

Implementation of Adaptive Traffic Lights to Reduce Traffic Congestion at Intersections through Efficient Strategies for Selective Use of Detectors

Erwin Romero C.¹, Brayan Torres Q.¹, Aldo Bravo L.²

¹ Universidad Peruana de Ciencias Aplicadas
Prolongación Primavera 2390, Santiago de Surco 15023, Lima, Peru
u20201b194@upc.edu.pe ; u20201b409@upc.edu.pe

² Universidad Peruana de Ciencias Aplicadas
Prolongación Primavera 2390, Santiago de Surco 15023, Lima, Peru
aldo.bravo@upc.pe Conference Centre - University of Toronto, Toronto.ca

Abstract – The increase in traffic congestion at urban intersections, particularly in Lima, reflects the need for dynamic solutions in traffic management. This study proposes an adaptive traffic light system designed and simulated in VISSIM, using selective detectors strategically placed in the most congested lanes. The methodology included calibration and validation of models based on real data, development of adaptive algorithms in VisVAP, and simulation of scenarios. The results demonstrated an average 20% reduction in delays, a 42% decrease in queue length, and an improvement in the level of service, eliminating the lowest performance categories. This adaptive and efficient approach can be replicated in other cities to optimize urban mobility and reduce costs associated with congestion.

Keywords: Adaptive Traffic Lights, Traffic Congestion, Road Management, Selective Detectors, Traffic Fluidity.

1. Introduction

Traffic congestion at urban intersections is a universal problem in contemporary cities, with a direct impact on transport efficiency, air quality and user experience. Various studies highlight that large metropolises lose hundreds of hours a year due to traffic, which generates economic losses and increases pollutant emissions. This problem is aggravated at intersections with fixed-cycle traffic light systems, which lack the flexibility to respond dynamically to variations in vehicle flow.

In this context, adaptive traffic lights have emerged as an innovative solution that allows for real-time traffic regulation. These systems, through the use of advanced algorithms and reinforcement learning, such as those proposed in [1], adjust the green and red light times based on information captured by flow detectors, managing to reduce both waiting times and traffic conflicts. For example, the use of techniques such as the Dueling framework Double Deep Q Network (D3QN) has shown an 18% reduction in waiting time and a 16% reduction in traffic conflicts [1]. Furthermore, strategies such as “Green Warning” have proven effective in reducing reaction times and improving traffic flow efficiency, offering 15% improvements in travel time under high demands [2].

The implementation of these systems, however, faces significant challenges, especially in contexts of high vehicle demand and limited resources. Research has explored various approaches, including the use of reinforcement learning and microscopic simulations such as VISSIM, to model complex traffic behavior, achieving reductions of 13.7% in total travel time under severe congestion conditions [3]. On the other hand, integrated solutions have been proposed, such as the use of variable lanes in combination with signal control, achieving a reduction in average delay by 25% and an increase in vehicular flow by 60% [4].

In terms of efficiency, models such as the Dynamic and Intelligent Traffic Light Control System (DITLCS) employing deep learning have shown significant reductions in queue lengths and delays, with up to a 68% improvement in overall performance [5]. Furthermore, the importance of analyzing congestion indicators such as delay and queue length fluctuations has been pointed out, identifying limitations in traditional traffic light control strategies [6].

This study proposes to reduce traffic congestion by implementing adaptive traffic lights through the selective placement of detectors on the most congested road at an intersection. Based on evidence from previous research, this strategy seeks to improve available resources, validating it in a specific scenario. The results obtained could be applicable to other growing

cities, offering an efficient and sustainable solution in vehicle traffic management with the improvement of vehicle congestion indicators (Delay, Queue Length and Level of Service).

2. Methodology and contribution

2.1. Methodology

The present study seeks to develop and evaluate an adaptive traffic light system to improve vehicular flow at congested intersections, improving indicators such as delay, queue length and level of service through selective detection strategies. In particular, the development of this plan is explained in detail in this part of the article. It first begins with the description of the current state, followed by data collection and model development. This process includes modeling the current situation, which must be calibrated and validated to reflect reality, thus allowing results to be obtained on vehicular congestion indicators through simulations. Once the evaluation of the current state is completed, the adaptive traffic light is implemented, starting with the configuration of the new traffic light phases and the placement of the detectors in the congested lane of the avenues, then the development of the adaptive algorithm. Finally, the current state files are integrated with the algorithm to perform a simulation that generates new results to be analyzed.

