Scientific Journals
of the Maritime University of Szczecin

Zeszyty Naukowe
Politechniki Morskiej w Szczecinie

2024, 78 (150), 131–149
ISSN 2392-0378 (Online)
DOI: 10.17402/609

Received: *16.05.2024*
Accepted: *10.06.2024*
Published: *30.06.2024*

Utilizing recurrent neural networks in sustainable urban transport and logistics

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Keywords: recurrent neural networks, sustainable urban transport, urban logistics, energy transition, machine learning, traffic management, infrastructure planning, zero-emission vehicles, energy efficiency, traffic flow prediction

JEL Classification: C63, R41, Q01, L91

Abstract

Urban centers, replete with diverse amenities and opportunities, simultaneously grapple with the challenges brought on by rapid urbanization, notably in the realms of transport and logistics. A pivotal move towards energy-efficient and sustainable systems is essential to mitigate these challenges. In this landscape, machine learning (ML), and particularly recurrent neural networks (RNNs), emerge as powerful tools for effectively addressing these urban complexities. This comprehensive review zeroes in on the deployment of RNNs within sustainable urban transportation and logistics, highlighting their adeptness in processing sequential data, a critical component in various forecasting and optimization tasks. We commence with a foundational understanding of RNNs, segueing into their successful applications in urban transport and logistics. This review also critically examines the constraints of current methodologies and potential avenues for enhancement. We scrutinize the application of RNNs across several areas, encompassing the energy shift in both passenger and freight transport, logistics management, integration of low- and zero-emission vehicles, and the energy dynamics of transport and logistics. Additionally, the role of RNNs in traffic and infrastructure planning is explored, particularly in forecasting traffic flow, congestion patterns, and optimizing energy usage. The crux of this review is to amalgamate and present the existing knowledge on the instrumental role of RNNs in facilitating the transition to energy-efficient urban transportation and logistics. Our goal is to highlight effective strategies, pinpoint challenges, and map out avenues for future research in this domain.

Introduction

Overview of urban transport and logistics challenges

Urban environments (Johnson & Munshi-South, 2017), while teeming with opportunities, face significant challenges due to rapid urbanization. Among various sectors, transportation and logistics are particularly impacted. As urban areas grow, so do their transportation and logistics needs (Letnik et al., 2018; Zhang et al., 2023). With this fact comes a set of interconnected issues, including congestion, energy intensity, environmental pollution, and excessive resource usage (Li, Rombaut & Vanhaverbeke, 2021; Kaspi, Raviv & Ulmer, 2022).

Congestion is a prominent issue in urban areas, impeding smooth transportation and resulting in increased travel time, decreased efficiency, and elevated levels of harmful emissions (Ma et al., 2017; Rajendran & Srinivas, 2020). The issue is compounded by the higher demand for transportation services in densely populated regions (Figure 1).

Energy intensity is another considerable challenge. Traditional modes of transportation and logistics operations heavily rely on fossil fuels, contributing to high levels of energy consumption and greenhouse gas emissions (Hofmann et al., 2019; Ullah, Mahmood & Khan, 2022). This has severe implications for environmental degradation and public health.

Environmental pollution is a direct consequence of the aforementioned issues. Vehicle emissions contribute to air pollution, while noise pollution from high traffic flow can detrimentally affect the quality of life in urban areas (Mueller et al., 2015; Xiong & Xu, 2021).

Finally, excessive resource usage in urban transportation and logistics further escalates the environmental impact. From the materials used in vehicle production to the physical space required for transport infrastructure, the resources consumed are substantial (Choi, Guo & Luo, 2020; Rajendran & Srinivas, 2020; Ren, Hao & Wu, 2023).

These challenges necessitate innovative solutions that can alleviate their impact and contribute to the sustainable development of urban environments. It is in this context that machine learning, particularly recurrent neural networks, offers a promising avenue for addressing these challenges, which we will explore throughout this review (Ling, Ma & Jia, 2022; Bastarianto et al., 2023).

The need for energy transition

The relentless urbanization and exponential growth of the transport and logistics sectors have precipitated a series of environmental challenges. The severity of these issues necessitates an immediate transition towards more energy-efficient and sustainable systems. This energy transition involves a fundamental shift from non-renewable energy sources, such as fossil fuels, towards renewable

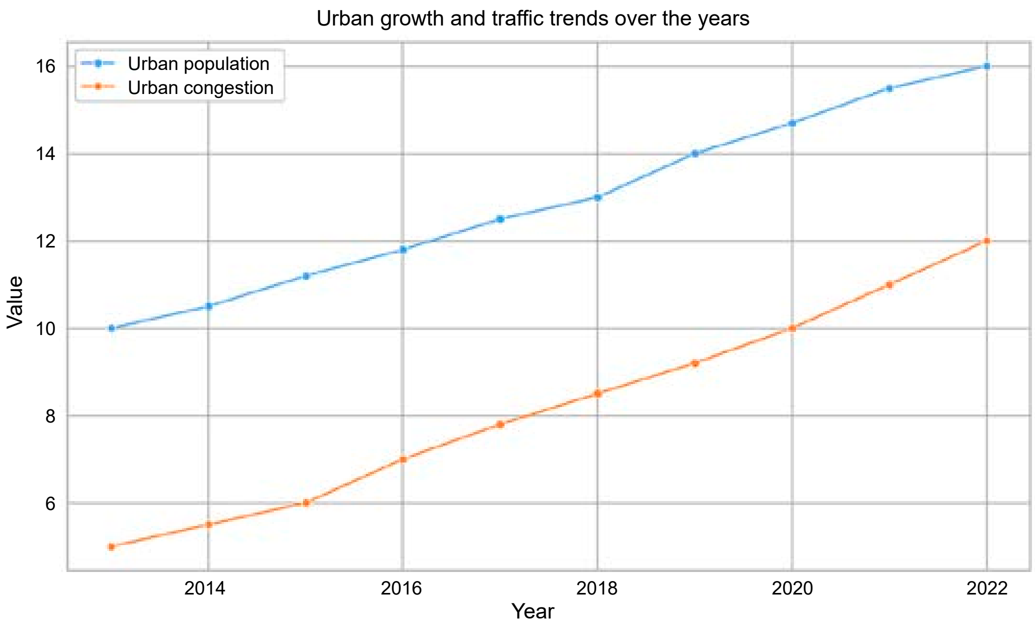

Figure 1. Urban growth and traffic trends over the years (based on data from Ritchie, Samborska & Roser (2023))

alternatives (Liu et al., 2021) like wind, solar, and hydrogen (Kovač, Paranos & Marciuš, 2021; Tian et al., 2022).

This transition not only reduces environmental impact but also holds considerable economic potential. Renewable energy sources are increasingly cost-competitive, and their integration can reduce dependence on volatile oil prices. Moreover, renewable energy technologies can generate new jobs, stimulating economic growth and resilience (Fatma et al., 2018; Go, Kahrl & Kolster, 2020; Dehghani-Sanij & Kashkooli, 2023).

