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A COMPARISON STUDY OF DETERMINISTIC AND METAHEURISTIC ALGORITHMS FOR STOCHASTIC TRAFFIC FLOW OPTIMIZATION UNDER SATURATED CONDITION

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Abstract

Traffic congestion is a perennial issue for most cities. Various artificial intelligence (AI) algorithms, which can categorize as deterministic and metaheuristic algorithms have been suggested to mitigate congestion. Although traffic flow is dynamic and stochastic in nature, most of the previous works evaluated the algorithms with a deterministic or non-stochastic traffic flow pattern. As such, the adaptiveness of those AI algorithms in dealing with stochastic traffic flow patterns is yet to be investigated. Therefore, this paper aims to explore the feasibility of both algorithm types in controlling stochastic traffic flow. In this work, a benchmarked traffic flow model is modified and developed as the simulation platform with the parameters extracted from the guidelines of Public Works Department Malaysia (JKR). Normal distribution function is embedded in the developed model to simulate non-uniform headway for inflow and outflow vehicles. Two commonly used algorithms, namely Fuzzy Logic and Genetic Algorithm are proposed as the adaptive controller to optimize the traffic signalization based on the instant stochastic traffic demand. The simulation results show the metaheuristic algorithm performs better than the deterministic algorithm. The mutation mechanism of the metaheuristic algorithm improves the exploration ability of the algorithm in seeking the optimum solution within the solution space without bounded by a set of fixed-computational rules.

Keywords:

Genetic Algorithm, Fuzzy Logic, Signal Optimization, Stochastic Flow, Saturated Condition

1. INTRODUCTION

The challenge of traffic congestion is a perennial issue for most countries, especially for those countries with a low modal share of public transport. This issue is exacerbated by rapid motorization and under-investment in infrastructure. As a result, congestion undermines the benefits of urbanization. Based on a study of the World Bank, Malaysia had lost 24.7 billion ringgits due to traffic congestion. Most of the losses were caused by travel delay, which was 19.6 billion ringgits or equivalent to 79.4% [1].

Due to the space constraint [2] and low modal share of public transport [3] in most of the Malaysian cities, traffic signal optimization has become the most cost-effective way to mitigate the local congestion issue [4]. Various artificial intelligence (AI) algorithms were proposed in the literature to relieve congestion [5]-[10].

Generally, all the reported algorithms can categorize into two types, namely deterministic and metaheuristic algorithms. The deterministic algorithm, such as Fuzzy Logic [11] [12], Artificial Neural Network [13] [14] and Q-Learning [15] [16], is an algorithm which will always produce the same output if given by a particular set of input, whereas the metaheuristic algorithm, such as Genetic Algorithm [17] [18], Particle Swarm Optimization [19] [20] and Ant Colony Optimization [21] [22], is a partial search algorithm that may provide an adequately optimized solution.

However, the simulated performances of these reported algorithms were evaluated based on a non-stochastic traffic flow model [23]. Although the actual traffic flow is dynamic and stochastic, most of the previous works still defined the charging and discharging rates of a traffic network as a fixed flow pattern [24]. The headway between two consecutive vehicles is usually defined as a constant. As such, the adaptiveness of those reported AI algorithms in controlling stochastic or non-deterministic traffic flow patterns is yet to be investigated.

Therefore, this paper aims to explore the feasibility of both deterministic and metaheuristic algorithms in controlling stochastic traffic flow. This work proposes Fuzzy Logic and Genetic Algorithm as the deterministic and metaheuristic approaches respectively to optimize the traffic signalization. Both algorithms are selected because they are the most common techniques reported in the literature.

A benchmarked traffic flow model is developed [25] as the platform to examine the functionality of both proposed algorithms. Normal distribution function [26] is embedded in the benchmarked model to improve the model by simulating non-uniform headways for inflow and outflow vehicles. The model parameters, such as geometric design, signal timing and saturation flow, are extracted from the guideline of Public Works Department Malaysia (JKR) [27] so that it can represent the traffic flow in Malaysia.

In this work, traffic demands are limited close to the network capacity to avoid the whole network collapse due to oversaturated conditions. Besides, the predetermined saturated traffic demands can effectively assess the feasibility of both the proposed algorithms in controlling stochastic traffic flow. If the algorithm is less adaptive, it is unable to clear all the vehicles at the intersection in every signal cycle. As a result, the queued vehicles will keep increasing as time and eventually cause the whole network collapse.

This paper is organized as follows: section 2 discusses the modification of traffic network modelling; section 3 explains the development of both proposed algorithms; section 4 presents the results and discussion and section 5 concludes the findings of this paper.