To facilitate understanding, this procedure has been structured in 4 stages with a total of 13 steps, represented in a flowchart illustrated in Fig. 1, designed to achieve the specific objectives of the study.

- Describe the current state by collecting field information at the study intersection
- Model the current behavior using Vissim software, at an intersection
- Design the Adaptive Traffic Light Cycle and algorithm for the model
- Vissim Software
- Analyze the results of the current situation with the implementation of the proposed solution.

It can be observed in Fig. 1 that one of the most important parts is calibration and validation, since these represent the reality of the situation at the intersection. In addition, validation is essential because, later, the analysis of the results of the parameters designed for the intersection in Vissim will be carried out.

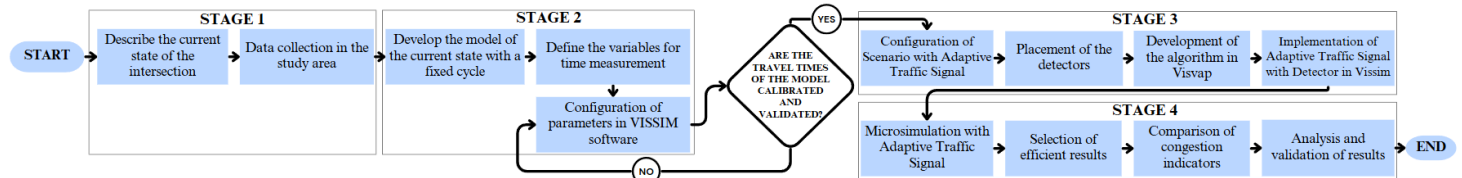


Fig. 1: Procedure Flowchart.

2.2. Contribution

This paper presents a novel strategy to mitigate traffic congestion by reducing the need to install detectors at all access points of an intersection. The strategy consists of selective placement of detectors, locating them exclusively on the road with the highest traffic flow, i.e., in the most congested direction. This strategic placement allows the traffic control system to function optimally without requiring additional sensors at each access.

To explain the arrangement of the detectors in the traffic light design, a flow chart was developed, as shown in Fig. 2, which facilitates understanding of the behavior generated by the activation of the detectors located at the accesses with the highest level of congestion.

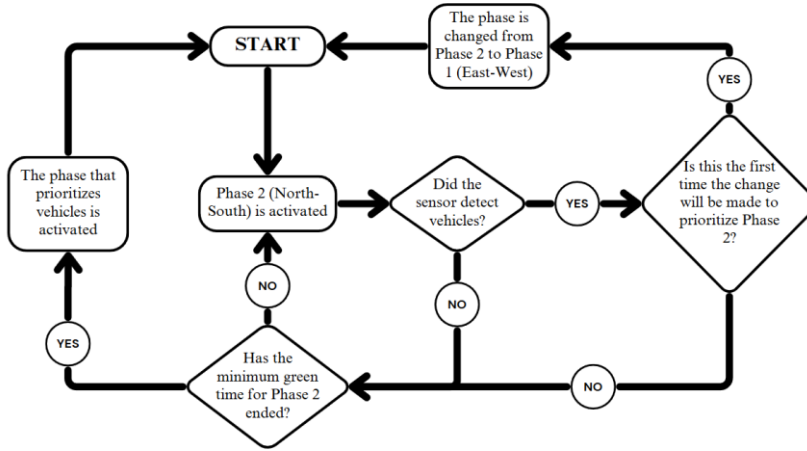


Fig. 2: Flowchart for the implementation of the adaptive traffic light.

3. Equations

This section presents a formal description of the key elements to determine the minimum number of runs required to ensure a statistically reliable representation of the simulated results of vehicular traffic, using microsimulation tools in VISSIM. For this case, analyses were carried out over a time period of 1 hour.

