm measures the proportion of the cycle time where queues occupy its detectors. The queuing information is passed to the optimiser, which then minimises the likelihood of the upstream junction creating a blocking queue [10]. Even though blocking-back is a well-understood problem [28], the literature on traffic signal control for CVs appears to ignore the issue. In literature for traffic signal control strategies for CVs, Goodall *et al.* [19] and He *et al.* [29] were the only studies to consider blocking-back. Goodall *et al.* [19] detected blocking-back using CV data. If vehicles were blocking a movement, then the movement that clears the blocking vehicles was given higher priority. In He et al. [29], vehicle platoon movements and ques lengths were used to prevent the creation of queue spillback that would cause blocking-back.

Here the control is decentralised, so a method of locally detecting blocking-back is developed. Blocking-back is detected by the MATS algorithm using CV position and speed data to determine if the vehicles are stationary during a stage that should permit the vehicles to travel. If blocking-back is detected, the MATS algorithm ends the current stage to allow vehicles in other lanes to traverse the junction on unobstructed routes. Although stage cancelling reduces service to the vehicles in the cancelled stage, it gives vehicles in other stages the opportunity to use the intersection to increase throughput and gives the downstream intersection

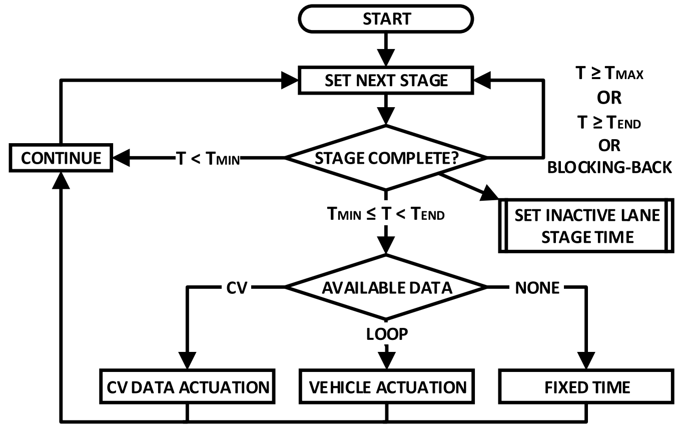


Fig. 1. Flowchart for the MATS algorithm.

time to clear the blocking traffic. Compared with back-pressure routing approaches [30], the MATS algorithm maintains a cyclic stage pattern and reduces the load on the downstream intersection rather than modifying its stage to serve stages with ‘high-pressure’.

3) Inductive Loop Data Integration: The green time extensions are applied when vehicles are detected in real-time on the existing inductive loops in the road network. The MATS algorithm extends the stage by one extension interval if a vehicle is detected in the previous extension interval. The actuation behaviour is defined based on the actuated timing parameter recommendations of the Federal Highways Administration Signal Timing Manual (STM) [31].

4) CV Data Integration: Real-time information from CVs is used to derive a stage extension time dynamically. If a CV is detected close to the intersection in an active lane, the time it takes for that vehicle to reach the intersections is estimated from the driver’s current speed and position. This time is added to the stage duration if it satisfies the acceptable travel time requirements set by Highways England [32]. The acceptable travel time factor is 1.67 times the free flow journey time. This factor times the average time headway between vehicles gives the time threshold for green extensions. The time for a CV to clear the intersection is:

$$t_{\text{clear,CV}} = \frac{d(\mathbf{x}_v, \mathbf{x}_i)}{v_{\text{vehicle}}} \tag{2}$$

where $t_{\text{clear,CV}}$ is the time it takes a CV to clear the intersection. $d(\mathbf{x}_v, \mathbf{x}_i)$ is the Euclidean distance between the 2-D Cartesian coordinates for the positions of the vehicle ($\mathbf{x}_v$) and the intersection $\mathbf{x}_i$ in meters. v_{vehicle} is the speed of the vehicle. This approach achieves control that is functionally similar to MOVA in that if continuous vehicle flow is present (oversaturation), the algorithm allows vehicles to proceed until the maximum green time is reached or the queue is dispersed, which maximises capacity. If the vehicle flow is undersaturated, the MATS algorithm allows vehicles to pass as long as unacceptable gaps do not appear in the flow.

5) Algorithm Overview: Figure 1 shows the flowchart for the MATS algorithm and highlights how the components of the algorithm integrate, and how MATS switches its mode of

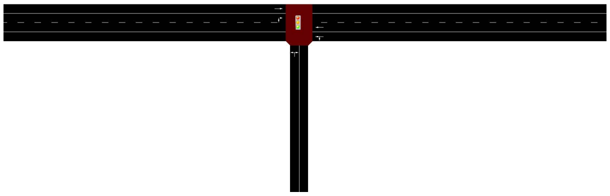


Fig. 2. SUMO model of the T-junction type intersection used in [3].

operation based on which data sources it has available to it. In order to reduce the computational load, the algorithm only makes control decisions if the remaining green time is less than a check threshold, which here is 5 s. The MATS algorithm extends traditional vehicle actuated systems by incorporating multiple data sources to compensate for the loss of CV or inductive loop data. CV data is only used if the CV penetration is high enough that using the data provides performance superior to fixed-time control.

