



# Development of a Modified Fuzzy Logic-Based System in Decongesting Traffic at Road Junctions

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## ABSTRACT

*Traffic congestion at road junctions is a growing concern in urban areas, significantly impacting travel time, fuel consumption, and environmental pollution. As cities expand and vehicle ownership increases, traditional traffic management systems struggle to handle the rising volume of vehicles, leading to frequent bottlenecks at key intersections. Existing traffic decongestion methods, such as fuzzy-based algorithms, suffer from design complexity and tuning inaccuracy. To address these limitations, this work proposes a modified fuzzy logic-based algorithm integrated with the Spider Wasp Optimization (SWO) algorithm for efficient traffic decongestion at road junctions. Traffic parameters including vehicle arrival rate, queue length, and waiting time were generated using a MATLAB R2023a-based stochastic traffic simulation model. These inputs fed into a fuzzy logic controller that determined adaptive green signal durations for each lane. The SWO algorithm, modeled on the predatory and resource allocation behavior of spider wasps, was employed to optimize the fuzzy rule weights and membership function parameters. System performance was evaluated using queue length, average vehicle delay, throughput, signal timing efficiency, green time utilization, and intersection delay index as performance metrics. Comparative simulation results demonstrated that the proposed hybrid SWO-fuzzy system outperformed the standalone fuzzy logic controller by reducing congestion, improving signal utilization efficiency, and enhancing traffic flow stability. The developed model exhibited adaptive capability to varying traffic scenarios without human intervention, thereby improving road safety, reducing fuel consumption, and enhancing commuter experience.*

## INTRODUCTION

The need for effective traffic decongestion at road junctions has become more pressing as urbanization accelerates and traffic volumes continue to rise. Innovative technologies, such as smart traffic management systems and data-driven algorithms, are increasingly being explored to ensure smoother traffic flow and reduce the negative impacts of congestion. Decongesting traffic at road junctions is a tough problem, but machine learning offers some promising solutions. One effective approach is predictive modeling, where algorithms study past traffic data to

anticipate future patterns. By getting a sense of when and where traffic is likely to build up, traffic management systems can tweak signal timings on the fly to keep things moving smoothly (Sanusi et al., 2020; Oyedokun et al., 2025). Another key technique in managing traffic decongestion is the use of numerical optimization strategies, where traffic signals are programmed to learn and adapt to real-time traffic conditions. Over time, the system improves its performance by learning from the outcomes of previous decisions, eventually achieving a more efficient traffic flow. This method is particularly effective in dealing with the

unpredictable nature of traffic, where static models may fall short (Zhang et al., 2023; Omidiora et al., 2023).

Traffic congestion at road junctions is a growing concern in urban areas, significantly impacting travel time, fuel consumption, and environmental pollution. As cities expand and vehicle ownership increases, traditional traffic management systems struggle to handle the rising volume of vehicles, leading to frequent bottlenecks at key intersections. This congestion not only causes frustration for commuters but also affects the efficiency of public transportation and emergency services. Addressing this issue requires innovative solutions that go beyond conventional traffic signal systems, including the integration of real-time data and advanced algorithms. Modern approaches such as adaptive traffic control systems and fuzzy logic-based algorithms offer the potential to optimize traffic flow, reducing delays and improving overall transportation efficiency at junctions (Marazi et al., 2023; Olagunju et al., 2025).

Decongesting traffic at road junctions using fuzzy logic is an innovative approach that leverages the flexibility of fuzzy systems to manage complex and uncertain traffic conditions. Unlike traditional binary logic, which requires precise inputs, fuzzy logic can handle imprecise data, such as varying levels of traffic density, speed, and vehicle types (Okediran and Oguntoye, 2023). In practice, this means that a fuzzy logic-based traffic management system can assess traffic conditions in real-time and make nuanced decisions, such as slightly extending or reducing green light durations based on the intensity of the traffic flow. This adaptability allows for more fluid traffic movement, reducing congestion by responding to the subtle changes in traffic patterns that rigid systems might overlook (Ayuba et al., 2018).