Analysis of 1-hour runs: A confidence level of 95% and a significance level of 0.05 were established.

$$\frac{\alpha}{2} = 0.025$$

To calculate the minimum number of runs required as shown in Table I, the following formula is used:

$$N = \left(t \left(\frac{\alpha}{2} \right) * \frac{s}{e} \right)^2 \quad (1)$$

Table 1: Calculation of minimum number of runs

APPLYING THE VALUES	SOUTH-NORTH INCA TRAILS (SECTION 1)	BENAVIDES EAST-WEST (SECTION 2)
	$N = \left(2.145 \times \frac{0.83}{0.462} \right)^2 \approx 15 \text{ runs}$	$N = \left(2.145 \times \frac{0.60}{0.335} \right)^2 \approx 15 \text{ runs}$

4. Materials and Tools

For the collection of field data, various materials were used such as: High-resolution camera , manual counters (pencil and paper), a 50-meter measuring tape and colored chalk.

In addition, data were collected in the field for two days (Tuesday and Thursday) from 6:00 am to 9:00 am, the peak time at the intersection. Vehicle types were analyzed and vehicles and pedestrians were measured. In addition, travel times were recorded in two sections: Section 1 (South-North) and Section 2 (East-West), delimiting 30 meters in each section to measure the displacements of each type of vehicle. With this data, speeds and frequencies were determined by type of vehicle and access. Geometric measurements of the intersection were also made, including sidewalks, lane dimensions and analysis of conflict points. Four traffic lights, vehicular and pedestrian, were identified at each access, with their phases as shown in Fig. 3 (a) and detailed cycles are displayed in Fig. 3 (b).

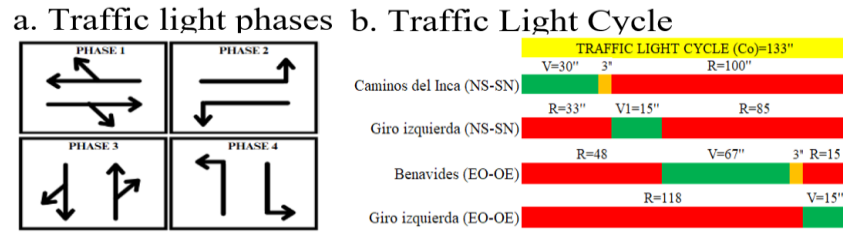


Fig. 3: Traffic light phases and cycle at the intersection. (a) Four phases are observed, (b) The traffic light cycle is 133 seconds and the green, red and amber times are observed for each phase.

For this research, the simulation software VISSIM was implemented as a tool, since it allowed for detailed modeling of the intersection under study and for evaluating the effectiveness of the adaptive traffic light in reducing traffic congestion. The data to be entered were as follows:

- Vehicle quantity by type
- Traffic light time
- Vehicle speeds
- Geometric dimensions of the intersection

5. Intersection Design

The design was carried out at the intersection of Caminos del Inca Avenue with Alfredo Benavides Avenue, in Lima, Peru as shown in Fig. 4, with the purpose of reducing vehicular congestion by implementing an adaptive traffic light. In addition, the strategy includes the installation of detectors 30 m. before the vehicle stopping area. Congestion indicators such as queue length, delay and level of service are calculated in sections 1 (South-North) and 2 (East-West), using the Vissim simulation software.

