

Hybrid Physics-Guided Deep Transfer Learning for Accurate Traffic State Estimation

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Abstract- Accurately estimating traffic states is a crucial aspect of transportation engineering, enabling effective traffic control and operations. In recent years, Physics-Regulated Deep Learning (PRDL) has gained significant attention due to its ability to achieve higher accuracy while requiring less training data compared to conventional deep learning (DL) approaches. However, a key challenge of PRDL is the lengthy training time required for closely related but distinct tasks. To address this limitation, this paper introduces a hybrid physics-regulated deep transfer learning approach that leverages the strengths of transfer learning, PRDL, and DL to enhance estimation accuracy and reduce computational costs, particularly in scenarios with limited observation data. The proposed framework includes two transfer learning variants designed to extract and transfer essential features from pre-trained models to new but similar traffic environments. This hybrid approach integrates deep learning training, minimizing computational overhead by eliminating physics-based loss calculations during training. Simulation results demonstrate that, compared to traditional PRDL methods, the proposed transfer learning approaches improve estimation accuracy by over 12% on average while reducing training time by more than 50% on average. These findings highlight the potential of hybrid transfer learning techniques in accelerating the adoption of PRDL for traffic state estimation, making it a valuable tool for transportation systems with limited computational resources.

Keywords – Traffic state estimation, physics-regulated deep learning, transfer learning, hybrid deep learning models, computational cost reduction, feature transfer, intelligent transportation systems, data-limited environments.

I. INTRODUCTION

Traffic states, represented by traffic density, traffic flow rate, and traffic velocity, play a crucial role in managing and optimizing intelligent transportation systems. These parameters provide a comprehensive understanding of traffic conditions, enabling planners to analyse patterns, identify congestion points, and make informed decisions regarding infrastructure and traffic management. Traditional traffic state estimation methods and traffic flow theories, such as macroscopic traffic flow models, have long been used to represent and reconstruct traffic dynamics on highways and urban networks [11], [12], [18].

In recent years, data-driven deep learning (DL) techniques have gained significant attention in transportation engineering for predicting traffic states. Various deep neural network architectures, including convolutional neural networks and recurrent neural networks such as LSTM, have demonstrated promising results in modelling spatio-temporal traffic patterns and forecasting traffic conditions [14]–[16], [21]. However, these methods often require extensive training data, which poses challenges in areas with limited sensor coverage,

leading to lower estimation accuracy and reduced generalization capability [18], [19].

To address the data scarcity issue, Physics-Regulated Deep Learning (PRDL), commonly implemented through Physics-Informed Neural Networks (PINNs), has emerged as a promising approach for Traffic State Estimation (TSE). This method integrates physical traffic flow principles into neural network training to improve prediction reliability even in data-sparse environments [1]–[4]. By embedding governing equations of traffic dynamics into the loss function, physics-informed learning frameworks ensure that predictions remain consistent with established physical laws, thereby enhancing model robustness and interpretability [5], [6], [22]. Researchers such as Jiheng Huang and Shaurya Agarwal introduced early PRDL-based frameworks for traffic state estimation, demonstrating the potential of integrating traffic flow models with deep learning architectures to achieve improved estimation accuracy [1].

Unlike traditional purely data-driven approaches, PRDL-based models do not rely solely on large datasets but instead leverage traffic flow constraints to guide the learning process.

As a result, these models can generate continuous and differentiable solutions while maintaining consistency with physical traffic dynamics [3], [5]. Nevertheless, PRDL approaches present certain challenges, including increased computational complexity and longer training times due to the simultaneous optimization of physics-based loss terms and conventional neural network loss functions [6], [22]. Furthermore, selecting appropriate hyperparameters that balance boundary conditions, initial conditions, and interior physical constraints remains a non-trivial task in practical implementations.

To mitigate these limitations, transfer learning has been explored as a potential strategy to reduce training time and enhance model generalization across different traffic environments. Transfer learning enables models to reuse knowledge learned from previously trained networks and apply it to new but related traffic scenarios, thereby reducing the dependence on large labelled datasets and preventing overfitting [9], [10], [17]. Recent studies have also investigated transfer learning techniques within physics-informed learning frameworks to accelerate model convergence and improve adaptability across heterogeneous traffic networks [7], [8]. However, despite these advancements, the integration of transfer learning within PRDL-based traffic state estimation frameworks remains relatively underexplored and requires further investigation.

