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Dinh Tuan HAI[1], **Do Van MANH**[2]*, **Nguyen Minh NHAT**[3]

GENETIC ALGORITHM APPLICATION FOR OPTIMIZING TRAFFIC SIGNAL TIMING REFLECTING VEHICLE EMISSION INTENSITY

Summary. Urbanization has created continuous growth in transportation demand, leading to serious issues, including infrastructure overload, disrupted traffic flow, and associated vehicular emissions. As a result, resolving these problems has become one of the primary missions of governments worldwide. The optimization of the traffic signal timing system is considered a promising approach to overcoming the negative consequences of increasing vehicle volume. In metropolises, oversaturated intersections, where the traffic density and vehicle exhaust emission levels are significant, have been considered as the priority to target. Several scientists have attempted to design traffic lights with the most appropriate timing. However, the majority of previous studies have not formed a comprehensive evaluation of essential factors, especially regarding the appropriate weighting of vehicle emission parameters. By assessing the all-inclusive relationship of critical elements with an emphasis on vehicle exhaust emissions, a performance index model using a genetic algorithm (GA) is established in this paper, demonstrated by data from a case study in Taiwan.

1. INTRODUCTION

As a consequence of urbanization, continuous growth in transportation demand has created critical matters, including infrastructure overload, traffic network pressure, and associated vehicular emissions, significantly affecting the transport network's effectiveness and security. The efficiency and safety of the traffic network are typically affected by the managing system, which could be enhanced by optimizing traffic signal timing schemes (Lin and Huang, 2010) [1].

Various researchers have attempted to generate models resolving traffic problems at complex large-scale intersections by minimizing time loss in these areas. For instance, Kwasnicka and Stanek (2006) [2] applied GA and microsimulation modules to minimize time losses and maximize the average vehicle speed inside a specific area. The proposed model is considered very scalable and applicable to any transportation system. One of the significant achievements of this investigation is that various timing plans parameters were examined. However, existent time control systems were not tested in this method. Another noteworthy signal timing system was established by Wang and Yang (2012) [3], who analyzed optimal signal timing by forming a scheme to diminish average delay. Their results were then compared to outcomes from other approaches using micro-simulation. The authors suggested that a drop in average delay and number of stops could be found by the tested method.

[1] Hanoi Architectural University; Km 10 Nguyen Trai Road, Thanh Xuan District, Ha Noi City, Vietnam; email: haidt@hau.edu.vn; orcid.org/0000-0002-3687-8566
[2] University of Transport and Communications; No.3 Cau Giay Street, Lang Thuong ward, Dong Da District, Hanoi, Vietnam; email: manhdv@utc.edu.vn; orcid.org/0000-0001-7824-0424
[3] Hanoi Architectural University; Km 10 Nguyen Trai Road, Thanh Xuan District, Ha Noi City, Vietnam; email: nhatnm@hau.edu.vn; orcid.org/0000-0003-1282-5192
* Corresponding author. E-mail: manhdv@utc.edu.vn

Nevertheless, a lack of solution connecting results from the experimented intersection to a street network was limited the robustness of Wang and Yang's approach. Guo *et al*. (2017) [4] also employed a GA to evaluate three fundamental parameters, namely, cycle length, green time, and the offset of the traffic network. The designed model is expected to minimize the sum and variance of the travel time in a regional urban street system. The model was computationally validated by testing data from China. The effectiveness of the network regarding signal-timing optimization, turning movement delays, and variance in travel time is believed to improve using the invented approach.

Although the abovementioned models have achieved remarkable findings concerning traffic efficiency, researchers have recently paid more attention to time losses and traffic safety, along with reducing vehicle exhaust emissions, which is mainly ignored in the mentioned research. One of the primary studies exploring this gap was carried out by Li *et al*. (2004) [5]. The authors exploited a case study from Nanjing city, China, to estimate the constraint of a minimum green time, which could optimize signal timing.

