Emerging Cutting-Edge Applied Research and Development in Intelligent Traffic and Transportation Systems, M. Shafik (Ed.)

doi:10.3233/ATDE241194

Application of Physics-Informed Deep Learning in Solving Safety-Related Road Transportation Problems - A Review

Md. Shohel PARVEZ[a] and Sara MORIDPOUR[a,1]
[a] *Civil and Infrastructure Engineering Department, School of Engineering, RMIT University, Melbourne, VIC 3000, Australia.*

Abstract. The goal is to bring together an in-depth analysis of physics-based deep learning approaches in transportation domains and classify them according to their applicability. To carry out the systematic literature search, a Preferred Reporting Items for Systematic Reviews and Meta-Analysis flowchart is used with certain inclusion and exclusion criteria. Different keyword searches are carried out in the Scopus and Web of Science databases, followed by relevant references and citation analyses to find eligible papers subject to a full-text peer review. Finally, the classification and analysis of these papers take place based on their applicability. 141 and 39 records were found by the initial database search and referencing and citation analysis respectively. A total of 65 documents were selected to carry out full-text reviews, and finally, 35 documents were included in the study. Based on the applications of physics-informed deep learning in transportation engineering, the authors classified the literature into three major categories: 1) safety assessment and safety analysis, 2) model preparation, and 3) prediction and estimation. Finally, this research also provides the challenges and future directions in this emerging field.

Keywords. Physics-informed, Deep Learning, Transportation, Safety, Model

1. Introduction

Traffic accidents are a major cause of death and serious injury around the world, negatively impacting the lives of citizens, the government, and the economy. There are nearly 1.35 million fatalities and disability resulting from traffic accidents each year, with an average of 3,700 fatalities occurring daily [1]. Moreover, about 40,000 people lost their lives in a traffic accident in 2020, and 2.1 million were admitted to emergency rooms because of traffic accidents in the U.S., resulting in an estimated $430 billion in total medical expenses, quality of life, and loss of life [2]. According to the World Health Organisation (WHO), road traffic fatalities account for about 3% of the Gross Domestic Product (GDP) in most countries [3]. Despite the financial losses and the potential for death or injury, there is still a lack of action to address this problem. In addition, due to economic growth, the number of people using motor vehicles has increased worldwide. However, the increased number of motor vehicles requires more roads and a higher demand for better measures of road safety, protection, and standards. Therefore, all these

[1] Sara Moridpour, Civil and Infrastructure Engineering Department, School of Engineering, RMIT University, Melbourne, VIC 3000, Australia, Phone: +61 3 9925 2407; E-mail: sara.moridpour@rmit.edu.au

imperatives highlight the risk mitigation and safety promotion efforts that must be disseminated globally.

Transportation technology has advanced rapidly in the last few decades. New opportunities for monitoring driver behaviour, vehicle communication, vehicle surveillance, and incident detection in transportation are presented by different technologies used by drivers (e.g., smartphones) and the usage of advanced sensor devices (e.g., smartphones, cameras). The widespread adoption of these technologies is due to the numerous benefits they offer. This brings us to the era of Big Data (BD), where huge amounts of data from multiple sources are being collected, processed, and stored [4]. For instance, the number of connected vehicles is growing at an accelerating rate and it was estimated that by 2020, one-fifth of all vehicles on the road will have an Internet connection and that the total volume of vehicles on the road worldwide will reach 300,000 Exabytes [5]. In addition, several studies have shown that these BD collection systems are effective and useful for safety assessment [6, 7].

However, the exploitation and management of large amounts of data is one of the biggest challenges of this new era. To extract valuable information, data must be thoroughly analysed. However, managing and analysing this data would appear chaotic if Artificial Intelligence (AI) was not available [4]. AI enables data analytics to be done efficiently, and this is the main reason AI is now attached to BD [8]. AI and Deep Learning (DL) can extract all data inputs and use them to develop new rules for analytics in the future. The 'AI machine' is fed with BD to transform it into an intelligent process. Therefore, it is possible now to reap vast benefits of BD in many areas through the application of AI techniques such as Natural Language Processing (NLP), Pattern Recognition (PR), and Machine Learning (ML) algorithms [9].

