International Journal of Computer Applications Technology and Research
Volume 4– Issue 7, 566 - 573, 2015, ISSN: 2319–8656

Techniques for Smart Traffic Control: An In-depth Review

Roxanne Hawi
School of Computing and Information Technology,
Jomo Kenyatta University of Agriculture and Technology
Nairobi, Kenya

George Okeyo
School of Computing and Information Technology,
Jomo Kenyatta University of Agriculture and Technology
Nairobi, Kenya

Michael Kimwele
School of Computing and Information Technology,
Jomo Kenyatta University of Agriculture and Technology
Nairobi, Kenya

Abstract: Inadequate space and funds for the construction of new roads and the steady increase in number of vehicles has prompted scholars to investigate other solutions to traffic congestion. One area gaining interest is the use of smart traffic control systems (STCS) to make traffic routing decisions. These systems use real time data and try to mimic human reasoning thus prove promising in vehicle traffic control and management. This paper is a review on the motivations behind the emergence of STCS and the different types of these systems in use today for road traffic management. They include – fuzzy expert systems (FES), artificial neural networks (ANN) and wireless sensor networks (WSN). We give an in depth study on the design, benefits and limitations of each technique. The paper cites and analyses a number of successfully tested and implemented STCS. From these reviews we are able to derive comparisons of the STCS discussed in this paper. For instance, for a learning or adaptive system, ANN is the best approach; for a system that just routes traffic based on real time data and does not need to derive any data patterns afterwards, then FES is the best approach; for a cheaper alternative to the FES, then WSN is the least costly approach. All prove effective in traffic control and management with respect to the context in which each of them is used.

Keywords: smart cities, intelligent traffic systems, artificial intelligent system, WSN, FES, ANN, traffic lights, road traffic

1. INTRODUCTION

The steady increase in the number of vehicles on the road has increased traffic congestion in most urban cities of the world. One approach most countries are taking to address this issue is the expansion of roadways. However, this approach still comes with its share of challenges. Demolition of older roads can be quite costly. Most urban cities lack the free space required for such a venture. Even with the improvements in road infrastructure, it is evident that the rate at which travelers buy vehicles has surpassed that of new infrastructure development. Also due to expansions, roads are able to serve more vehicles; consequently utilizing the additional capacity. This is consistent with the 'fundamental law of highway congestion' suggested by Downs [1] who avers that increasing road supply invariably increases vehicle traffic.

With inadequate space and funds for the construction of new roads, and the growing imbalance between traffic demand and transportation resources; it is increasingly obvious that countries must move beyond the traditional model of just building roads to solve traffic problems [2]. This is demonstrated in a survey done by CBT in Britain. The report supports that expansion and building of new roads will do very little to help solve the congestion issue. CBT survey found that nearby local roads suffered up to 137% more traffic after the bypasses opened, and reductions on the roads intended to be relieved were less than expected [18].

Therefore, managing of traffic flow needs to be a combination of physical infrastructure, new ways of thinking and new technologies. Smarter transport transcends infrastructure [2]. In light of this, smart traffic control systems have gained a lot of interest.

These smart traffic control systems use advanced technologies such as image processing, computer vision, intelligent controls and artificial intelligence to make traffic routing decisions; a task typically done by traffic officers e.g. policemen or traffic marshals. Other application areas include: surveillance, management of freeway and arterial networks, intersection traffic light control, congestion and incident management [3].

1.1 Background and motivation

Other than inadequate infrastructure developments, other factors that have prompted scholars to further investigate use of smart traffic control systems include:

1.1.1 Weakness in current traffic control systems:

Almost all urban cities in the world use traffic lights to control the traffic on the roads. The lights switch from red, which means stop, to green, which means move. Over time there has been developments of different types of traffic light control systems, the most commonly used being static traffic lights and vehicle actuated lights.

Static traffic lights' timing and switching patterns are predetermined despite prevailing traffic conditions for the different lanes. They do not operate with real time data. Consequently this means they do not take into account the non-uniform and ever changing nature of traffic conditions. It does not matter whether at a particular period of time route one has more cars than route two; the green light allocation time and pattern still remains the same for all routes. The lack of intelligent strategies in these devices does very little in improving the road network performance and traffic congestion levels.

This was demonstrated in Kenya when the country recently experienced a setback when the Nairobi County Government pulled out policemen from the roads to test the newly automated traffic lights that had an additional counter feature – that counts down from one light to the other. This meant that the motorists could then know how long to wait before moving [4]. However, this operation was not successful; there was a traffic gridlock in most parts of the city with some motorists spending close to 4 hours in bumper to bumper traffic. [4]

Vehicle-actuated traffic lights were an attempt to enhance the static lights. They combine preset time cycles with proximity sensors. These sensors can activate a change in the cycle time or the lights when cars are present. This is due to the assumption that roads with fewer cars may not need a regular cycle of green lights. However the downside of these traffic lights is that they are not adaptive. They depend on having some prior knowledge of traffic flow patterns at the intersection so that signal cycle times and placement of proximity sensors may be customized for the intersection. This means that the signal time/extension is still a fixed value. Also proximity sensors will only activate a change in signal light when cars are present, they do not count cars. [10]

1.1.2 Advancements in the field of Artificial Intelligence (A.I):

A.I. is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence [5]. The ability of these systems to emulate human intelligence has therefore led to artificial intelligent systems pervading our everyday life. For instance, A.I. is used in a number of scenarios e.g.: banks – automatic check readers, signature verification systems; digital cameras and mobile phones – automated face/voice detection and focusing; web – automatic location recognition from your web surfing, automatic fraud detection just to mention a few.

