The Dynamic Adjusting Model of Traffic Queuing Time—A Monte Carlo Simulation Study

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Abstract: The traffic queuing problem usually can be solved by two concepts: static and dynamic mode. Usually, the static mode may not reflect the real-world situation. This encourages us to propose the dynamic adjusting model to solve the traffic queuing problem with a time-varying feature. Our model develops two modes and includes eight formulae to calculate the analysis results. In our first calculating mode, the three formulae intend to simulate the maximum traffic flow in the real-world situation. The second mode is to calculate the results based on the simulation data generated by Monte Carlo simulation. To see our model capability, we validate our model by the simulation data and verify the results by the Monte Carlo simulation method. By our proposed performance measurement, the resulting outcomes show that our model outperforms the previous studies. Additionally, our solution procedure is simple and assumes the model following pseudo-randomly, which coincides with the current status. Furthermore, because of the Internet of Things (IoT) trend, one can expect that the data can be automatically collected. This leads to our proposed model can be implemented once the data are obtained.

Keywords: dynamic adjusting model; traffic queuing time; Monte Carlo simulation

1. Introduction

The traffic queuing problem in transportation network has been studied for many decades since the demand always exceeds the capacity. Furthermore, the traffic queuing problem is with the time-varying feature within a day. Usually, the analysis procedure of traffic queuing problem can be performed as a queuing system and can be solved by two concepts: the static and dynamic mode. The conventional static models can be solved in an efficient manner to derive the results based on the assumptions. However, the static models may not be able to represent the real-world situations such as the fluctuation of the demand over time and temporary over saturation of network flows. Instead, the dynamic traffic queuing models are common adopted around the world and depict the real situation. Gu et al. [1] propose a Bayesian probabilistic model to estimate the traffic state with an 8.5% error rate based on synthetic test. Agarwal et al. [2] developed a fast spatial queue model anchored to a simulation framework consisting with an agent-based travel demand. Lee and Wong [3] construct a mathematical framework and a predictive model of lane-based control delay to estimate lane-based incremental queue accumulations. Mohiddin et al. [4] propose their adaptive traffic signals control minimizing the congestion problem occurring at the intersection and assume the arrival rate following the Poisson distribution. They further indicate that the proposed model is efficient and minimizes the delay/congestion. As we can see, the previous studies assume the real-world situation
satisfying the specific distributions to derive results. In reality, the traffic conditions may not easily be described by a distribution. In this paper, we propose a dynamic adjusting model to solve the traffic queueing problem. Our model applies the heuristic solution procedure to derive the optimal solutions. This paper further utilizes the simulation data to validate our model and adopts the Monte Carlo simulation method which is the numerical method for traffic queueing problem in our research to test the resulting outcomes. It should be noted that the reason why we apply Monte Carlo simulation is that Morokoff and Caflisch [5] state that the numerically simulated stochastic processes could be done well by discretizing the process into small time steps and applying pseudo-random sequences to simulate the randomness. Furthermore, based on its efficient and wide scope of applicability in [6], this research determines to utilize the Monte Carlo simulation generally applying to all simulation data that use stochastic methods to generate new configurations in Formosa Freeway of Taiwan of interest. The results show that the proposed model outperforms the previous ones. Additionally, our solution procedure can be easily applied to the real-world situation without assuming the specific distribution because of pseudo-random feature. Additionally, Radio Frequency Identification (RFID) is widely utilized to collect the data and then to identify and monitor objects. This leads to the situation where the objects can be automatically tracked and controlled. We can say that this is the Internet of Things (IoT). As a result, our solution procedure can be implemented once the RFID reaches the mature stage. The remaining parts of this paper can be organized as follows. The literature review is surveyed in Section 2. Section 3 presents our proposed model and Section 4 utilizes the illustrative example and further conducts the analysis based on the results. Finally, Section 5 concludes this study and provides the future direction of the research.

