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REVIEW

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Advanced computing to support urban climate neutrality

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Abstract

Background Achieving climate neutrality in cities is a major challenge, especially in light of rapid urbanization and the urgent need to combat climate change. This paper explores the role of advanced computational methods in the transition of cities to climate neutrality, with a focus on energy supply and transportation systems. Central to this are recent advances in artificial intelligence, particularly machine learning, which offer enhanced capabilities for analyzing and processing large, heterogeneous urban data. By integrating these computational tools, cities can develop and optimize complex models that enable real-time, data-driven decisions. Such strategies offer the potential to significantly reduce greenhouse gas emissions, improve energy efficiency in key infrastructures and strengthen the sustainability and resilience of cities. In addition, these approaches support predictive modeling and dynamic management of urban systems, enabling cities to address the multi-faceted challenges of climate change in a scalable and proactive way.

Main text The methods, which go beyond traditional data processing, use state-of-the-art technologies such as deep learning and ensemble models to tackle the complexity of environmental parameters and resource management in urban systems. For example, recurrent neural networks have been trained to predict gas consumption in Ljubljana, enabling efficient allocation of energy resources up to 60 h in advance. Similarly, traffic flow predictions were made based on historical and weather-related data, providing insights for improved urban mobility. In the context of logistics and public transportation, computational optimization techniques have demonstrated their potential to reduce congestion, emissions and operating costs, underlining their central role in creating more sustainable and efficient urban environments.

Conclusions The integration of cutting-edge technologies, advanced data analytics and real-time decision-making processes represents a transformative pathway to developing sustainable, climate-resilient urban environments. These advanced computational methods enable cities to optimize resource management, improve energy efficiency and significantly reduce greenhouse gas emissions, thus actively contributing to global climate and environmental protection.

Keywords Deep learning, Time series forecasting, Energy management, Traffic management, Fleet management, Climate neutrality

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Background

One of the main goals to achieve urban climate neutrality is to reduce greenhouse gas emissions. Consequently, cities, municipalities and regions are implementing various solutions to address this challenge and improve climate resilience across all sectors [1, 2]. This paper focuses on two key sectors that can be effectively optimized using advanced computational methods: the energy supply [3] and transportation [4]. In climate-neutral cities, not only must buildings be adapted or constructed according to high energy efficiency standards, but their energy needs must also be covered by sustainable and optimized supply systems. In addition, transport networks and infrastructures should ensure safety, convenience and fast public transit [5]. Thus, traffic flows should be supported by multimodal transport systems, responsive traffic signals and dynamically adaptable signage that enable the efficient movement of people and goods.

Effective computing approaches are one of the means by which cities can become less carbon intensive. Such approaches are generally part of artificial intelligence (AI) and range from simple scheduling and allocation techniques to more advanced optimizations supported by deep neural networks (DNN) and other machine learning (ML) approaches [6]. For example, for efficiently contributing to a sustainable energy ecosystem model of a city or a region, it is necessary to combine analysis, optimization and simulation tools. Such commonly used models are good predictors of the general energy dynamics. However, they can be inadequate when it comes to the large number of parameters, many end users, the assessment of different environmental impacts and the diversity of resources. This is where forecasting models based on ML offer enormous advantages. Based on historical data, they can be trained to accurately predict the future demand of a large group of consumers [7, 8]. Their predictions can be used to develop more efficient strategies to logistically satisfy the demand in an efficient and climate-neutral way. Furthermore, by analyzing such predictive models, we can identify the regularities of how society behaves empirically and develop strategies that lead to reducing behaviors that hinder climate-neutral goals. In recent years, many ML methods have emerged that can support these efforts, such as deep learning, ensemble models, tree-based models, and so on.

The electrification of public transportation in cities is on the rise [9], as electric busses are promising due to their high energy efficiency [10]. In this context, the challenges related to the sustainable development of energy storage systems for electric vehicles must be adequately addressed, which includes the configuration of physical infrastructures and a wide range of related services [11]. In addition, traffic forecasting is crucial for the development of an intelligent prediction system that can contribute to traffic management and travel time reduction. It is important to combine and consider spatiotemporal dependencies with other data that may have an impact on traffic patterns. Models based on ML can be very robust and at the same time react efficiently to dynamic traffic changes.

The important goal is also to develop and integrate high-level traffic and fleet management that enables globally optimal and integrated transportation of passengers and goods. Here, innovative dynamic balancing and priority-based management of vehicles can be used to develop fleet and traffic management solutions through machine learning and data fusion [12]. These improve the capabilities of transportation authorities and operators and enable them to become effective conductors of future mobility networks [13]. The innovations have the potential to reduce urban traffic and congestion, reduce pollution and improve quality of life [14].

At a time of unprecedented urbanization and the urgent need to combat climate change, the pursuit of urban climate neutrality is one of the greatest global challenges. As cities grow in population and complexity, so do their energy needs, carbon emissions and resource consumption. Advanced computing, with its enormous capacities for data analysis, simulation and optimization, is becoming an important key to revolutionizing urban landscapes. The integration of advanced computing technologies promises to enable cities to harness vast data streams, develop complex climate models and implement real-time, data-driven strategies that can drastically reduce greenhouse gas emissions, improve energy efficiency and strengthen urban resilience. This paper highlights the role of advanced computing in shaping the future of urban climate- neutrality and offers a compelling pathway to sustainable, green cities that not only adapt to the changing climate, but also actively contribute to its mitigation and long-term preservation.

The intersection of advanced computing and urban climate neutrality has attracted considerable research attention in recent years. Here, we provide an overview of existing work that highlights the various applications of advanced computing technologies to promote sustainability and urban climate neutrality. Data-driven approaches have become an essential part of optimizing urban energy consumption and reducing carbon emissions. Researchers have used advanced data analytics techniques such as ML and predictive modeling to analyze energy consumption patterns and forecast future demand. A review focusing on electricity demand forecasting [15] concludes that 90% of studies nowadays apply AI methods compared to 10% of traditional engineering and statistical methods to solve energy forecasting problems. This shows a clear trend and points to the usefulness of state-of-the-art computational methods in this sector. These methods can be very flexible and robust. For example, a regression model for electric load [16] by Al-azzawi et al., is able to account for non-trivial changes in demand during the COVID-19 pandemic. Moreover, such a methodology can become even more effective with a smart infrastructure such as an IoT-enabled smart grid [17].