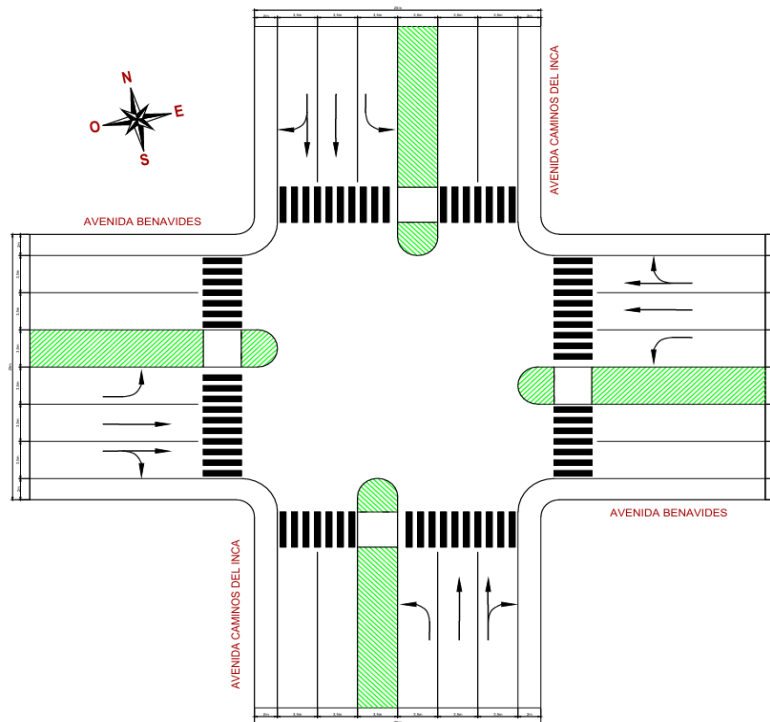


Fig. 4: Floor plan of the intersection.

5.1. Microsimulation of the Current Scenario

5.1.1. Intersection Modeling and Simulation

Vissim software for the intersection, previously collecting information on the geometry, speeds, and vehicle and pedestrian flow data. The map was activated in Vissim, drawing entry and exit routes with the "Links" command and connecting them with "Connector". Then, conflict points were added and priorities between vehicles and pedestrians were assigned. The vehicle flows were configured with "Vehicle Inputs", assigning volumes according to vehicle type and route. For the traffic light cycle, "Signal Control" was used, adjusting the green, red and amber light times Fig. 5 (a). Once the modeling was finished, the simulation was carried out Fig. 5 (b).

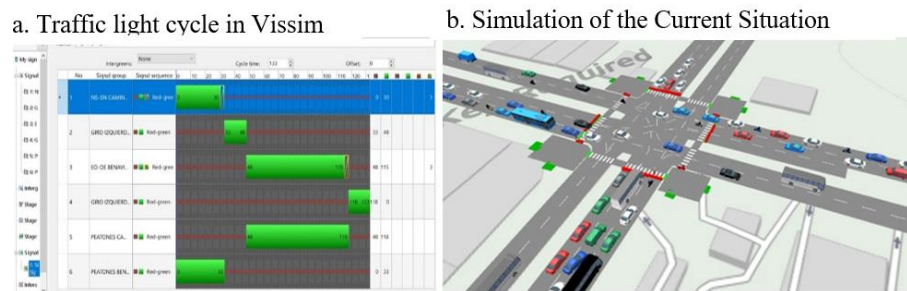


Fig. 5: Traffic light cycle and simulation of the current situation.

5.1.2. Calibration and Validation

Statistical analysis for calibration and validation was carried out using the randomization test for the difference in means, implemented with the StatKey tool. During this procedure, the combination that generated the most favorable statistical results was identified.

❖ Current model calibration

The following procedures were carried out based on capacity 1 on Tuesday:

- Simulation variables:** The start time, start date, and number of simulations were set. The simulation period was set to 1 hour (3600 seconds) with an additional 10 minutes. Field travel time data from sections 1 and 2 were used to calibrate the model, as shown in Table 2.
- Wiedemann Parameter Settings:** The Wiedemann 74 and Forward Vision Assist parameters were adjusted. The results obtained during calibration are presented in Table I.
- Null Hypothesis Test (Nonparametric):** The virtual tool StatKey was used to evaluate the differences in the mean travel times of sections 1 and 2 with a significance level of 0.05 and that the one-tail probability exceeds 95% confidence between the field data and VISSIM, as shown in Fig. 6 (a) and (b).

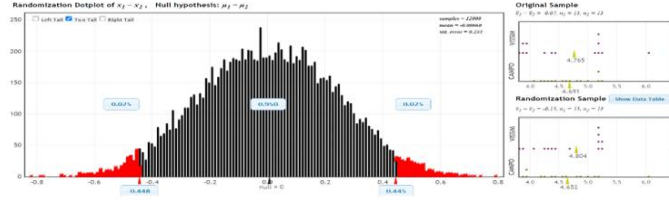
❖ Validation of the current model

Thursday was used and the travel times were measured on Caminos del Inca and Benavides avenues, the results of which are presented in Table 2. The procedure was similar to that of the calibration: the minimum number of necessary runs was determined, the Wiedemann parameters and the Forward Visual Distance were adjusted, the validation results are displayed in Table 2 and a null hypothesis test was applied, illustrated in Fig. 6 (c) and (d).

