Title

Intelligent Traffic Signal Control for Signalized Intersections

Introduction

Traffic congestion poses a significant problem in both developing and developed countries. There are numerous downsides caused by traffic congestion, the most prominent of which is traffic delays (Bull et al., 2003; Falcocchio & Levinson, 2015). It is an area of concern for many a person, who has to drive through congested roads, as this can affect work productivity, efficiency, and energy levels. This problem is primarily due to the high use of vehicles on roads, driving behaviors, and traffic light management systems. The traffic light management system is crucial toward controlling vehicle movement at intersections. Unfortunately, unorganized systems can cause traffic congestion, as they cannot respond to sudden changes in real-time traffic fluctuations adaptively, or dynamically (Bull et al., 2003; Falcocchio & Levinson, 2015).

Advancements in science and engineering technology have rendered our lives much more manageable, as computers have become much more accessible. They help research solutions by equipping machines with human intelligence and sensors, to operate with or without human supervision, based on artificial intelligence (AI), and various other sub-areas such as robotics, medical applications, and gaming technologies (Akhtar & Moridpour, 2021; Jacome et al., 2018; Koukol et al., 2015; Wang et al., 2018). Thus, intelligent solutions in transportation systems are a must, especially for controlling traffic signals to dynamically respond to traffic demand in real-time. Recently, many research works have attempted to improve transportation systems, either via improvements on the vehicles themselves, or through the transportation infrastructure (Jia et al., 2018). Traditional methods often cannot yield satisfactory results, as the model cannot work precisely due to insufficient information, or limitations in the inherent control system.

All of the signal timing parameters under traditional traffic signal controls (TTSC) rely on an iterative cycles, and thus have a limited response to cope with traffic demands. No action is taken when there are no vehicles nearby. When the traffic is beyond control and is not adequately timed, a traffic officer is deployed at the intersections to ease the traffic flow, especially during peak hours. However, it is costly and inefficient to have traffic officers manage traffic congestion. Hence, traffic management must tackle conventional traffic signal control problems and deficiencies through integration of intelligent traffic signal control (ITSC).

In this work, a novel ITSC model is suggested in reference to the combination of fuzzy logic and probabilistic methods, such as Bayesian networks (BNs). The aim of the suggested model is to decrease the wait time and loss of time for motorized vehicles, or vehicles at road intersections under a mixed traffic demand setting. Another aim is to make good use of the features of rule-based and predictive reasoning in ITSC for predicting traffic flow levels, especially during peak hours. The suggested model is divided into two sections. The first section of the suggested model consists of two modules; next phase module (NPM), and the green phase module (GPM). These two modules utilize fuzzy logics. The second section of the suggested model employs a defuzzification crisp output from the two aforementioned modules, as an input variable for a BN, to decide whether to continue with the green state or phase, or to swap to a new state or phase, based on the level of traffic urgency from the two aforementioned crisp output modules. This section is known as the selection module (SM). Subsequently, the proposed model was be compared to the traditional traffic signal controls (TTSC) relay using an iterative cycle model (fixed-period), and evaluating it using an open source road simulation from the SUMO simulator.

Objective

The first research objective aims to investigate two popular intelligent control methods associated with probabilistic reasoning, namely, fuzzy logic control (FLC), and Bayesian networks (BNs), which are generally under the smart traffic system and traffic light control systems (TLCSs). An in-depth examination of the current applications and design specifications in traffic light technology is needed. The capability of the FLC and BN control methods in the field of the intelligent transportation system are thoroughly investigated. The critical parameters involved in the performance evaluation between ITSC and TTSC are then extracted. The questions for the first objective are summarized as follows:

Q1: What is the purpose of using fuzzy logic control and Bayesian networks for probabilistic reasoning across intelligent transportation systems and traffic management?

Q2: How are fuzzy control logic and Bayesian networks currently designed in literature?

Q3: What are the essential features involved in evaluating intelligent traffic signal control and traditional traffic signal controls?

The second research objective aims to combine both the aforementioned methods of probabilistic reasoning in an ITSC application that explicitly explains the inferential process by integrating the FLC and BN to a lower the wait time and time loss with regards to the motorized vehicles, or vehicles at road intersection under a mixed traffic demand setting. The inputs were selected based on the practical applicability setting of the green phase duration. The green phase durations decision was based on the level of traffic urgency from the NPM and GPM. The designed ITSC (based on two methods of probabilistic reasoning) were evaluated using the microscopic road traffic simulation software, SUMO. The questions for the second objective are summarized as follows:

Q4: Among the valuable inputs in traffic conditions, which inputs are characterized by their practical applicability?

Q5: What type of network topology is used for evaluating the proposed method?

Q6: How can the fuzzy logic control and Bayesian networks be comprehensively integrated in a detailed manner?

Problem Statement

Traffic lights are an essential technical tool for monitoring and managing vehicle traffic flows during intersection congestion. The aim is to regulate the smooth passing of vehicles to reduce traffic congestion. The current traffic light control system is based on TTSC. Although TTSC has advantages, it also creates several challenges, especially during peak hours. This occurs due to the nature of traffic flow, which is unpredictable, and occurs randomly. TTSC is ineffective when handling sudden traffic volumes, and generally produces a high waiting time for stationary vehicles during peak hours, due to its limited response to address traffic demands. Thus, traffic officers are deployed to overcome this situation based on their experience and intuition. However, this situation proves another weakness of the TTSC, since the officers depend on their own expert judgement to overcome the problem. Furthermore, TTSC has been established and used for many years. Hence, ITSCs are needed to intelligently change the phase signal based on the level of traffic urgency.

Although existing research has reported that ITSC based on FLC shows a much better performance than fixed-period controllers, most recent studies only focused on non-mixed traffic demands. The authors considered passenger cars only, and ignored other vehicles such as lorries, buses, and motorcycles. In mixed traffic demands, traffic flows are diverse, since the roads consists of different vehicles of varying operating characteristics. In addition, due to the lack of discipline on the road lanes, they can occupy any available space across the roads, and unconsciously build up lengthy queues at intersections.

Relevance and Importance of Research

In this section, the scientific research relevance of this study is explained. It contributes to the existing literature in two ways. Firstly, an in-depth literature review on FLC and BN control systems was performed. This literature review provides valuable insights into FLC and BN under the smart traffic systems. It also presents the proposed FLC and BN approaches in the ITSC system. It describes the current design criteria and performance of the FLC and BN in ITSC. It also discusses the essential features involved in creating the ITSC using FLC and BN control systems, such as road traffic simulations, variation network topologies, traffic scenarios, performance metrices, and comparison procedures.

Secondly, the proposed method of ITSC based on the combination of FLC and BN was evaluated using a road traffic simulation for improving traffic signal controls, and then compared with a fixed-period controller. The integration between FLC and BN was found lacking in terms of literature on ITSC. Thus, this work evaluated the performance of this combination for ITSC, in order to improve the traffic signal control systems by means of a road traffic simulation.

Background of the study

Conventional Traffic Light Control Systems

The function of a traffic signal is to safely guide commuters at intersections by controlling the traffic flow via alternating green, yellow, and red signals. In addition, it is also used to reduce stops, delays, and travel duration of the commuters. Traffic flow can be controlled in two ways, namely, signal phasing, and signal timing. In this research, signal timing was considered to operate at the traffic flow of the intersection, by allocating the green time to each approach at these intersections, while considering other users as well.

Before diving further into ITSC, a much closer look at traffic signal timing fundamentals is a must. Cycle length, traffic phase, fixed-period, and vehicle actuated signals are fundamentals of traffic signal timing. A cycle length is a cycle and phase of traffic signals for each direction at an intersection, or, the time period required to complete displaying each phase in one cycle while the signal lasts continuously. A phase is a set of traffic flow movements according to the green light’s intervals during one cycle.

Signal timing may be classified into three types, namely, predetermined period or fixed programmed control (FPC), vehicle triggered control (VTC), and adaptive or intelligent plans (Bajpai & Mathew, 2011; Kamal et al., 2020). FPC operates traffic flow without considering the demands on the road. The drawback of using FPC is that the controller does not follow real-time traffic fluctuations, and there are no green light extensions. VTC is a control method which uses a sensor to detect the presence of incoming vehicles, and changes the traffic signal to allow the outgoing vehicles to pass an intersection. Although the VTC performs better than FPC, VTC timing is short-term, and works only under the limitation of a given range. VTC decision-making is also limited to one direction, and does not cover the whole intersection.

Thus, an adaptive approach was proposed to overcome both control method problems, as the adaptive approach is able to better adapt to sudden real-time traffic changes, and efficiently control the road network traffic. According to Prasetiyo et al. (2015), an adaptive system is needed for optimizing traffic lights at an intersection, since traffic flow fluctuates. ITSC can optimize traffic flow by relying on its responsiveness to dynamically changing traffic signal timings and signal phases, based on the level of traffic demand. In order to minimize delays and reduce time loss and travel time, ITSC algorithms must be able to adjust cycle lengths, or split timing (or phase sequence or offset) of the traffic signals.

During the past few decades, artificial intelligence computing technology (AICT) has been utilized to manage the field of unclear information, also known as probabilistic reasoning. FLC and BN controls are examples of probabilistic reasoning. Thus, a closer look at both control methods is needed in order to understand their current usage, their design specification, and the evaluation methodology involved in the traffic management control system.

Fuzzy Logic Controller Theory

The Fuzzy Logic theory (FLC) enables a controller to mimic human perception and experiences when dealing with uncertainty and randomness of specific applications (Zadeh, 1965, 1968). FLC is classically used with AICT, and has been widely used in research and development across various areas, such as business management, health management, engineering technology, and mathematics and software computing. Moreover, FLC has been used together in numerous fields and demands, such as signals for controlling traffic, robotic control systems, home appliances such as washing machines, business analytics, and health and psychological analytics. The FLC layout is displayed in Figure 1.