In the context of urban transport and logistics, the energy transition includes, but is not limited to, the adoption of low- and zero-emission vehicles (Muratori et al., 2023), energy-efficient routing, and renewable energy in logistics operations. As we endeavor to execute this energy transition efficiently, advanced technologies such as machine learning come into play (Li et al., 2020; Vanegas Cantarero, 2020).

Role of machine learning

Machine learning (ML) is a subset of artificial intelligence that enables computers to learn from and make decisions based on data (Choi, Guo & Luo, 2020). In the realm of urban transport and logistics, ML can provide invaluable assistance in handling the complexities and dynamics of these systems (Khera & Kumar, 2020).

ML algorithms can analyze vast amounts of data generated by urban transport and logistics systems, learn patterns, make predictions, and even recommend optimal decisions. They can help optimize routes (Wang & Wang, 2021), predict energy consumption, manage vehicle schedules, inform infrastructure planning, and contribute to safety management (Pineda-Jaramillo, Barrera-Jiménez & Mesa-Arango, 2022). ML can also play a significant role in managing and balancing energy demand and supply in these systems, thereby aiding the energy transition process (Rana et al., 2022; Wang et al., 2022).

Among various ML techniques, recurrent neural networks (RNNs) hold particular promise for applications in urban transport and logistics (Deng et al., 2023) due to their proficiency in handling sequential data. In the forthcoming sections of this review, we delve into how RNNs can be leveraged to drive the energy transition in these areas (Ayoub Shaikh, Rasool & Rasheed Lone, 2022; Goel, Goel & Kumar, 2023).

Significance and objectives of the review

This review holds significant importance in the field of urban transport and logistics, a sector undergoing rapid transformation in the face of global urbanization and environmental challenges. The objectives of this review are twofold, as explained in the following.

We aim to provide a comprehensive overview of how recurrent neural networks can be effectively implemented in urban transport and logistics systems. Given their ability to process and analyze sequential data, RNNs are uniquely positioned to address complex, dynamic problems in these sectors. This review synthesizes existing literature to highlight innovative applications of RNNs, ranging from traffic flow prediction to energy-efficient routing.

Another key objective is to bridge the gap between theoretical research and practical applications. By examining diverse case studies and current implementations, this review sheds light on the real-world impact of RNNs. This includes an exploration of both successes and challenges, providing valuable insights for practitioners, policymakers, and researchers alike.

This review underscores the relevance of RNNs in promoting sustainable urban development. By facilitating more efficient and environmentally friendly transport and logistics systems, RNNs contribute to the broader goals of reducing urban congestion, lowering greenhouse gas emissions, and promoting the use of renewable energy sources.

Finally, this review aims to identify gaps in the current research landscape and suggest directions for future studies. It also seeks to inform policy by providing evidence-based recommendations for integrating RNNs into urban transport and logistics strategies, with a focus on sustainability and efficiency.

Through this review, we intend to provide a comprehensive resource for academics, industry professionals, and policymakers, fostering a deeper understanding of the potential of RNNs in reshaping urban transport and logistics for a more sustainable future.

Literature research methodology

In this chapter, we elucidate the systematic methodology employed for the literature review, aiming to explore the utilization of recurrent neural networks in sustainable urban transport and logistics.

Objective of the literature review

The primary objective is to gather, critically review, and synthesize existing literature. This approach aims to highlight current research trends, identify gaps, and propose directions for future research.

Search strategy

The literature was sourced from academic databases, including Google Scholar, IEEE Xplore, and ScienceDirect. Keywords such as "recurrent neural networks", "urban transport", and "sustainable logistics" were used. The selection was guided by relevance to RNNs in urban transport and logistics, with a focus on articles that demonstrated practical applications or theoretical advancements.

Time frame

The review focused on publications from the last decade, providing contemporary insights into the field.

Selection process

Publications were initially screened based on their titles and abstracts. The relevance and impact of the studies were further assessed by examining their methodologies, findings, and contributions to the field.

Data extraction and synthesis

Key information was extracted from each study, including objectives, methodologies, findings, and conclusions. These data points were then synthesized to present a cohesive understanding of the current landscape of RNN application in urban transport and logistics.

Evaluation of sources

Each source was evaluated for credibility, with preference given to peer-reviewed academic journals and authoritative publications. Limitations and biases within the studies were critically assessed to ensure a balanced and comprehensive review.

Recurrent neural networks (RNNs)

Fundamentals of RNNs

Recurrent neural networks are a type of artificial neural network designed to recognize patterns in sequences of data, such as text, speech, or time series data. These networks are "recurrent" in nature as they perform the same task for every element of a sequence, with the output being dependent on the computations of previous elements. This allows RNNs to exhibit temporal dynamic behavior and handle inputs of varying lengths, making them particularly useful for tasks such as speech recognition, natural language processing, and many others where such sequential data is common (Qin et al., 2019; Choi, Guo, et al., 2020; Cossu et al., 2021).

At a high level, RNNs process sequences by iterating through the sequence elements and maintaining a "state" containing information relative to what it has seen so far. In other words, the hidden state acts as the network's memory. It captures information about what occurred in all the previous time steps. The output at time step t is calculated using the current state at time t and the input at this time (Kaur & Mohta, 2019; Yang, 2019; Weerakody et al., 2021).

However, standard RNNs suffer from a key problem: vanishing gradients (Majumdar & Gupta, 2019). As the network learns, it backpropagates errors from the output layer back through the network to update weights. However, for long sequences, these gradients can become vanishingly small, effectively preventing the network from learning long-range dependencies (Sajedian, Kim & Rho, 2019; Ruiz, Gama & Ribeiro, 2020).

This challenge led to the development of more sophisticated types of RNNs, such as long short-term memory (LSTM) (Yang et al., 2020) and gated recurrent units (GRUs) (Majumdar & Gupta, 2019). These variants include mechanisms known as "gates" that allow the model to control the flow of information to and from the memory state, providing a solution to the vanishing gradient problem and making it possible for these models to learn from data where relevant events occur over longer periods (Liu et al., 2019; Sahoo et al., 2019).

In the context of urban transport and logistics, the sequential nature of traffic data, energy consumption records, and logistical timelines make RNNs, particularly their more advanced forms, a promising tool for modeling and predicting these dynamic systems. This potential is discussed further in the sections that follow.

Advantages and limitations of RNNs

The primary advantage of RNNs lies in their ability to handle sequential data. Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs, making them ideal for tasks where temporal dynamics and time dependencies matter. This makes them extremely valuable in applications such as speech recognition (Zhou, Liu & Gravelle, 2020; Sun, Li & Ma, 2023), natural language processing (Wu et al., 2020), and time-series prediction, including urban transport and logistics optimization (Vlachas et al., 2019; Zhu et al., 2022).

