Assessment of Route Choice Models for Dynamic Traffic Assignment using Microscopic Simulation

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ABSTRACT

Travel forecasting models predict changes in the travel patterns and propose improvements. This study evaluates the parameters in route choice models, such as binomial, proportional, multinomial logit, and C-logit in microscopic simulation-based dynamic traffic assignment. The average Geoffrey E. Havers (GEH) index of each route choice model was tabulated when comparing the simulated flow of the junctions with the observed flow. The results indicated that the binomial model generally yields the lowest GEH value, but since the model does not consider the travel costs in the decision process, it is not suitable for traffic impact studies. As for the proportional and multinomial logit models, the K-Shortest Path (K-SP) value has greater impact on the assignment results. With a K-SP value of 1, the proportional and multinomial logit models generated the lowest GEH index when the alpha factor was set to 3.0 and the scale factor was set to 25, respectively. Lastly, for the C-logit model, the assignment results are more sensitive to the calibration of the scale factor and beta values compared to the K-SP and gamma factor. A lower GEH index is always observed for the scale factor of 25 and the combination with a beta value of either 0.1 or 0.15, regardless of the values of gamma and the initial K-SP. When comparing the calibrated models with the original model, the C-logit model showed higher deviations, whereas the logit and proportional models showed no significant differences. These findings highlight the importance of parameter calibration, apart from providing significant insights into route choice modeling, especially in replicating the real route choice behavior of motorists in Malaysia.

Keywords-route choice model; dynamic traffic assignment; microscopic simulation

I. INTRODUCTION

In developing countries, such as Malaysia, the development of new areas is inevitable and essential for the growth of the country. However, the development of new areas with the construction of new buildings and infrastructure typically attracts more people and vehicles, increasing the overall traffic volume [1, 2]. The increased travel demand leads to congested traffic scenarios, resulting in slower speeds, longer travel times, and increased vehicle queues. This contributes to global environmental problems, such as Greenhouse Gas (GHG) emissions and noise pollution, thereby hindering the achievement of sustainable development [3]. Therefore, accurate traffic assignment becomes crucial to ensure that the transportation network can accommodate the increased demand without leading to severe congestion. Effective traffic assignment can reduce the trip duration, time loss, waiting time, departure delay, and excessive congestion [4]. It helps the infrastructure by determining the traffic flow over each network arc based on its characteristics and the total flow over the entire area [5].

Traffic assignment involves distributing traffic demand, typically expressed by an origin-destination matrix, across the network to ascertain traffic flows along its links. The four-stage demand model, which utilizes the static assignment method, is ineffective in describing the dynamic characteristics of the transportation systems [6]. Studies have highlighted that the Malaysian traffic modeling approaches often depend on static and deterministic methods, which are limited in capturing the time-dependent dynamics of the traffic flow and demand [7]. The persistent use of empirical and static models in urban road networks has been stressed and the adoption of more dynamic and simulation-based approaches has been proposed. It has been also mentioned that the reliance on deterministic methods underscores the need for Malaysia to transition toward advanced and dynamic modeling techniques to better manage its increasingly complex transportation challenges. Therefore, the Dynamic Traffic Assignment (DTA) model has gained popularity due to the ever-increasing computational power of modern workstations and its ability to capture the time-dependent dynamics of the traffic flow and demand [8]. This study introduces a new perspective by exploring the potential application of DTA within Traffic Impact Assessment (TIA), a methodology that has yet to be widely implemented in Malaysia. By addressing the limitations of traditional deterministic methods, this study seeks to improve traffic modeling practices. It also lays a foundation for integrating dynamic and real-time traffic simulations into planning frameworks, thereby enhancing the accuracy of the transportation analysis and decision-making processes. The assessment of existing route choice models is a critical step toward achieving this objective, ensuring that the models can effectively replicate driver behavior and traffic dynamics in a localized context.