The pseudocode for the MATS algorithm is presented in Algorithm 1. The semantics for the pseudocode are based on a combination of the Python programming language [33] and American Mathematical Society notation [34], where '//' infers a comment rather than a command, and '**DO**' describes in plain English an action to be taken by an external part of the program.

III. Testing Framework

A. Case Study 1

Figure 2 illustrates the T-junction type intersection used to assess the performance of the MOVA algorithm in [3]. The OD matrix for the model is given in Table II. The OD matrix is reported to yield flows that operate the intersection close to its saturation point.

B. Case Study 2: A Realistic Testing Framework

The microsimulation testing framework presented in this paper is based on the road network in the Selly Oak area of Birmingham (UK): the roadway from Selly Oak (latitude/longitude: 52.439177, −1.940248) to the Warwickshire Country Cricket Club (latitude/longitude: 52.455288, −1.907067) (see Figure 1). This area covers 8.26 km^2 with 12 signalised intersections, and 64 inductive loop detectors. This area is chosen since it covers the route with the highest number of working loop detectors within Birmingham. Also, traffic signal data from this area were available for public use [25]. Additionally, high volumes of traffic were observed in this area due to the presence of large retail and residential centres, and key sites of trip generation such as a 1000+ bed hospital and the University of Birmingham. The specification of the testing framework and details of how it overcomes the limitations of previous work identified in Section I are presented in the following sections.

1) Road Network Modelling: A road network model for this testing framework was created using OpenStreetMap (OSM) data [26] and vehicle flow data from the Birmingham and West Midlands traffic data portal [25]. Figure 3 shows the modelled

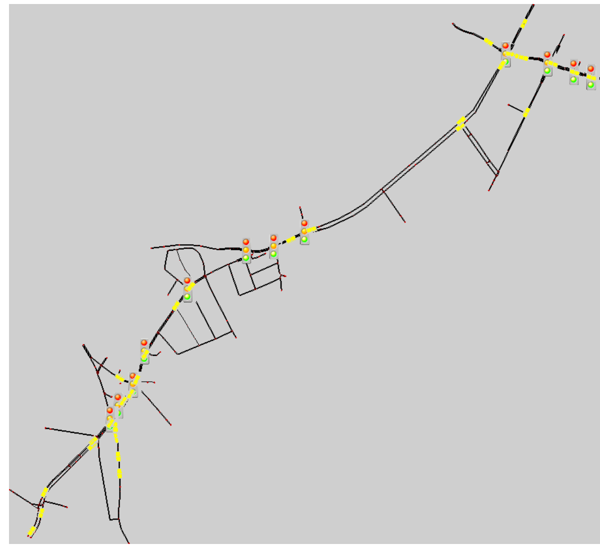


Fig. 3. SUMO representation of the Selly Oak road network. Intersections with traffic signals are highlighted with the red-amber-green light block (12 in total). The locations of the inductive loops are marked with yellow rectangles.

Selly Oak road network (Birmingham, UK) in SUMO [35]. The extent of the network and the number of intersections are greater than the models typically used in the literature. The Four-Step Model (FSM) [36] approach was used for demand modelling in this study and is described in the following sections.

a) Trip generation: From the flow data publicly available in Birmingham and West Midlands traffic data portal, the time-dependent frequency of use for each origin and destination point in the network was estimated. In this study, flow data of weekdays (Monday-Friday, excluding holidays) in 2016 and 2017 were used. Each detector was matched to its corresponding origin or destination lane in the road network model. The flow information was then translated to the total trips per hour going to/from the corresponding lane over 24 hours.

b) Trip distribution: Using the information from the previous step, the trips were distributed between connected Origin-Destination (OD) pairs, and an OD matrix was formed from collected flow data. As there were no prior travel survey information or turn counts available for the network, the initial traffic was assigned proportionally using the methodology originally proposed by Robillard [37]. The OD matrix was then calibrated using the Furness method [38], to ensure the OD matrix was consistent with the loop detector flow data after assignment. All vehicle flows are uniformly distributed across their insertion intervals.

c) Mode choice assignment: With the trips determined, the next step was to allocate each trip a mode of travel (e.g. car, motorcycle, Light Goods Vehicle (LGV), Heavy Goods Vehicle (HGV)), bus). The UK Department for Transport provides information about the distribution of different vehicle types on a regional basis in the VEH0104 dataset [39]. The distribution of vehicles registered in the West Midlands area of the UK, where Birmingham is located, is:

Cars	82.7%	**Motorcycles**	3.0%	**LGVs**	12.3%
HGVs	1.6%	**Buses**	0.4%		

Algorithm 1 MATS Algorithm Pseudocode

```
begin MATS
    DO: Gather CV data from the communications channel, collect flow data from inductive loops
    remainingTime ← stageDuration − elapsedTime
    if remainingTime ≤ checkThreshold then
        // Get loop extension time if loop data available
        if loopDataForControlledLanes then
            if ANY(lastDetectTime ≤ extensionThreshold) then
                loopExtendTime ← loopStageExtension
            else
                loopExtendTime ← 0
        else
            loopExtendTime ← NONE
        // Get CV extension time if CV data available
        if CVpenetration > CVPthreshold then
            if nearestVehicleSpeed ≥ 0.01 and nearestVehicleIsInRange then
                cvExtendTime ← nearestVehicleDistance / nearestVehicleSpeed
                if cvExtendTime > 2×loopStageExtension then
                    cvExtendTime ← 0
            else
                cvExtendTime ← 0
        else
            cvExtendTime ← NONE
        // Select extension from the available data, default to fixed-time plan
        if loopExtendTime ≠ NONE and cvExtendTime ≠ NONE then
            stageExtendTime ← max(loopExtendTime, cvExtendTime)
        else if loopExtendTime = NONE and cvExtendTime ≠ NONE then
            stageExtendTime ← cvExtendTime
        else if loopExtendTime ≠ NONE and cvExtendTime = NONE then
            stageExtendTime ← loopExtendTime
        else
            stageExtendTime ← max(0, fixedTimeDuration − elapsedTime)
        // Update stage time to fall within the upper and lower green time bounds
        stageDuration ← elapsedTime + max(stageExtendTime, remainingTime)
        stageDuration ← max(stageDuration, minGreenTime)
        stageDuration ← min(stageDuration, maxGreenTime)
    // If this is a new stage set a preliminary green time based on the queue length
    else if newStage and numberOfCVs > 0 then
        if lastVehicleDistance ≠ NULL then
            queueClearanceTime ← lastVehicleDistance × (maxGreenTime/maxQueueLength)
            stageDuration ← max(queueClearanceTime, minGreenTime)
            stageDuration ← min(queueExtendTime, maxGreenTime)
        else
            stageDuration ← minGreenTime
    // If no vehicles are moving due to blocking back then end stage
    else if elapsedTime > minGreenTime and remainingTime > checkThreshold and numberOfCVs > 0 and not queueIsMoving then
        DO: Set stage to end
    else
        DO: Continue
    // Continue stage if time remaining, else transition to next stage
    if elapsedTime < stageDuration then
        elapsedTime ← elapsedTime + timeStep
    else
        DO: Transition to next stage
        elapsedTime ← 0
        stageDuration ← 0
```

TABLE II

OD MATRIX FOR THE T-JUNCTION MODEL. ROWS DENOTE ORIGINS, COLUMNS DENOTE DESTINATIONS. FLOWS ARE IN VEHICLES PER HOUR

	East	West	South
East	–	948	48
West	750	–	198
South	162	162	–

The vehicle type distribution data from the VEH0104 dataset are used for mode choice assignment, improving the testing framework's realism over studies that only consider passenger cars.

d) Route choice allocation: With the trips and travel modes determined, the routes used for each trip can be calculated. The Selly Oak network is a local area with few alternative paths between origins and destinations. It is reasonable to assume that drivers in the network follow the shortest path to their destination. Dijkstra's algorithm [40] for finding the shortest path between two nodes was used for this localised road network.

C. Simulation Parameters

Microsimulation was used to test whether the MATS algorithm offers improved intersection management compared to TRANSYT and MOVA. The simulations were performed using the open-source SUMO *(version 0.30.0)* microsimulation environment [35], and were controlled using Python [33]. The MATS algorithm was tested with and without loop data, and under non-ideal communication channel conditions. The parameter configurations for the various simulation scenarios are explained below.

1) CV Penetration: In order to understand how the number of CVs present in the network can affect intersection management, simulations were run across a range of CV penetrations. The CV presence in the network was incremented from 0% to 100% in steps of 10%.

2) Traffic Demand: The amount of traffic in the network is a contributory factor in determining how effective a traffic signal control strategy is. Case Study 1 uses one hour of static demand that is close to the intersections saturation point. Case Study 2 tests 24-hours of low, average, and high flow levels so that the change in performance of the signal control strategies at varying demand levels can be assessed. By analysing the data collected from the loop detectors in the Selly Oak study, the base case shows average flow levels. The high and low demand cases were defined as being $\pm 20\%$ of the average flow experienced by the detectors, respectively.

3) Car-Following Model: Here, the Krauss model [41] was used as the car-following model as it produces stable collision-free traffic flow and is well validated. The Krauss model has been shown to outperform other traffic-flow models in mixed traffic scenarios [42]. It is also stable at the 0.1 s simulation time-step, which was needed to represent the wireless communication system dynamics. Table III describes the parameters used in the Krauss car-following model for the five considered vehicle modes (cars, motorcycles, LGVs, HGVs, and buses). Both connected and unconnected vehicles have the same car-following parameters as it is assumed that CVs ability to share data with a traffic signal controller does not affect driver behaviour.