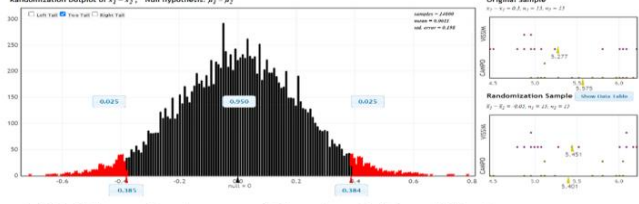
Table 2: Travel time results

RESULTS	SOUTH-NORTH INCA TRAILS (SECTION 1)	BENAVIDES EAST-WEST (SECTION 2)
	<i>Average travel time (s)</i>	<i>Average travel time (s)</i>
Field Capacity 1	4.69	5.57
Field Capacity 2	4.73	5.52
Calibrated	4.76	5.28
Validated	4.78	5.29

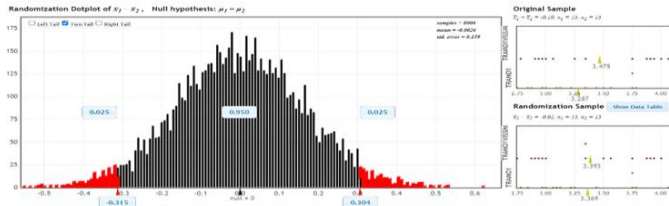
a. Null hypothesis test of Section 1 (South-North) of the Inca Trails, calibrated



b. Null hypothesis test for Section 2 (East-West) Benavides, calibrated



c. Null hypothesis test Section 1 (South-North) Inca Trails, validated



d. Null hypothesis test of Section 2 (East-West) Benavides, validated

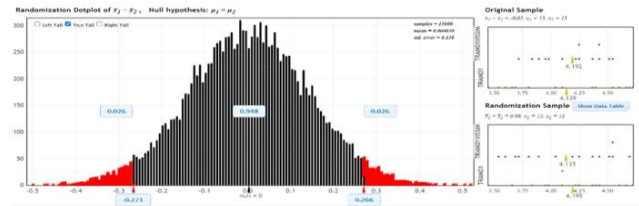


Fig. 6: Results of the null hypothesis test. (a) It is observed that the difference in means is -0.07 and they are within the range of the left and right tail (confidence limits) that varies between -0.448 to 0.445, (b) The difference in means is 0.3 and they are within the range that varies between -0.385 to 0.384, (c) The difference in means is -0.19 and they are within the range that varies between -0.315 to 0.304, (d) The difference in means is -0.03 and they are within the range that varies between -0.271 to 0.266. This means that for a confidence level of 95% and a significance level of 0.05 the current model is already calibrated and validated.

5.2. Implementation and Simulation of the Proposal

❖ PUA File Development

The traffic light programming was updated, maintaining the number of vehicular and pedestrian phases, configuring the adaptive cycle in two stages with "Stage": stage 1 (left turn Caminos del Inca, EO-OE and pedestrians Caminos del Inca) and stage 2 (left turn Benavides, NS-SN and pedestrians Benavides), maintaining a total cycle of 133 seconds. In addition, detectors were installed on Av. Benavides to ensure a constant flow, with three-meter-long sensors and joint activation in a common port, located 30 meters from the vehicular stopping point Fig. 7 (a). Finally, the PUA files of the programmed phases were exported using VISSIG- Signal Controller > File > Export > PUA.

❖ Development of the VAP File

The algorithm was coded in the VisVAP program, assigning functionality to the sensors, with Headway being representative as shown in Fig. 7 (b). In the programming, the initial condition was established that the phase corresponding to the North-South and South-North movement was active, using the Stage_active indication (2). This procedure is shown in Fig. 7 (b). Finally, the files with the VAP extension were generated for the adaptive traffic light cycle. To perform this action, Compile- Generate VAP File was entered.