Transport systems involve many components and numerous stakeholders, each of which has its own set of objectives that differ widely from one another. When it comes to transportation safety challenges, the emphasis is on traffic crash monitoring and assessment, crash modelling, crash detection and prevention, traffic crash frequency analysis, crash severity mitigation, obstacle detection, driver or operator behaviour identification, human factors, etc., to reduce accidents among transportation users [10]. For this purpose, processing all data that can potentially be collected and deriving valuable insights is important. Therefore, to address above-mentioned problems and improve the efficiency and safety of transport systems, several applications of AI have emerged over time. In recent decades, as we move into an era of significantly higher computational power than the previous decades, interest in ML and AI has increased among researchers and practitioners in the field of transportation [11]. Most areas of transportation use AI, but there is still a lack of knowledge exchange in various cases. For example, despite their impressive empirical results and some initial successes, most ML techniques are currently unable to extract meaningful knowledge and information from this huge volume of data [12]. In addition, data-based models may be highly consistent with observations, but predictions may be physically contradictory or inconsistent because of extrapolation or observational bias that may result in poor generalisation performance [13]. For this reason, there is an urgent need to integrate basic physical laws and domain understanding by 'training' ML models on governing physical rules that can provide strong theoretical limits and inductive biases on top of observational constraints. Therefore, it is necessary to engage in a process of physics-informed learning by which prior knowledge deriving from our observations, empirical data, physical data, or mathematical knowledge can be used to enhance a learning algorithm's performance.

Many engineering areas like earth systems, climate science, turbulence modeling, material discovery, quantum chemistry, biological sciences, hydrology, etc., can benefit from advances in physics-based deep learning [13]. Especially, in transportation engineering, physics-informed deep learning is useful to practitioners and has been widely adopted in projects dealing with object detection, autonomous driving, or system condition estimations [14-17]. However, it is crucial to undertake a comprehensive analysis of the physics-informed deep learning techniques employed in transportation engineering. Some reviews have provided a partial overview of physics-informed deep-learning techniques utilised in different areas of engineering and science [18-20]. According to the literature, there is currently no review that systematically categorises the extensive application range of physics-informed deep learning techniques. Therefore, this paper aims to present a series of research papers on the latest developments in this emerging field and discuss the issues and future directions we, as the research community, need to focus on to make the most of the advanced physics-based deep-learning technologies for transportation engineering applications.

To achieve this objective, this review serves as a valuable addition to the current literature, providing a full review and understanding of physics-informed deep-learning techniques in studies involving the areas of transportation engineering. In doing so, this contribution expands upon existing literature in various aspects. Firstly, this paper proposes a novel classification system that can be employed to categorise the applications of physics-informed deep learning techniques employed in transportation areas. Secondly, this paper provides an in-depth analysis of physics-informed deep learning studies, particularly employed in transportation areas. Finally, it deliberates on the advantages and disadvantages of physics-informed deep learning technologies in transportation areas and offers future potential applications in transportation areas.

The paper follows this structure. Section 2 outlines the review methodology and introduces the taxonomy employed for literature classification. Section 3 presents the literature review results focused on the applications of physics-informed deep learning technologies in transportation engineering. Section 4 provides a comprehensive analysis and discussion of the identified literature. Finally, the conclusion section specifies potential future applications of physics-informed deep learning technologies in transportation areas.

