Journal of Computer and Communications, 2023, 11, 82-100
https://www.scirp.org/journal/jcc
ISSN Online: 2327-5227
ISSN Print: 2327-5219

Discrete Event Simulation-Based Evaluation of a Single-Lane Synchronized Dual-Traffic Light Intersections

Chimezie Calistus[1], Ogharandukun Martin[2], Abdullahi Monday[3], Essien Joe[4]

[1]Department of Electrical/Electronic and Computer Engineering, Veritas University, Abuja, Nigeria
[2]Department of Pure and Applied Physics, Veritas University, Abuja, Nigeria
[3]Department of Computer Science, Air Force Institute of Technology, Kaduna, Nigeria
[4]Department of Computer and Information Technology, Veritas University, Abuja, Nigeria
Email: chimeziec@veritas.edu.ng, Ogharandukunm@veritas.edu.ng, m.abdullahi@afit.edu.ng, essienj@veritas.edu.ng

How to cite this paper: Calistus, C., Martin, O., Monday, A. and Joe, E. (2023) Discrete Event Simulation-Based Evaluation of a Single-Lane Synchronized Dual-Traffic Light Intersections. *Journal of Computer and Communications*, **11**, 82-100.
https://doi.org/10.4236/jcc.2023.1110006

Received: September 18, 2023
Accepted: October 22, 2023
Published: October 25, 2023

Abstract

This research involved an exploratory evaluation of the dynamics of vehicular traffic on a road network across two traffic light-controlled junctions. The study uses the case study of a one-kilometer road system modelled on Anylogic version 8.8.4. Anylogic is a multi-paradigm simulation tool that supports three main simulation methodologies: discrete event simulation, agent-based modeling, and system dynamics modeling. The system is used to evaluate the implication of stochastic time-based vehicle variables on the general efficiency of road use. Road use efficiency as reflected in this model is based on the percentage of entry vehicles to exit the model within a one-hour simulation period. The study deduced that for the model under review, an increase in entry point time delay has a domineering influence on the efficiency of road use far beyond any other consideration. This study therefore presents a novel approach that leverages Discrete Events Simulation to facilitate efficient road management with a focus on optimum road use efficiency. The study also determined that the inclusion of appropriate random parameters to reflect road use activities at critical event points in a simulation can help in the effective representation of authentic traffic models. The Anylogic simulation software leverages the Classic DEVS and Parallel DEVS formalisms to achieve these objectives.

Keywords

Multi-Core Processing, Distributed Computing, Event-Driven Modelling, Discrete Event Simulation, Data Analysis and Visualization

1. Introduction

Discrete Event Simulation (DEVS) is an effective modelling and analysis tool for complex systems, such as traffic signal control systems. However, there are a number of challenges associated with the use of DEVS for traffic signal control. It has been observed that it can be difficult to coordinate events in a simulation, particularly in a dynamic environment like traffic control [1]. To implement and manage effectively, a single lane traffic light system at intersections, is essential to ensure that traffic signals, vehicle movements, and pedestrian actions are correctly synchronized in order to capture realistic interactions and outcomes [2]. In traffic control systems, as decisions are frequently made in real-time in response to altering circumstances, it can be difficult to incorporate real-time decision-making into a discrete event simulation. It has been affirmed that given certain complex conditions, DEVS can be deficient in managing real-time control as smoothly as dedicated control algorithms [3], despite the fact that it can provide insights into the overall system behavior. In addition, it is difficult to validate and verify the accuracy of a DEVS model, especially when comparing simulation results with real-world data [4]. Model validation necessitates ensuring that the simulation output corresponds to real-world observations across a broad range of scenarios though this can be resource-intensive and error-prone [5]. Also, it has been observed that simulation execution can be computationally intensive and time-consuming, depending on the complexity of the simulation model and the level of detail included [6]. Strike a balance between the level of detail and computational efficacy, particularly for large-scale traffic networks can be challenging. Modelling human behavior precisely in traffic simulations using DEVS in correlation with pedestrian and motorist behavior, response to traffic signals, pedestrian yielding, and lane changes, has proven to have a significant effect on simulation outcomes [7]. Realistically capturing these behaviors requires sophisticated modelling techniques. Due to the large number of potential variables and factors that can influence traffic control outcomes, undertaking exhaustive scenario analysis using DEVS can be challenging endeavor including identifying the most pertinent study scenarios. Real-world traffic systems are susceptible to numerous sources of uncertainty, such as weather conditions, incidents, and road closures, in terms of uncertainty and sensitivity analysis. Incorporating uncertainty and undertaking sensitivity analyses in DEVS can be difficult though understanding the robustness of control strategies for DEVS requires this knowledge.

Nevertheless, efficient traffic control measures can still be managed with Discrete Event Simulation (DEVS) by employing a methodical, multi-step approach. To address these challenges, a combination of domain expertise, meticulous model development, validation against real-world data, and ongoing refinement of the simulation approach is required [7]. DEVS is a computational technique used to model and analyze dynamic systems with discrete state changes over time. DEVS has been used to simulate and investigate the behavior of traffic flow, vehicle movements, and signal timing at intersections in the context of traffic light control. A scenario of traffic signal control is modelled as a discrete event system, in which events occur at discrete points in time and cause the system's state to change [8]. In the simulation model, the intersection, roads, lanes, vehicles, and traffic signals are represented as entities. The event-driven nature of the DEVS requires events as a trigger for simulation alterations. In the context of traffic light control, events may include the arrival of a vehicle at an intersection, the state change of a traffic signal, or the departure of a vehicle from an intersection. A simulation clock monitors the simulation's present time and advances in discrete time steps. The Event Queue is used to schedule and execute events based on their timestamps while the simulation engine processes events in chronological order and consequently updates the system's state.

Based on observed traffic patterns or data, effective Traffic Flow Modelling for DEVS records vehicle arrivals, departures, and movements [7]. The characteristics of each vehicle include speed, winding behavior, and route. The simulation model contains logic for controlling the intersection's traffic signals and implementation of signal timing schemes, phase sequences, and coordination strategies based on actual control principles. As the simulation clock advances, events are dequeued and processed from the event queue [8]. In DEVs implementation, when a vehicle approaches at an intersection, the simulation calculates its behavior based on traffic regulations, signal state, and the movements of other vehicles. Events induce simulation model state alterations. For instance, a green traffic signal turns red, a vehicle changes lanes, or the phase of a signal shifts. Over time, simulation outputs such as data on vehicle queues, waiting periods, signal conditions, and overall intersection performance are collected. These outputs can aid in evaluating the effectiveness of various signal control strategies [7] [9]. By simulating various signal timing configurations and control strategies, traffic engineers can evaluate the effectiveness of various approaches. It is also possible to compare key performance indicators such as average latency, queue length, and throughput to identify optimal signal timings. To assure the model's veracity, simulation results are validated against real-world data and observations. Thus, Discrete Event Simulation provides a versatile and efficient method for analyzing the effects of various traffic light control strategies, enabling traffic engineers to make informed decisions regarding signal timing optimization, intersection design, and traffic management. Utilizing Discrete Event Simulation can effectively allow effective traffic control measures. This study presents a novel method for efficiently managing traffic flow at a Single Lane intersection using Discrete Events Simulation. On the basis of the simulation results, it can be concluded that the incorporation of minor enhancements and the inclusion of various parameters, such as multiple lanes, collision detection, and variable speeds for different vehicles, can generate a highly accurate representation of a traffic intersection.