Microscopic traffic simulators are tools designed to realistically replicate the movement of individual vehicles within a road network. They have proven valuable in transportation feasibility studies, not only because they can capture the full dynamics of time-dependent traffic events, but also due to their ability to incorporate behavioral models that reflect drivers' responses to Intelligent Transportation Systems (ITS) [9]. The DTA software includes Aimsun, VISSIM, Cube, Dynameq, and TransModeler [10]. These tools are designed to handle the complexity of urban traffic systems, offering various levels of simulation detail and integration capabilities. Besides being able to combine static and dynamic methods in one environment [11], Aimsun is a superior DTA model due to its integration of multi-level simulations, real-time data processing, multi-modal capabilities, and user-friendly interface [12], making it a comprehensive and effective tool for modern traffic management and urban planning. The Aimsun microsimulation model returns small errors for vehicle flow, travel speed, and total travel distance [13]. There are two algorithms provided in Aimsun, known as Stochastic Route Choice (SRC) and Dynamic User Equilibrium (DUE). SRC computes the least-cost route at the end of each user-defined departure interval and allocates vehicles among this and previously determined least-cost routes using discrete choice functions. Meanwhile, DUE involves an iterative process with the goal of ensuring that for each origin-destination pair and user-defined departure time interval, the travel times experienced by vehicles departing during the same period are both minimal and equal. The different assignment algorithms reproduce different levels of access to travel time information. Both DUE and SRC are valuable, but SRC offers advantages in terms of computational efficiency and scalability for handling extensive network simulations, making it particularly suitable for practical implementation in transportation planning and operations [14]. Although DUE is a widely accepted approach for many strategic planning applications, SRC has been increasingly used in practice for traffic operation purposes, and has prompted this study. Simulation-based models often require a systematic calibration of many parameters and inputs. The result may be less accurate than that from a static model if the inputs are unreliable. Model calibration aims to reduce the differences between the network's simulated and observed traffic patterns [15]. Besides the road network, the calibration of a traffic microsimulation model involves two other main components, which are the driver behavior and travel behavior. The driver behavior components include models for vehicle following, lane changing, and gap acceptance. The travel behavior components encompass origin-destination flows and route choice models. However, there is limited information available on the calibration of traffic simulation models, as most studies concentrate on driving behavior alone, although route choice also plays a pivotal role in the calibration process [16]. Even though route choice modeling is quite challenging due to the complexity of human behavior and uncertainty of travelers' perceptions, it is an important part of a DTA model in order to accurately predict the traffic conditions in transportation networks [17].

Existing studies primarily focus on driving behaviors, such as car-following and lane-changing, with limited attention being paid to the route choice model calibration, which is a critical determinant of DTA performance. There is a lack of comprehensive studies evaluating the sensitivity of the DTA model outputs to parameter calibrations in different route choice models, such as binomial, proportional, multinomial logit, and C-logit. The aforementioned advanced models offer various approaches to capturing the complexities of route selection. Each model has unique strengths and limitations that affect its applicability in different traffic modeling scenarios. Authors in [18] investigated the traffic assignment techniques for the user equilibrium and system optimal principle and divided them in a multi-modal network using the binomial logit function solution method. Meanwhile, the logit method is commonly deployed in stochastic traffic assignment because it is easy to understand and has obvious advantages in large networks. However, it has the problem of Independence of Irrelevant Alternatives (IIA) [19]. To reduce the influence of IIA characteristics, the C-logit model adds commonality factors for the impact of path overlap. Compared to the multinomial logit model, the C-logit model has a simpler closed-form analytical probability expression, requires less calibration work, and represents a more realistic route choice behavior [20]. Although it has been shown that Machine Learning (ML) models can bring great improvements in forecasting accuracy, their application in this context requires further research. ML models outperform the multinomial logit models when more data are available for model training. However, when there are less training data, the multinomial logistic model still works well because it has a starting point in the behavioral assumptions without having to learn as much from the data from scratch [21]. Therefore, this study will focus on the four fundamental route choice models that are still used by current traffic practitioners with limited data.

The route choice model determines the selection of specific routes of a given transportation network for each driver. Authors in [22] employed various route choice models and corresponding parameters to analyze the driver behavior and optimize the traffic flow during emergencies. These route choice models, and their respective parameters were utilized to simulate different scenarios of driver behavior and assess their impact on the traffic conditions within the network during emergency evacuations. Authors in [23] explored various parameter changes in the C-logit model to understand their impact on the route choice behavior. Some of the parameters studied include the commonality factor, θ value, penalty value, and bias values. Authors in [9] found that, in the logit and C-logit models, the scale factor (θ) and initial K-SP were identified as significant parameters during the calibration process. Similarly, in the proportional route choice model, the alpha factor played a crucial role in influencing the route choice process. Adjusting these parameters led to changes in the route choices made by drivers in the simulation, impacting factors, such as the route utilization, travel times, and overall network performance. Therefore, the factors most likely to be utilized by the user to choose between alternative routes, such as the perceived travel times, route length, travel conditions, etc., are implicitly represented by the route choice functions, which are the reflective model of user behavior [24].