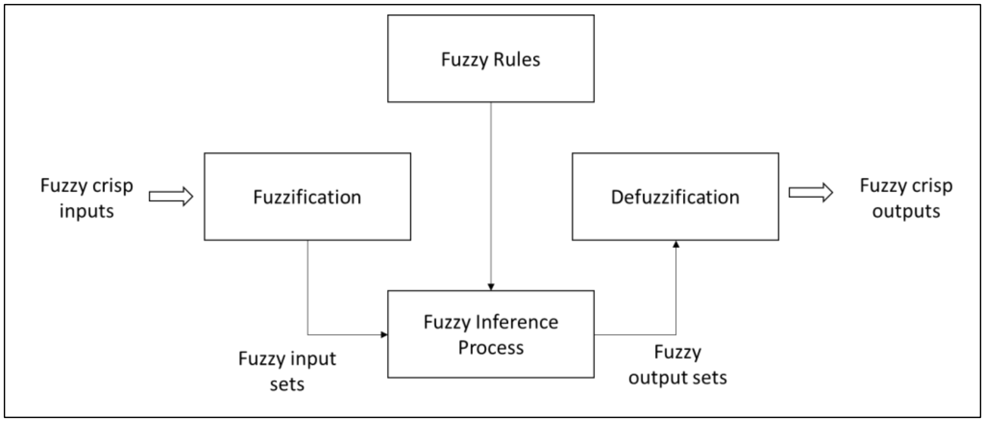


Figure 1 A process layout of fuzzy logic control (FLC).

In the classical set theory or binary logic, an object can be defined by two sets of logic values which are either "true" or "false", known as crisp sets. These crisp sets represent the evidence and outcomes of certain events, such as those in the Bayesian network (BN). However, crisp sets fail to answer uncertainty, since it shows full fellowship. Full fellowship refers to either 0 or 1. For example, the queue length is 150m, and the number of incoming vehicles is 20. FLC is used to express and define the 'uncertainty' by a membership or fellowship function (MF or FF or μ_F), and to decide on whether the components in a vague set are continuous, or discontinuous. In short, MF illustrates the level of truth of uncertain sets in graphical forms (i.e., triangular, trapezoidal, Gaussian, sigmoid, or a bell form), in linguistic terms. MF maps elements to real numbers between 0 and 1 (Zadeh, 1965, 1968). For example, let parameter "F" be a fuzzy group, and "N" a filled-in group (real number). The MF defines them as the point, or level of fellowship of a component "c" in the fuzzy set "F", of which, for every fuzzy number of "N", $\mu_F(c):N\rightarrow[0,1]$ (Zadeh, 1965, 1968). For example, a queue length of about 50m is a member of the medium queue length set, with a level of fellowship of 0.5.

The use of linguistic terms makes this easier to understand, since it allows the FLC algorithm to work based on human perception, as compared to other intelligent methods such as neural networks. Secondly, the processing stage involves rules and inferential processes which are based on IF (antecedent part), and/or THEN (consequence part) statements. For example, "IF the (queue length is very small), and the (number of incoming vehicles is very low), THEN the (extend level is short)”. The rule-based method can be developed using expert knowledge or trial-and-error, or automatically-generated using genetic or neural algorithms.

Lastly, the fuzzy set inputs generated during the processing stage are then changed into a crisp number. This is known as the defuzzification stage. This stage aims to identify a real number as a typical of the fuzzy number, with any developed defuzzification method (Hooda & Raich, 2017; Ross, 2010).

Bayesian Network Theory

The Bayesian Network (BN) Theory represents the cause and effect probabilistic relationship via graphical topology, and expresses the level of uncertainty domain, by way of a conditional probability table (or CPT) (Akhtar & Moridpour, 2021; Kjærulff & Madsen, 2008).

The graphical topology is by way of a directed acyclic graph (DAG). The network is formed from arcs and nodes, as displayed in Figure 2. Random variables represent the nodes and arcs (or links) that show the influences, or direct connections between the associated variables (causal connections). The random variables can be either discrete, or continuous values. Discrete variables are countable values, and in the form of integer numbers. For instance, the value of transportations arriving at a crossroad counts 50 vehicles. Continuous variables are measurable values within a certain range, and can take any type of value, such as integer or decimal formats. For example, the queue length, or traffic jam length, can be any value within the assigned range of the lane area detector between 0 to 100. For example, the value of queue length at an intersection measures 55.5 meters.

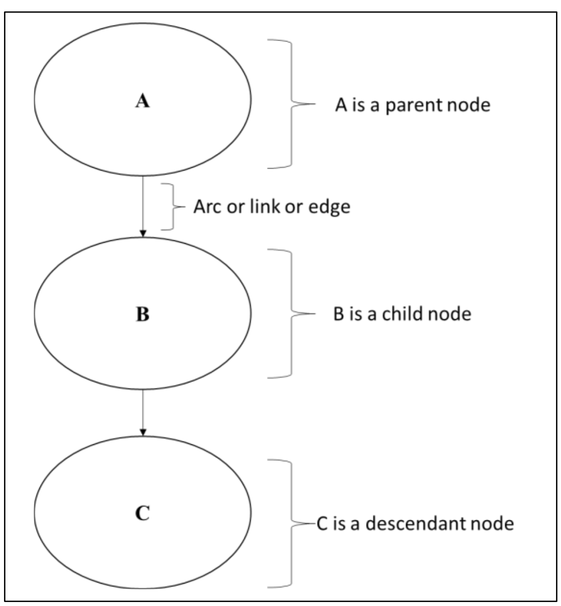
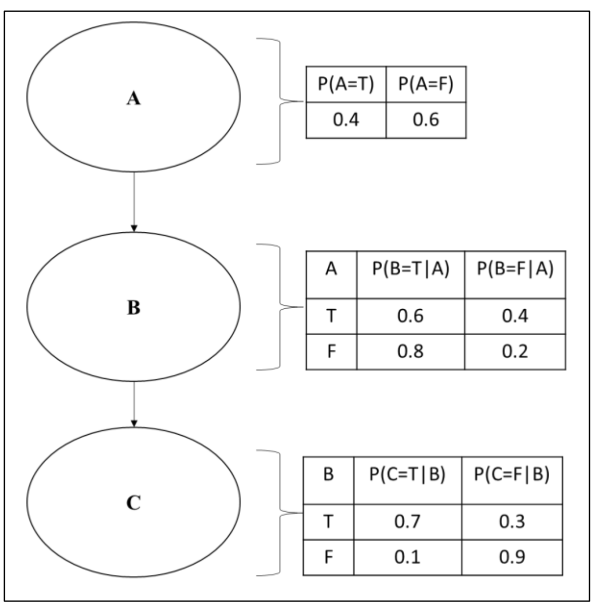


Figure 2 The simple causal topology of a BN.

BN comprises three main topologies; causal chains, common causes, and combined effects. Figure 2 depicts an example of a causal chain topology. The second event is the cause of the first event, which in turn, causes the third event. The BN model can be either qualitative or quantitative. The network topology can be explained using a family analogy to show the qualitative relationship between the corresponding variables. For example, the figure 2 shows the nodes represented as a "parent" is associated with node A, and the node represented as a "child" is associated with node B. The "parent" node is determined to be node C, which is a "descendant" of node A. In comparison, node A is the "ancestor" of node C. The arc is directly connected to show the direction of the effect and is only directly connected if the random variables residing in the parent node acts as a catalyst for the other node.

The next step is to specify the conditional probability distribution (or CPD) for each node in the BN, as displayed in Figure 3. This step is known as a qualitative relationship. This relationship can be displayed by way of CPT. Firstly, the prior probabilities of all original causes (root or parent nodes) need to be determined. Secondly, all probability values of each child nodes are identified. Then, all the possible outcomes of those parent nodes are recombined. All possible outcomes must sum up to 1. The conditional independence in Figure 3 is P(Node_C | Node_A, Node_B) = P(Node_C | Node_B). The reasoning in BN can be carried out using two approaches, i.e., diagnostic reasoning and predictive reasoning. Diagnostic reasoning is derived from observations, and updates the 'belief' for each possible outcome (prior probability). Predictive reasoning is based on the information given to new beliefs about such effects, after considering the evidence, and following the directions of the topology links (posterior probability).



P(A=T)	P(A=F)
0.4	0.6

A	P(B=T|A)	P(B=F|A)
T	0.6	0.4
F	0.8	0.2

B	P(C=T|B)	P(C=F|B)
T	0.7	0.3
F	0.1	0.9

Figure 3 The conditional probability table for each node.

After ensuring that the conditional probability distribution is complete, the conditional probability is then calculated using Bayes theorem. Bayes theorem is a mathematical equation that explains the probability of the event being updated based on the provided proof (Downey, 2013). Simply put, this theorem explains the process of learning. There are four important fragments which need to known before calculating the conditional probabilities. Previous paragraphs already mentioned the two fragments, namely posterior, and prior. Further two fragments are the chances of the proof, considering the fact that hypothesis is true (likelihood), and the chances of the proof, in any event (marginal probability). Equation 1 shows the mathematical equation for Bayes theorem, and can be interpreted as follows:

$$P(A|B) = P(B|A) * \frac{P(A)}{P(B)} \quad \text{or} \quad POSTERIOR = \frac{LIKELIHOOD*PRIOR}{MARGINAL\ PROBABILITY} \qquad \text{(Equation 1)}$$

In certain cases, the probability of some events may be unknown, but it is known that the chance of an unknown event occurring is under certain conditional probabilities. Meaning, the group probability of event A_i ($i = 0,1,2\ldots m$) is not directly known, but it can be calculated via a known group probability of countable events (or discrete), B_k ($k = 0,1,2\ldots m$). This phenomenon is known as the total probability rule (Downey, 2013). The rule is related to marginal and conditional probabilities. Thus, the total probability (Equation 2) equation can be interpreted as follows:

$$P(A) = \sum_{k=0}^{m} P(B_k) * P(A|B_k) \qquad \text{(Equation 2)}$$

Bayes equation with the total probability rule can then be reinterpreted as follows:

$$P(B_k|A_i) = \frac{P(B_k)*P(A_i|B_k)}{\sum_{k=0}^{m} P(B_k)*P(A_i|B_k)} \qquad \text{(Equation 3)}$$

Let's go through some simple examples to calculate the conditional probability using Bayes theorem. From Table 1, imagine that there are 100 cars at a car sales.