2. Review of Literature

Discrete Event Simulation (DES) finds extensive application in many domains, efficiently tackling and resolving intricate challenges, while providing comprehensive support in areas including Defence, transportation, and healthcare. Discrete-event-based methods are particularly well-suited for systems whose behavior can be characterized as being influenced by stochastic factors, where interconnected components change their states at discrete time intervals. The importance of utilizing distributed or Parallel Discrete Event Simulation (PDES) techniques for discrete event models on multiprocessor systems has been highlighted in a study conducted by [10]. Discrete-event simulation is not only easily comprehensible, but it also possesses a high degree of expressiveness and effectiveness [8] [11]. The problem of Urban Traffic Light Scheduling, which aims to determine the optimal cycle time for each traffic light to maximize traffic flow, has been studied [7] and compared with other techniques such as the Cell DEV technique [10]. The Cell DEVS methodology was employed to develop a comprehensive library that encompasses various traffic models. This formal modelling technique establishes the definition of each cell within a space as an autonomous entity. A comparative study conducted by [12] utilized 3D Maya-based fundamental models and visualization tools. The library offers a wide range of models, including a one-lane, one-direction traffic cellular model, a bidirectional traffic cellular model, pedestrian control systems, crossings equipped with traffic lights or stop signs, traffic monitoring models, roundabouts, a controller designed for a bridge with alternating traffic lights, highway tolls, and highway interchanges. In another investigation, the authors [13] employed a discrete-event and hybrid traffic simulation model based on Sim Events to investigate the intelligent transport system. This work contrasted with the conventional the Intelligent Transportation System (ITS) which monitors and controls physical components, such as Connected Automated Vehicles (CAVs). A discrete-event and hybrid simulation framework based on Sim-Events was utilized to develop a traffic simulation model for an urban test facility [14]. This model was designed to aid in the evaluation of safety and performance of an Intelligent Transportation System through testing. The infrastructure encompasses several road and lane configurations, together with a comprehensive instrumentation system, specifically designed for the purpose of evaluating Connected and Autonomous Vehicles (CAVs) [14]. A research conducted by [15] examined traffic at a microscopic level. The research encompasses the evaluation of the effectiveness of innovative control algorithms for connected and autonomous vehicles (CAVs) in different traffic scenarios, the analysis of event-driven features of transportation systems, and the investigation of the impacts caused by communication delays. In their study, the researchers [15] [16] employed the discrete event simulation (DEVS) methodology to model and simulate the flow of information pairs within an autonomous transportation system (ATS). The authors emphasized the importance of possessing a foundational understanding of previous discussions over the future of DEVS in order to engage in meaningful dialogue on the subject. In order to gain a deeper understanding of the developmental path that DEVS has embarked upon, particularly with regards to its user base and the envisioned directions for its future. This study examined DEVS literature that specifically addresses its prospective advancements [17]. The study combines a quantitative bibliometric analysis of the literature on Modelling and Simulation with a qualitative evaluation of DEVS [5]. The issue of traffic congestion has been widely acknowledged as a significant problem in major urban areas, especially during times of higher usage [16]. The author [18] carried out an analysis of variance methodologies to investigate the factors that influence the operation of traffic lights. The study aimed to identify the essential aspects and determine the ideal combination among them. The case study was conducted to evaluate the efficacy of different green/red percentages and cycle times in mitigating network congestion.

In a similar study, Wang *et al.* (19) developed a gap acceptance model utilizing the discrete choice theory to examine the behavior of gap acceptance at an intersection. In their analysis, the researchers incorporated variables such as lead gap, space gap, time gap, and remained distance. The findings indicate that the space gap has a greater impact on the driver's gap acceptance behavior compared to the time gap, primarily due to variations in speed. In their study, researchers [20] observed that when the distance between vehicles was insufficient, drivers appropriately reduced their speed. V2V technology enables the communication between vehicles, allowing one vehicle to receive information regarding the speed, distance, space availability, and location of the preceding vehicle. In their study, Greguric *et al.* [21] examined traffic flow parameters, including speed, flow, and density, and investigated their interrelationships using a macroscopic simulator. The researchers observed a substantial decrease in traffic density. In a comparative study, Yang *et al.* [22] developed a geometry-based vehicle-to-vehicle propagation model. This model incorporates information about the surrounding environment, including buildings. The researchers utilized GEMV2 (version 1.1) to simulate the V2V propagation model within the designated area. The study involved the simulation of 1000 vehicles, which were randomly assigned to selected origins and destinations. Based on the simulation results, it was observed that the presence of buildings and vehicles had a detrimental effect on the reliable communication range [16]. The study revealed that the performance of V2V communication technology was observed to deteriorate in environments where there was no direct line of sight. In light of these challenges, it is imperative to advance the integration of Vehicle to Infrastructure (V2I) communication technology within Intelligent Traffic Systems. Chen *et al.* [23] devised an adaptive signal controller that utilized Vehicle-to-Infrastructure (V2I) communication technology to gather data on average delay time, queue length, travel time, and vehicle speed. The acquired data was utilized as input for a simulation model developed with VISSIM, a microscopic multi-modal traffic flow simulation software. In a previous work, researchers [24] proposed the development of a Predictive Congestion Minimization Algorithm (PCMA) that utilizes real-time traffic conditions as a basis for its predictions. The present state of the road was determined based on the occupancy of each road segment. If the level of occupancy above a threshold value set by the user, the predictive model would provide alternative routing methods. The study encompassed the development of a decentralized adaptive traffic signal control system based on phase design. The authors emphasized that these detectors utilize vehicle-to-infrastructure (V2I) communication to detect vehicles. Using this information, the controller predicts the wait length for the next 20 seconds within a five-second time interval for optimization purposes. In a separate investigation, the authors [25] devised a tiny simulator known as ISR-TFS. This simulator encompassed both roundabout intersections (RI) and crossroad intersections (CI), with each intersection accommodating traffic flow from four distinct directions. The intersections of RI and CI were conceptualized as a three-dimensional matrix representing time and space, wherein each cell is represented by a physical location. The process of cell selection and speed profiling was determined by the availability of the physical area. The vehicle's trajectory was modified to circumvent traffic congestion by the utilization of a route following controller, as per the communication received from ITMS via V2I. In contrast, a previous study [25] proposed the creation of an intersection that is divided into tiles of size n-by-n. These tiles are allocated based solely on their availability. The intersection controller evaluates reservation requests from vehicles based on the specified decision criteria. It determines the appropriate location, speed, maximum acceleration rate, and gives updates on the state of the tiles. The researchers observed a notable decrease in the frequency of traffic stops at an intersection through the utilization of a tiny traffic simulator known as VISSIM. This finding serves as evidence supporting the effectiveness of the proposed methodology.