A commercially available microscopic simulator software, such as the Aimsun Next, was selected in this study as the four basic route choice functions, namely the binomial, proportional, multinomial logit, and C-logit models, are readily available in the software. The four fundamental route choice models were systematically calibrated and assessed in a microscopic simulation environment. The objectives are twofold: (1) to evaluate the suitability and accuracy of these models in replicating real-world traffic behavior, and (2) to identify the key parameters that influence the assignment results. Therefore, this study aims to provide practical insights for researchers, transportation planners, and engineers to ensure that the simulated traffic patterns closely match real-world data. This will enhance the reliability of DTA models for traffic impact studies, which can then lead to more precise predictions and informed decisions.

II. METHODOLOGY

In this study, Bertam was identified as the most appropriate study area due to its strategic location in Kepala Batas, Penang, Malaysia. The choice of Bertam as the study area introduces a novel dimension to the traffic impact studies due to its socio-economic transition from the agricultural to the mixed-use development, which creates unique traffic patterns and challenges. This context provides an opportunity to tailor calibration efforts to a rapidly urbanizing area, demonstrating the adaptability and robustness of DTA models in addressing local issues. Its socio-economic transition from the agricultural to the mixed-use development provides a unique backdrop for analyzing the traffic dynamics, besides enriching the understanding of the urban mobility challenges, effective traffic management strategies, and sustainable urban planning initiatives in the rapidly evolving urban environments. Figure 1 shows the road network of the study area. A preliminary site survey was conducted to determine the road system in the study area. Information, such as the number of lanes, speed limit, and road capacity, must be obtained from site visits, road maps, and submittal plans. A zoning system specific to the study area was then created based on the available land use information. The study area was specifically chosen to limit the number of alternative routes in order to simplify the assignment process.

Data collection was conducted to obtain the classified turning volumes at major junctions and screenline data. A total of ten junctions namely junction A (abbreviated as JA), JB, JC, to JJ were selected in this research. Junctions JA-JD are four-legged signalized junctions, JE is a four-legged roundabout, JF is a left-in-left-out junction, junctions JG-JI are three-legged stop-controlled junctions, and lastly, JJ is a three-legged signalized junction. The traffic volumes at these ten junctions were collected from Tuesday, May 23 to Thursday, May 25, 2023, from 06:30 to 09:30, 11:30 to 14:30, and 16:30 to 19:30. The traffic volumes were then analyzed to determine the most critical peak hour traffic flow for subsequent assessment. Passenger car equivalents were used to convert the unit from veh/h to a passenger car unit, or pcu/h, using the passenger car equivalent values listed in Table I.

TABLE I. PASSENGER CAR EQUIVALENT VALUES

Vehicle classification	Passenger car equivalent
Passenger car	1.00
Small lorry with 2 axles or large van	1.75
Heavy vehicle with 3 axles or more	2.25
Bus	2.25
Motorcycle	0.33

Fig. 1. Road network of the study area.

Subsequently, the road network inventory data were used to create the centroids, sections, and intersections in the Aimsun Next simulation software. The traffic flow data were then utilized to develop the base OD matrix, which is without the proposed development and has 25 zones. The experimental simulation must be route-based in which an OD matrix was developed using the collected data and loaded into the Aimsun Next model. DTA was then performed. The OD matrix was fixed to ensure that the same demand volumes were used in all assignment models for the road network, since the aim is to study the route choice models and no thet demand volumes.

These route choice models were then evaluated for their suitability and accuracy in replicating real-world route choice behavior, as well as for their complexity in the application and calibration process. A key component of this study is the systematic evaluation of the suitability of existing route choice models for their incorporation into DTA. This process focuses on ensuring that these models can accurately reflect the driver behavior and traffic patterns in the study area. The goal of the evaluation is to identify the models and parameter calibrations that provide the highest level of reliability to enable a successful implementation of DTA in TIA. Therefore, to achieve this objective, only the calibration of the parameters in the route choice models was performed to ensure an effective comparison. This structured approach ascertains that the outcomes are both practical and adaptable to real-world scenarios. The parameters that need to be calibrated to control the route behavior for each OD pair are presented in Table II.