Moreover, RNNs' ability to handle variable-length input and output sequences provides further flexibility in modeling complex patterns in data. This allows RNNs to tackle tasks such as language translation (Karyukin et al., 2023), where the lengths of the input and output sentences may not match (Jain et al., 2020; Vlachas et al., 2020).

However, RNNs have a few notable limitations. One of the most significant is the vanishing gradient problem, where the contribution of information decays geometrically over time, making the network's learning process incapable of learning long-term dependencies. This limitation can prevent RNNs from effectively learning from data where a longer context is critical (Dong et al., 2020; Le et al., 2021).

RNNs can also suffer from the exploding gradients problem, where large error gradients accumulate and result in very large updates to neural network model weights during training. Careful configuration and the adoption of advanced training techniques are required to mitigate this issue (Kag, Zhang & Saligrama, 2019; Ribeiro et al., 2020).

Variants of RNNs (LSTM and GRUs)

To overcome the challenges associated with conventional RNNs, several variants have been introduced, with long short-term memory and gated recurrent units being the most notable (Hu et al., 2020) (Figure 2).

LSTM is a type of RNN architecture that uses special units in addition to standard units. LSTM units include a "memory cell" that can maintain information in memory for long periods. As a result, LSTMs can remember and recall information over long sequences, mitigating the vanishing gradient problem and enabling the model to learn long-term dependencies (Agarwal, Yadav & Vishwakarma, 2019; Hu et al., 2019; Singh et al., 2022).

GRUs, another popular RNN variant, are similar to LSTM but have a simpler structure. It combines the forget and input gates into a single "update gate" and merges the cell state and hidden state. While this results in a model that is easier to compute and requires fewer resources, it may not have the same representational power as LSTM (Jordan, Sokół & Park, 2021; Saud & Shakya, 2020).

Both LSTM and GRUs have shown remarkable success in dealing with sequence prediction problems, owing to their ability to capture long-term dependencies. Therefore, these RNN variants are often favored for complex tasks involving sequential data, such as those found in urban transport and logistics contexts.

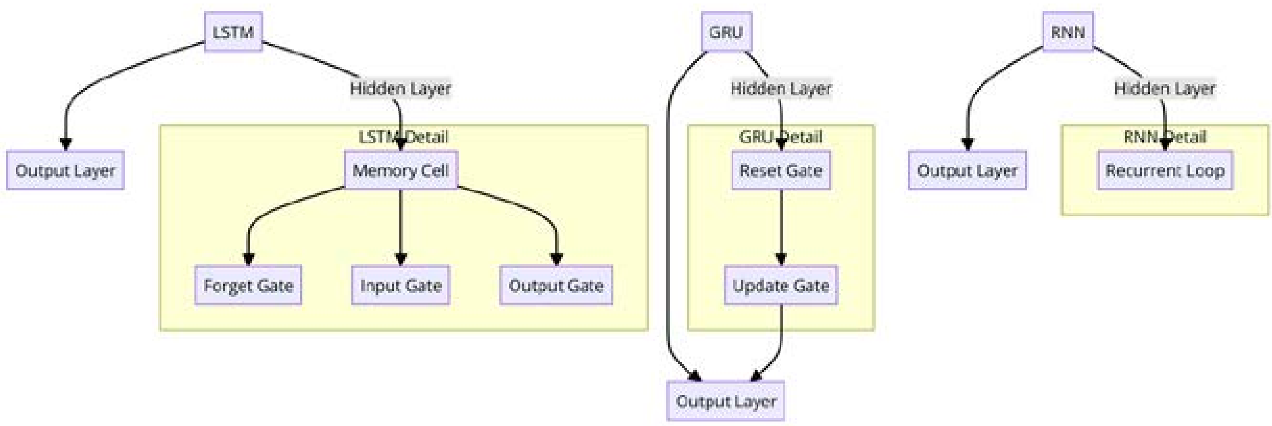

Figure 2. Simple comparison of RNN variants (self-made)

Energy transition in passenger and freight transport

Current challenges and solutions

The transport sector, encompassing both passenger and freight services, is a major consumer of energy, primarily fossil fuels. The relentless demand for transport services, spurred by economic growth and urbanization, further aggravates this energy usage, leading to escalating greenhouse gas emissions and associated environmental impacts (Jian et al., 2020; Naegler et al., 2021; Gedik, Uslu & Lav, 2022). These issues pose significant challenges to the sustainability of our urban environments (Figure 3).

In passenger transport, one key challenge is the high dependency on personal cars powered by fossil fuels. This not only results in high emissions but also exacerbates congestion in urban areas. Similarly, in freight transport, the extensive use of heavy-duty trucks and other large vehicles contributes significantly to the overall emissions and energy intensity of the sector (Füllemann et al., 2020; Goes et al., 2020; Gedik et al., 2022).

The energy transition in these sectors, therefore, involves a decisive shift towards more sustainable and energy-efficient systems. Solutions to these challenges can be broadly categorized into technological advancements, behavioral changes, and policy interventions (Guo et al., 2021; Yuan et al., 2021).

Technological advancements include the development and adoption of low- and zero-emission vehicles such as electric, hybrid, and hydrogen-powered vehicles. The transition to these vehicles can significantly reduce the emissions and energy intensity of transport. Additionally, advancements in digital technologies, such as intelligent transport systems, can enhance the efficiency of these sectors by optimizing routes, managing demand, and reducing congestion (Naegler et al., 2021; Hainsch et al., 2022) (Figure 4).

Behavioral changes involve shifts in societal norms and behaviors to adopt more sustainable modes of transport. This includes embracing public transport (Tainio et al., 2021), cycling, walking, and car-sharing over personal car use. For freight transport, this could involve optimizing load capacities and leveraging co-modality, where goods are transported using a combination of different modes of transport to reduce emissions (Li, Liu & Wang, 2022; Paulauskas et al., 2022).

Policy interventions can also play a crucial role in steering the energy transition in transport. These interventions can range from regulations and standards, which mandate emission reductions and energy efficiency, to incentives and subsidies that promote the use of sustainable vehicles and fuels (Zhang et al., 2020; Ning et al., 2021).

Despite the progress made in these areas, several challenges remain, including the high costs associated with new technologies, behavioral inertia, and the need for significant infrastructural changes. It is in addressing these challenges that advanced technologies such as machine learning and, more specifically, recurrent neural networks can offer substantial contributions. In the following sections, we delve into these opportunities (Noussan et al., 2020; Bjerkan, Ryghaug & Skjølsvold, 2021; Rixhon et al., 2021).