2. Methodology

To carry out the systematic literature search, the authors employed Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) [21]. The authors set some inclusion criteria for a study in this review, such as the authors' consideration of peer-reviewed journals, conference proceedings, or dissertations; the study was written in English, was not an extended publication, and was not published before the year 2020. In addition, the search was limited to areas of transportation science and technology consistent with the objectives of this review. From two databases, including the Web of Science and Scopus, the final literature search was carried out on 31 January 2024. The authors chose these two databases because of their large amount of scientific data and relevant journals [22]. They also contain valuable information from a variety of sources, including journal articles, books, series of books, reports, conference papers, and editorials [23]. During the database search, the authors used a limited set of keywords, which were specifically employed in the title, abstract, and keywords. Therefore, “physics-informed”, “physics-guided”, “physics-aware”, “physics-integrated”, “physics-based”, “physics-constrained”, “deep learning”, “artificial intelligence”, “neural network”, “traffic safety”, “road safety”, “transportation”, “road user safety”, were the keywords used to search the literature. Furthermore, some records have been added based on relevant references and citation analysis. To select a record: first, the authors looked at the data from the study and focused on factors like publication date, type, and former version; second, the authors examined each paper's title and abstracts to analyse its contents. The selected papers were reviewed to confirm that the paper uses machine learning and governing physical equations in the field of transportation. In addition, the studies had to be in English as a requirement. Only a study that met all the above-mentioned inclusion criteria was considered for inclusion. However, the categorisation of the studies to be analysed is a key issue in this review paper. To achieve this objective, the authors divided the collected studies into three main groups, based on the application areas of transportation, such as safety assessment and safety analysis, model preparation, and prediction and estimation.

3. Results

141 and 39 records were found by the initial database search and referencing and citation analysis; as a result, the authors found a total of 180 records with duplicate entries after the preliminary search. To screen the records received, the authors used exclusion criteria derived from the scope review methodology to eliminate duplicate records. In the first phase, all retrieved records were subject to a title screening to identify and remove records that did not meet the study goals. In the second phase, abstracts were carefully examined based on inclusion/exclusion criteria. As a result, the remaining 65 articles were examined to confirm their eligibility. The rest of the articles were subject to an in-depth review of the complete articles to ensure eligibility. To calculate the exact number of articles, the authors carefully analysed the articles by considering the year of publication (last five years), the language format, the type of document, and the design criteria of the study. Between 2020 and 2024, 35 articles have been found, each employing physics-guided artificial intelligence in transportation areas. To explain the methodology used in this study, Figure 1 provides a PRISMA flowchart.

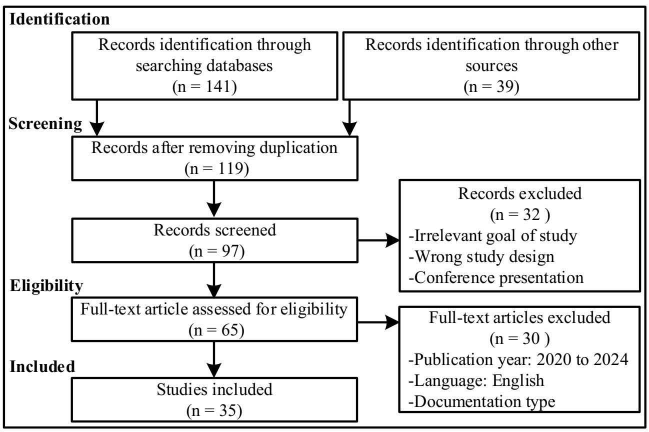

Figure 1. Employed methodology in this study.

4. Discussion

The goal of this research is to identify and explore the literature on applications of physics-based deep learning in the transportation field. During the investigation, various applications related to physics-informed deep learning were revealed, showing their evolutionary path toward increasing complexity over time. The authors found different types of applications for physics-informed deep learning in transportation areas. However, the authors divided the obtained literature into three major categories, including safety assessment and safety analysis, model preparation, and prediction and estimation. For the category of safety assessment and safety analysis, the authors discuss all aspects related to safety analysis and safety assessment such as crash risk and severity analysis, estimating traffic variables, driver behaviour assessment, and safety-related performance analysis and safety assessment. For model preparation, the authors discuss all literature related to different model preparations by using physics-informed deep learning. Finally, for prediction and estimation, the authors discuss all literature related to estimating or predicting different aspects of transportation areas like traffic flow, traffic state, vehicle trajectory, etc., by using a physics-informed deep learning technique.

