Application of SUMO in Simulation of Optimized Traffic Light Timing derived using Artificial Neural Network and GIS

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Keywords: ann, gis, sumo, traffic light timing optimization, traffic simulation

Abstract

One of the common issues in urban cities is traffic congestion especially at signalized intersection which may be caused by static and inefficient traffic light timings. The long waiting times at the traffic light led to significant amount of time loss, higher car emissions and higher fuel usage. During peak hours, the pre-set timing may be unfit to handle the higher traffic volumes than usual, which resulting in slow vehicle movement and increased travel time. Furthermore, the current technique used in setting the traffic light timing might not include spatial data or intelligent prediction tools that is capable to analyse the unpredictable characteristics of traffic in urban areas. This gap highlights the need for traffic light timings that is suitable for different traffic conditions throughout the day instead of constant fixed timing for all day. Hence, this study aims to derive optimal traffic light timing at junction by integrating Geographical Information System (GIS) and Artificial Neural Network (ANN) models. Unlike the current fixed-time signal control practice, the ANN was chosen to conduct predictive modelling that did not rely on human in making predictions. It is solely depending on data without relying on manual assumptions or fixed timing. The study used historical and current traffic volume data as well as the existing signal timing parameters to develop ANN models to predict optimal green time allocations based on different traffic demand patterns at the intersections.

1. Introduction

Traffic congestion is a major challenge in urban areas worldwide, including Malaysia, with significant impacts on public health, environmental quality, and economic productivity (Akhtar, 2024). In average, people in Malaysia, Klang Valley especially, spend 580 hours annually in traffic congestions. This led to estimated fuel-loss of RM6.8 billion per year and air pollution which one of the major causes is carbon monoxide emitted by vehicles that could further exacerbate environmental degradation (Kasinathan, 2024). Due to traffic congestion, economically, Malaysia is projected to lose between RM10-20 billion annually, which is approximately equivalent to 1.1-2.2% of the national Gross Domestic Product (GDP) (Akhtar, 2024).

Hence, mitigation measures are needed to address congestion. Intelligent Transportation Systems (ITS) and infrastructure enhancement introduced for this purpose, including tidal flow systems (Jun, 2023) and the adoption of emerging communication technologies to support real-time traffic management (Chan, 2022). However, in Malaysia, intersections in urban area still rely on conventional fixed-time traffic control system which operate based on predetermined timing plans that may not be able to adapt effectively with different traffic congestions. In addition, traditional signal systems depend on infrastructure-based sensor which the maintenance cost could be high and has limited spatial coverage that could result in inefficient traffic control under fluctuating demand (INRIX, 2022).

Geographical Information Systems (GIS) is essential tool in transportation planning and traffic management that could enable spatial analysis, visualization by integrating of traffic-related data (Ang et al., 2022; Modi et al., 2022). GIS could help in identifying traffic congestion hotspots, evaluating traffic patterns, and assessing alternative of traffic management strategies. GIS combination with Artificial Intelligence (AI) enhances decision-making process through predictive and data-driven analysis (Erkek, 2025).

One of the AI-based decision-making techniques is Artificial Neural Networks (ANN) that is suitable for modelling complex, non-linear and dynamic traffic system that could be influenced by multiple factors including traffic volume, road geometry and temporal variations. Compared to traditional analytical models, ANN can learn from historical data without predefined assumptions that makes them effective for short-term traffic prediction. ANN models could outperform conventional statistical methods in predicting traffic flow and adapting to unexpected conditions such as abnormal traffic patterns as demonstrated by a previous study during the COVID-19 pandemic (Ghanim et al., 2022).

One of the biggest problems with the current transportation system is still urban traffic congestion, especially in fast-growing areas like Shah Alam. Traffic congestion has become a daily problem around Shah Alam, where some of the intersection drivers must wait up to 199 seconds, although there is no traffic because of ineffective and static traffic signal timings. These long wait times lead to a significant amount of time loss, higher car emissions, and higher fuel usage. During peak hours or unforeseen disruptions, traditional traffic light control systems that rely on pre-set or time-of-day-based signal cycles are unfit to handle the dynamic and variable nature of traffic volumes which resulting in slow vehicle movement and increased in travel time. In addition, current traffic light control methods do not include spatial data or intelligent prediction tools that are able to analyse for unpredictable characteristic of traffic in urban areas. This gap highlights that an adaptive method for signal optimization is required.