Simulation Model Integrating V2V and V2I Features

The V2V and V2I systems rely on the availability of road segments, the behavior of traffic light control systems, and the arrival rate of vehicles to determine the overall queuing status within the specified system boundary. A study conducted by [19] utilized a discrete event simulation environment to examine this approach. A comparable methodology had been used to create a discrete event simulation model for a traffic intersection at an urban traffic signal intersection, utilizing the ARENA software [17]. The model presented an optimal duration for the green phase signal to effectively minimize queue length. In a separate study, researchers [16] utilized the JamSim software to develop a discrete event simulation of a signalized intersection. The purpose of this simulation was to analyses the timing of the green phase in relation to the average waiting time experienced in each lane. The authors have proposed five distinct green light phases based on their observation of real-time traffic flow across varying levels of low, medium, and high traffic volume. The traffic simulation model was not fully representative of the actual scenario, as it made the assumption that if one link was in the green phase, the other three links would automatically be in the red phase. In their study, Benzaman & Sharma [3] developed a discrete event simulation model for a traffic light control system at a single intersection. The model was based on a Queueing theory approach, specifically utilizing an accelerated traffic discharging model. Through the implementation of a model, notable enhancements in traffic flow were observed, specifically in the reduction of the number of vehicles in queue and the average waiting time. A proposed model has been developed to decrease the travel time of vehicles by analyzing both straightforward movement and turning movement, considering various combinations of uniform and varying vehicle arrival rates [16]. The findings from the analysis of vehicle flow characteristics, including speed, lane gap, and position, indicate a significant decrease in travel duration.

3. Methods

This work utilizes simulation and quantitative evaluation within an exploratory context to assess the dynamics of a single road lane in a case study. The study was conducted by breaking down the main steps into the following:

Step 1: Definition of context;

Step 2: Evaluation of real life scenario and relevant parameters;

Step 3: Design of model;

Step 4: Deduction of simulation parameters, events and appropriate values based on step 2;

Step 5: Simulation and interpretation of results.

In order to ensure clarity and relevance, it was essential to establish a specific setting for the study that closely aligns with realistic road systems in real-life scenarios. The background was further assessed in order to emphasize potential non-deterministic, deterministic, and general stochastic dynamics. This facilitated the advancement of the model. The tool utilize for the investigation is the Anylogic modeling package. Anylogic supports DEVS modelling through the utilization of event points, which consist of queues and delays. In order to accurately simulate stochastic processes, it is necessary to combine suitable random parameters with capacity control.

The methodology employed in this study encompasses event management, parallel execution, and model deconstruction. The study utilizes both sequential First-In-First-Out (FIFO) events and parallel stochastic events to maintain effective synchronization of and appropriate near replication of real life scenario. This methodology facilitates a comprehensive examination and validation of system characteristics, including but not limited to performance metrics, reliability, and practical feasibility. Furthermore, the technique provides a versatile and structured framework for the modelling and simulation of dynamic systems. Many scholars argue that DEVS has considerable utility as a tool for decision-makers seeking to understand the behavior and performance of systems [13]. This is primarily attributed to its heightened effectiveness in managing complex and large systems [18]. Discrete Event System specifications (DEVS) offer a rigorous and quantitative framework for the purpose of modelling, simulating, and analyzing dynamic systems across various domains, including engineering, computer science, and operations research [16]. The foundation of this study is rooted on the core principle of conceptualizing DEVS as an assemblage of atomic and composite models, each possessing distinct characteristics in terms of their state and behavior. Atomic models are used to represent the core components of a system, whereas composite models are employed to depict complex systems in a hierarchical manner by merging both atomic and other composite models. The primary theoretical construct explored in this study is the notion of "events" within the DEVS framework. Events are discrete incidents that result in alterations to the states of models. The sequence of events is handled within the context of simulation time. The formal and mathematical framework emphasizes a collection of core notions and logical techniques that enable the representation, analysis, and execution of simulations as discrete time points unfold. The primary components of the mathematical framework utilized in this study are events, state variables, simulation clock, event queue, event-driven modelling, analysis, and visualization. Each event is accompanied with a timestamp that denotes the specific moment at which it is intended to be processed [17]. In the proposed methodology, the state variables serve as representations of the traits or characteristics inherent to the simulated system. The variables undergo modifications in reaction to events and establish the present state of the system at any given moment. The measurement of simulation time is facilitated by a simulation clock, which progresses as events are sequentially processed. The simulation clock ensures that events are executed in a correct sequential manner. The chosen mechanism entails arranging events in an event queue according to their individual timestamps. The event queue assumes the responsibility of preserving the temporal sequence of events, hence enabling the orderly advancement of the simulation [16]. The construction of the models follows an event-driven methodology, wherein changes in the system's state are initiated by events. The models define the effects of events on state variables and determine the timing of event occurrences.

The simulator facilitates the categorization of two traffic light controlled junctions across a road by utilizing a mix of traffic light management standard duration, street level rate of travel of approximately 30 km/h and random number based on probability density function in a triangular probability distribution to simulate the distribution of vehicular traffic over the one-hour simulation period. For normal road use, the study utilizes time delay period of 60 seconds; this time adheres to internationally accepted duration for traffic light delay [12]. The current investigation employs a hybrid approach that combines Event Scheduling and Activity scanning approaches. Every individual event is examined in isolation and assessed according to the distinct relationship between the entity and the resource. The event scheduling approach is notable for its simplicity, while it heavily relies on low-level programming approaches [17].