Prediction methods that focus on building energy demands also show that AI-related tools such as support vector machine, neural networks and random forests [18] perform better than statistical tools such as linear regression and ARIMA [19]. Accurate energy planning and management in the early design phase can even prevent the construction of more energy-inefficient buildings [20]. Simulation tools such as EnergyPlus have been used to simulate the impact of different energy-efficient strategies on the energy performance of buildings [21]. These approaches help identify optimal energy-saving strategies. ML models have also been used to decide whether and what type of heat pump at the household level leads to an energy-efficient property of the building [22]. The study on the urban ecosystem model [23] discusses the importance of sustainable development by reducing energy consumption and minimizing environmental impact. The usual first step in creating a model is to understand the past and current situation. To this end, an ecosystem model must be created that combines analysis, optimization and simulation modules. Such models improve the understanding of system dynamics and are therefore valuable tools for the development of sustainable energy systems tailored to the availability of local energy sources.

In the past, the demand for precise modeling and prediction in forecasting has led to the emergence of various ML methods. The field of statistics provides various models for univariate time series analysis. These models include the moving average (MA), autoregressive (AR), and autoregressive integrated moving average (ARIMA) [24]. These models are particularly suitable when only limited data is available. Several of these techniques were later extended to account for multivariate data and covariates, including VARIMA [25], ARMAX and ARIMAX [26]. Initially, methods used traditional machine learning techniques, where temporal dependencies were taken into account by adding lag features, and considered the challenges as tabular issues [27–29]. The introduction of more complicated neural network-based models, such as RNN [30], where neuron connections can form a cycle, led to better accuracy [31]. These models are suitable for managing temporal dependencies. With advances in modeling temporal data, innovations such as LSTM cells [32] were quickly integrated into forecasting. Alongside the progress with LSTMs, convolutional neural networks (CNNs) [33] gained traction. Initially developed for image classification, they were modified for time series analysis [34]. Recently, the focus has shifted to the development of models that are specifically tailored to time series analysis. For example, the N-BEATS [35] structure excels in forecasting scenarios with a large amount of data. Similarly, DeepAR [36] is a renowned forecasting neural network that uses LSTM cells to estimate parameters of a probability distribution, providing deeper insights into model uncertainty. It can work with multivariate time series, including future and past covariates. More recently, transformer-based [37] networks, such as Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting, have been used for forecasting tasks. While deep learning methods are widely used in forecasting, other successful strategies should not be overlooked [38, 39].

The emergence of intelligent transportation solutions has been instrumental in reducing emissions caused by urban mobility. Petelin et al. presented a real-time traffic control system that reduces congestion and lowers emissions through adaptive traffic signal control in ref. [40]. The optimization of transport processes within a logistics chain is presented in ref. [41]. The authors look at reducing the costs of transportation, storage or production processes and increasing efficiency in the execution of logistics operations. The overarching goal is to make more effective use of the means of transportation, technologies and human resources involved. In order to reduce logistics costs, shorten transportation time and increase the efficiency of logistics operations, Zhang et al. propose the use of a Mixed Integer Non-linear Program (MINLP) model [42]. The general algebraic modeling system is used to build the model to fully integrate each parameter of logistics transportation, the total distribution time of the supply chain network, the coverage radius of the logistics base, the number of users, the total capacity of the logistics base, the type of rail and road transportation. The non-linear model is solved with a MINLP-based solver.

Suhua shows how intelligent logistics can improve people's quality of life [43]. The paper proposes an optimization system for logistics engineering based on ML and AI. Based on the classifier chain and the combined classifier chain, an improved multi-label chain learning method for high-dimensional data is proposed. Lv discusses the application of AI in the e-commerce logistics system [44]. The AI-based algorithms are used to accurately calculate the relationship between the supply and demand of goods and the optimal path of actual logistics distribution. In addition to accurately predicting stock levels, the use of AI also optimizes the associated inventory variables, e.g., sorting period.

A recent review by Giuffrida et al. provides an overview of the advances related to last mile delivery [45]. In it, the optimization techniques are divided into traditional optimization models, machine learning approaches and mixed methods. The performance of a future reconfigurable and autonomous vehicle fleet in a highly dynamic operational scenario is evaluated in ref. [46]. When operating in a harsh environment under high risk of damage, the fleet must react to adversarial actions in real time. To account for the complexity and dynamics, the authors formulate an intelligent agent-based model for the decision-making process during fleet operations by combining real-time optimization with AI. The ML method is employed to optimize fleet management and achieve sufficient output to reduce operational costs in ref. [47]. This is obtained by reducing the waiting time of trucks and the idle time of excavators in a mine based on the best selection of the fleet.

Another survey, by Alexandre et al., outlines ML-based solutions for public bus transportation and goes into detail on the modeling of solutions for travel time prediction or passenger flow prediction [48]. Electric vehicle (EV) charging infrastructure has been optimized using computational methods to ensure efficient energy distribution and integration with renewable energy sources [49]. Yoo et al. propose a new approach to solve the problem of designing bus networks and setting frequencies, as the transportation network must meet the needs of both users and operators [50]. The proposed algorithm uses reinforcement learning for a simultaneous optimization of three key components: the number of bus lines, the route design and the service frequency. The algorithm is able to suggest the best set of bus routes without predetermining the total number of bus routes, which also reduces the total computation time. The bus routes can be dynamically adjusted according to the passenger demand in real time. Ma et al. formulated a two-stage stochastic programming model to minimize the total cost of vehicle travel time and the penalty for rejecting requests [51]. Vector similarity-based clustering and adaptive large neighborhood search algorithm were used to solve it.

Main text

Methods

Efficient advanced computing approaches are one of the means by which cities can become less energy and carbon intensive. Advanced computing approaches encompass a wide range of techniques and methodologies that go beyond traditional computing methods. These approaches often use cutting-edge technologies and methods to solve complex problems, such as achieving urban climate neutrality. Below we categorize these approaches into software and hardware-based. Please note that this list is not exhaustive and that these are just a few examples of advanced computational approaches.

Software approaches include machine learning and deep learning [52], which use neural networks to analyze and learn from large data sets. These techniques are often used in applications such as pattern recognition and recommendation systems, where they excel at recognizing complex patterns and making accurate predictions. Further notable software-based approaches are Swarm Intelligence [53] and Evolutionary Algorithms [54]. These methods are inspired by the collective behavior of decentralized systems such as insect swarms or bird flocks and by the principles of natural selection and evolution. They are particularly effective in solving optimization and decision-making problems because they harness the power of distributed problem-solving and iterative improvement. In addition to these approaches, simulators [55] play an important role in areas such as traffic management and other similar concepts. Through the use of computer models, simulations can replicate complex systems or processes, enabling detailed analysis, experimentation and prediction of behaviors and outcomes in different scenarios. This capability is invaluable when it comes to testing hypotheses and understanding the potential impact of different variables in a controlled, virtual environment, which in turn contributes to effective planning and decision-making.