Environmental protection in urban areas is becoming an area of interest in many countries and in modern life. Manh Do Van *et al.* (2021) suggested reducing emissions by analyzing the correlation between driver behavior and vehicle exhaust emissions [6]. More specifically, fuel consumption and emissions were critical factors investigated in conjunction with signal cycle length, vehicle delay, and performance index function. Recently, arguing that previous models did not take into account real-time signal timing algorithms for minimizing total vehicular emissions, Khalighi and Christofa (2015) [7] advanced an emission-based strategy to organize a real-time signal scheme reducing emissions in analytically polluted zones. Vehicle activity data was used along with the vehicle-specific power approach in a system combining former traffic flow based on analytical models. Although a reduction in total emissions at signalized intersections was reported using the proposed emission-based optimization method, the authors suggested that this emission-based method should be applied when improving the air quality is the primary emphasis.

Following the development trend of traffic signal control, Lin *et al*. (2015) [8] used vehicle-specific power to analyze traffic emissions based on vehicular trajectory. The connection between traffic emissions and delay was established by quantifying regression analysis. A displayed optimization approach considering the control, constraint, and target variables was then designed. Although a multi-objective method was formed that presented the development trend of traffic signal management, the limitation of this study is that the results are only valid for a single intersection. Differently, Yu *et al*. (2016) [9] criticized that former research did not assess sufficient issues and that the weights of values of different factors were not reasonably adjusted based on real traffic flow. To overcome this inadequacy, they offered a fuzzy-based method considering traffic capacity, vehicle cycle delay, cycle stops, and exhaust emissions. Different weight coefficients of various objectives were given by the fuzzy compromise programming approach, and the optimized signal cycle and effective green time were found using a GA. Similarly, looking at the impacts of emissions' weight on the results of optimization, Kou *et al*. (2018) [10] analyzed data from a typical intersection in Beijing under actual conditions to form a multi-objective signal timing optimization model examining the trade-off between vehicle emissions and traffic efficiencies. Different weighting factors of emissions and traffic efficiency were employed to judge different signal timing structures. More recently, Ding *et al.* (2019) [11] emphasized that the conflict between environmental and traffic control needs to be resolved in any process of controlling the traffic network. They developed a bi-objective set optimization system to reduce delays and exhaust emissions on arterial roads. A valuable point of the study is that more pollutant types were taken into account. Furthermore, the demerits of previous models, as stated by the authors, were resolved by utilizing a modified hierarchical method containing improvements in targeting the priority of a multi-objective set. Several studies have attempted to optimize traffic control time according to vehicle emissions [6, 12, 13].

Although the above literature review shows that existing research has evaluated vehicle emissions in the traffic control system. A limitation remains regarding the formation of a real-time signal timing optimization approach, which comprehensively considers principal issues while appropriately fitting the weights of each analytical factor, especially vehicle emissions. For that reason, a comprehensive performance index model using a GA to assess the appropriate correlation between traffic signal optimization and vehicle exhaust emissions, validated by actual traffic data from an intersection in Taiwan, is established in this paper.

Particularly, this study aims to provide a suitable and flexible computational model for optimally processing traffic light signals at an intersection in an urban area, considering the reduction of pollution from vehicles and other objectives simultaneously by the GA. In addition, a few special techniques, such as providing the appropriate constraint functions and the suitable calculation parameters of the GA, were proposed in this study to support the suggested model escape of the locally optimal results and find the globally optimal result. The hypothesis model was validated by optimizing the signal control time at an intersection in an urban area in Taichung City, Taiwan. The organizational structure of this research is as follows. The first part introduces the weaknesses of current methods used to optimize traffic signal systems and the advantages of the GA application. The second part explains how to establish a theoretical model to be used in traffic signal optimization by applying the GA method at intersections. Then, the third section describes the collection of data and the pre-processing of the initial traffic data. The last part provides the obtained results, comments, and suggestions for future research.

2. GA EMISSIONS-BASED TRAFFIC SIGNAL TIMING MODEL DEVELOPMENT

Table 1 describes fundamental variables influencing the results. These factors, namely, the average delay, number of stops, traffic capacity, and vehicle exhausted emissions, are selected based on the literature review. The use of these elements is described in the following sections.