Fuzzy logic systems are particularly effective in handling the unpredictability of traffic at junctions,

where various factors like weather, time of day, and driver behaviour can influence congestion. By using a set of fuzzy rules, the system can evaluate multiple inputs simultaneously, such as vehicle queue lengths, waiting times, and pedestrian crossings, to determine the optimal signal timings (Samrudh et al., 2017). Hybrid AI models in traffic control represent a significant step forward in managing urban mobility. These systems combine multiple computational techniques to optimize signal timings and route decisions in real time. Recent work demonstrated that combination of Optimisation Algorithms with fuzzy logic, not only enhances the system's adaptability but also ensures that micro-level adjustments, like signal timing, align with macro-level traffic trends (Sule and Adegoke, 2024).

The Spider Wasp Optimizer (SWO) module plays a central role by emulating the natural collective behaviours of spider wasps to identify optimal solutions. In the context of traffic control, SWO adjusts strategies based on real-time data, effectively navigating the complex urban road network. Its ability to rapidly converge on optimal or near-optimal solutions makes it a vital component in scenarios where traffic conditions change unpredictably (Ekinci et al., 2024). Other Optimisation algorithms like Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), and Firefly Algorithm, often struggle with issues such as premature convergence, high computational costs, and poor global search ability (Ogundepo *et al.*, 2022, Oguntoye *et al.*, 2025; Olayiwola *et al.*, 2023), making SWO a more efficient and reliable choice for Traffic Control enhancement. The development of SWO leverages complex biological behaviours (hunting, nesting, and mating) to balance global exploration and local exploitation effectively, often yielding high-quality solutions for challenging optimization problems (Abdel-Basset et al., 2023; Atanda et al., 2023). In

this study, a traffic decongestion at road junctions was developed using a modified fuzzy logic-based algorithm. The Spider Wasp Optimizer (SWO) was introduced to modified the fuzzy logic-based algorithm.

## **METHODOLOGY**

### **Traffic Data Acquisition**

Traffic data used in this study were numeric and generated through simulation in MATLAB R2023a to emulate real-world traffic flow conditions. The simulated dataset comprised vehicle arrival rates, queue lengths, and waiting times, produced using a Poisson probability distribution model to represent random vehicle arrivals and a Gaussian distribution to model variations in queue lengths and waiting times. These stochastic models effectively replicated unpredictable events, including sudden surges in traffic flow and irregular vehicle movements at intersections. The resulting dataset provided a robust and diverse foundation for evaluating the fuzzy logic controller and optimizing its performance under dynamic traffic scenarios.

### **Data Preprocessing**

The simulated traffic data generated in MATLAB were preprocessed to ensure consistency and accuracy before being used as inputs to the fuzzy logic controller. Outliers were removed, and all numeric parameters vehicle arrival rate, queue length, and waiting time were normalized to a common scale to facilitate efficient processing and rule evaluation within the fuzzy inference system. This preprocessing step ensured reliable input data for the optimization and decision-making stages.

### **Development of a modified fuzzy logic-based algorithm using Spider Wasp Optimizer (SWO)**

The development of the modified fuzzy logic-based algorithm began with the initialization of the fuzzy logic system. Simulated traffic data, including vehicle counts and queue lengths from

multiple directions, were generated in MATLAB to represent realistic intersection conditions. The iterative optimization process is summarized in Algorithm 1. These inputs were categorized into linguistic variables: Vehicle Density (V) and Queue Length (Q), with corresponding fuzzy sets *Low*, *Medium*, and *High* for vehicle density, and *Short*, *Medium*, and *Long* for queue length. The fuzzy system's output is the green time allocation ( $T_{(g)}$ ), also represented in linguistic terms—Short, Medium, and Long. Gaussian and triangular membership functions were employed to map the input variables to their corresponding fuzzy sets. The Gaussian functions were used for variables with smooth transitions, providing better continuity between fuzzy regions, while the triangular functions were applied where distinct boundaries between linguistic terms were required. This combination enabled the fuzzy system to effectively capture uncertainty and variability in traffic patterns. To ensure the fuzzy logic controller performs optimally, an objective function is defined to minimize both vehicle delay and queue length. Each candidate solution  $X_i$  in the optimization process consists of membership function parameters (centers and widths) and rule weights. These parameters directly influence how the fuzzy inference engine processes traffic data, making them the key tuning elements for the Spider Wasp Optimizer. The Spider Wasp Optimizer (SWO) was initialized with a predefined population size  $N$ , representing multiple candidate solutions or agents. Each agent  $X_i$  encodes a complete set of fuzzy system parameters, including the centers and widths of the membership functions for vehicle density and queue length, as well as the weights of fuzzy rules. This encoded form was crucial for the optimizer to perform evolutionary operations that mimic the hunting and resource allocation behaviour of spider wasps. The initial