Table 1 The example of solving problem with Bayes theorem formula

	Expensive	Not Expensive	*Total row values*
New	10	20	30
Not New	30	40	70
Total column values	40	60	100

The conditional probabilities for expensive and non-expensive cars can be calculated using the following the steps below:

- The chance of the car being the new edition is P(New):

  $P(New) = \frac{30}{100} = 0.3$ (Equation 4)

- The chance of the car being expensive is P(Expensive):

  $P(Expensive) = \frac{70}{100} = 0.7$ (Equation 5)

- The chance that the car is new and expensive is P(Expensive | New):

  $P(Expensive \mid New) = \frac{10}{30} = 0.33$ (Equation 6)

- The chance that the expensive car is new P(New | Expensive):

  $P(New \mid Expensive) = \frac{10}{40} = 0.25$ (Equation 7)

- Then, multiply P(New) and P(Expensive | New) together:

  $P(New) * P(Expensive \mid New) = P(New)P(Expensive \mid New)$ (Equation 8)

- Next, multiply P(New) and P(Expensive | New) together:

  $P(Expensive) * P(New \mid Expensive) = P(Expensive)P(New \mid Expensive)$ (Equation 9)

- Compare the two multiplications side by side:

  $P(Expensive)P(New \mid Expensive) = P(New)P(Expensive \mid New)$ (Equation 10)

- Turn them into the Bayes theorem formula as shown in equation 1 to find the probability of P(New | Expensive):

  $P(New \mid Expensive) = P(New) * P(Expensive \mid New) \,/\, P(Expensive)$ (Equation 11)

- Insert the calculated values into the Bayes theorem to find the probability of P(New | Expensive):

  $P(New \mid Expensive) = 0.33 * \frac{0.3}{0.7} = 0.1414$ (Equation 12)

The Example above shows a method to calculate the conditional probability using Bayes theorem via fractions. From this example, it can be concluded that the values of the variables must be known from expert knowledge, or trial-and-error. In addition, the calculation can be more difficult or complex, if many variables are involved in some events, and the complexity of the designed network.

Literature Review

Fuzzy Logic Type-1

Fuzzy logic control has been actively used in improving ITSC, as the rule-based method is a plausible choice for controlling traffic uncertainties (Jacome et al., 2018; Singh et al., 2013; Wang et al., 2018).

During the early stages of designing an adaptive traffic light control system, research works only focused on type-1 of fuzzy logic. In 2015, an ITSC model using the fuzzy control approach was proposed, which was fit for adapting the inconsistencies of the arriving group of motorized vehicles, by optimizing the green signal timing switching scheme (Adam et al., 2014). The proposed model had less vehicles waiting at a junction, which contrasted the fixed-period control scheme. Another model of ITSC using fuzzy logic control was designed to optimize traffic signals for reducing the waiting time at a four-way intersection, with the right and left directions for each lane (Ibrahim & Aldabbagh, 2016). The proposed method showed promising results, with the reduction of the mean time to wait of passenger cars being between 2 to 20%, which was in contrast with the fixed-period control. Babangida, Peter, and Luhutyit (2017) designed an ITSC model using a fuzzy inference system for an isolated three-lane intersection, busing U-turn directions, which aimed to reduce the traffic congestion, such as vehicle delays in the traffic network. The proposed model was conducted using three different approaches of oversaturation, and the results showed an improvement of 65.35% compared to fixed-time control. AlNaser and Hawas (2019) demonstrated an optimum current-period traffic light control utilizing the fuzzy logic method (FLM) for adjusting the split phase at a single intersection with a turning direction. This was tested using two different traffic road simulations; SYNCHRO and FuzzyTech. The FuzzyTech software provided a better optimal solution compared to the SYNCHRO software for any type of traffic flow combination.

In Fuzzy logic control, it is possible to classify it into two groups, i.e., Mamdani and Sugeno (Hooda & Raich, 2017; Ross, 2010). The purpose of the Sugeno Fuzzy method aims to observe the output fellowship functions of green time in a linear or constant form. Some studies attempted to use the Sugeno Fuzzy method in ITSC. Erwan, Oyas, and Selo (2015) presented ITSC using a Sugeno Fuzzy inference system with the aim of reducing the number of vehicle queues, and allowing a high passing rate of vehicles at a single four-way intersections (Prasetiyo et al., 2015). Ria, Graha and Deden (2020) also designed an adjustive traffic signal using the Sugeno fuzzy control approach for a four-way intersection without turning movements, to adaptively determine the period of the green signal linearly by analyzing the density of lanes, such as the number of vehicles, road length, and road width as an inputs (Kartikasari, 2020).

Fuzzy Logic Type-2

However, type-1 fuzzy logic cannot produce a reliable accuracy when there is an expansion in information, which subconsciously increases the amount of regulations, and produces high computational costs (Mittal et al., 2020). Hence, a type-2 fuzzy logic control was designed for ITSC applications to overcome the aforementioned problem by reducing the difficulties of generating the rule-based model without increasing or decreasing the number of rules, and by allowing compatibility with time-variant systems (Akhtar & Moridpour, 2021; Mittal et al., 2020). For example, an ITSC using two-level fuzzy logic control was aimed at the red phase, which needed to be changed to the green phase, based on traffic phase urgency at an intersection lane (Ge, 2014). The performance of the proposed method showed a reduction in the average vehicle delay at three different traffic flows (low, medium, and high), versus the predetermined-time control. A novel fuzzy logic control with two selectors based on three variables was proposed to manipulate green signals for emergency vehicle pre-emption, while halting the interferences with red signals at a single intersection (Homaei et al., 2015). This proposed approach showed lower average delays, and average queue lengths, by comparison with fixed-interval controls. Other than that, a two-stage fuzzy logic which consisted of three components, namely, green signal traffic volume, red signal traffic volume, and option component, was proposed (Su, 2017). The approach showed good performance for the reduction of average delays, effectively optimizing the traffic flow, and responsivity to real-time demands. Furthermore, two primary levels of the ITSC models using fuzzy logic controls at an isolated junction were able to lower the mean delay period, and the queue lengths of the vehicles (Babhulkar, 2018). In another study, a two-phase hybrid system consisting of an ideal, dynamic, and novel eight-stage light signal control method for an isolated junction using a fuzzy controller was planned (Kooykhi & Ekbatanifard, 2018). The designed method consisted of three modules assigned to allocate data gathered using a wireless sensor network attached to the fuzzy controller, which showed a higher efficiency, and lower traffic congestion, but a lower performance for prioritizing emergency vehicles, as opposed to the common two-stage and four- stage systems. However, the overall performance was better than the common two-stage and four-stage systems. An ITSC timer based on three fuzzy logic control models can optimize the green signal duration, and allow a higher passing rate of vehicles at an intersection (Anyakrawati et al., 2018). An ITSC model was designed with three methods, namely, adaption of the state duration, adaption of the state cycle, and adaption of synchronously state durations using fuzzy logic controls (Vogel et al., 2019). Based on the measure of effectiveness (MoE) during normal traffic demand, the adaption of a synchronous state duration and cycle using fuzzy logic control performed much better than the earlier two adaptation methods. However, it performed lower during higher demands, but was still better against predetermined-interval controls. The ITSC using a fuzzy logic control by Joy et al. (2018) handled high emergent traffic flows by prioritizing the lanes with maximum traffic flow in real-time using camera images. The proposed model had less delay time by allocating the time slot depending on the real-time traffic demand. However, using data captured by cameras has significant drawbacks toward the input control system. For example, the camera needs to be installed at different heights at the traffic junction, and is sensitive to environmental conditions such as fog.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

The FLC signal works according to a rule based approach. This rule based approach simulates human perception and decision making by utilizing historical data, and works randomly. The fellowship functions mathematically represent it with some extent of possession to either 1, or 0. The controller's output is also random, preventing ideal results. The controller is also unable to select the rule base adaptively. Hence, an approach was developed based on the integration of FLC and neural networks in traffic signal control applications, known as ANFIS. Prior work (Mathur et al., 2016; Stojčić, 2019) demonstrated that the ANFIS system can adaptively learn from input-output samples gathered using detector devices, and provides a separate output. The model applies neuro-learning rules to determine and regulate the fellowship functions according to the system preferences. The features of fuzzy logic which can transform human knowledge into a rule-based approach for covering up the lack of human interpretability of the neural network is interesting in itself. Seesara and Gadit (2015) proposed an ITSC using an ANFIS model to control the fluctuations in various traffic conditions at an intersection. The data was gathered through an electromagnetic sensor. The sensors count the vehicles passing through the intersection and the incoming vehicles headed towards the intersection. The proposed model tuned the parameters of the fellowship functions and automatically selected the rules based on the traffic conditions, which achieved a low average delay against the fuzzy controller model. A novel ANFIS model using real-time traffic density from the processing image data of CCTVs was proposed too (Awoyera et al., 2019). The model depicted a minimal mean waiting line distance and stop period against fuzzy logic, neural networks, and fixed-time control. Similar research was also presented by Andayani et al. (2019), whereby the duration of a green light at an intersection could be adaptively changed upon the road density and width from the processing of video data. It obtained an accuracy of 98.6%. A combination between an Elman recurrent neural network (RCNN) and fuzzy logic was proposed (Nae & Dumitrache, 2019). This had been effectively lower during the delays of vehicles in current time traffic saturation conditions. The model indicated that the variable changed in the incoming and outgoing paths from the fellowship function of the fuzzy inference process. In normal traffic conditions, the proposed model showed a reduction in waiting time, but this was higher in busy traffic compared to adaptive fuzzy systems and neural networks. However, neural networks showed no improvement under normal traffic, and had a lower delay than adaptive fuzzy systems. Overall, the results by the proposed model were better in performance versus the two compared methods. However, the ANFIS model needed thousands or millions of known input-output labeled samples for matching-up with the trained data in the learning phase to achieve the desired output of the system. Otherwise, the system might be defective, caused by limited information. In this case, a simple algorithm such as a Bayesian network (BN) is a suitable choice when handling limited data, for example, against neural network-based applications such as ANFIS.

