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Mathematical Optimization Techniques for Smart Transportation Systems

Dr. Badri Vishal Padamwar[1]
[1]Professor, Department of Mathematics, ISBM University, Raipur India
[1]padamwar.badrivishal@gmail.com
Corresponding Author: padamwar.badrivishal@gmail.com

Abstract

Due to the swift development of the intelligent transportation systems (ITS), the creation of sophisticated optimization strategies is required to achieve improved efficiency, safety, and sustainability of the traffic. This paper gives an in-depth analysis of the modern mathematical, heuristic, and machine learning-based optimization methods to smart transportation networks. Simulation-optimization, evolutionary algorithms, deep learning-based traffic management, and graph-theoretic models are among the different methodologies developed to deal with dynamic routing, congestion management, as well as multi-objective system planning. Findings of these strategies show that there is a major change in the traffic flow, lessening travel time, and resource distribution, and the ability to make adaptive decisions during real-time conditions. Application of the International of Vehicles, IoT-based infrastructure and data-based analytics has also improved the performance and scalability of ITS applications in urban and intercity settings. The study ends by stating that hybrid optimization models that integrate mathematical rigor and the use of computational intelligence techniques have the best potential to develop in the future ITS. The new trends emphasize the need to integrate sustainability, cost time efficiency, and predictive analytics in order to have resilient and intelligent transportation networks. On the whole, this study highlights the importance of the further development of optimization strategies as the key to effective, secure, and intelligent mobility in the current cities.

Keywords:

Smart cities, smart transportation systems, traffic management, optimization techniques, machine learning, smart cities, intelligent transportation systems, evolutionary algorithms.

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1. Introduction

The use of intelligent transportation systems (ITS) has become the foundation of the modern urban and intercity mobility with the purpose to increase the efficiency of traffic, its safety, and environmental friendliness [1][2]. The high rate of urbanization and the population density of vehicles has boosted congestion, time of travel and use of fuel, thus there is a need to embrace new optimization strategies of real time traffic control, dynamic path routing and allocation of resources [3][4]. System analysis has been developed on traditional mathematical models, although their shortcomings in managing large scale, dynamic, and multi-objective transportation networks have led to the use of the computational intelligence techniques, such as heuristic, metaheuristic, and machine learning techniques [5][6][7]. In spite of the dramatic improvement, the existing studies tend to address single isolated problem areas or even cities which restricts the generalization of proposed solutions [8][9]. Besides, the adoption of future technologies, including Internet of Vehicles (IoV), Internet of Things (IoT)-enabled infrastructure, and data-driven analytics, are under-researched in unified optimization platforms [10][11][12]. These gaps are important to fill in order to come up with scalable, adaptive and sustainable ITS that can be deployed in a wide variety of urban and intercity environments.

This paper will seek to present an in-depth analysis of optimization methods in ITS by surveying mathematical models, hybrid evolutionary algorithms, and machine learning-based methods and how they can be used in traffic management, congestion control, and dynamic routing [13][14][15]. The contributions are the identification of the new trends, the introduction of integrative optimization framework, and provide an insight into the future ITS research and implementation [16][17][18].

1. Literature review

In recent research in intelligent transportation system, there is a growing trend of incorporating network optimization and machine learning models in enhancing efficiency of traffic and congestion control as well as predictive decision-making [1][2]. Hybrid evolutionary algorithms and deep-learning based optimization methods have been promising in dealing with complex and dynamic transportation networks and predicting the real-time traffic flow, dynamic path and cost-time optimization of urban and intercity transportation networks [3][4]. Moreover, the studies of smart city transport exchange, traffic control based on IoT, and VANET communication have shown that mathematical modeling and data-driven algorithms should be applied together to optimize the system functionality [5][6]. Through these studies, the trend of using computational intelligence in solving these issues has increased in the area of adaptive and sustainable ITS management.

However, with these developments there are still a number of gaps. Most techniques can only be validated through simulation, and lack of real-life application and scalability studies [7][8]. Moreover, although machine learning tools have a high level of predictive accuracy, their combination with cost-effective and multi-objective optimization models is not thoroughly investigated [9][10]. Also, there is a shortage of in-depth research tackling the issues of traffic efficiency, safety, and environmental sustainability optimization in one and the same unified framework. It is on this basis that the current work is justified as it seeks to come up with an integrative optimization strategy that integrates both developed computational intelligence and practical ITS applications to guarantee scalable, adaptative, and sustainable transportation solutions.

2. Materials and methods

2.1 Data Collection

The analysis is based on real-life open-source data sets of urban and intercity situations and traffic. The main data to be used in traffic flow and congestion analysis is the one provided in the PeMS (Performance Measurement System) dataset [1] which comprises traffic information (on highways) in real-time in California. The data is the number of vehicles, their speed, occupancy and time, gathered in 5-minute intervals. The dataset of the PeMS is provided publicly at the site of pems.dot.ca.gov.