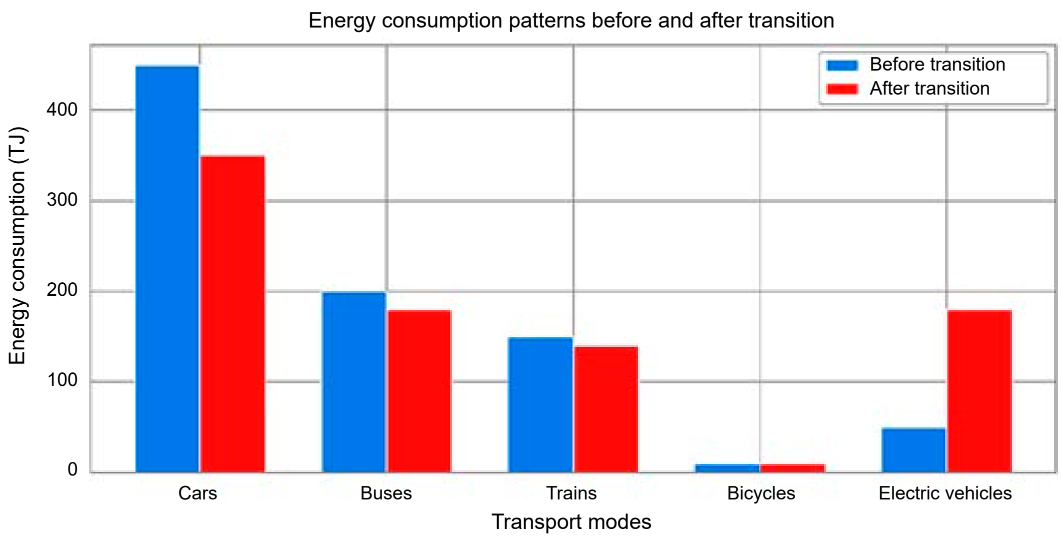

Figure 3. Energy consumption patterns (based on data from Ritchie & Roser (2023))

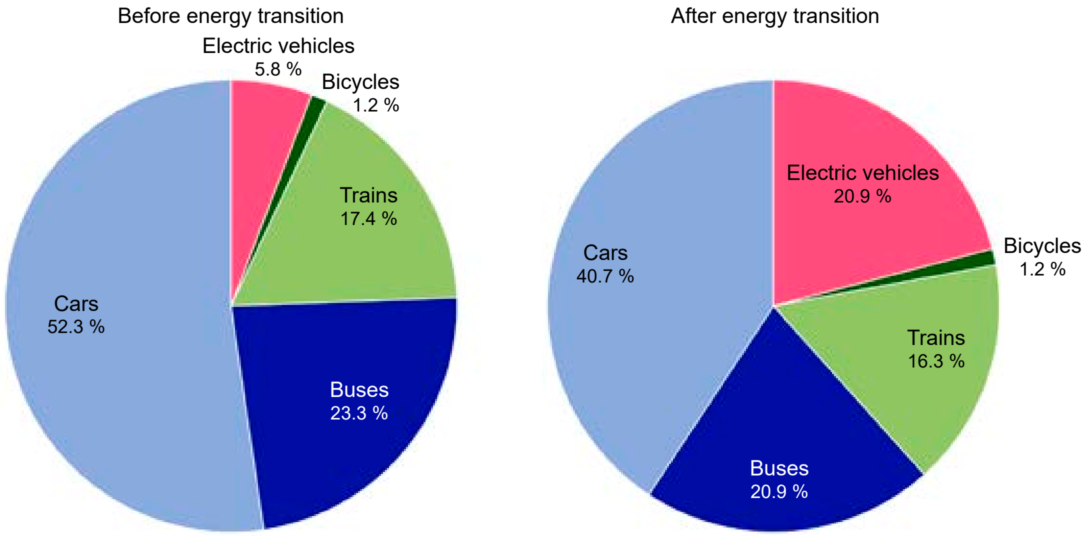

Figure 4. Energy consumption – general (based on data from Ritchie & Roser (2023))

Applications of RNNs

The dynamic nature of urban transport and logistics systems is aptly captured by the advanced capabilities of recurrent neural networks. Given the intricate sequence patterns inherent in traffic flow, vehicle usage, and energy consumption, RNNs stand out as robust tools for modeling and predicting the nuances of these systems (DiPietro & Hager, 2020; Weerakody et al., 2021; Liao et al., 2022). In the context of the energy transition for passenger and freight transport, RNNs shine across multiple applications. They significantly enhance demand forecasting, tapping into historical data to enable more effective vehicle and route planning, thereby leading to notable energy savings (Su et al., 2019; Chaturvedi et al., 2022). They also excel in route optimization by calculating the most energy-efficient pathways, accounting for a variety of factors, including traffic conditions, road gradients, and vehicle load (Su et al., 2019; Chaturvedi et al., 2022). The predictive maintenance capabilities of RNNs are particularly impactful, anticipating potential vehicle component failures, thus minimizing downtime, enhancing operational efficiency, and prolonging the lifespan of transport vehicles, all contributing to a leaner energy footprint (Kumar Sharma et al., 2022). Furthermore, RNNs adeptly estimate energy consumption for varying vehicle operating conditions, playing a critical role in energy management and the strategic development of charging infrastructures for electric vehicles, an essential component of modern sustainable urban ecosystems (Bedi, Venayagamoorthy & Singh, 2020; Lara-Benítez et al., 2020).

In practice, various cities have successfully implemented RNNs to optimize their transport and logistics systems. For instance, the city of Los Angeles uses RNNs to analyze and predict traffic patterns, allowing for dynamic traffic signal adjustments that reduce congestion during peak hours. Similarly, Singapore has deployed RNNs to manage its public transportation system, predicting bus arrival times and optimizing routes based on real-time traffic conditions, which enhances efficiency and passenger satisfaction. In freight logistics, companies like DHL have integrated RNNs to forecast demand and optimize delivery routes, resulting in significant reductions in fuel consumption and delivery times.

Use of low- and zero-emission vehicles

Current challenges and solutions

The deployment of low- and zero-emission vehicles (LEVs and ZEVs), including electric vehicles (EVs), hybrid vehicles, and hydrogen fuel cell vehicles, is a critical strategy in the energy transition of the transport sector. These vehicles not only reduce or eliminate tailpipe emissions but can also be more energy-efficient than traditional internal combustion engine vehicles, particularly when powered by renewable energy (Ledna et al., 2022; Rosales-Tristancho et al., 2022) (Figure 5).

However, the widespread adoption of LEVs and ZEVs presents a range of challenges:

- High upfront costs: despite decreasing costs, LEVs and ZEVs can still be significantly more expensive upfront than their conventional counterparts.