population was randomly generated, providing diverse starting points for the optimizer to explore the search space. This population serves as the foundation for iterative improvement through SWO's exploration and exploitation phases. During each iteration, the SWO entered the search phase, where both exploration and exploitation strategies were applied. In the exploration phase, new candidate solutions were generated. In the exploitation phase, a more focused search was carried out using the best solution and Levy flight-based mutations. This dual-phase mechanism enabled the optimizer to balance global search (to avoid local minima) with local refinement (to improve promising solutions), thus ensuring effective tuning of the fuzzy system. After each iteration, the fitness of all agents was evaluated using the objective function defined earlier. The solution with the best performance-i.e, the one yielding the minimum combined value of average delay and queue length-was identified and stored as  $X_{best}$ , representing the optimal set of fuzzy membership function parameters and rule weights. Specifically, the optimized centers and widths of the membership functions, along with their corresponding rule weights, were extracted from  $X_{best}$  and implemented into the fuzzy inference system. This step ensured that the fuzzy controller evolved over time, becoming more efficient and adaptive in managing varying traffic conditions.

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**Algorithm 1 Pseudo-Code for SWO-Fuzzy Logic-Based Traffic Control Algorithm** (Sui et al. 2024)

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BEGIN

// Step 1: Initialize SWO Parameters

Set population size (N)

Set maximum iterations ( $T_{max}$ )

Initialize spider wasp positions randomly within the search space

// Step 2: Define Fuzzy Logic Membership Functions

Define membership functions for traffic variables (e.g., vehicle count, queue length, waiting time)

Establish fuzzy rule base for traffic signal control

// Step 3: Evaluate Fitness Using Fuzzy Logic

FOR each spider wasp  $i$  in the population DO:

Evaluate fitness based on fuzzy logic decision rules applied to current traffic data

END FOR

// Step 4: Perform SWO Operations to Optimize Signal Timing

FOR each spider wasp  $i$  in the population DO:

Apply SWO operations:

- Hunting: Update position to explore new solutions

- Trapping and Immobilization: Refine positions based on promising regions

Enforce boundary constraints and update positions using Gaussian mutation if necessary

END FOR

// Step 5: Update Fuzzy Rule-Based Decisions Dynamically

Adjust fuzzy logic membership functions and rule weights based on the improved traffic data feedback

// Step 6: Repeat Optimization Process

IF convergence criteria met OR iteration  $t$  equals ( $T_{max}$ ) THEN:

EXIT loop

ELSE:

Increment  $t$  and return to Step 3

END IF

// Step 7: Apply Optimized Traffic Control Parameters

Update traffic signal timings using the optimized parameters from the best solution found

END

### Implementation of the Developed Algorithm

The implementation of the developed Spider Wasp Optimizer (SWO)-Fuzzy Logic Controller for decongesting traffic at road junctions was carried out using MATLAB R2023a. The key toolboxes required include the Fuzzy Logic Toolbox for designing and simulating the fuzzy inference system, the Global Optimization Toolbox for implementing the SWO algorithm, and for modelling traffic signal control logic. Additionally, the Statistics and Machine Learning Toolbox was utilized for analyzing traffic data and generating stochastic traffic patterns. The simulation was executed on a system with a minimum specification of an Intel Core i7 processor, 16 GB RAM, and a 64-bit Windows 10 operating system to ensure smooth and efficient processing.