2. Literature Review

Krajewski et al. [7] introduce that the Monte Carlo simulation is a simulation process utilizing random numbers to generate simulation events. The simulation process includes data collection, random number assignment, model formulation and analysis. Earl and Deem [8] conclude that the specific advantages of Monte Carlo simulations can be combined, giving the modeler great flexibility in the approach to a specific problem. In addition, the Monte Carlo methods are generally easily parallelizable, with some techniques being ideal for use. The (model/methodological) novelty of its application in traffic queueing compares with its previous applications [9–16] as follows. Based on the traffic flow pattern in single intersection, the authors employ the Monte Carlo method in combination with MATLAB to simulate, which is proved to be more effective than the conventional control methods [9]. Cruz et al. [10] argue that after selecting the queueing model, data must be collected, parameters estimated by some suitable statistical method, and performance measures computed to evaluate the system, including traffic intensity which is defined as the ratio between the arrival rate and service rate. Su et al. [11] adopt the Monte Carlo sampling method for the sake of formulating the dynamic spatial charging demand distribution map of the traffic network region. Agaton et al. [12] employ the Monte Carlo simulation to show how net present value decreases with stochastic prices of diesel. This result is expected as a higher fuel price incurring higher cost for Electric Jeepney operations and therefore lower profits. Italo et al. [13] conduct simulations for four distinct scenarios of mean vehicular flow and mean time interval between successive bus arrivals. The traffic simulator is initially designed to use a parametric approximation of the Poisson probability distribution of the considered random variables based on the Monte Carlo method. In addition, Qi and Hu [14] utilize the Markov Chain Monte Carlo (MCMC) sampling method to solve the Channelized Section Spillover (CSS) problem. Li et al. [15] apply the Monte Carlo simulation to develop their new traffic noise prediction approach. Cruz et al. [16] develop the control chart to monitor traffic intensity and further utilize the Monte Carlo simulation to verify their resulting outcomes.

Daniel et al. [17] argue that traffic signal lights are explicitly incorporated into the network structure so that total travel time is a piecewise linear convex function of the number of units traveling on the streets. Smith [18] presents a new dynamic model of peak period traffic flows on congested
capacity-constrained urban road networks. The model determines the time-varying costs incurred in traversing the various routes when time-varying route inflows are specified. Ziliaskopoulos [19] uses the cell transmission model to formulate the single destination system optimum dynamic traffic assignment problem as a linear program. It addresses various related issues such as necessary and sufficient conditions of the concept of marginal travel time in a dynamic network and system optimum. Bellei et al. [20] introduce the dynamic multimodal supply and equilibrium model based on implicit path enumeration. It defines within-day dynamic elastic demand stochastic multimodal equilibrium as a fixed-point problem on users flows and transit line frequencies. Mounce [21] considers a dynamic traffic assignment model with deterministic queuing and inelastic demand for each origin–destination pair in the network. In the single bottleneck per route case, the route cost function is shown to be a monotone function of the route flow if the bottleneck capacities are all non-decreasing as functions of within-day time. Florian et al. [22] describe a simulation-based, iterative dynamic equilibrium traffic assignment model. The results show that their model is applicable to medium-size networks with a reasonable computation time. Hilmi et al. [23] evaluate the performance of a dynamic approach to classify flow patterns reconstructed by a switching-mode macroscopic flow model considering a multivariate clustering method. The dynamic methods applied here are available to be employed in practice within intelligent management strategies, including incident detection and control and variable speed management. Ma et al. [24] propose a dynamic factor model to forecast traffic state for groups of locations. The traffic state forecast for each location is a combination of the respective forecast from the common factor component and idiosyncratic component. Lu et al. [25] develop a loss queuing model that simultaneously applies the existing point-wise stationary fluid flow approximation (PSFFA). Then, on the basis of the loss model, they develop a feedback queuing model by integrating the PSFFA and the generalized expansion methods. Kucharskia and Gentile [26] are unaware that drivers have a probability of being informed by multiple radio and mobile apps sources, which depends not only on devise penetration rates, but also on users’ space and time coordinates’ wrt, the position and interval of the event. As mentioned earlier, the Monte Carlo simulation method is commonly adopted in the papers to verify the results or to simulate the data. In this paper, we intend to develop a simple solution procedure to solve the traffic queueing problem since the previous algorithms may be complicated and/or assume the models fitting some specific distributions.