2.1. Model Conceptual Framework

Fig. 1 displays the model conceptual framework. As can be seen in the framework, objective functions are a combination of average delay, number of stops, traffic capacity, and vehicle emissions. The normalization process of the objective functions is then affected by the variables and constrained optimizations, namely, necessary cycle length, safe pedestrian crossing, and available effective green time. Then, the GA is applied at the final stage to optimize the fitness function to form an optimal traffic signal timing scheme.

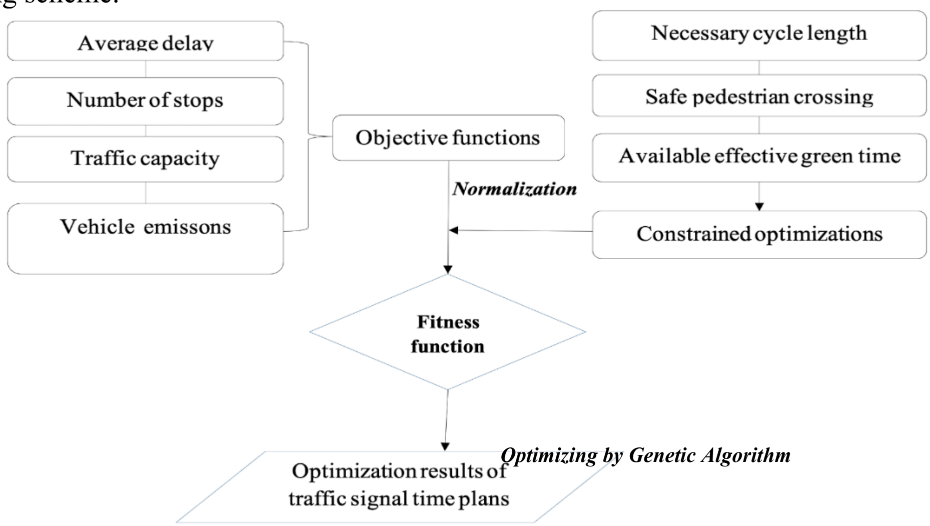


Fig. 1. Model conceptual framework

2.2. Normalization of Objective Functions

As discussed in the previous section, the consideration of multi- objectives optimization simultaneously at the isolated intersection will be presented by generating a fitness function based on performance index objective functions referred to as traffic safety, traffic efficiency, and environmental protection.

Table 1

Nomenclature

Notation	Definition
CL	Cycle Length or Cycle Time
PCU	Passenger Car Unit
AD_I	Average vehicle delay in seconds
C	Cycle time
ij	To describe phase i^{th} in the group of lane j^{th}
t_{ij}	Effective green times
Xij	The proportion of traffic flow to traffic capacity
T	The analyzed period
k	The incremental hysteresis
I	The upstream filter correction factor
vij	Traffic flow
L	Total loss-time
$\sum_i \left(\frac{v}{s}\right)_{ci}$	The total value of critical lane group traffic flows ratio
Xc	The critical v/c proportion
yi	The proportion of actual volume to saturated traffic volume (Sij)
Hi	The total number of stops function
Cap	The traffic capacity (pcu/h)
qj	Traffic arrival, traffic flow of lane group j
Lj	The length of the entrance section of the signalized intersection
dj	The average delay of the vehicle in lane group j
EFPCUij	The standard car unit emission factor (g/(pcu.h)
EFIPCUij	The Standard Car Unit Idling Emission Factor (g/(pcu.km)
D	The distance of pedestrians crossing the street
Sp	The pedestrian velocity
W_E	The crosswalk's width (ft)
Nped	The number of pedestrians crossing in green time intervals
EI	Total vehicle exhausted emission at the intersection (g/h)
Cmin	The cycle length's minimum value (s)
Cmax	The cycle length's maximum value (s)
tij,min	The minimal result of effective green time
tij,max	The maximum value of effective green time
Sij	The saturation flow rate
r_i	Saturation flow of pedestrian crossing
$\bar{p}_{ij}$	The arrival rate of non-motorized vehicles during i^{th} phase and lane group j
Min PI	Fitness function
AD_0, NTD_0, H_0, C_{ap0}, E_0	The initial values of average vehicle delay, the average delay of non-motorized vehicle delay, number of stops, capacity, and vehicle exhaust emissions, respectively.