Consequently scholars; especially in developed countries are now interested in investigating the application of A.I in vehicle traffic management systems. The basic idea behind this being, if these systems can mimic human reasoning, then they can effectively be used to control traffic in place of traffic officers.

Developing countries are also catching up with this approach. IBM opened a commercial technology research facility in Nairobi, the first of its kind in Africa. The lab's research agenda includes the development of cognitive computing technologies which integrate learning and reasoning capabilities enabling experts to make better decisions in search for solutions to Africa's most pressing challenges [6]. In an effort to tackle the traffic congestion problem, IBM partnered with a Kenyan internet service provider, Access Kenya, to develop a pilot solution to enable Nairobi commuters to use their mobile phones to get advice on driving routes through the city depending on estimates of traffic congestion. The project dubbed Twende-Twende is a mobile application that uses specialized algorithms to do image processing and interpret visual data received from closed-circuit television (CCTV) cameras positioned around Nairobi. Motorists are then able to get information on a) what areas to avoid because of congestion by suggesting alternative routes and b) updates on road conditions to allow them get from point A to point B safely. This information is retrieved via an SMS-based query for basic phones and on smart phones the service is accessed via an application through which users can view a map of the city showing route options and potential traffic hotspots. The project's main focus is data collection, analysis and information dissemination, it does not actively control traffic on the roads [7].

1.1.3 Sensor Networks:

Advancement in very large scale integration (VLSI) and semiconductor technologies have enabled the development of smaller, tiny, low power, and inexpensive sensors and controllers/microprocessors. Furthermore, developments in wireless technologies have made it possible for the use of sensors to collect large amounts of environmental data at minimal costs. These networks comprise of many sensors that cooperate to monitor and collect data about traffic conditions on the roads.

Although sensor network technology for highway and traffic management is a relatively new solution to alleviating highway congestion; they have potential to be one of the sustainable solutions to road congestion. These networks have gained popularity because they provide a cheaper alternative to that of expansion of roadways and implementation of A.I systems, especially in emerging economies.

Pascale et al. [8], introduce an intelligent transport system (ITS) that uses a wireless sensor network (WSN) to monitor traffic. Their system comprises of a network of traffic sensors deployed throughout the roads that collect and forward measurements to a remote server. The server aggregates and processes macro-parameters of the traffic flows arising from heterogeneous monitoring systems, then distributes the data to traffic management centers, road control units (RCU) and information providers. The macro-parameters can be used for traffic analysis and management [8].

In this paper we present the motivations behind emergence and use of smart traffic control systems in road traffic management; we further describe the design, benefits and the limitations of the different types of smart traffic control system (STCS) in use today. The outline of the paper is as follows. In section I we have described what STCS are and the factors that influenced their application in road traffic management. Section II describes the methods used as well as parameters considered when selecting and analyzing the related works reviewed in this paper. In section III we present the different types of STCS in use, their design and benefits. In section IV, the limitations of each technique (STCS) are analyzed. Section V we briefly discuss our insights on reviewed work and give some suggestions and recommendation. Finally our concluding remarks are given in section VI.

2. METHODS

The works reviewed in this paper were selected and analysed based on the following criteria:

a) Approaches used to make traffic routing and light signal allocation decisions. For instance adaptive (learning) versus non-adaptive strategies; offline versus real time strategies; and hybrid strategies.
b) Number and types of parameters/variables (input and output) used. We review systems that use single variables (e.g. traffic quantity) and ones that use several variables (e.g. traffic quantity, waiting time, past and present traffic data knowledge) to make traffic routing decisions.
c) Traffic data collection methods used (such as sensor types) and communication methods applied (such as multi-hop or single-hop) to transmit collected data.
d) STCS that control traffic at an isolated junction or multiple intersection junction or both.

e) Ways to improve overall performance of already existing intelligent/smart systems (STCS) in use.

3. SMART TRAFFIC CONTROL TECHNIQUES USED BASED ON THEIR SYSTEM ARCHITECTURE

Smart traffic light controls are dynamic. This means that they use real time data to make priority based decisions. They use advanced communication systems based on sensors and/or RFID tags to collect data and provide the system with information on the current situation on the roads (such as number of vehicles on individual roads or how long vehicles have been waiting for green light). The smart system then processes this information and makes decisions; that is, it automatically determines the duration of each traffic light signal based on prevailing traffic situation on the roads. Commonly used systems include fuzzy expert systems (FES), artificial neural networks (ANN) and wireless sensor networks (WSN).

3.1 Fuzzy expert systems (FES)

FES is a suitable approach to dynamic traffic signal control because of the nature of uncertainties on road traffic where the traffic distributions fluctuate non-uniformly. Fuzzy logic is a field started by Zadeh [9]. It is a superset of Boolean logic that has been extended to handle partial truths between completely false (0) and completely true (1). This is in an attempt to mimic or reflect how humans think, to model our sense of words when describing certain phenomena as well as our common sense in decision making. The sensors collect data from the environment which in turn is fed into the fuzzy logic controller (FLC) for processing. The inference process in a FLC is similar to the way traffic officers handle the traffic flow at a typical roundabout [10; 11]. The FLC's objective is to control operations in systems by making decisions that utilize rules expressed with the uncertainty of human terms such as cool (slightly cold) or warm (slightly hot). Therefore FLCs are a suitable approach to traffic signal control because it assigns green or red light signal based on urgency or as traffic fluctuates; and selects the best decision that will minimize congestion at a particular interval. For instance, a lane could also have low or medium traffic as opposed to just no traffic (0) or high traffic (1).