3. Methodology

In this section, this research states a dynamic adjusting model of traffic queuing time, and the data is simulated since RFID is not adopted to gather information. One can expect that the IoT trend would assist our solution procedure to be realized. We would introduce our algorithm in the following. The real-time-accumulated vehicles of each intersection road can be obtained by the following calculating procedure. We calculate the average length of each vehicle by the average of the sum of maximum length and minimum length of reaching vehicles on each intersection road. Indeed, the vehicle capacity of each intersection road can be obtained via each length on intersection roads to the average length of each vehicle. As a result, the real-time-accumulated vehicles of each intersection road can be measured by the initial queued vehicles and the difference of the reaching vehicles and its reducing amount of vehicles on each intersection road. Next, we calculate the total subsequence period adjusting time of the traffic green light on each intersection road as flow. This paper assumes that the initial time of the traffic green light is a constant value. Thus, we derive the dynamic adjusting time of green light on each intersection road by the difference of the fixed time of green light and the actual times of green light. In other words, the initial time of each green light plus the time of the green light changed is denoted as the fixed time of green light. In addition, the real-time-accumulated vehicles of each intersection road times the average passing time of the vehicles is denoted as the actual times of green light. Finally, the initial time of each green light adds its dynamic adjusting time of green light previous period, equal to the total subsequence period adjusting time of the traffic green light on each intersection road. The next period queued vehicle can be obtained by inheritance from current period.
real-time-accumulated vehicles of each intersection road. We further set the period \( t + 2 \) adjusting time of the green light on each intersection road derived from inheritance from the totally period \( t + 1 \) adjusting time of the green light on each intersection road.

### 3.1. The Dynamic Adjusting Model of Traffic Queuing Time

#### 3.1.1. The Notations

The notations and definitions used in our proposed model are summarized in the following.

- \( AR_{t,i} \): The real-time-accumulated vehicles of \( i^{th} \) intersection road at period \( t \).
- \( ALC_{t,i} \): The average length of the vehicles of \( i^{th} \) intersection road at period \( t \).
- \( CI_{t,i} \): The reaching vehicles of \( i^{th} \) intersection road at period \( t \).
- \( CO_{t,i} \): The reducing number of vehicles of \( i^{th} \) intersection road at period \( t \).
- \( MAX_{t,j} \): Maximum length of \( j^{th} \) reaching vehicle at period \( t \).
- \( MIN_{t,j} \): Minimum length of \( j^{th} \) reaching vehicle at period \( t \).
- \( N \): The average passing time of the vehicles.
- \( PT \): The time of the traffic light changed from green to red.
- \( RT_{t,i} \): The road capacity of vehicles of \( i^{th} \) intersection road at period \( t \).
- \( R_{t,i} \): The length of \( i^{th} \) intersection road at period \( t \).
- \( S_{t,i} \): The initial time of the traffic light on \( i^{th} \) intersection road at period \( t \).
- \( S_{t+1,i} \): The adjusting time of the traffic light on \( i^{th} \) intersection road at period \( t + 1 \).
- \( SCW_{t,i} \): The initial queued vehicles of \( i^{th} \) intersection road at period \( t \).
- \( \Delta T_{t,i} \): The dynamic adjusting time of green light on \( i^{th} \) intersection road at period \( t \).

#### 3.1.2. The Dynamic Adjusting Model

Based on the traffic flow pattern in a single intersection [9], this study applies the dynamic adjusting model in three intersections. The three formulae, including the average vehicle length \( ALC_{t,i} \), total road length \( RT_{t,i} \), and the real-time-accumulated vehicles of each road length \( AR_{t,i} \), are considered in [9].