4.1. Literature Related to Safety Analysis and Safety Assessment

One study used the Physics of electromagnetic fields to determine the risk and severity of crashes by modelling the safety-aware interactions of various road users by analysing traffic movement videos through artificial intelligence [24]. A further study proposed a physics-based deep reinforcement learning model that leverages physics-based knowledge and the equilibrium and consensus principles of control theory to regulate the 2D car-following performance of connected automated vehicles both in terms of stability-related longitudinal control performance and in terms of precise lateral track-tracking performance [25]. In another study, an adaptive physics-based trajectory reconstruction framework was proposed that identifies the optimal filtering magnitude, minimizes local acceleration variance in stable conditions, and is compatible with realistic vehicle acceleration dynamics and typical driver behaviour [26]. To enhance the safety of adaptive cruise control vehicles, Machine Learning and physical knowledge were used to automatically determine the optimal longitudinal distance from ego- to leading-vehicle for a safer solution [27]. Moreover, PIAug, a physics-based data augmentation method, was introduced to illustrate the use case of PIAug by modelling high-speed, aggressive motion predictions on a low-speed dataset [28]. In addition, a research paper introduced a physics-driven distributed longitudinal control strategy based on deep reinforcement learning under communication failure to stabilise traffic oscillations for connected and automated vehicles [29]. In another study, a physics-based machine learning framework was developed to identify and estimate traffic flow from small-scale observations made by probe vehicles [16]. In another paper, they introduced a new approach based on deep learning using physics to quickly identify vehicle cornering a key parameter in the vehicle stability control model and control algorithms called stiffness coefficient [30]. TrafficFlowGAN, a physics-related flow based generative adversarial network, was used to quantify the uncertainty of dynamic systems using partially observed data to estimate traffic variables such as traffic density and velocity [31].

4.2. Literature Related to Model Preparation

A quantile-regression car-following model was designed by combining the principles of physics with stochasticity and deep learning to fully capture the genuine regularities of car-following behaviours [17]. In addition, another paper re-introduced vehicle-related inputs such as velocity to enhance the precision based on previous models by combining the idea of the fusion model with the concept of physics-based deep learning to develop a new model with higher precision [32]. Furthermore, PICGAN (physics-informed conditional generative adversarial network) was developed to improve multi-step car-following models in mixed traffic flow conditions to leverage the power of physics and deep learning [33]. In another study, they combined the traditional traffic flow model and the machine learning approach to develop and test a new model called physics-guided machine learning using the neural network framework [14]. DoubleGAN, a physics-informed deep learning model, was proposed to embed stochastic properties into a deep learning structure based on physics to capture the uncertainty from the vehicle trajectory data and introduce a stochastic car following model to provide the generator with previous physics data [34]. Another study developed a neural network-based car-following model based on physics-based models that combine the benefits of physics-based models (data-efficient and easy to interpret) with deep learning-based models (being generalizable) [35].

