OPEN ACCESS
International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-3, February 2019

Intelligent Traffic Management System Based on Historical Data Analysis

Frederick Egyin Appiah-Twum, Jerry John Kponyo, Isaac Acquah

Abstract*: The problem of vehicular traffic congestion is ubiquitous yet non-trivial. It is increasingly worsening by the day all around the world with severe vehicular traffic taking its toll on all road users. With the upsurge in urban traffic jams, innovative control strategies are therefore essential to allow efficient flow of vehicular movement. It is thus not surprising that a myriad of novel control strategies has been developed over the past years to manage the ever-growing urban gridlock. Many of the currently used traffic control strategies are based on the relatively inefficient fixed-time traffic systems, like in the case of Ghana, or on a central traffic-responsive control system, which is challenging to implement and even much more difficult to maintain. As a consequence of inefficiencies in traffic control, road users are saddled with inconveniently longer waiting times in queues. To mitigate this problem, we proposed a distributed artificial intelligence and multi-agent system as a viable approach to manage the traffic menace. The proposed system uses historical data for traffic management and was designed and implemented using Simulation of Urban Mobility (SUMO) software. The result obtained in the comparison of the current fixed time-controlled system and designed system clearly indicated that the proposed system outperformed the fixed-time cycle controllers in every key performance index selected for evaluation.

Index Terms*: Traffic management system, intelligent transportation systems, fixed timed controllers, iterative tuning strategy, multi connect architecture associative memory.

I. INTRODUCTION

A. Overview

The prime objective of this work was to design a distributed self-sufficient traffic management system capable of changing itself to meet the demands of current road usage, while alleviating the deleterious effects of fixed cycled controllers in place, without necessarily making any major changes to the limited road resources or infrastructure in place. The system does this by using historical data, which is statically collected and analysed over a period of time. The data obtained from the analysis is the run through a linear regression algorithm to give a fair prediction of what traffic will be like. Newly collected traffic information is fed as an input to the system, compared to the pre-existing stored traffic patterns and iteratively tuned until the traffic is optimized. Each iteration then becomes the input of the next iteration. The designed system is capable of efficient traffic management. In the event

Manuscript published on 28 February 2019.
***** Correspondence Author (s)
Frederick Egyin Appiah-Twum*, B.Sc. in Telecommunications Engineering from the Ghana Technology University College in Accra, Ghana.
Jerry John Kponyo, B.Sc. and MSc. degrees in Electrical Engineering at the Kwame Nkrumah University of Science and Technology (KNUST), Kumasi,
Isaac Acquah, BSc. degree in Computer Engineering at the Kwame Nkrumah University of Science and Technology (KNUST), Kumasi,

B. Literature Review

Several practical models for traffic management and control have been proposed over the years. [2] highlighted the inadequacies of prior time-dependent models. They proposed a model with the arrivals considered Markovian and individualistically distributed with respect to the Poisson arrival rate. Where there are multiple lanes controlled by the same traffic light, they assumed that all the lanes are equal. Hence, a single server case with no overtaking, in modelling for fixed-time cycled controllers. [3] allowed for a somewhat more general departure method of the delayed vehicles, [4] improved [3] approach to allow for clearness. He let Y be a discrete random variable with pgf Y (z) = E(zY) where [3] presumed *Y* to be of complex Poisson type, and assumed all moments of *Y* exist. [4] represented the average and variance of *Y* by μY and σ^2 Y, correspondingly. To have stability, it was essential that the number of arriving vehicles be less than the maximum number of vehicles that could depart. [5] initially tackled an expert system method to this problem. After their influential work, expert systems like the French System were realised. Although traffic-waiting time was reduced, they were extremely slow due to the fact that they processed tremendous volumes of data. The system proposed by [6] was founded on the broadcast of data in a network of traffic signals. They presumed street configuration in the form of a grid, with many simplifications. They proposed one processor at each intersection that communicates nonstop with the four processors at adjacent intersections. The operation of the system was built on a set of co-operating real-time expert systems operating in combination with a simulation-based planner. [7] also described a traffic light controller designed by means of a simple predictor. Quantities taken during the current cycle were used to test several likely settings for the next. The setting resulting in the minimum number of queued vehicles was executed. The system appeared to be exceedingly adaptive. Since it only involved information of one cycle, it could not respond to strong fluctuations in traffic flow effectively. In this case, the system adapted hurriedly, causing poor performance. [8] presented a method to eradicate glitches with [7]. Traffic detectors positioned at either side of junctions in conjunction with vehicle identifiers were used to quantify the ratio of delayed of vehicles at junctions. This implementation allowed the prediction of the projected average delay with a filter function to even out arbitrary fluctuations. The control system attempts to abate not only the overall delay, but the aggregated deviations from the mean delay also. An information span of about fifteen minutes was used to define the ideal settings for the next cycle, and even with a modest optimization algorithm;

*Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)*

the system performed well compared to pre-set and actuated controllers. A fuzzy logic system for a single junction that mimics human intelligence has been attempted [9]. A drawback of the controller is its overdependence on the pre-set quantification fuzzy variables. System failure is imminent if the summed quantity of traffic varies. Additionally, the results indicated system was only tested on a single traffic junction which made it inconclusive. [10] employed fuzzy logic in monitoring various junctions. Controllers received additional data about vehicles at the previous and next junctions and supported green waves. The system outclassed a fixed controller and was optimal in both light or heavy traffic. The controller easily handled varying traffic flow but required different constraint settings per junction. [11] compared the use of evolutionary algorithm approaches to a traffic light for a single virtual intersection using the common fixed traffic light controller in [12]. They discovered similar results for both systems. Unfortunately, they did not attempt to implement their system on several combined intersections, since dynamics of such a network of traffic nodes is further complicated and learning or creating controllers for these intersections could show additional interesting behaviours and research questions.

C. Recurrent Traffic Flow Patterns

In urban traffic management, the Highway Capacity Manual (HCM) has become the most commonly used methodology to label signalized intersections [13]. Iterative Tuning (IT) strategy is associated with the conceptual frameworks concerning previous traffic flows. The initial parameter considered is the Daily Traffic Pattern (DTP) which is the summary of traffic flows for a 24-hour daily period. From the investigation provided by [14], DTPs of working days are alike since events are almost the same with the exception of working days before holidays or weekends, where the afternoon's traffic densities may contrast. Thus, working days are characterised by two modules:

- Normal Working Days: working days excluding days predating holidays.
- Last Working Days which are the working days predating holidays.

Daily Traffic Signal Schedules (DTSS) is the next parametric quantity considered. DTSS are the phase intervals for a junction over a 24-hour period. For a junction with DTPs of phases being recurrent, traffic weights in all segments are recurrent and recurrent phase intervals then become practical. The basis for the use of Iterative Tuning (IT) strategy is the recurrence of Daily Traffic Signal Schedules. The hypothesis drawn here is urban infrastructure including routes, dwellings, and places of business, vary gradually. The graphs (figures 1 – 4) below confirm the recurrence of traffic.