On the hardware side, high-performance computing and distributed computing involve the use of supercomputers or clusters of high-performance servers to process large-scale simulations, weather forecasts and complex mathematical calculations. Edge computing [56] is another hardware approach that brings computation and data storage closer to the data source (e.g., IoT devices) to reduce latency and improve real-time processing for applications such as autonomous vehicles and smart cities.

Advanced computing approaches

In recent years, we have witnessed great progress in the field of computer science, especially in the field of AI. The prevailing methodology for this is ML, which involves methods for training computer models using data, thus avoiding explicit programming and human intervention. This results in computer models that are not constrained by expert knowledge and can use the patterns present in the data to fulfill the task at hand. The three currently most popular and effective classes of approaches are deep learning, ensemble models and tree-based models, which were also used in our work.

The deep learning method consists of training a multilayer model, usually an artificial neural network (ANN), on data using gradient-based training, which is usually executed on GPU hardware that enables fast and more energy-efficient implementation. ANN as a function is essentially a composition of parametrized linear functions and fixed element-wise non-linear functions. Its characteristics are determined solely by the values of its parameters. It is known that ANNs can approximate any function with arbitrary precision [57]. In other words, if there exists a function that returns energy consumption or traffic flow status from available data, there also exists an arbitrarily accurate ANN that can do the same. However, the user still needs to find such an ANN using optimization methods, a process known as ANN training. An example of such a model is shown in Fig. 1. ANN model can consists of many applications of linear and non-linear maps, in which case we speak of a deep neural network. It is known [58] that the deeper ANN is the higher capacity the model has which means that deeper ANNs are able to capture a wider range of functions.

If the training data for ANN is a time series, which is the case for many real-world problems in the energy and transportation sectors, the ANN model also needs a mechanism to take the past into account. For example, when modeling energy demand, the future prediction of ANN cannot be based only on current features, such as the current weather, day of the week, time of day, etc., but also requires access to past weather data. Therefore, a sufficiently large (i.e., wide) ANN is needed that can process several days of data as a single input. However, very wide ANNs can lead to overfitting since the number of parameters of an ANN grows quadratically with the width. But there is also another, and more efficient way, for ANNs to know about past data. A special architecture known as a recurrent neural network (RNN) can be used. An example of this is shown in the Figure. 2. Such ANNs contain feedback loops that allow the network to remember previous inputs. Therefore, an RNN can be fed with one instance of weather data at a time. In this way, an ANN with a small width (and therefore a manageable number of model parameters) can be used, which nevertheless takes past data into account.

The simplest way to implement ANN with feedback loops is the Elman network [59], also known as simple recurrent network (SRN). The action of an SRN layer is defined as

$$\mathbf{h}_t = \tanh\left(W\mathbf{x}_t + U\mathbf{h}_{t-1} + \mathbf{b}\right), \tag{1}$$

where $\mathbf{x}_t$ is the input to the layer at time step t, $\mathbf{h}$ is the activation of the layer, $\mathbf{b}$ is the bias vector and W and U are matrices. In this way, a given layer activation depends only on the values coming from the previous layer and on the previous activation of the same layer. Therefore, $\mathbf{h}$ contains the information about previous activations that allow SRN to have a memory about the previous inputs.

Historically speaking, RNNs were seldomly used because of their inability to capture long-term correlations [60]. These problems were overcome by the introduction of gated units such as the long short memory (LSTM) and the gated recurrent unit (GRU) [61]. The idea behind gated RNN is that they use gates that determine whether the information should remain in the layer or be forgotten. For comparison, with SRN, past information is forgotten at a constant rate. But gated RNN can

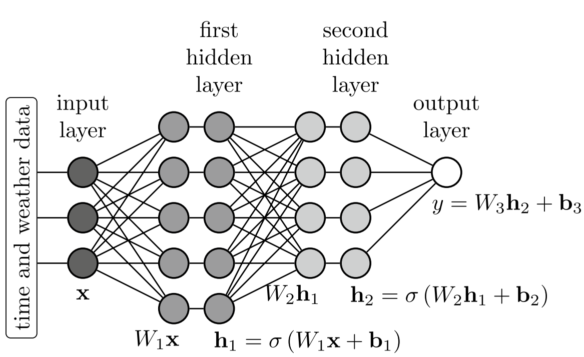

Fig. 1 Depiction of a feedforward artificial neural network model with two hidden layers where every step of model calculation is explicitly shown. W_i are matrices and σ is element-wise non-linear function

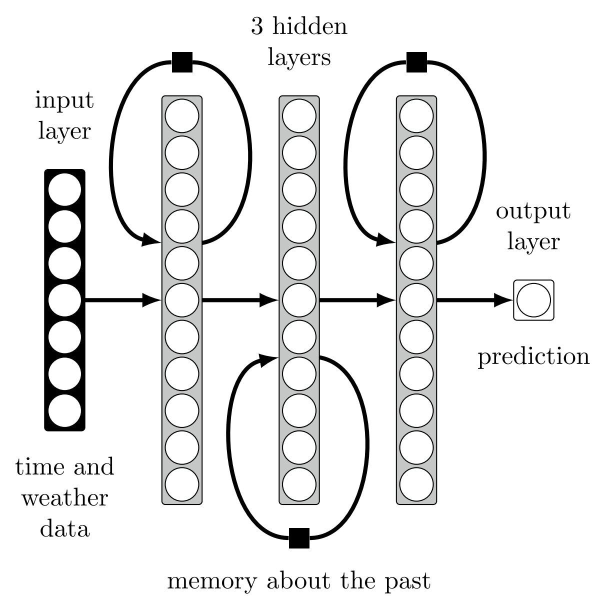

Fig. 2 Example of RNN model architecture with three hidden layers. Connections between layers are depicted with arrows and one step delay with black squares. Hidden layers get input from the previous time step as well as from the preceding layer

control in which cases the information is lost and therefore such RNN can be trained to use long-range dependencies. The details of the actions in LSTM and GRU can be found in refs. [62, 63], respectively.