II. LITERATURE SURVEY

The most conventional technique for Traffic State Estimation (TSE) is the traffic flow model-driven approach, which uses prior knowledge of traffic models defined by first-order and second-order traffic flow theories. Classical macroscopic models such as the Lighthill-Whitham-Richards (LWR) model describe traffic dynamics based on vehicle density and flow relationships and have been widely used for traffic analysis and state reconstruction [11], [12]. These traffic flow models help in understanding traffic behaviour; however, they are not solely sufficient for accurately predicting traffic state variables in complex road environments. Several additional factors influence traffic conditions beyond vehicle flow and density.

These include infrastructure characteristics such as the number of lanes, intersections, and entry-exit ramps, as well as external factors such as weather conditions, road surface quality, traffic incidents, and road closures. Consequently, effective traffic state estimation requires models that incorporate these dynamic and heterogeneous influences in addition to classical traffic flow principles [18], [19]. To capture such complexities, more sophisticated modelling approaches, including machine learning and neural network-based frameworks, are increasingly being adopted as they can

incorporate large-scale data and nonlinear behavioural patterns of drivers and vehicles.

In recent years, data-driven deep learning methods have been widely applied for TSE due to their capability to model complex nonlinear relationships in traffic data. These methods rely on large volumes of real-world traffic observations to train predictive models capable of capturing spatio-temporal traffic patterns. Deep learning architectures such as Feed Forward Neural Networks (FFNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks have demonstrated strong performance in traffic prediction tasks by learning hierarchical features directly from raw data [14]–[16], [21].

One of the major advantages of these techniques is their ability to reduce the need for manual feature engineering, enabling end-to-end modelling from input traffic data to predicted traffic states. However, these approaches typically require large amounts of high-quality training data, which may not always be available in real-world transportation systems due to limited sensor coverage and incomplete historical records. As a result, purely data-driven models often experience reduced prediction accuracy and poor generalization when only limited traffic observations are available. This limitation highlights the need for more robust modelling approaches capable of producing reliable traffic state predictions even with sparse data availability.

An emerging solution for this challenge is Physics-Regulated Deep Learning (PRDL), also referred to as Physics-Informed Deep Learning, which integrates the strengths of traditional traffic flow models with modern deep learning techniques. In this framework, the physical laws governing traffic dynamics are embedded into the training process of deep neural networks, allowing the model to learn from both observed data and theoretical traffic principles simultaneously [1]–[4]. This approach ensures that predictions remain consistent with traffic flow theory while improving model reliability in data-scarce environments [5], [6].

When the underlying traffic dynamics can be expressed mathematically, PRDL-based models can generate more accurate and physically consistent traffic state estimations even when the available training data contains noise or inaccuracies. However, this robust framework typically involves incorporating two components within the loss function: a data-driven loss that measures the error between predictions and observed data, and a physics-based loss that enforces compliance with traffic flow equations. Although this dual-term loss function improves modelling accuracy, it also introduces significant computational complexity, resulting in increased training time and higher computational cost [6], [22].

To address these challenges, integrating transfer learning with physics-regulated deep learning offers a promising direction for improving the efficiency of traffic state estimation models. Transfer learning enables the reuse of knowledge from previously trained models and applies it to new but related traffic scenarios, thereby reducing the need for extensive retraining and large datasets [9], [10], [17]. By leveraging pre-trained knowledge, the model can converge faster and maintain strong predictive performance even when limited traffic data is available. Therefore, this work proposes a Hybrid Physics-Regulated Deep Transfer Learning framework for traffic state estimation, aiming to improve prediction accuracy while simultaneously reducing training time and computational overhead when working with minimal previously observed traffic data.