Thus, this study aims to develop open-source and reproducible traffic signal time optimisation workflow that integrates data from OpenStreetMap (OSM) in ANN modelling. The workflow integrate ANN and GIS to address congestion with a microscopic simulation using Simulation of Urban Mobility (SUMO) at a signalised intersection in Section 13, Shah Alam. The intersection was selected for this study due to its persistent congestion during peak hours where the vehicles waiting times could reach 199 seconds per cycle since the existing signal control system operates using static timing plans. This limits its responsiveness to traffic demand during different hours. This study proposed a data-driven signal optimisation framework that could improve traffic flow efficiency and reduce congestion at urban intersections by applying traffic optimisation that is spatially aware using ANN-based prediction of optimal green times and evaluation through traffic simulation.

ANN are helpful at short-term prediction and pattern recognition by predicting an optimal timing of the signals based on various traffic input data such as current traffic volume and historical traffic volume, while GIS offers spatial information on traffic distribution, road layout and visualization output. Previous studies have demonstrated ANN-GIS-based signal optimisation in several regional contexts (Wang et al., 2020; Wang et al., 2021; Wei & Ju, 2024).). However, limited studies have explored fully open-source and reproducible spatial-intelligent workflows integrating OSM, ANN modelling, and SUMO simulation within Southeast Asian urban traffic environments.

By creating a model based on GIS and ANN, this research aims to close this gap and enhance traffic signal timing in Section 13, Shah Alam. Through a dynamic and data-driven system, the goal is to improve commuter experience, traffic flow and vehicle wait times. With the help of geospatial analysis and AI, this study aims to provide a scalable and flexible solution to the issue of urban traffic congestion. However, the new optimal timing predicted by the ANN needs to be evaluated using simulation software like SUMO to see whether the optimal timing improved the traffic flow and volume. Without a proper evaluation, the new signal timings may not be suitable with the expected outcomes in the real-world scenarios.

2. Literature Review

2.1 ANN and GIS for Optimizing Traffic Signal Timing

ANN is a computational model that is modelled based on the structure and functions of biological neural networks. The information that passes through a neural network changes the structure of the ANN because the network changes or learns in a sense-based on the input and output. Nonlinear statistical data modelling tools or ANNs are used to identify patterns or explain complex connections between input and outputs (Qamar & Zardari, 2023).

ANN mimics the behaviour of biological neurons. The ANN has an input layer, hidden layer(s), and output layer. An ANN draws inspiration from our brain or the biological neural network system. Their name and form are inspired by the human brain, and they replicate the way real neurons communicate with one another (Qamar and Zardari, 2023). Due to the limitations of conventional fixed-timing systems. ANN have become essential tools for optimizing the traffic light signals. According to various recent studies, ANNs are effective at adjusting to traffic conditions in real time.

The study of traffic signal optimization has gained a lot of interest lately because many researchers want to analyse how to shorten travel time and ease traffic congestion (Wang, 2025). The integration of ANN and GIS provides a strategy for enhancing traffic light signal timings. While GIS provides spatial information about traffic conditions, including vehicle numbers, speed, and congestion levels, ANN models then use this data to make real-time predictions and dynamic adjustments to signal timings. Especially during peak traffic hours, this combination enables adaptive traffic signal control, which can greatly cut down on traffic, travel time, and waiting time at crossings. In order to maximize traffic flow and reduce delays, GIS-AI system could adjust signal timings by integrating metaheuristic algorithms (Khasawneh & Awasti, 2023). This method can also be applied to large cities by dividing the city into zones that are optimized according to local traffic patterns.

The combination of GIS and metaheuristics methods could provide an effective technique to predict traffic in real time at signalized road crossings (Zhong, 2025). The combination of GIS and data-driven approach such as ANN could greatly boosted traffic flow prediction and enabled more flexible traffic light management. This hybrid solution could enhance the standard models if it can predict traffic behaviour accurately and allowing for dynamic adjustment to signal timings based on real-time data.

Road layouts, traffic volumes, and intersection locations are just a few examples of the useful geographical data that GIS provides. They can be paired with ANN ability to identify complex patterns in historical traffic data. Dynamic signal control systems response instantly might change traffic condition by this combination. The usage of GIS data could aid in observing and analysing traffic flow patterns (Wang et al., 2024). These patterns then incorporated into ANN models to predict congestion and adjust signal timings appropriately. For example, ANN models can predict traffic volume at junctions based on real-time traffic data, which GIS can map to identify the best timings for green and red lights to reduce delays.

Hence, in comparison to traditional methods, the combination of ANN and GIS for traffic light signal timing optimization provide a very intelligent and adaptable solution since ANN is ideal for dynamic signal control because it can learn complex traffic data from both historical and current traffic data compare to the system that only depends on pre-set cycle and are unable to react to changes in traffic based on current conditions. In order for ANN to predict traffic flow and adjust signal timing properly, GIS component will enhance the model with spatial insights such as traffic volume, road layout and congestion are. It is expected that ANN could perform better than traditional method because it allows for precise real-time prediction and modification. ANN was selected for this study due to its ability to provide data-driven, responsive traffic signal optimization that adjusts to changing traffic in various conditions.