2. METHODOLOGY

This section discusses the development of traffic network model. An arterial traffic network along Jalan UMS, Kota

Kinabalu, Malaysia is modeled as the platform to investigate the feasibility of both the proposed algorithms. The location of signalized intersections is circled in the map, as shown in the upper part of Fig.1. The distance between each intersection is 1km, 2km and 3km respectively. The bottom part of Fig.1 illustrates the number of lanes for each approach at every intersection with the traffic flow directions. The Table.1 tabulates the geometric parameters.

In order to simulate non-uniform headway traffic flow behavior, the normal distribution function [26] is introduced to simulate the inflow and outflow traffic flows, as shown in Eq.(1).

$$f\left(q\,|\,\bar{q},\sigma\right)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(q-\bar{q})^2}{2\sigma^2}} \tag{1}$$

where, q is the inflow/outflow rates, $\bar{q}$ is the average inflow/outflow rates, σ is the standard deviation.

The Eq.(2) shows the cumulative density function (CDF), where x is the inflow/outflow vehicle. A random number will be generated randomly, the q has the smallest CDF value that is higher than the generated random number [26].

$$F\left(q\right)=\int_{-\infty}^{\infty} f\left(q\right)dt = f\left(x\leq q\right) \tag{2}$$

Table.1. Geometric Parameters

Parameter	Value
Grade (terrain level)	0.0%
Width of lane	3.25m
Width of median	1.00m
Horizontal alignment angle	0.00°
Left-turning radius	18.0m
Right-turning radius	12.5m

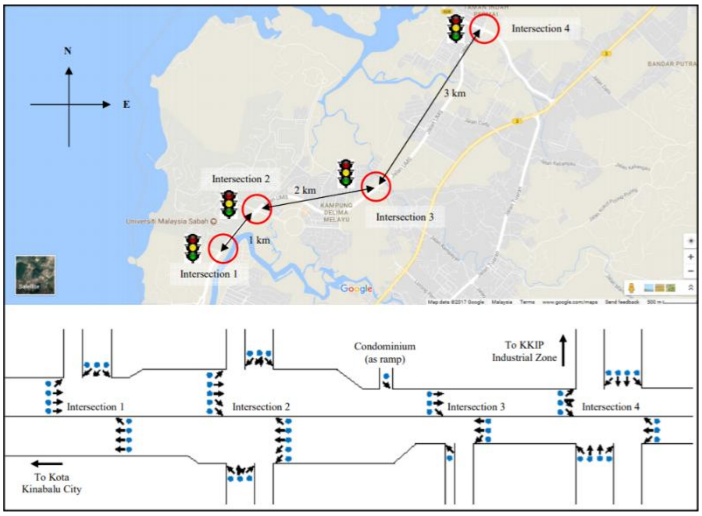


Fig.1. Arterial traffic network along Jalan UMS [28]

3. ADAPTIVE SIGNAL CONTROLLER

This section discusses the development of deterministic and metaheuristic-based traffic signal controller.

3.1 FUZZY LOGIC BASED SIGNAL CONTROLLER

Fuzzy Logic as a semantic rule-based algorithm is employed as the computational algorithm to determine the optimum traffic signal timings. It calculates the suitable cycle time based on the critical demands of all traffic phases and then allocates green timing based on the inflow vehicles fraction of each traffic phase.

The Fig.2(a) shows the framework of Fuzzy Logic based traffic signal control system. Generally, Fuzzy Logic consists of four mechanisms, namely fuzzification, rule base, inference and deffuzification [29]. The framework of Fuzzy Logic is shown in Fig.2(b).

The fuzzification consists of several appropriate defined membership functions to describe the crisp data. A membership function is a curve that defines how each point in the input space is mapped to a membership value. The input space is referred to as the universe of discourse. During the fuzzification process, the controller will convert the crisp input values, which are inflow vehicles and the number of vehicles in queue, to fuzzy set values. The conversion process is based on the corresponding membership degrees, which is in between 0 and 1.

Rule-base is a collection of if-then rules. It maps the fuzzy inputs with the respective fuzzy outputs. In this work, all rules contain all the information about how to tune the cycle time. Based on the inputs, each computation may execute three to four rules in the rule-base. The inference engine is used to deduce a logical conclusion using the rule base. The inference engine formulates the mapping from the given inputs to an output using the concept of fuzzy logic. In this work, Mamdani system is used.