### Evaluation Measure

Performance for decongesting traffic at road junctions was evaluated using queue length, average vehicle delay, throughput, signal timing efficiency, green time utilization, and intersection delay index. These performance metrics were calculated using the following formulas:

**Queue Length (QL):** Queue length represents the number of vehicles lined up at an intersection waiting for the green signal. It is a direct indicator of congestion and traffic buildup at a junction  $Q_t$  = queue length (number of vehicles) at time step  $t$  and  $T$  = total number of time steps in the simulation. A reduction in queue length after deploying the SWO-Fuzzy controller indicates improved vehicle discharge rates and signal timing effectiveness.

$$QL_{avg} = \frac{1}{T} \sum_{t=1}^T Q_t \quad (1)$$

**Average Vehicle Delay (AVD):** Average vehicle delay measures the time each vehicle spends waiting at the signal beyond normal travel time. It is one of the most important indicators of traffic efficiency.  $N$  = total number of vehicles,  $T_i^{actual}$  = actual time taken by vehicle  $i$  through the junction, and  $T_i^{ideal}$  = travel time without any signal delay. Lower average vehicle delay implies that the signal controller is allowing smoother and faster passage of vehicles through the intersection

$$AVD = \frac{1}{N} \sum_{i=1}^N (T_i^{actual} - T_i^{ideal}) \quad (2)$$

**Throughput (TP):** Throughput is the total number of vehicles that successfully pass through the intersection during a simulation period. It indicates how effectively the controller handles traffic flow.  $N_{out}$  = total number of vehicles that exit the junction, and  $T$  = total time (in seconds or simulation steps). Higher throughput under the SWO-Fuzzy system suggests improved traffic mobility and reduced congestion.

$$TP = \frac{N_{out}}{T} \quad (3)$$

**Signal Timing Efficiency (STE):** Signal timing efficiency reflects how well the green and red phases are coordinated to minimize unnecessary stops and maximize lane usage.  $V_g$  = number of vehicles discharged during the green phase, and  $T_g$  = duration of green signal. Higher STE values indicate that green time is being utilized effectively, minimizing idle periods and wasted capacity.

$$STE = \frac{V_g}{T_g} \quad (4)$$

**Green Time Utilization (GTU):** Green Time Utilization measures how much of the allocated green signal time was used for actual vehicle movement.  $T_g^{used}$  = time during which vehicles

were actively moving in green phase, and  $T_g^{\text{allocated}}$  = total green time allocated for that phase. A high GTU percentage signifies that the green time was not wasted, and the controller correctly predicted traffic demand.

$$GTU = \frac{T_g^{\text{used}}}{T_g^{\text{allocated}}} \times 100\% \quad (5)$$

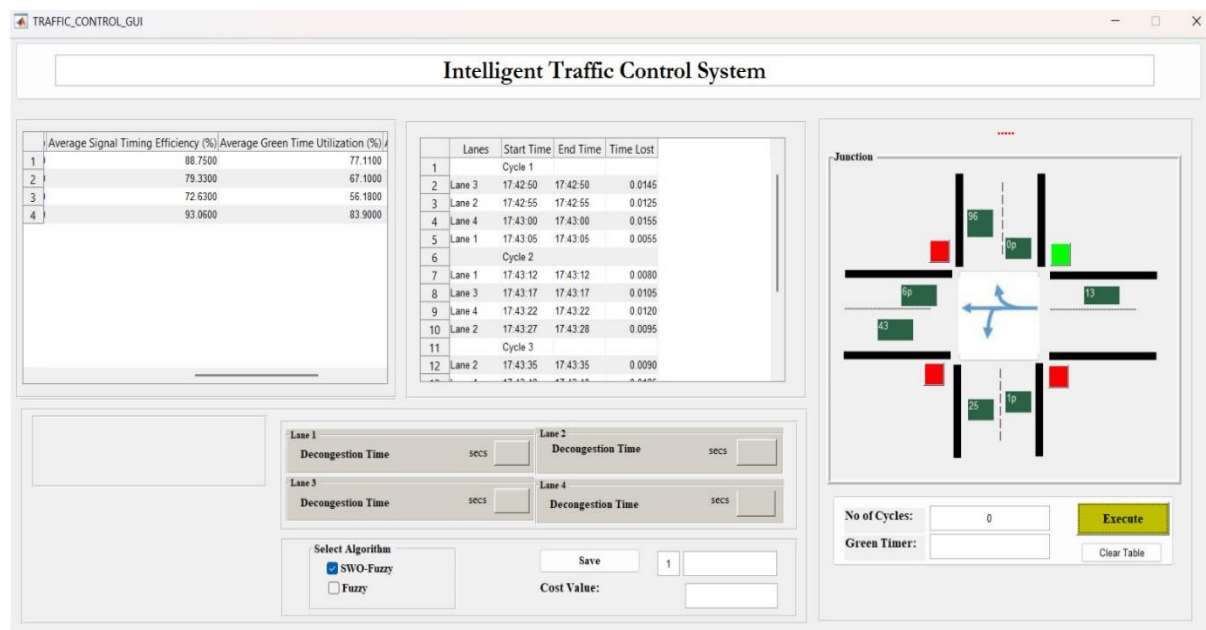
**Intersection Delay Index (IDI):** Intersection Delay Index is a normalized measure used to evaluate the overall delay efficiency of the junction.  $AVD$  = average vehicle delay (as previously defined), and  $C$  = cycle time (total duration of one full signal cycle). A lower IDI