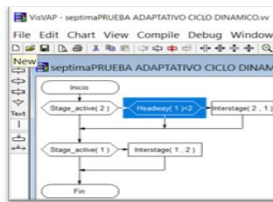
❖ Simulation with the Proposed Solution

microsimulation were considered. In addition, for the Adaptive Traffic Light configurations, the cycle time was changed from fixed to variable Vap, the VAP was uploaded in the logic file and the PUA in the interstage. Finally, the simulation was run with the proposal and contribution as illustrated in Fig. 7 (c).

a. Detectors placed on Av. Benavides



b. Algorithm in VISVAP



c. Simulation with the proposed solution



Fig. 7: Detectors, algorithm and simulation of the intersection with adaptive traffic lights.

6. Results of the Current and Proposed Situation

Vissim were determined, such as: Delay, queue length and service level of the intersection. The results are shown in Table 3 (a).

After implementing the Adaptive Traffic Light with the algorithm created in Visvap and the efficient placement of the detectors on Av. Benavides, the traffic congestion indicators were obtained as shown in Table 3 (b).

Table 3: Results of the congestion indicators.

RESULTS CURRENT SITUATION	a CURRENT SITUATION						b WITH ADAPTIVE TRAFFIC LIGHT					
	SOUTH-NORTH INCA TRAILS (SECTION 1)			BENAVIDES EAST-WEST (SECTION 2)			SOUTH-NORTH INCA TRAILS (SECTION 1)			BENAVIDES EAST-WEST (SECTION 2)		
Delay(s)	4.76			5.28			3.86			4.11		
	Movements						Movements					
Movement Number	13						13					
Tail length (m)	120.25						69.38					
Service level	TO	B	C	D	AND	F	TO	B	C	D	AND	F
	0	3	30	97	35	30	22	103	70	0	0	0

7. Analysis of Results

The implementation of the adaptive traffic light system with detector at the intersection was evaluated using congestion indicators, allowing a detailed analysis of its impact on reducing congestion. Although the study was conducted in a specific environment, the results suggest that the approach can be replicated at similar urban intersections to improve mobility.

❖ Average Delay

The average delay on sections 1 and 2 showed a considerable decrease after the implementation of the adaptive system. In section 1, the comparative analysis Fig. 8 (a) shows an improvement of 19.03%, with a difference of 0.9067 seconds compared to the situation without adaptive traffic lights. On the other hand, section 2 Fig. 8 (b) registered an improvement of 22.11%, with a difference of 1.1667 seconds. These improvements were achieved thanks to the installation of selective detectors on the most congested road, which allowed the traffic light cycle to be dynamically adjusted to the vehicular flow, especially during peak hours. This approach, depending on the specific demand of each access, could be applied effectively at other intersections with high congestion problems on certain roads.

❖ Tail Length

The comparative graph in Fig. 8(c) shows the queue length for the thirteen intersection movements before and after implementing the adaptive traffic light. A notable decrease of 42.30% is observed, equivalent to a difference of 50.8689 meters. This improvement was especially marked in the movements with the highest flow, where the adaptive system allowed to respond effectively to traffic fluctuations, avoiding the accumulation of vehicles. This reduction not only benefits the mobility of the intersection under study, but also provides a management model that can be replicated in other critical urban intersections, especially in cities with high vehicle density.

❖ Service Level

The analysis of the service level before and after the implementation of the adaptive traffic light Fig. 8(d) reveals a considerable transformation. Initially, the thirteen intersection movements presented service levels A (0), B (3), C (30), D (97), E (35) and F (30). After the implementation, the levels improved substantially, with results of A (22), B (103), C (70), D (0), E (0) and F (0). This change demonstrates improved vehicular fluidity and a more satisfactory travel experience, consolidating the approach of selective use of detectors as an effective strategy to improve the quality of service at congested intersections. This model is flexible and scalable, with the potential to be applied in various urban areas to solve vehicular congestion problems.