Bayesian Networks

Bayesian networks (BNs) possess the likelihood of diagrammatical forms which are accustomed to define the cause and effect relationships over different events via a directed acyclic graph (DAG), and conditional likelihood tables (CPTs) for the prediction, detection, and for providing reasoning, besides offering intuitive insight and decision making under uncertainty and time series predictions (Akhtar & Moridpour, 2021). However, the probabilistic form in traffic systems research is relatively new, and are classified into two main areas. The first area is related to traffic congestion estimation and forecasting, while the second is for accident detection and crash prediction (Akhtar & Moridpour, 2021).

Traffic Congestion Estimation and Forecasting

Afrin and Yodo (2020) explained that traffic congestion is divided into two types, namely, recurring congestion, and nonrecurring congestion. Recurring congestion regularly occurs during the morning and evening rush hours, causing long delays among commuters. Nonrecurring congestion occurs due to unexpected events that lead to sudden changes in traffic volume, such as vehicle incidents, special occasions, road repair and improvement, and harsh weather conditions. It is essential to know the cause of traffic congestion in order to manage it accurately. Kim and Wang (2016) proposed a BN model to identify the leading cause of traffic congestion, and the critical scenarios for traffic prediction, by ranking and prioritizing a systematic framework. The proposed model was capable of predicting and diagnosing the leading causes of traffic congestion accurately.

Traffic Accident Detection and Crash Prediction

Road traffic accidents can occur anytime (Kurebwa & Mushiri, 2019; Touahmia, 2018), primarily due to human behavior on the road (Wangdi et al., 2018). Speeding during a red signal without stopping, or sudden lane changes without any signals are the leading causes of traffic accidents. Thus, enhancing the safety at crossroads has been a prime reason in non-rural traffic systems to help road users arrive safely at their destination. Wyder et al. (2015) proposed a maneuver prediction model based on a naive Bayesian filter algorithm, and right-of-way assessment based on a regression model. The proposed model aims to estimate traffic at all-way stop intersections with various geometries and sizes of these intersection networks. Although the proposed model can be used to classify trajectories correctly, and has a low prediction time of vehicles approaching stop intersections, the model cannot withstand abrupt driver conduct. The proposed prediction model overestimates the prediction time of approaching vehicles by more than a second, due to sudden breaks before approaching the intersection's stop line. A BN probabilistic model was proposed to predict stop-or-go conduct on the basis of ongoing courses measurements from sonar detectors for red-light-running forecast (Chen et al., 2019). This work replaced traditional RLR predictions based on an inductor loop detector with a radar sensor because of the high sampling frequency and non-embedded sensors. It infers that the traffic state at other positions and can obtained using traffic information at any location. The proposed model outperformed the predictors based on the inductor loop sensor, and can reduce potential traffic accidents and improve safety at signalized intersections.

Traffic Flow Estimation and Forecasting

Focusing on time series predictions or real-time predictions alone is insufficient to avoid traffic congestion, since traffic flow constantly evolves through time and space. It is evident to consider upstream flow and other traffic attributes such as volume, density, and speed of flow prediction to divert drivers to a less congested path. Zhu et al. (2016) formed a connection of dependence based on two type of variables, i.e., continuous and discrete, by employing a linear conditional Gaussian by considering speed and information area to increase the forecast accuracy of traffic flow. Jin and Ma (2019) proposed a combination of a BN and a Gaussian regression model for traffic state estimation in different traffic flow scenarios by offline training and online estimation at the signalized intersection according to detector data, and connected car information. Han and Ahn (2021) proposed a model as a reference to the Bayesian Inference (BI) along with Deep Learning (DL) using connected automated vehicle (CAV) data at a headway network to examine the characteristics of every mode under diverse road transports via numerical experiments for traffic flow rate estimation. The proposed model performed reasonably well in high demand scenarios, but had a low performance in low demand scenarios. It had a positive outcome relating to clarity, and low penetration of the likelihood function compared to DL.

Traffic Light Detection and Estimate the Traffic Signal

Traffic lights are an important feature for controlling traffic flow at intersections. However, current traffic lights use fixed cycles, and may cause heavy traffic at intersections. In order to cope with conventional traffic lights such as fixed-time control, several proposed models have utilized BN models for intelligent decision making, estimation of switching times, as well as detection and mapping for traffic lights. Ozatay et al. (2016) presented a computation according to the Semi-Hidden Markov Models (SHMMs) with the help of BBN for tracking the switching time of fixed-time traffic light parameters. The authors developed a model using the Markovian state's sequence to maximize the given probability measurements and parameters to allow the BN to track and update the latest estimations of periods and state durations during the switching time of fixed-time traffic light based on GPS floating car data. However, the proposed method only focused on estimation and tracking of the switching time of fixed-time traffic control, and not on controlling traffic lights adaptively. Hosseinyalamdary and Yilmaz (2017) proposed a model for the detection and mapping of traffic lights using a Bayesian filter to tackle the shortcomings in detecting the geometry of varying-state traffic lights. However, this method only focused on detecting and locating traffic lights, and was not related to traffic light control systems, or for the reduction of traffic congestion. Zhengxing et al. (2020) established a smart solution form for traffic light changes with time according to a dynamic BN. This model structure was constructed using K2 algorithms, and realized the dynamic inference through the fusion of time window and forward backward algorithms based on real-time traffic information. However, the proposed method was not tested under mixed traffic demand conditions, and was only tested across two directions (East to West, and West to East).

Fuzzy-Bayesian Network (FBN)

There is a good probabilistic medium which is good for describing the cause and effect relationship by directing the possible event into an acyclic graph (DAG). It is known as the Bayesian network (BN). Inferences are expressed using CPT. In addition, fuzzy sets are also useful to express human expertise or knowledge in linguistic terms, such as ‘small’, ‘medium’ or ‘high’ in reference to the level of fellowships among fuzzy groups, for better understandability. Thus, there are many techniques to integrate both tools in different types of applications.

For example, FBN can be integrated by comparing the compatibility of existing conditional probability (CP) from across experts with CP created using fuzzy rules for predicting the ecology of a bird’s population affected by railway construction (Liu et al., 2015). The proposed model utilizes three steps for producing workable CPs using the defining compatibility of the antecedent, by setting the level of satisfaction for each rule. Lastly, grouping all suggested findings using the same verbal parameters using the fuzzy tools needs to be carried out. The FBN approach is also capable to solve uncertain problems associated with machine fault diagnosis (Tang & Liu, 2007). The developed method is based on the coefficient method which is obtained by multiplying the probabilities with related fuzzy fellowship values, into one value with a simple network structure. The same approach was adopted for exploring the causal relationships among risk factors of tunnel-induced damage in a broad and detailed manner (Zhang et al., 2016). The developed method is able to cope with multiple state variables, as well as their uncertain causal relationship inferences. This method utilizes fuzzification by defining the fuzzy probabilistic group among the fitting fellowship functions, and is defuzzied using the α-weighted assessment approach. The intended plan assumes the fellowship values as probabilities. Another application which uses the same FBN approach as noted above was also used to estimate the probabilities from the historical frequency of floods (Salinas et al., 2016). The fellowship function was constructed from linguistic terms of historical flood frequency information, and was updated using the observed data with the fuzzy's prior probability distributions.

Summarization from the literature review

The related works above are divided into three categories: FLC, BN and FBN. The related works based on the FLC method can be divided into three sub-categories; Fuzzy Type-1, Type-2, and ANFIS. Most of the present research works only tested the proposed control method under non-mixed traffic demand conditions. Also, they only focus on one type of vehicle, i.e., passenger cars. In addition to that, most researchers gathered traffic information using an inductor loop sensor. This sensor cannot detect vehicles in broad areas along lanes, and directly measures the queue length, or number of vehicles every second.

In research works on BNs, the researchers mainly focus on two main areas; traffic congestion estimation and forecasting, as well as and accident detection and crash prediction (Akhtar & Moridpour, 2021). Other researchers attempted to use the BN method for traffic lights. Ozatay et al. (2016) used the BN method to estimate and track the switching time of fixed-time traffic light parameters, but not to control the traffic light system itself. Hosseinyalamdary and Yilmaz (2017) used the BN method to detect and locate traffic lights unrelated to traffic control signals. Zhengxing et al. (2020) established a smart solution form for the change in the traffic light's time using the dynamic BN method. However, the proposed method only tested two directions (East to West, and West to East).

In the present works on FBN, the combination of FLC and BN can be difficult, as fuzzy fellowship values and probabilities address different uncertainties. The probability concept is a subjective probability, and depends on the likeliness of an event's occurrence, i.e., a value which must sum up to 1. Fuzzy logic uses the fuzzy set fellowship with a certain level of real fellowship value between 0, and 1. The mentioned FBN methods vary from one another because they are accustomed to the various features with different notations, which makes it hard to decide which method is better for solving uncertainty problems. Moreover, the FBN approach is rarely seen in traffic light control management in the literature. Therefore, it can be concluded that the FBN method has not yet been used to control traffic signals.

Thus, this project seeks to implement the FBN method for controlling phase signals based on traffic urgency levels from NPM and GPM. The proposed model consists of two sections. The first section has two sub-sections: NPM and GPM. These two mentioned modules are made up using the fuzzy rule-based approach. In the second section, the proposed model uses the defuzzification crisp output from the two aforementioned modules as an input variable for the BN to choose an option to prolong the green state, or to switch to a new state based on the traffic urgency levels. This section module is known as SM. The FLC and BN are integrated into one value. Subsequently, the model decides which module has a high probability to switch to a new phase, or to continue the green phase. This work aims to lower the time to wait and time loss of vehicles at crossroads under a mixed traffic demand setting. The developed method works against a constant time traffic controller, and was evaluated using an open-source traffic simulation using the SUMO simulator. In addition, a user-friendly Python library, Simpful, was proposed to facilitate the definition, analysis, and interpretation of the fuzzy inference systems (Spolaor et al., 2020).