2.2 Traffic Simulation with SUMO

Traffic simulation is one of the techniques that could be used to explore traffic movement and behaviour using computer models. It will mimic and analyse the traffic movement within transportation network, which in this study, is at road intersection that has traffic light. The goal is to explore the traffic flows under different conditions and to test the impact of traffic management strategies without disrupting the real-world traffic as it is conducted on computer and software only.

There is several software that could be used for running the simulation including SUMO which is a widely used open-source, microscopic traffic simulation software designed to model and analyse vehicle movement. It enables multi-modal transportation systems and provides detailed control over traffic elements such as traffic lights, vehicle routes, and lane changes. One of its key features is its TraCI API, which provides users to makes interaction with the environment in real-time. These feature render SUMO as an ideal tool to assess and optimize signal timings in urban areas. These features make SUMO particularly well designed to analyse and refine traffic signal timing in urban scenarios (Lopez et al., 2018).

SUMO is one of the platforms that provide easy integration with Python. The platform supports AI and ML model integration with the simulation workflow as a complementary tool for researchers. Furthermore, SUMO includes tools for network design, importing data from OSM, traffic demand modelling and graphical output of spatial representations, making it a complete platform for traffic simulations.

Traffic flow can be modelled using SUMO in isolated intersection under the initial fixed signal phase durations, and measured with the queue length, vehicle delay, and traffic flow. These outputs can be used to feed into a second optimization layer, where a rule-based algorithm iteratively changed signal timings to facilitate the operation of intersections. The SUMO simulation environment allowed the researchers to experiment with and fine-tune its model in a controlled setting and verify that the optimized signal timings reacted accordingly to real-traffic conditions. The results indicated that traffic operation can be enhanced, and reduced delay can be achieved as compared to fixed-time traffic signals.

The application of SUMO is essential for traffic simulation environment to measure the performance of the proposed reinforcement learning model. The traffic simulation tool like SUMO is used to generate the realistic traffic simulation scenarios and evaluate the performance of the PPO algorithm for the optimization of traffic signal timings. SUMO+TraCI acted as the interface and allows the user to collect traffic and vehicle movement data and adapt signal phases according to learned policies using PPO agent. Meanwhile, the integration framework facilitates a precise testing of the ability of the PPO algorithm to alleviate traffic congestion and improve traffic flow under different scenarios.

OSM can be used to create detailed and editable digital road maps, which in turn was the basis of constructing realistic road network models. After clean-up processing, the maps can be imported into SUMO via tools such as NetConvert so to set up an operation simulation environment. Besides that, SUMO supports microscopic traffic simulation by consuming dynamic road weights produced by a Deep-Neuro-Fuzzy model based on humidity, rain, road constructions, and accidents. The traffic light control, flow of vehicles and route optimization can be simulated in the SUMO framework using Dijkstra Algorithm that the realistic city maps that can be transformed from OSM data. A custom-made GUI can also be created to interact with SUMO aiming to display traffic behaviour with different parameters simulated.

3. Methods

This study adopts a structured workflow to optimize traffic signal timing by integrating GIS and ANN techniques. The overall methodology was illustrated in Figure 1 and consists of four (4) main phases which is preliminary study, data acquisition, ANN modelling and simulation and validation.

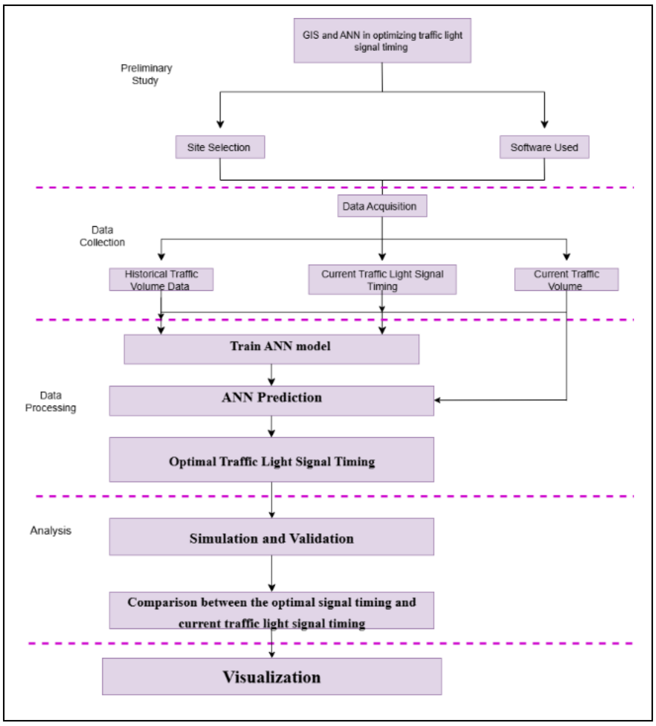

Figure 1. Methodology Flow

3.1 Preliminary Study

The preliminary study establishes the research scope through site selection and software identification. Figure 2 shows the selected study area that is the signalized intersection at Section 13, Shah Alam.