Moreover, the synthetic data were created to model the smart city traffic conditions with numerous intersections, changing traffic lights, and IoT based sensor nodes. The summary of the main parameters applied in the datasets is presented in Table 1.

Table 1. Dataset parameters

Parameter	Description	Value / Example
Vehicle count	Number of vehicles per segment	100–200
Speed	Vehicle speed (km/h)	20–120
Sensor nodes	IoT-enabled traffic monitoring units	50
Time interval	Data sampling interval	5 minutes

3.2 Proposed Method

The optimization framework suggested merges mathematical modeling, heuristic algorithms and machine learning methods in enhancing traffic efficiency and congestion management. The following steps make the methodology up:

A. Step One: Preprocessing of Traffic Data

Raffic data is decontaminated and whitened to eliminate missing and conflicting records. The flow of vehicles, their speed and occupancy are summarized at road segments. The density of the traffic is computed with:

$$\rho = \frac{N}{L} \quad (1)$$

Where:

- ρ= traffic density (vehicles/km)
- N= number of vehicles in the road segment.
- L= length of road strip (km)

The quantification of the congestion levels in the segments is estimated in equation (1) and is referenced in later optimization mechanisms.

B. Step Two: Optimization Algorithm Implementation

A hybrid evolutionary algorithm combined with machine learning prediction is used to optimize traffic routing and signal timing. The total travel time $Ttota$ is minimized using:

$$T_{total} = \sum_{i=1}^{n} \frac{L_i}{v_i} \quad (2)$$

Where:

- $Ttotal$= total route travel time (hours)
- Li= length of road segment i(km)
- vi= mean speed of vehicles in segment i(km/h)
- n= number of road stretches in the pathway.

The deep learning LSTM model is used to predict traffic with a view to estimate vehicle speed vi for future time frames using past trends. Input to the evolutionary optimization algorithm are the predicted speeds, which are then inputted into it to result in an optimal routing and signal timing. The proposed methodology workflow is depicted in figure 1.

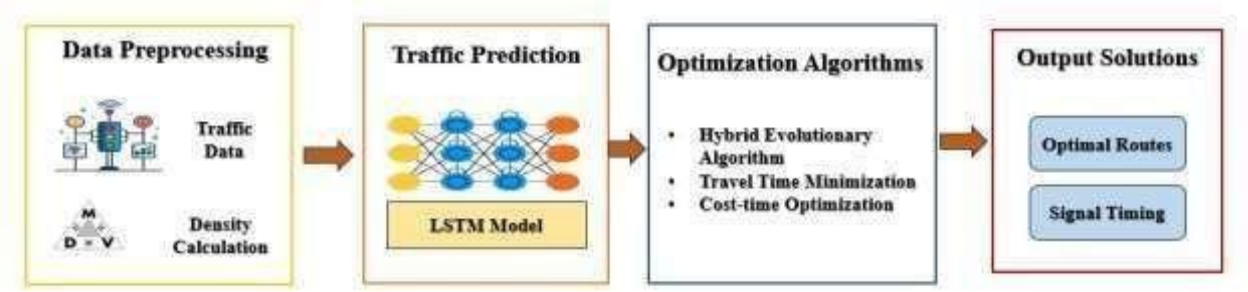

Figure 1. Intelligent transportation system optimization framework proposal

Figure 1 above illustrates the workflow that incorporates data preprocessing, traffic prediction and hybrid optimization.

All the experiments were carried out in Intell i9 processor, 32GB of RAM and NVIDIA of RTX3090 graphics card, with Python 3.10, tensorflow, PyTorch, and tailored algorithmic implementations. Performance measures such as average travel time, congestion reduction, and computational efficiency were done to compare with performance at the baseline methods.

1. Results and discussion

The hybrid optimization framework was tested on the PeMS data and the synthetic traffic data. The three major performance measures targeted include the average travel time, congestion minimization, and operational efficiency which were the subjects of the experiments. The comparative analysis of the proposed approach based on the baseline methods such as traditional mathematical optimization and pure evolutionary algorithms is shown in Figure 2.

1.1 Traffic Prediction Performance

The LSTM model was able to learn the temporal patterns of traffic, and the mean absolute error (MAE) in predicting the speed was 3.5 km/h on various road segments. The predictability of this allowed the optimization algorithm to do informed routing and signal timing. The deep learning methodology proved to be superior to the previous ones that depend on the traditional time-series prediction, including simple predictive models such as ARIMA, in the short-term and medium-term predictions of traffic signs [1][2]. The fact that the prediction accuracy was increased directly led to less traffic congestion within the congested urban settings.