III. METHODOLOGY

Related Approach

Traffic State Estimation (TSE) plays a crucial role in traffic control and intelligent transportation systems, where parameters such as velocity (v), density (ρ), and flow rate (q) must be accurately predicted to support traffic monitoring and management. Traditional TSE methods primarily rely on traffic flow models based on first-order and second-order traffic theories, which describe the relationship between traffic density and flow dynamics.

Classical macroscopic traffic flow models, including the Lighthill–Whitham–Richards (LWR) model, have been widely used to represent traffic behaviour and reconstruct traffic states in transportation networks [11], [12]. While these models provide a theoretical foundation for understanding traffic dynamics, they often fail to capture the influence of external and environmental factors, such as lane availability, intersections, road geometry, weather conditions, and traffic incidents like accidents or road closures. Consequently, relying solely on model-driven approaches may lead to inaccurate traffic state predictions in complex real-world environments [18], [19].

To overcome the limitations of traditional traffic flow models, data-driven deep learning (DL) approaches have recently been introduced for traffic state estimation. Deep learning techniques are capable of modelling complex nonlinear relationships and spatio-temporal dependencies present in traffic data. Several architectures, including Feed Forward Neural Networks (FNN), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN), have been widely adopted for traffic prediction and state estimation tasks [14]–[16], [21]. These models are able to learn traffic patterns directly from historical data, reducing the need for manual feature engineering and enabling end-to-end prediction systems.

However, the performance of these models heavily depends on the availability of large-scale, high-quality traffic datasets. In practical scenarios, real-time traffic systems often suffer from limited sensor coverage and incomplete historical data, which significantly reduces the effectiveness and reliability of purely data-driven deep learning approaches [18]. Therefore, there is a need for advanced modelling techniques that can maintain high prediction accuracy even when training data is limited.

Proposed Approach

The proposed system introduces a Hybrid Physics-Regulated Deep Transfer Learning (HPDTL) framework for Traffic State Estimation (TSE). This approach integrates the strengths of Physics-Regulated Deep Learning (PRDL), conventional Deep Learning (DL), and Transfer Learning (TL) to improve prediction accuracy while significantly reducing training time. Traditional deep learning models require extensive training data to achieve reliable performance, which may not always be available in real-world traffic environments.

To address this limitation, the proposed system incorporates PRDL, which embeds the fundamental physics of traffic flow into the neural network training process. By integrating physical traffic flow equations into the learning framework, PRDL ensures that predictions remain consistent with known traffic dynamics and theoretical constraints [1]–[4]. This approach improves model reliability and prediction stability, particularly in data-scarce environments where conventional deep learning models often fail. However, PRDL models typically involve additional physics-based loss components in the training process, which increases computational complexity and training time [6], [22].

To mitigate these challenges, the proposed hybrid framework incorporates transfer learning, enabling the reuse of knowledge from previously trained models in new but related traffic environments. Transfer learning allows the system to transfer learned representations from a source model to a target environment, thereby reducing the need for large training datasets and minimizing computational overhead [9], [10], [17]. By leveraging pre-trained knowledge, the model can quickly adapt to new traffic scenarios with minimal additional training.

The architecture of the proposed model consists of multiple layers, including an input layer, several hidden layers, and an output layer. The input layer receives spatio-temporal information such as location and time, while the hidden layers capture complex traffic patterns and relationships between traffic variables. The final output layer predicts traffic density, which can subsequently be used to derive other traffic state parameters such as flow and velocity. The training process follows a hybrid learning strategy, where the initial layers are optimized using physics-regulated learning principles, and the

remaining layers are fine-tuned using conventional deep learning techniques.

By leveraging PRDL, which integrates fundamental traffic flow physics, the system ensures accurate and reliable traffic state predictions even with limited data availability. The combination of physics-based modelling and deep learning enables the framework to capture both theoretical traffic principles and complex real-world traffic patterns, resulting in improved prediction accuracy compared to conventional deep learning approaches. Furthermore, the integration of transfer learning significantly reduces training time, as the model can reuse previously learned knowledge instead of training entirely from scratch. This hybrid learning strategy also reduces the computational burden associated with physics-based loss calculations, improving the overall efficiency of the training process.