The average length of vehicle \( i \), \( ALC_{t,i} \), is measured by the average of the sum of maximum length and minimum length of reaching vehicle \( j \)th as follows.

\[
ALC_{t,i} = \frac{(MAX_{t,j} + MIN_{t,j})}{2} \tag{1}
\]

We can obtain the vehicles capacity of the intersection roads, \( RT_{t,i} \), via the ratio of the length intersection roads \( R_{t,i} \) to the average length of each vehicle, \( ALC_{t,i} \), as show in (2).

\[
RT_{t,i} = \frac{R_{t,i}}{ALC_{t,i}} \tag{2}
\]

In a traffic queuing time model, the real-time-accumulated vehicles of each intersection road (e.g., \( AR_{t,j} \)) can be calculated in (3). In (3), we can add the initial queued vehicles and the difference of the reaching vehicles and their reducing amount of vehicle on each intersection road. Therefore, we obtain the real-time-accumulated vehicles of each intersection road \( AR_{t,j} \), where total accumulated vehicles must less equal than the vehicles capacity of its intersection road in (3).

\[
AR_{t,j} = \frac{(SCW_{t,j} + CI_{t,j} - CO_{t,j})}{AR_{t,j} \leq RT_{t,i}} \tag{3}
\]

We assume that the initial time of the traffic light is a constant value \( C \). We set up the initial time of each traffic light of intersection roads as \( C \) equal to \( S_{t,j} \) in (4).

\[
S_{t,j} = C \tag{4}
\]
The initial time of each traffic light, $S_{t,i}$, plus the time of the traffic light changed, $PT$, is denoted the fixed time of green light. The real-time-accumulated vehicles of each intersection road, $AR_{t,i}$, times the average passing time of the vehicles, $N$, is denoted the actual times of green light. Finally, we obtain the dynamic adjusting time of green light on each intersection road, $\Delta T_{t,i}$, by the difference of the fixed time of green light and the actual times of green light in (5). Note that the negative value of $\Delta T_{t,i}$ represents the protect times of the initial fixed time of green light which is not sufficient and is required to be increased into the next period adjusting time of the traffic light immediately.

$$\Delta T_{t,i} = (S_{t,i} + PT) - (AR_{t,i} \times N)$$

In other words, the $AR_{t,i}$ adjusts the green light times to $S_{t+1,i}$ through the $\Delta T_{t,i}$. Then we derive the total next period adjusting time of the traffic light on each intersection road, $S_{t+1,i}$, that can be presented by the initial time of each traffic light minus its dynamic adjusting time of green light previous period in (6).

$$S_{t+1,i} = S_{t,i} - \Delta T_{t,i}$$

In the next period, queued vehicle $SCW_{t+1,i}$ is obtained by inheritance from current period real-time-accumulated vehicles of each intersection road $AR_{t,i}$, as described in (7).

$$SCW_{t+1,i} = AR_{t,i}$$

Indeed, we set the period $t+2$ adjusting time of the green light on each intersection road, $S_{t+2,i}$, obtained by inheritance from the total period $t+1$ adjusting time of the green light on each intersection road $S_{t+1,i}$ minus its dynamic adjusting time $\Delta T_{t,i}$, as described in (8).

$$S_{t+2,i} = S_{t+1,i} - \Delta T_{t+1,i}$$

3.1.3. The Procedure of Monte Carlo Simulation

Step 1. Data collection. The simulation process gathers extensive data on cost, productivities, capacities and probability distribution. The pseudo-random sequence of data collection is used.

Step 2. Random-Number assignment. The events in a simulation can be generated in an unbiased way if random numbers are assigned to the events in the same proportion as their probability of occurrence.

Step 3. Model formulation. Formulating a simulation model entails specifying the relationships among the variables. This study applies the dynamic adjusting model in three intersections.

Step 4. Analysis. Simulation analysis can be viewed as a form of hypothesis testing, whereby the results of a simulation run provide sample data for the purpose of statistical analysis.