4.3. Literature Related to Prediction and Estimation

One study suggested a physics-informed multi-step real-time conflict-based model for vehicle safety prediction by combining physics (e.g. traffic shockwave property) and data-driven properties extracted from deep learning techniques to enhance road safety and prediction performance [36]. One thesis introduced a physics-based deep learning model for traffic state prediction by embedding deep learning neural networks with the power of the underlying physical laws of traffic flow to improve traffic condition predictions based on partial and limited sensing measurements [37]. In addition, STDEN is a physics-based deep learning model, also known as Spatio-Temporal Differential Equation Network, proposed in another study that integrates the physical dynamics of traffic flow into the framework of deep neural networks [38]. In addition, a recent study proposed a new hybrid traffic state estimation methodology called Observer-Informed Deep Learning, which combines an observer using a Partial Differential Equation and a deep learning paradigm to predict spatial and temporal traffic states using boundary sensing data [39]. A further study provided an overview of the architecture design of physics-based deep learning computational graph models and how these models are optimised for traffic state prediction [40]. In that study, by looking at the data, problem types, and goals as they changed, the authors showed possible architectures for physics-based deep learning graph models and compared them using the same data set from the real world. In another study, a physics-aware learning-based trajectory prediction model for congested traffic was proposed based on the capture of shockwaves in an interconnected vehicle environment [41]. Combining physics-driven and data-driven models, a new Social Force- constrained Gated Recurrence Unit model was designed to predict vehicle trajectory [15]. That model is derived from the Gated Recurrent Unit Encoder–Decoder framework and includes social force limitations to improve and complement the model input derived from vehicle time series trajectory data that describes driving and interactive vehicle behaviour while driving as well as interactions between adjacent vehicles and the environment. In addition, the transformer neural network with self-awareness as physics-uninformed neural network and intelligent driver model as physical model were used to develop the physics-informed transformer-intelligent driver model as a Physics-Informed Deep Learning framework to predict vehicle trajectory [42]. As an integrated framework, a non-linear programming model was developed to predict the physics-based joint traffic status and queue profile using traffic flow models and observations from the corridor level and local segment level using heterogeneous data sources [43]. In another study, a physics-based deep learning framework was introduced to combine second order traffic flow models with neural networks to solve traffic state estimation problems, which encoded traffic flow models into deep neural networks to standardise the learning process for improved data throughput and estimation accuracy [44]. In addition, a paper introduced a physics-based deep learning framework that incorporates data-driven and model-driven elements to perform efficient highway traffic state estimates with obtained data from loop detectors utilising traffic density as traffic variables [45]. In another study, a traffic state estimation model was proposed combining the computational graph and physics-based deep learning techniques [46]. In that study, the authors used the computational graph approach to achieve the traffic fundamental diagram parameters. Then, they used the physics-based deep learning approach to determine accurate traffic state estimates. In addition, a traffic flow theory and a deep learning neural network were used to develop a physics-informed deep learning technique to solve the problem of data sparseness and sensor noise in traffic state estimation [47, 48]. Similarly, another paper incorporated data-driven and model-driven components to introduce a physics information-based neural network framework to merge the benefits of both methods and to overcome their weaknesses that can utilise speed data to determine traffic state estimations for a traffic network [49]. By using spatiotemporal graph convolution neural network and traffic flow models and maintaining the law of traffic flow, a study proposed a framework named PSTGCN (physics-informed spatiotemporal graph convolution neural network) based on physics-informed deep learning theories to estimate the traffic state [50]. Another study looked at the performance of a physics-informed neural network strategy for traffic state prediction and model parameter identification under real-world conditions by applying a first-order macro-scale traffic flow model with two physical parameters: traffic density and traffic flow [51]. Another paper introduced a better paradigm by combining model-driven components with data-driven components called physics-based deep learning with a fundamental diagram learner, which incorporates machine learning terms into model-driven components to learn a functional version of a fundamental diagram, for example, a map from traffic density to traffic flow or velocity [52]. In addition, a recent study proposed a way to combine Eulerian observations with Lagrangian observations using physics-based deep learning that leverages the Lighthill-Whitham-Richards model and two basic traffic diagrams to predict traffic states at observations-free locations, particularly to estimate traffic density [53].