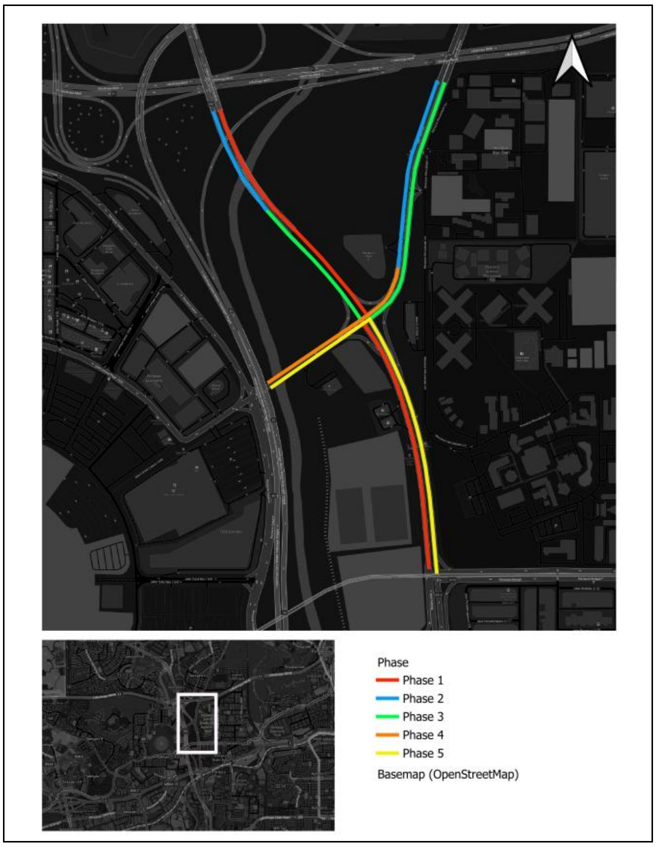

Figure 2. Map of Study Area
(Source Basemap: OpenStreetMap)

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The intersection is well-known for experiencing recurrent congestion due to high traffic demand from multiple highways and other roads. This intersection was chosen based on its strategic location and persistent traffic delay issues.

3.2 Data Acquisition

In this study, the data acquisition stage involves collection of important traffic-related data that is required for ANN modelling. There were three (3) main datasets used which are historical traffic volume data, current traffic volume data and existing traffic light timing parameters for each signal phase at the selected intersection. The datasets represent both historical and current traffic conditions that serve as inputs for the ANN model. The collected data were pre-processed and imported into ANN framework ensuring their consistency and suitability for the model training and testing.

3.3 ANN modelling and Optimization

The optimisation process of the traffic light timing was conducted by using ANN modelling that began with importing historical traffic volume data, current traffic volume data and existing signal timing data into the neural network modelling environment. The datasets were prepared in CSV format and organised according to traffic movement characteristics observed at the study area.

Before model training, all input and target datasets need to undergo normalisation to improve the training efficiency and prediction performance. Since the traffic volume and signal timing variables both contain different numerical ranges, it is necessary to conduct normalization to prevent variables with larger magnitudes to dominate the learning process. The normalization process standardised the datasets within consistent numerical range to improve the model stability and convergence.

The ANN model was developed using three-layer feedforward neural network that consists of input layer, hidden layer and output layer. The historical traffic volume and current traffic volume data were used as input variables while current signal timing data represented the target output. In this study, the ANN was designed to model the nonlinear relationship between traffic volume patterns and the allocation of traffic signal timing.

Levenberg-Marquardt backpropogation algorithm was used to train the network. The algorithm provides fast convergence and high accuracy for function fitting application. The datasets were divided into training (70%), validation (15%) and testing (15%) subsets to reduce overfitting effects as well as improving the model generalisation capability. The model iteratively adjusted its internal weights during the training to minimise the prediction errors.

The optimal traffic light timing was then predicted by using the trained model under varying traffic volume conditions. The outputs generated from the model is the prediction of the timings which were later integrated into SUMO for simulation purposes. The reliability and prediction capability of the ANN model was assessed using regression plots, performance plots and error histograms.

3.4 Simulation of Optimized Traffic Light Timing

In this study, SUMO was used to simulate the optimized traffic signal timing produced by the ANN model. It is an open-source and microscopic traffic simulation software that could help in detailed modelling of road networks, traffic flows and signal control system. SUMO provides flexible platform to evaluate the effect of different traffic light timing configurations on traffic performance in terms of delay, queue length and vehicle throughput. The traffic network for the study area was imported into SUMO from OSM. Then, the network editing and configuration were conducted in NETEDIT, which is a graphical tool in SUMO that is used to edit and reorganize the road geometry, lane connections and traffic light control logic.