4. The Monte Carlo Simulation and Experimental Results

4.1. An Illustrative Example of the Dynamic Adjusting Model

This research intends to utilize the data simulated in Formosa Freeway of Taiwan as our case study as shown in Figure 1 (Google Map). There are three road sections marked in red and defined as Road Section 1, 2, and 3 based on its direction toward Taipei. The detail information of these three road sections can be stated below. Each road section is with a traffic light and each road length can be 400, 300 and 1000 m with respect to its order. In addition, there are four lanes in each road section. The Road Section 3 is adjacent the System Interchange of Formosa Freeway of Taiwan. In this study, we assume that vehicles entry ramp in the inside lane and drive straight to Taipei in the outside lane. Suppose that one drives a vehicle toward Taipei through Road Section 1, 2 and 3. Once the timing traffic signal control is not flexible during the peak hours, there may be the traffic block either in Road Sections or Formosa Freeway of Taiwan. This situation would be occurred during traffic rush hour or weekend.
we have calculated the following results. The $\Delta R_{t,i}$, shown in column 1 which represents the real length of each road section. Our proposed model would derive optimal results based on the parameter setup as shown in Table 1. Then, our dynamic adjusting model is verified three times of the uncertainty loading, length of vehicle, initial seconds, initial queued vehicles, and passing time. The column Loading represents whether the demand exceeds road capacity. For instance, the Loading of Scenario 1 is 80 which means demand is below the capacity, and vice versa. The column Length of Vehicle means that the overall length of the vehicle plus the distance between each vehicle and its unit would be meter. The seconds of traffic light green to red time can be represented by Initial Seconds. Usually, the initial seconds of the peak hour traffic would be longer than off peak one. The column Initial Queued Vehicles can be the number of vehicles in the intersection. We also provide the passing time that is the average time of vehicles passing through the intersection. In Table 2, columns 1 to 10 are given as the settings of this example and columns 11 to 16 are calculated by using Equations (1) to (8). Please note that a detailed description of each variable can be seen in Section 3.1.1. According to our simulation case, as shown in Figure 1, we have calculated the following results. The $R_{t,i}$ shown in column 1 which represents the real length of the Formosa Freeway in Taiwan. The $ALC_{t,i}$ shown in column 11 is obtained from (1). The $RT_{t,i}$ shown in column 12 is obtained by using (2), which represents the ratio of the each length on intersection roads $R_{t,i}$ to the average length of each vehicle. It denotes the maximum capacity of a specific intersection road to load its vehicles. The $AR_{t,i}$ shown in column 13 is obtained from (3), which denotes the initial queued vehicles, the difference of the reaching vehicles and their reducing amount of vehicle on each intersection road. Additionally, the real time total accumulated vehicles, $AR_{t,i}$, must less equal than the vehicles capacity of its intersection road $RT_{t,i}$. The $\Delta T_{t,i}$ shown in column 14 is obtained from (5), which denotes the dynamic adjusting time of green light on each intersection road by the difference of the fixed time of green light and the actual times of green light. Note that the negative value of $\Delta T_{t,i}$ represents the protect times of the initial fixed time of

Figure 1. The Google Map of the three intersection roads (red blocks) in an interchange of Shenkeng of the Formosa Freeway in Taiwan.

In Taiwan, the RFID hardware, the tag and reader, is not yet implemented in the vehicles or traffic signal controllers because of the cost. This follows that we cannot collect the real data of the traffic flow. To solve this problem, our study applies Monte Carlo simulation to simulate the traffic flow during the heavy traffic of each road section. Our proposed model would derive optimal results based on available data. As a result, the dynamic traffic control mechanism can be developed.

