

Hybridization of FA-YOLOv8 Model with Zebra Optimization Algorithm for Improving Traffic Light Detection and Tracking Under Low-Light Conditions

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Abstract—Traffic-light detection and tracking under low-light conditions remain difficult because signal heads can be small, dim, blurred, low in contrast, or affected by glare and reflections. This study develops a hybridization of Firefly Algorithm–You Only Look Once version 8 (FA-YOLOv8) with the Zebra Optimization Algorithm (ZOA) for offline analysis of recorded dashcam video under rainy, night-time, and cloudy conditions. YOLOv8 detects traffic-light candidates, FA performs attraction-based coordinate refinement and supports tracking continuity, and ZOA acts as an enhancement layer that adaptively searches FA control settings rather than replacing FA as the refinement mechanism. A controlled within-dataset comparison uses 300 real-world dashcam frames containing approximately 900 annotated traffic-light instances; the same annotated sequences support parameter adaptation and the baseline-versus-hybrid comparison, so the reported results characterize within-dataset behavior rather than held-out generalization. Compared with baseline FA-YOLOv8, MOTP increases from 31.84% to 37.59% under rainy conditions and from 49.47% to 72.50% under cloudy conditions. At night, Recall increases from 54.70% to 80.34% and F1-Score from 61.73% to 75.56%. Tracking continuity also improves in the reported point estimates: IDF1 rises from 72/90/85% to 82/94/90% for rainy/night/cloudy conditions, while identity switches fall from 95/18/45 to 48/8/22. These observations show that ZOA-based enhancement changes FA search behavior and is associated with improvements in several localization and identity-tracking measures within the evaluated sequences, although detection changes remain condition-dependent.

Keywords—Traffic light detection; traffic light tracking; YOLOv8; firefly algorithm; zebra optimization algorithm; low-light conditions; adaptive parameter optimization; identity tracking

I. INTRODUCTION

Traffic-light perception requires reliable detection, localization, and tracking across consecutive road frames [1]. Under low-light conditions, weak contrast, glare, reflections, and rain blur can distort candidate locations and interrupt temporal continuity. These effects motivate a framework that can refine detected coordinates while adapting its search behavior to the illumination condition rather than relying on fixed optimization parameters.

The central problem addressed here is not simply low-light detection; it is the parameter sensitivity of FA when it is used to refine and track YOLOv8 detections. FA offers a useful attraction-based local search mechanism, but its convergence and exploration–exploitation behavior depend on control parameters [2]. A fixed configuration can therefore behave

differently when the scene changes from cloudy to night-time or rainy conditions.

YOLOv8 is retained as the detection backbone and is not the main novelty of this study. The contribution lies in the optimization layer placed around the detector output: FA refines candidate coordinates, HSV analysis supports traffic-light state recognition, and ZOA adapts the FA control parameters to the current search difficulty.

Accordingly, the proposed method hybridizes FA-YOLOv8 with ZOA rather than replacing FA with another tracker. ZOA is introduced specifically as an enhancement layer for the existing FA-YOLOv8 framework: FA remains responsible for attraction-based coordinate refinement and temporal continuity, while ZOA searches the FA control settings, including the maximum generation setting and the parameters alpha, beta, and gamma. This complementary division targets FA parameter sensitivity while preserving the original refinement mechanism.

The contributions are fourfold. First, a FA-YOLOv8-ZOA hybridization is formulated for low-light traffic-light detection and tracking. Second, ZOA is used to enhance the existing FA-YOLOv8 framework through adaptive FA parameter search across rainy, night-time, and cloudy conditions. Third, the baseline FA-YOLOv8 and proposed hybrid are evaluated using detection/localization and identity-tracking metrics. Fourth, the analysis distinguishes condition-dependent changes and explicitly limits its conclusions to the offline, within-dataset experiment rather than claiming real-time deployment, independent generalization, or universal optimizer superiority.

II. RELATED WORK

A. Low-Light Traffic-Light Perception

Low-light traffic-light detection is difficult because illumination changes simultaneously affect color, contrast, and object boundaries [3]. Deep detectors improve robustness over handcrafted methods, yet small and distant signals remain vulnerable to missed detections and unstable boxes when glare, rain reflections, or weak illumination suppress visual evidence [4]. These studies motivate robust perception, but they do not directly address the parameter sensitivity of an optimization-based refinement layer placed after detector output.

