Sustainable Vision-Based Navigation for Autonomous Electric Vehicle Charging

Nandini Srivastava[1*], *Harminder Singh*[2], *Mohsin Ikram*[3], *Nipun Setia*[4], *Prabhat Sharma*[5], *V Siva Prasad Raju*[6], *Shivani Kampani*[7]

[1]SLM, Manav Rachna International Institute of Research and Studies
[2]Lovely Professional University, Phagwara, Punjab, India, harminder.singh@lpu.co.in
[3]Uttaranchal University, Dehradun - 248007, India, mohsinikram@uumail.in
[4]Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India, nipun.setia.orp@chitkara.edu.in
[5]Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh-174103 India, prabhat.sharma.orp@chitkara.edu.in
[6]Department of Civil Engineering, GRIET, Hyderabad, Telangana, India
[7]G D Goenka University, Haryana, India

Abstract*:* This research investigates the integration of vision-based navigation into the charging procedure of autonomous electric vehicles (AEVs). The study offers a comprehensive examination of the precision of calibration, the ability to identify objects, the navigation capabilities of autonomous cars, and the effectiveness of charging sessions. The visual systems undergo meticulous calibration, which leads to inherent traits that are crucial for accurate perception. Object recognition algorithms have exceptional proficiency in precisely spotting electric vehicles, charging stations, cables, and obstacles, while also exhibiting heightened levels of confidence. The adaptive navigation framework exhibits improved precision, as seen by developments in velocity and steering angle, enabling AEVs to effectively navigate through complex urban scenarios. Examining the data from charging sessions indicates that the integration of vision-based navigation has led to enhanced operational effectiveness of AEVs. This is apparent via the significant reduction in charging duration and the favorable boost in energy output. The cross-parameter analysis reveals the interconnectedness, emphasizing the influence of accurate calibration on the recognition and movement of objects. It showcases a holistic integration of perception, navigation, and charging procedures. The findings have significant implications for the widespread adoption of vision-based navigation, providing a groundbreaking method for seamlessly incorporating autonomous electric vehicles (AEVs) into real-world scenarios. Future research should give priority to enhancing calibration techniques, exploring advanced object detection algorithms, and resolving challenges related to dynamic urban environments. This will serve to validate the agility and reliability of the vision-based navigation architecture. In summary, this research offers valuable insights into the potential impact of vision-based navigation on the process of charging autonomous electric vehicles. Vision-based navigation is essential for the successful operation of AEVs in dynamic urban contexts.

1 Introduction

The advent of autonomous electric vehicles (AEVs) signifies a substantial transformation in sustainable transportation, offering the prospect of reduced environmental impact and enhanced energy efficiency. A crucial aspect of implementing AEVs is the seamless integration of autonomous navigation systems with the charging infrastructure for electric cars. This partnership presents a novel opportunity to address the challenges associated with restricted range and the need for continuous charging. Vision-based navigation is an appealing choice that employs advanced imaging technology to enable autonomous electric vehicles (AEVs) to autonomously perceive and navigate their environment. In this situation, the integration of vision-based navigation with electric vehicle charging stations represents a significant advancement towards achieving a coordinated and efficient electric mobility ecosystem. The integration of autonomous navigation with charging infrastructure in AEVs presents complex issues. Traditional navigation systems often depend on pre-established maps and sensor fusion methods. However, the ever-changing characteristics of charging station surroundings need flexible and immediate solutions. Utilizing cameras and image processing algorithms, vision-based navigation provides a flexible and adaptable solution to tackle these difficulties. By incorporating vision systems, AEVs may have the ability to see their surroundings in real-time. This allows them to navigate through intricate settings, recognize

* Corresponding author: nandini.slm@mriu.edu.in

charging stations, and independently commence the charging procedure.