Depending on the selected route choice model, the generated parameter combinations are listed below:

- Binomial: Probability: 0.3, 0.5, and 0.9, initial K-SP: 1, 2, and 3, and the maximum number of routes is 3.
- Proportional: Alpha factor: 0.5, 1.0, 1.5, 2.0, 2.5, and 3.0, initial K-SP: 1, 2, and 3, and the maximum number of routes is 3.
- Multinomial logit: Scale factor: 25, 50, 75, and 100, initial K-SP: 1, 2, and 3, and the maximum number of routes is 3.
- C-logit: Scale factor: 25, 50, 75, and 100, beta: 0.1, 0.15, 0.5, and 1.0, gamma: 0, 1, and 2, initial K-SP: 1, 2, and 3, and the maximum number of routes is 3.

TABLE II. PARAMETERS OF EACH ROUTE CHOICE MODEL

Route choice model	Parameters
Binomial	Probability
Proportional	Alpha factor
Multinomial logit	Scale factor
C-logit	Scale factor
	Beta
	Gamma

The combinations tested in this study go beyond the parameter calibration scope of [9] by including a wider range of parameter values and unique combinations, such as the inclusion of parameter calibration for the binomial route choice model, thus providing new insights into their interdependencies and impact on traffic modeling. Due to the fact that this study only aims to assess and calibrate the parameters in the route choice models, no variable manipulation is done on the vehicle behavior models, such as car-following and lane-changing. Meanwhile, in terms of the cost function settings for each link, it remained in its default state, which is using the default cost function that represents the link travel time in seconds composed of a section travel time plus the turn movement travel time.

Once the base model is calibrated, the road network can be assessed to obtain the simulated flow. The average GEH index of each route choice model is then tabulated by comparing the junctions' simulated flow with the observed flow collected in the field. The GEH index is one of the criteria that is recommended by various road administrations and used in traffic modeling to compare two sets of traffic volumes. The GEH index is expressed as:

$$GEH_j = \sqrt{\frac{2(K_j - M_j)^2}{K_j + M_j}} \quad (1)$$

where K_j is the observed flow at link j and M_j is the modeled flow for the same link [25]. A GEH index below 5.0 at a measurement point indicates a favorable alignment between the modeled and observed volumes, and 85% of the volumes in a traffic model should have a GEH less than 5.0 for all measurement points [26]. A GEH value between 5.0 and 10 indicates that further investigation for error is warranted, and a value greater than 10 implies a major and unacceptable error.

III. RESULTS AND DISCUSSION

A. Peak Hour Traffic Flow

The data from the traffic survey, which indicate the current traffic volume fluctuation during the morning and evening peak hours at all surveyed junctions, are depicted in Figure 2. The graph shows that the morning peak hour is from 07:00 to 08:00, whereas the evening peak hour is from 17:15 to 18:15. The traffic in the morning peak hour is higher with a total of 21,907 pcu/h than in the evening peak hour with only 21,758 pcu/h. Among all surveyed junctions, junction JA recorded the highest traffic volume in both peak hours with 3,694 pcu/h, which can be attributed to its proximity to high-density areas and significant trip-generating zones. Junction JF has the lowest traffic volume in both peak hours with 719 pcu/h in the morning peak hour and 855 pcu/h in the evening peak hour, likely due to limited connectivity and fewer trip-attracting facilities. Owing to the fact that most of the junctions had higher traffic flow in the evening peak hour compared to the morning peak hour, only the evening peak flow rates were adopted in this study.

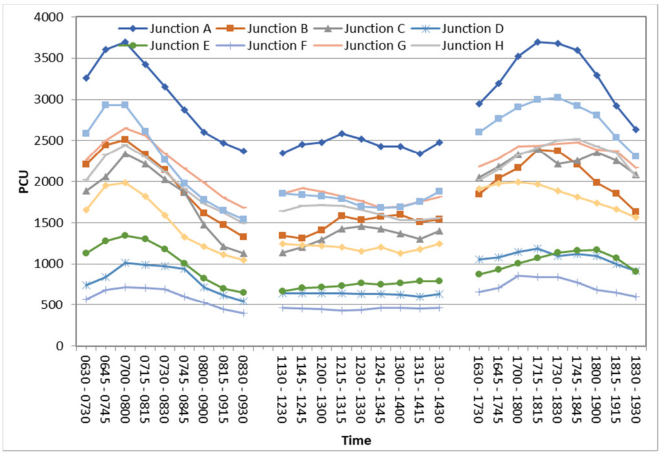

Fig. 2. Recorded traffic volume.