4.4. Challenges and Future Applications

Although there are many benefits to using physics-informed deep learning in transportation applications, this approach has limitations and challenges. Recently, one study presented the limitations and challenges in training physics-informed deep learning architecture of traffic flow models [54]. In addition, the availability of data is a fundamental premise of physics-based deep learning. The era of Big Data (BD) has resulted in more data being available, but that data may not be up-to-date and may be irrelevant or in new formats [18]. However, this new data might not be usable in its current form or generate noisy datasets that are hard to work with in training programs while applying PIDL techniques. In addition, these new sources of information must be verified. Finally, the increase in data can also provide data sources that are highly complex or highly variable in format and type. Variable data can be extremely challenging to process and format, resulting in slow processing times and poor user experience. Furthermore, PIDL model selection is the process of selecting one final model from a set of candidate models (i.e., Gaussian model or neural networks) and different strategies (i.e. physics-based loss function, hybrid model, or architecture) to solve any predictive modelling problem. The model complexity, efficiency, performance, and available resource properties must be considered during model selection. Although the model selection is well-developed and well-investigated in PIDL, there still needs to be general model selection guidelines [55]. Recent PIDL studies raise another potential problem in identifying the appropriate weights. When several equations are included in the model's loss function, the weights of each physical penalty term for each equation are typically pre-defined by the user, triggering the learning process in PIDL models. There is no general approach to the determination of the right weight to estimate a model parameter, and its value is subject to difficulty.

To accelerate the development of PIDL, further research is needed to develop new adaptive sampling strategies. Furthermore, labelling is expensive and may require domain-specific expertise in several transport applications. As a result, a new avenue of research and practical applications is opened by developing hybrid models that learn with fewer labels. In selecting models, it is necessary to establish a well-defined set of guidelines on selecting PIML models concerning various model types and integration strategies to enhance their performance and extend their scope of use. In addition, there is a need for further attention to the strategy of tuning and optimizing model parameters for setting the right weight.

5. Conclusion

This paper presented a literature review of physical-informed deep learning techniques for applications in transportation areas. The study also categorises the reviewed articles according to their similarity and application area. Moreover, the challenges of applying physics-informed deep learning methods to address practical transportation problems and future research needs have also been discussed. To exploit the full potential of advanced physics-informed deep learning techniques for applications in transportation, the authors intend to compile a collection of research articles presenting the latest developments in this emerging field and to provide an overview of the challenges and future directions to be pursued by the research community.

Limitations

One of the main areas of improvement was that some of the full texts, databases, and grey literature were missing from the review. Furthermore, only the English language studies were included. Critical non-English language studies may, therefore, be excluded from the scope of the study.