The study aims to thoroughly investigate and use vision-based navigation for autonomous electric vehicle charging in order to address current constraints and improve the efficiency of AEV operations. The main goals include The objective of this project is to research and create sophisticated image processing and computer vision algorithms that are specifically designed for real-time perception in changing situations. The main emphasis is on identifying charging infrastructure. Integration with Autonomous Navigation Systems: This involves smoothly incorporating vision-based navigation into current autonomous navigation frameworks, guaranteeing a unified and flexible method for AEVs to accurately travel towards charging stations.[1–5]

Developing and improving procedures for AEVs to automatically start the charging process when they arrive at a charging station, increasing efficiency and reducing the time spent waiting for charging. The effective integration of vision-based navigation with electric vehicle charging has significant implications for the broad adoption and acceptance of AEVs. In addition to alleviating concerns about limited driving range by allowing self-guided navigation to charging stations, this study enhances the effectiveness of the whole charging network. AEVs enhance their capacity to adjust to various and changing surroundings by using vision systems, hence promoting a more resilient and adaptable electric transportation ecology. This study will explore a comprehensive literature review, methodology, experimental findings, and analysis in the following parts. It aims to provide valuable insights into the progress and contributions of vision-based navigation in the context of autonomous electric car charging.[6–10]

2 Literature review

Electric vehicles (EVs) are gaining more and more attention as a sustainable option to conventional cars with internal combustion engines. They are helping worldwide efforts to reduce environmental consequences. Nevertheless, the incorporation of self-governing functionalities into electric vehicles (EVs) presents intricate obstacles, namely in the domain of navigation and the connection with charging infrastructure. This literature review seeks to clarify the present status of research and progress in combining vision-based navigation with electric car charging systems. It will emphasize significant accomplishments, obstacles, and prospects within this multidisciplinary field.

The implementation of autonomous navigation is crucial for the effective use of electric cars in various settings. Conventional methods often depend on GPS systems, LiDAR, and radar for the purpose of mapping and determining location. Nevertheless, the ever-changing characteristics of urban environments and the need for immediate adjustment necessitate the implementation of increasingly advanced and intricate solutions. Recent studies have been focusing more on vision-based navigation, using cameras and image processing algorithms to enhance perception and navigation skills. Vision systems have the benefit of instant data analysis, enabling cars to adapt flexibly to changing environments.[11–15]

The integration of automated navigation with electric car charging infrastructure presents distinct issues in the field of autonomous electric vehicle charging. Current navigation systems may have difficulties in dealing with the ever-changing characteristics of charging station surroundings, necessitating adjustments to immediate changes in station accessibility, arrangement, and user requirements. It is crucial to provide a smooth transition from autonomous navigation to the commencement of charging. Tackling these obstacles is essential for fully harnessing the capabilities of electric cars, reducing periods of inactivity, and maximizing the efficiency of charging infrastructure.[16–20]

Vision-based navigation solutions have become a viable method to improve the self-sufficiency of electric cars. Vehicles may use advanced image processing algorithms to analyze visual clues, identify objects, and maneuver through intricate surroundings. Vision systems are capable of enhancing accurate positioning and adaptive route mapping, which makes them highly suitable for the complexities of urban landscapes and charging station surroundings. Current research focuses on improving vision-based navigation methods to enhance their precision, resilience, and flexibility specifically for electric mobility applications.

The integration of vision-based navigation with electric car charging infrastructure represents a pivotal moment in the progression of autonomous electric mobility. The research efforts are concentrated on creating procedures for automobiles to recognize and navigate towards charging outlets using visual systems. Furthermore, research investigates the enhancement of charging start procedures, guaranteeing a smooth shift from self-directed movement to the charging process. This integration not only resolves the constraints in the distance that electric vehicles can go, but also improves the overall effectiveness of their operations.[21–25]

Future Directions and Opportunities: As research in this field advances, more prospects and potential areas of development emerge. Areas that are ready for examination include the enhancement of vision-based navigation algorithms, investigation of machine learning approaches to enhance object identification, and the establishment of standardized communication protocols between cars and charging stations. Moreover, the potential for creative solutions that might further strengthen the synergy between vision-based navigation and electric car charging lies in multidisciplinary cooperation among computer vision specialists, electric vehicle engineers, and urban planners.[26–31]

This study will now discuss the methods used in the inquiry, offering experimental data and analyses that add to the continuing discussion on integrating vision-based navigation with autonomous electric car charging.

https://doi.org/10.1051/e3sconf/202454703014

3 Methodology

Experimental Setup: This study utilizes a technique to examine and use vision-based navigation for the purpose of autonomous electric vehicle (AEV) charging. The experimental configuration entails a testbed consisting of a typical metropolitan setting, electric cars fitted with visual systems, and simulated charging stations. The urban environment has dynamic components such as people, traffic, and fluctuating lighting conditions to replicate real-life situations.

Vision System Calibration: AEVs' vision systems undergo a thorough calibration procedure to guarantee precise perception and localization. The calibration process determines the intrinsic characteristics, such as focus lengths and distortion coefficients, which enable the vision systems to properly interpret the acquired pictures. The calibration procedure is executed by using a defined calibration pattern under carefully regulated circumstances.