Tracking adds a temporal requirement: a correct detection must remain spatially stable and preserve its identity across frames [5]. Existing low-light tracking work commonly

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focuses on detector design, preprocessing, or tracking architecture [5], [6]. In contrast, the present study focuses on a narrower problem inherited from the baseline FA-YOLOv8 framework: how to enhance FA search behavior when fixed control settings become less suitable as illumination conditions change.

B. Firefly Algorithm as the Baseline Refinement Mechanism

The Firefly Algorithm (FA) is a swarm-based optimizer in which weaker candidate solutions move toward brighter, higher-fitness solutions [7]. Its attraction mechanism has previously been applied to object tracking [8]. In the baseline FA-YOLOv8 framework, this behavior is used to refine detected traffic-light coordinates and support continuity across frames [9]. The main limitation relevant to this study is not the absence of a refinement mechanism, but the sensitivity of FA convergence and search behavior to fixed control settings.

In the baseline FA-YOLOv8 formulation used in this study, each firefly represents a candidate traffic-light coordinate, and its brightness represents the quality of that candidate [9]. The implemented light-intensity relationship is expressed as:

$$I_i = I_0 e^{(-\gamma * fitness_i)} \quad (1)$$

where, I_i is the updated light intensity of candidate i , I_0 is the initial intensity, γ is the light-absorption coefficient, and $fitness_i$ represents the candidate quality. A weaker candidate moves toward a stronger candidate using the implemented update:

$$x_i(t+1) = x_i(t) + \beta[x_j(t) - x_i(t)] + \alpha * L() \quad (2)$$

where, alpha controls randomized step size, beta controls attraction toward the better candidate, and $L()$ denotes the stochastic Lévy-flight component used in the implementation. The process iterates until the termination criterion is met and the best coordinate is returned. These parameters are effective only when appropriately tuned; static settings can be suboptimal when the illumination condition changes [10].

C. Zebra Optimization Algorithm for FA Parameter Adaptation

ZOA models zebra foraging and defensive behavior through complementary search phases [11]. In this work, ZOA is not used as an independent replacement for FA and is not treated as a competing tracker. Instead, it is embedded as an enhancement mechanism that searches FA control settings and retains settings that improve the implemented FA fitness. This design is consistent with the thesis objective of improving the existing FA-YOLOv8 framework rather than replacing its attraction-based refinement stage.

This role separation defines the hybridization studied here: FA performs localized coordinate refinement, whereas ZOA modifies how FA searches by adapting its control settings [12]. Prior work establishes the individual usefulness of FA and ZOA, but does not directly address this specific use of ZOA as a parameter-enhancement layer for FA-YOLOv8 in low-light traffic-light tracking. The proposed design therefore targets parameter sensitivity in the baseline framework without changing the YOLOv8 detector itself.

III. PROPOSED HYBRIDIZATION OF FA-YOLOv8 WITH ZOA

As illustrated in Fig. 1, the processing pipeline begins with prerecorded dashcam frames and YOLOv8 candidate detections. HSV-based pixel analysis supports traffic-light state recognition, after which FA refines candidate coordinates. For each processed frame containing traffic-light candidates, the baseline FA configuration is evaluated first, ZOA searches alternative FA control settings, and the selected settings are used for the final FA refinement pass. The refined detections are then evaluated using detection, localization, and identity-tracking measures. Thus, the adaptive feedback shown in Fig. 1 is applied during offline frame processing rather than as a once-per-sequence global tuning stage.

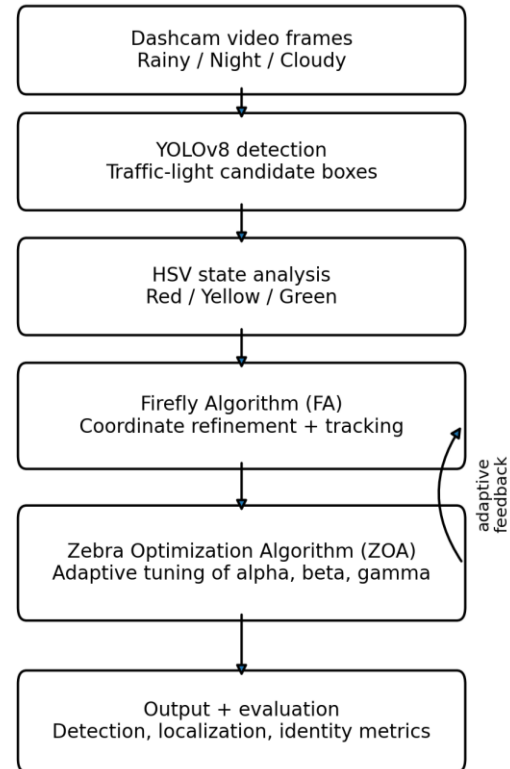


Fig. 1. Processing flow of the proposed FA-YOLOv8-ZOA hybridization.