References

[1] W.H.O., Global status report on road safety 2018. https://www.who.int/publications/i/item/9789241565684, 2018.
[2] Control, C.f.D. and Prevention, Transportation safety. Availableat: https://www. cdc. gov/transportationsafety/index. html, 2023.
[3] W.H.O., Road Traffic Injuries. https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries, 2022.
[4] Tselentis, D.I., E. Papadimitriou, and P. van Gelder, The usefulness of artificial intelligence for safety assessment of different transport modes. Accident Analysis & Prevention, 2023. 186: p. 107034.
[5] Xu, W., et al., Internet of vehicles in big data era. IEEE/CAA Journal of Automatica Sinica, 2017. 5(1): p. 19-35.
[6] Theofilatos, A., et al. Willingness-to-Pay for Usage-Based Motor Insurance. in Transportation Research Board 96th Annual Meeting (January 8-12, 2017) Washington, DC. 2017.
[7] Tselentis, D.I., G. Yannis, and E.I. Vlahogianni, Innovative motor insurance schemes: A review of current practices and emerging challenges. Accident Analysis & Prevention, 2017. 98: p. 139-148.
[8] Kibria, M.G., et al., Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks. IEEE access, 2018. 6: p. 32328-32338.
[9] Xu, X., et al., Artificial intelligence for edge service optimization in internet of vehicles: A survey. Tsinghua Science and Technology, 2021. 27(2): p. 270-287.
[10] Machin, M., et al. On the use of artificial intelligence techniques in intelligent transportation systems. in 2018 IEEE wireless communications and networking conference workshops (WCNCW). 2018. IEEE.
[11] Abduljabbar, R., et al., Applications of artificial intelligence in transport: An overview. Sustainability, 2019. 11(1): p. 189.
[12] Iten, R., et al., Discovering physical concepts with neural networks. Physical review letters, 2020. 124(1): p. 010508.
[13] Karniadakis, G.E., et al., Physics-informed machine learning. Nature Reviews Physics, 2021. 3(6): p. 422-440.
[14] Zhang, Z., et al., Empirical study of the effects of physics-guided machine learning on freeway traffic flow modelling: model comparisons using field data. Transportmetrica A: Transport Science, 2023: p. 1-28.
[15] Li, H., et al., A physical law constrained deep learning model for vehicle trajectory prediction. IEEE Internet of Things Journal, 2023.
[16] Barreau, M., et al. Physics-informed learning for identification and state reconstruction of traffic density. in 2021 60th IEEE Conference on Decision and Control (CDC). 2021. IEEE.
[17] Liu, J., et al., A quantile-regression physics-informed deep learning for car-following model. Transportation research part C: emerging technologies, 2023. 154: p. 104275.
[18] Xu, Y., et al., Physics-informed machine learning for reliability and systems safety applications: State of the art and challenges. Reliability Engineering & System Safety, 2023. 230: p. 108900.
[19] Sharma, P., et al., A Review of Physics-Informed Machine Learning in Fluid Mechanics. Energies, 2023. 16(5): p. 2343.
[20] Huang, B. and J. Wang, Applications of physics-informed neural networks in power systems-a review. IEEE Transactions on Power Systems, 2022. 38(1): p. 572-588.
[21] Mulrow, C.D., Systematic reviews: rationale for systematic reviews. Bmj, 1994. 309(6954): p. 597-599.
[22] Li, J. and A. Hale, Output distributions and topic maps of safety related journals. Safety science, 2016. 82: p. 236-244.
[23] Chadegani, A.A., et al., A comparison between two main academic literature collections: Web of Science and Scopus databases. arXiv preprint arXiv:1305.0377, 2013.
[24] Arun, A., et al., A physics-informed road user safety field theory for traffic safety assessments applying artificial intelligence-based video analytics. Analytic methods in accident research, 2023. 37: p. 100252.
[25] Shi, H., et al., Physics-informed deep reinforcement learning-based integrated two-dimensional car-following control strategy for connected automated vehicles. Knowledge-Based Systems, 2023. 269: p. 110485.
[26] Makridis, M.A. and A. Kouvelas, Adaptive physics-informed trajectory reconstruction exploiting driver behavior and car dynamics. Scientific reports, 2023. 13(1): p. 1121.
[27] Jurj, S.L., et al., Increasing the safety of adaptive cruise control using physics-guided reinforcement learning. Energies, 2021. 14(22): p. 7572.
[28] Maheshwari, P., et al., PIAug--Physics Informed Augmentation for Learning Vehicle Dynamics for Off-Road Navigation. arXiv preprint arXiv:2311.00815, 2023.
[29] Shi, H., Mixed Platoon Control Strategy of Connected and Automated Vehicles Based on Physics-Informed Deep Reinforcement Learning. 2023, The University of Wisconsin-Madison.