A widespread suggested objective function that simulated the effectiveness of traffic efficiency is the average control delay, which has been expressed in various studies by the following expression [14]:

$$AD_I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left\{\left[\frac{0.5\left(1-\frac{t_{ij,lg}}{C}\right)^2}{1-\left[\frac{\min\left(1,X_{ij,lg}\right)t_{ij,lg}}{C}\right]}+900T\left[\left(X_{ij,lg}-1\right)+\sqrt{(X_{i,lg}-1)^2+\frac{8kIX_{ij,lg}}{c_{ij,lg}T}}\right]v_{ij}\right]\right\}}{\sum_{i=1}^{n}\sum_{j=1}^{m}v_{ij}} \tag{1}$$

Where AD_I, other notations of formula (1), and other formulae in this article were denoted by nomenclature (Table 1).

However, several scholars have shown the disadvantages of single-objective optimization, such as Gao *et al*. (2012) [15], who mentioned the detrimental effect of single-objective optimization in traffic signal timing optimization on other objectives. Hence, many researchers have attempted to handle this problem by optimizing more than a single objective. A few studies indicated the traffic capacity and number of stops that maximize traffic capacity and minimize vehicle stops using different formulae.

The number of stops [16, 17] can be calculated by the expression:

$$H_I=0.9\sum_{i=1}^{n}q_i\cdot\left(\frac{1-{t_{ij}}/{C}}{1-y_i}\right) \tag{2}$$

The traffic capacity [18, 19] can be calculated by the following formula:

$$C_{ap}=\sum_{i=1}^{n}S_{ij}\frac{t_{ij}}{C} \tag{3}$$

As mentioned above, environmental protection is one of the major considerations when city governments issue policies and attempt to protect the health of people living in urban areas. Thus, a few scholars have made efforts to provide a comprehensive model that can evaluate the impacts of fuel consumption and vehicle emissions in the current public research [20, 21]. Hence, we provided a hypothetical model formulation including vehicle exhausted emissions in accordance with the following formula [5, 16].

$$E_I=\sum_{j=1}^{n}\left(EF_{ij}^{PCU}.q_j.L_j+\frac{1}{3600}.EFI_{ij}^{PCU}.q_j.d_j\right) \tag{4}$$

A wide-ranging model was generated by normalizing multiple objectives, employing the minimum value of average delay, the number of stops, vehicle emissions, and the maximum significance of traffic capacity.

$$\begin{cases} F_1 = \min AD_I \\ F_2 = \min H_I \\ F_3 = \min(-C_{ap}) \\ F_4 = \min E_I \end{cases} \tag{5}$$

This is equivalent to:

$$\text{Min PI}=\min\left(\alpha\left(\sum_{i=1}^{n}\frac{AD_I}{AD_0}+\sum_{i=1}^{n}\frac{H_I}{H_0}+\left(\sum_{i=1}^{n}-\frac{C_{ap}}{C_{ap0}}\right)\right)+\beta\sum_{i=1}^{n}\frac{E_I}{E_0}\right)\ , \tag{6}$$

where: PI: The performance index function; AD_0: Values of average delay; H_o: Number of stops C_{ap0}: Traffic capacity; E_0: Vehicle emissions respectively.

Different settings were expressed by the values of α and β. This could assist model users in comparing traffic efficiencies and vehicle emissions at a specific intersection. More specifically, if α is higher than β, decision-makers are suggested to focus more on traffic efficiencies and vice versa.

2.3. Constrained Optimizations

2.3.1. Defining the appropriate upper bound and lower bound for the empirical model

Many stochastic methods have a problem in searching the global optimization values because the proposed model could be stopped at the local values easily. Various solutions have been suggested by researchers to deal with this current situation. However, providing suitable constraint functions is more convenient than another to limit feasible areas for variables and decrease computing time [22].