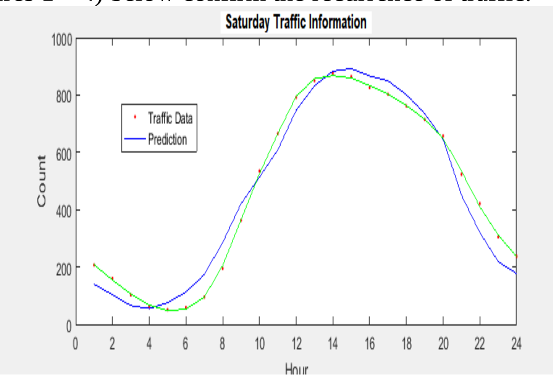

Figure 1. Saturday traffic information

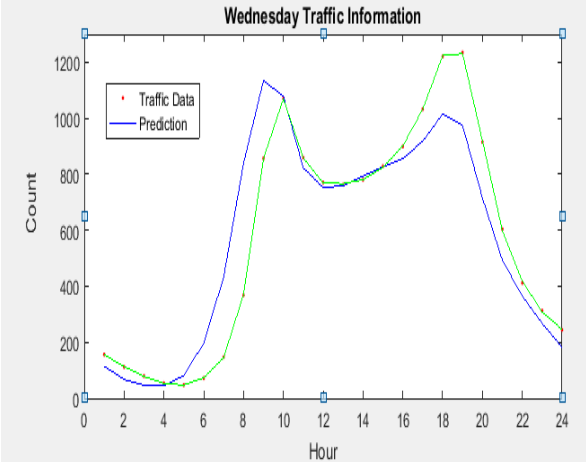

Figure 2. Wednesday traffic information

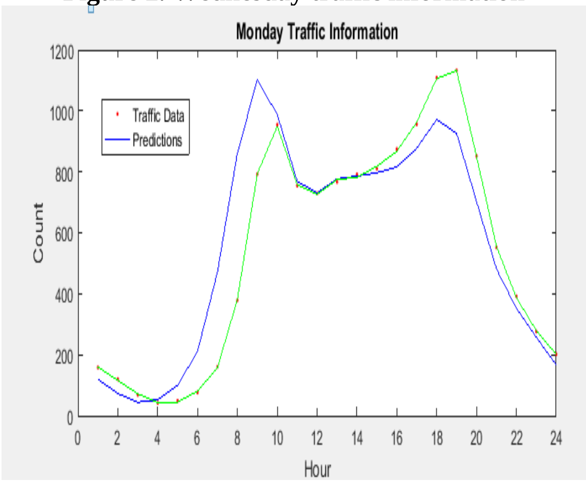

Figure 3. Monday traffic information

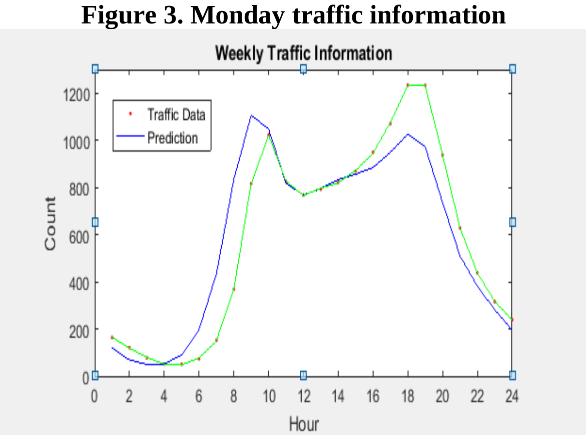

Figure 4. Weekly traffic information

The foundation for IT strategy is the recurrence of the DTP. On a daily basis, there is an occurrence of traffic flows $x_{j,i}^{\omega}(\tau)$ where ω becomes the index of working days; and ω ∈ W where W is the set of working days. n^{ω} is used to describe the number of working days. The average (M), standard deviation (S) and coefficient of variation (V) in equations (1), (2) and (3) respectively are utilized to analyse the variations.

$$M = \frac{1}{n^{\omega}} \sum_{\omega \in W} x_{j,i}^{\omega}(\tau) \qquad (1)$$

$$s = \sqrt{\left(\frac{1}{n^{\omega}-1} \sum_{\omega \in W} (x_{j,i}^{\omega}(\tau) - M)\right)^2} \qquad (2)$$