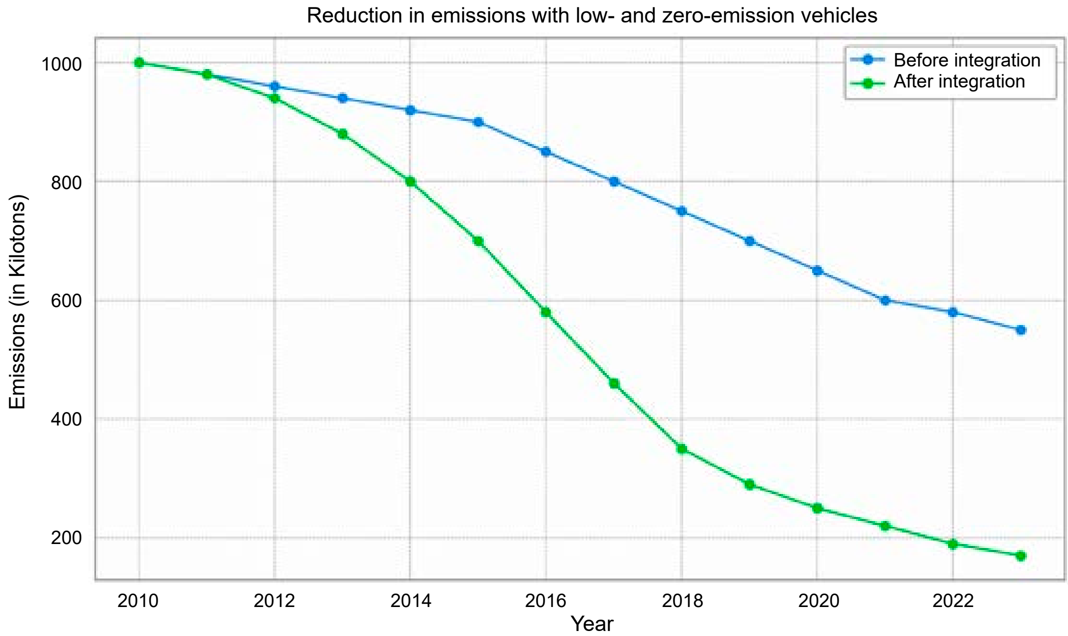

Figure 5. Potential reduction in emissions with low- and zero-emission vehicles (based on data from Leard & McConnell (2020))

This cost barrier can deter potential buyers, slowing the rate of adoption (Miele et al., 2020; Breed, Speth & Plötz, 2021).

- Range anxiety: for electric vehicles in particular, limited driving range and long charging times compared to refueling conventional vehicles can cause "range anxiety" among potential users (Breed, Speth & Plötz, 2021; Rosales-Tristancho et al., 2022).
- Infrastructure requirements: the shift to LEVs and ZEVs requires significant supporting infrastructure, including charging stations for electric vehicles and hydrogen refueling stations for fuel cell vehicles (Breed, Speth & Plötz, 2021; Rosales-Tristancho et al., 2022).
- Variable renewable energy supply: while electric and hydrogen vehicles can run on renewable energy, the variability of these energy sources can pose challenges to ensuring a consistent supply (Forrest et al., 2023; Rosales-Tristancho et al., 2022).

Despite these challenges, various solutions are being pursued:

- Technological innovation: ongoing advances in battery technology and hydrogen fuel cells are continually increasing the range of these vehicles and reducing their costs.
- Infrastructure development: governments and private companies around the world are investing in the necessary infrastructure to support LEVs and ZEVs, including widespread charging and refueling networks (Hochreiter & Schmidhuber, 1997; Breed, Speth & Plötz, 2021).
- Policy incentives: various incentives such as subsidies, tax rebates, and low-emission zones are being used to encourage the purchase and use of LEVs and ZEVs (Hochreiter & Schmidhuber, 1997; Rosales-Tristancho et al., 2022).
- Integration with renewable energy grids: advanced energy systems are being developed to align the charging of electric vehicles with periods of high renewable energy production.

As with other aspects of the energy transition in transport, machine learning techniques like RNNs can play a crucial role in these solutions, particularly in demand forecasting, infrastructure planning, and the integration of vehicle charging with renewable energy supplies. This potential is explored further in the following sections (van Triel and Lipman, 2020; Forrest et al., 2023; Hou et al., 2023).

Applications of RNNs

Recurrent neural networks, with their ability to handle sequential data and long-term dependencies, can offer unique advantages in managing the transition to low- and zero-emission vehicles (Hou et al., 2023).

Harnessing historical charging patterns, environmental conditions, and a suite of relevant variables, RNNs adeptly project the future requirements for electric vehicle charging facilities. This foresight is not merely about matching supply with demand but extends to refined load management on the power grid, ensuring that energy distribution is both balanced and sustainable, thus preventing the kind of surges that strain infrastructure and can lead to outages (Hou et al., 2023; Nespoli, Ogliari & Leva, 2023).

Beyond mere demand forecasting, RNNs play a strategic role in establishing optimal charging schedules. By analyzing and adapting to fluctuations in energy pricing, grid demands, and the intermittent nature of renewables, they ensure electric vehicles are charged in a cost-effective and grid-friendly manner, promoting the integration of sustainable energy practices (Pulvirenti, Rolando & Millo, 2023).

The strategic placement of charging infrastructure is another domain where RNNs contribute significantly. By anticipating the uptake of low-emission vehicles (LEVs) and zero-emission vehicles (ZEVs), as well as their respective energy requirements, these networks are pivotal in crafting a blueprint for future development that aligns with projected demand curves (Kiani et al., 2020; Hou et al., 2023).

RNNs also offer predictive capabilities that extend to the health of the vehicles themselves, particularly their batteries. By forecasting battery life and potential degradation pathways, they pave the way for preemptive maintenance and timely battery replacement, thus ensuring both the operational efficiency and the extended lifespan of the fleet (Shamsi et al., 2022; Adedeji, 2023).

Practical applications of RNNs in managing low- and zero-emission vehicles are evident in several pioneering initiatives. For example, Tesla's electric vehicle fleet uses RNN-based algorithms to predict battery life and manage charging schedules, ensuring optimal performance and energy efficiency. Similarly, the European Union's project on electric freight corridors employs RNNs to forecast energy needs and strategically place charging stations along key transport routes. This approach not only facilitates efficient energy management but also supports the seamless operation of long-haul electric trucks.

These applications of RNNs underscore their role as a cornerstone technology in the shift towards a more sustainable and efficient transportation ecosystem, with far-reaching implications for environmental stewardship, urban planning, and the evolution of smart cities.

Energy intensity of transport and logistics

Current challenges and solutions

The transport and logistics sector is one of the largest consumers of energy worldwide, contributing substantially to global greenhouse gas emissions. The energy intensity, or energy consumed per unit of transport output, is often high due to factors such as inefficient vehicle technology, traffic congestion, poor route planning, and low load factors in freight transport (Sharapiyeva et al., 2019) (Figure 6).