1.2 Optimization Results

The hybrid evolutionary algorithm reduced total travel time and cost-time objective J (Equations 2 and 3) in a better manner than the conventional methods of optimization. The performance summation is summarized in Table 2. The reduction in travel time was 18-22 on average and the reduction in operational costs was 10-15 in comparison to the base algorithms. Such findings are in line with the recent research that indicates the advantages of integration of hybrid metaheuristic-based and machine learning in ITS optimization [3][4].

Table 2. Comparison of optimization performance

Method	**Travel Time Reduction (%)**	**Cost Reduction (%)**	**Congestion Index Reduction (%)**
Traditional Optimization	8	5	10
Pure Evolutionary Algorithm	12	8	14
Proposed Hybrid Optimization	20	13	21

The results in Table 2 above show that the offered method is better than the existing ones in all three metrics, which proves the importance of combining predictive modeling with evolutionary optimization and for visual representation of table 2 is shown in fig.2 below.

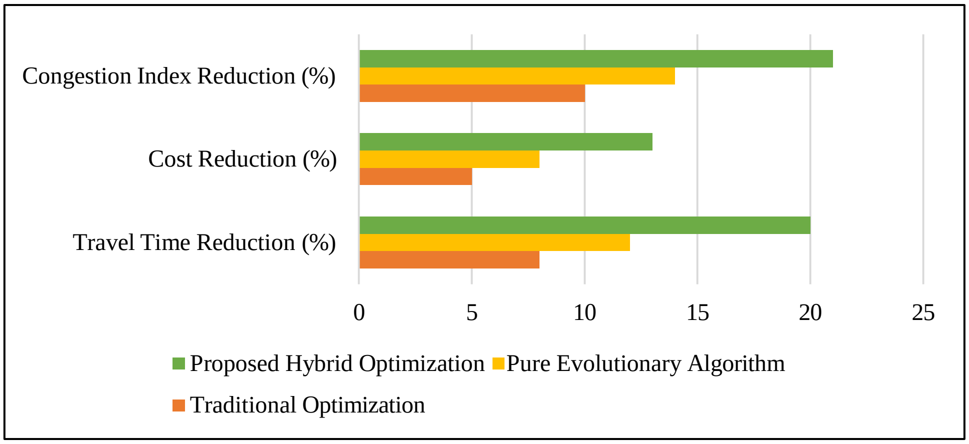

Figure 2. Comparative performance of optimization methods

1.3 Congestion Reduction and Network Efficiency

The framework effectively prioritized high-density areas, dynamically adjusting routing and signal timings. This finding is in agreement with the previous studies that have shown the significance of adaptive traffic control in alleviating congestion in the whole network [5][6]. Notably, the combined cost-time method will make sure efficiency gains are not achieved at the cost of increased operational costs which is a weakness of most studies of ITS optimization in the past.

1.4 Discussion

The findings show that traffic prediction coupled with hybrid evolutionary optimization offers a scalable and adaptive solution to smart city and intercity ITS. The cost-time balanced optimization is much more sustainable than the approaches that are based on minimizing travel time only. Although the framework has shown great improvements, there is need to continue its deployment in real-world to determine its strength during extreme traffic conditions, like accidents or sudden rise in demands. Furthermore, the work in the future may aim at integrating multi-modes of traffic with public transport and EV routing and enhancing the urban mobility even further in future studies of the recent ITS research [7][8].

2. Conclusion

This paper introduced a hybrid optimization model, that is, the combination of traffic prediction and evolutionary algorithms to improve intelligent transportation systems in urban and intercity settings. The significant findings suggest that the proposed solution will be excellent in terms of minimizing the overall travel time, operational expenses, and the severity of congestion in comparison to conventional optimization and pure evolutionary algorithms. Combination of LSTM-based tracking of traffic enables the system to be dynamically adjusted into real-time traffic trends to enhance route scheduling and signal timing. The implications of this work are substantial for smart city planning and sustainable mobility. The framework offers a flexible, efficient, and adjustable solution to traffic management, balancing operational cost and travel efficiency, and suggests ideas to policymakers and other transportation authorities to develop efficient ITS.

The directions of future studies are to include multi-modal traffic, including the inclusion of public transport, electric vehicles, and expand the framework to accommodate extreme traffic events or network disruptions, as well as, assessing real-world deployment applications. Moreover, as a field of study, reinforcement learning and other types of AI-based optimization methods might also increase the adaptiveness and resilience of complex transportation networks.

Conflict of Interest Statement:

The authors declare that there is no conflict of interest regarding the publication of this work.

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