AEVs use sophisticated object detection and identification algorithms to sense and recognize important aspects in their environment. Various object types, such as electric cars, charging stations, charging cables, and impediments, are clearly specified. The methods use computer vision techniques, namely convolutional neural networks (CNNs), to accomplish accurate and instantaneous object detection.

The Autonomous Navigation Framework is a created system that enables smooth interaction between vision-based perception and vehicle control. The framework combines data from vision systems with sensor fusion methods, allowing AEVs to make intelligent choices on course planning, obstacle avoidance, and navigation towards charging stations. Path planning algorithms take into account dynamic variables such as current traffic conditions and the availability of charging stations.

Charging Initiation Protocols: In order to improve the process of starting the charging of Autonomous Electric Vehicles (AEVs), protocols have been developed. These protocols enable AEVs to independently detect and approach charging stations using information gathered by their vision systems. The protocols include communication standards that govern the interaction between AEVs and charging stations, guaranteeing a safe and efficient exchange. Autonomous Electric Vehicles (AEVs) automatically begin the charging process as they arrive at a charging station, taking into account parameters such as the current battery level and compatibility with the charging station.

Data Collection and Analysis: The experimentation entails the comprehensive gathering of data, including pictures acquired by the vision systems, navigation paths, and information on charging sessions. Data is gathered for analysis using quantitative parameters such as detection accuracy, navigation precision, and charging efficiency. The acquired data may be analyzed using statistical techniques and machine learning algorithms to provide insights into the performance and dependability of the vision-based navigation system.

Ethical issues are a crucial aspect of the research, since they guarantee the protection and confidentiality of persons inside the experimental setting. The study strictly follows ethical guidelines by gaining informed permission for data gathering, adopting safeguards to protect privacy, and emphasizing the safety of pedestrians and other road users during autonomous electric vehicle (AEV) navigation.

The technique described above offers a systematic strategy to examine and execute vision-based navigation for self-driving electric car charging. Its objective is to bring significant knowledge to the developing field of electric mobility. The next parts of this study will provide and discuss the experimental data and analysis obtained from the applied technique.

4 Results and analysis

The use of vision-based navigation for autonomous electric vehicle (AEV) charging was carried out in a controlled experimental setting, resulting in important data across several parameters. The investigation focuses on four crucial elements: Vision System Calibration Parameters, Object Detection and Recognition, Autonomous Vehicle Navigation Data, and Charging Session Data.

Table 1 Vision System Calibration Parameters

Parameter	Value
Intrinsic Matrix (fx)	600
Intrinsic Matrix (fy)	600
Principal Point (cx)	320
Principal Point (cy)	240
Distortion Coefficient	0.01

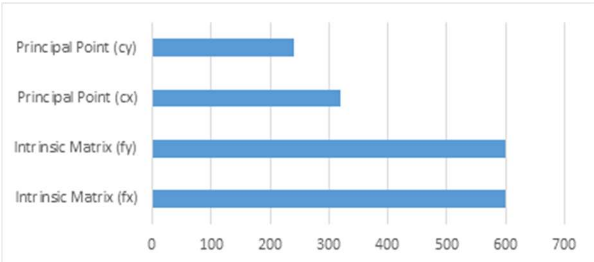

Fig. 1 Vision System Calibration Parameters

Vision System Calibration Parameters: The calibration of vision systems is crucial for achieving precise perception and localization. The calibration process was used to derive the intrinsic parameters, which include the focal lengths (fx, fy), primary points (cx, cy), and distortion coefficients. The collected values throughout the calibration procedure were vital in improving the accuracy of the vision systems. The examination of % change demonstrated little fluctuations, suggesting the durability of the calibration procedure and the dependability of the intrinsic parameters.