Methodology

The Designed Modules of Proposed Method

The design structure of the Fuzzy-Bayesian Network (FBN) traffic light controller was made up of three modules, as displayed in Figure 4. The suggested model had three modules, namely, NPM, GPM, and SM. In the first module, the NPM function chooses a red state which is deemed most urgent based on the transport movement of traffic urgency, with the exception of the green state. At the same time, the GPM module only observes the traffic urgency level of green states. Then, the SM decides on whether it needs to change to a new state, or to continue with the green state based on the likelihood of congestion urgency levels from across both modules.

The lane area detector (E2) available in the SUMO simulator, which is similar to a vehicle tracking camera (Gudwin, 2016). It can interpret and convert the captured images into traffic flow data in real-time (Tiwari, 2017). The processed data acts as an input data for the controller. The first reason for the lane area detector was used instead of an inductive sensor, because the lane area detector is able to detect vehicles along broad area along lanes. It directly measures the queue length in meters for every simulation step (or second), as the inductor loop does not have that functionality (Gudwin, 2016). Additionally, the inductor sensor is likely to become damaged due to the state of the road's surface, as it is installed under the road (Chen et al., 2019). Finally, unlike the inductor sensor, the E2 detector can be mounted on a traffic light or along the traffic light's structure.

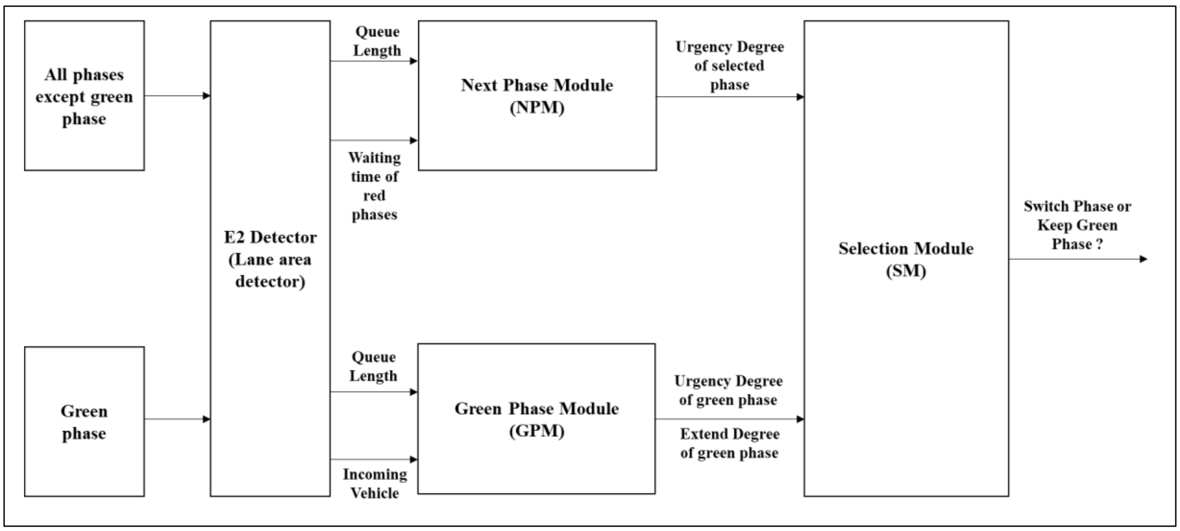


Figure 4 The proposed design structure of ITSC and its three modules: NPM, GPM and SM.

Next Phase Module

This module has two jobs. The first job is to calculate the urgency levels for all states which are not green. The second job is to select all non-green states with high traffic urgency levels.

There are dual entry linguistic parameters, and single outcome linguistic parameters for the NPM unit. The first entry is the queue length, which retrieves the traffic jam's length of vehicles in meters during a red state. The second input is the waiting time of vehicles at each lane in seconds during the red state. An outcome of the NPM is the urgency levels for all non-green states. Thus, the fellowship functions of queue length, waiting time of the red state, and the urgency levels of traffic for all non-green states can be defined as follows. The type of fellowship function shape is used in this project (triangular shape).

The domain or range values of the queue length (x_QueueL) is noted as [0, 100]. There were a total of five fuzzy values, namely, too short (or TSH), short (or SHT), medium (or MED), long (or LNG), and too long (or TLG). The fellowship function of queue length is displayed in

Figure 5. The domain, or range values of waiting time for all current red states (x_RedWaitT) was denoted as [0, 100]. There are five fuzzy values, namely, TSH, SHT, MED, LNG, and TLG. The fellowship function of the waiting time of all current red states is displayed in Figure 6. The domain or range values of traffic urgency (y_Urgency) was [0, 100]. There are five fuzzy values, namely, zero (or Z), low (or LW), medium (or ME), high (or HG), and too high (or TH). The fellowship function of the flow urgency is displayed in Figure 7.

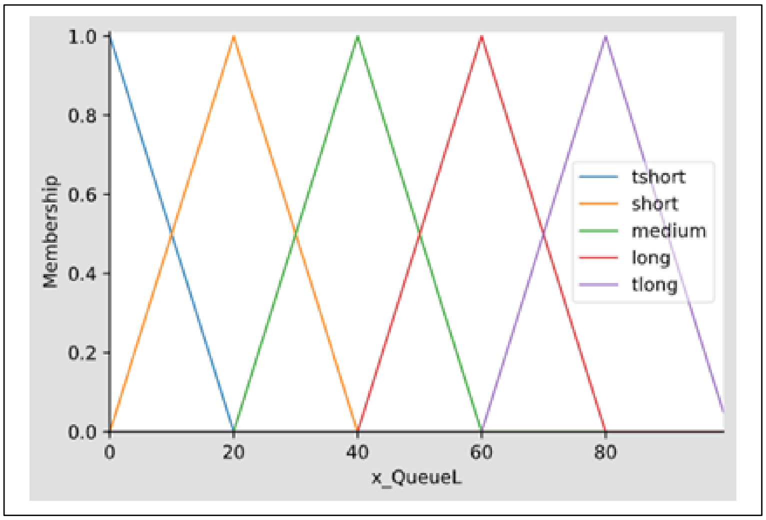


Figure 5 The NPM input fellowship function of queue length.

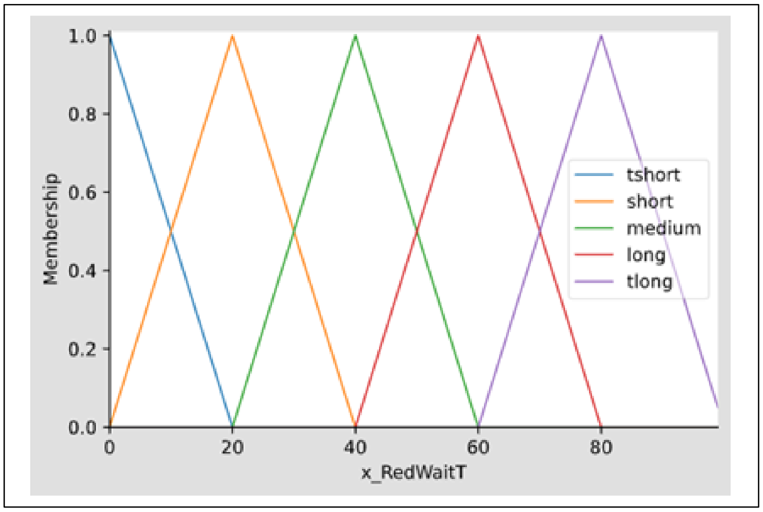


Figure 6 The NPM input fellowship function of waiting time for all non-green phases.

The next step was to express human expertise, or knowledge using a fuzzy order approach by means of the IF-Then rule structure. The set of fuzzy rules were mapped by combining the set of fuzzy rules input to the corresponding output, by configuring them in the matrix structure displayed in Table 2. As previously mentioned, these rules can be expressed in linguistic terms, or in the IF-THEN rule form. For example, “If the queue length of the selected non-green phase is very short, and the waiting time of the selected non-green phase is very low, then the urgency level of the selected phase is zero”. An example of the IF-THEN form is: “IF the selected queue length is too short, AND the waiting time of the selected phase is too low, THEN the urgency level of the selected phase is zero.” The fuzzy inference can be performed using the MAMDANI system, which is better known as the max-min composition. Then, the output fuzzy value from the fuzzy inference process will be converted into a real crisp value output using the defuzzification process through area or center of gravity method, referred to as the centroid method.

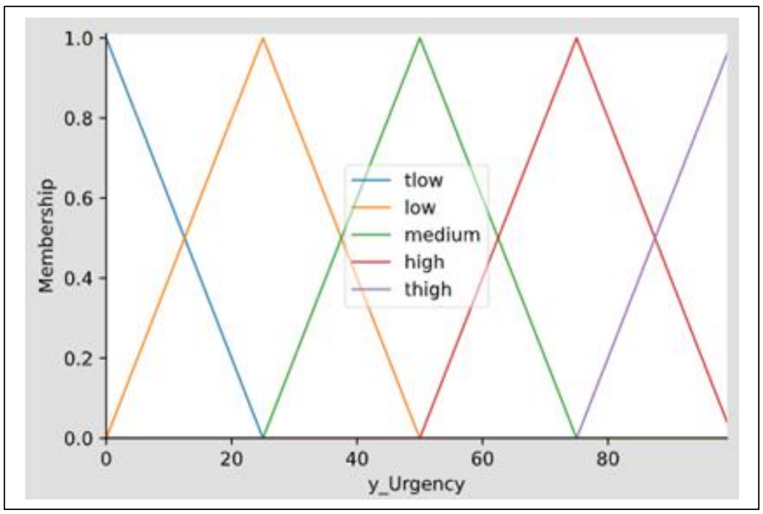


Figure 7 The NPM output fellowship function of road traffic urgency level.

Table 2 The mapping of fuzzy rules in matrix structures for NPM module.

Queue Length (QL)	Waiting time of all phases except green phase (WT)				
	TSH	SHT	MED	LNG	TLG
TSH	Z	LW	LW	ME	ME
SHT	LW	LW	LW	ME	ME
MED	LW	ME	ME	HG	HG
LNG	ME	ME	HG	HG	TH
TLG	ME	ME	HG	TH	TH

Green Phase Module

This module has two jobs. The first job is to calculate the urgency levels of the current green phase. The second job is to select the green phase with a high traffic urgency to decide whether to continue the green phase, or to terminate it.