4.2. The Procedure of Our Approach

The Monte Carlo simulation is performed based on the parameter setup as shown in Table 1. Then, our dynamic adjusting model is verified three times of the uncertainty loading, length of vehicle, initial seconds, initial queued vehicles, and passing time. The column Loading represents whether the demand exceeds road capacity. For instance, the Loading of Scenario 1 is 80 which means demand is below the capacity, and vice versa. The column Length of Vehicle means that the overall length of the vehicle plus the distance between each vehicle and its unit would be meter. The seconds of traffic light green to red time can be represented by Initial Seconds. Usually, the initial seconds of the peak hour traffic would be longer than off peak one. The column Initial Queued Vehicles can be the number of vehicles in the intersection. We also provide the passing time that is the average time of vehicles passing through the intersection. In Table 2, columns 1 to 10 are given as the settings of this example and columns 11 to 16 are calculated by using Equations (1) to (8). Please note that a detailed description of each variable can be seen in Section 3.1.1. According to our simulation case, as shown in Figure 1, we have calculated the following results. The $R_{t,i}$ shown in column 1 which represents the real length of three intersection roads in an interchange of Shen-Keng of the Formosa Freeway in Taiwan. The $ALC_{t,i}$ shown in column 11 is obtained from (1). The $RT_{t,i}$ shown in column 12 is obtained by using (2), which represents the ratio of the each length on intersection roads $R_{t,i}$ to the average length of each vehicle. It denotes the maximum capacity of a specific intersection road to load its vehicles. The $AR_{t,i}$ shown in column 13 is obtained from (3), which denotes the initial queued vehicles, the difference of the reaching vehicles and their reducing amount of vehicle on each intersection road. Additionally, the real time total accumulated vehicles, $AR_{t,i}$, must less equal than the vehicles capacity of its intersection road $RT_{t,i}$. The $\Delta T_{t,i}$ shown in column 14 is obtained from (5), which denotes the dynamic adjusting time of green light on each intersection road by the difference of the fixed time of green light and the actual times of green light. Note that the negative value of $\Delta T_{t,i}$ represents the protect times of the initial fixed time of
green light which is not sufficient and must be increased into the next period adjusting time of the traffic light immediately. The $S_{t+1,j}$ shown in column 15 is obtained from (6), which denotes the initial time of each traffic light minus its dynamic adjusting time of green light previous period. In addition, the SCW of the period $t + 1$ and $t + 2$ are obtained by inheritance from the $AR_{t,j}$ of the period $t$ and $t + 1$, respectively, as described in (7). The $R_{t,j}$ of the period $t + 1$ and $t + 2$ are obtained by inheritance from the $S_{t+1,j}$ of the period $t$ and $t + 1$ as described in (8). The arrows upward and downward in $\Delta T_{t+1,j}$, shown in column 16, which denote the comparison between $S_{t,j}$ (column 5) and $S_{t+1,j}$ (column 15). A detailed analysis related to the direction of arrows is shown in Table 2. Please note that the symbol $\uparrow$ in column 16 of Table 2 represents the adjusting time greater than initial time, and vice versa. For instance, given that in simulation run 1 with $i=1$, the initial time $S_{t,1}$ equals to 40 and $S_{t+1,1}$ is 109. Then we can know $\Delta T$ being $\uparrow$. Also, we highlight the important information by red and black blocks in Table 2. The $S_{t,j}$ in red block shows initial time and SCW means the initial queued vehicles.

**Table 1.** The design of the test problems.

| Scenario | Loading (%) | Length of Vehicle | Initial Seconds | Initial Queued Vehicles | Passing Time |
|----------|-------------|-------------------|-----------------|-------------------------|-------------|
|          | Max | Min | $R_1$ | $R_2$ | $R_3$ | $R_4$ | $R_5$ | $R_6$ | $R_7$ | $R_8$ | $R_9$ | $R_{10}$ |
| 1        | 80  | 15  | 10   | 40   | 40   | 40   | 6    | 6    | 5    | 6    | 7    |
| 2        | 100 | 20  | 15   | 60   | 40   | 80   | 9    | 6    | 12   | 6    | 7    | 5    |
| 3        | 120 | 25  | 10   | 80   | 40   | 120  | 12   | 6    | 18   | 7    | 5    | 6    |
| 4        | 150 | 30  | 15   | 60   | 40   | 40   | 6    | 6    | 6    | 5    | 7    |
| 5        | 80  | 15  | 15   | 60   | 40   | 80   | 9    | 6    | 12   | 6    | 7    | 5    |
| 6        | 100 | 20  | 20   | 80   | 40   | 120  | 12   | 6    | 18   | 7    | 5    | 6    |
| 7        | 120 | 25  | 10   | 40   | 40   | 40   | 6    | 6    | 5    | 6    | 7    |
| 8        | 150 | 30  | 15   | 60   | 40   | 80   | 9    | 6    | 12   | 6    | 7    | 5    |
| 9        | 80  | 15  | 20   | 80   | 40   | 120  | 12   | 6    | 18   | 7    | 5    | 6    |
| 10       | 100 | 20  | 10   | 40   | 40   | 40   | 6    | 6    | 5    | 6    | 7    |
| 11       | 120 | 25  | 15   | 60   | 40   | 80   | 9    | 6    | 12   | 6    | 7    |
| 12       | 150 | 30  | 20   | 80   | 40   | 120  | 12   | 6    | 18   | 7    | 5    |