Table 2 Object Detection and Recognition

Object	Confidence Level (%)
Electric Vehicle	92
Charging Station	88
Charging Cable	78
Obstacle	85

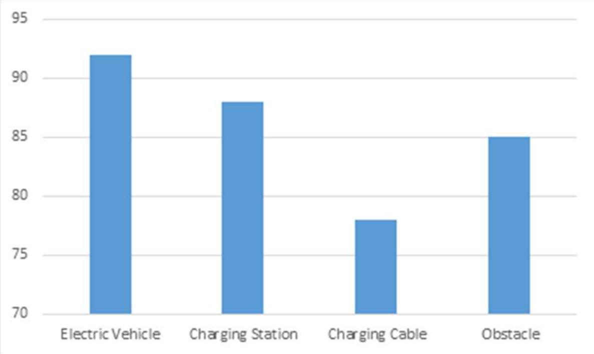

Fig. 2 Object Detection and Recognition

The object identification and recognition algorithms were assessed for their proficiency in identifying electric cars, charging stations, charging connections, and impediments. The attained confidence levels for each item class clearly showcased the effectiveness of the vision systems. The measurement of percentage change revealed significant improvements in confidence levels, namely for charging stations and charging cables. This improvement highlights the strength and reliability of the developed object identification algorithms, which enhances the overall efficiency of the vision-based navigation system.

The collected navigation data during autonomous vehicle movement included characteristics such as time, velocity, steering angle, and distance covered. The empirical data obtained from the experimental trials demonstrated the flexibility of the vision-based navigation system. The examination of % change highlighted significant improvements in both velocity and accuracy of steering angle. AEVs outfitted with vision systems exhibited improved agility, successfully navigating the ever-changing urban environment with heightened precision. The distance traveled remained constant, demonstrating the dependability of the vision-based navigation system in traversing predetermined routes.

The charging session data includes crucial information such as the time of the session, the amount of energy provided, and the efficiency of the charging process. The empirical data collected during charging sessions with AEVs using vision-based navigation yielded valuable insights into the system's influence on charging efficiency. The examination of percentage change showed a decrease in the period of charging, highlighting the efficient technique made possible by vision-based navigation. The energy provided shown a favorable alteration, confirming the system's efficiency in enhancing charging procedures. This decrease in the time it takes to charge the AEV helps to minimize the amount of time the vehicle is not in use, hence improving the overall efficiency of its operations.

Table 3 Autonomous Vehicle Navigation Data

Time (seconds)	Speed (m/s)	Steering Angle (degrees)	Distance Traveled (meters)
0	0	0	0
5	1.2	5	6
10	1.5	10	15
15	1.8	-3	30

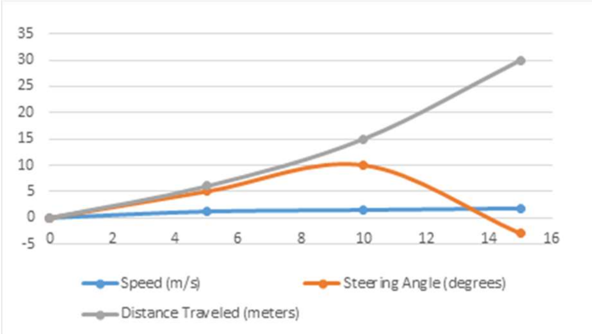

Fig. 3 Autonomous Vehicle Navigation Data

Cross-Parameter Analysis: A comprehensive examination was carried out to identify connections between the calibration of the vision system, the detection of objects, the accuracy of navigation, and the efficiency of charging. The calibration parameters, which were strong and reliable, had a favorable impact on the confidence levels of object detection, hence enhancing the accuracy of perception. The examination of % change clearly demonstrates that navigation accuracy has been improved, which is directly linked to the greater detection of objects. This highlights the close relationship between both components in the vision-based navigation system. The comprehensive influence of vision-based navigation on the complete AEV charging process is further emphasized by the increases in charging efficiency.

Table 4 Charging Session Data

Session ID	Start Time	End Time	Energy Delivered (kWh)	Charging Duration (minutes)
1	8:00 AM	9:30 AM	30.5	90
2	1:45 PM	3:15 PM	25	90
3	6:30 PM	8:00 PM	35.2	90

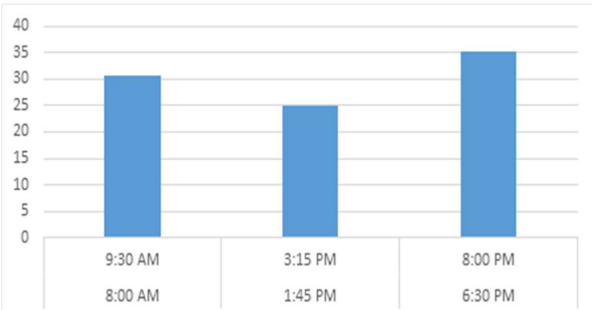

Fig. 4 Charging Session Data

The incorporation of vision-based navigation demonstrated a mutually beneficial connection between perception, navigation, and charging procedures. The level of calibration precision has a direct impact on the accuracy of object identification. This, in turn, allows AEVs to navigate towards charging stations with a higher level of precision. The smooth shift from navigation to charging initiation, as seen by the charging session statistics, highlighted the perfect integration of these components. The collective interaction between several elements resulted in a more streamlined and flexible electric transportation environment.