TABLE III

THE KRAUSS CAR-FOLLOWING MODEL PARAMETERS FOR THE CONSIDERED VEHICLE TYPES [43]

Parameter (*unit*)	**Car**	**MC**	**LGV**	**HGV**	**Bus**
Acceleration $(\mathrm{m/s^2})$	2.6	5.0	2.0	1.3	1.0
Deceleration $(\mathrm{m/s^2})$	4.5	9.0	4.0	3.5	3.5
Driver Imperfection - σ	0.5	0.5	0.5	0.5	0.5
Reaction Time - $\tau(\mathrm{s})$	1.0	1.0	1.0	1.0	1.0
Length (m)	4.3	2.2	6.5	7.1	12.0
Min. Gap (m)	2.5	2.5	2.5	2.5	2.5
Max. Speed $(\mathrm{km/h})$	180	200	160	130	85

***L/HGV**: Light/Heavy Goods Vehicle*
***MC**: Motorcycle*

4) Control Strategies: In order to assess the performance of the proposed MATS algorithm, the results were compared with those from TRANSYT plans calibrated on an average flow case in the Selly Oak area. TRANSYT signal timing plans were produced using the TRANSYT 15 software. Separate timing plans were calibrated for off-peak (00:00-06:00, 20:00-00:00), peak (06:00-11:00, 16:00-20:00) and inter-peak flows (11:00-16:00).

5) Intersection Configuration: Intergreen times for each intersection were set per the UK Government guideline intergreen times [44]. The MATS algorithm (Algorithm 1) was configured with an extension interval of 2 s per the work of Bonneson and McCoy [45]. The minimum and maximum green times were 2 and 10 times the intergreen time for the intersection, respectively. The junction control region was defined as a circle with radius 250 m [46] centred on the intersection. The check interval for the MATS algorithm was 5 s, not 1 s, to allow sufficient time for decisions in the event of long communication latencies and high levels of packet loss.

6) Stochastic Effects: Many of the processes within the simulation rely on randomness to generate values, especially the traffic generation process. All random number generators used in the codes for this research were drawn from seeded uniform distributions so that the results are repeatable. As the system is stochastic, each simulation must be repeated to create a sample space, and the results averaged in order to determine the typical performance resulting from the underlying system dynamics. The sample space for this research contains 50 repetitions per experiment.

7) Communication Channel, Errors, and Delays: Where CVs transmit information, data were sent at a rate of 10 Hz based on the ETSI CAM [47] specification. Messages were transmitted via an IEEE 802.11p [48] Dedicated Short-Range Communication (DSRC) channel. Research on IEEE 802.11p networks shows that signal strength is high enough within a 250 m radius to allow messages to be received correctly [46], [49], and that packet latency of approximately 50 ms are achievable at vehicles speeds of up to 90 km/h [49]. In this research, CAMs were received by the intersection controller with ideal information content, but with a delay of 100 ms.

In order to assess the lower-bound performance of the MATS algorithm, it was tested under non-ideal conditions. In the non-ideal case, the MATS algorithm was tested with a CAM generation rate of 1 Hz instead of the usual 10 Hz. The packet loss in the system was set to 50%. Finally, Gaussian noise of the form $X \sim \mathcal{N}(\mu, \sigma^2)$, with mean $\mu = 0$ and variance $\sigma^2 = 2.79$, was added to GPS measurements (i.e. the position ±5 m in both the x and y coordinates, typical for differential GPS systems [50]).

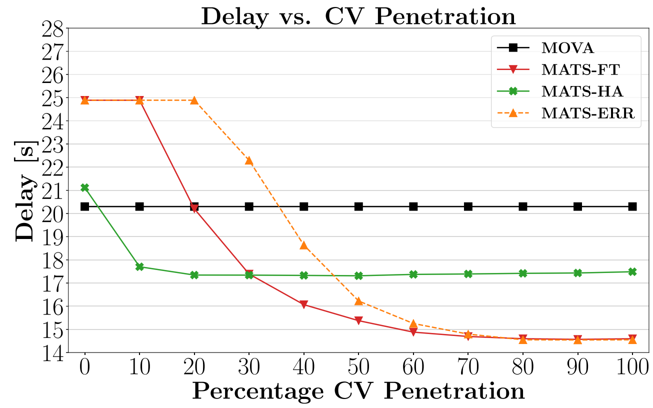


Fig. 4. Comparison of the mean delay of the MATS algorithm with MOVA on Case Study 1.

IV. Results and Discussion

A. Performance Indicators

Mean travel time delay and mean stops were selected as the performance indicators for this research. Delay and stops are primary components on which TRANSYT optimises signal timings [51] and allow comparison. Free-flow travel times were the basis for delay calculations. In this study, free-flow travel time is the time a vehicle takes to make its journey at the speed limit, unimpeded by external factors such as other traffic or signalised intersections. Travel-time delay characterises the excess time a vehicle takes to complete its journey compared to the free-flow travel time along the same route. As simulation was used to study the traffic dynamics, the time delay T_{delay} for a vehicle is defined as:

$$T_{\text{delay}} = T_{\text{exit}} - T_{\text{enter}} - T_{\text{freeflow}} \tag{3}$$

where T_{enter} and T_{exit} are the times a vehicle enters and exits the simulation, respectively. T_{freeflow} is the time it takes the vehicle to make its journey on an unobstructed route. Delay time indicates the amount of time actually saved compared to the complete journey time and highlights the performance limitations of each method.