$$V = \frac{S}{M} \qquad (3)$$

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

If the coefficient of variation of traffic flow within a certain period of time is infinitesimal, traffic flows are comparable and the DTP is recurrent. Thus, the coefficient of variation is used to denote the repetition of daily traffic patterns for various periods. For each intersection, already existing historical traffic data patterns of the full day are stored in memory. For an arbitrary *junction* $j \in J$, xj, $i(k) \in X$, $\forall i \in Fj$ is compiled over the complete day, with X signifying newly compiled traffic information; *Fj* represents the collection of lane groupings of junction *j*; with *k* denoting the index of cycles. In anticipation of a special event, traffic flows vary. Hence, the pattern checking algorithm is used to confirm if new traffic flows *(X)*, are recurrent with all classes of pre-existing traffic flow pattern information (X_h) or not. A Pearson product-moment correlation coefficient γ (for the current iteration) is then computed to quantify the linear correlation among *X* and X_h. γth is then used as the threshold Pearson coefficient. If $\gamma \geq \gamma th$, traffic patterns *X* are recurrent with historical traffic flow patterns X_h. If $\gamma < \gamma th$, traffic patterns *X* are recurrent with historical traffic flow patterns. In both modules of working days pre-existing traffic information is updated in Equation. (4) to try to adapt to the gradually altering traffic situations.

$$X_h = (\alpha X X_h h + \beta X),\ if\ \gamma\gamma < \gamma \geq \gamma th; \qquad (4)$$

The variables α and β are weighted coefficients that satisfies the condition: $\alpha + \beta = 1$. This condition is mandatory in the regulation of the updating speed and not necessarily in the behaviour of iterative tuning strategy. The modified traffic flows X_h is deposited in a database to represent pre-existing traffic flow patterns, X_h, which are correspondingly the most significant input of the IT strategy.

For an arbitrary junction j ∈ J, constructed on the modified traffic flows $\overline{X_h}$, traffic flows $X_j(k)$ for all lane collections are recovered. For a particular phase p ∈ P_j with phase intervals $u_{j,p}(k)$, with P_j representing the group of phases of a junction j, where there is one or more similar lane groups $x_{j,i}(k)$ with vehicles which have the right of way $X_j(k)$ with i ∈ $F_{j,p}$, and $F_{j,p}$ becoming the collection of the lane groups of that arbitrary junction j that has vehicles with the right of way during phase p. Maximum phase occupancy $o_{j,p}(k)$ is then computed, $\frac{x_{j,i}(k)}{n_i{}^{lg}}$ and road capacities $su_{j,p}(k)$, which are conveyed in equation (5)

$$o_{j.p}(k) = max_{i \in F_{j.p}} \frac{\left\{\frac{x_{j.i}(k)}{n_i^{lg}}\right\}}{su_{j.p}(k)} \qquad (5)$$

With $n_i{}^{lg}$ representing the lanes in the lane group i; s signifying the saturation flow per lane which is presumed to be static. After that, phase occupancy $o_{j,p}(k)$ is changed into phase occupancy error $e_{j,p}(k)$ in equation. (6). As in equation (7), where $e_{j,p}(k)) \in E_j(k)$, ∀p ∈ P_j as the phase occupancies of error approach zero, $o_{j,p}(k)$ at junctions are well-adjusted and delay time is practically curtailed. $E_{j,p}(k)$ is the vector to characterise phase occupancy errors of junction j.

$$e_{j.p}(k) = O_{j.p} - \frac{\sum_{p \in Pj} O_{j.p}(k)}{n^p} \qquad (6)$$

$$e_{j.p}(k) \to 0 \qquad (7)$$

With n_p signifying the quantity of the controller phases assigned to the junctions. Presuming $E_j(k)$ is attained from equation (5) along with equation (6). Already existing signal duration $U_{j.h}(k)$ is recalled from the database of traffic signal schedules U_h. The tuning technique for the traffic controller phase splits is modelled in equation (8)

$$\widehat{U}_j(k) = U_{j.h}(k) + LE_j(k+1)$$
$$L = I\lambda \qquad (8)$$
$$U_j(k) = C\{\widehat{U}_j(k)\}$$