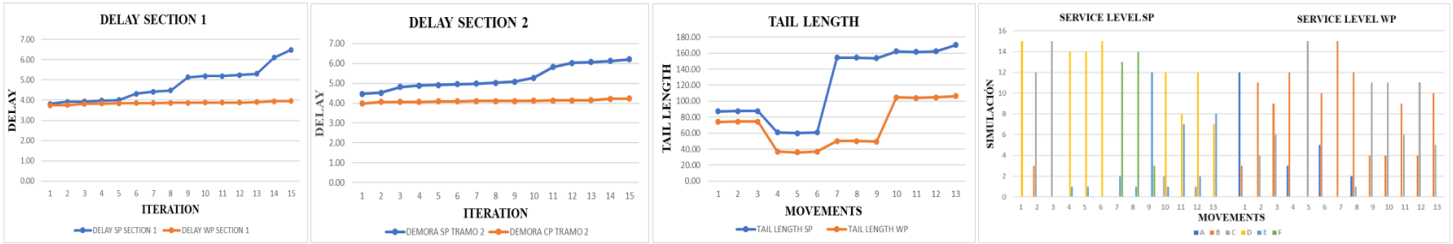


Fig. 8: Comparative vehicular result without proposal (SP) with the solution proposal (WP) of the congestion indicators.

8. Conclusion

To mitigate traffic congestion problems, this research implemented an adaptive traffic light programmed in VisVap, improving the operation of an intersection previously managed with a fixed traffic light that presented deficiencies. Additionally, specific strategies were designed for the use of detectors in critical lanes, with the aim of improving indicators such as delay, queue length and level of service. The results indicated that, compared to the current traffic light cycle, the adaptive traffic light achieved delay improvements of 19.03% and 22.11% in sections 1 and 2, respectively. Regarding the queue lengths of the thirteen intersection movements, an average improvement of 42.30% was recorded. Likewise, a considerable increase in service levels was observed: level A increased by 22 points, B by 103 and C by 70, with no records at levels D, E and F. These results show that the implementation of the proposed adaptive traffic light improves mobility at urban intersections, and serves as a model to optimize traffic management in other cities with limited resources. As future work, it is proposed to evaluate the performance of the VisVAP algorithm, whose coding has been effective in prioritizing vehicles on Benavides Avenue. It is recommended to adjust the traffic light logic sequence to incorporate variables that prioritize public transportation, improving the accuracy of the model. Although the analysis focuses on one intersection, the proposed adaptive traffic light could be applied to others with similar characteristics, offering a useful solution to traffic problems. It is also planned to improve the detectors through data prediction and machine learning, especially in intersection networks. Other professionals are encouraged to continue researching in this field to optimize traffic in the country.

Acknowledgments

Este trabajo fue realizado con el apoyo de la Dirección de Investigación de la Universidad Peruana de Ciencias Aplicadas (UPC), a través del incentivo UPC-EXPOST-2025-1. Los autores agradecen este respaldo, el cual fue fundamental para el desarrollo de la investigación.

References

- [1] G. Zhang, F. Chang, J. Jin, and H. Huang, "Multi-objective deep reinforcement learning approach for adaptive traffic signal control system with concurrent optimization of safety, efficiency, and decarbonization at intersections", *Accident Analysis & Prevention*, vol. 199, p. 107451, 2024.
- [2] E.F. Grumert and I. Pereira, "Heads-Up green in connected traffic signals", *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 23334-23345, 2022.
- [3] Y. Han, M. Wang, and L. Leclercq, "Leveraging reinforcement learning for dynamic traffic control: A survey and challenges for field implementation", *Communications in Transportation Research*, vol. 3, p. 100104, 2023.
- [4] F. Zhao, L. Fu, X. Pan, T.J. Know, and M. Zhong, "Investigating the effect of network traffic signal timing strategy with dynamic variable guidance lanes", *Sustainability*, vol. 14, no. 15, p. 9394, 2022.
- [5] N. Kumar, S. Rahman, and N. Dhakad, "Fuzzy inference enabled deep reinforcement learning-based traffic light control for intelligent transportation system", *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 8, pp. 4919-4928, 2020.
- [6] D. Singh, T. Ameen, and A. Ahmad, "Analysis of delay and queue length variation at three-leg signalized intersection under mixed traffic condition", *Innovative Infrastructure Solutions*, vol. 6, no. 2, p. 12, 2021.