Addressing the energy efficiency of transport and logistics is riddled with hurdles, most notably due to the reliance on outdated vehicles and technologies. These energy-inefficient options, still in widespread

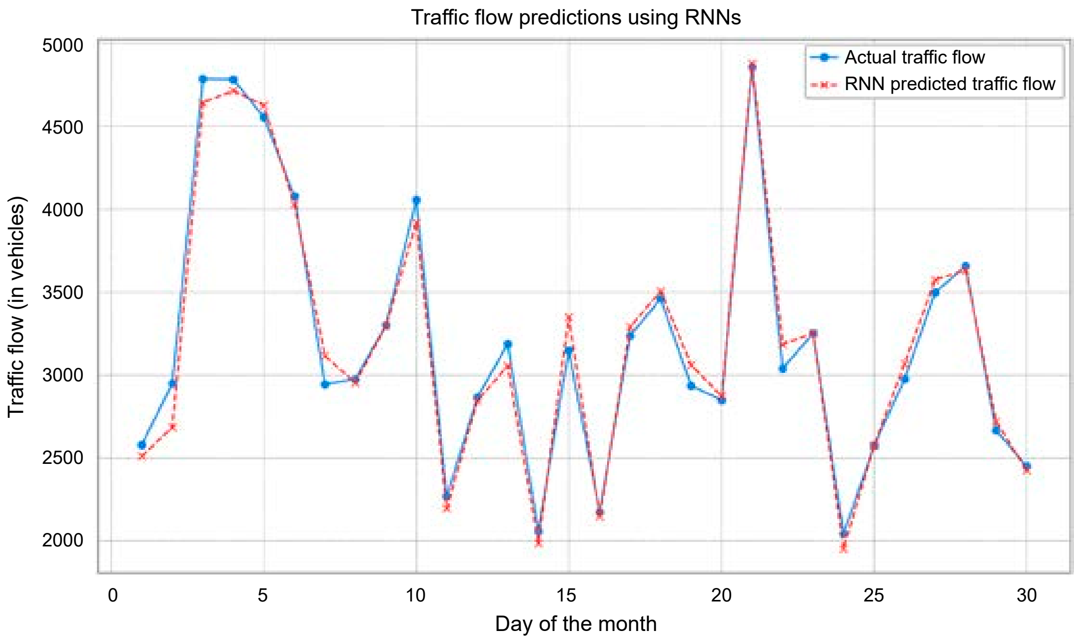

Figure 6. Traffic flow predictions using RNNs (GitHub, 2023)

use, represent a major barrier to modernization. The shift to state-of-the-art, energy-saving alternatives often involves significant investment and presents complex logistical challenges (Yan et al., 2021). This situation is further exacerbated by the persistent problem of traffic congestion in urban centers, which not only aggravates fuel consumption but also inflates the energy demands of transportation systems due to prolonged idle times and stop-and-go traffic patterns (Jamal & Khan, 2021). Compounding these issues is the lack of optimized routing and load management in freight transport. The failure to maximize the carrying capacity of vehicles and to plan the most direct, traffic-free routes leads to redundant trips and, consequently, excessive energy use. Such inefficiencies underscore the need for smarter logistics planning and the adoption of advanced technologies to reduce the overall energy footprint of transport operations (Du et al., 2023).

The transition to energy-efficient vehicles and technologies is an essential move towards sustainability. Embracing low- and zero-emission vehicles, coupled with the integration of smart transport systems and digital logistics, can significantly curb energy usage (Fiori et al., 2021). To further enhance these gains, advanced traffic management and optimized routing are paramount. These systems not only reduce congestion but also trim down travel distances and duration, which is especially beneficial in freight transport, where improved load planning optimizes vehicle capacity and slashes energy per freight unit (Fernández, Caraballo & López, 2019; Li, Wang & He, 2020). Policy interventions play a pivotal role in complementing these technological strategies. By enacting regulations and offering incentives, governments can steer the transport sector towards greater energy efficiency. Such measures may encompass fuel efficiency standards, financial support for adopting green technologies, and initiatives to limit non-essential travel and freight movements (Sharapiyeva et al., 2019).

RNNs, given their aptitude for handling complex, time-series data, can offer considerable benefits in addressing these challenges, as discussed in the following sections.

Applications of RNNs

In addressing the challenges of energy intensity in transport and logistics, RNNs find a number of notable applications:

- **Traffic prediction**: RNNs can effectively predict traffic patterns based on historical data, allowing for improved traffic management and reduction in energy use due to congestion (Nan et al., 2022).
- **Route optimization**: by learning from past data about road networks, traffic patterns, and delivery schedules, RNNs can determine optimal routes for vehicles, significantly reducing energy use (Song et al., 2022).
- **Load optimization**: for freight logistics, RNNs can help optimize the allocation of cargo to different vehicles based on their capacities, the destinations of the goods, and other factors, improving the energy efficiency per unit of freight (Asha et al., 2023).
- **Energy consumption modeling**: RNNs can model and predict the energy consumption of different vehicles under varying conditions, which can inform strategies for the energy-saving operation of vehicles and the planning of energy infrastructure (Kim et al., 2023).

These applications, leveraging the power of RNNs to process sequential data and capture temporal dependencies, offer significant opportunities for reducing the energy intensity of urban transport and logistics.

In a practical example, UPS has utilized RNNs to optimize its delivery routes, significantly cutting its fuel consumption and operational costs. By analyzing historical delivery data and traffic patterns, RNNs help UPS make real-time route adjustments that avoid congestion and minimize energy use. Another notable application is the use of RNNs by the Port of Rotterdam to predict cargo movements and optimize logistics operations, which has resulted in improved energy efficiency and reduced emissions in port activities.

Traffic and logistics infrastructure planning

Current challenges and solutions

Constructing a robust infrastructure is central to the efficacy and sustainability of transport and logistics systems, yet it is fraught with complexities. Urban centers worldwide are expanding rapidly, heightening the strain on existing infrastructure to meet escalating transport demands (Liu & Su, 2021). Concurrently, the imperative to integrate environmental sustainability into this infrastructure is pressing, necessitating the incorporation of clean energy solutions sources (Umar et al., 2020). Moreover, the pace of technological innovation, including the emergence of autonomous vehicles and drone delivery systems, combined with evolving consumer behaviors, calls for a flexible and progressive approach to infrastructure development (Pan et al., 2021).

Addressing these challenges demands an effective multifaceted approach, blending the power of data analytics with the foresight of progressive policymaking. Utilizing sophisticated data-driven techniques, including machine learning, allows urban planners and policymakers to anticipate and meet the burgeoning needs of modern cities. This approach ensures that infrastructure development is not just reactive but proactively aligned with future transportation and logistics demands (Li et al., 2021). Integrating cutting-edge technologies such as electric vehicle charging stations, autonomous transport systems, and smart traffic management is critical. This integration must be holistic, adapting to the evolving technological landscape systems (Liu et al., 2022). Furthermore, innovative policy measures play a fundamental role in shaping this landscape. Through strategic incentives and regulations, governments can steer infrastructure development towards sustainability, ensuring that new infrastructures are not only technologically advanced but also environmentally responsible.

Future directions. The future of RNNs in urban transport and logistics is poised for significant advancements. With an influx of data and enhanced computational capabilities, the precision and practicality of these models are expected to soar (Hu et al., 2019; Sun et al., 2021). Integrating RNNs with diverse disciplines, such as operations research and urban planning, could yield more holistic solutions (Fields et al., 2020). The advent of real-time decision-making systems using RNNs will revolutionize traffic and logistics operations (Chen et al., 2021). Policymaking can also greatly benefit from the insights provided by RNNs, leading to more informed and progressive transport policies (Nama et al., 2021). Furthermore, RNNs could foster greater public involvement in planning processes through advanced forecasting and visualization tools (Fields et al., 2020). As these technologies become more prevalent, addressing ethical concerns such as fairness, transparency, and privacy will be increasingly crucial (Tu et al., 2022).