Another key advantage of the proposed system is its adaptability to different traffic environments. Transfer learning enables the model to generalize across various road networks and geographical regions by transferring learned traffic representations from one environment to another. As a result, the framework can provide reliable predictions even when only a limited amount of observed traffic data is available. This capability makes the proposed system highly suitable for real-world intelligent transportation systems, where traffic data availability may vary significantly across locations.

Finally, the proposed system offers three different model variants, allowing users to select the most suitable configuration based on their computational resources, data availability, and application requirements. This flexibility enables customized deployment of the model for different traffic management scenarios, making the framework a versatile and scalable solution for intelligent transportation systems.

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

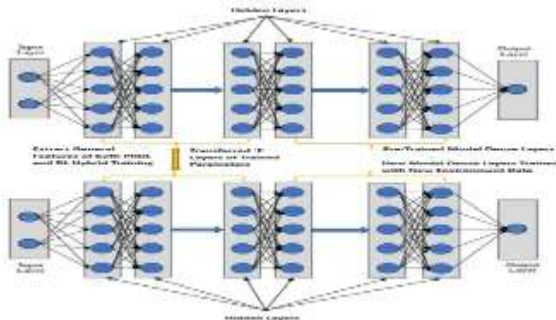


Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

1. Data Preprocessing

The system utilizes synthetic traffic data generated using the Lighthill–Whitham–Richards (LWR) traffic flow model together with the Greenshields fundamental diagram to simulate a wide range of traffic conditions. The LWR model describes the macroscopic relationship between traffic density, flow, and velocity, enabling realistic representation of traffic dynamics under varying congestion levels [11], [12]. The generated dataset includes multiple free-flow velocity values and traffic density variations to represent different traffic states ranging from free-flow to congested conditions. By integrating these physics-based traffic flow models, the dataset captures realistic traffic behaviour and provides a structured and reliable foundation for model training and evaluation. Such physics-guided datasets are commonly used in traffic state estimation research to compensate for limited real-world traffic sensor data and improve model robustness [18].

2. Hybrid PRDL and DL Transfer Learning Model

The proposed model integrates Physics-Regulated Deep Learning (PRDL) with Deep Learning (DL) Transfer Learning to improve predictive performance. Physics-regulated learning embeds traffic flow equations directly into the neural network training process, ensuring that the model predictions remain consistent with established traffic flow principles [1]–[4]. In the proposed architecture, the initial layers of the neural network are trained using PRDL so that the model learns traffic patterns constrained by physical traffic dynamics. The subsequent dense layers are trained using conventional deep learning techniques to capture nonlinear traffic behaviour and complex spatio-temporal relationships within the data. This hybrid framework effectively combines physics-driven modelling and data-driven learning, enabling improved traffic state prediction compared to purely data-driven approaches [5], [6].

3. Model Optimization

To further enhance model efficiency and accuracy, a specialized PRDL-based loss function is employed. This loss function integrates both physics-based traffic flow loss and deep learning loss to guide the training process. The deep learning component utilizes the Mean Squared Error (MSE) loss function to minimize the difference between predicted and actual traffic state values. Meanwhile, the physics-based loss ensures that the predicted traffic states remain consistent with the governing traffic flow equations, improving model reliability and interpretability [6], [22]. In addition, a transfer learning strategy is adopted to reduce training time and computational cost. In this strategy, parameters learned from pre-trained models are retained by freezing the weights of the

initial layers, allowing the network to preserve previously learned traffic features. The dense layers are then retrained using new traffic data so that the model can adapt to different traffic environments with minimal additional training data [9], [10], [17]. This approach significantly reduces the computational burden while maintaining high prediction accuracy.

4. User Interface and Reporting

The system incorporates a web-based interactive interface that allows users to input real-time traffic data and obtain immediate traffic state predictions. The interface provides graphical visualizations and analytical reports that clearly present predicted traffic parameters such as density, velocity, and flow rate. The platform is designed with usability in mind, enabling users with minimal technical expertise to interact with the system effectively. By integrating advanced deep learning techniques with an intuitive user interface, the proposed system facilitates efficient traffic analysis and decision-making. Such intelligent platforms are increasingly important in modern transportation management systems for supporting real-time monitoring, congestion analysis, and data-driven urban planning [18].