L is characterizing the tuning function and is computed as L = *λI; I* then become the identity matrix of a suitable dimension; λ should be approximated testing and evaluation, and this does not adversely hamper the performance. C{} is the parameter that considers the system constraints. For phase $U_{j.p}(k) = C\{\widehat{u_{j.p}}(k)\}$, with $U_{j.p}(k) \in U_p(k)$, ∀p ∈P_j, constraints being well thought-out. As shown in equation (9), function C{} takes phase constraints into consideration. For safety, longest phase time U_{max} and shortest phase time U_{min} for each of the phases are predefined.

$$U_{min} < \widehat{U}_j(k) < U_{max} \qquad (9)$$

Equation (9) is realized by:

$$C\{\widehat{U}_{j.p}(k)\} = \begin{Bmatrix} \widehat{U}_{j.p}(k), & if U_{min} < \widehat{U}_j(k) < U_{max} \\ U_{max}, & if \widehat{U}_{j.p}(k), \geq U_{max} \\ U_{min}, & if \widehat{U}_{j.p}(k), \leq U_{min} \end{Bmatrix}$$

$$C = \sum_{p \in Pj} U_{j.p}(k) + t_L \qquad (10)$$

The constraints also take into account the of cycle length in equation (11).

$$C = \sum_{p \in Pj} U_{j.p}(k) + t_L \qquad (11)$$

Where C is represents the cycle length and t_L characterizes the total time lost per cycle. This is shown in Eq. (12) as:

$$c\{\widehat{U}_{j.p}(k)\} = \frac{\{\widehat{U}_{j.p}(k)\}}{\sum_{p \in Pj} U_{j.p}(k)}(C - t_L) \qquad (12)$$

Equations Eq. (10) and Equation. (12) are calculated alternately until the constraints equation (9) and equation (11) are satisfied synchronously. Moreover, phase durations are regulated to be accurate to the resolution of the controllers. As phase durations $U_j(k)$ ∈ U, ∀j ∈ J, ∀k is obtained, with U as the vector of phase lengths for the complete day, they will be used for the next time with recurrent traffic flows, deposited in the database as traffic signal schedules U_h.

D. *Data Sources*

This paper is grounded on data documented within random working periods of morning, afternoon and evening where roads are normally busy in the Kumasi Metropolis in the Ashanti Region, Ghana. Various intersections were considered at various random intervals and days with the necessary extrapolations made to give a stable traffic pattern in the metropolis. This traffic information is given in table 1.

Table 1. Data source

LOCATION	SESSION	ARRIVAL	DEPARTURE
		Average No. cars/hour	Average No. cars / hour
Tech-to-Top High	MORNING	45	60
Top High-to-Oforikrom	MORNING	53	71
Amakom-to-Oforikrom	MORNING	40	50
Aboabo-to-Oforikrom	MORNING	11	12
Oforikrom-to-Anloga	MORNING	75	81
Tech-to-Top High	AFTERNOON	30	50
Top High-to-Oforikrom	AFTERNOON	49	55

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

Amakom-to-Oforikrom	AFTERNOON	36	50
Aboabo-to-Oforikrom	AFTERNOON	11	10
Oforikrom-to-Anloga	AFTERNOON	58	63
Tech-to-Top High	EVENING	40	55
Top High-to-Oforikrom	EVENING	55	76
Amakom-to-Oforikrom	EVENING	45	60
Aboabo-to-Oforikrom	EVENING	13	15
Oforikrom-to-Anloga	EVENING	88	91

II. PROPOSED SYSTEM

The proposed system conceptually shown in figure 5, uses a historical data input, which is encoded into a construct, that the Multi-Connect Architecture Associative memory can process. Most of the processing of the system is done in the MCA. Iterative control strategy [15] iteratively sets the phase splits of the traffic controller. The system thereby requires pre-existing data input. Newly collected traffic flows are gathered over a period for statistical analysis. A pattern checking algorithm which is a correlation pattern recognition algorithm is used to check whether the newly collected traffic flows are recurrent with any previously processed historical traffic flow pattern. A Pearson product-moment correlation coefficient is computed through careful analysis to quantify the linear correlation between the newly collected and historical data traffic patterns, non-recurrent data is made recurrent by a pattern updating algorithm. The updated traffic flows are stored in the database to be pre-existing traffic flow information which are also the inputs of IT strategy. After the processing, the system response with the associated traffic signal schedules are sent to the central processing station, which interfaces the traffic light controller with the proposed system.