B. Binomial Model

In the binomial model, the probability of choosing each path is determined using a binomial (k-1, p) distribution where k is the number of possible paths and p is the probability of "success". The significant route choice parameter of the binomial route choice model is the probability. This model simply considers the time at which the path was estimated and not the travel cost. Therefore, choosing larger values of p will result in a greater frequency of using the more recent paths, whereas choosing lower values of p will increase the likelihood of using the oldest paths. In this study, by considering the probability of 0.3, 0.5, and 0.9, and with the initial K-SP value ranging from 1 to 3, the total number of experiments generated is 9 (3 × 3). The GEH was calculated to evaluate the goodness-of-fit of each model to the observed data of the studied junctions. According to the results obtained, the lowest GEH index is observed from the combination of an initial K-SP of 1 and a probability value of 0.5 when the binomial route choice model is used. The highest GEH index among the nine combinations is generated with the combination of an initial K-SP of 3 and a probability value of 0.3. The results indicate that the K-SP and the probability values have a significant impact on the assignment results in the binomial model.

C. Proportional Model

In the proportional model, the alpha factor is a function of the different path costs, and when the alpha factor is equal to 1.0, the probability is inversely proportional to the path costs. As a result, the alpha factor can be used to minimize the potential impact of minor changes in travel times on the driver's decisions. In this study, with the alpha factor of 0.5, 1.0, 1.5, 2.0, 2.5, and 3.0 and with the initial K-SP value ranging from 1 to 3, the total number of experiments generated is 18 (6 × 3). In general, the model was also able to generate simulation results that were in good agreement with the observed values. Subsequently, the average GEH index of each junction simulated by different combinations based on the proportional route choice model for K-SP 1, 2, and 3 was calculated. Based on the results obtained, the lowest GEH index is observed when the initial K-SP value is set to 1 and the alpha factor is set to 3.0.

Comparing the simulated results of this study with the results of [9], there is a similarity between them that can be explained. In [9], the acceptable GEH and relative gap were observed when the initial K-SP value was equal to 1 for all the alpha factor values ranging from 0.5 to 3.0 with an increment of 0.5. In this study, the GEH index of all the combinations of an initial K-SP value of 1 and alpha factor values ranging from 0.5 to 3.0 with an increment of 0.5 is the lowest compared to the initial K-SP values of 2 and 3. Among the eighteen combinations, the highest GEH index resulted from the alpha factor calibration and initial K-SP value of 0.5 and 3, respectively. The results obtained in [9] also yield similar findings as it was also observed that GEH is also unacceptable under the same combination. This finding corroborates the results of [9], where the significance of the initial K-SP values in enhancing the reliability of the model was demonstrated. Therefore, for the proportional model, the K-SP value has greater impact on the assignment results compared to the alpha factor. However, when the initial K-SP value is set to 2 or 3, both models yield similar assignment results regardless of the alpha factor.

D. Multinomial Logit Model

In the multinomial logit model, the scale factor is a critical parameter to be calibrated. It influences the decision based on utility differences regardless of the measurement units and affects the standard error of the distribution of the projected travel times. Therefore, the scale factor will determine whether there is a tendency to use many alternative routes or whether the alternative choices are concentrated on a small number of routes. In this study, scale factors of 25, 50, 75, and 100 were adopted with initial K-SP values ranging from 1 to 3, and the total number of experiments generated is 12 (4 × 3). The results indicated that the GEH index was always lower when the scale factor calibration was set at 25 and, ironically, a higher GEH index was observed when the scale factor was calibrated at either 50 or 75. However, the results obtained in this study are in contrast to those attained in [9], where it is mentioned that only the scale factor of 60 or 100 generates acceptable GEH and relative gap values, regardless of the lambda value and the initial K-SP parameter. However, authors in [9] only used the scale factors of 10, 60, and 100 in their analysis and did not include the scale factors of 25, 50, and 75. The divergence not only indicates that lower scale factors can generate better assignment results, but also highlights the necessity of context-specific calibrations, confirming the findings from localized microsimulation studies that emphasize on tailored parameter settings.