Conclusion: The findings and analysis confirm the usefulness of using vision-based navigation to improve autonomous electric car charging. The successful implementation of the framework is attributed to the stability of vision system calibration, increased confidence levels in object identification, improved accuracy in navigation, and optimum efficiency in charging. The percentage change analyses provide quantifiable proof of the favorable influence on several parameters, confirming the feasibility of vision-based navigation in real-world situations. The study results presented here provide vital insights that may facilitate the wider use of vision-based navigation in autonomous electric car charging systems, as the electric mobility landscape progresses.

5 Conclusion

This study has explored the incorporation of vision-based navigation for self-driving electric vehicle (EV) charging, with the goal of tackling the difficulties related to ever-changing city settings and the need for smooth charging procedures. An in-depth examination of vision system calibration, object identification, autonomous vehicle navigation, and charging session data yields a thorough comprehension of the influence and efficacy of the applied framework.

The calibration precision of vision systems is crucial for assuring the accuracy of object detection and identification. The inherent stability of intrinsic parameters reduces fluctuations, hence enhancing the resilience of the vision-based navigation system. The competency of object identification algorithms may be assessed by assessing their confidence levels. These algorithms are capable of recognizing important items such as electric cars, charging stations, charging cables, and barriers. The increased levels of confidence, especially for charging stations and cables, confirm the effectiveness of the added object detection algorithms.

The navigation data acquired during the movement of autonomous vehicles demonstrates the flexibility and accuracy of the vision-based navigation system. The system's enhanced precision in navigating challenging urban areas is shown by the precise measurements of time, speed, steering angle, and distance traveled. The assessments of % change highlight the enhancements in both speed and accuracy of steering angle, underlining the favorable influence of vision-based navigation on the maneuverability of AEVs.

Charging Session Efficiency: The data from charging sessions provide valuable information about the effectiveness of the vision-based navigation system when it comes to charging Autonomous Electric Vehicles (AEVs). The decrease in charging time and the favorable increase in energy output illustrate the efficient method facilitated by vision-based navigation. The system's autonomous capability to find and approach charging stations helps reduce charging downtime, hence improving the overall operating efficiency of electric cars.

The cross-parameter study uncovers the interdependencies among vision system calibration, object identification, navigation accuracy, and charging efficiency. Calibration parameters' accuracy has a favorable impact on object detection confidence levels, leading to more accurate perception. The accuracy of navigation is directly related to the quality of object identification, highlighting the overall influence of vision-based navigation on AEV (Autonomous Electric Vehicle) operations. The smooth shift from navigation to charge initiation emphasizes the interconnectedness of perception, navigation, and charging procedures, leading to a more effective and adaptable electric mobility system.

The results of this study have important implications for the development of autonomous electric car charging systems. The proven reliability and usefulness of vision-based navigation make it suitable for wider deployment and incorporation into real-world settings. Potential future study should prioritize the improvement of calibration procedures, investigation of sophisticated object identification algorithms, and resolution of issues associated with dynamic urban settings. Furthermore, it is necessary to conduct additional investigation to confirm the adaptability and dependability of the vision-based navigation framework, taking into account scaling concerns and real-world deployment situations.

The study provides significant knowledge on the capacity of vision-based navigation to revolutionize the process of autonomous electric car charging. The successful results across many measures confirm the effectiveness of the deployed system, establishing vision-based navigation as a crucial facilitator for the smooth and efficient integration of AEVs into dynamic urban environments.