4. Discrete Event System Specification and Modelling

The Discrete Event System Specification (DEVS) formalism offers a method for defining a mathematical entity known as a model. A conceptual framework is constructed by the utilization of a model to depict and elucidate the workings of a system. In essence, a model has a temporal framework, inputs, states, and outputs, along with algorithms that govern the determination of subsequent states and outputs based on the existing states and inputs. In this study, the utilization of Anylogic Modelling tool, is deployed to facilitate the coordination of communication among the models, time management, and the synthesis of specifications as defined by the modeler. This enables the execution of the model simulation using either the Classic DEVS or the Parallel DEVS formalisms.

4.1. Discrete Event System Specification (DEVS) Formalization

The DEVS model can be classified into two categories: atomic and coupled [24]. The atomic model comprises a collection of states, including an initial state, and encompasses two distinct forms of state transitions: internal and external. Each state is accompanied by a time-advance output, as well as ports that can function as either inputs or outputs [17]. In order to develop the atomic model for this research, the input ports that receive external events are identified alongside the output ports that transmit external events. A set of state variables and parameters is established, consisting of two state variables named "phase" and "sigma." When external events are not present, the system remains in its current phase for a duration determined by the variable "sigma". The specification of the time advance function that governs the timing of internal transitions is provided. This function yields the value of the "sigma" state variable when it is present [23]. The internal transition function, which determines the subsequent state of the system after the time specified by the time advance function has passed, is combined with the external transition function. The external transition function is responsible for determining the system's state changes in response to incoming inputs. The result is the repositioning of the system into a distinct "phase" and "sigma," so preparing it for its subsequent internal transition. During the process of implementation, the computation of the next state relies on several factors, including the current state, the input port, the value of the external event, and the duration this evaluation is limited to the movement of time that has passed in the current state. The confluent transition function is utilized in situations where an input is received concurrently with the occurrence of an internal transition. The default definition involves the application of the internal transition function followed by the application of the external transition function to the resultant state.

Variable Specification

1) Delays (T_d) at junction A and junction C incorporates the standard delay due to traffic light configuration (T_t) plus the varied time of travel of different cars (T_s). Hence for either junction, $T_d = T_t + T_s$.

2) Access to the junctions follows First-In-First-Out order.

3) Delay due to movement of vehicles across the connecting road, B is randomly varied with probability density function sampled across a triangular probability distribution to reflect stochastic vehicular travel dynamics which includes overtaking, drivers' speed discretion, length and breadth of the road, de-

sign of the roads and condition of the road.

4) Maximum capacity of cars that can be on the road at every point is set to 100.

The notations for time and dependent variables used in the simulation are as defined in Table 1.

A total of 20 simulation experiments were performed to evaluate the performance of the system under hypothetical normal use. Vehicular capacity of the road B is set to 100 vehicles at every point in time. All simulations were set to run for 1 hour. Data for the simulation experiment is shown in Table 2 as simulation results of model under hypothetical normal use. Simulation results of a model under hypothetical normal use" in the context of discrete event simulation refers to the outcomes or data generated by running a simulation model when it is subjected to a set of conditions that represent what is considered typical or standard usage in the real-world system being modeled.

In essence, while performing a discrete event simulation aimed at assessing the "simulation outcomes of a model under hypothetical normal utilization," one effectively does the simulation under circumstances that replicate the anticipated typical conditions in the actual system. The outcomes derived from this simulation can function as a fundamental or benchmark for comprehending the expected performance of the system under typical conditions. The data defined in Table 2 holds significant value in facilitating well-informed decision-making processes, enhancing the efficiency of the system, and guaranteeing that the real-world system can effectively fulfil its anticipated performance benchmarks.

The Mean of Simulation Series enables the examination of a more reliable and indicative evaluation of system performance by aggregating outcomes from numerous iterations of simulation.

Table 1. List of variables.

Variable	Description
T	Total duration of the simulation
Tm	Average time spent by vehicles in the model
Ta	Time spent on junction A
Tb	Time spent on connection road B
Tc	Time spent on junction C
Ne	Number of vehicles to enter model during simulation
Na	Number of vehicles on junction A
Nb	Number of vehicles on junction B
Ne	Number of vehicles on junction C
Xe	Number of vehicles to exit the model
N	Total number of vehicles in the model

Table 2. Simulation results of model under hypothetical normal use.

Exp.id	Cars in the Model					Efficiency (%)
	Ne	Na	Nb	Nc	Xc	
1	55	1	0	0	54	98.18
2	54	3	0	1	50	92.59
3	63	8	0	1	54	85.71
4	55	6	0	1	48	87.27
5	54	2	0	1	51	94.44
6	62	12	0	1	49	79.03
7	49	1	0	1	47	95.92
8	46	1	0	0	45	97.83
9	52	2	0	0	50	96.15
10	59	2	0	1	56	94.92
11	73	15	0	1	57	78.08
12	54	2	0	0	52	96.30
13	65	8	0	1	56	86.15
14	65	6	0	1	58	89.23
15	67	8	0	1	58	86.57
16	78	20	0	1	57	73.08
17	61	4	0	1	56	91.80
18	77	18	0	1	58	75.32
19	49	2	0	1	46	93.88
20	80	22	0	1	57	71.25

4.2. DEVS Models Simulation and Results

The simulation models how vehicles travel through the two junctions. As well as how all vehicles integrate with the road network and traffic light delay systems over a period of one hour (3600 seconds). This evaluation is limited to the movement of automobiles only consequently, all other forms of mobility within the road model are disregarded.

The purpose of the simulation is to evaluate the implication of variable time delays across the two junctions on vehicular traffic in **Figure 1**. The simulation incorporates various scenarios, including: 1) the arrival of a vehicle at the traffic light controlled junctions, either when the road is clear or when the vehicle joins a queue; 2) vehicles entering the junction only after the preceding vehicle has exited; 3) vehicles accessing the junctions according to the First-In-First-Out (FIFO) principle; 4) the average speed of travel is set to street limit of 30 km/h; 5) the duration spent on each junction due to vehicular speed is based on the

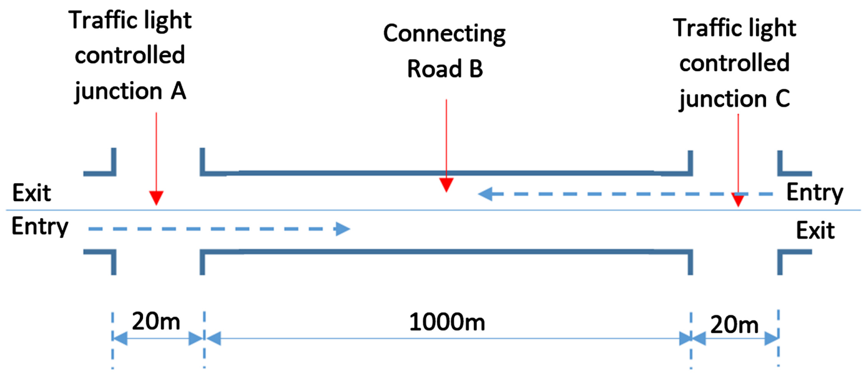

Figure 1. Single-lane synchronized dual-traffic light intersections.