reflects a more efficient intersection with minimal delays relative to the signal cycle length.

$$IDI = \frac{AVD}{C} \quad (6)$$

## RESULTS AND DISCUSSION

The implementation of the developed model was carried out through a custom-built Graphical User Interface (GUI), presented in Figure 1, which served as the operational platform for configuring and executing the control algorithms. The GUI displays relevant operational parameters such as cycle numbers, start and end times for each lane, and computed performance indices.



**Figure 1:** Graphical User Interface for the SWO-Fuzzy Traffic Signal Control Model

It also features algorithm selection options, enabling the user to switch between SWO-Fuzzy and Fuzzy modes, along with visual indicators of traffic light status for each approach at the junctions. This interactive setup provided a convenient means of monitoring and controlling the simulation process while ensuring accurate data capture for analysis.

### Result with Fuzzy Logic Controller

The traditional Fuzzy Logic Controller (FLC) was evaluated as a baseline for traffic decongestion across four junctions, with performance averaged over ten operational cycles. Results from Table 1, showed high Average Queue Lengths (26–28 vehicles) and Delays exceeding 500 seconds, indicating limited adaptability during peak periods. Throughput remained steady at around 50–52 vehicles per cycle, but Signal Timing Efficiency and Green Time Utilization varied widely,

highlighting inconsistent performance across junctions. The Intersection Delay Index ranged from 0.584 to 1.450, confirming uneven flow efficiency. Overall, while the FLC achieved

moderate control, it lacked responsiveness to dynamic traffic conditions, underscoring the need for an adaptive optimization-based approach such as the proposed SWO-Fuzzy system.

Table 1: Average Performance Metrics for Fuzzy Logic Controller

Junction	Average Queue (veh)	Average Delay (s)	Average Throughput (veh/min)	Signal Timing Efficiency (%)	Average Green Time Utilization (%)	Average Intersection Delay Index
1	26	508.06	50.27	76.77	69.94	0.754
2	26	502.32	51.07	71.88	62.86	1.008
3	27	516.49	50.92	64.29	50.34	1.450
4	28	518.35	51.74	77.51	69.31	0.584

### Result with SWO-Fuzzy Controller

The SWO-Fuzzy Controller, combining the Spider Wasp Optimizer with fuzzy logic, was evaluated under identical traffic conditions as the FLC baseline. Results from Table 2, showed substantial performance gains, with throughput increasing to 83–86 vehicles per cycle compared to 50–52 under FLC, and delays reduced to below 505 seconds across all junctions. Signal Timing Efficiency peaked at 93.06% and Green Time Utilization

reached 83.90%, reflecting more effective coordination of signal phases with real-time traffic demand. Additionally, the Intersection Delay Index values were lower (0.377–1.160), confirming smoother flow and reduced congestion. Overall, the SWO-Fuzzy system demonstrated superior adaptability and efficiency, significantly outperforming the traditional FLC in optimizing traffic movement across all junctions.