The future of urban transport and logistics will undoubtedly be shaped by advances in artificial intelligence and machine learning, with RNNs playing a crucial role in this transformation (Iyer, 2021).

Development and the adoption of clean energy in transport and logistics. In this context, RNNs can offer considerable advantages in handling time-series data and forecasting future trends, as elaborated in the following sections (Zhang, 2020) (Figure 7).

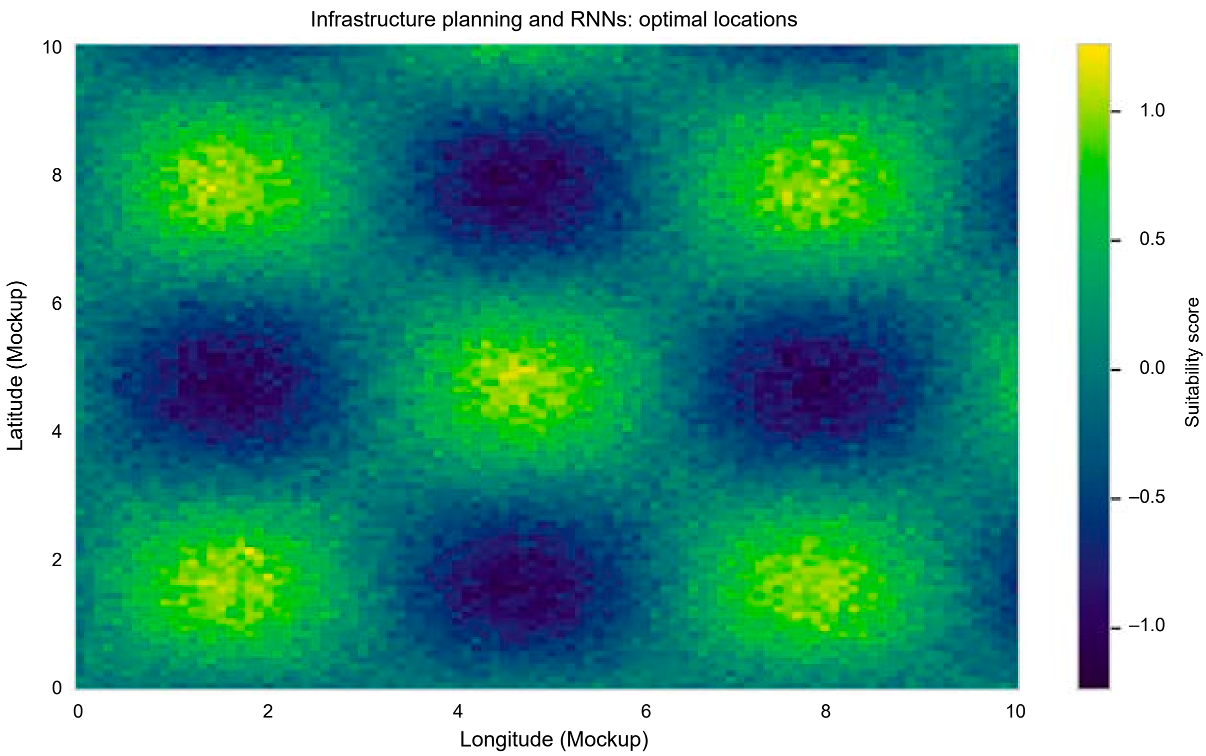

Figure 7. Example of infrastructure planning and RNNs: optimal locations (based on randomly generated data)

Applications of RNNs

RNNs are proving to be an instrumental tool in infrastructure planning, owing to their ability to understand and predict complex patterns (Azad & Wang, 2021). RNNs have become an invaluable asset in infrastructure planning, showcasing their capability to analyze and predict intricate patterns. They adeptly handle demand prediction, leveraging historical data, population growth, economic trends, and other relevant factors to accurately forecast future transport and logistics requirements. This foresight is crucial for guiding the development of new infrastructure at the optimal time and place (Yi et al., 2022). For pinpointing strategic locations for infrastructure such as charging stations, RNNs consider a myriad of variables, including population density, road networks, and existing facilities (Hainsch et al., 2022). Moreover, they play a key role in resource allocation, optimizing the use of existing infrastructure based on predicted needs (Abdullah et al., 2023). RNNs also excel in scenario planning by modeling various future conditions, such as demographic shifts or policy changes, to evaluate their impact on infrastructure demands, thus aiding in resilient and adaptable urban planning (Jeong, Kim & Yi, 2020).

A notable practical implementation of RNNs in infrastructure planning is seen in the development of smart cities like Barcelona. The city's infrastructure planning leverages RNNs to predict future transport needs based on population growth and urban development trends. This predictive capability allows for proactive infrastructure development, such as the placement of new public transport lines and charging stations for electric vehicles. Additionally, in New York City, RNNs are used to plan and manage infrastructure upgrades, ensuring that expansions in subway lines and road networks align with anticipated increases in commuter traffic.

Traffic management

Current challenges and solutions

Managing traffic in urban areas is a multifaceted challenge, exacerbated by factors such as rapid urbanization and a growing number of vehicles, leading to widespread congestion. This congestion not only prolongs travel times but also escalates fuel consumption and emissions, contributing to environmental degradation (Rocha Filho et al., 2020). Ensuring road safety is another complex aspect, demanding constant vigilance to protect diverse road users, including drivers, pedestrians, and cyclists (Sheikh & Liang, 2019). Moreover, the transportation sector's substantial role in air pollution and climate change underscores the urgency of mitigating its environmental impact (Shabana et al., 2020).

Addressing these issues involves the deployment of advanced technologies, such as intelligent transportation systems (ITS), which employ data, artificial intelligence, and communication technologies to streamline traffic flow and enhance safety (Ning et al., 2021). Infrastructure improvements are also vital, including the creation of dedicated lanes for public transport and cyclists and the introduction of modern roundabouts, all aimed at improving traffic dynamics and safety (Marusin, Marusin & Ablyazov, 2019). Policymaking plays a critical role, with strategies such as implementing congestion charges, establishing low-emission zones, and promoting public and non-motorized transport as key components of a comprehensive approach to traffic management (Sheikh & Liang, 2019; Shabana et al., 2020). In this technological and policy landscape, RNNs emerge as a pivotal tool, capitalizing on their strength in processing time-series data to enhance prediction accuracy and, thus, significantly contribute to advanced traffic management solutions.