When we model demand or traffic flow, we are essentially training a model that can statistically describe human behavior. Since features such as the time of day, day of the week, month and year strongly influence how we function, they need to be accessible to the model in a way that is most useful to us. An important observation is that these features are periodic and not ordinal. For example, Sunday is one day before Monday (periodic) and not six days before Monday (ordinal). There is a simple way to introduce this property directly into the data, which usually helps the model to train faster and achieve better accuracy with smaller data sets. Periodic time variables can be coded ordinally as

$$t_o = t \ (\mathrm{mod}) \ t_0, \tag{2}$$

where t is the linear time and t_0 is the period of this time variable (1 day, 1 week or 1 year). However, we can convert these characteristics into a periodic form by using

$$t_p = \begin{bmatrix} \sin(2\pi t/t_0) \\ \cos(2\pi t/t_0) \end{bmatrix}. \tag{3}$$

In this variant, the model sees points at the end of the period that are close to those at the beginning of the period. On the other hand, using eq. (3) doubles the number of input nodes for periodic time variables. This leads to a larger network, but with modern approaches and hardware this is rarely a limiting factor.

Machine learning models can often present a formidable challenge for people who are not well-versed in the intricacies of the field [64]. The complex algorithms, parameter tuning and feature engineering required can be intimidating and difficult to grasp for non-experts. Considering this hurdle, AutoML (Automated Machine Learning) [65] tools have proven to be valuable solutions. These tools have been developed to streamline and automate the process of ML, making it accessible to a wider audience. By simplifying the model development process, AutoML enables non-experts to use the power of ML for their applications without the need for an in-depth understanding [66] of the underlying technology. This democratizes the field and enables more widespread adoption [67].

As highlighted in ref. [68], AutoGluon simplifies the process of ML by automatically selecting algorithms, tuning hyperparameters and assembling stacks, reducing the need for in-depth ML expertise. When processing tabular data, AutoGluon creates a robust predictive model by firstly training several base learning models, including popular algorithms such as neural networks, random forests and gradient boosting machines. These baseline models are then subjected to a comprehensive hyperparameter optimization process to determine the best-performing configurations. AutoGluon then applies an automated stack ensembling strategy where the predictions of these different models are combined layer by layer to improve the overall prediction performance. This ensemble approach capitalizes on the strengths of the individual models and often outperforms the accuracy of the individual models. AutoGluon's ability to deliver high performance with minimal manual intervention is also confirmed by its evaluation in the AutoML Benchmark (AMLB) study [69], where it consistently outperformed other models in various scenarios.

Computational challenges

Achieving urban climate neutrality through advanced computing has several significant challenges. One major obstacle is handling the vast amounts of complex data needed for thorough climate modeling and analysis. Urban environments are complex systems in which factors such as traffic, infrastructure and local weather are closely and deeply interlinked. This complexity requires the development of sophisticated algorithms capable of processing large amounts of data, often in combination with complex simulations. Another challenge lies in real-time decision-making, which is essential for real-time and effective interventions. This requires high-performance computing to process data quickly and accurately. In addition, safeguarding sensitive urban data is crucial, as breaches could have serious consequences for city residents. The ever-changing nature of technology and data sources makes matters even more complex, requiring flexible computing infrastructures that can adapt to new innovations such as edge computing to address the needs of dynamic urban settings. These challenges highlight the importance of developing cutting-edge computing solutions and supporting ongoing research in this area.

Urban energy management

Forecasting energy demand has significant potential to drive climate-neutrality efforts in cities. By accurately predicting energy consumption patterns, cities can proactively develop and implement targeted energy efficiency initiatives and demand reduction strategies. These forecasts enable local authorities to optimize resource allocation to renewable and low-carbon energy sources to encourage the transition away from fossil fuels. In addition, data-driven insights into residential gas consumption enable the development of personalized conservation campaigns that raise awareness and encourage residents to adopt energy-saving behaviors. As cities strive for climate neutrality, forecasting residential gas consumption becomes an important tool to align urban planning with sustainability goals, reduce emissions and promote a culture of conscious energy consumption at the household level.

Heating load forecasting for urban areas is an especially important special case since space heating has been recognized as the most energy-intensive end use in EU households accounting for about 70% of total energy consumption in buildings [70]. Because such large proportion of energy is consumed for heating, especially during winter months, its modeling is a crucial component of energy management. Possible inaccuracies in heating load forecasting can lead to serious disturbances in energy transportation chains. District heating and combined heat and power systems also benefit from this type of forecasting. Successful operation of both systems stands on solving a problem of optimal planning of heating resources. In order to search for an efficient schedule which achieves that heating resources meet demand as close as possible, a short-term forecast is required. This means that we have important use cases that require accurate heating load forecasting for both several days into the future (for energy transportation) and several hours into the future (for district heating).

Demand–response and load balancing

Demand–response and load balancing are critical components of modern urban energy management that are essential for optimizing energy consumption, improving grid stability and reducing environmental impact. In the context of a growing urban population and the increasing electrification of various sectors, demand–response strategies enable cities to allocate energy resources efficiently by incentivizing consumers to shift their electricity consumption to off-peak hours. This not only relieves pressure on the electricity grid at peak times, but also enables the integration of renewable energy sources such as solar and wind energy by adapting energy production to the demand. Load balancing, on the other hand, is about distributing energy loads evenly across the grid to prevent overloading or underusage of the infrastructure, resulting in less wasted energy and higher system reliability. Together, demand–response and load balancing are powerful tools in the urban energy manager's toolbox, promoting sustainability, grid stability and cost efficiency in a world increasingly reliant on reliable and environmentally friendly energy sources.

To achieve efficient energy balancing, we need high-quality forecasting models that can predict both the demand and production of energy. The scheduling of assets within the energy infrastructure can then be based on the predictions of such forecasting models. Predicting future demand and production is not an easy task and depends on both natural and societal factors. In the following section, we show how advanced computational approaches can be used to acquire high-quality forecasting models for the energy sector. We have chosen the natural gas demand forecasting problem as a use case because gas demand is closely linked to district heating demand, which is a major source of energy consumption in Europe.

Case study Ljubljana: gas consumption forecasting

To demonstrate the ability of the modern computational approaches, we trained recurrent neural network models to forecast gas consumption in a city of Ljubljana, Slovenia, up to 60 h into the future. Previous work on this problem has shown that deep neural networks perform the best [31], considering several standard ML models. In this section, we perform a further comparison to address which deep learning architectures and feature transformations are best suited for this type of energy demand forecasting. We tested three different RNN architectures (SRN, GRU and LSTM) and for two different encodings of time variables (ordinal and periodic).