A. YOLOv8 Detection and HSV State Analysis

YOLOv8 is responsible for candidate localization, class prediction, and confidence information. HSV analysis is used within the detected region to help distinguish the red, yellow, and green traffic-light states. The metaheuristic stages operate on the detected candidates; they do not replace YOLOv8 feature extraction or class prediction.

B. FA Coordinate Refinement and ZOA Parameter Adaptation

FA begins with candidate positions derived from the detector output. Candidate fitness is evaluated, brightness is updated, and weaker fireflies move toward better candidates according to the attraction and stochastic movement terms in Eq. (1) and (2). ZOA operates at the parameter level: candidate settings are sampled within the implementation bounds, evaluated by running FA, and retained when the resulting FA

fitness improves. The selected settings are then returned to FA for the final coordinate-refinement pass. This preserves FA as the refinement mechanism while using ZOA only to enhance its search configuration.

Operationally, the implementation searches a parameter vector containing maximum generations together with alpha, beta, and gamma. The implemented fitness is $F = \max(0, N - 0.1D)$, where N is the number of traffic-light candidates, and D is the sum of pairwise Euclidean distances among candidate centers. The optimizer therefore favors configurations that preserve candidate count while reducing spatial dispersion; Precision, Recall, F1-Score, IDF1, and IDSW are evaluation measures reported after processing rather than weighted terms inside the ZOA fitness function. The implementation searches max generation in [50, 200], alpha in [0.1, 0.5], beta in [0.5, 2.0], and gamma in [0.1, 1.0]. The archived code uses a ZOA population size of 1 and one ZOA update iteration per processed frame. The baseline FA initialization uses five fireflies with max generation = 100, alpha = 0.2, beta = 1.0, and gamma = 0.2. These implementation details define the parameter-enhancement mechanism evaluated in this study.

IV. EXPERIMENTAL SETUP

A. Dataset and Selection Criteria

The experimental evaluation uses prerecorded real-world traffic-light video captured with a vehicle-mounted dashcam and processed offline. The data contain 300 selected frames and approximately 900 annotated traffic-light instances, divided equally across rainy, night-time, and cloudy conditions, as summarized in Table I. The same annotated sequences are used as feedback during ZOA adaptation of the existing FA-YOLOv8 outputs and for the subsequent baseline-versus-hybrid measurements; YOLOv8 is not retrained during ZOA adaptation. Accordingly, this study is a controlled within-dataset comparative evaluation of the incremental effect of adding ZOA-based enhancement to FA-YOLOv8 rather than an independent held-out generalization experiment. Because this study evaluates offline recorded video, online throughput, FPS, and embedded real-time deployment are not defined as primary experimental objectives.

TABLE I. DATASET DISTRIBUTION UNDER SELECTED LOW-LIGHT CONDITIONS

Condition	Frames	Annotated TLs	Primary Challenge
Rainy	100	300	Reflection and rain blur
Night	100	300	Low illumination
Cloudy	100	300	Inconsistent lighting
Total	300	900	Controlled within-dataset comparison

The dataset was filtered according to the predefined selection criteria summarized in Table I: traffic lights had to be visible from a direct frontal view, motion blur had to remain limited, object size had to be detectable, and severely overexposed, extremely dark, fully occluded, or excessively blurred cases were excluded. These criteria define the controlled scope of the reported results and should be considered when interpreting performance outside the evaluated low-light scenes.

B. Evaluation Metrics

Performance is evaluated with MOTP, Precision, Recall, and F1-Score to describe detection and localization behavior. Because the proposed method also targets temporal continuity, the analysis includes IDF1, IDSW, Mostly Tracked (MT), Partially Tracked (PT), and Mostly Lost (ML). These metrics are used to compare the same baseline and enhanced framework under the three conditions listed in Table I.

The principal experimental control is baseline FA-YOLOv8 versus the proposed FA-YOLOv8-ZOA framework because the research objective is to determine the incremental effect of using ZOA to enhance the previously developed FA-YOLOv8 model. The broader study also contains supporting comparisons with other optimization-based YOLOv8 variants, but the present article does not make a universal claim that ZOA is superior to every possible parameter-search strategy. Its central question is whether the addition of ZOA-based parameter enhancement changes the performance of FA-YOLOv8 under the tested low-light conditions.