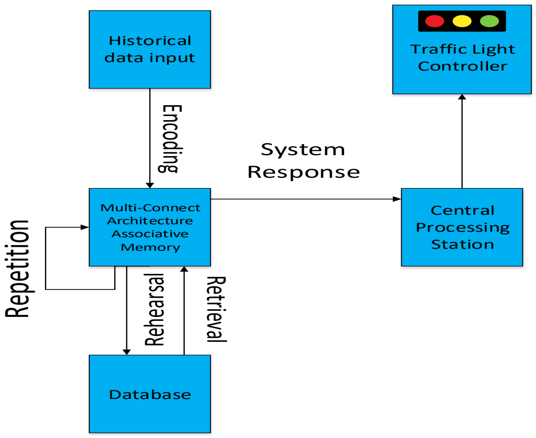

Figure 5. System design

III. SIMULATION RESULTS

An important factor to consider in the comparison of fixed timed traffic-controlled system and the proposed system is the type of key performance indicators, which are performance measurements that evaluate the success or the failure of a systems. Since the aim of the research is to eliminate congestion in the Kumasi Metropolitan, Key Performance Indicators chosen have a direct influence on traffic congestion. The table 2 below indicates the particular KPIs chosen to evaluate the performance of the systems in comparison.

Table 2. KPIs

Key Performance Indicators	Units
Vehicular Speed	[m/s]
Trip Waiting Time	[s]
Trip Time Loss	[s]
Trip Duration	[s]

A. Trip Time Loss

The first KPI measure is the trip time loss, which gives an indication of the time lost due to driving below the ideal speeds. Ideal speeds include the individual speed factor which is used to sample a vehicle speed factor from a normal distribution and slowdowns due to time loss at intersections. Scheduled stops are not measured in the trip time loss measurements. Figure 6 shows the comparison of the current and proposed systems in terms of their trip time losses. The red shows the trip time loss for the proposed system with the blue representing the current fixed time-controlled system.

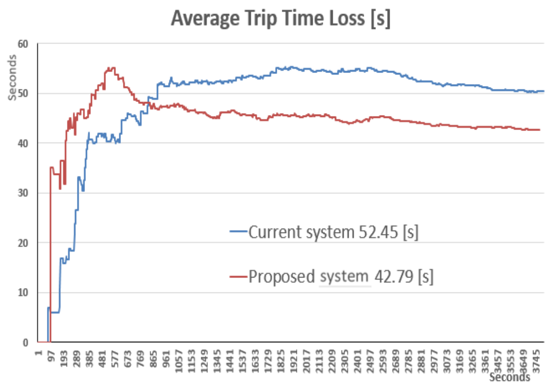

Figure 6 Average Trip Time Loss

B. Trip Duration

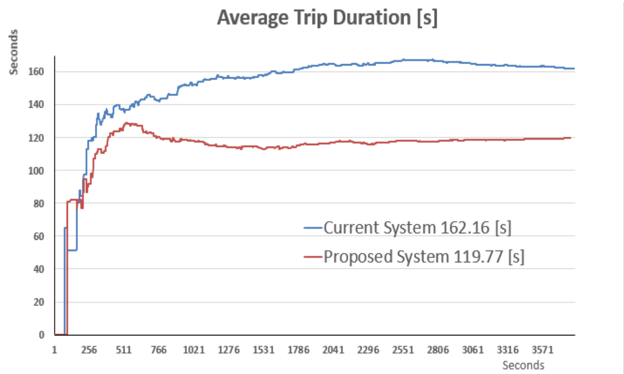

Figure 7 Average Trip Duration

The trip duration is the time required by an individual to accomplish a particular route. The trip duration is measured in simulation seconds. Below (figure 7) is an assessment of the current and proposed systems in terms of their trip duration. The red shows the proposed system with the blue expressing the current fixed time-controlled system