In addition, we are interested in how models with different number of layers compare to each other. Models with 1 to 5 layers were tested. In order to have a reliable comparison, the number of model parameters is set to 4000 for all models. To accomplish this, two models with different layer widths are created for each model instance (for each unit type and each layer count). The two models had a parameter count just below 4000 and just above 4000, so the error of the model with 4000 parameters is the weighted sum of the two models whose parameter count is close to 4000. In this way, the model instances are truly comparable.

The models were trained on a dataset of 8 seasons of hourly gas consumption collected from a large gas distribution company in Slovenia. More details about the dataset and the problem can be found in ref. [71]. The accuracies of the models for different unit types, different number of layers and different time data feeds are shown in Fig. 3. As expected, the SRN models proved to be the least accurate. This can be attributed to the fact that SRN is not able to account for long-term dependencies. For a small number of layers, the LSTM unit is clearly superior, while for deeper architectures the LSTM and GRU units are comparable. The use of periodic time data feeding (t_p) is advantageous, but a significant difference is only evident for a small number of layers. In the other cases, it appears that the networks have sufficient capacity and a large enough data set to learn this periodicity from the ordinal time representation.

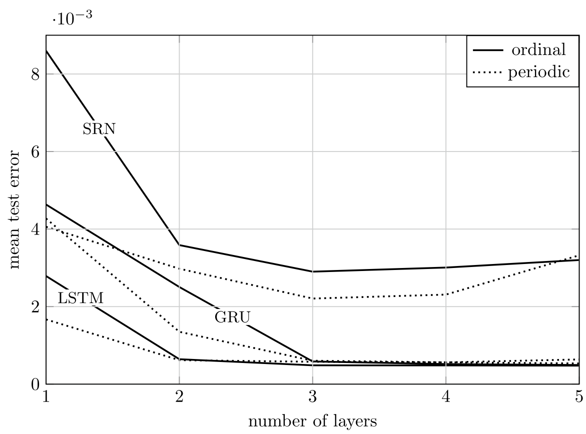

Fig. 3 Test error of RNN models for different units and for two types of data feeding [(t and $\tilde{t}$ defined in Eqs. (2) and (3)] with respect to the number of layers without using dropout. All models used have an overall number of parameters equal to 4000 and are therefore comparable

The training time of the neural network is very important as it can be extremely long [60], especially in this case where we have RNNs with long sequences. The comparison of training times is shown in Table 1. The fastest unit is SRN, which was to be expected as this unit involves the fewest computations. LSTM has a much higher training time and GRU has the highest. The training was performed with the Adam algorithm [72] using Keras [73] and the Theano [74] library. The hardware employed was a cluster with 48 Intel Xeon E5-2680 v3 processors and 1 TB RAM. In addition, a Tesla K80 GPGPU was used.

The models examined in this section show exceptional accuracy compared to previous work where ML was applied on the same dataset [31, 71]. The best models developed for this study (e.g., LSTM with 3 layers) have a mean test error of $0.48 \cdot 10^{-3}$ of the maximal daily demand, while existing models from the literature range from $1.06 \cdot 10^{-3}$ to $3.87 \cdot 10^{-3}$ of the maximal daily demand [31]. This is a two-fold improvement in accuracy due to a more thorough exploration of different deep learning architectures (different types of units, number of layers, and time encoding strategies). We have thus shown that careful fine-tuning and optimization of ML models can lead to extremely accurate forecasting models for the energy sector and enable efficient energy management. This fine-tuning and extensive training comes at a higher computational cost, but thanks to the immense advances in hardware, such extensive architectural search has now become possible. Furthermore, the computational costs required to train exceptionally accurate models are greatly outweighed by the potential for savings in the energy sector, both financially and environmentally.

Urban mobility management

Urban mobility, in particular the prediction and optimization of traffic flow, plays an important role in the pursuit of urban climate neutrality. Accurate prediction of traffic flow enables cities to take proactive measures to minimize congestion, reduce fuel consumption and cut emissions. Using data-driven insights from sensors, GPS devices and historical traffic patterns, cities can anticipate peak traffic times and congestion hotspots to facilitate the implementation of dynamic traffic management strategies. These strategies include real-time adjustments to traffic signal timing [75], lane management and rerouting to ensure smoother traffic flow and avoid idling, which helps reduce greenhouse gas emissions from vehicles. In addition, advanced traffic flow prediction models help develop and implement efficient public transportation systems, ride-sharing services and cycling networks that promote the adoption of sustainable mobility options that further reduce the use of private vehicles and their associated environmental impact. Ultimately, integrating traffic flow forecasting into urban mobility planning [76] enables cities to proactively reduce emissions, improve transportation efficiency and promote a more sustainable and climate-neutral urban environment.

The synergy between urban mobility and climate neutrality is seen by the potential of traffic flow prediction to bring a change in traffic behavior. Beyond reducing congestion and emissions, accurate forecasting models enable cities to make informed decisions about infrastructure development, such as the strategic placement of electric vehicle charging stations, bike lanes and

Table 1 Training times in hours

#Layers	On CPU			On GPU		
	SRN	LSTM	GRU	SRN	LSTM	GRU
1	1.1	2.0	2.2	6.0	11.3	16.4
2	1.6	2.9	3.5	9.9	20.6	30.2
3	1.9	4.0	4.7	13.8	28.6	42.8
4	2.3	5.0	5.9	17.7	36.5	54.5
5	2.6	6.0	7.0	21.6	44.7	68.3

pedestrian-friendly zones. This approach encourages a modal shift to greener alternatives and promotes a culture of sustainability. Using innovative technologies, such as machine learning and real-time data analytics, traffic flow forecasting gives urban planners and policy makers the tools they need to implement responsive traffic management solutions that adapt to changing travel patterns and evolving urban dynamics. As cities strive for climate neutrality, integrating traffic flow forecasting into comprehensive mobility strategies embodies a forward-looking approach that not only addresses the immediate challenges of traffic congestion, but also promotes long-term sustainability goals through smarter traffic management and reduced carbon emissions.

Transport optimization, which includes traffic flow prediction, logistics optimization and dynamic fleet management, has an important role in urban mobility. Namely, accurate predictions of traffic flow enable cities and companies to implement dynamic routing and scheduling, which makes logistics operations more efficient. Optimizing logistics increases the efficiency of the supply chain and reduces costs and environmental impact by minimizing unnecessary transportation and optimizing the use of resources. Dynamic fleet management, enabled by real-time data and advanced technologies, allows for flexible decision-making and optimization of routes, vehicle deployments and schedules to adapt to changing demands and conditions. These approaches are important not only to improve transportation and logistics operations, but also to reduce the environmental footprint of urban mobility systems.