V. RESULTS AND DISCUSSION

A. Adaptive FA Parameter Behavior

Table II shows that ZOA returns different mean FA parameter values for the three illumination conditions, supporting the premise that one fixed FA configuration is not equally suitable for every scene type. Rainy conditions require the largest mean maximum generation, while the night-time subset uses a lower mean alpha and a higher mean gamma. These differences indicate condition-dependent search behavior rather than a single global parameter setting.

TABLE II. MEAN ADAPTIVE FA PARAMETERS GENERATED BY ZOA

Condition	Max Gen	α	β	γ
Rainy	155.83	0.25	1.56	0.47
Night	139.08	0.15	1.42	0.59
Cloudy	125.25	0.21	1.33	0.33

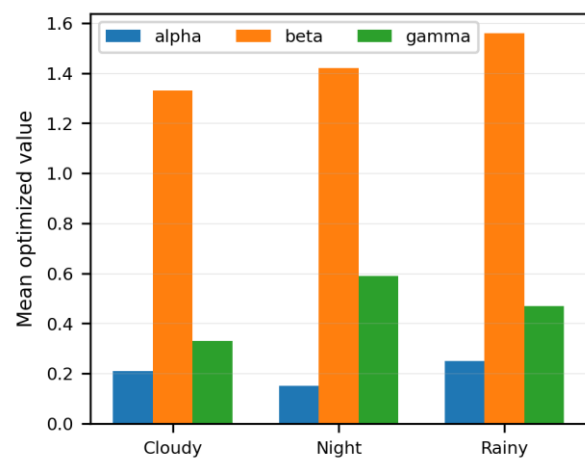


Fig. 2. Mean FA parameter values produced by adaptive ZOA tuning.

The parameter analysis in Table II and Fig. 2 provides mechanism-level evidence for the proposed hybridization. In

baseline FA-YOLOv8, the control settings are relatively static, whereas the hybrid framework changes them through ZOA. Within the tested data, this enhancement is associated with condition-dependent FA search behavior and changes in localization and tracking continuity.

B. Detection and Localization Results

As shown in Table III, under rainy conditions, MOTP increases from 31.84% to 37.59%, while Precision increases from 73.94% to 100%. Recall decreases from 25.45% to 22.92% and F1-Score decreases slightly from 37.83% to 37.29%. The 100% Precision value should therefore not be interpreted as perfect overall detection: it occurs together with low Recall, indicating a conservative operating point in which the reported detections contain no counted false positives while a substantial proportion of annotated traffic lights remain undetected. The rainy result therefore indicates improved localization precision and fewer false detections, but not a uniform improvement in detection completeness.

TABLE III. DETECTION AND LOCALIZATION RESULTS

Metrics	Conditions (FA-YOLOv8)			Conditions (Hybrid)		
	Rainy	Night	Cloudy	Rainy	Night	Cloudy
MOTP (%)	31.84	32.84	49.47	37.59	39.74	72.50
Precision (%)	73.94	71.11	100.00	100.00	71.21	100.00
Recall (%)	25.45	54.70	25.57	22.92	80.34	35.25
F1-Score (%)	37.83	61.73	40.72	37.29	75.56	52.15

The night-time results in Table III show a different pattern. MOTP increases from 32.84% to 39.74%; Recall rises from 54.70% to 80.34%; and F1-Score rises from 61.73% to 75.56%, while Precision remains nearly unchanged at 71.11% versus 71.21%. These changes indicate stronger detection completeness together with improved localization behavior under night-time illumination.

Cloudy scenes in Table III provide the strongest localization gain: MOTP increases from 49.47% to 72.50%, Recall rises from 25.57% to 35.25%, and F1-Score increases from 40.72% to 52.15%, while Precision remains at 100%. As in the rainy result, 100% Precision should be read together with the relatively low Recall rather than as evidence of perfect detection. Across the three conditions, the results show improvements in several, but not all, detection and localization measures.

C. Tracking Continuity and Identity Consistency

Table IV and Fig. 3 show that identity continuity improves in the reported point estimates for all three evaluated environments. IDF1 increases from 72% to 82% in rain, 90% to 94% at night, and 85% to 90% in cloudy scenes. Identity switches fall from 95 to 48, 18 to 8, and 45 to 22, respectively. MT also increases, while ML decreases across all three conditions.