[30] Koysuren, K., A.F. Keles, and M. Cakmakci. Online Parameter Estimation using Physics-Informed Deep Learning for Vehicle Stability Algorithms. in 2023 American Control Conference (ACC). 2023. IEEE.
[31] Mo, Z., et al. Trafficflowgan: Physics-informed flow based generative adversarial network for uncertainty quantification. in Joint European Conference on Machine Learning and Knowledge Discovery in Databases. 2022. Springer.
[32] Xu, L., J. Ma, and Y. Wang, A Car-Following Model considering the Effect of Following Vehicles under the Framework of Physics-Informed Deep Learning. Journal of Advanced Transportation, 2022. 2022.
[33] Ma, L., et al., A physics-informed generative car-following model for connected autonomous vehicles. Entropy, 2023. 25(7): p. 1050.
[34] Mo, Z. and X. Di. Uncertainty quantification of car-following behaviors: physics-informed generative adversarial networks. in the 28th ACM SIGKDD in conjunction with the 11th International Workshop on Urban Computing (UrbComp2022). 2022.
[35] Mo, Z., R. Shi, and X. Di, A physics-informed deep learning paradigm for car-following models. Transportation research part C: emerging technologies, 2021. 130: p. 103240.
[36] Yao, H., Q. Li, and J. Leng, Physics-informed multi-step real-time conflict-based vehicle safety prediction. Accident Analysis & Prevention, 2023. 182: p. 106965.
[37] HUANG, A.J., Developing A Physics-informed Deep Learning Paradigm for Traffic State Estimation. 2023, University of Central Florida Orlando, Florida.
[38] Ji, J., et al. STDEN: Towards physics-guided neural networks for traffic flow prediction. in Proceedings of the AAAI Conference on Artificial Intelligence. 2022.
[39] Zhao, C. and H. Yu, Observer-Informed Deep Learning for Traffic State Estimation With Boundary Sensing. IEEE Transactions on Intelligent Transportation Systems, 2023.
[40] Di, X., et al., Physics-Informed Deep Learning For Traffic State Estimation: A Survey and the Outlook. Algorithms, 2023. 16(6): p. 305.
[41] Yao, H., X. Li, and X. Yang, Physics-aware learning-based vehicle trajectory prediction of congested traffic in a connected vehicle environment. IEEE Transactions on Vehicular Technology, 2022. 72(1): p. 102-112.
[42] Geng, M., et al., A physics-informed Transformer model for vehicle trajectory prediction on highways. Transportation research part C: emerging technologies, 2023. 154: p. 104272.
[43] Lu, J., et al., Physics-informed neural networks for integrated traffic state and queue profile estimation: A differentiable programming approach on layered computational graphs. Transportation Research Part C: Emerging Technologies, 2023. 153: p. 104224.
[44] Shi, R., Z. Mo, and X. Di. Physics-informed deep learning for traffic state estimation: A hybrid paradigm informed by second-order traffic models. in Proceedings of the AAAI Conference on Artificial Intelligence. 2021.
[45] Shi, R., et al., Physics-informed deep learning for traffic state estimation. arXiv preprint arXiv:2101.06580, 2021.
[46] Zhang, J., et al., Physics-informed deep learning for traffic state estimation based on the traffic flow model and computational graph method. Information Fusion, 2024. 101: p. 101971.
[47] Huang, A.J. and S. Agarwal, Physics-informed deep learning for traffic state estimation: illustrations with LWR and CTM Models. IEEE Open Journal of Intelligent Transportation Systems, 2022. 3: p. 503-518.
[48] Huang, A.J. and S. Agarwal. Physics informed deep learning for traffic state estimation. in 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC). 2020. IEEE.
[49] Usama, M., et al., Physics-Informed Neural Networks (PINNs)-Based Traffic State Estimation: An Application to Traffic Network. Algorithms, 2022. 15(12): p. 447.
[50] Shi, Z., et al., Physics-Informed Spatiotemporal Learning Framework for Urban Traffic State Estimation. Journal of Transportation Engineering, Part A: Systems, 2023. 149(7): p. 04023056.
[51] Inzunza, D. and P. Goatin. A PINN approach for traffic state estimation and model calibration based on loop detector flow data. in 2023 8th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). 2023. IEEE.
[52] Shi, R., et al., A physics-informed deep learning paradigm for traffic state and fundamental diagram estimation. IEEE Transactions on Intelligent Transportation Systems, 2021. 23(8): p. 11688-11698.
[53] Rempe, F., A. Loder, and K. Bogenberger. Estimating motorway traffic states with data fusion and physics-informed deep learning. in 2021 IEEE International Intelligent Transportation Systems Conference (ITSC). 2021. IEEE.
[54] Huang, A.J. and S. Agarwal, On the Limitations of Physics-informed Deep Learning: Illustrations Using First Order Hyperbolic Conservation Law-based Traffic Flow Models. IEEE Open Journal of Intelligent Transportation Systems, 2023.
Xu, Z. and J.H. Saleh, Machine learning for reliability engineering and safety applications: Review of current status and future opportunities. Reliability Engineering & System Safety, 2021. 211: p. 107530.