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-3, February 2019

C. Vehicular Speed

This is the measure of the speed with which a vehicle traverses the network in the simulation. Vehicular speed is computed in meters per simulation seconds. An assessment of the current and proposed systems in terms of their vehicular speeds is provided in figure 8. The red represents the performance of the proposed system, with the blue showing that of the current fixed time-controlled system.

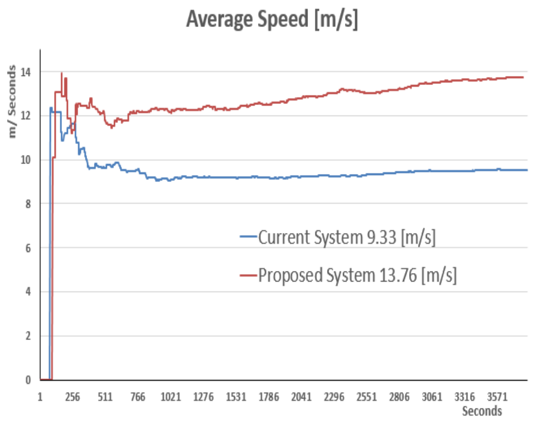

Figure 8 Vehicular Speed

D. Queue Waiting Time

The last KPI evaluated is the time in which a particular vehicle has to stop and wait. Scheduled stops are not considered when measuring the queuing times of vehicles. The queue waiting time is a direct measure of congestion in the system. Below is the comparison of the current and proposed systems in terms of their trip time losses. The red signifies the proposed system with the blue representing the current fixed time-controlled system.

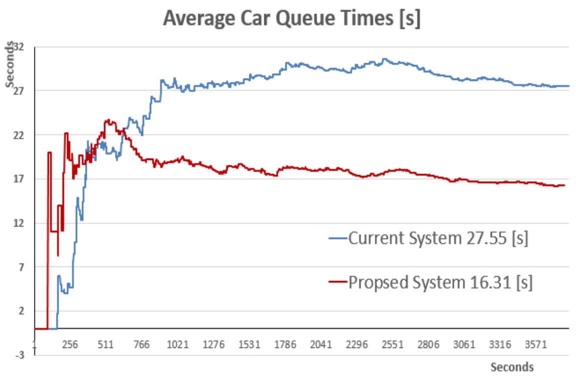

Figure 8 Average Queue Waiting Times

IV. CONCLUSION

In this research, an intelligent traffic monitoring system that uses historical traffic data to learn and continuously optimize the duty cycles of traffic controllers was designed. The results show a superior performance in comparison with the existing fixed timed model. The design when implemented has the potential to efficiently manage the flow of traffic in the Kumasi metropolis by enhancing the phase and split times of traffic controllers, enabling them cope with the erratic behaviour of traffic in the region. The system was implemented in the SUMO environment. The results obtained in the comparison of the current and proposed systems indicated clearly that the proposed system outperformed the current fixed time cycle controllers in every key performance indicator selected.

Moreover, the management of the traffic was drastically improved in the selected region.

ACKNOWLEDGMENT

I would like to thank all the members of Dr Kponyo's virtual research lab at the Kwame Nkrumah University of Science and Technology, Ghana.