sum of delay due to traffic light timing and a random variable with Probability Density Function (PDF) spread across triangular probability distribution; 6) the duration that vehicles spend between each junction being a random variable, with a PDF spread across triangular probability distribution. Access to the junctions is FIFO based while road use dynamic is stochastic, with considerations to vehicular overtaking. The variables representing the constraints are explicitly defined as;

The simulation experiments focused on the relationship between the cars driving through the road model (**Figure 2**), applying the variables defined for the simulation Ne, Na, Nb, Nc, and Xc and their corresponding time factors, Tm, Ta, Tb and Tc (**Table 1**). The simulation is based on the premise that traffic rules are same and the traffic signal layout is identical on both sides of the road. This assumption is made in order to obtain equivalent simulation results for both sides. Therefore, the assessment is restricted to the movement on one side of the road.

The model as presented in **Figure 3** above, is broken into three main event points, Junction A, Connecting Road B and Junction C. The event points are represented by a combination of a delay object and a queue object. The queue represents the number of vehicles at the particular event point while the delay component models the average duration the vehicles may spend at the event point.

Compression of equal times is defined as follows;

Tea = Tab = Teab,

Teb = Tac = Teac.

The simulation was carried out in two phases and for five different scenarios.

Phase 1:

1) Evaluation of the model under hypothetical normal condition.

2) Evaluation of the model under hypothetical normal condition whilst varying the delay (Tb) due to time spent on the road B.

Phase 2:

1) Evaluation of the model when the time spent on junction A is less than time spent on junction C: Tac < Tab.

Figure 2. Road model channel evaluated.

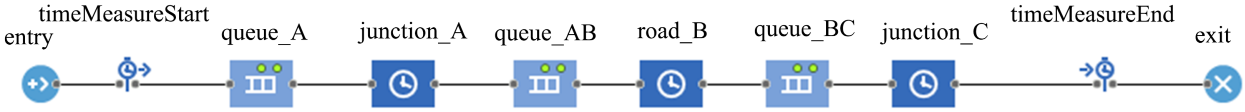

Figure 3. Anylogic software model of evaluated road lane.

2) Evaluation of the model when time spent on junction A is greater than time spent on junction C: Tab > Tac.

3) Evaluation of the model when time spent on junction A is equal to time spent on junction C: Tab = Tac.

Phase 1a: Simulating the model under normal use:

The under listed considerations were considered for the initialization of the model variables.

Length of road (L) = 1000 m

Traffic light stop time = 60 seconds

Traffic light move time = 60 seconds

Movement across road B is stochastic at average speed of 30 km/h

Based on the above considerations, the time variables were set as follows,

Tb = triangular (1.06, 1.33, 1.6) seconds;

Ta = triangular (60.036, 60.04, 60.044) seconds;

Tc = triangular (60.036, 60.04, 60.044) seconds.

Figure 4 shows AnyLogic's DEVS-based simulation approach for modelling and analyzing the time spent on junctions and connections in a traffic simulation. This is valuable for determining traffic behavior for road network optimization, and making data-driven decisions for transportation planning and management. The efficiency distribution of a model under normal use shown in Figure 5 provides a comprehensive view of how well the model performs in real-world scenarios, considering both average performance and the variation in performance across different tasks and inputs. The determination of the mean of vehicles in the model (Figure 6) was conducted by executing the simulation for a duration of 1 hour. The number of vehicles was recorded at consistent intervals throughout this period, and subsequently, the average of these recorded values was computed. This analysis offers valuable insights into the movement of vehicles, patterns of congestion, and a useful metric for evaluating and enhancing the efficiency and capacity of the systems.

Phase 1b: Simulating the model whilst varying Tb:

The under listed time variables were used for the simulation.

Based on the above considerations, the time variables were set as follows,

Ta = triangular (60.036, 60.04, 60.044) seconds;

Tc = triangular (60.036, 60.04, 60.044) seconds.

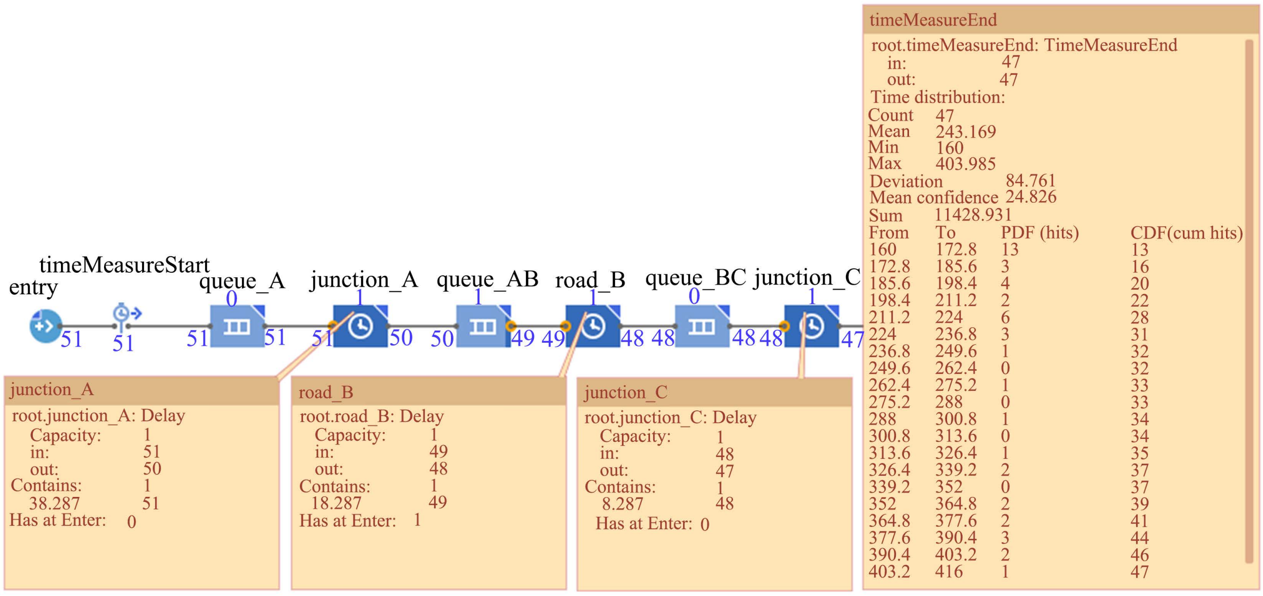

Figure 4. Anylogic DEVS simulation for Ta = Tb.