Khiang et al [11] present a fuzzy logic traffic light controller. Their system uses two input variables; quantity of traffic on the arrival side (arrival) and quantity of traffic on the queuing side (queue) collected from the sensors on the lanes. Their system controls traffic on multiple lanes simultaneously i.e. North and south lanes move together while east and west lanes move together. When North and South have green light, East and West stop (queue). The fuzzy controller observes the density of north and south as one side and east and west as another side. Their system then determines green light allocation and extension based on the side that has the highest traffic quantity. From their experiments, they are able to demonstrate that their fuzzy logic traffic light controller performs better than the fixed-time (static) controller.

From a comparison made between the performance of the fuzzy logic controller and that of a fixed-time (static) controller; [11] observed from the results that the fuzzy logic controller had a lower average waiting time – a difference of 6 minutes.

Fahmy [10] later presents another system FLATSC that uses fuzzy logic controller to manage traffic at a four intersection roundabout. However, unlike Khiang et al system, his system employs another input variable, waiting time, to determine green light allocation and extension. FLATSC therefore uses traffic quantity and waiting time to determine the priority degree (output variable) for each lane on the roundabout. The output value is the green light time/extension for each lane. The lane with the highest output value gets allocated the green light. When cars in one lane move the other lanes stop. The green light extension was not a fixed value; it was dependent on real time data collected from the sensors. The value changed as the traffic variables fluctuated from cycle to cycle and/or lane to lane. This ensured that traffic was controlled based on prevailing traffic conditions on the roads.

From a comparison with the fixed controller and vehicle actuated systems, FLATSC proved to be more effective in managing the changing traffic patterns. In addition FLATSC attempted to resolve starvation. Starvation describes a situation whereby some lanes end up always getting last priority because they usually get the least traffic consequently ending up always queuing for the longest time during a cycle. FLATSC addressed this issue by incorporating waiting time as a factor in determining green light allocation. For instance a lane that has low traffic but very high waiting time still has a chance of getting a high priority degree just as a lane with high traffic but low waiting time; depending on the fuzzy inference.

3.2 Artificial neural networks (ANN)

The major difference between ANN (learning systems) and FES is that; while an FES uses present knowledge to make decisions, in a learning system, the decisions are computed using the accumulated experience or knowledge from successfully solved examples. Since ANNs try to mimic the human brain they possess an adaptive feature that allows each node within the network to modify its state in response to past and present knowledge. [12; 3]

Patel et al. present an ANN system used to control traffic. The input given to the ANN models are the list of data collected by the sensors which are placed around the traffic lights. The sensors give the traffic light ANN model all the data which are related to the past and present traffic parameters. The model then processes this input and selects the most suitable output that suits current traffic situation. These results are then used by the traffic lights to set the timing for the red and green lights. In their ANN approach they evaluate that for the ANN to produce accurate decisions it required 83 neural nodes, their system produced 73% accuracy level for the derived solutions.

Michael et al. [28] also present a neural networks based traffic light controller called Environment Observation Method based on Artificial Neural Networks Controller (EOM-ANN) to control urban traffic. Their approach is different from [3;13] because they also incorporate mathematical strategies (EOM) to make signal allocation decisions. EOM is a mathematical methodology for obtaining timing plans for isolated intersections. It achieves this by calculating the minimal green time for each phase then to prevent congestion an additional green time is allocated to each lane that still has cars even after getting green light. However the downside of EOM is that it sets traffic light timing based on averages of the basic parameters. Due to the fact that these figures are constants, the EOM doesn't incorporate the real time nature of traffic which means that the traffic parameter values (data) keep changing every time, this is further backed by [13] that traditional mathematical methods have limitations when they are applied in traffic control. The EOM-ANN is an attempt to resolve this issue of real time data, [28] propose use of ANN to obtain this traffic data patterns. That way, the green light timing and allocation is based on actual/prevailing traffic conditions rather than analytical calculations. [28]

EOM-ANN uses the feed-forward method with 8 neural nodes in total for input, hidden and output layers. It is further divided into two modules; reviser and the neural. The former defines correct traffic light timing and the latter provides the most appropriate value for the current traffic behaviour. The inputs of the ANN are the number of light, medium and heavy vehicles. [28]

From a comparison between static time controller and EOM, EOM-ANN reported better traffic flow and congestion management. The average traffic flow of the individual controllers was as follows: static controller - 82.55, EOM - 68.70 and EOM-ANN registered an average of 53.75. [28]

3.3 Wireless Sensor Networks (WSN)

In the event WSN is used to not only collect traffic data but also actively control road traffic, additional functionalities are incorporated into the network's controller. An algorithm is embedded to control the traffic lights – it generates routing decisions based on sensor data aggregated. Unlike some A.I systems, WSN does not require vehicles to have additional systems such as RFID tags to control and manage traffic. As a result WSN are cost inexpensive and make it a more practical than ANN and FES approaches especially in emerging economies.