In this study, a vehicle is defined as being stopped if its speed is less than 0.01 m/s. The total number of stops a vehicle makes on its journey were recorded for analysis. To normalise the results in Case Study 2, the mean delay and mean stops are represented per kilometre. The mean data points are banded by the 5th and 95th percentiles of their corresponding dataset as indicators of variability.

The results also compare the mean delays and the mean stops in terms of the percentage reduction between them. The percentage reduction is calculated by:

$$100\left(1 - \frac{x}{x_{\text{ref}}}\right) \tag{4}$$

which yields the percentage reduction between a result value from the MATS algorithm x, and the corresponding reference value from the MOVA or TRANSYT results, x_{ref}.

To establish how the performance of the MATS algorithm differs depending on the quality and availability of input data, three varieties of the MATS algorithm are defined and compared:

- **MATS-FT**: The MATS algorithm combining data from fixed-time plans and CVs
- **MATS-HA**: The MATS algorithm with hybrid actuation, combining data from fixed-time plans, inductive loops, and CVs
- **MATS-ERR**: MATS-FT but under imperfect communication channel conditions.

The fixed time plan was derived from the TRANSYT plan. The times given by the TRANSYT plan were truncated in the MATS algorithm if they exceed the junction's maximum green time value. During initial testing, it was found that the use of loop data was detrimental to the performance of the MATS-HA variant at 0% CV penetration. The negative behaviour was due to placing the algorithm in a network with imperfect coverage. In the case study, the loop placement was for a SCOOT system. It was found during testing that the loop coverage is too degraded to be beneficial at 0% CV penetration, so loop detectors are only used in the presence of CV data for this case study, and the base level of performance is fixed-time.

In Sections IV-B and IV-C, the results of the tests on the two case studies are presented. First, the results comparing the MATS algorithm to MOVA are discussed. Secondly, the results comparing the MATS algorithm to TRANSYT on the realistic testing framework are discussed.

B. Case Study 1: Comparison With an Actuated Controller

The MATS algorithm is compared to the state-of-the-art vehicle actuated signal controller of MOVA using the single intersection case study developed in [3]. In that study, it was demonstrated that at a single intersection with ideal loop detector data and traffic conditions just below saturation, the average delay is 20.3 s using MOVA. Figure 4 shows the difference in delay between MOVA and the MATS algorithms for CV penetrations from 0%–100%. Table IV shows the percentage difference in delay between the MATS algorithm and MOVA. Under the same traffic conditions and ideal communication conditions, the MATS-FT algorithm showed lower mean delay

TABLE IV

BENCHMARK RESULTS OF THE MATS ALGORITHM AGAINST MOVA ON CASE STUDY 1. THE PERCENTAGE REDUCTION IN AVERAGE DELAY AT 10%, 30% 50%, 70% AND 100% CV PENETRATION ARE SHOWN

Algorithm	**CV Penetration**				
	10%	**30%**	**50%**	**70%**	**100%**
MATS-FT	-22.16%	13.11%	24.1%	27.4%	27.9%
MATS-HA	-4.27%	14.64%	14.66%	14.14%	13.46%
MATS-ERR	-22.16%	-22.16%	19.8%	26.82%	28.2%

than MOVA above 20% CV penetration, with mean delay reductions of 20%-28% above 30% CV penetration. Under non-ideal communication conditions, the MATS algorithm reduces mean delay better than MOVA above 40% CV penetration, with reductions in mean delay between 19%-29% above 40% CV penetration. When both inductive loop and CV data are used in the MATS-HA algorithm, the MATS-HA algorithm reduces mean delay between 12%-15% compared with MOVA for CV penetrations $\geq$10%. The MATS-FT and MATS-ERR use fixed-time plans up to 10% and 20% CV penetration, respectively, indicating that for this case study, there is a threshold below which CV data is not beneficial. The MATS-HA algorithm does the best at 0% CV penetration as it can use loop detectors to actuate signal timings, but is worse than MOVA as its actuation strategy is not as sophisticated. The results show that the MATS algorithm is better than the state-of-the-art vehicle actuation strategy MOVA, and that loop detector data is useful at low CV penetrations but can limit performance at high CV penetrations.

C. Case Study 2: Test on a Realistic Road Network

Tables V show the results from the benchmarking of MATS against TRANSYT on the low, average, and high traffic demand cases. The numbers in Tables V(A), (B), and (C) show the percentage reduction in the average delay and the average number of stops compared to TRANSYT at 10%, 50%, and 100% CV penetration.