According to the issues of traffic efficiency and traffic safety in traffic signal timing optimization, the most common reason for using a constraint function is to find the upper bound and lower bound values for cycle times and effective green times in the suggested model, which is done using the following expressions, respectively.

$$\left.\begin{array}{c} C_{min} \leq C \leq C_{max} \\ t_{ij,min} \leq t_{ij} \leq t_{ij,max} \end{array}\right\} \tag{7}$$

A few studies attempted to assume the lower bound and upper bound values for suggested constraint functions that lacked a scientific basis, and the suggested model took time to analyze [23-25]. Several scholars provided explanations based on trusted scientific publications. Specifically, the minimum condition of cycle time is calculated by the following equation [14, 26, 27].

$$C_{min} = \frac{L \cdot X_c}{X_c - \Sigma_i \left(\frac{v}{s}\right)_{ci}} \tag{8}$$

Meanwhile, the minimum values of effective green times are computed by the following formulae [28].

$$t_{ij,min} = 3.2 + \frac{D}{S_p} + 0.27\, N_{ped}, \text{ for } W_E \leq 10\text{ft} \tag{9}$$

$$t_{ij,min} = 3.2 + \frac{D}{S_p} + 0.27 \frac{N_{ped}}{W_E}, \text{ for } W_E \geq 10\text{ft} \tag{10}$$

Following equation (8), if the proposed model simply applies provided conditions above to support the empirical model to escape the local optimizations, the empirical model still takes time for computations. Hence, we provided other scientific evidence to generate a comprehensive constraint function. The maximum value of cycle length is suggested by [14, 27] and follows the expression below.

$$C_{max} \geq 120 \text{ (s)} \ \ \text{(Exceptional cases: } C_{max} \geq 180 \text{ (s))} \tag{11}$$

According to condition that the saturation flow of the next phase is not greater than the current phase diagram to avoid traffic jams from being happening. The following equation should be utilized in the empirical model [29, 30].

$$\frac{C_{min}}{0.95}\left(\frac{v}{s}\right)_{ci} \leq t_{ij} \leq C_{max} - L - (n-1)\frac{C_{min}}{0.95}\left(\frac{v}{s}\right)_{ci} \tag{12}$$

2.3.2. Generating the constrained optimizations

As mentioned in the previous section, the more suitable the applied constraint function, the more the empirical model approaches the global optimization values. Besides defining the appropriate for upper bounds and lower bounds of variables, the suitable linear or non-linear constraint function supports the proposed model's ability to obtain global optimization value directly. The most popular linear constraint function was published in several studies referring to the relationship between cycle time and effective green times [26].

$$\sum_{i=1}^{n} t_{ij} = C - L \tag{13}$$

Moreover, the Webster formula is a well-known traditional method for calculating the optimal cycle time for critical movements at signalized intersections, presenting several disadvantages in some particular cases [31, 32]. Thus, we suggested using the traffic flow data of lane groups as a basic unit for analysis, and the effective green time allocation was computed for the critical group lanes in the major-minor roads of the signalized intersection by the below formula.

$$t_{ij,lg} = \frac{\Sigma_i \left(\frac{v}{s}\right)_{ci} . C}{X_{ij}} \tag{14}$$

2.4. Genetic Algorithm

Existing analytical studies revealed that GA-based methods demonstrated better performance than traditional techniques, which are based on optimization practice, natural evolution, and a heuristic algorithm. It should be noted that chromosome design, fitness function, and appropriate operators are core elements of GA design in this paper.