Yousef et al. [15] present an adaptive traffic light control system for single and multiple intersections using WSN. Their system uses the WSN to route traffic based on traffic density and waiting times. It is composed of: sensors that detect the presence of vehicles and have a memory that stores their waiting times on each road. It also has an intelligent traffic controller that processes the sensor data then employs two algorithms traffic system communication algorithm (TSCA), traffic signal time manipulation algorithm (TSTMA) to route traffic based on the traffic variations of all lanes of the intersections at a particular time and traffic control algorithm on multiple intersections (TCAMI).

TSCA main objective is to enable exchange of information between the sensors' base station (BS) and the controller using a direct routing scheme approach. This means all sensors are within range of the BS and directly communicate with it. On the other hand, TSTMA main responsibility is to set the traffic signal duration in an efficient and dynamic manner such that traffic flow is maximized while at the same time ensuring minimal average queue length (AQL) and average waiting time (AWT). TSTMA makes use of the traffic information gathered at the traffic BS from the sensors to calculate in intelligent manner, the expected queue length, for the next traffic cycle, and then schedule efficient time setting for the various traffic signals. TSTMA achieves this objective through three main techniques: (a) Dynamic selection and ordering of the traffic phases based on the number of lanes allowed in the intersection; (b) Dynamic adaptation to the changes in the arrival and departure rates and thus dynamic decisions about queues' lengths and their importance; (c) Dynamic control of the traffic cycle timing of the green and red periods. TCAMI main objective is coordination and setting of traffic parameters and conditions on the multiple intersections in general and on the successive intersections in specific, with the objective of minimizing delays, caused by stopping, waiting and then speeding up during road trips (also known as green wave – where drivers need not stop on multiple intersections thus achieving, if implemented correctly, an open route for the vehicles). When TCAMI is executed on each intersection it will generate traffic information, which in turn represents an input to the subsequent intersection, and so on. As such, the traffic flow will be controlled in a flexible manner. [15]

To show efficiency of proposed scheme, [15] compared the system to the traditional traffic light control approach which uses static plans i.e. fixed time control. The results indicate that the proposed system had a better performance rate in managing traffic; its AWT was much lower at 2.98 minutes compared to 7.87 minutes of the fixed time controller. A low AWT means that the flow of traffic is increased hence lower AQT of 9 cars as opposed to 36 cars per queue in the fixed time controller. The dynamic approach was able to handle queues quickly with less cars accumulating on a lane during the observed time. [15]

Bhuvaneswari et al. [16] further support [15] by developing a traffic congestion control system ATSWSN that is adaptive in nature. However it differentiates from Yousef et al [15]. in that the time slots allocated for each route is not only based on traffic density, but also on emergency conditions and speed patterns of incoming traffic. Their system collects real time data using IR sensors and the microcontroller's scheduled algorithm processes this data and determines which direction gets green light priority. The duration of the green light is dynamically calculated based on the weighted speeds of all the vehicles in the waiting queue factoring in any emergencies.

When compared to the conventional fixed time approach, ATSWSN registers a higher traffic flow rate and as a result lower average waiting time. This is because the clearance time is inversely proportional to delay factor, slow moving vehicles are allotted more clearance time than fast moving vehicles. Further, by scaling the delay factor by the emergency factor, the clear route parameter is kept high when an emergency vehicle enters the lane. Thus, both the direction and time to be cleared are chosen optimally. They observed that in the fixed time approach, the waiting time increased as the number of vehicles increased irrespective of their speeds and speed factors [16].

3.4 Hybrids

To overcome the limitations of the individual implementations of ANN and FES approaches, such as; lack of learning ability of fuzzy systems and lack of inference process of ANNs (mentioned in section IV of this paper); Patel et al. [3] developed a hybrid intelligent decision making system (IDUTC) for urban traffic control applications.

The sensors (closed loop detectors) placed on the roads collect traffic data; volume (traffic quantity) and occupancy (wait time) of each lane. However IDUTC only computes its decisions based on one parameter, the traffic quantity. Using the volume data, five traffic parameters are computed that describe in more detail the traffic flow of the intersection lanes. They are: 1) highest saturation, 2) the cross saturation, 3) the saturation difference of the traffic, 4) the volume difference and 5) the required green time extension. The four parameters from the previous time frame which were stored in a memory device (the saturation difference was not included) and the five parameters for the current time frame become inputs to the ANN. This is fed into the IDUTC as crisp values. The ANN then processes all the system data, past (collected and stored from previous cycles) and present. The ANN output provides the input for the FES. The FES performs inference and assigns a fuzzy label/values to the input received. Then FES fires the rules based on these fuzzy values. The defuzzification unit converts the computed decisions into crisp values that are used to determine green light allocation and extension for each traffic light. The cycle goes on repeating and tries to change the traffic light timings condition so as to ensure that IDUTC self-adjusts according to the situation. IDUTC integrates the learning abilities of an ANN and the knowledge-based decision-making ability of the FES. The back propagation-based ANN allowed the system to learn and adapt to the dynamically changing environment and the FES was employed for decision making using the IF-THEN rules. [3]

A summary of the simulations for the IDUTC system, the ANN, and the FES approaches indicate that: the IDUTC system provided 95% correct decision rate and an average waiting time of 2.186 minutes. It relieved intersection congestion better than the ANN approach which provided 73% correct decision rate and an average waiting time of 2.958 minutes. While the FES approach correct decision rate was equal to that of IDUTC, it was observed that the computed decision did not lead to a better reduction in the wait times. The FES had an average wait time of 2.975 minutes which is lower than the other two approaches. [3]

4. STCS DESIGN CONSTRAINTS

Singh. et al [14] aver that most automated traffic control systems not excluding STCS; have the following general limitations:

a) If the position of vehicle does not come in alignment of infrared rays then IR sensor would not give response.
b) If the vehicle is under faulty condition in the range of IR rays then the response given by IR sensor would not be accurate.
c) If a single camera is used as a vision sensor for acquiring the image of traffic then it is difficult to detect the space between two vehicles means projection of camera would be crucial factor for measuring the traffic density.