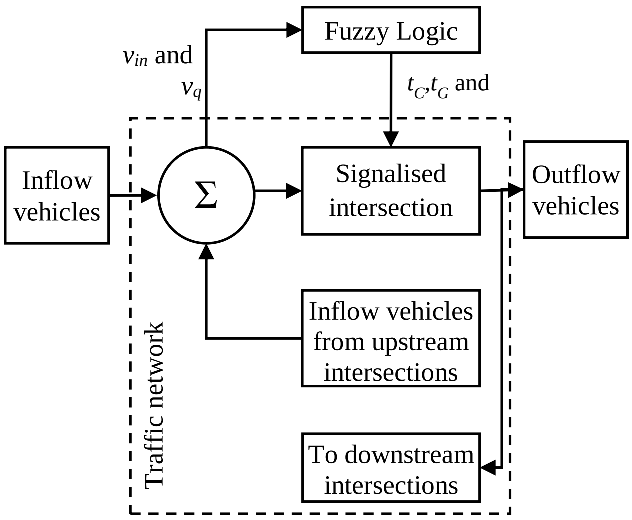


Fig.2(a). Control diagram of Fuzzy Logic based signal controller

Defuzzification is the process of determining a quantifiable result based on the given rules and membership degrees. In contrast to the fuzzification, this process converts the fuzzy values into a crisp output data. During the defuzzification, AND function will be used in the implication process to determine all the truthness degrees for each rule. Then, it will aggregate all the truthness degrees based on OR function to form a single geometric shape, the total area of the created shape, and determine the centroid of the shape. This centroid value is the output of Fuzzy Logic or equivalent to the optimum cycle time. Finally, the algorithm will allocate the suitable green timing based on the actual demand of each traffic phase.

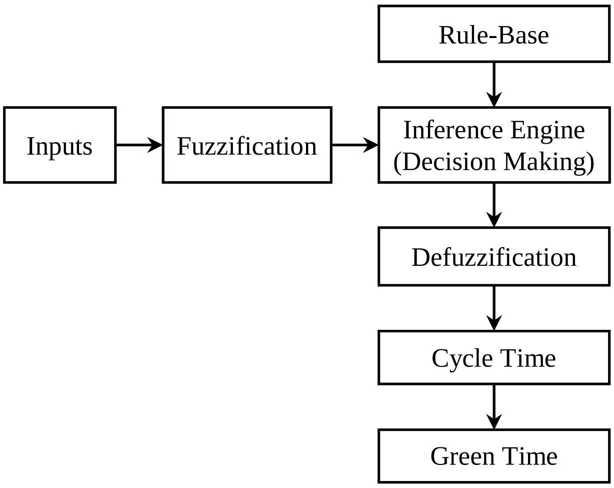


Fig.2(b). Framework of Fuzzy Logic

3.2 GENETIC ALGORITHM BASED SIGNAL CONTROLLER

Genetic Algorithm (GA) is an algorithm that exploits probability search method to optimize traffic signalization based on the Darwinian evolutionary theory: Survival of the fittest [30]. The Fig.3 illustrates the framework of GA, where GA consists of three mechanisms, namely initialization, evaluation and reproduction.

During the initialization stage, 50 chromosomes are randomly generated and each of them is encoded with the information of optimum cycle time for each traffic phase. Since this work has considered pedestrian crossing time, the cycle time is bounded in between 45s and 120s, as suggested by JKR manual.

The evaluation mechanism calculates the fitness of each chromosome. A novel metamodel and fitness function are designed, as stated in Eq.(3) and Eq.(4) respectively, to estimate the performance of each chromosome in minimizing the traffic delay. In this work, chromosomes that lead to the smallest travel delay will receive the highest fitness value as a reward, otherwise, the chromosome will receive lower fitness value.

$$\bar{t}_d = \left[\frac{\sum (t_d \cdot q_{in})}{\left[\sum q_{in}\right]} \right] \tag{3}$$

$$R = \frac{1}{\bar{t}_d} \tag{4}$$

where t_d is travel delay, q_{in} is inflow vehicles, R is the fitness value or reward value.

The reproduction process can further divide into two parts, namely crossover and mutation. During the crossover process, chromosomes with higher R are preferentially to be selected as parents. The rank selection technique is implemented to keep diversity in the mating pool so that pre-mature can be avoided. With a predefined crossover probability, P_x, both selected parents will proceed with the crossover process, as described in Eq.(5) and Eq.(6).

$$offspring\_1 = (\alpha)(parent\_1) + (1\text{-}\alpha)(parent\_2) \tag{5}$$

$$offspring\_2 = (1\text{-}\alpha)(parent\_1) + (\alpha)(parent\_2) \tag{6}$$

where α is the crossover factor.