Figure 5 shows the plots of mean delay per kilometre and the mean number of stops per kilometre for three traffic demand scenarios. As shown in Figure 5, the MATS algorithm resorts to using the fixed-time plan in the absence of CV data (0% CV penetration). As shown in Figure 5, the grey lines for both delay and number of stops are straight for TRANSYT. These lines are expected to be straight as TRANSYT does not use CV data, so its performance is invariant with increases in CV penetration. The results are discussed in further detail under two categories (stops and delays) in the following sections:

1) Stops: It can be seen in Figures 5(b), (d), and (f) that there is little difference in the average number of stops made across the MATS algorithm variants compared with TRANSYT, even with the addition of inductive loops. Across all of the stop results, it can be seen that as the CV penetration increases the variability in the number of stops made by vehicles reduces. The reduction in variability shows that vehicles

TABLE V

BENCHMARK RESULTS OF THE MATS ALGORITHM AGAINST TRANSYT FOR THE THREE DEMAND CASES. THE PERCENTAGE REDUCTION IN AVERAGE DELAY AND AVERAGE NUMBER OF STOPS AT 10%, 50%, AND 100% CV PENETRATION ARE SHOWN

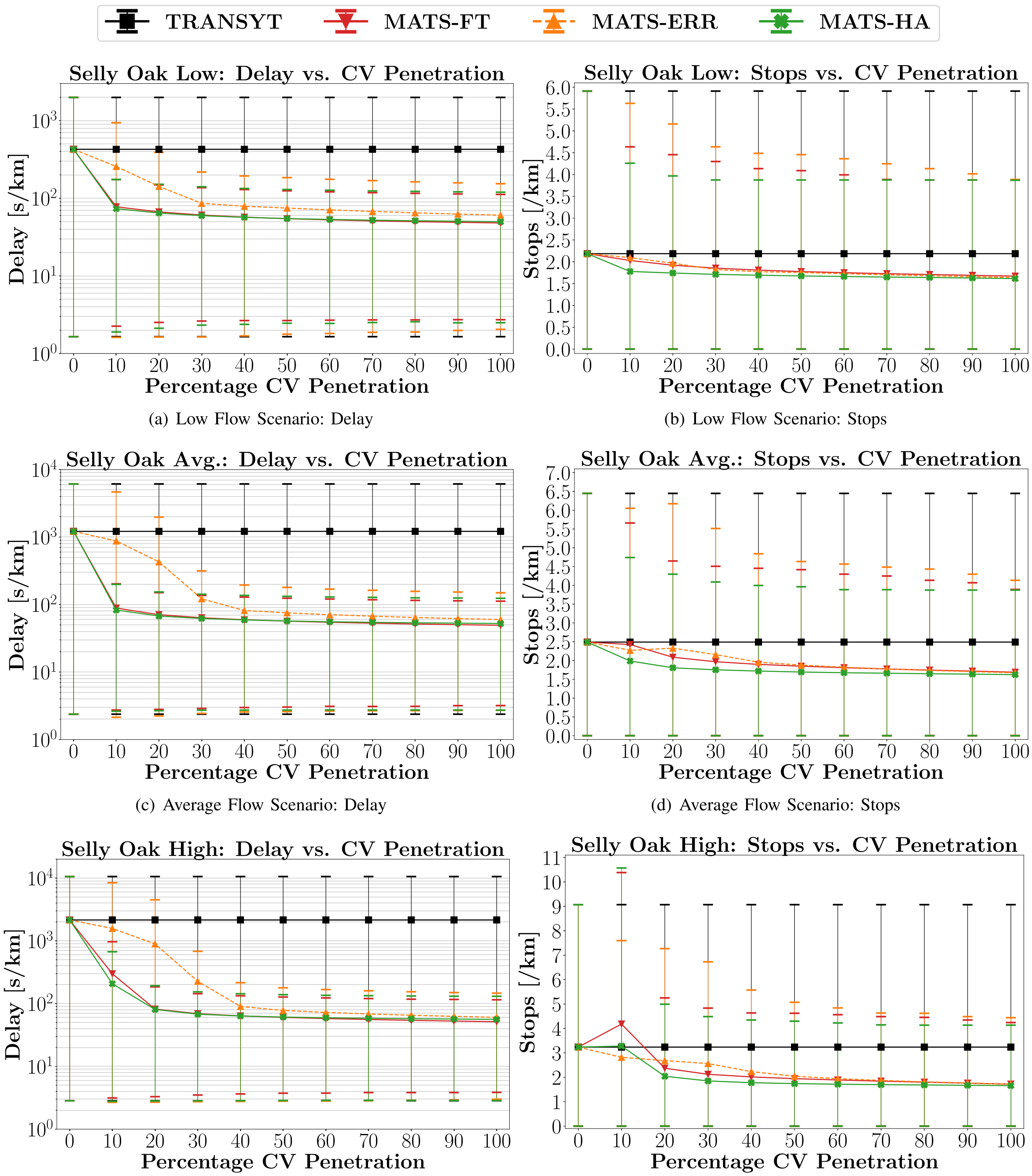
A: Low Traffic Demand						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	82%	7%	87%	19%	89%	24%
MATS-HA	83%	19%	87%	23%	88%	26%
MATS-ERR	40%	4%	82%	20%	86%	25%
B: Average Traffic Demand						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	93%	3%	95%	26%	96%	32%
MATS-HA	93%	20%	95%	32%	96%	35%
MATS-ERR	28%	9%	94%	25%	95%	33%
C: High Traffic Demand						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	86%	-29%	97%	40%	98%	47%
MATS-HA	90%	-1%	97%	46%	97%	49%
MATS-ERR	27%	13%	96%	37%	97%	47%

which stop many times, stop less frequently when there are CVs present in the network. The variability remains wide even at high CV penetrations due to the varied route lengths in the network resulting from its large size.