Below are the specific limitations with respect to the design of each of the mentioned STCS:

4.1 FES

Although use of fuzzy expert systems in traffic light control systems enhances the efficiency of traffic movement in roads, the downside of such systems is that, they do not have the ability to learn, they are not adaptive. Meaning, they do not incorporate past knowledge or experiences to make current decisions; rather they only make decisions based on the current knowledge they have of the situation. For this reason, it becomes quite challenging to modify the system's parameters whenever necessary. For instance; changing the green light duration time for a single lane only; based on the discovery that it usually gets more cars on average would be very tasking.

4.2 ANN

While [28;13;3] demonstrated that using ANN to manage traffic was effective; ANNs training process in most cases is a time-consuming task requiring the application of input training patterns in an iterative manner. This was experimentally proven by Barbosa and Pinto [17]; they successfully managed to show that by increasing the amount of data the performance of the ANN system improved. The error margin was lower when training was extended to 15 minutes of collecting data as opposed to 5 minutes.

Also another drawback of ANNs is the lack of rules or guides to support the decisions to be made; resulting in development of solutions that are mostly specific or case base problems. This means no explanation or guarantee that the solution chosen is the optimum one [17]. This is proven by Patel et al. where they demonstrate that the ANN had a correct decision rate of 73% as opposed to the IDUTC (hybrid system) and FES which both had a 95% rating. They further realized in their experiments that the ANN approach had difficulty in generalizing on the various numbers and the combinations of traffic parameters and required cycle-time adjustments (desired outputs) .[3]

4.3 WSN

Owing to the fact that sensors are micro-electric devices, they operate on a limited energy budget. For this reason WSNs are faced with the problem of having to regulate their energy consumption. This can be a daunting task especially when dealing with large complex traffic networks with multiple intersections. The interdependency of each intersection on its neighbors makes it extremely important to ensure that the different sensors in each intersection are in constant communication to ensure real time data processing. This consequently takes a toll on the energy consumption rate of the sensors especially if the distance between them is wide. The wider the distance between nodes and BS the higher the attenuation rate; consequently leading to increased power needed during data transmission/communication. Failure of a node could lead to massive traffic congestion; also, a downside of this is that motorists will avoid this lane and move to the lanes with lower AWT. This could lead to an increase in congestion levels on the lanes that usually get first priority.

4.4 Hybrid

The initial implementation cost can be quite costly, considering that A.I is still considerably a new research area in traffic control. Also the fact that a hybrid is a combination of two or more STCS, the development time can take a long time in an attempt to ensure successful integration of the different systems.

5. DISCUSION

From the review of the different STCS used, some open issues arise for each technique. Firstly we discuss the general open issues that need to be addressed in all the STCS techniques reviewed:

We start with *starvation.* This is one of the general open issues that come up in any STCS in an attempt to ensure that no lane at any particular time is neglected for as long as there are cars queuing. How to solve starvation is still an open issue particularly because traffic quantity (TQ) and waiting time (WT) are usually isolated from each other. That is, most STCS systems use only one of them to determine traffic light signal allocation. Also another reason is that naturally, overtime as traffic quantity increases (assuming there is a continuous flow of traffic in and out of all lanes at a junction) the average waiting time of vehicles also increases.

Some scholars like [10] and [15] try to resolve starvation by presenting a system that uses both parameters (TQ and WT) to determine green light allocation and extension. However, overtime our assumption is that the lanes that usually have low traffic volumes will end up experiencing some level of starvation especially during peak hours.

The other general open issue is *controlling traffic signals in a large scale traffic network* (i.e. simultaneously controlling traffic for multiple intersections). Srinivasan et al. [19] state that it is crucial for traffic signal control systems to have the capability to examine both the microscopic level of the situation (the traffic state of each intersection) as well as the macroscopic level of the situation (the overall traffic state of the traffic network)

Yousef et al [15] implement an adaptive traffic light control system that controls traffic across multiple intersections using WSN. However, for a large-scale traffic management system, it may be quite difficult to ensure and or even to determine whether the traffic network is flowing smoothly and assess its current state. Also due to the non-uniform nature of traffic in traffic networks, predicting the effects of modifying any of the traffic control parameters is a difficult task [19]. For instance; consider the following network arrangement. There are three networked intersections that are coordinated linearly; A, B and C respectively. Such that, whenever lane 1 in intersection A is green, lane 1 in B and C also get green light. In the event that the STCS needs to control traffic based on the following scenario: the traffic on lane 1 in A is high but that of B requires green light for lane 2 instead with lane 1 having no cars (least priority) and intersection C requires green light on lane 3 and its lane 1 requires second priority (next in line); then it becomes very difficult to determine how to synchronize the lights across the intersections to ensure minimal traffic congestion while at the same time ensuring that all lanes get green light priority when needed.