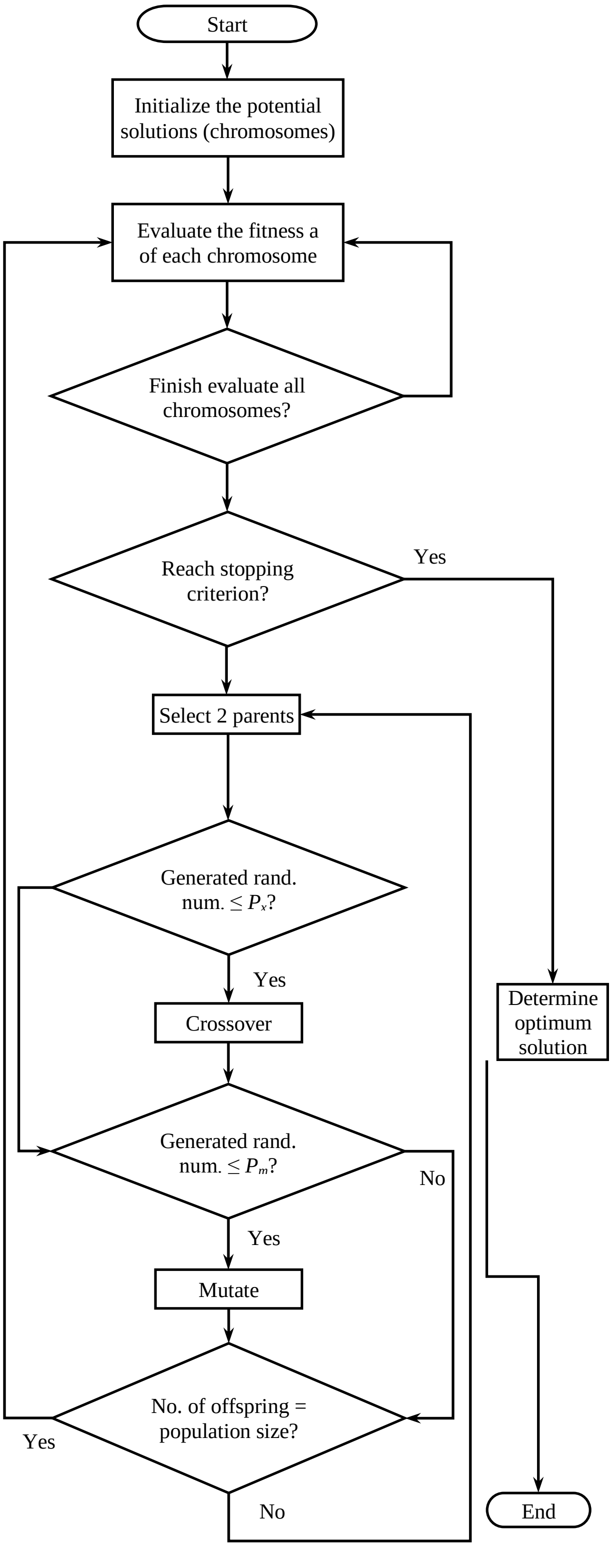


Fig.4. Framework of Genetic Algorithm

The mutation mechanism is used to keep diversity in the newly produced offspring population. All the offspring will have a small mutation probability P_m to mutate its chromosome. If the mutation occurred, a random value within the solution space will be generated and replaced to the respective offspring.

4. RESULTS AND DISCUSSION

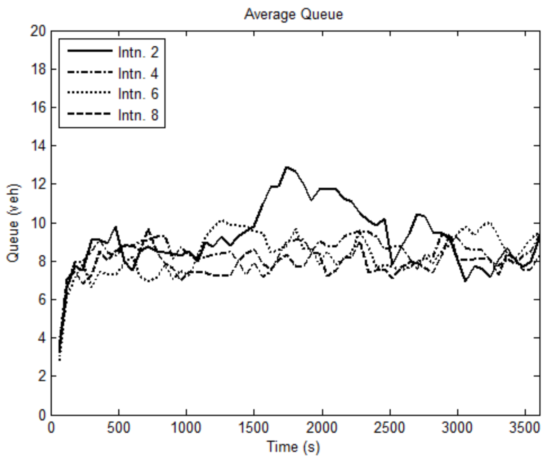
The robustness of both proposed algorithms is tested under two cases, namely deterministic traffic flow and stochastic traffic flow. The performances of Fuzzy Logic (FL) under the two cases are shown in Fig.4 and Fig.5, whereas the performances of Genetic Algorithm (GA) under the same cases are illustrated in Fig.6 and Fig.7. The performance measurements of these results are tabulated in Table.2.