Nevertheless, among the twelve combinations generated from the initial K-SP values ranging from 1 to 3, with a scale factor calibration of 25, 50, 75, and 100, the lowest GEH index is generated when the scale factor was calibrated to 25 and the initial K-SP value was calibrated to 1. In contrast, the combination of a scale factor of 75 and an initial K-SP of 2 produced the largest GEH index when the multinomial logit route choice model was used. Additionally, the multinomial logit model also showed the same trend as the proportional model. That is, the K-SP value influences the assignment results more than the scale factor, and both models produce similar assignment results regardless of the scale factor when the initial K-SP value is set to 2 or 3.

E. C-Logit Route Choice Model

Several researchers have reported the shortcomings of the multinomial logit model [27, 28]. It has been mentioned that the logit function tends to produce unstable results due to its inability to differentiate between two alternative routes when there is a high degree of overlap. Therefore, the C-logit model, which is an adaptation of the logit model, was introduced. In the C-logit model, apart from the scale factor, there are the gamma and beta parameters, which are used to calculate the "commonality factor". The gamma factor is a positive parameter, usually taken in the range of 0 to 2, whose influence is smaller than that of beta and which has the opposite effect on the choice. The commonality factor is used to capture the correlations between the alternatives. Therefore, the commonality factor is directly proportional to the degree of overlap, since, highly overlapping paths have a larger commonality factor, and thus lower utility compared to similar paths [9]. In this study, scale factors of 25, 50, 75, and 100, beta values of 0.1, 0.15, 0.5, and 1.0, a gamma value from 0 to 2, and initial K-SP values ranging from 1 to 3 were considered, and the total number of experiments generated is 144 (4 × 4 × 3 × 3). The results indicated that a lower GEH index is always observed for the scale factor of 25 combined with a beta value of either 0.1 or 0.15, regardless of the values of gamma and initial K-SP. However, among the 144 combinations generated by considering the parameters of beta, gamma, scale factor and initial K-SP, the highest GEH index is produced by the combination of a scale factor of 25 and a beta value of 0.1, regardless of the values of gamma and initial K-SP. Hence, the assignment results based on the C-logit model are more sensitive to the calibration of the scale factor and beta values compared to the K-SP and gamma factor. Additionally, the results also indicated that the logit model exhibits lower GEH values compared to the C-logit model, but with very little difference overall.

F. Performance of Calibrated Route Choice Models Against the Original Uncalibrated Model

This section evaluates the performance of the calibrated route choice models (binomial, proportional, logit, and C-logit) against the original, uncalibrated model, focusing on delay, flow, travel time, and volume/capacity ratio. The same GEH analysis was conducted to identify the best parameter values for each route choice model by comparing the simulated traffic flows between the calibrated and uncalibrated models. Based on the results, portrayed in Figure 3, the C-logit model shows the largest deviations in delay, especially at congested junctions such as JC and JD, whereas the logit and proportional models are closer to the uncalibrated model. In addition, the C-logit model shows significant deviations from the uncalibrated model in terms of flow, especially during peak periods. This is evident at JC and JD, where its flow predictions diverge the most. The logit model achieves the best fit, followed by the proportional and binomial models, which show moderate alignment. In terms of travel time, the C-logit model shows the largest deviations, diverging significantly from the uncalibrated model at heavily trafficked junctions, whereas the logit and proportional models closely mimic the uncalibrated model's travel time trends, with minimal deviations. Furthermore, the C-logit model exhibits consistent deviations in V/C ratio trends, with its predictions diverging notably at JC and JD. The logit and proportional models maintain closer alignment with the uncalibrated model, whereas the binomial model exhibits slight mismatches.

When comparing the calibrated models to the original model, the C-logit model consistently has the highest GEH values, indicating significant deviations from the original Aimsun model. Conversely, the logit and proportional models maintain lower GEH values relative to the original model, suggesting that their calibrated outputs align more closely with the uncalibrated simulation. The observed discrepancies in GEH indices between the calibrated and uncalibrated models emphasize the importance of calibration in aligning the simulation outputs with real-world traffic behavior. The C-logit model, which exhibits the lowest GEH compared to the site traffic but the highest GEH compared to the original model, highlights the disparity between the uncalibrated simulation results and actual site conditions. While the uncalibrated Aimsun model provides a baseline for comparison, it fails to accurately replicate observed site-specific traffic conditions. Calibration, as evidenced by the C-logit model, bridges this gap and produces results that align more closely with site conditions. This study underscores the importance of tailoring the simulation parameters to the observed site data to ensure accurate and actionable outputs for traffic management and planning. Calibration should be considered a fundamental step in the microsimulation process to achieve results that reflect the real-world traffic dynamics.