These tracking results form the clearest observed pattern in the current experiment: after ZOA-based enhancement, the reported sequences show fewer identity switches and higher IDF1. They complement the detection metrics because temporal association can improve even when a frame-level

metric such as Recall or F1-Score does not improve. The interpretation is restricted to the evaluated runs and does not claim statistical variability across repeated stochastic trials.

TABLE IV. TRACKING AND IDENTITY CONSISTENCY RESULTS

Conditions	IDF1 (%)	IDSW	MT (%)	PT (%)	ML (%)
Rainy	72 -> 82	95 -> 48	45 -> 58	40 -> 34	15 -> 8
Night	90 -> 94	18 -> 8	80 -> 88	18 -> 11	2 -> 1
Cloudy	85 -> 90	45 -> 22	65 -> 74	30 -> 23	5 -> 3

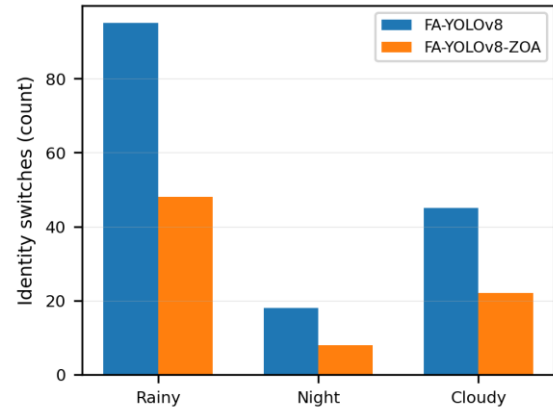


Fig. 3. Reduction in identity switches after YOLOv8 was hybridized with ZOA.

D. Qualitative Detection and Tracking Behaviour

The representative outputs in Fig. 4 are consistent with the quantitative observations. Baseline FA-YOLOv8 detects traffic-light candidates in all three environments but shows moderate coordinate and continuity stability in difficult frames. After ZOA-based parameter enhancement is introduced, the illustrated outputs show more stable localization and stronger identity preservation, particularly under night-time and cloudy illumination.



Fig. 4. Representative inputs, baseline FA-YOLOv8 outputs, and proposed FA-YOLOv8-ZOA outputs for cloudy, night, and rainy scenes.

E. Extension Beyond the Baseline FA-YOLOv8 Study

This work extends the previously published FA-YOLOv8 framework [2]. The earlier study established the feasibility of combining FA with YOLOv8 for traffic-light detection; the present study adds ZOA as an enhancement layer for adaptive FA parameter search, condition-specific parameter analysis, and a broader evaluation of localization and identity continuity [13].

Unlike approaches that primarily modify detector architecture, enhancement preprocessing, or multi-camera fusion [1], [2], the proposed contribution operates at the optimization/refinement stage. Its purpose is not to replace FA, but to enhance how the FA component searches and refines coordinates after YOLOv8 has produced candidate detections.

VI. CONCLUSION

This study hybridizes FA-YOLOv8 with the Zebra Optimization Algorithm as an enhancement mechanism for offline traffic-light detection and tracking under selected low-light conditions. YOLOv8 supplies candidate detections, FA remains responsible for attraction-based localization refinement, and ZOA searches FA control settings to adapt the refinement behavior to illumination-dependent difficulty.

Within the controlled same-sequence comparison, the hybrid shows favorable changes in several localization and tracking point estimates. Rainy MOTP and Precision increase, cloudy MOTP increases substantially, night-time Recall and F1-Score improve, and the reported identity metrics show higher IDF1 and fewer identity switches in all three tested conditions. At the same time, rainy Recall and F1-Score do not improve, and the 100% Precision cases coexist with low Recall. These findings therefore support a narrower conclusion: ZOA-based enhancement modifies FA search behavior and is associated with improvements in selected metrics within the evaluated offline sequences; they do not establish real-time deployment performance, universal optimizer superiority, or independent generalization to unseen traffic scenes.

Future work should follow the constraints already identified in this study by expanding the dataset to more diverse intersections, camera viewpoints, and more severe visibility conditions such as fog, heavy rain, extreme glare, tunnel exits, overexposure, and stronger occlusion. If the framework is later adapted for online or vehicle-based deployment, computational efficiency, hardware-specific runtime, and embedded implementation should then be evaluated explicitly. Additional road-object classes and broader traffic-scene coverage can also be investigated without changing the central role of ZOA as an enhancement to FA-YOLOv8.

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DECLARATIONS

Declaration on Generative AI. OpenAI ChatGPT was used to assist with manuscript organization, drafting, and language refinement. The authors critically reviewed the AI-assisted text and remain fully responsible for the scientific ideas, experimental values, interpretations, references, originality, and final manuscript.