From the observation (Fig.4 and Fig.6), the performances of queue dissipation for both FL and GA are very similar. They are able to maintain the average queue length and average delay at the minimum level. However, the GA is slightly better than FL since it can minimize the travel delay below 60s while the travel delay with FL controller is near to 60s. From the results, the queue at the critical intersection is discharged by compromising the interest of other intersections. For example, Fig.6(b) @*t*=500s, GA compromises the interest of Intersections 2, 4 and 8 to reduce the queue at Intersection 6. As such, the delay at Intersection 6 can be distributed to other intersections, thus the average delay for the entire network can be reduced.

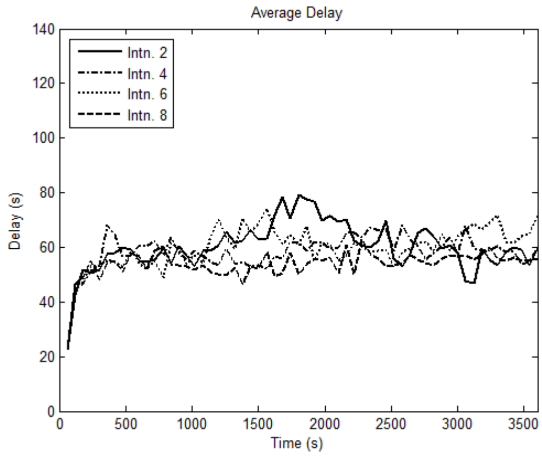
As shown in Fig.5, FL is inadequate to cope with the stochastic traffic flow. The ineffectiveness of FL in clearing all the queued vehicles in each cycle (Fig.5(a)) has resulted in the accumulation of vehicles within the network. The number of vehicles in queue keeps on increasing with time and eventually might cause the entire network collapse.

In contrast to FL, GA has shown better performance in the second case study, where it can maintain the queued vehicles at the minimum level, as illustrated in Fig.7(a). Since the average delay is directly proportional to the queue length, the average delay experienced by the GA is also kept at the minimum level, as shown in Fig.7(b).

From the Fig.6 and Fig.7, it can be observed that GA has shown similar performance in both cases. This shows that GA is able to determine the near-optimum solution with a partial knowledge about the traffic flow pattern.

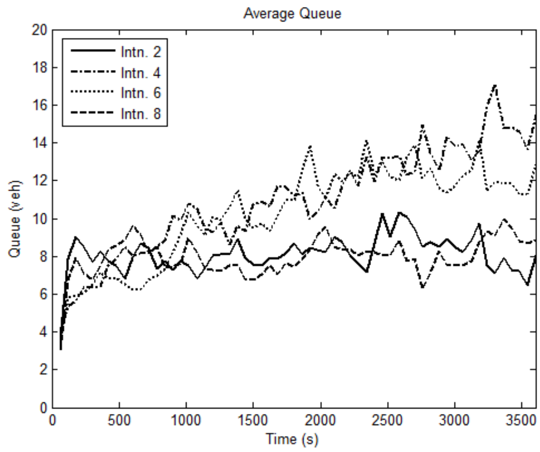


(a) Average queue

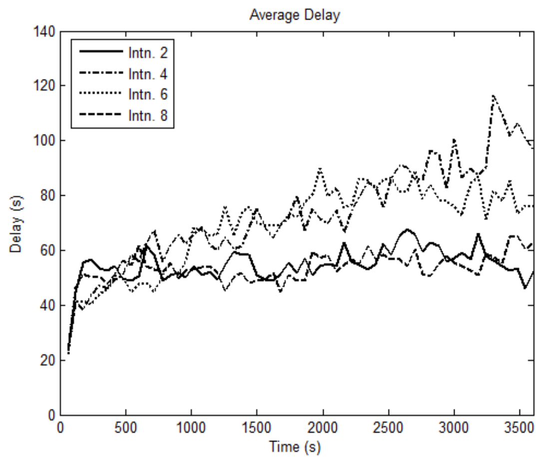


(b) Average delay

Fig.4. Performance of FL with deterministic traffic flow



(a) Average queue



(b) Average delay

Fig.5. Performance of FL with stochastic traffic flow

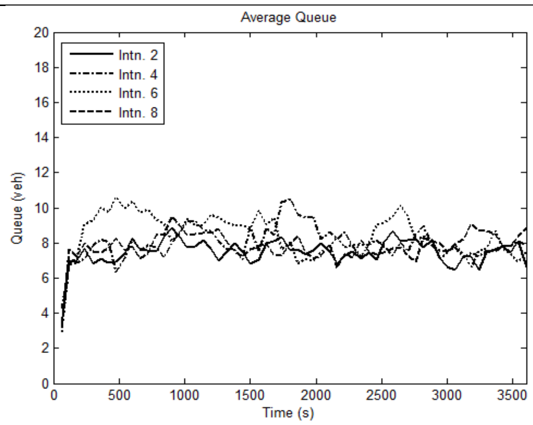
Overall, GA improves the network flow by reducing 3.8% in average delay under the second case study as compared to FL (Table.2). With the mutation mechanism, GA is able to have better exploration in solution space because it is not constrained by a deterministic computation process.