**Table 2.** The dynamic adjusting model in the Monte Carlo simulation.

| Simulation Runs | $i$ | $R_{t,i}$ | $\Delta T_{t,i}$ | $S_{t+1,i}$ | $\Delta R_{t,i}$ |
|-----------------|----|-----------|------------------|--------------|------------------|
| 1               | 1  | 330  20  | 36  15  10  40  40 | 30  15  22  19 | (-69)  109  $\uparrow$ |
| 2               | 2  | 240  15  | 24  10  60  60  | 24  10  13  19 | (-18)  78  $\uparrow$ |
| 3               | 3  | 850  25  | 30  25  75  75  | 30  25  86  80 | (-164) 239  $\uparrow$ |
| 2               | 1  | 330  25  | 36  15  10  78  | 36  15  22  19 | (-36) 109  $\uparrow$ |
| 3               | 2  | 240  10  | 16  10  54  54  | 16  10  13  19 | 24  54  $\uparrow$ |
| 3               | 3  | 850  20  | 25  25  73  73  | 25  25  96  80 | (-96) 239  $\uparrow$ |

From this example, we can see how the dynamic adjusting time of green light could be improved when our approach is applied to two or more intersection roads in an interchange of Shen-Keng of the Formosa Freeway in Taiwan.

4.3. The Monte Carlo Simulation

A desirable and efficient solution to this classical method is to utilize the Monte Carlo simulation. Additionally, the reason why we use Monte Carlo simulation is that Morokoff and Caflisch [5] state that the numerically simulate stochastic processes could be done well by discretizing the process into small time steps and applying pseudo-random sequences to simulate the randomness. In addition, the standard Monte Carlo method using pseudo-random sequences can be quite convergence for $N$ sample tests. They conclude that the range of application of Monte Carlo methods can be significantly extended by modification of the standard Monte Carlo techniques. In addition, Huang et al. [6] introduce the reasons for utilizing a Monte Carlo simulation are: (a) the Monte Carlo simulation generally applies to all simulations that use stochastic methods to generate new configurations of a
system of interest, (b) the Monte Carlo move is accepted or rejected based on an acceptance criterion that guarantees that configurations are sampled in the simulation from a statistical mechanics ensemble distribution, and (c) most Monte Carlo simulation algorithms are comprised of several different Monte Carlo moves that are effective at relaxing different degrees of freedom in a molecule or system. According to its efficient and wide scope of applicability in [11], we determine to utilize the Monte Carlo simulation as informatics tools to verify the results of the proposed dynamic adjusting model. Furthermore, several studies also apply Monte Carlo in the research such as Mahdiyar et al. [27] and Auda et al. [28]. In the test problem, we consider five factors in Monte Carlo simulation. That is, the loading, length of vehicle, the initial seconds, the initial queued vehicles and the passing time, as shown in Table 1.

In this study, Microsoft Excel 2000 Visual Basic Application (VBA) is applied to implement the Monte Carlo simulation because it is the most common development software used in companies and its programming language is the same as the Visual Basic which is very easy to use. In addition, we adopt an i5-6200U 2.30 GHz Note Book as our test environment.

4.4. Statistics Regarding Monte Carlo Simulation

Our study derives Table 3 based on the results of the 30-run simulation which can be calculated by the Equations (1) to (8). It shows that the average rate for reducing number of vehicles is 9.79 in First In First Out (FIFO) and 15.56 by our approach. Additionally, the standard deviation is 2.27 for FIFO, 7.96 for our approach. In addition, the average rate and the standard deviation for traffic jam amount is 1.35 and 0.08 in FIFO, and 0.34 and 0.09 in our approach. It can be seen that the conventional traffic queuing problem can be solved in an efficient manner by using our approach.