REFERENCES

1. Wang, Y., Wang, D., Jin, S., Xiao, N., Li, Y., & Frazzoli, E. (2016). Iterative tuning strategy for setting phase splits with anticipation of traffic demand in urban traffic network. IET Control Theory & Applications, 10(12), 1469-1479.
2. R. Chrobok, O. Kaumann, J. Wahle, and M. Schreckenberg, “Different methods of traffic forecast based on real data,” European Journal of Operational Research, vol. 155, no. 3, pp. 558–568, 2004.
3. H. C. Manual, Highway Capacity Manual, 4th ed. Washington, DC, 2000.
4. Rechenberg, "Evolution strategy: Nature's way of optimization. In Bergmann, editor, Methods and Applications, Possibilities and Limitations.” Lecture notes in Engineering, pp. 106– 126, 1989
5. H. Taale, M. Preuß, T. Back, A. Eiben, J. de Graaf and C. Schippers, "Optimizing traffic light controllers by means of evolutionary algorithms.", EUFIT, 1999
6. J. Lee, K. Lee, K. Seong, C. Kim, and H. Lee-Kwang, "Traffic control of intersection group based on fuzzy logic.", Proceedings of the 6th International Fuzzy Systems Association World Congress, pp. 465–468., 2018.
7. K. Tan, M. Khalid and R. Yusof, "Intelligent traffic lights control by fuzzy logic.", Malaysian Journal of Computer Science, vol. 9, no. 2, 1996.
8. H. Liu, J. Oh and W. Recker, "Adaptive signal control system with on-line performance measure", In 81st Annual Meeting of the Transportation Research Board, 2002.
9. Proceedings Volumes, vol. 30, no. 8, pp. 937-942, 1997.
10. Findler and Stapp, "Distributed Approach to Optimized Control of Street Traffic Signals", Journal of Transportation Engineering, vol. 118, no. 1, pp. 99-110, 1992.
11. Zozaya G.C. and Hendrickson C. T. Expert system for traffic signal setting assistance. Journal of transport engineering, Vol. 113(2) 1987. pp. l08-126.
12. J. van Leeuwaarden, "Delay Analysis for the Fixed-Cycle Traffic-Light Queue", Transportation Science, vol. 40, no. 2, pp. 189-199, 2006.
13. J. N. Darroch, G. F. Newell, and R. W. J. Morris. Queues for a vehicle-actuated traffic light. Operations Research, 12(6):882–895, 1964.
14. L. Igbinosun and S. Omosigho, "Traffic flow model at fixed control signals with discrete service time distribution", Croatian Operational Research Review, vol. 7, no. 1, pp. 19-32, 2016.
15. F. V. Webster, “Traffic signal settings,” Department of Scientific and Industrial Research Road Research Laboratory, Tech. Rep., 1958.

AUTHORS PROFILE

Frederick Egyin Appiah-Twum received his B.Sc. in Telecommunications Engineering from the Ghana Technology University College in Accra, Ghana. He is currently an M.Phil. student with the department of Electric/Electronic Engineering. His research interests are in traffic management, Smart systems and Artificial Intelligence. Frederick is a member of the Ghana Institution of Engineers.

Jerry John Kponyo was born in 1980 in Konongo, Ghana. He received his B.Sc. and MSc. degrees in Electrical Engineering at the Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana and his PhD from the University of Electronic Science and Technology of China (UESTC). He has been a Senior Lecturer at the Kwame Nkrumah University of Science and Technology, Kumasi, Ghana since August 2015 with a focus on teaching and research. He is currently the Dean of the Faculty of Electrical and Computer Engineering, KNUST. His research interests are; Applying Ant Colony Optimization to Vehicular Ad hoc Networks (VANETS), Artificial Intelligence, IoT and Wireless and Mobile Communications. He has authored a number of International Conference and Journals articles. Jerry John Kponyo is a member of IEEE and the Ghana Institution of Engineering.

Isaac Acquah received his BSc. degree in Computer Engineering at the Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana. He majored in Biomedical Engineering during both his Masters and Doctoral Studies at the University of Surrey, England and Korea University, Republic of Korea, respectively. He has been a lecturer with the Department of Computer Engineering, KNUST from 2008. He is also a member of the IEEE and the Ghana Institution of Engineering

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)