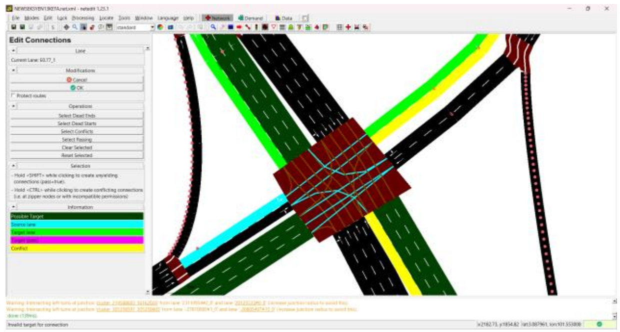


Figure 3. SUMO Netedit tool for editing lane connections at intersection

The green times that was predicted using ANN were directly inserted into SUMO traffic light logic files that then allow simulation to dynamically reflect changes in signal allocation across different time intervals. This could ensure the signal allocation to be appropriate to variations in traffic demands, especially for dominant movements such as the flow for straight or right-turns during the peak hours. The consistency and robustness of the optimized signal timing were evaluated by running multiple simulations across different time intervals.

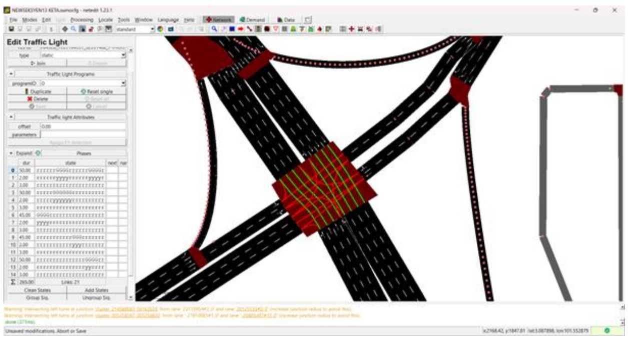


Figure 4. NETEDIT interface

The traffic volume data were used as input routes in SUMO as the dataset represent the real-world demand across different time periods, particularly during peak hours which this study interested in. Figure 4 illustrates the SUMO simulation model that is developed for the selection intersection. The routes were assigned based on vehicle movements for each direction and lane. All four approaches at the intersection with their respective lanes and traffic directions were included in the network layout. Each approach contains the designated straight, left-turn and right-turn lanes according to the intersection geometry. The signal control logic was set up to match the existing phasing plan of Phase 1 to Phase 5 corresponds to the northbound, southbound, eastbound and westbound directions.

After the ANN model had generated the optimized green time values for each phase, these new signal timings were integrated into the SUMO to assess performance improvements. Each traffic signal phase is represented using several rows of state information, where each row specifies the signal colour (green, yellow, or red) assigned to all lane groups at a particular stage of the cycle as shown in Figure 5. For this intersection, the complete signal cycle is structured into fifteen rows, numbered from 0 to 14. These rows are grouped into sets of three to form one complete movement phase, as SUMO requires each traffic phase to include a green stage, a yellow transition, and a red-clearance interval.

	dur	state	next	name
0	86.90	rrrrrrGGGGrrrrrrGGGGr		
1	3.00	rrrrrryyyyrrrrrryyyyr		
2	199.00	rrrrrrrrrrrrrrrrrrrrr		
3	64.63	rrrrrGGGGGGrrrrrrrrrr		
4	3.00	rrrrryyyyyyrrrrrrrrrr		
5	199.00	rrrrrrrrrrrrrrrrrrrrr		
6	38.20	GGGGrrrrrrrrrrrrrrrrr		
7	3.00	yyyyrrrrrrrrrrrrrrrrr		
8	90.00	rrrrrrrrrrrrrrrrrrrrr		
9	36.87	rrrrrrrrrrrGGGrrrrrrr		
10	2.00	rrrrrrrrrrryyyrrrrrrr		
11	90.00	rrrrrrrrrrrrrrrrrrrrr		
12	111.61	rrrrrrrrrrrrrrrGGGGrr		
13	2.00	rrrrrrrrrrrrrrryyrrrr		
14	199.00	rrrrrrrrrrrrrrrrrrrrr		
Σ	1128.21	Links: 21		

Figure 5. SUMO Traffic Signal State Rows Representing Phase 1 to Phase 5

The ANN-predicted green times were directly inserted into the SUMO traffic light logic files, allowing the simulation to dynamically reflect changes in signal allocation across different time intervals as shown in Figure 6. This approach ensured that the signal allocation across appropriately to variations in traffic demands, especially for dominant movements such as straight and right-turn flows during peak hours. By running multiple simulations across different time intervals, the consistency and robustness of the optimized signal timing were evaluated.