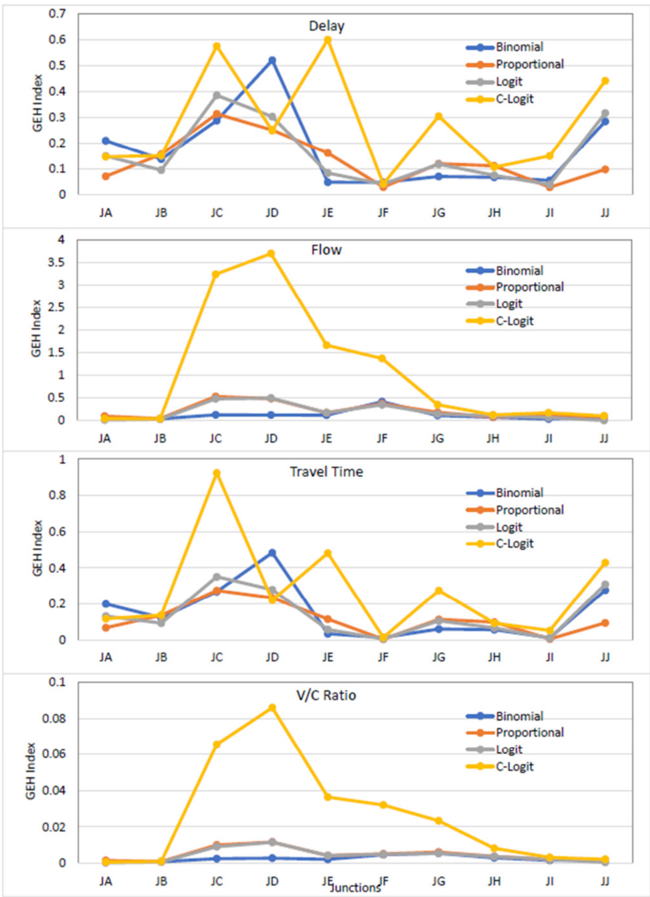

Fig. 3. Average GEH index plotted against junctions for the calibrated binomial, proportional, logit, and C-logit route choice models.

IV. CONCLUSION

This study critically assesses the impact of key parameters in various route choice models for Dynamic Traffic Assignment (DTA) using microscopic simulation in a Malaysian context, providing deeper insights into parameter sensitivities and their influence on assignment accuracy. Specifically, it highlights how parameter calibration significantly improves the alignment between simulated and observed traffic flows, thus advancing the precision of route choice modeling in DTA applications. The results emphasize that the binomial model's sensitivity depends on the calibration of both the K-Shortest Path (K-SP) and the probability values. In contrast, the proportional and multinomial logit models exhibit stronger dependencies on the scale factors, with notable impacts at lower scale settings. Furthermore, the calibration of the scale factor and the beta values are more sensitive in the C-logit model as compared to the K-SP values in the proportional and logit models, providing enhanced flexibility in capturing overlapping route scenarios. In summary, this study has shown that the parameters used in different route choice models have a significant impact on the assignment results. It makes a significant contribution by proposing the integration of DTA into Traffic Impact Assessment (TIA) to overcome the limitations of deterministic methods. Additionally, it underscores the importance of route choice model evaluation and calibration as a critical precursor to DTA implementation to ensure that traffic modeling aligns with the local driver behavior and network characteristics.

The calibration of parameters in the route choice model complements previous work that focused only on the car-following and lane-changing behavior, and has filled a critical knowledge gap in the practical application of the route choice models by demonstrating the nuanced effects of parameter adjustments. By highlighting the sensitivity of the key parameters and the effectiveness of different models, this study provides valuable insights for traffic consultants and engineers to achieve greater reliability in simulating real-world traffic behavior, which is crucial for effective urban planning and traffic management. Future research should extend this work by incorporating diverse network configurations and exploring the integration of Machine Learning (ML) techniques to further enhance model accuracy and scalability.

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