Thesis derivation. This manuscript is derived from and substantially reorganizes the experimental work reported in the first author's Master of Science thesis. The journal article focuses on the FA-YOLOv8-to-FA-YOLOv8-ZOA hybridization, adaptive parameter behavior, and condition-wise detection/tracking evaluation.

REFERENCES

- [1] A. Salemi and M. A. Mohamad, "Critical Review of Object Detection Techniques for Traffic Light Detection in Intelligent Transportation Systems." doi: <https://dx.doi.org/10.14569/IJACSA.2025.0161072>.
- [2] A. Salemi, M. A. Mohamad, and Z. Musa, "Hybrid Firefly Algorithm and You Only Look Once v8 Framework (FA-YOLOv8) for Traffic Light Detection," 2026. doi: [10.1109/icseecs65227.2025.11279255](https://doi.org/10.1109/icseecs65227.2025.11279255).
- [3] P. Zhong et al., "Low-Light Object Tracking: A Benchmark," Aug. 2024, [Online]. Available: <http://arxiv.org/abs/2408.11463>
- [4] A. Yi and N. Anantrasirichai, "A Comprehensive Study of Object Tracking in Low-Light Environments," *Sensors*, vol. 24, no. 13, Jul. 2024, doi: [10.3390/s24134359](https://doi.org/10.3390/s24134359).
- [5] A. Albouchi, S. Messaoud, S. Bouaafia, M. A. Hajjaji, and A. Mtibaa, "Implementation of an improved multi-object detection, tracking, and counting for autonomous driving," *Multimed. Tools Appl.*, vol. 83, no. 18, 2024, doi: [10.1007/s11042-023-17444-w](https://doi.org/10.1007/s11042-023-17444-w).
- [6] K. R. Ranipa and K. R. Bhatt, "Illumination Condition Effect on Object Tracking: A Review," *European Journal of Academic Essays ISSN*, vol. 1, no. 11online, pp. 27–31, 2014, [Online]. Available: www.euroessays.org
- [7] V. Kumar and D. Kumar, "A Systematic Review on Firefly Algorithm: Past, Present, and Future," *Archives of Computational Methods in Engineering*, vol. 28, no. 4, 2021, doi: [10.1007/s11831-020-09498-y](https://doi.org/10.1007/s11831-020-09498-y).
- [8] T. Kumar, K. Kumar, K. Dhanuk, A. K. Bhargava, and M. K. Sharma, "Firefly algorithm driven intelligent system for multi-objective multimodal transportation optimization," *Systems and Soft Computing*, vol. 7, 2025, doi: [10.1016/j.sasc.2025.200424](https://doi.org/10.1016/j.sasc.2025.200424).
- [9] F. S. Hsieh, "Comparison of a Hybrid Firefly–Particle Swarm Optimization Algorithm with Six Hybrid Firefly–Differential Evolution Algorithms and an Effective Cost-Saving Allocation Method for Ridesharing Recommendation Systems," *Electronics (Switzerland)*, vol. 13, no. 2, 2024, doi: [10.3390/electronics13020324](https://doi.org/10.3390/electronics13020324).
- [10] M. K. Hoang, T. A. Le, K.-X. Thuc, T. Van Luyen, X.-S. Yang, and D. W. K. Ng, "Firefly Algorithm for Movable Antenna Arrays," *IEEE Wireless Communications Letters*, pp. 1–1, Sep. 2024, doi: [10.1109/lwc.2024.3456899](https://doi.org/10.1109/lwc.2024.3456899).
- [11] E. Trojovska, M. Dehghani, and P. Trojovsky, "Zebra Optimization Algorithm: A New Bio-Inspired Optimization Algorithm for Solving Optimization Algorithm," *IEEE Access*, vol. 10, 2022, doi: [10.1109/ACCESS.2022.3172789](https://doi.org/10.1109/ACCESS.2022.3172789).
- [12] M. Eslami, H. Shareef, and M. Khajezadeh, "Firefly algorithm and pattern search hybridized for global optimization," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2013. doi: [10.1007/978-3-642-39482-9_20](https://doi.org/10.1007/978-3-642-39482-9_20).
- [13] W. He, S. Ma, C. Wang, and Q. Zhang, "Improve zebra optimization algorithm with adaptive oscillation weight and golden sine operator," Feb. 05, 2024. doi: [10.21203/rs.3.rs-3820826/v1](https://doi.org/10.21203/rs.3.rs-3820826/v1).