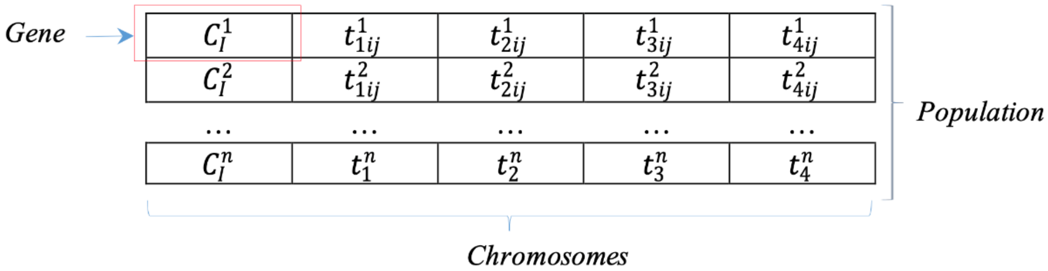


Fig. 2. Four-phase signalized intersection's chromosome code

The individual chromosome was used to code the timing plan at a specific intersection. In this research, a specific chromosome-designed cycle time (C_I) and efficient green times (t_{ij}) were used.

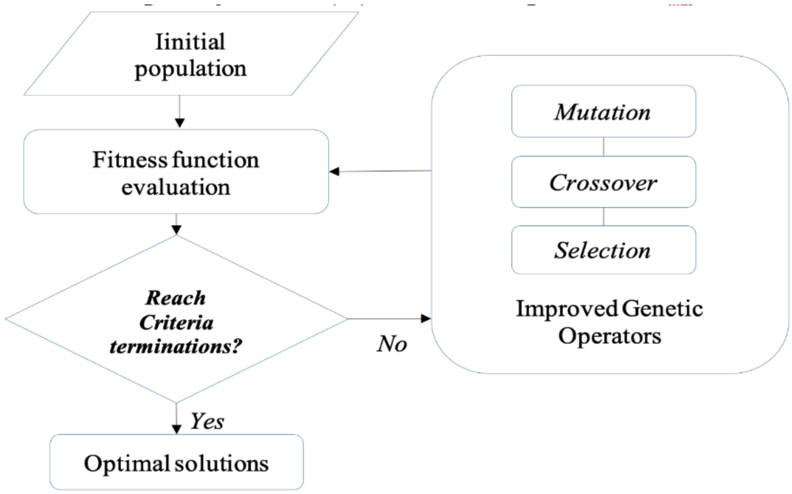


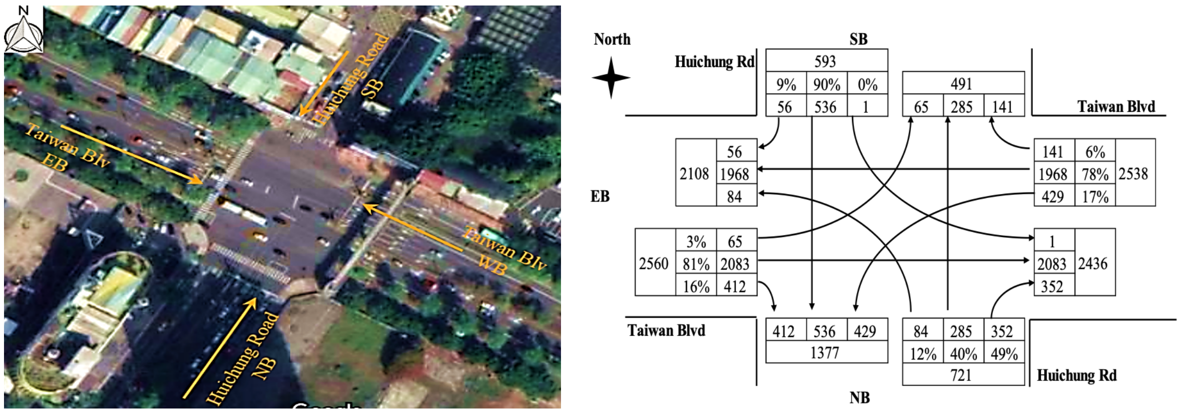
Fig. 3. The GA Process

The application of GA comprises the following phases:

- An initial population is created based on the outcome of chromosomes' encoding. Two encoding techniques, namely, binary coding and number coding, are considered; the real number coding method is chosen because of its advantages.
- Criteria terminations are assessed based on GA's process and the fitness function's condition to determine the globally optimum values.
- If the terminate conditions are not satisfied, the evolutionary practice could be improved by developing the GA's operators to re-calculate the function and acquire optimal outcomes.