The specific open issues pertaining to the individual STCS techniques are described below:

5.1 FES

Defining rules. Where do these rules come from? [23]. There are no specific universal criteria used to derive rules and membership functions (degree to which a variable is associated with a term) of this system. Each developer has their own criteria. This is because the linguistic variables (set of terms expressed in natural language that can represent possible values that a system variable can take [22]) and their membership functions vary in type and number from one system to the next. While some applications like fuzzylite [22] derive the rules for you, it is still quite difficult to determine how the application arrived at those rules. Further, the more variables (input/output) a system has, the more complex it becomes to define rules. As for their accuracy levels (i.e. how correct the decisions are), this can only be determined during an iterative testing phase; which in our opinion is not ideal especially if one is dealing with a large knowledge base of rules. In the event the FES fails to meet standards, developer is left with the difficult task of modularizing the rules and possibly the inference process (which if changed affects everything else).

Adaptability. Owing to the fact that FES are not learning systems, it becomes very difficult to ensure that they are adaptable. They work for specific data values that have already been assigned probability factors [24]. This means, for out of the box scenario, an FES cannot provide decision as the rules for the exception are not coded [24]. More importantly, because the membership functions and the rules are dependent on each other, a change in one will necessitate a change in the other [23]. A change in any of the parameters (input/output variables) will require reorganization of part or entire knowledge base depending on the number of parameters being changed. This can be a daunting task especially if you have many membership functions. For instance an FES with 3 membership functions will yield 9 rules while one with 6 membership functions will yield 36 rules four times more than the latter. Consequently a system with many rules can be quite complex to make adaptable or flexible to changes, yet [22] and [23] suggest that the more rules a system has the more accurate the decisions will be because more case scenarios will be factored in the rules.

5.2 ANN

Optimality of solution. ANN derives solutions based on past and present knowledge that is fed into it. Therefore, in the event the data training of the system is improper, it could lead to incorrect decisions. Further, because ANN does not give explanations for its decisions [3; 17; 24]; determining beforehand whether the new knowledge extracted is the best solution can be quite difficult. ANN follows the theory of 'garbage in garbage out' [24]. This remains an open issue because an important aspect in intelligent system design is decision explanation, which involves supplying a coherent explanation of its decisions [25]. This is required for acceptability of the solution and correctness of the reasoning [3].

Offline vs online methods of learning. Backpropagation being the most popular approach used to train ANN [2; 26]; an open issue that usually comes up with this approach is, when to use offline methods (batch leaning) or online methods (single step learning) during the learning process. Offline/batch learning requires that all training data is available because learning is only performed after a full set of training data is presented. On-line/single-step learning is suitable for when training data is produced by an on-going process meaning training data is not available prior to the process. This means that learning for a single step is performed after presentation of a single training pattern. However both methods have their share of limitations; batch learning can take a bit longer because weights are only updated after a full set of training data is presented. Single-step learning can reduce the adaptability performance of the system because weights are updated based on the last training pattern presented; this means the solution derived for the next predicted pattern is specific to one single previous pattern. On the other hand, the two methods also have their strengths when compared to each other; single-step training is faster while batch method yields lower residual error due to more data information as proved by [17] that increasing the training data of an ANN results in more correct solutions. [27]

Despite the benefits of each method, considering that the nature of traffic is uncertain and keeps fluctuating, the question of when to use these methods when it comes to smart transport systems is still debatable. Scholars like [27] suggest use of on-line methods is a better approach to transport traffic management. However, Pinto et al [17] insist that for an ANN to provide more accurate solutions the training time has to be extended to incorporate more data and that includes more past data not just single training pattern. With that in mind, then perhaps the best solution is to incorporate both methods in one system. Start with single-step learning to fasten the learning process and then batch learning to reduce error rate and improve accuracy of final result [27].

5.3 WSN

Techniques for regulating energy consumption in large traffic WSN networks (multiple intersections). It is evident that an increase in the distance between a node and a base station will trigger the need to use more transmission power. Thus, in the design of WSN, short range transmission (multi-hop) should be considered, in order to reduce attenuation as well as minimize power consumption during transmission. In multi-hop communication the sensor nodes serve as relays for other sensor nodes, and must co-operate with each other to find the most efficient route to transmit sensor data towards the BS. However, in an attempt to make the network more energy efficient by splitting up large distances between nodes into several shorter distances, WSN designers are faced by yet another challenge, routing [20].

This *routing* problem, that is, the task of finding a multi-hop path from a sensor node to the base station, is one of the most important challenges and has received immense attention from the research community [20]. This challenge is especially experienced in networks that use switching techniques. To conserve power, transceivers are designed to have switching states: active, idle and sleep states. Where active is when the nodes are receiving and transmitting, idle is when the sensor is on but not transmitting or receiving any data and sleep state is when the sensor is off. Designers thus have the task of deciding how and when it is appropriate to implement each state in order to conserve energy and still maintain network efficiency

In such networks, the sensor nodes are switched off when not in operation. In [21] it is observed that most transceivers operating in idle mode have power consumption almost equal to the power consumed in receive mode. Thus, it is better to completely shut down the transceiver rather than leave it in the idle mode when it is not transmitting or receiving. As a consequence, during these down-times, the sensor node cannot receive messages from its neighbors nor can it serve as a relay for other sensors [20]. Consequently if node 1 wants to send data to node 2, but node 2 is in sleep state this might cause some communication/network.