There may be dual entry linguistic parameters and single outcome linguistic parameters for the GPM unit. The first entry is the queue length. The queue length retrieves the jam's length across the vehicles in meters during green phase, and the second input detects the incoming vehicles within the green state. An outcome of the GPM is the urgency level of green state. Thus, the fellowship function of the queue length, incoming vehicles, and the urgency level of the traffic condition in the green state can be defined as follows. The fellowship function's shape used in this project was triangular.

The domain, or range of values for the queue length (x_QueueL) was [0, 100]. There were five fuzzy values, namely, TSH, SHT, MED, LNG, and TLG. The fellowship function of the queue length is displayed in Figure 8. The domain, or range of values of incoming vehicles in the current green states (x_G_ArrivalV) was [0, 100]. There were five fuzzy values, namely, too small (TSM), small (SM), medium (MED), large (LG), and too large (TLG). The fellowship function of the incoming vehicles of the current green state is displayed in Figure 9. The domain, or range of values of the traffic urgency levels in the current green state (y_GUrgency) was [0, 100]. There were five fuzzy values, namely, Z, LW, ME, HG, and TH. The fellowship function of the transport movement urgency is displayed in Figure 10.

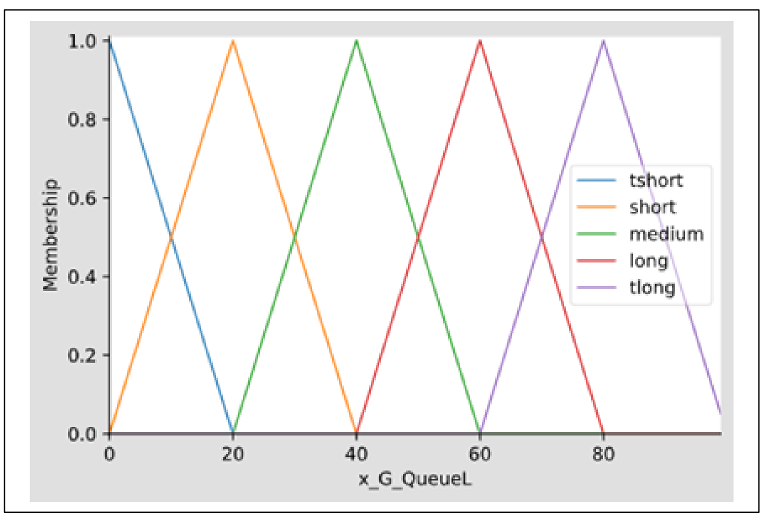


Figure 8 The GPM input fellowship function of queue length.

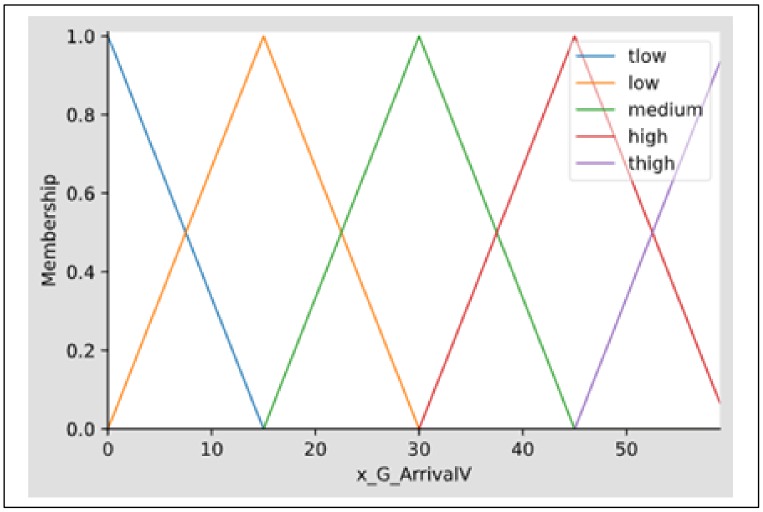


Figure 9 The GPM input fellowship function of incoming vehicles.

This exact process was performed on the GPM module. The fuzzy orders were mapped by combining the fuzzy rules input to correspond to the output set by configuring them in a matrix structure, as displayed in Table 3. Next, it was expressed in linguistic terms, in IF-THEN rule form. For example, "If the queue length of the current green phase is very short and the number of incoming vehicles of the current green phase is very small, then the urgency level of the current green phase is zero." An example of the IF-THEN form is: "IF the current green phase queue length is too short AND the number of incoming vehicles of the current green state is too small, THEN the urgency level of the current green phase is zero." Subsequently, the rules were then inferred with the MAMDANI system, and the inferred fuzzy output values were converted through the defuzzification process using the centroid method.

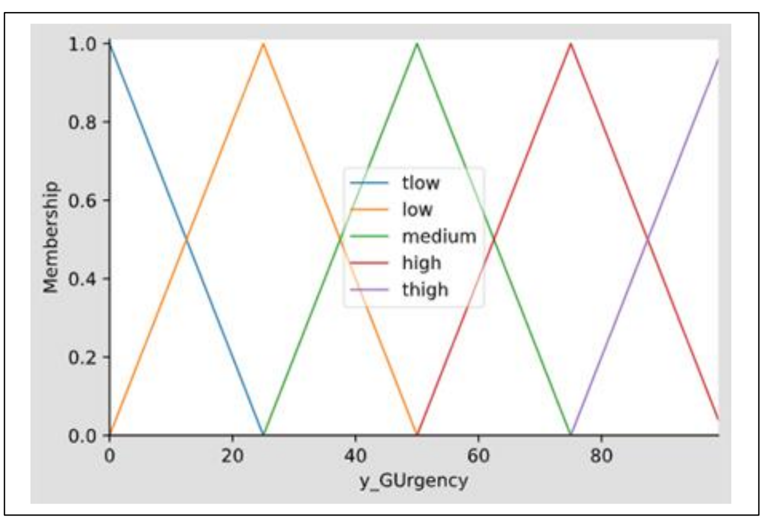


Figure 10 The GPM output fellowship function of road traffic urgency level.

Table 3 The mapping of fuzzy rules in matrix structures for GPM module.

Queue Length (QL)	Incoming vehicles (IVs)				
	TSM	SM	MED	LG	TLG
TSH	Z	LW	LW	ME	ME
SHT	LW	LW	LW	ME	ME
MED	LW	ME	ME	HG	HG
LNG	ME	ME	HG	HG	TH
TLG	ME	ME	HG	TH	TH

Selection Module

The two fuzzy output values from the NPM and GPM were considered input variables for the SM module. This module used the FBN approach to decide when to switch to a new phase, or to terminate the green phase, according to the current urgency levels.

The simple network displayed in Figure 11 is an example. This type of network is referred to as an intercausal Bayesian network. This topology was used to explicitly show the interaction, or better qualitative relationships between different causes or reasons and the simultaneous effects they have on the desired results (Kjærulff & Madsen, 2008). This type of topology shows the causes of the two variables which seem to become dependent on each other. For example, the traffic urgency levels from the NPM and GPM can each trigger the decision-making process, on whether to change to a new phase, or to continue with the green phase. This evidence corresponds to the converging connection, "NPM Urgency?→ Selection?←GPM Urgency", depending on the availability of evidence in the child node ("selection?"), or for one of its descendants (i.e. parent nodes).

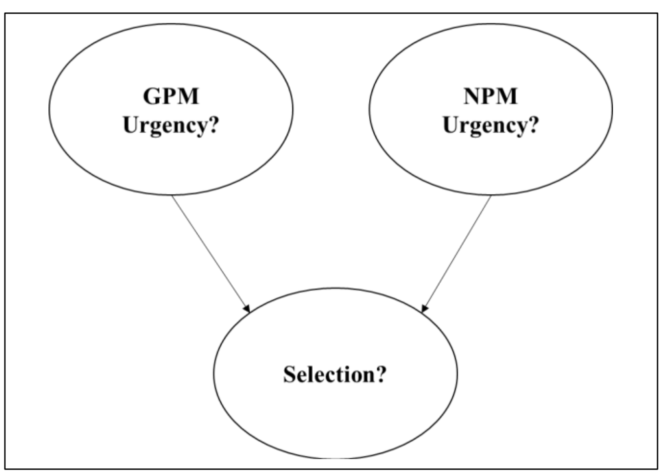


Figure 11 The intercausal layout of Bayesian network.

The next step was to specify the CPD for each node in the network using the CPT form, as mentioned in the Bayesian network theory. All possible outcomes of urgency levels from both modules were determined. The conditional dependent probabilities of the decision nodes were specified according to the given evidence supplied from the reasons (parent nodes).

The integration of fuzzy and Bayesian networks can be developed by multiplying the probabilities with the corresponding fuzzy fellowship values into one value, known as the fuzzy Bayesian equation (Tang & Liu, 2007; Yang, 1997). This approach supports the fuzzy values on the evidence node (child node), representing the fuzzy set, the hypotheses node (parent node) representing the fuzzy variable, or both nodes altogether. Furthermore, this approach helps to enhance the reasoning approach via conditional probability, by minimizing the complexity of the control system, and ensuring that it suits the decision maker.

Experiment Setup

Signalized Intersections

Intersections are defined as connections where at least two or multiple paths cross or meet, to construct all kinds of junctions, namely crossroads (Findley et al., 2016). There are three types of intersections, namely unsignalized intersections, signalized intersections, and alternate intersections. In this experiment, signalized intersections were considered for experimenting on the capability of proposed method in terms of traffic signals to control the traffic phase at the crossroads, based on the traffic urgency levels.

The design of the intersection was design using “Netedit” from the traffic simulator software, namely SUMO. This intersection consisted of single lanes or straight paths. No right turns, and left turn lanes or directions. This single intersection had two way crossings. The first cross was in the East to West, and the West to East direction. The second cross was from the North to South, and South to North direction. Figure 12 shows the single intersection with one lane which was designed using “Netedit”, SUMO.