Traffic flow forecasting

Predictive modeling for urban traffic management often relies on real-time traffic conditions to generate up-to-date forecasts [77]. However, in many cities, infrastructural limitations prevent the collection of real-time data. This poses a challenge to the development of effective forecasting methods without the benefit of real-time data showing the interplay between current traffic flow and past data. Our research therefore focuses on alternative modeling techniques. At the center of our approach is comprehensive feature engineering that circumvents the need for instantaneous traffic updates. In this context, we use a recently introduced dataset [40] that describes traffic flow patterns from 2013 to 2020 in Ljubljana, Slovenia. This dataset facilitates the creation of models that combine historical traffic data with covariates such as weather conditions and public holidays. The previous article explains in detail which ML models are best suited for the use case and how to optimally set their hyperparameters. However, such a process of model selection and configuration requires a lot of expert knowledge about the different ML models. Therefore, in order to successfully model the traffic patterns, one must know and be able to collect the traffic data and one must know how to use this data to create models.

The Municipality of Ljubljana traffic data set (MOL-TR), used in this study, comprises a comprehensive collection of traffic-related information from the city of Ljubljana. This dataset comes from a network of traffic counting stations strategically distributed across the city's streets, especially on heavily traveled routes. These stations continuously monitor and record vehicle movements and categorize them into eight different vehicle types, including cars, motorcycles, busses and various types of trucks. The dataset covers the period from 2013 to 2020 and includes a total of 2,041,086 vehicle counts taken at 59 individual measuring stations, with data recorded every day at 15-minute intervals. This comprehensive dataset provides valuable insights into daily and weekly traffic volumes and reveals recurring peaks during morning and afternoon rush hours and variations in traffic volume during weekends. It also accounts for missing data, relocation of monitoring stations and data collection errors, making it a valuable resource for traffic modeling. The inclusion of weather data and information on public holidays further enriches the dataset and enables a comprehensive analysis of various factors influencing traffic behavior in the city of Ljubljana. As already mentioned in the context of using models, in our study we evaluate the use of AutoML for predicting traffic flow. For our study, we use the AutoGluon framework, which is designed to combine multiple ML models without requiring expert knowledge about their use and configuration. A common feature across various AutoML platforms is the need to set a time limit for model training. For our study, we set a modest time budget of one minute.

Choosing an appropriate prediction metric can be a complex task as it needs to align with our specific forecasting goals. In this study, we used mean absolute error (MAE) [78] as our chosen metric for reporting all results. MAE is defined as:

$$\mathrm{MAE} = \frac{1}{C}\sum_{c}\left|y_c^{\text{forecast}} - y_c^{\text{true}}\right| \tag{4}$$

where y_c^{forecast} and y_c^{true} represent the predicted and measured number of vehicles that pass the measuring station c within a certain time interval. It is important to note that this summation excludes missing values. The variable C corresponds to the total number of measuring stations.

For the model evaluation, we use a 4-fold train–test split with an Expanding Window Validation strategy [79]. In this configuration, the four test sets correspond to different time periods: 2016–2017, 2017–2018, 2018–2019 and 2019–2020. This approach allows us to evaluate the performance of the models in different and increasingly recent segments of the dataset, providing a robust assessment of their predictive capabilities over time. Table 2 compares different ML models (random forest [18], linear regression, neural networks [80] and AutoGluon) based on their MAE accuracy [81]. Several notable findings emerge from this comparison. As highlighted in the original paper, each model significantly outperforms the baseline mean predictor model. This indicates that each model can recognize certain traffic patterns and use these insights to predict the forthcoming traffic flow. In all test splits, the AutoGluon model provides the most accurate forecasts and outperforms the other models. This is not surprising as AutoGluon uses a diverse ensemble of ML models. It consistently outperforms the second best neural network across different years. This suggests that AutoML tools can serve as a user-friendly alternative to conventional ML models.

In summary, our study highlights the significant potential of AutoML tools as indispensable aids for people with limited expertise in ML. While a basic understanding of ML is still essential, these tools significantly automate the labor-intensive aspects typically associated with model development, thereby reducing the burden on users. The methodology outlined in this study, which leverages AutoML for tabular and forecasting tasks, offers both advantages and drawbacks compared to more traditional approaches. One of its key strengths is AutoML's ability to often surpass the performance of manually tuned ML models, providing optimized results with minimal effort from the user. However, the automated nature of AutoML can sometimes obscure the inner workings of model selection and tuning, making it harder for users to apply domain-specific knowledge for fine-tuning. Despite these limitations, the practical use of AutoML shows great potential, simplifying the modeling process and allowing for more efficient/effective outcomes. This approach broadens access to ML, making it more available to a wider range of users, including those who may not have deep technical expertise. Integrating AutoML tools is, therefore, an important step in expanding the usability of advanced machine learning techniques.

Table 2 MAE computed between the measured and predicted number of vehicles using various ML models

Model	Year	MAE	Std MAE
Baseline (Mean)	16–17	39.412	0.000
Baseline (Mean)	17–18	40.102	0.000
Baseline (Mean)	18–19	39.945	0.000
Baseline (Mean)	19–20	40.891	0.000
Linear regression	16–17	18.042	2.165
Linear regression	17–18	19.532	2.277
Linear regression	18–19	17.924	2.383
Linear regression	19–20	17.642	2.014
Random forest	16–17	12.624	2.982
Random forest	17–18	22.632	6.232
Random forest	18–19	16.832	2.945
Random forest	19–20	13.989	2.593
Neural network	16–17	9.192	1.082
Neural network	17–18	11.892	1.347
Neural network	18–19	10.720	1.998
Neural network	19–20	10.204	0.934
AutoGluon	16–17	8.623	1.065
AutoGluon	17–18	10.792	1.492
AutoGluon	18–19	10.261	1.890
AutoGluon	19–20	9.409	0.952

The evaluation was conducted on data from a previously unseen year. Each model underwent 20 rounds of training and evaluation across four distinct train/test splits

Logistics optimization

Optimizing logistics through the use of data-driven routing, load consolidation and efficient delivery scheduling can reduce the carbon footprint of freight transportation. The integration of logistics optimization also encourages the adoption of electric vehicles [82] or alternative fuel vehicles, resulting in cleaner transportation options. In addition, optimized logistics systems [83] can boost the growth of local markets and circular economies by reducing the need for long-distance transportation and encouraging sustainable consumption habits. As cities work toward climate neutrality, optimizing logistics becomes an important step in creating greener, more efficient urban ecosystems that balance economic growth and environmental protection. As freight transportation usually shares infrastructures with passenger transportation, freight transportation in urban areas has become a problem and requires appropriate solutions [84].