In contrast, FL computes the solution based on the fixed computation procedure. It follows the predefined rules and membership function in computing the centroid of an aggregated geometric shape. When the traffic condition changed to stochastic behavior, FL might need to re-tune its membership function so that it can describe the scenario more accurately. In this paper, since the rules and membership functions of FL are non-adaptive, it can be observed that the FL is inadequate to cope with the case which differs from its nominal settings. As a result, the queue keeps on increasing until the entire network collapses.

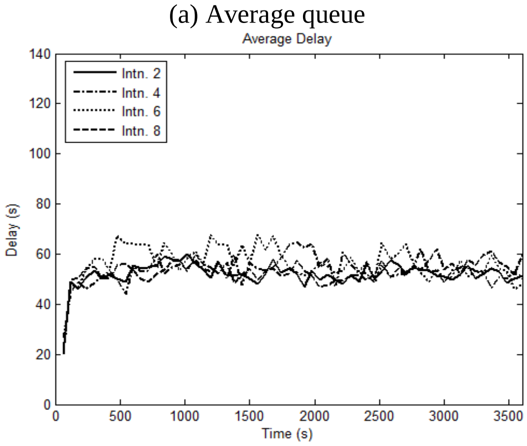
In conclusion, the deterministic algorithm with fixed computational procedure is inadequate to cope with a stochastic traffic scenario, while the metaheuristic algorithm with the mutation mechanism may be able to seek the optimum solution by having a wider exploration in solution space.

Table.2. Summary Table

Measured Parameters		Fuzzy Logic		GA	
Parameter	**Unit**	**DT**	**ST**	**DT**	**ST**
veh_{in}	veh	48.010	48.001	48.003	48.007
veh_{out}	veh	47.244	47.178	47.272	47.257
$\overline{veh}_q$	veh	8.166	8.378	7.761	8.019
Travel delay	s	56.673	57.203	53.851	55.045
Fuel wastage	ℓ	846.5	854.3	804.2	822.1
Remarks: DT: Deterministic traffic flow, ST: Stochastic traffic flow					

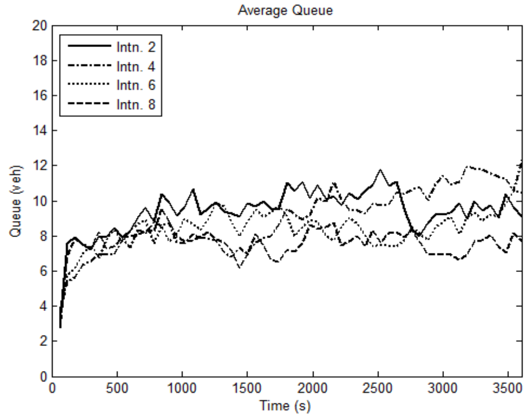


(a) Average queue

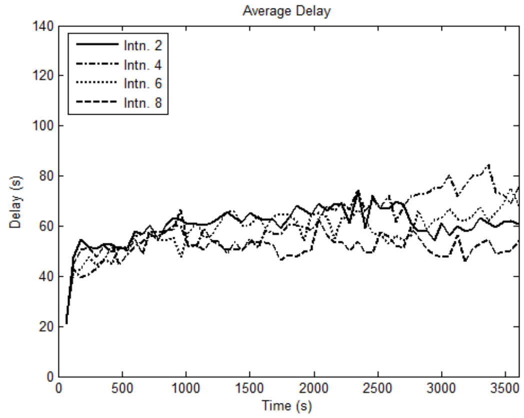


(b) Average delay

Fig.6. Performance of GA with deterministic traffic flow



(a) Average queue



(b) Average delay

Fig.7. Performance of GA with stochastic traffic flow

5. CONCLUSION

This paper has discussed the performances of deterministic and metaheuristic algorithms in controlling stochastic traffic flow.

A benchmarked arterial traffic is developed as the platform for the study. Normal distribution function is embedded in the model to allow the model to simulate a non-uniform headway for inflow and outflow vehicles. As such, this non-uniform traffic flow pattern will pose more challenges to the artificial intelligence (AI) in determining optimum solution under a stochastic scenario.