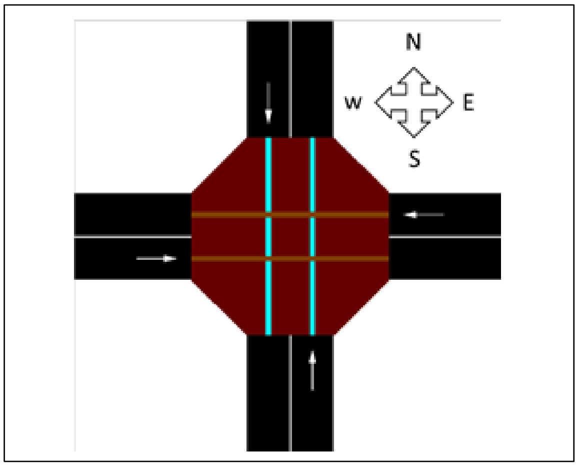


Figure 12 A design of single intersection with one lane.

The crossroad's performance variables taken into consideration were the incoming number of vehicle arrivals, the queue length of vehicles, and the stop time of vehicles. These variables were measured using the E2 detector, and each detector had a length of 100 meters. Figure 13 shows the design of single intersection after adding the E2 detector.

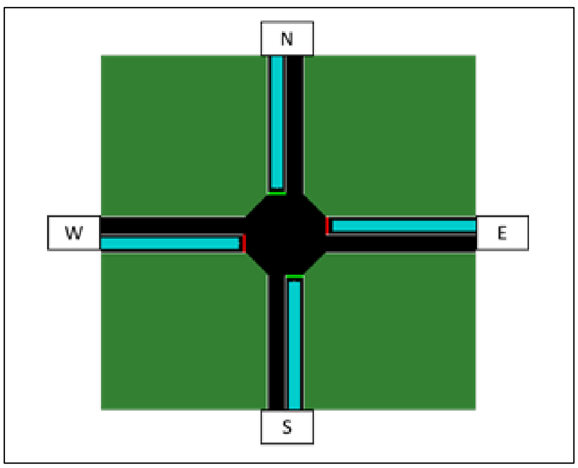


Figure 13 A design of single intersection after added the E2 detector.

The Allocation of Incoming Vehicles

In this project, the allocation of incoming vehicles is known as discrete, or a countable distribution event (Ge, 2014). The allocation of incoming vehicles were randomly distributed in four different directions within a specific period of time. Thus, this allocation can be done using the most common distribution method, namely Poisson distribution. Poisson distribution will count the number of incoming vehicles that appear randomly and independently within a specific period of time. The Poisson distribution function is written as follows (Jarosz, 2021; Supharakonsakun, 2021):

$$f(X = n;\ A) = \frac{A^n\ e^{-A}}{n!}$$

The function shows that n is the number of events which took place (where, n is equal to a whole number from 0, to infinity), A is the average number of events which successfully took place within a specific period of time, and f (X=n; A) is the probability of vehicles in an event which occurred in a given period of time. For example, the experiment expected that the incoming vehicles numbered 200 within an hour. However, the number of success happenings were only estimated at around 165 vehicles in an hour. Thus, the probability of incoming vehicles was only around 0.00119. This simulation set the range value of the traffic flow at intersection, starting from 200, and ending at 1800 vehicles per hour.

Mixed Traffic Demands

One of SUMO traffic simulator software's specialty is its ability to generate any type of vehicles for enabling an actual traffic situation during an experiment or simulation process (Gudwin, 2016). In this project, two types of passenger cars, namely long and short, buses and motorcycles, were considered for simulating the traffic simulation as closely as possible, to an actual traffic environment as shown in Figure 14. Table 3 shows the parameter settings of different types of vehicles used in the simulation. The sigma, or driver flaws showed a range value from 0 to 1 (Gudwin, 2016). The minimum gap for the small vehicles was 2.5 meters, and for heavy vehicles such as buses, 3 meters. The maximum speed, acceleration, deceleration, and length of the vehicle values are shown in Table 3.

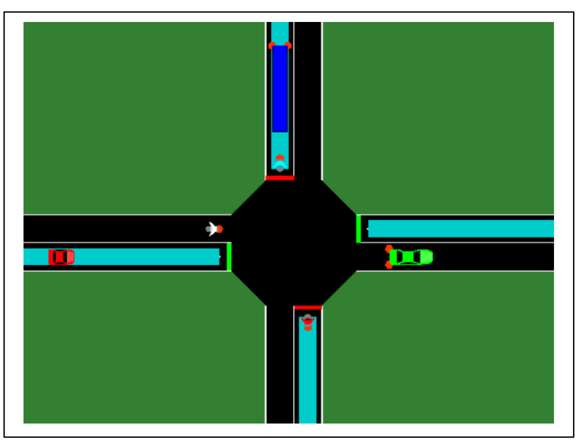


Figure 14 The mixed traffic demands settings.

Table 4 The properties of vehicle in traffic simulation.

Vehicle types	Acceleration (m/s^2)	Deceleration (m/s^2)	Sigma (from 0 to 1)	Length of vehicle (m)	Minimum gap between the vehicles (m)	Maximum speed (m/s)
Passenger Car (short)	2	4.5	0.5	5	2.5	14
Passenger Car (long)	2	4.5	0.5	3	2.5	14
Motorcycle	2	4.5	0.5	10	2.5	14
Bus	2	4.5	0.5	1.5	3	14

Simulation Results and Discussions

As mentioned before, there were two main types of performance or factors being evaluated, namely, the mean vehicular wait time at the intersection, and the mean vehicular time loss. The data collected can be observed via an output file generated via the SUMO traffic simulator, tripinfo.xml (Gudwin, 2016). This file holds the vehicle's trip info at the intersection, such as wait time, time loss, as well as a range of other values. The measured data was then organized in an excel form, using their mean values in the result. A comparison was made between the fixed period controller, and the proposed method, namely, FBN. Both methods were simulated under the same types of settings. The simulation settings were set as follows:

i. The simulation process was set to 3600 time steps (seconds), equivalent to 1 hour, with different types of vehicles.
ii. The controllers were simulated at a single intersection, and where there were no right turn lanes, and left turn lanes.
iii. The total cycle time of traffic signals was set at 60 seconds. The green period was set to 25 seconds, and the red period (yellow and red signal) was set to 5 seconds.
iv. The simulation started with the green signal from the North-South direction, and the red signal from the West-East direction, and vice versa.
v. The vehicles were distributed randomly using Poisson distribution.
vi. The controllers were simulated under different range of traffic flows, which was set from 200 to 1800 vehicles, per hour (VPH).

The mean vehicle waiting time depicted the amount of time vehicles needed to wait at an intersection during the red signal, or due to the traffic congestion. The mean vehicle time loss showed the loss period of vehicles, where they could not cross the intersection, despite the traffic signal displaying a green signal for permitting the vehicle to cross the intersection, as well as due to low speeds at the intersection. The lower the value of the mean vehicular time loss and the mean vehicular waiting time, the better the performance of the controller in controlling the traffic flows, and in handling the wait time of the vehicles on the road.

The Mean Vehicular Waiting Time

The Table 5 and Figure 15 shows the mean vehicular wait time (in seconds) for two different kinds of traffic controller systems, namely, the fixed period controller (current technology), and the Fuzzy-Bayesian network (proposed method), at a single intersection, over a different range of traffic flows, starting at 200 VPH, and ending at 1800 VPH.

According to Figure 15, the proposed method and fixed period controller (or fixed time intervals) showed different mean values of wait time at different traffic flows. At 200 VPH, the proposed method had a low mean value of wait time (in seconds), and a fixed period controller (or fixed time intervals). Probably in fixed period controller situations, the vehicles needed to wait for a certain amount of time, as the period of activated phase on empty roads ended, as the controller was programmed for not considering the traffic situations.

At 1600 VPH, the graph shows very huge differences between the proposed method, and the fixed period controller, with a 12.64 seconds difference. At this point, the fixed period controller might not prioritize the lanes which should have longer green times, as the controller was programmed without green extensions. The proposed method deduced the wait times of the vehicles from 49.24 seconds to 36.6 seconds, since this method considered the traffic urgency on the roads, and it prolonged the green phase across certain periods, while taking into account the traffic urgency of the other lanes. Although the mean value of wait time at 1800 VPH was 13.3 seconds higher than that at 1600 VPH, the proposed method still showed a reduction in mean value of vehicles wait time versus the fixed period controller. The differences in seconds between these two methods at 1800 VPH was 2.52 seconds. Overall, the proposed method showed a significant reduction in the mean value of vehicle wait times versus the fixed period controller.

Table 5 The mean vehicular waiting time.

Average Vehicular Waiting Time		
Flow (vehicles/hour)	Conventional Method (Fixed Time Intervals)	Fuzzy-Bayes Method (Proposed Method)
200	10.97	9.92
400	14.24	13.95
600	20.38	18.79
800	23.58	23.11
1000	26.92	26.68
1200	30.42	29.81
1400	34.9	34.59
1600	49.24	36.6
1800	52.42	49.9

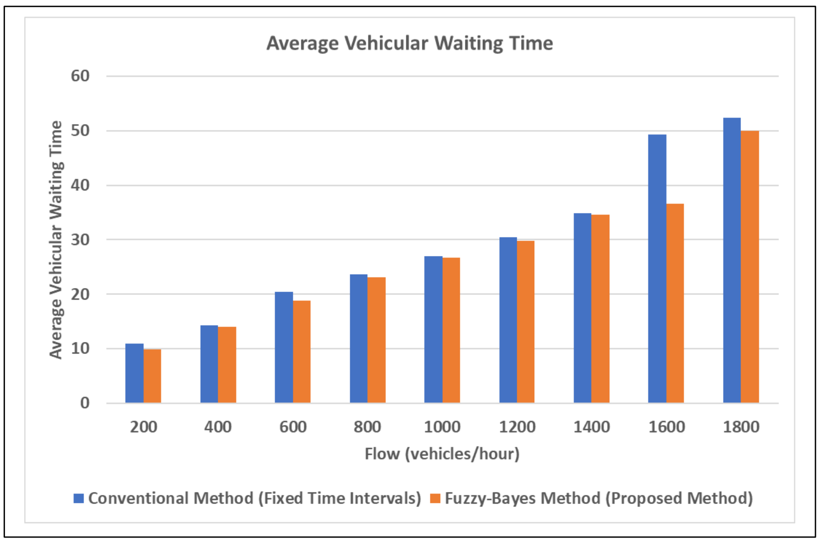


Figure 15 The graph of mean vehicular waiting time.