3. DATA COLLECTION

The data is collected from actual traffic flow recorded at an intersection in Taichung City. Taichung City is the second-largest city in Taiwan and is centrally located in the western half of the country. In recent years, this city has experienced rapid growth with much significant transport infrastructure. Long-term infrastructure in public transport has been increasingly promoted to reduce the negative impact of personal vehicles. The local government is developing the Mass Rapid Transit system to encourage citizens to use the public transport system, and the city bus is the most popular mode of public transport in the city. The rapid growth is leading to a rising number of private vehicles, which is putting more pressure on the city's transportation systems. During peak hours, traffic congestion, especially at particular intersections, is threatening the efficiency, quality of the network, and the safety of citizens as pollutant emissions are boosted.



(a) (b)

Fig. 4. The traffic flow rate of Taiwan Boulevard - Huichung Road during peak hours

Actual traffic statistics at the Taiwan Boulevard - Huichung Road intersection are analyzed to validate the research. This intersection was selected because it is located on one of the highest traffic density roads in the city. The rush periods usually last from 7:00 a.m. to 8:00 a.m. and from 5:00 p.m. to 6:00 p.m. The traffic flow data from 7:00 a.m. to 8:00 a.m. and the location of collected data are displayed in Fig 4.

Currently, Taiwan Boulevard - Huichung Road intersection has four phases, and traffic flow data was collected here from 7:00 a.m. to 8:00 a.m. every day of the week for one month using the camera detector and then calculating the average value. The variety of vehicle types (e.g., buses, motorcycles, trucks, taxis) was calculated and transferred to the passenger car unit (PCU). The number of cars is presented in Fig. 4b for each phase movement. The total number of cars was 6412 PCU during the observation time. The number of vehicles traveling on the arterial road equals 5098 cars, which is nearly four times the number of vehicles traveling on the minor road (1314 cars). Hence, this is a special intersection, and the cycle time is 180 seconds as determined by the traffic experts. However, the computation time for each phase was not rational or optimized. Therefore, it is necessary to use scientific methods to optimize traffic signal control time here and replicate this process for other complex intersections in the arterial road as Taiwan Boulevard.

4. RESULTS AND DISCUSSION

Based on the collected traffic flow data, the fitness function was formed using expressions (1) to (6). Traffic geometry statistics and actual traffic flow records were used following formulas (7) to (14) to determine constrained conditions. The model's efficiency was tested by applying different scenarios.

a) $\alpha = 0.4 < \beta = 0.6$ Vehicle emissions are more significant than traffic efficiency.
b) $\alpha = \beta = 0.5$ Both issues equally important.
c) $\alpha = 0.6 > \beta = 0.4$ Traffic efficiency is more important than vehicle emissions.

The optimal global value of the fitness function can be approached by following an appropriate process of GA formulation. It is worth noting that the GA's operators, population size, reproduction techniques, and stopping measures demonstrate a clear influence on the efficiency of the GA. Table 2 displays the critical influences of the GA's practice.

Besides establishing suitable constraint functions that could support the process to avoid the local optimum values, the selection of the GA's calculation parameters also plays an important role in helping the algorithm escape the local optimal values. After consulting with scholars, reviewing references [33-43], and analyzing experimental results, the authors propose the parameters for the GA's operators that could be applied in other studies in this field according. These parameters are presented in Tab. 2 below.

In fact, the authors have changed the value of the crossover ratio (from 0.5 to 0.95) and used the spread factor value [43] to evaluate the effectiveness of the algorithm in this case. The experimental results show that the crossover rate of 0.5 is the most appropriate.