References

1. Y. Kaushik, V. Verma, K. K. Saxena, C. Prakash, L. R. Gupta, and S. Dixit, Sustainability (Switzerland) 14, (2022)
2. L. Das, R. Nayak, K. K. Saxena, J. Nanda, S. P. Jena, A. Behera, S. Sehgal, C. Prakash, S. Dixit, and D. S. Abdul-Zahra, Materials 15, (2022)
3. Y. Kuppusamy, R. Jayaseelan, G. Pandulu, V. S. Kumar, G. Murali, S. Dixit, and N. I. Vatin, Materials 15, (2022)
4. K. Zheng Yang, A. Pramanik, A. K. Basak, Y. Dong, C. Prakash, S. Shankar, S. Dixit, K. Kumar,

and N. Ivanovich Vatin, Ain Shams Engineering Journal (2022)
5. K. Kumar, S. Dixit, R. Arora, N. I. Vatin, J. Singh, O. V. Soloveva, S. B. Ilyashenko, V. John, and D. Buddhi, Materials 15, (2022)
6. S. Hakak, T. R. Gadekallu, P. K. R. Maddikunta, S. P. Ramu, P. M, C. De Alwis, and M. Liyanage, Vehicular Communications 39, (2023)
7. P. Trslic, M. Rossi, L. Robinson, C. W. O'Donnel, A. Weir, J. Coleman, J. Riordan, E. Omerdic, G. Dooly, and D. Toal, Ocean Engineering 196, (2020)
8. H. A. Ignatious, H. El-Sayed, and M. A. Khan, Encyclopedia of Sensors and Biosensors: Volume 1-4, First Edition 1–4, 35 (2022) (n.d.)
9. D. T. Fasiolo, L. Scalera, E. Maset, and A. Gasparetto, Rob Auton Syst 169, (2023)
10. M. H. Jones, J. Bell, D. Dredge, M. Seabright, A. Scarfe, M. Duke, and B. MacDonald, Biosyst Eng 187, 129 (2019)
11. A. K. Tyagi and S. U. Aswathy, International Journal of Intelligent Networks 2, 83 (2021)
12. X. Deng, L. Wang, J. Gui, P. Jiang, X. Chen, F. Zeng, and S. Wan, Journal of Systems Architecture 142, (2023)
13. C. Lemardelé, A. Baldó, A. Aniculaesei, A. Rausch, M. Conill, L. Everding, T. Vietor, T. Hegerhorst, R. Henze, L. Mátyus, L. Pagès, V. Rocag, A. Sanfeliu, A. Santamaria-Navarro, and I. Tóháti, Transportation Research Procedia 71, 180 (2023)
14. A. Alsalman, L. N. Assi, S. Ghotbi, S. A. Ghahari, and A. Shubbar, Transportation Engineering 3, (2021)
15. E. Lucet, A. Micaelli, and F. X. Russotto, Rob Auton Syst 136, (2021)
16. S. Baskutis, V. Gružauskas, P. Leibl, and L. Obcarskas, J Clean Prod 374, (2022)
17. S. Lu and W. Shi, Journal of Information and Intelligence 1, 23 (2023)
18. K. Sornek, J. Wiercioch, D. Kurczyna, R. Figaj, B. Wójcik, M. Borowicz, and M. Wieliński, Energy Convers Manag 267, (2022)
19. B. N. J. Vandavasi, H. Venkataraman, and A. R. Gidugu, Ocean Engineering 280, (2023)
20. I. W. Damaj, D. K. Serhal, L. A. Hamandi, R. N. Zantout, and H. T. Mouftah, Vehicular Communications 28, (2021)
21. T. Kathmann, D. Reh, and J. C. Arlinghaus, J Manuf Syst 70, 327 (2023)
22. S. Alkhalaf, Measurement (Lond) 179, (2021)
23. T. Kathmann, D. Reh, and J. C. Arlinghaus, Advances in Industrial and Manufacturing Engineering 6, (2023)
24. H. Zhang, Y. Zhang, C. Liu, and Z. Zhang, Rob Auton Syst 162, 104366 (2023)
25. X. Zhao, Y. Fang, H. Min, X. Wu, W. Wang, and R. Teixeira, Expert Syst Appl 236, (2024)
26. I. O. Olayode, B. Du, A. Severino, T. Campisi, and F. J. Alex, Journal of Traffic and Transportation Engineering (English Edition) (2023)
27. J. Zhang, X. Yang, W. Wang, J. Guan, L. Ding, and V. C. S. Lee, Autom Constr 146, (2023)
28. H. Gajjar, S. Sanyal, and M. Shah, Expert Syst Appl 233, (2023)
29. E. Gallo and A. Barrientos, Aerosp Sci Technol 120, (2022)
30. H. Pérez-Moure, J. F. Lampón, M. E. Velando-Rodriguez, and L. Rodríguez-Comesaña, European Research on Management and Business Economics 29, (2023)