Several ambitious projects illustrate the importance of advanced computing in transforming logistics to reduce environmental impact and improve overall efficiency. The CONDUCTOR project [85] is dedicated to the development, integration and demonstration of advanced traffic and fleet management systems and aims to seamlessly integrate different means of transportation while improving interoperability. This is achieved through an innovative dynamic balancing and priority-based management of vehicles, including automated and conventional vehicles. Some important features of this process related to advanced data processing are:

- Machine learning and data fusion: CONDUCTOR uses machine learning and data fusion to develop next-generation simulation models and tools. These technologies enhance the capabilities of transportation authorities and operators to make informed decisions and become the conductors of future mobility networks.
- Autonomous Vehicle Integration: The project focuses on upgrading existing technologies to centralize control and put autonomous vehicles at the center of future urban transportation systems. This approach increases the safety, responsiveness and overall efficiency of traffic and fleet management.
- Explainable AI: to support decision-making processes and ensure their transparency in meeting sustainability goals and societal interests.

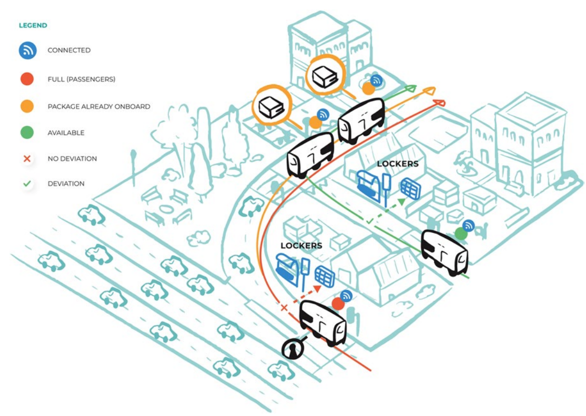

Fig. 4 CONDUCTOR's Use case 3 sketch (source [87])

Logistics service providers (LSPs) are struggling with increasing demand and unreliable traffic conditions, leading to challenges in maintaining reliability in the delivery process. This has led to low usage rates and empty miles for delivery vehicles, impacting customer satisfaction and business efficiency and contributing to emissions and congestion, especially in city centers where the number of delivery vehicles is expected to increase by 36% by 2030 due to the growth of e-commerce. At the same time, the transportation landscape continues to evolve, with a shift toward more flexible, on-demand passenger transportation services and high-capacity options driven by vehicle automation. In this context, there is an opportunity to explore integrated solutions that combine parcel delivery and passenger trips, known as 'freight-on-transit' or 'ride-parcel-pooling' (RPP), to optimize multimodal transportation networks through load-balancing strategies. The CONDUCTOR project aims to simulate and evaluate the effectiveness of these strategies [86] to address the challenges of growing e-commerce while considering their impact on service quality and individual costs for stakeholders, including LSPs.

The demand for the delivery of goods in cities has increased over the last decade. The introduction of e-commerce, boosted with various crises, is responsible for this shift and the increased traffic caused by last-mile delivery. The urban logistics use case in the CONDUCTOR project (Fig. 4) investigates and proposes solutions for last mile parcel delivery based on the integration of urban goods delivery with on-demand transportation services. The aim of the use case carried out in Madrid is to propose and simulate different strategies for coordinating passenger and freight transport that reduce the volume of traffic associated with last-mile parcel delivery, exploiting synergies with on-demand passenger transport services [88]. If these vehicles offer the possibility of transporting parcels together with passengers (e.g., with a special locker in the vehicle), there could be room for integrated use for passenger and freight transport. Requests for the delivery of parcels and requests for passenger trips can be combined in the algorithms used to optimize the service. Additional stops for parcel delivery can be set up on routes that are already used for passenger transport, time slots that would remain unused if only passenger trips were considered can be used for parcel delivery, etc. A comprehensive understanding of passenger demand patterns is key to identifying off-peak time slots [89]. Vehicle capacity allocation strategies should anticipate and respond to temporary but abrupt changes in passenger demand, e.g., due to events or disruptions in other services or modes. As shown in ref. [88], the main benefits of this approach are expected to be the reduction of: (i) the average travel time of the vehicles involved, (ii) the total distance traveled by delivery vehicles, (iii) the number of vehicles used to deliver goods, and (iv) transportation emissions.

These concepts could be taken even further by envisioning a sustainable multimodal transportation system in which transportation decisions are based on efficiency, societal impact and real-time information. To achieve this, we need to explore the benefits of connected and automated transportation for the entire set of operations, research optimal decision-making processes and identify new business models. Therefore, in recent years, the concept of synchromodality [90] is strongly promoted in scientific and political circles to achieve more environmentally friendly transportation.

Fleet management

Effective fleet management, including the integration of electric busses (EBs), plays a transformative role in advancing urban climate neutrality [91]. Using smart fleet management systems, cities can optimize routes, minimize idle time and improve maintenance practices, resulting in lower fuel consumption and emissions. The integration of EBs into the fleet represents a sustainable alternative to conventional diesel-powered busses, significantly reducing greenhouse gas emissions and improving air quality. However, electric busses require dedicated charging infrastructure due to their limited range and longer recharging times, making them less flexible than diesel busses and requiring special attention when planning and scheduling daily routes [92]. An overview of the problem of planning and scheduling electric busses can be found in [93, 94]. An intelligent charging infrastructure for EBs ensures efficient energy use and minimizes the load on the grid during peak demand.

The global shift toward electric urban transportation is evident, driven by continuous advances in various evolving technologies [95, 96]. These technologies undergo rigorous testing to determine their reliability and suitability for specific applications. EBs rely on high-capacity batteries, which often need to be charged during the day, and complex powertrain management systems. This requires testing in a wide range of road conditions and driving scenarios that are influenced by road characteristics and climatic conditions.