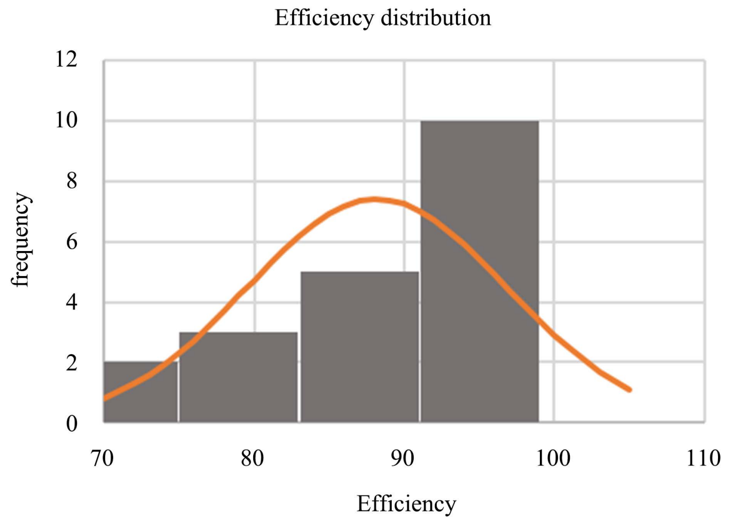

Figure 5. Efficiency distribution of model under normal use.

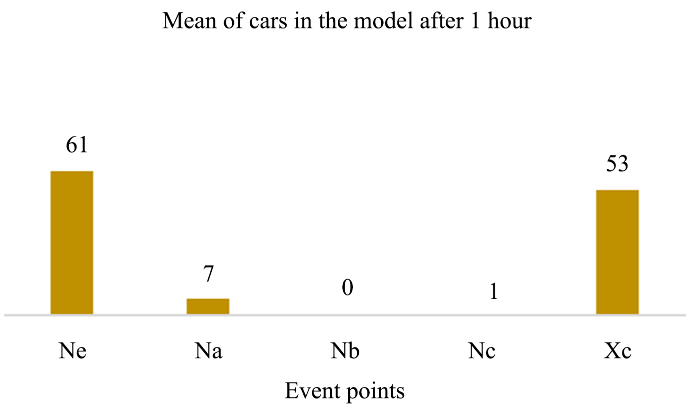

Figure 6. Mean of vehicles in model after 1 hour.

Series 1: Tb is approx. 90% less than normal; Tb = triangular (0.013, 0.133, 0.146) seconds;

Series 2: Tb is set to normal; Tb = triangular (1.06, 1.33, 1.6) seconds;

Series 3: Tb is 90% more than normal; Tb = triangular (2.27, 2.527, 2.78) seconds;

Series 4: Tb is 300% more than normal; Tb = triangular (3.59, 3.99, 4.39) seconds.

Ten simulations were run for each series.

Applying the Mean of simulation series for varying Tb (Table 3), the model did not indicate any substantial drop in efficiency even as Tb increased. Irrespective of uniformity in variance at lower and higher ends of the Tb with respect to the normal values of (1.06, 1.33, 1.6) seconds.

Phase 2 Simulations:

These simulations evaluate the performance of the model over three different categories of experiments. The images Figures 7-10 present the mean performance of the model at different event points throughout the experiments.

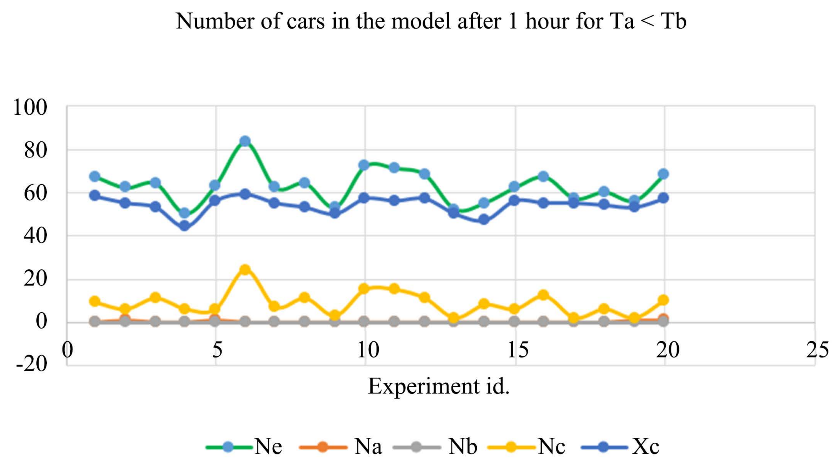

Figure 7. Cars in model after 1 hour for Ta < Tb.

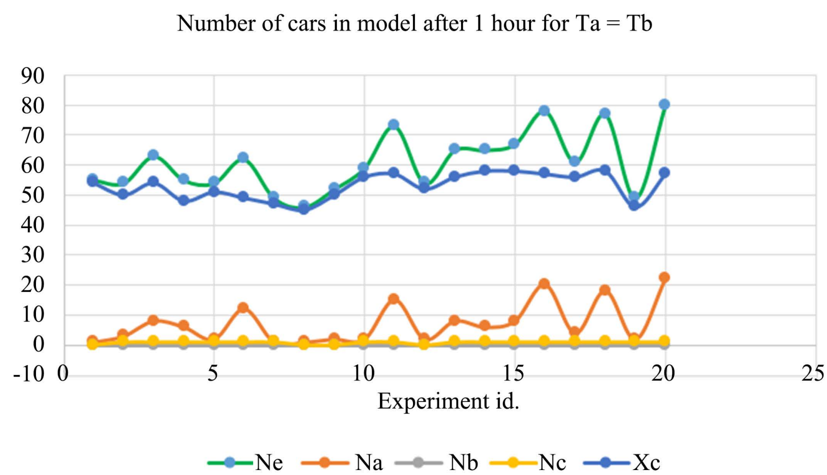

Figure 8. Cars in model after 1 hour for Ta = Tb.