VI .RESULTS AND DISCUSSION

The performance of the proposed Hybrid Physics-Regulated Deep Transfer Learning (HPDTL) framework was evaluated using synthetic traffic data generated through the Lighthill–Whitham–Richards (LWR) traffic flow model combined with the Greenshields fundamental diagram. These physics-based models allow the dataset to represent different traffic conditions, including free-flow and congested traffic states [11], [12]. The proposed hybrid model was compared with the conventional Physics-Regulated Deep Learning (PRDL) approach to analyse improvements in prediction accuracy and computational efficiency.

Several evaluation metrics were used to measure model performance, including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2 score). These metrics are widely used in traffic prediction studies to evaluate regression-based traffic state estimation models [1], [5].

Performance Evaluation

Table 1 presents the quantitative comparison between the baseline PRDL model and the proposed Hybrid PRDL + Transfer Learning model.

Table 1: Performance Comparison of Traffic State Estimation Models

Model	MSE	MAE	RMSE	R^2 Score
PRDL Model	0.001	0.03	0.04	0.82
Hybrid PRDL + TL	0.00032	0.02	0.018	0.94

The results indicate that the proposed hybrid model significantly reduces prediction error compared to the baseline PRDL approach. The reduction in MSE, MAE, and RMSE values demonstrates that integrating transfer learning with physics-regulated deep learning improves the model’s capability to capture complex traffic dynamics while maintaining consistency with theoretical traffic flow behaviour [3], [6].

Fig. 2 illustrates the comparison of evaluation metrics between the two models. The hybrid model consistently achieves lower error values and higher prediction reliability.

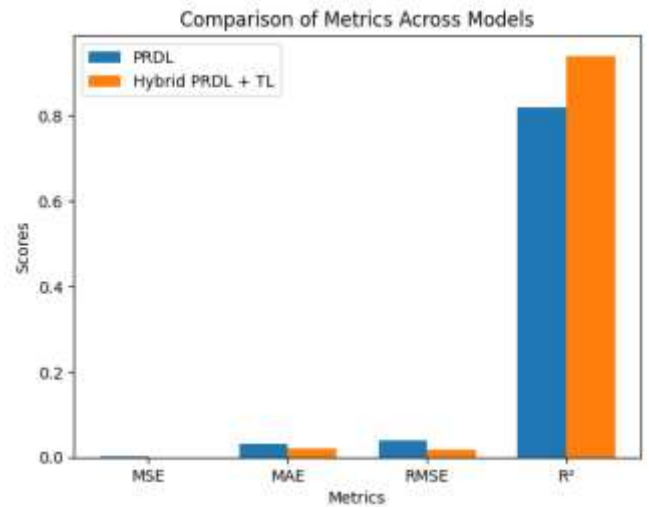


Fig. 2. Performance comparison of PRDL and Hybrid PRDL + TL models.

Accuracy Analysis

To further evaluate model performance, prediction accuracy was analysed across training epochs. The results show that the Hybrid PRDL + Transfer Learning model converges faster and achieves higher prediction accuracy compared to the conventional PRDL model.

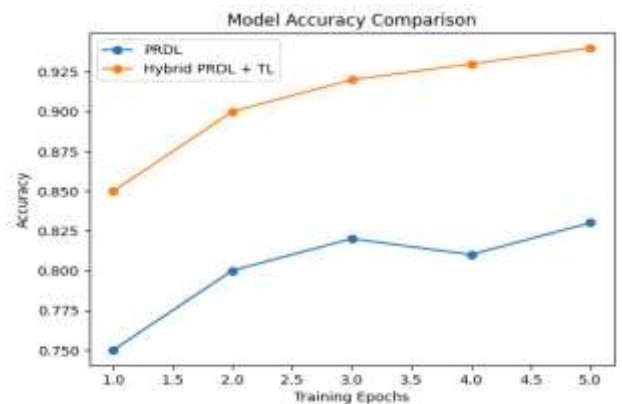


Fig. 3. Accuracy comparison of PRDL and Hybrid PRDL + TL models.