Table 2: Average Performance Metrics for SWO-Fuzzy Controller

Junction	Average Queue (veh)	Average Delay (s)	Average Throughput (veh/min)	Average Signal Timing Efficiency (%)	Average Green Time Utilization (%)	Average Intersection Delay Index
1	38	490.83	86.19	88.75	77.11	0.446
2	37	488.52	85.46	79.33	67.10	0.853
3	39	503.24	83.75	72.63	56.18	1.160
4	39	503.85	85.80	93.06	83.90	0.377

### Comparative Analysis between FLC and SWO-Fuzzy Controller

The comparative analysis between the traditional FLC and the SWO-Fuzzy Controller in Table 3,

highlights the latter's superior performance across key metrics. While the Average Queue Length increased slightly (33.25 to 38.25 vehicles), the SWO-Fuzzy system achieved a 67.87% rise in throughput and a 6.03% reduction in delay, indicating faster queue clearance and improved flow. Signal Timing Efficiency and Green Time Utilization rose by 19.70% and 18.39%,

respectively, demonstrating more effective phase coordination. Most notably, the Intersection Delay Index decreased by 45.34%, confirming substantial efficiency gains. Overall, the SWO-Fuzzy Controller outperformed the traditional FLC, validating the integration of metaheuristic optimization for adaptive and congestion-resilient traffic management.

Table 3: Comparative Performance Metrics for FLC and SWO-Fuzzy Controller

Metric	FLC (Average)	SWO- Fuzzy (Average)	Percentage Improvement (%)
Average Queue (veh)	33.25	38.25	-15.04 (↑ queue but processed faster)
Average Delay (s)	528.49	496.61	6.03 ↓
Average Throughput (veh/min)	50.79	85.30	67.87 ↑
Average Signal Timing Efficiency (%)	70.11	83.94	19.70 ↑
Average Green Time Utilization (%)	60.41	71.52	18.39 ↑
Average Intersection Delay Index	1.297	0.709	45.34 ↓

### Discussion of Results

The comparative analysis between the traditional Fuzzy Logic Controller (FLC) and the SWO-Fuzzy Controller demonstrates that while FLC maintained shorter average queue lengths, the SWO-Fuzzy approach achieved notable improvements in delay reduction, throughput, and overall efficiency. The SWO-Fuzzy system consistently produced higher throughput values and lower delays, indicating superior adaptability and responsiveness to dynamic traffic conditions. It also achieved higher signal timing efficiency and green time utilization, reflecting better coordination of signal phases and more effective use of available green periods. Additionally, the lower intersection delay indices recorded under the SWO-Fuzzy method confirm its ability to minimize vehicle idling and improve overall intersection performance. Collectively, these results establish the SWO-Fuzzy controller as a more efficient and adaptive approach to urban

traffic management, offering substantial performance gains over conventional fuzzy control systems despite marginal increases in queue lengths.

### CONCLUSION

The results of this study align with previous research demonstrating the benefits of combining fuzzy logic with metaheuristic optimization for traffic signal control. For instance, Odeh et al. (2015) developed a hybrid fuzzy-genetic algorithm that significantly improved traffic signal performance compared to classical fuzzy logic controllers, reporting reductions in delays and enhancements in throughput. Similarly, Abdou et al. highlighted that metaheuristic algorithms such as genetic algorithms outperform deterministic controllers by better exploring solution spaces and adapting timing to stochastic traffic demands. Research also suggests that adaptive fuzzy logic



systems combined with optimization methods effectively manage traffic under varying and uncertain conditions. The use of the Spider Wasp Optimizer as a novel metaheuristic in this work extends this growing body of literature by offering superior adaptability and efficiency, validating the integration of fuzzy logic and metaheuristics as a promising approach to intelligent urban traffic management.