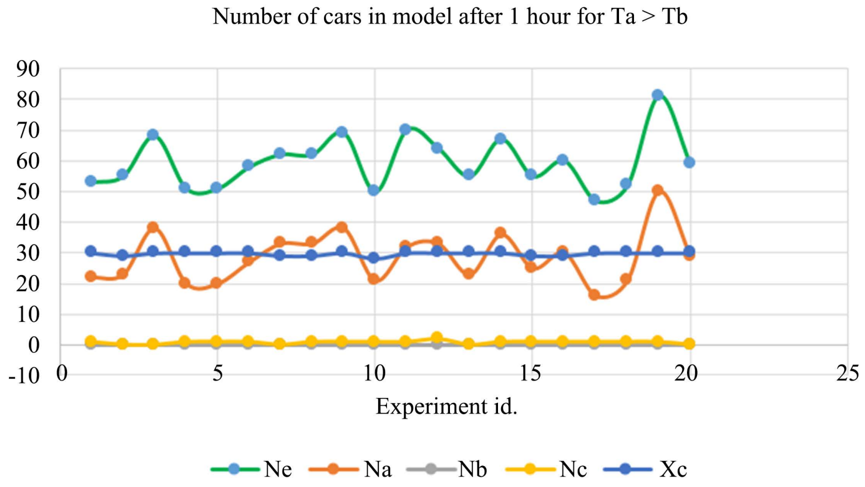

Figure 9. Number of cars in model after 1 hour for Ta > Tb.

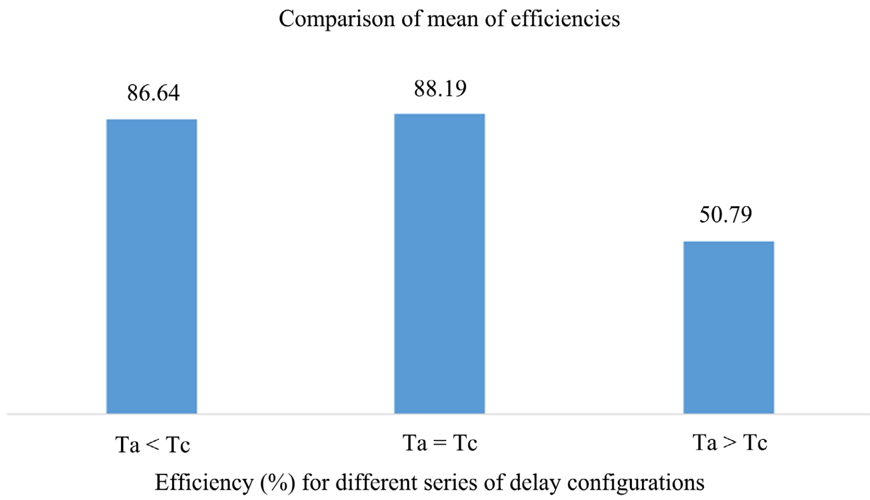

Figure 10. Comparison of mean of efficiencies.

Table 3. Mean of simulation series for varying Tb.

Series mean values	Tb (seconds)	Ne	Na	Nb	Nc	Xc	Efficiency (%)
Series 1	(0.013, 0.133, 0.146)	62.8	7.6	0	1	54.2	86.59
Series 2	(1.06, 1.33, 1.6)	60.9	7.15	0	0.8	52.93	88.19
Series 3	(2.27, 2.53, 2.78)	59.6	5.6	0	0.8	53.2	89.76
Series 4	(3.59, 3.99, 4.39)	64.1	8.6	0.1	1	54.3	85.67
Mean of Means		61.85	7.24	0.025	0.9	53.66	87.55

As Ta increased, efficiency was observed to drop. For experiments carried out within Ta < 45 secs, efficiency remained relatively stable. Hence the efficiency was not necessarily affected by variance between Ta < Tc, Ta = Tc, and Ta > Tc; but mainly by increasing Ta.

5. Discussion of Findings

Key deduction from the simulation is that higher delays at the point of entry had a disproportionate effect on the efficiency of the model when compared to delay at the point of exit. Also increased time delay on the connecting road B had little or no effect on the mean efficiency of the model after a one-hour period of simulation. As Ta increased above Tc, there is a substantial disruption of traffic efficiency enough to undermine road use optimization measures related to the connecting road network. Hence the implication of road design, speed limit and other road management measures on the connecting road are significantly weakened.

The majority of contemporary traffic lights employ three main types of control systems: pre-timed traffic lights, sensor-based traffic lights, and countdown timer-equipped traffic lights [23]. Irrespective of the approach taken, having in-depth information of the implication of different timing configurations on the road network in invaluable for traffic managers. This study provides an insight into the implication of delays at different traffic light-controlled junction on the overall quality of road use. As a result, the facilitates the generation of more precise outcomes in predictive road use management [26]. This study therefore deduces that optimal traffic signal timing is can be characterized by proper delay management at both the points of entry and exit; especially in short road networks of approximately 1 km.

The presence of traffic congestion on roadways is a significant contributing factor to the diminished productivity and declining standards observed in contemporary urban areas [23]. This research presents an innovative method for managing traditional traffic control through the utilization of a Discrete Event Simulation-based strategy.

6. Conclusion

The simulation highlighted the capacity of Discrete Event simulation to reveal underlying details of a system. The model accommodates stochastic vehicular movement dynamics inherent in typical single roads connected across two traffic light-controlled junctions. It therefore highlights the DES approach's invaluable ability for evaluation of stochastic systems. Simulations like this can therefore be used to make critical road design and traffic light configuration decisions. The study employed parallel and distributed DEVS methodologies to analyze the circumstances and requirements of travel through a single road network across two traffic light-controlled junctions. The objective was to evaluate underlying factors that may constrain the exit of at least 90% of the cars that entered the model during a one-hour simulation period. The utilization of Anylogic simulation software facilitated the assessment of both the anticipated mobility dynamics and the underlying factors that influence efficient flow of traffic. Whilst the model revealed the significant effect of increased delay times at point of entry, it does not make a definite statement against striking a balance between road design and efficient traffic light management configurations. This is especially because the model does not include internal exits within the connecting road. Additional study is therefore required in this area.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Abohashima, H., Gheith, M. and Eltawil, A. (2020) A Proposed IoT Based Smart Traffic Lights Control System within a V2X Framework. 2020 2*nd Novel Intelligent and Leading Emerging Sciences Conference* (*NILES*), Giza, 24-26 October 2020, 338-343. https://doi.org/10.1109/NILES50944.2020.9257874

[2] Benzaman, B. and Pakdamanian, E. (2019) Discrete Event Simulation of Driver's Routing Behavior Rule at a Road Intersection. 2019 *Winter Simulation Conference* (*WSC*), National Harbor, 8-11 December 2019, 1801-1812. https://doi.org/10.1109/WSC40007.2019.9004870

[3] Benzaman, B. and Sharma, D. (2017) Discrete Event Simulation of a Road Intersection Integrating V2V and V2I Features to Improve Traffic Flow. 2017 *Winter Simulation Conference* (*WSC*), Las Vegas, 3-6 December 2017, 3054-3065. https://doi.org/10.1109/WSC.2017.8248026