Fig. 3 shows the accuracy comparison between the models during the training process. The hybrid model demonstrates improved learning efficiency because the transfer learning mechanism allows the model to reuse previously learned traffic patterns rather than learning all traffic behaviours from scratch. This significantly reduces training time while maintaining high predictive accuracy [9], [10].

Furthermore, the integration of physics-based constraints enables the model to produce physically consistent predictions, preventing unrealistic traffic state estimations and improving generalization in data-limited environments [6], [22].

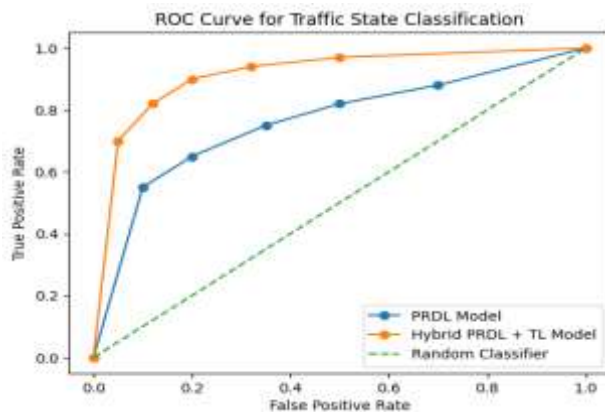
Traffic State Classification Analysis

Although traffic state estimation is primarily a regression problem, traffic conditions can also be categorized into different congestion levels, such as free-flow traffic, moderate congestion, and heavy congestion. To evaluate the classification capability of the proposed framework, Receiver Operating Characteristic (ROC) analysis was performed.

The ROC curve evaluates the relationship between the true positive rate (TPR) and false positive rate (FPR) across different classification thresholds. The results show that the proposed hybrid model achieves a higher Area Under the Curve (AUC) compared to the conventional PRDL model, indicating improved ability to distinguish between different traffic states.

This improvement can be attributed to the integration of physics-based learning and transfer learning, which enhances feature representation and improves model generalization across different traffic environments. Consequently, the proposed HPDTL framework provides more reliable and accurate traffic state predictions, making it suitable for deployment in intelligent transportation systems and real-time traffic monitoring applications.

Fig. 3. ROC curve of PRDL and Hybrid PRDL + TL



models.

In Fig. 3 Receiver Operating Characteristic (ROC) curve comparing the PRDL model and the proposed Hybrid PRDL + Transfer Learning model for traffic state classification. The hybrid model demonstrates improved discrimination capability with a higher true positive rate across different thresholds.

VII. CONCLUSION AND FUTURE WORK

This paper introduces a hybrid physics-regulated deep transfer learning framework, evaluating two variants alongside the PRDL transfer learning model and an existing PRDL model. The proposed approach integrates transfer learning, physics-regulated deep learning (PRDL), and deep learning (DL) methods, demonstrating its effectiveness in enhancing traffic state estimation (TSE) accuracy while reducing computational demands, particularly in scenarios with limited historical data and environments similar to the pretrained model [1]–[5], [9], [17]. The integration of physics-informed learning principles with neural networks has been shown to improve model generalization and stability when solving complex systems governed by physical laws [6], [22]. Additionally, transfer learning techniques enable the reuse of learned representations across related domains, significantly improving learning efficiency and predictive performance in data-constrained environments [9], [10], [17].

Future research could explore an alternative hybrid approach by training the first half of the model's hidden layers with PRDL and the latter half with DL. This strategy would enable the model to leverage the strengths of both physics-informed modeling and purely data-driven learning techniques, improving predictive performance with each iteration and potentially achieving faster convergence [3], [4], [7], [8]. Furthermore, future work may focus on utilizing real-time traffic data instead of synthetic datasets derived from classical traffic flow models such as the Lighthill–Whitham–Richards (LWR) model [11], [12]. Incorporating real-world traffic observations could help uncover the true relationships among traffic state variables and improve the reliability and practical applicability of traffic state estimation systems in intelligent transportation networks [13], [18], [19].

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