Table 2

Critical factors of the formulated GA

Factors	Values	Techniques use
Population size	200	-
Selection	-	Uniform
Reproduction	0.05 x Population Size	Elite count
Mutation probability	0.1	Adaptive feasible
Crossover probability	0.5	Intermediate

Table 3

Optimal results of different scenarios

Factors	T1 (s)	T2 (s)	T3 (s)	T4 (s)	C (s)	Average-delay (s)	Emission (g/h)	Number of stops (Stops/h)	Capacity (Pcu/h)
Initial values	**86**	**31**	**31**	**16**	**180**	**51.65**	**7212.11**	**4830.05**	**12698.33**
α=0.4; β= 0.6	75	11	45	8	155	45.63	6599.41	4735.09	12883.23
α= 0.5; β= 0.5	78	11	44	11	160	46.61	6699.49	4728.81	12920.00
α=0.6; β= 0.4	81	18	44	5	164	46.88	6726.03	4675.63	12998.78

Table 4

Initial and calculated value comparison (Initial value = 100%)

Factors	α=0.4; β= 0.6	α= 0.5; β= 0.5	α=0.6; β= 0.4
Average delay	88.0 %	90.3 %	90.8 %
Emissions	91.5 %	92.9 %	93.3 %
Number of stops	98.0 %	97.9 %	96.8 %
Capacity	101.5 %	101.7 %	102.4 %

The statistics from the Tab. 2 demonstrate that for four-phased intersections, the proposed model provides shorter effective green times and cycle lengths than other scenarios. In addition, the three-phased intersection received better objective functions' statistics than original function numbers. Tab. 3 and Tab. 4 compare the statistics for different scenarios. It can be seen that a positive correlation was found for the weight and value of the emission function. This outcome suggests that the change in the weight of the formulated function (PI) could assist decision-makers in reducing vehicle emissions. Moreover, the value of traffic capability, number of stops, and average delay were also revealed to reflect traffic efficiency. As can be seen, from the statistics, the traffic capacity is more sensitive to a change in α in comparison to changes in other coefficients.

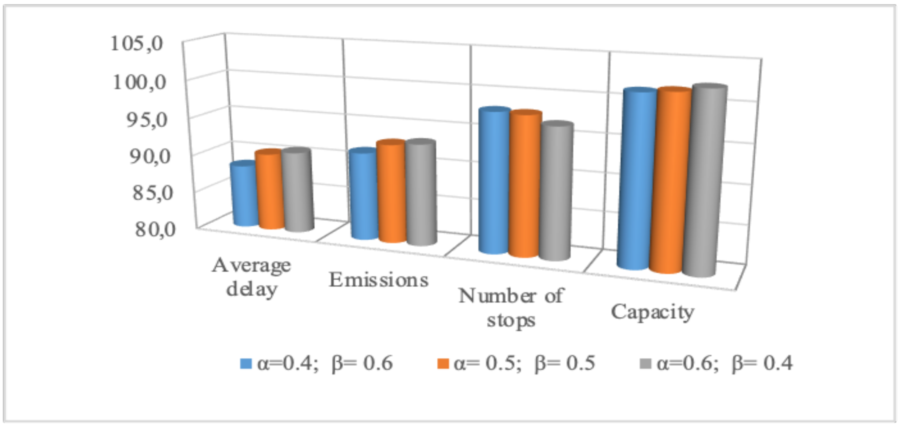


Fig. 5. Initial and calculated values comparison (initial value =100%)

5. CONCLUSIONS AND RECOMMENDATIONS

The increase in the number of vehicles on the road (as a consequence of urbanization) is creating serious traffic problems, including low efficiency, time loss, and polluted air quality. Consequently, there is an urgent need to investigate a method that can enhance traffic network efficiency regarding critical factors; an optimal signal timing scheme at complex intersections is considered an effective solution.

Some researchers have explored this area using various performance indexes. However, few studies have attempted to optimize real-time signal timing schemes based on vehicle emissions while regarding other significant parameters. This paper proposed a GA emissions-based model to generate a comprehensive performance index that presents an optimal traffic signal timing scheme and minimum exhausted emission.

Noteworthy benefits of the proposed model are its capabilities to form optimal traffic signal timing plans, minimize vehicle emissions, and determine critical parameters' weights better than other models. Although the significant performance of the proposed model is revealed in the present case study, the data was collected from a single intersection. Future works can improve the robustness of the proposed model by testing various traffic flow data from different types of intersections.

Acknowledgments

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