In addition, there are visible peaks in the MATS-FT and MATS-HA variants at 10% CV penetration in the high demand case. The peaks occur as a result of frequent switching between fixed-time and adaptive modes due to the sparsity of CV data, resulting in a slightly higher frequency of stops. Conversely, MATS-ERR does not exhibit the same peaks due to a relaxation in the frequency of switches between modes due to communication delays. However, it can be seen that the behaviour of the MATS algorithm variants stabilises for CV penetrations above 10%.

From Table V(B), it can be seen that the MATS algorithm provides reductions of up to 35% over TRANSYT under average traffic demand. Additionally, the effects of imperfect communication conditions do not significantly impact the performance of the MATS algorithm in terms of the number of stops made. From Tables V(A) and (C), it can be seen that the MATS algorithm can achieve greater reductions in the number of stops as the traffic demand increases.

2) Delay: Looking at results in Figures 5(a), (c), and (e) and Tables V(A), (B), and (C), it can be seen that the MATS algorithm offers significant reductions in delay at all levels of traffic demand. In addition to reducing the mean delay, the MATS algorithm significantly reduces the delay variability experienced by drivers with CV penetrations above 10%. In the case of imperfect communication conditions,



(a) Low Flow Scenario: Delay

(b) Low Flow Scenario: Stops

(c) Average Flow Scenario: Delay

(d) Average Flow Scenario: Stops

(e) High Flow Scenario: Delay

(f) High Flow Scenario: Stops

Fig. 5. Plots of mean delay per kilometre and mean stops per kilometre for each of the three flow scenarios (low, average, high). Each plot compares the performance of the MATS algorithm with and without loop information (MATS-FT), and MATS with errors (MATS-ERR), to TRANSYT. The bands on the data represent the 5th and 95th percentiles of the data as indicators of variability.

the MATS algorithm's performance is degraded compared to MATS-FT but still offers reductions in delay and variability compared with TRANSYT, emphasising its robustness. Across the results, there is some variability in the delay even at high CV penetrations due to the varied route lengths in the network resulting from its large size.

In Figures 5(a), (c), and (e), the MATS-ERR variant under-performs the MATS-FT and MATS-HA variants across all demand cases. The discrepancy between MATS-ERR and the other MATS algorithm variants can be attributed to MATS-ERR overestimating or underestimating the queue clearance time and stage extensions due to the noise, error, and delay in the communication channel. However, the effects of the non-ideal communication channel conditions were overcome by 30% CV penetration. Despite the non-ideal communication channel, MATS-ERR reduces delay and delay variability. Interestingly, the mean in the MATS-ERR plot lines lies close to the upper-bound of the error bars, suggesting some skew towards vehicles on longer journeys being less well served than those on shorter journeys. As with the results for the number of stops, the skew results from lower mode switching frequency due to the sparsity of CV data are greater under high traffic demand. These results suggest that at low CV penetrations and higher traffic demands, less frequent data transmissions reduce the amount of mode switching, which is beneficial in decreasing the number of stops but detrimental to reducing delay.

It can be seen from the comparison between the MATS algorithm and TRANSYT, that under average demand, the MATS algorithm reduces delay up to 96%. Table V(B) indicates that by 10% CV penetration up to 93% delay reduction can be achieved, which was most of the maximum achievable delay reduction of 96%. Additionally, Figures 5(a), (c), and (e) show that by 30% CV penetration MATS-ERR reduces delay almost as well as MATS-FT. These results suggest that with a relatively low proportion of CVs in the road network, significant delay reductions can be achieved using the MATS algorithm even under non-ideal communication channel conditions. These findings were consistent when comparing the MATS algorithm with TRANSYT under low and high traffic demands seen in Tables V(A) and (C).

Comparing MATS-FT to MATS-HA in Figures 5(a), (c), and (e), the results suggest that in the presence of CV data, the data from inductive loops does not significantly improve the performance of the algorithm. In terms of deploying the MATS algorithm, given an existing system with degraded roadside infrastructure, it would be more beneficial to re-calibrate the fixed-time plan than to restore the loop hardware. Having a reliable fixed-time instance provides the most robust fall-back behaviour for the MATS algorithm, and that having even a small amount of CV data provides most of the benefits of using the proposed adaptive traffic control system. Therefore, MATS-FT is the best implementation for use in existing but degraded road networks.