Scholars have suggested some strategies to resolve this routing problem, they include: 1) *wake-up on demand* where a node switches to active state only when needed and 2) *adaptive duty cycling strategy*, when not all nodes are allowed to sleep at the same time; instead, a subset of the nodes in a network remains active to form a network backbone. However, a significant amount of power is consumed when switching from sleep mode to transmit mode in order to transmit a packet. [21]

Perhaps then the most sustainable approach to energy consumption currently is regenerative power sources for the nodes such as solar charged batteries. However rechargeable batteries are more expensive than disposable ones. Therefore designers are forced to make the difficult decision of a trade-off between cost and energy consumption.

5.4 Hybrid

While this area of research is still fairly new, there still exist few studies done. However one major issue with these systems is *cost*. This is in the context of both design and their implementation particularly the implementation cost considering that A.I is still a new open ground research area. Patel et al [3] come up with a hybrid IDUTC that actually strives to reduce the design components of a hybrid system while still at the same time improving the system's performance. In the IDUTC we see that they successfully manage to reduce the design of the system with regards to the individual approaches. Their system has 55 nodes that produces an overall correct decision rate of 95% as opposed to ANN individual approach which requires 83 nodes in order to produce a correct decision rate of 73% overall. The ANN approach required more neural nodes than the ANN in IDUTC, which led to slower training and a higher implementation cost [3].

6. CONCLUSION

A review on the use of technology to control and manage traffic was presented in this paper. It is observed that the implementation of smart technology in transportation systems has a substantial impact on traffic levels. While the static systems provide a simpler method of automatically controlling traffic; they do not have the flexibility needed on most urban junctions which serve non uniform traffic from the various approaches/roads. Advancement in AI has further led to the development of intelligent traffic control systems. The main objective of these smart systems is to have the traffic lights mimic the human intelligence thus eliminating the need of having traffic officers control traffic on the roads. These intelligent systems provide a way for the lights to change from red to green based on current traffic conditions. Though these systems provide substantial benefits to management of traffic, FES and ANN are a branch of A.I. that is still an emerging field in IT; hence the implementation of such systems as stand alone is still quite costly, especially in the developing countries. Another STCS alternative to using the A.I systems is sensor networks. These networks have gained popularity especially due to the low cost of implementation compared to the A.I based systems. The network is comprised of many sensors that cooperate to monitor and collect data about traffic conditions on the roads. This information is then forwarded to a controller that processes the data into meaningful information. Using an algorithm the controller is able to make routing decisions based on current traffic conditions.

Although smart traffic control systems still have some limitations to what they can achieve intelligently, the future still holds a lot of promise for these systems. Researchers especially in the field of A.I are working hard to find ways to overcome these limitations in order to make them completely efficient. From this paper it is evident that smart systems are the way forward for road traffic control.

7. REFERENCES

[1] Downs, A. (1962). "The law of peak hour expressway congestion". *Traffic Quarterly* 16(3):393–409. Retrieved from http://worldcat.org/issn/00410713

[2] IBM (2013). "A Vision for a smarter city – How Nairobi can lead way into a prosperous and sustainable future." Retrieved from http://www-05.ibm.com/za/office/pdf/IBM - A Vision for a Smarter City – Nairobi.pdf

[3] Patel, M., & Ranganathan, N. (2001). "IDUTC: An Intelligent Decision-Making System for Urban Traffic-Control Applications". *IEEE Transactions on Vehicular Technology, 50(3), 816-829*. Retrieved from http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=933315&url=http%3A%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D933315

[4] Ndonga, S. (2014). "Gridlock in Nairobi as Traffic Lights put to test" Retrieved from http://www.capitalfm.co.ke/news/2014/02/gridlock-in-nairobi-as-traffic-lights-put-to-test/

[5] "Basic Question". Retrieved from http://www-formal.stanford.edu/jmc/whatisai/node1.html

[6] IBM (2013). "IBM Opens Doors to First African Research lab – Continent's Grand Challenges in its Sights". *IBM News Room*. Retrieved from http://www-03.ibm.com/press/us/en/pressrelease/42409.wss

[7] Deedrick, T. (2014). "IBM's New Research Center in Kenya Is Poised to Impact the Region's Growth". Retrieved from http://www.ibmsystemsmag.com/power/trends/ibmresearch/IBM%E2%80%99s-New-Research-Center-in-Kenya-Is-Poised-to-Im/?page=2 "PDCA12-70 data sheet," Opto Speed SA, Mezzovico, Switzerland.

[8] Pascale, A., Nicoli, M., Deflorio, F., Dalla Chiara, B., & Spagnolini, U. (2012). Wireless sensor networks for traffic management and road safety. *IET Intelligent Transport Systems, 6(1), 67-77*. Retrieved from http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=6157101&url=http%3A%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D6157101

[9] Zadeh, L.A. (1965). Fuzzy sets. *Information and Control, 8(3), 338–353*. Retrieved from http://www.cs.berkeley.edu/~zadeh/papers/Fuzzy%20Sets-Information%20and%20Control-1965.pdf

[10] Fahmy, M. M. M. (2007). "An adaptive Traffic Signaling for Roundabout with Four Approach Intersections Based on Fuzzy Logic." Journal of Computing and Information Technology (CIT), 15 (1), 33-45. Retrieved from http://cit.srce.unizg.hr/index.php/CIT/article/view/1625/1329