The Mean Vehicular Time Loss

The Figure 16 and Table 6 compares the mean values vehicular time losses between the fixed period controller, and the proposed method over different traffic flows, starting at 200 VPH, and ending at 1800 VPH.

As reported in Table 6, the mean value of vehicular time loss in the fixed period controller increased gradually between the low traffic flow, and the high traffic flow. However, the mean values at the vehicular time loss reduced significantly in the proposed method. At 200 VPH, the differences between the fixed period controller and the proposed method were determined to be 1.56 seconds. Although there was a slight decreased in the proposed method, the number of vehicles across the intersection during the green signal was still higher than the fixed time period controller, because the controller extended the green signal until there was an urgency in the traffic condition at the other direction.

However, at 1600 VPH, there was a sudden drop in the mean values associated with the vehicular time loss of the proposed method. There is a possibility that the proposed controller works efficiently and effectively at this stage, by extending the green signal during the rush hour, and eventually increases the vehicle's movement speeds to across the intersection. At 1800 VPH, there was a slight drop in the mean values associated with the vehicle time loss of proposed method, with a 4.6 seconds difference versus the fixed period controller. Overall, the performance of the proposed method for the mean vehicle time loss were much lower compared to the conventional method.

Table 6 The mean vehicular time loss.

Average Vehicular Time Loss		
Flow (vehicles/hour)	Conventional Method (Fixed Time Intervals)	Fuzzy-Bayes Method (Proposed Method)
200	28.00176871	26.44329114
400	33.39085324	32.71106667
600	43.49186404	41.08673961
800	48.56599026	47.6777592
1000	54.48477151	53.61503365
1200	59.83452747	58.62053592
1400	67.4937619	66.80412371
1600	94.57165282	69.9255
1800	98.47945494	93.91068148

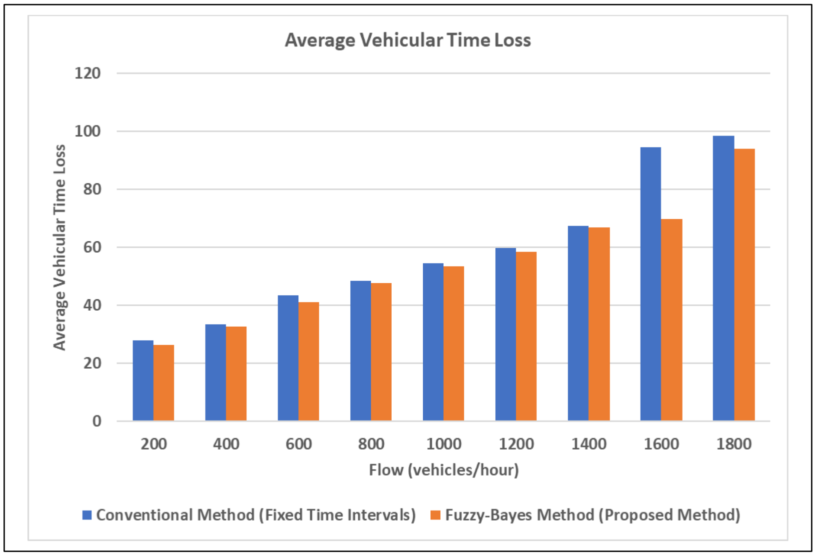


Figure 16 The graph of mean vehicular time loss.

The Mean Vehicle Travel Time

There was one additional performance factors which had been evaluated, namely, the mean vehicle travel time. The reason was to know the period of travel from one direction, to another direction, as a comparison against the proposed method with the fixed period controller.

The Table 7 and Figure 17 shows the mean vehicle traveling time across two different kinds of traffic controller systems, namely, the fixed period controller, and the Fuzzy-Bayesian Network, at a single intersection over different ranges of traffic flows, starting at 200 VPH, and ending at 1800 VPH.

At low traffic flow conditions (200 VPH), there was a slight drop in the mean value of the vehicle's traveling time using the proposed method. The travel time spent driving to the destination for the proposed method in seconds was 1.65 seconds lower than that of the fixed period controller. The graphs for the proposed method continued to drop when the traffic flows keep increasing. However, the fixed period controller had a high mean value in terms of travel time, since the controller followed a fixed program, of which, the controller couldn't change, or be activated into a new phase, although there were no vehicles on the roads at the current time.

At 1600 VPH, there was a sudden drop in in the mean value of the vehicle's traveling time using the proposed method. The differences in travel time in seconds between the fixed period controller, and the proposed method was 24.67 seconds. At this point, the proposed method showed a huge significant drop in travel time, and showed a better performance at high traffic flows. Although, at 1800 VPH, there was a small difference in travel time, which was around 4.59 seconds. The proposed method still achieved a lower travel time among the commuters. Thus, the overall performance of the proposed method in terms of the mean vehicular traveling time was better than the fixed period controller.

Table 7 The mean vehicular travelling time.

Average Vehicular Travel Time		
Flow (vehicles/hour)	Conventional Method (Fixed Time Intervals)	Fuzzy-Bayes Method (Proposed Method)
200	110.2	108.55
400	115.71	114.99
600	125.71	123.32
800	130.79	129.9
1000	136.65	135.78
1200	142.18	140.94
1400	149.86	149.16
1600	177.01	152.34
1800	181	176.41

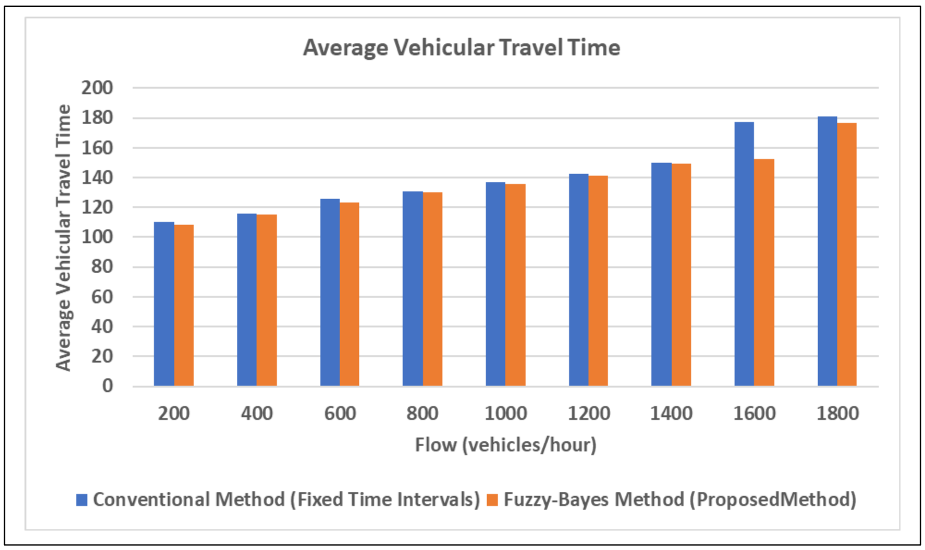


Figure 17 The graph of mean vehicular travelling time.

Conclusions

In this research, an integration of two famous probabilistic reasoning between the fuzzy logic control, and the Bayesian network was developed. This method had not yet been used for controlling the traffic urgency degrees at the road intersections. Thus, this research introduced this method in traffic control systems, with the objective to reduce the average vehicle waiting times, and the time loss of vehicles at intersections. Additional performances have also have been evaluated, namely, the mean vehicle travel time, with the aim to reduce the travel time spent for driving. The integration between fuzzy logic controls and the Bayesian network was developed by multiplying the membership values from fuzzy logic controls with the probabilistic values from expert knowledge, into a new probabilistic value. There were three modules, namely, the next phase module, the green phase module, and the selection module. The next phase module function chose a red state based on the most urgent traffic condition, which was a reflection of the transport movement, with the exception of the green state. At the same time, the green phase module only observed the traffic urgency levels of the green states. Subsequently, the selection module decided if it needed to change into a new state, or to continue with the green state based on the likelihood of congestion urgency levels from across both modules. The developed method was used against a constant time traffic controller, and evaluated using an open-source traffic simulation using the SUMO simulator, which considered the traffic urgency from both the next phase module, and the green phase module, under mixed traffic demands. The results showed that there was a significant drop in mean values of the vehicles wait time, time losses, and the travel time. Furthermore, the proposed method worked well in low traffic flows and high traffic flows. In future works, the proposed method can be improved by trying other notations, such as groups with probabilistic distributions and fuzzy state values, by considering their respective information, or by using the virtual evidence approach.

Abstract

Traffic congestions occur due to imbalances, or inconsistencies in traffic demands and traffic management. Intersection conflicts are one of the major sources of traffic congestion, especially during peak hours. The traffic light system was created to allocate a certain phase of cycle time for controlling the motions of traffic flows, and reducing traffic congestion. However, current traffic signal control systems performances such as fixed period controllers are not so responsive to real-time traffic. Hence, traffic management methods and systems must tackle conventional traffic signal control problems and deficiencies, by integrating intelligent traffic signal controls (ITSCs). This project sought to implement a Fuzzy-Bayesian network method for controlling the phase signals based on traffic urgency levels from next phase modules, and green phase modules. The model helps to decide which module has a high probability to switch to a new phase, or to continue in the green phase. The performances from across both methods were evaluated based on the average time to wait, and the time loss of vehicles at crossroads under a mixed traffic demand settings. The developed method was compared against constant time traffic controllers, and evaluated using an open-source traffic simulation which utilized the SUMO simulator. The end results showed that the proposed method worked better in low and high traffic flows, compare to the fixed period controller.

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