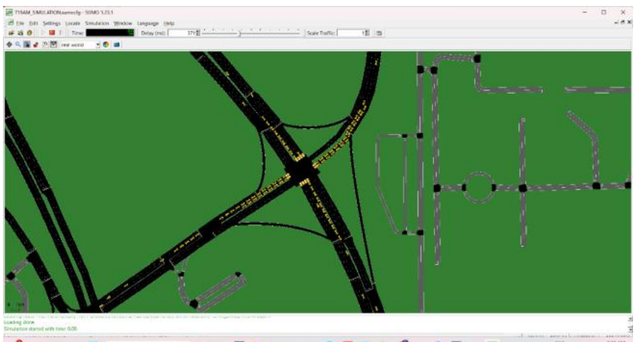


Figure 6. Simulation of traffic flow and signal control in SUMO

The simulation results demonstrated that the ANN-optimized signal timings generally improved traffic performance compared to the existing signal plans. The SUMO simulation enables the evaluation of vehicle throughput by showing the number of vehicles that can pass through the intersection under the new signal timing configuration as shown in Figure 7. The evaluation process involved running two (2) separate simulation scenarios, existing fixed time signal timing and optimized signal timings produced by the ANN model. By simulating these two conditions under almost the same traffic demand, the performance differences could be directly attributed to the signal timings adjustment. SUMO will automatically record several key performance indicators (KPIs) during each running simulation, such as vehicle throughput using Simulation output detector. These indicators were then compared the vehicle volume pass the traffic light intersection.

Figure 7. Output for Simulation of Traffic Volume

3.5 Visualization and Evaluation

The simulation results were then integrated with GIS-based visualization. The traffic conditions under both existing and optimized traffic light timings were mapped for a clearer visual comparison. The side-by-side visual comparison enables intuitive assessment of congestion reduction and signal timings improvement at the intersection.

4. Results and Discussion

4.1 ANN Model Performance

The performance for the ANN model varied across phases due to the differences in traffic flow patterns and data consistency. Phase 1 and Phase 5 demonstrated a good predictive variability as shown by the R^2 value of 0.61 and 0.77 respectively. On the other hand, Phases 2, 3 and 4 showed weaker relationships with R^2 values that is less than 0.30. This indicates phases with more stable or higher traffic volume could provide better learning conditions for ANN model. The phases with lower traffic volume resulted a less accurate predictions. Despite that, the ANN models for all phases still captured the underlying relationship between input traffic volume and the traffic light timing that prove ANN could serve as practical tool for optimizing the traffic light timing when it is trained with sufficient and balanced data.

4.2 Comparison of Current and Optimal Traffic Light Timing

The next analysis is the comparison of the current traffic light timing with the optimized timing for all five (5) phases at the intersection. By averaging the output of the ANN-predicted timing, results that is stable and consistent can be ensured. The comparison is presented in Figure 8 that include percentage of changes for each phase during peak periods.

In Phase 1, the optimal traffic light timing produced using ANN model show moderate adjustments between peak periods. The optimized green time increased by approximately 4.01% to 7.36% during the morning peak (7:00-10:00AM) to accommodate higher straight-through traffic from both northbound and southbound approaches. The adjustments support smoother vehicle discharges and reduces queue formation. However, during evening peak (4:00-7:00PM), the green time was slightly reduced by about 1.56% to 3.55% that indicate lower demand for straight movements and allowing green time to be reallocated to other phase.

The largest timing changes is recorded in Phase 2 during the morning peak. The optimized timing shows increase of approximately 16.71% to 20.28% that reflects heavy northbound traffic demand at the intersection. The increase helps in reducing the congestion and improve throughput.