## REFERENCES

- Abdel-Basset, M. (2023). Spider Wasp optimizer in traffic flow optimization. *Computers and Industrial Engineering*. <https://doi.org/10.1016/j.cie.2023.xxxxx>
- Abdou, A. A., Farrag, H. M., Tolba, A. S., and Tolba, A. S. (2022). A Fuzzy Logic-Based Smart Traffic Management Systems. *Journal of Computer Science*, 18(11), 1085-1099.
- Atanda, O. G., Ismaila, W., Afolabi, A. O., Awodoye, O. A., Falohun, A. S., & Oguntoye, J. P. (2023, April). Statistical Analysis of a deep learning based trimodal biometric system using paired sampling T-Test. In *2023 International Conference on Science, Engineering and Business for Sustainable Development Goals (SEB-SDG)* (Vol. 1, pp. 1-10). IEEE.
- Ayuba, P., Zachariah, B., and Damuut, L. P. (2018). Modification of fuzzy logic rule base in the optimization of traffic light control system. *Science World Journal*, 13(2), 6–11.
- Ekinici, S., Izci, D., Turkeri, C., and Ahmad, M. A. (2024). Spider Wasp optimizer-optimized cascaded fractional-order controller for load frequency control in a photovoltaic-integrated two-area system. *Mathematics*, 12(19), 3076. <https://doi.org/10.3390/math12193076>
- Marazi, N. F., Majumdar, B. B., Sahu, P. K., Panda, S., and Koramati, S. (2023). Traffic congestion assessment tool for urban roads based on traffic and geometric characteristics: A case of Hyderabad, India. *Journal of Transportation Engineering*, 149(11), 1–15. <https://doi.org/10.1061/jtpubs.0000xxxx>
- Odeh, S. M., Mora, A. M., Moreno, M. N., and Merelo, J. J. (2015). A hybrid fuzzy genetic algorithm for an adaptive traffic signal system. *Advances in Fuzzy Systems*, 2015(1), 378156.
- Ogundepo, O. Y., Omeiza, I. O. A., & Oguntoye, J. P. (2022). Optimized textural features for mass classification in digital mammography using a weighted average gravitational search algorithm. *International Journal of Electrical and Computer Engineering (IJECE)*, 12(5), 5001-5013.
- Oguntoye, J. P., Ajagbe, S. A., Adediji, O. T., Awodoye, O. O., Adetunji, A. B., Omidiora, E. O., & Adigun, M. O. (2025). An Improved Chicken Swarm Optimization Techniques Based on Cultural Algorithm Operators for Biometric Access Control. *Computers, Materials & Continua*, 84(3).
- Okediran, O. O., & Oguntoye, J. P. (2023). Analysis of critical success factors for information management performance. *LAUTECH Journal of Engineering and Technology*, 17(1), 175-186.
- Olagunju, K. M., Adebisi, A. A., Adeliyi, T. T., Oguntoye, J. P., Igbekele, E. O., & Osunade, S. (2025). State-of-the-Art Research in Intrusion Detection Systems (IDS) for Network Attack Detection: A Review. *NIPES-JSTR ISSUE*, 7(1), 974-981.
- Olayiwola, D. S., Olayiwola, A. A., Oguntoye, J. P., Awodoye, O. O., Ganiyu, R. A., & Omidiora, E. O. (2023). Development of a Fingerprint Verification and Identification System Using a Gravitational Search Algorithm-Optimized Deep Convolutional Neural Network. *Adeleke University Journal of Engineering and Technology*, 6(2), 296-307.
- Omidiora, E. O., Akanni, A. O., and Abdulhameed, I. A. (2023). Analysis of simulated annealing to decongest traffic in a multi-road coordinated intersection. *FUOYE Journal of Engineering and Technology*, 8(2), 156–161.
- Oyedokun, I. O., Ganiyu, R. A., Oguntoye, J. P., & Mojeed, Y. O. (2025). Development of an Enhanced Internet of Things-Based Wearable Human Tracking Security System with Integrated Distress Alert Mechanism. *Journal of Engineering Research and Reports*, 27(12), 135-147.

- Sanusi, B. A., Adeyemo, Z. T., Omidiora, E. O., Olabiyisi, S. O., Olowoye, A. O., and Oyediran, M. O. (2020). Decongesting traffic at coordinated junctions in a multi-road intersection using graph coloring based technique. *Research and Applications of Web Development and Design*, 3(2), 1–10.
- Sule, H., and Adegoke, A. A. (2024). A hybrid traffic controller system based on flower pollination algorithm and type-2 fuzzy logic optimized with crow search algorithm for signalized intersections. *Soft Computing*, 28, 7227–7249. <https://doi.org/10.1007/s00500-024-09643-w>
- Zhang, Y., Macke, W., Cui, J., Hornstein, S., Urieli, D., and Stone, P. (2023). Learning a robust multiagent driving policy for traffic congestion reduction. *Neural Computing and Applications*, 35, 1–14. <https://doi.org/10.1007/s00521-023-xxxx-x>