Two commonly used AI algorithms, namely Fuzzy Logic (FL) and Genetic Algorithm (GA), are proposed as the adaptive signal controllers in this work. FL represents the deterministic algorithm, whereas GA represents the metaheuristic algorithm. The adaptiveness of both the proposed algorithms are tested under two cases, which are the conventional deterministic and the stochastics traffic flow patterns.

The simulation results show that both proposed algorithms have similar performance under the first case study. Since the traffic flow pattern is in a fixed-pattern, both algorithms can minimize the average delay at minimum level. This is also because the parameters of both the algorithms are well-tuned with the case, and then tested with it again. This scenario is similar to using the training set data to train the algorithm and then using the same data to examine its feasibility.

Under the second case study, FL is inadequate to handle the stochastic traffic flow. As a result, the queued vehicles accumulate in every cycle and eventually cause the entire network to collapse. On the other hand, GA has shown better performance. With the mutation mechanism, GA is able to explore the solution space without being bound by the fixed-computational procedure.

In the future, GA can be improved by introducing an adaptive metamodel in its fitness function.

Table.3. Glossary

Glossary	Definition
Capacity	Maximum flow rate during a specified time
Cycle	A complete sequence of traffic signal indications
Delay	Extra travel time experienced by each vehicle
Demand	Number of vehicles desiring service on the road
Headway	Distance between two consecutive vehicles

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REFERENCES

[1] F.G. Sander, L.C. Blancas and R. Westra, "Malaysia Economic Monitor: Transforming Urban Transport", *Working Paper, Work Bank Group*, Vol. 1, No. 1, pp. 1-93, 2015.

[2] Y. He, A. Tablada and N.H. Wong, "A Parametric Study of Angular Road Patterns on Pedestrian Ventilation in High-Density Urban Areas", *Building and Environment*, Vol. 151, No. 15, pp. 251-267, 2019.

[3] S. Baharum, S. Haron, I. Ismail and J.M. Diah, "Urban Bus Service Quality through Sustainable Assessment Model", *International Journal of Supply Chain Management*, Vol. 8, No. 3, pp. 576-585, 2019.

[4] S. Wang, X. Xie, K. Huang, J. Zeng and Z. Cai, "Deep Reinforcement Learning-Based Traffic Signal Control using High-Resolution Event-Based Data", *Entropy*, Vol. 21, No. 8, pp. 1-16, 2019.

[5] H. Jung, S. Choi, B.B. Park, H. Lee and S.H. Son, "Bi-Level Optimization for Eco-Traffic Signal System", *Proceedings of International Conference on Connected Vehicles and Expo*, pp. 29-35, 2016.

[6] S. Srivastava and S.K. Sahana, "Nested Hybrid Evolutionary Model for Traffic Signal Optimization", *Applied Intelligence*, Vol. 4, pp. 113-123, 2017.

[7] O. Yi, R.Y. Zhang, J. Lavaei and P. Varaiya, "Conic Approximation with Provable Guarantee for Traffic Signal Offset Optimization", *Proceedings of IEEE Conference on Decision and Control*, pp. 229-236, 2018.

[8] S. Srivastava and S.K. Sahana, "Bat Algorithm-Based Traffic Signal Optimization Problem", *Proceedings of IEEE Conference on Soft Computing for Problem Solving*, pp. 927-936, 2018.

[9] H.N.A. Aziz, H. Wang, S. Young and S.M.A. Al-Islam, "Investigating the Impact of Connected Vehicle Market Share on the Performance of Reinforcement-Learning Based Traffic Signal Control", Technical Report, Office of Scientific Technical Information, U.S. Department of Energy, 2019.

[10] Z. Li, Q. Cao, Y. Zhao, P. Tao and R. Zhuo, "Krill Herd Algorithm for Signal Optimization of Cooperative Control with Traffic Supply and Demand", *IEEE Access*, Vol. 7, pp. 10776-10786, 2019.

[11] K. Chatterjee, A. De and F.T.S. Chan, "Real Time Traffic Delay Optimization using Shadowed Type-2 Fuzzy Rule Base", *Applied Soft Computing*, Vol. 74, pp. 226-241, 2019.

[12] M. Balta and I. Ozcelik, "A 3-Stage Fuzzy-Decision Tree Model for Traffic Signal Optimization in Urban City via a SDN based VANET Architecture", *Future Generation Computer Systems*, Vol. 104, pp. 142-158, 2020.