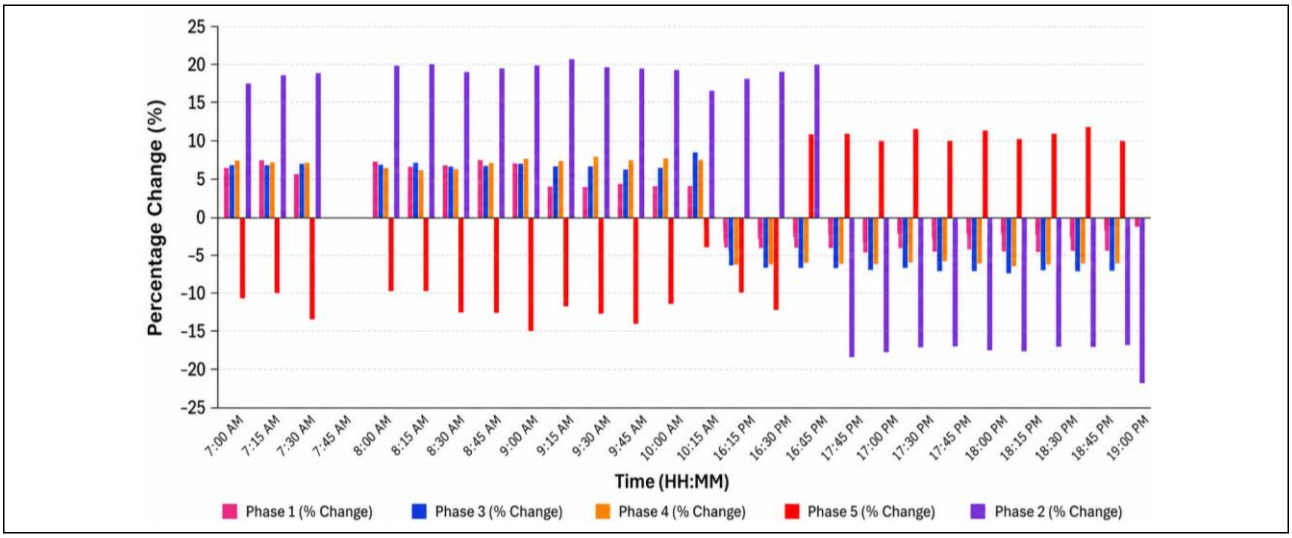


Figure 8. Comparison of Existing and Optimised Traffic Light Timing

However, during the evening peak, the optimized timing is reduced by about 16.39% to 22.22% which suggest lower northbound demand as the traffic shifts toward outbound directions. The results demonstrate the model effectiveness in redistributing green time based on strong directional and temporal traffic variations.

For Phase 3, the adjustments for the traffic light timing were relatively small and stable as during the morning peak, there is slight increase by about 6.23% to 8.48%, corresponds to moderate westbound traffic demand. In the evening peak however, the timing is decreased by approximately 2.10% to 7.00% reflecting reduced traffic flow. The smaller magnitude of changes indicates consistent traffic patterns and ANN avoided unnecessary over-adjustment for this phase.

On the other hand, Phase 4 showed moderate changes in both peak morning and evening periods. The optimized green time increased by approximately 6.09% to 7.59% during the morning peak to accommodate higher eastbound traffic volumes. During the evening period, the optimized green time was reduced by 5.62% to 7.15% that indicates lower demand in that direction. These adjustments reflect the ANN model's ability to adapt signal timing based on observed traffic variations and improve overall intersection efficiency.

In Phase 5, there is contrasting adjustments observed between peak periods. During the morning peak, approximately 3.33% to 13.97%, the optimized green time was reduced, suggesting the existing signal plan over-allocated green time despite relatively lower southbound demand. However, during the evening peak, the optimized green time is increased by about 6.81% to 11.47% to accommodate higher southbound traffic volumes associated with evening commuting patterns.

Overall, the phase that experience the most significant timing adjustments is Phase 2 that highlights strong directional traffic imbalance in northbound approach. The morning peak periods showed positive increases in optimized green time for Phases 1 to 4 due to concentrated inbound commuting traffic. On the other hand, the evening peak periods exhibited reductions in several phases as the traffic demand is redistributed toward outbound directions. Phases with higher variability in traffic demand received larger adjustments, whereas a more stable phases experienced minimal changes. The findings confirm that the optimized traffic light timings are more adaptive and responsive to varying traffic conditions as compared to fixed-time control that support improved intersection performance.

4.3 Simulation of Traffic Light Timing

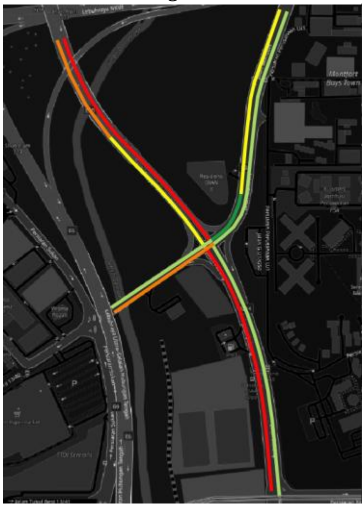
The effectiveness of the traffic light timings for both the existing and ANN-optimized ones then were simulated using the SUMO platform as shown in Figure 9. The simulation assessed the traffic performance indicators such as vehicle throughput, waiting time and queue discharge rates. The simulation results show that the optimized traffic light timing successfully passing through the intersection increased, while the average waiting times per cycle were reduced. This improvement indicates a smoother traffic flow and more efficient utilization of available green time.