Applications of RNNs

Recurrent neural networks, including their sophisticated forms such as long short-term memory and gated recurrent units, are revolutionizing traffic management with their exceptional ability to predict sequential patterns. They are particularly effective in forecasting traffic flow by analyzing historical data, which plays a crucial role in managing congestion and optimizing routes (Bhatia et al., 2022). RNNs also excel in real-time incident detection and prediction, such as identifying traffic jams or accidents, thereby enabling more efficient response and management strategies (Babbar & Bedi, 2023). Furthermore, these networks can optimize traffic signal timings based on predicted traffic flows, significantly improving the efficiency of traffic movement and reducing wait times for commuters (Modi et al., 2022).

Future directions

As we look towards the future of urban transport and logistics, the role of RNNs is anticipated to grow significantly. With the influx of data and advancements in computational capabilities, these models are expected to become more accurate and versatile, enhancing their applicability in various aspects of urban mobility and logistics planning (Choi et al., 2020). The potential of RNNs in interdisciplinary applications, where they could be integrated with other machine learning techniques or even different fields such as operations research or urban planning, opens up avenues for more holistic and robust solutions operations (Bai et al., 2021).

In the realm of real-time decision-making, RNNs are poised to play a transformative role. Their ability to process and analyze sequential data makes them ideal for developing systems that can manage traffic and logistics operations more dynamically and responsively. Moreover, the integration of RNNs into policymaking processes could lead to the formulation of more effective and proactive strategies for urban transport and logistics, ensuring that policies are data-driven and adaptive to changing trends and needs (Ang et al., 2022).

Another promising area is public engagement in transport and logistics planning. RNNs, with their advanced forecasting and visualization capabilities, can make transport data more accessible and understandable to the public, fostering greater involvement in planning and decision-making processes (Ang et al., 2022).

However, as RNNs and similar machine-learning technologies become more widespread, ethical considerations will become crucial. Issues surrounding fairness, transparency, and privacy must be addressed to ensure that the deployment of these technologies is responsible and equitable (Welch & Widita, 2019).

In conclusion, the trajectory of urban transport and logistics is set to be profoundly influenced by the advancements in artificial intelligence and machine learning, with RNNs being at the forefront of this technological revolution (Fig. 8) (Iyer, 2021).

Conclusions

The transformative potential of recurrent neural networks in urban transport and logistics extends far beyond mere technological advancements. These systems represent a pivotal shift towards a more sustainable, efficient, and responsive urban fabric. As we harness the power of RNNs, we must recognize their role in not only enhancing operational efficiencies but also in driving a paradigm shift in urban mobility.

Integrating RNNs into urban transport is not just a step towards digitalization but a leap towards environmental stewardship. By optimizing routes, reducing congestion, and supporting the adoption of electric vehicles, RNNs contribute significantly to reducing the carbon footprint of urban areas. The future of urban transport, shaped by RNNs, promises greater accessibility and inclusivity. Enhanced traffic management and predictive logistics planning will lead to more equitable urban spaces, where mobility is a right, not a privilege.

The role of RNNs in streamlining transport and logistics operations holds the promise of substantial

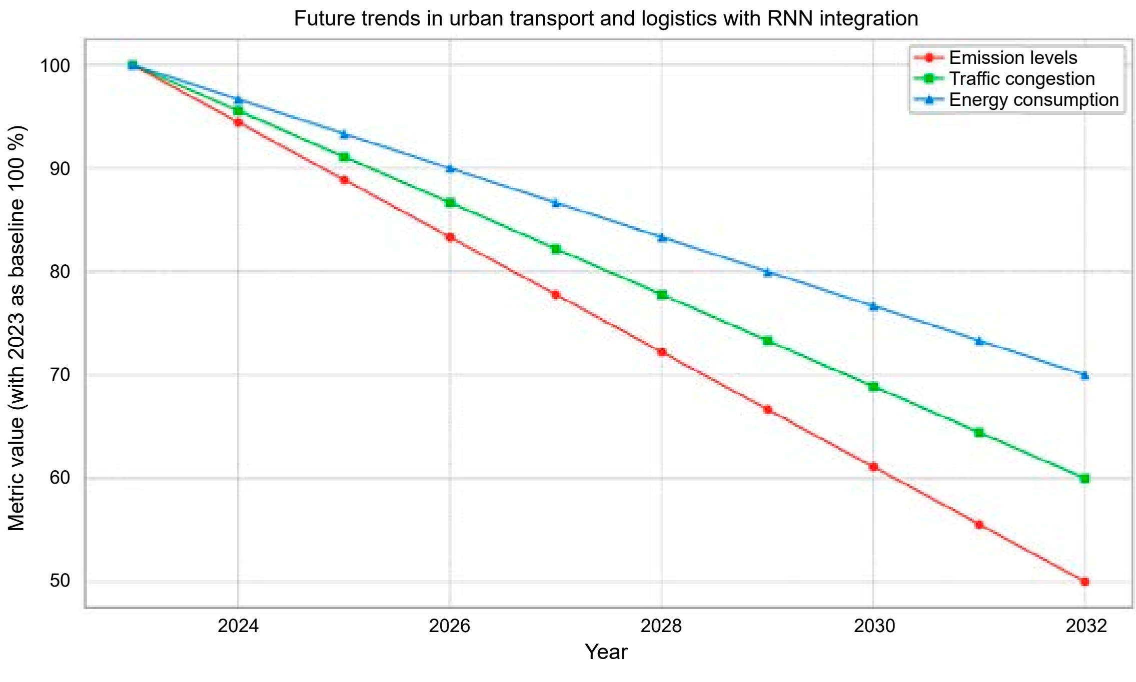

Figure 8. Future trends in urban transport and logistics with RNN integration (based on data from Teter and Voswinkel (2023))

economic benefits. Reduced operational costs, enhanced efficiency, and lower environmental impact all contribute to a more robust urban economy. Moreover, the insights provided by RNNs can guide policymakers in creating more informed, dynamic, and responsive urban transport policies. This data-driven approach allows for adaptable strategies that can evolve with the changing needs of urban populations.

As we embrace the capabilities of RNNs, we must also address the ethical implications of such technologies. Ensuring fairness, transparency, and privacy in the use of RNNs is paramount to building trust and acceptance among the public. The true potential of RNNs lies in their ability to be integrated with other disciplines. Collaboration across fields like urban planning, environmental science, and social sciences will lead to more comprehensive and sustainable urban transport solutions.

In conclusion, RNNs are not just shaping the future of urban transport and logistics; they are redefining it. Their impact, reaching far beyond the realms of technology, paves the way for smarter, more sustainable, and more equitable urban environments. As we stand on the brink of this revolution, it is crucial to navigate these advancements with a balanced approach, considering not just the technological possibilities but also the societal and environmental responsibilities they entail.

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Cite as: Durlik, I., Miller, T., Kostecka, E., Pusty, T., Łobodzińska, A. (2024) Utilizing recurrent neural networks in sustainable urban transport and logistics. S*cientific Journals of the Maritime University of Szczecin, Zeszyty Naukowe Politechniki Morskiej w Szczecinie* 78 (150), 131–149.