[4] Chiacchio, F., Iacono, A., Compagno, L. and D'Urso, D. (2020) A General Framework for Dependability Modelling Coupling Discrete-Event and Time-Driven Simulation. *Reliability Engineering & System Safety*, **199**, Article ID: 106904. https://doi.org/10.1016/j.ress.2020.106904

[5] Collins, A.J., Sabz Ali Pour, F. and Jordan, C.A. (2023) Past Challenges and the Future of Discrete Event Simulation. *The Journal of Defense Modeling and Simulation*, **20**, 351-369. https://doi.org/10.1177/15485129211067175

[6] Essien, J. and Uloko, F. (2023) Intelligent 3-Way Priority-Driven Traffic Light Control System for Emergency Vehicles. *Open Journal of Applied Sciences*, **13**, 1207-1223. https://doi.org/10.4236/ojapps.2023.138095

[7] Sumaryo, S., Halim, A., Ramli, K. and Joelianto, E. (2019) Queueing Theory Based Accelerated Traffic Discharging Model in Front of Emergency Vehicle on Intersection. *International Journal of Vehicle Autonomous Systems*, **14**, 213-238. https://doi.org/10.1504/IJVAS.2019.099829

[8] García-Nieto, J., Alba, E. and Olivera, A.C. (2012) Swarm Intelligence for Traffic Light Scheduling: Application to Real Urban Areas. *Engineering Applications of Artificial Intelligence*, **25**, 274-283. https://doi.org/10.1016/j.engappai.2011.04.011

[9] McCrea, J. and Moutari, S. (2010) A Hybrid Macroscopic-Based Model for Traffic Flow in Road Networks. *European Journal of Operational Research*, **207**, 676-684. https://doi.org/10.1016/j.ejor.2010.05.018

[10] Frough, O., Khetwal, A. and Rostami, J. (2019) Predicting TBM Utilization Factor Using Discrete Event Simulation Models. *Tunnelling and Underground Space Technology*, **87**, 91-99. https://doi.org/10.1016/j.tust.2019.01.017

[11] Sharma, P. (2015) Discrete-Event Simulation. *International Journal of Scientific & Technology Research*, **4**, 136-140.

[12] Spall, J.C. and Chin, D.C. (1997) Traffic-Responsive Signal Timing for System-Wide Traffic Control. *Transportation Research Part C: Emerging Technologies*, **5**, 153-163.

https://doi.org/10.1016/S0968-090X(97)00012-0

[13] Ullrich, O. and Lückerath, D. (2017) An Introduction to Discrete-Event Modeling and Simulation. *Simulation Notes Europe*, **27**, 9-16. https://doi.org/10.11128/sne.27.on.10362

[14] Wainer, G. (2019) Traffic Modeling and Simulation: A Devs Library. *Proceedings of the* 2019 *Summer Simulation Conference*, Berlin, 22-24 July 2019, 1-11.

[15] Zhang, Y., Cassandras, C.G., Li, W. and Mosterman, P.J. (2019) A Discrete-Event and Hybrid Traffic Simulation Model Based on SimEvents for Intelligent Transportation System Analysis in Mcity. *Discrete Event Dynamic Systems*, **29**, 265-295. https://doi.org/10.1007/s10626-019-00286-w

[16] Essien, J. (2023) Enhancing Feature Discretization in Alarm and Fire Detection Systems Using Probabilistic Inference Models. *Journal of Computer and Communications*, **11**, 140-155. https://doi.org/10.4236/jcc.2023.117009

[17] Essien, J. and Chimezie, C. (2023) Ultrasonic Sensor-Based Embedded System for Vehicular Collusion Detection and Alert. *Journal of Computer and Communications*, **11**, 44-57. https://doi.org/10.4236/jcc.2023.118004

[18] Abas, Z.A., Ee-Theng, L., Rahman, A.F.N.A., Abidin, Z.Z. and Shibghatullah, A.S. (2015) Enhanced Scheduling Traffic Light Model Using Discrete Event Simulation for Improved Signal Timing Analysis. *ARPN Journal of Engineering and Applied Sciences*, **10**, 8135-8140.

[19] Wang, N., Tang, L. and Pan, H. (2017) Effectiveness of Policy Incentives on Electric Vehicle Acceptance in China: A Discrete Choice Analysis. *Transportation Research Part A*: *Policy and Practice*, **105**, 210-218. https://doi.org/10.1016/j.tra.2017.08.009

[20] Gunagwera, A. and Zengin, A.T. (2022) A Longitudinal Inter-Vehicle Distance Controller Application for Autonomous Vehicle Platoons. *PeerJ Computer Science*, **8**, e990. https://doi.org/10.7717/peerj-cs.990

[21] Gregurić, M., Mandžuka, S. and Vidović, K. (2020) Advanced Applications for Urban Motorway Traffic Control. In: Karabegović, I., Eds., *NT* 2019: *New Technologies*, *Development and Application II*, Springer, Cham, 395-400. https://doi.org/10.1007/978-3-030-18072-0_45

[22] Yang, M., Ai, B., He, R., Chen, L., Li, X., Li, J., Zhang, B., Huang, C. and Zhong, Z. (2019) A Cluster-Based Three-Dimensional Channel Model for Vehicle-to-Vehicle Communications. *IEEE Transactions on Vehicular Technology*, **68**, 5208-5220. https://doi.org/10.1109/TVT.2019.2911929

[23] Cheng, S., Li, L., Chen, X. and Wu, J. (2020) Model-Predictive-Control-Based Path Tracking Controller of Autonomous Vehicle Considering Parametric Uncertainties and Velocity-Varying. *IEEE Transactions on Industrial Electronics*, **68**, 8698-8707. https://doi.org/10.1109/TIE.2020.3009585

[24] Werth, B., Pitzer, E., Backfrieder, C., Ostermayer, G. and Affenzeller, M. (2019) Surrogate-Assisted Microscopic Traffic Simulation-Based Optimisation of Routing Parameters. *International Journal of Simulation and Process Modelling*, **14**, 223-233. https://doi.org/10.1504/IJSPM.2019.101006

[25] Bento, L.C., Parafita, R., Rakha, H.A. and Nunes, U.J. (2019) A Study of the Environ-Mental Impacts of Intelligent Automated Vehicle Control at Intersections via V2V and V2I Communications. *Journal of Intelligent Transportation Systems*, **23**, 41-59. https://doi.org/10.1080/15472450.2018.1501272

[26] Salimifard, K. and Ansari, M. (2013) Modeling and Simulation of Urban Traffic Signals. *International Journal of Modeling and Optimization*, **3**, 172-175. https://doi.org/10.7763/IJMO.2013.V3.261