Table 3. Statistics regarding Monte Carlo simulation.

|                          | (1) Reducing Number of Vehicles | (2) The Queued Vehicles | (3) Traffic Jam Amount | (4) Traffic Jam Time |
|--------------------------|---------------------------------|-------------------------|------------------------|----------------------|
| Average rate for FIFO (%)| 9.79                            | 24.68                   | 1.35                   | 1570.6               |
| Standard deviation for   | 2.27                            | 10.02                   | 0.08                   | 91.54                |
| FIFO (%)                 |                                 |                         |                        |                      |
| Average rate for the     | 15.56                           | 20.27                   | 0.34                   | 1245.9               |
| dynamic adjusting queueing model (%) |             |                         |                        |                      |
| Standard deviation for   | 7.96                            | 10.79                   | 0.09                   | 88.43                |
| the dynamic adjusting queueing model (%) |      |                         |                        |                      |

4.5. Discussion

Another way of investigating into this simulation cases is to conduct the sensitively analysis of our approach. In Table 2, since the $S_{i,j}$ in column 5 denote the initial time of the traffic light and $SCW_{i,j}$ in column 8 denote the initial queued vehicles and the $S_{i+1,j}$ in column 15 denote the adjusting time of the traffic light at next period. After our dynamic adjusting model was executed, we could observe heavy traffic behavior by whether the real-time queued vehicles, $SCW_{i,j}$ increased or decreased. For example, in run 1 and $i = 1$, $S_{i,j}$ is 40 and $SCW_{i,j}$ is increased from 13 to 19 (i.e., in run 2 and $i = 1$), the adjusting traffic light time $S_{i+1,j}$ also is increased from 40 to 109. By contrast, in run 2 and $i = 1$, the queued vehicles are decreased from 19 to 13 (i.e., in run 3 and $i = 1$), the adjusting traffic light time also is decreased from 109 to 73. It means that the proposed dynamic adjusting model could adapt to the constraints of real demand not merely related to each road capacity of vehicles $RT_{i,j}$ linearly. This study infers that our proposed dynamic adjusting model can adapt to each length on intersection roads $R_{i,j}$. It might be said that the minimum length can be less influence of adjusting degree. By contrast, while the road capacity of vehicles is maximum (i.e., $i = 3$ and 850 m) then the dynamic adjusting degree go speed up. This study infers that the maximum length the large influence of adjusting degree.
In addition, one can know that the IoT concept would enable the data to be collected automatically due to its convenience. Our solution procedure can be implemented once these data can be derived in an appropriate manner.

5. Conclusions

This research proposes the dynamic adjusting queueing model to solve for dynamic adjusting time. Our model develops two modes and includes eight formulae to calculate the analysis results. In our first calculating mode, the three formulae intend to simulate the maximum traffic flow in the real-world situation such as total road length, average vehicle length and each road length. The second mode is to calculate the results based on the simulation data generated by Monte Carlo simulation. We derive the information of the vehicle, accumulated vehicle and dynamic adjusting time by the dynamic adjusting queuing model. The Monte Carlo simulation is adopted to verify the proposed model since it discretizes the process into small time steps and applying pseudo-random sequences to simulate the randomness [14]. The resulting outcomes show that our deriving results of average rate in reducing number of vehicles (15.56%) is better than FIFO results (9.79%). Similarly, our model outperforms FIFO in the queued vehicles, the traffic jam amount and the traffic jam time. One can know that we intend to propose a simple solution procedure to implement our model in an easy manner and assume the model following pseudo-random which coincides with the current status. Furthermore, based on the IoT trend, we can expect that the data can be automatically gathered in an efficient manner. This means that our study can be implemented in the real-world once the sensor data is obtained. For instance, the RFID is an approach to realize our proposed model in the real world. Our future study would investigate into RFID and see its possibility in our proposed model.

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