Several research findings suggest that electric vehicle (EV) batteries are more stressed on hilly terrain than on flat roads. Recent studies on the effects of climatic conditions on the energy consumption of electric vehicles have shown that battery consumption increases in winter, which is associated with lower energy recovery [49, 97]. Including climate parameters in mathematical models improves simulations, but conducting physical tests of EBs in regions with harsh climates provides more reliable results. We have studied numerous benchmark EB routes in cities across Europe and found that while these urban routes provide valuable test environments, they may not subject EBs to sufficiently challenging conditions in terms of distances, temperatures and road gradients. To address this issue, we proposed a test route in Idrija, Slovenia, which is characterized by challenging incline sections [49]. The bus route in Idrija has a total length of 19.6 km, a maximum elevation of 443 m, a minimum elevation of 300 m, a total ascent/descent of 539 m with a maximum gradient and a maximum slope of 25% and is characterized by a continental climate with long, cold winters and high summer temperatures. According to ARSO [98], the maximum difference between the average daily maximum temperatures and the average daily minimum temperatures is about 25°C in one year. Conducting tests with EBs and integrating transportation, energy storage and charging systems into real-world benchmarking would allow for a more comprehensive assessment and validation of new technologies. The expected benefits of these benchmark results would also extend to future developments, including further improvements to technical solutions, particularly in similarly geographically challenging areas.

Public transportation networks in modern cities are multimodal and extremely complex. He et al. propose methods to support efficient multi-criteria trip planning [99]. An interesting study on vehicle-to-grid technology, where unused electric vehicles can serve as decentralized energy storage for the power grid to balance demand fluctuations, was investigated in ref. [100]. ML algorithms help predict traffic patterns and thus facilitate the efficient allocation of resources and the development of environmentally friendly transport solutions [101, 102]. Dynamic route planning is becoming increasingly relevant. With dynamic route planning, different routes can be found as the optimal choice, taking several criteria into account, see Fig. 5a. The traffic network can be mapped in a graph so that intersections are represented by vertices and paths by edges, see 5b. With weighted edges, it is possible to identify the length of route parts, the degree of traffic congestion or the status of traffic regulation and transform the problem into a graph problem in which the role of different nodes and edges is examined by different graph measures [103]. An approach for shared subway shuttle busses based on crowd sourced mobile data, which includes prediction of passenger flows at stations and dynamic route planning was studied in ref. [104]. Further, Wang et al. propose a metric learning-based prediction algorithm to capture demand patterns and develop a route planning optimizer for efficient bus deployment considering traffic dynamics [105]. Thus, advanced computing helps in the development and simulation of electric (and autonomous) vehicles and accelerates their integration into urban fleets.

Climate models and simulations carried out with the help of high-performance computers provide valuable insights into the effects of transportation-related emissions on air quality and give political decision-makers pointers for sustainable urban planning and transport policy. In addition, the electrification of the fleet is in line with renewable energy targets, as cities can power the EBs with clean energy sources and thus further reduce their carbon footprint [106]. ML and linear programming are essential for fleet management, especially for EBs. Effective management requires both theoretical and practical testing. EBs require special charging and planning due to their limited range. Real-world testing, such as in Idrija, Slovenia, validates performance. Smart charging and dynamic route planning improve operations. Informed policy regulations

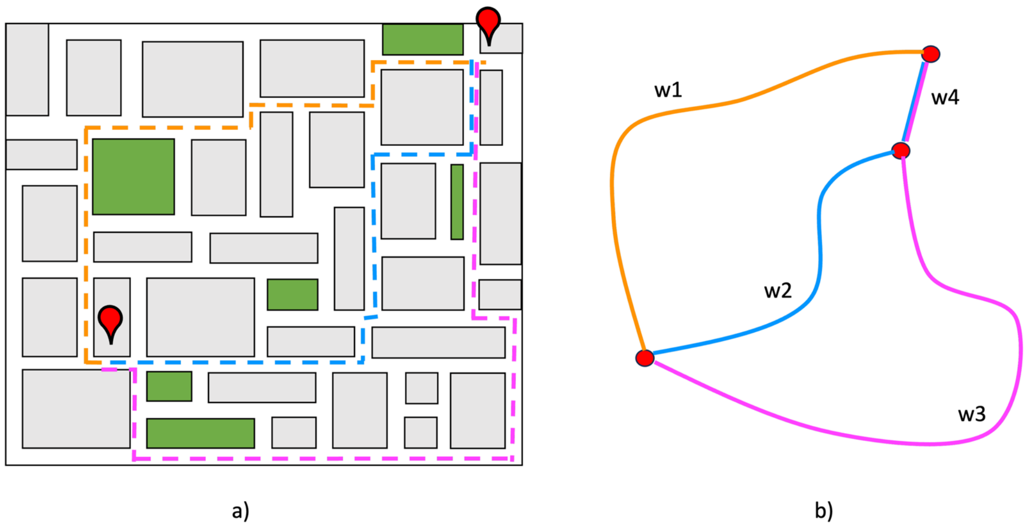

Fig. 5 **a** Presented are different routes from the origin to the destination, while considering multiple criteria. **b** Traffic network with selected routes is mapped into the graph, where meeting points between different routes are presented by vertices and paths between them are presented by edges. Weights on edges could identify different route conditions (e.g., path distance, level of congestion or speed limit), that have an impact on the travel time, travel comfort or carbon footprint

support the sustainable integration of EBs, aligning with renewable energy goals and improving air quality.

Conclusions

Addressing urban climate neutrality requires the power of advanced computing. This paper focuses on the areas of energy supply and transportation and highlights the role of machine learning, deep learning and ensemble models in addressing the complex challenges of urban climate neutrality. The integration of cutting-edge technologies, advanced data analytics and real-time decision-making processes represents a pathway to developing sustainable, climate-resilient urban environments. These advanced computational methods enable cities to optimize resource management, improve energy efficiency and significantly reduce greenhouse gas emissions, thus actively contributing to global climate and environmental protection. As cities pursue climate neutrality, energy, traffic and fleet management become a cornerstone strategy to create cleaner and more efficient urban systems that prioritize environmental wellbeing alongside efficient energy use and public transport.

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Author contributions
Gr.P. prepared the background part. Gr.P., R.H., Ga.P. and V.V. wrote the main manuscript text. R.H. prepared figures 1-3 and table 1, Ga.P. prepared table 2, Gr.P. prepared figure 4, and V.V. prepared figure 5. All authors reviewed the manuscript.

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Data availability
The data sets that were created and/or analyzed as part of the current study are not publicly available due to proprietary reasons, but can be obtained from the corresponding author on request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
All authors declare that they have no conflict of interest or other interests that could be perceived to influence the results and/or discussions reported in this paper.

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