[11] Khiang, T. K., Khalid, M., & Yusof, R. (1997). Intelligent Traffic Lights Control by Fuzzy Logic. *Malaysian Journal of Computer Science, 9 (2), 29-35.*. Retrieved from http://www.researchgate.net/publication/229029935_intelligent_traffic_lights_control_by_fuzzy_logic

[12] Beattie, A. (2011). "What is the difference between artificial intelligence and neural networks?" *Technopedia*. Retrieved from http://www-technopedia.com/2/27888/programming/what-is-the-difference-between-artificial-intelligence-and-neural-networks

[13] Dai, Y., Hu, J., Zhao, D., & Zhu, F. (2011). "Neural network based online traffic signal controller design with reinforcement training". *Intelligent Transportation Systems (ITSC), 1045-1050*. Paper presented at 14th International IEEE Conference, Washington, DC. Retrieved from http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=6083027&url=http%3A%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D6083027

[14] Singh, Y. P., & Mittal, P. K. (2013). "Analysis and Designing of Proposed Intelligent Road Traffic Congestion Control System with Image Mosaicking Technique*". International Journal of IT, Engineering and Applied Sciences Research (IJIEASR), 2 (4), 27-31*. Retrieved from http://www.irjcjournals.org/ijieasr/apr2013/7.pdf

[15] Yousef, K. M., Al-Karaki, J. M., & Shatnawi, A. M. (2010). Intelligent Traffic Light Flow Control System Using Wireless Sensor Networks. *Journal of Information Science and Engineering, 26, 753-768*. Retrieved from http://www.iis.sinica.edu.tw/page/jise/2010/201005_02.pdf

[16] Bhuvaneswari, P.T.V., Arun raj, G.V., Balaji, R., Kanagasabai, S. (2012). "Adaptive Traffic Signal Flow Control using Wireless Sensor Networks". *IEEE Computer Society, 85-89*. Paper presented at 4th International Conference on Computer Intelligence and Communication Networks. Retrieved from http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=6375077&url=http%3A%2F%2Fieeexplore.ieee.org%2Fxpls%2Fabs_all.jsp%3Farnumber%3D6375077

[17] Barbosa, M. R., & Pinto, G. C. (n.d). "Exploring the use of Neural Networks in urban traffic management". *Business Sustainability I*, 287-292. Retrieved from http://labve.dps.uminho.pt/bs11/CD/PDF/47%20-%20pp%20287-292%20-%20Pinto%20G.C.,%20Barbosa%20M.R..pdf

[18] CBT. (2012). "Going Backwards the new road programme." Retrieved from http://bettertransport.org.uk/sites/default/files/research-files/Roads_to_Nowhere_October2012_web_spreads_0.pdf

[19] Srinivasan, D., Choy, M. C., & Cheu, R. L. (2006). "Neural Networks for Real-time Traffic Signal Control". *IEEE Transactions on Intelligent Transportation Systems, 7 (3), 261-272*. Retrieved from http://www.jhuapl.edu/spsa/PDF-SPSA/Srinivasan_etal_IEEETITS06.pdf

[20] Dargie, W. & Poellabauer, C. (2010). Fundamentals of Wireless Sensor Networks Theory and Practice (1st ed.). John Wiley and Sons Ltd.

[21] Wikipedia. (n.d). "Sensor Node". Retrieved from http://en.wikipedia.org/wiki/Sensor_node.

[22] Rada-Vilela, J. (2014). "Fuzzylite-paper 3.1 a fuzzy control library. Retrieved from http://www.fuzzylite.com

[23] Watts, M. J. (n.d). "Fuzzy Systems". Retrieved from http://mike.watts.net.nz/Teaching/IIS/Lecture6.pdf

[24] Nagori, V. & Trivedi, B. (Find out). "Which type of Expert system? Rule Base, Fuzzy or Neural is most suited for evaluating motivational strategies on human resources: - An analytical case study." *International Journal of Business Research and Management (IJBRM), 3, (5), 249-254*. Retrieved from http://www.cscjournals.org/manuscript/Journals/IJBRM/volume3/Issue5/IJBRM-113.pdf

[25] Davis, R., Buchanam, B. & Shortcliffe, E. (1977). "Production rules as a representation for a knowledge-based consultation program." *Artificial Intelligence*, 8, 15–45. Retrieved from http://www.inf.ufpr.br/alexd/ARTIGOS_IA/Davis_Buchanan_Shortlife_1977.pdf

[26] Annunziato, M. & Pizzuti, S. (n.d). "A Smart-Adaptive-System based on Evolutionary Computation and Neural Networks for the on-line short-term urban traffic prediction". Retrieved from http://www.researchgate.net/publication/228578769_A_Smart-Adaptive-System_based_on_Evolutionary_Computation_and_Neural_Networks_for_the_on-line_short-term_urban_traffic_prediction

[27] Goerke, N. (n.d). "Which one is better between online and offline trained neural network?" Retrieved from http://www.researchgate.net/post/Which_one_is_better_between_online_and_offline_trained_neural_network

[28] Michael, B.W. & Areolino de Almeida Neto. (2014). "Optimization of Traffic Light Timing based on Artificial Neural Networks". *Paper presented at 17th IEEE International Conference on Intelligent Transportation Systems*. Retrieved from http://scl.hanyang.ac.kr/scl/database/papers/ITSC/ITSC14_HTML/media/files/0179.pdf