3) Hypothesis Testing: As the simulations were stochastic, hypothesis tests were performed on the delay and stop data in order to assess its statistical independence across the 50 experiment runs, and incremental increases in CV penetration. Here, the null hypothesis H_0 was that the mean stops and delay data at CV penetrations greater than 0% were drawn from the same normal distribution as the mean delay for 0% CV penetration. The alternative hypotheses H_1 tested were that the mean delay and stop data for all simulated CV penetrations greater than 0%. A two-sample independent T-test was performed between H_0 and each H_1, and the p-value was determined.

The hypothesis testing determined that all scenarios reject the null-hypothesis with $p < 0.001$. The results indicate that the addition of connected vehicles into the transport network changes the MATS algorithm such that it meaningfully impacts the delays and number of stops experienced by road users in all cases where CVs were present. The rejection of the null hypothesis also confirms that there was a significant reduction in delay in all cases for CV penetrations as low as 10%, which addresses the gap in previous research.

V. Conclusion

In this paper, the MATS algorithm that augments existing traffic signal control systems with CV data was introduced. A microsimulation testing framework that comprehensively covers the parameters that need to be explored to simulate traffic signal controllers that use CV data was also presented. In initial tests, the MATS algorithm reduced delays better than the MOVA algorithm. Under the testing framework, the MATS algorithm was shown to outperform the industry-standard TRANSYT traffic signal timing algorithm under increasing traffic demands through the combination of data from CVs, existing fixed-time plans, and roadside infrastructure. Furthermore, the framework highlights that assessing connected traffic signal control strategies at multiple CV penetrations and in the presence of communication errors is critically important.

Simulating the MATS algorithm on the introduced testing framework's realistic simulation case study in Selly Oak, Birmingham, UK demonstrated that the MATS algorithm was highly robust across a spectrum of scenarios. The MATS algorithm outperforms TRANSYT at minimising delay across varying traffic demands and offers significant performance improvements even in the presence of imperfect communication conditions and measurement noise. The MATS algorithm offers reductions in the average delay of up to 96% and the number of stops up to 33% over TRANSYT, for networks with 0-100% connected vehicle presence. The results confirm that significant reductions in delay can be achieved for CV penetrations as low as 10%, highlighting that not all the vehicles in the road network need to be connected to achieve delay reductions. In comparison with MOVA, the MATS algorithm reduced mean delay better than MOVA for CV penetrations above 20%, and achieved reductions in the mean delay of 20%-28% for CV penetrations above 30%.

The findings showed that for networks where the loop placement is imperfect, such as in older, degraded urban networks, the performance of the MATS algorithm is hindered at low CV penetrations when attempting to use data from these loops. Further work should address the issues of data from partial or degraded roadside infrastructure in order to improve how the MATS algorithm generalises to other road networks.

In conclusion, this study has found that the MATS algorithm addresses the identified issue of enhancing existing traffic signal control systems in urban environments with increasing numbers of CVs, and operates robustly in realistic scenarios provided under a comprehensive testing framework. The presented testing framework improves on those in previous literature in terms of scale, traffic demand levels, vehicle types considered, resolution of CV penetrations tested, and communication channel error sources considered. In future work, the testing framework can be improved by accounting for both pedestrian and vehicle movements, and through estimating the prevailing CV penetration. Further testing scenarios could include lane closures due to disabled vehicles, and response to emergency service vehicles. Future trials should also investigate how the MATS algorithm applies to other urban road networks with different demands, and in other countries.

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Craig B. Rafter (Student Member, IEEE) received the M.E. degree in electronics and computer engineering from University College Dublin in 2015. He is currently pursuing the Ph.D. degree with the University of Southampton, sponsored by the Transportation Research Laboratory, with a focus on effects of traffic signal control using connected vehicle data on the transport network. He has completed the Ph.D. training program in next generation computational modeling from the Engineering and Physical Sciences Research Council Centre.

Bani Anvari (Member, IEEE) received the M.Sc. degree in advanced architectural studies from UCL in 2009, and the Ph.D. degree in mixed traffic modeling from Imperial College London in 2014. She is currently a Lecturer in intelligent mobility with the Centre for Transport Studies, UCL. Her research interests include traffic and infrastructure modeling, autonomous vehicles, and vehicle-to-vehicle/vehicle-to-infrastructure communications in order to create intelligent transportation systems.

Simon Box received the Ph.D. degree in automotive sensor simulation from the University of Cambridge in 2007. He currently holds a visiting researcher position at the University of Southampton, and he is also an Architect for simulation at Aurora Innovation. His research interests include autonomous vehicle systems simulation, traffic simulation, and sensor simulation.

Tom Cherrett is currently a Professor of logistics and transport management at the University of Southampton. He lectures on the topics of transport planning, freight and passenger systems, and construction management. His research interests include core goods distribution and retail logistics optimization within and between our urban areas, smartphone technology use in logistics, and using remote monitoring technology with optimization techniques to effectively manage waste and recyclable collection in urban areas.