[13] L. Jiang, Y. Li, Y. Liu and C. Chen, "Traffic Signal Light Control Model based on Evolutionary Programming Algorithm Optimization BP Neural Network", *Proceedings of 7th IEEE International Conference on Electronics Information and Emergency Communication*, pp. 564-567, 2017.

[14] G.B. Castro, A.R. Hirakawa and J.S.C. Martini, "Adaptive Traffic Signal Control based on Bio-Neural Network", *Procedia Computer Science*, Vol. 109, pp. 1182-1187, 2017.

[15] C.H. Wan and M.C. Hwang, "Value-Based Deep Reinforcement Learning for Adaptive Isolated Intersection Signal Control", *IET Intelligent Transport Systems*, Vol. 12, No. 9, pp. 1005-1010, 2018.

[16] H. Ge, Y. Song, C. Wu, J. Ren and G. Tan, "Cooperative Deep Q-Learning with Q-Value Transfer for Multi-Intersection Signal Control", *IEEE Access*, Vol. 7, pp. 40797-40809, 2019.

[17] E.A. Sofronova, A.A. Belyakov and D.B. Khamadiyarov, "Optimal Control for Traffic Flows in the Urban Road Networks and its Solution by Variational Genetic Algorithm", *Procedia Computer Science*, Vol. 150, pp. 302-308, 2019.

[18] C.P. Luis, A.L.C. Miguel and M.M. Ivan, "Automated Optimization of Intersections using A Genetic Algorithm", *IEEE Access*, Vol. 7, pp. 15452-15468, 2019.

[19] H.S.E. Chuo, M.K. Tan, A.C.H. Chong, R.K.Y. Chin and K.T.K. Teo, "Evolvable Traffic Signal Control for Intersection Congestion Alleviation with Enhanced Particle Swarm Optimisation", *Proceedings of IEEE 2nd International Conference on Automatic Control and Intelligent Systems*, pp. 92-97, 2017.

[20] H. Jia, Y. Lin, Q. Luo, Y. Li and H. Miao, "Multi-Objective Optimization of Urban Road Intersection Signal Timing based on Particle Swarm Optimization Algorithm", *Advances in Mechanical Engineering*, Vol. 11, No. 4, pp. 1-9, 2019.

[21] M. Elgarej, M. Khalifa and M. Youssfi, "Traffic Lights Optimization with Distributed Ant Colony Optimization based on Multi-Agent System", *Proceedings of International Conference on Networked Systems*, pp. 266-279, 2016.

[22] H. Min, "On Signal Timing Optimization in Isolated Intersection based on the Improved Ant Colony Algorithm", *Proceedings of International Symposium on Parallel Architecture, Algorithm and Programming*, pp. 439-443, 2017.
[23] J.L. Elidrissi, A. Tajer, A.N.S. Moh and B. Dakkak, "A SUMO-Based Simulation for Adaptive Control of Urban Signalized Intersection using Petri Nets", *Proceedings of 4th World Conference on Complex Systems*, pp. 1-6, 2019.
[24] L. Shu, J. Wu and Z. Li, "Hierarchical Regional Control for Traffic Grid Signal Optimization", *Proceedings of IEEE International Conference on Intelligent Transportation Systems*, pp. 3547 3552, 2019.
[25] X. Wu and H.X. Liu, "A Shockwave Profile Model for Traffic Flow on Congested Urban Arterials", *Transportation Research Part B: Methodological*, Vol. 45, No. 10, pp. 1768-1786, 2011.
[26] B.S. Kerner, "Failure of Classical Traffic Flow Theories: Stochastic Highway Capacity and Automatic Driving", *Physica A: Statistical Mechanics and Its Applications*, Vol. 450, pp. 700-747, 2016.
[27] Public Works Department Malaysia, "*A Guide to the Design of Traffic Signals*", Arahan Teknik (Jalan) 13/87, 1987.
[28] M.K. Tan, H.S.E. Chuo, R.K.Y. Chin, K.B. Yeo and K.T.K. Teo, "Optimization of Traffic Network Signal Timing using Decentralized Genetic Algorithm", *Proceedings of IEEE 2nd International Conference on Automatic Control and Intelligent System*, pp. 62-67, 2017.
[29] S. Spolaor, M.S. Nobile, G. Mauri, P. Cazzaniga and D. Besozzi, "Coupling Mechanistic Approaches and Fuzzy Logic to Model and Simulate Complex Systems", *IEEE Transactions on Fuzzy Systems (Early Access)*, pp. 1-12, 2019.
[30] S. Mirjalili, "*Evolutionary Algorithms and Neural Networks Theory and Applications*", Springer, pp. 43-55, 2018.