The traffic volumes increased consistently for Phases 1 to 4 during the morning peak period after the optimized traffic light timings were implemented. For example, for Phase 1, the traffic volume increased from 449 to 481 vehicles at 8:00AM with similar improvements observed in Phases 2, 3 and 4. The three phases represent the main inbound and through movements where traffic demand was the highest. By allocating a longer green times at the traffic light to heavily loaded approaches, the intersection was able to serve more vehicles within the same cycle length, improving overall discharge efficiency. The results indicate that the optimized traffic light could enhance peak-hour performance without requiring additional lanes or geometric modifications.

Phases with lower traffic demand such as Phase 4 showed small changes in traffic volume. The findings suggest that the optimized traffic light timing prioritised critical traffic movements and avoiding unnecessary green time allocation to underutilised phases. The results also indicate that the improvement in signal efficiency improve the intersection's ability to handle existing traffic more effectively.

The most significant improvement during the evening peak period was observed in Phase 5 which is the southbound movement. The number of vehicles passing through this approach with the optimized timing increased consistently, depending on the time interval and reflecting higher congestion pressure.

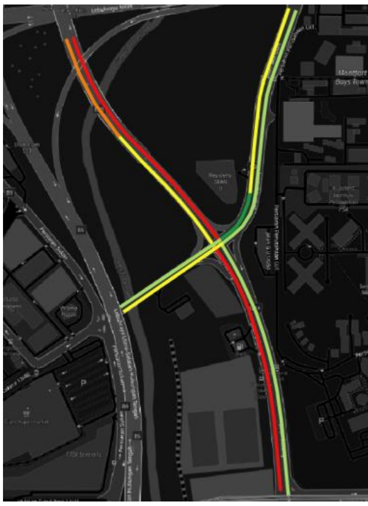
Existing Volume



New Volume

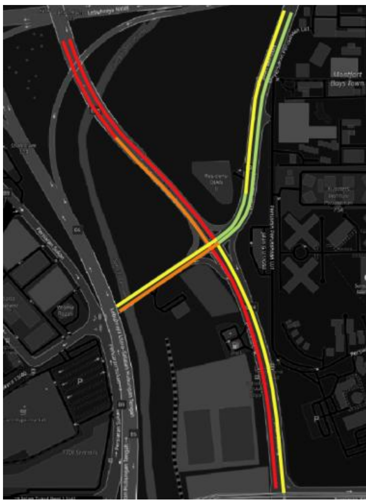
Morning Peak (8:00AM)

Phase	Existing Volume		New Volume	
	Right	Straight	Right	Straight
Phase 1		449		481
Phase 2	45	237	56	295
Phase 3	33	96	36	103
Phase 4	8	28	11	30
Phase 5	23	91	21	83



Mid-Day Transition (10:00AM)

Phase	Existing Volume		New Volume	
	Right	Straight	Right	Straight
Phase 1		298		310
Phase 2	31	160	39	201
Phase 3	11	49	20	53
Phase 4	3	11	3	12
Phase 5	11	54	11	52



Evening Peak (6:00PM)

Phase	Existing Volume		New Volume	
	Right	Straight	Right	Straight
Phase 1		478		468
Phase 2	45	259	38	215
Phase 3	24	83	26	78
Phase 4	8	25	8	23
Phase 5	29	116	32	129

Figure 9. Comparison of Traffic Volume between Existing Volume and New Volume for Selected Time
(Source Basemap: OpenStreetMap)

By allowing more vehicles to clear the intersection during each cycle, the ANN-derived optimized traffic light timing had effectively responded to this demand. This had led to the reduce of the likelihood of congestion.

5. Conclusions

This study demonstrated pilot implementation framework for traffic light timing optimisation under Malaysian urban traffic conditions. The effectiveness of ANN in optimizing the traffic light timings was demonstrated based on existing traffic volume conditions. The ANN model used historical and current traffic volume data to generate green time durations that fit different traffic volume at different time for different signal phases. The timings then were evaluated using traffic simulation to observe the improvement in the traffic volume using SUMO and configured using NETEDIT. The simulation results showed that the optimized traffic light timings derived using ANN did provide improvement in the traffic performance in terms of vehicle throughput at the intersection. The findings indicate that ANN-derived optimisation enhances the efficiency and data-driven traffic signal management to reduce dependency on conventional fixed-time approaches.

In conclusion, the application of SUMO in simulation of the traffic with the optimized traffic light timings could provide a practical platform to evaluate their effectiveness before implementing them in real-world. The study demonstrated the possibility of using scalable and reproducible workflow that integrate ANN modelling and open-source traffic simulation software for future and smart transportation and intelligent traffic control studies.

Acknowledgements

The authors would like to thank Universiti Teknologi MARA for supporting and funding the presentation of this study at FOSS4G 2026.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT in order to improve the writing structure. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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