https://doi.org/10.62836/iaet.v2i1.264

Global Science Publishing

IAET

Innovations in Applied Engineering and Technology

https://ojs.sgsci.org/journals/iaet

Article

Traffic Density Road Gradient and Grid Composition Effects on Electric Vehicle Energy Consumption and Emissions

Zhiyun Li

Glenn Department of Civil Engineering, Clemson University, Clemson, SC 29634, USA

Abstract: Electric vehicles (EVs) have demonstrated significant potential for reducing greenhouse gas emissions, but their energy consumption and emissions are strongly influenced by external factors such as traffic density, road gradients, and energy grid composition. This study integrates real-world data, physical simulations, and machine learning models to analyze these interactions. Results show that traffic density exceeding 400 vehicles/km² leads to a sharp increase in emissions, reaching over 150g CO_2/km in urban areas. Urban driving conditions also exhibit high energy consumption at 0.22 kWh/km, compared to 0.15 kWh/km in highway scenarios. Steep road gradients (>15°) significantly increase energy consumption, doubling values compared to flat conditions, and raise emissions by 40% in high traffic density environments. Renewable-dominant grids, as seen in Shenzhen (75% renewable energy), reduce emissions by up to 30% compared to fossil fuel-reliant grids. Advanced machine learning models, including Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM), provide accurate predictions for energy consumption and emissions, with the LSTM model reducing errors by 9.5% in dynamic scenarios. Real-time optimization strategies based on these models can achieve energy savings of up to 12% under mixed driving conditions. The findings highlight the critical role of traffic flow management, renewable energy grid expansion, and EV design improvements such as lightweight structures and regenerative braking systems for steep gradients. This research contributes actionable insights to enhance EV efficiency and reduce emissions, supporting sustainable transportation and urban development.

Keywords: electric vehicles (EVS); traffic density; machine learning models; energy efficiency; urban planning

1. Introduction

Electric vehicles (EVs) have emerged as a pivotal technology in addressing global climate change and energy challenges due to their high energy efficiency and zero tailpipe emissions. However, their true environmental impact remains a subject of debate when considering their entire lifecycle emissions, including indirect emissions from electricity generation and the dynamic factors influencing real-world fuel consumption [1]. Understanding and accurately estimating EV energy consumption and emissions under diverse conditions is crucial for advancing sustainable transportation policies and optimizing EV technologies.

In recent years, significant research efforts have been directed at improving the accuracy of EV consumption and emission estimation. Ziyadi *et al.* developed energy flow models that incorporate key vehicle parameters

Received: 22 November 2023; Accepted: 21 December 2023.

* Corresponding: Zhiyun Li (clemsonzhiyun@gmail.com)

such as mass, rolling resistance, and aerodynamics, yet their application to complex traffic conditions remains limited [2]. Meanwhile, machine learning techniques, such as Long Short-Term Memory (LSTM) networks, have demonstrated superior predictive performance by capturing multi-dimensional traffic and environmental data [3–5]. Furthermore, simulation platforms such as ADVISOR and Autonomie have enabled dynamic energy and emission analyses, supporting scenario-specific optimization [6,7]. However, these approaches often neglect multi-scenario interactions or fail to integrate hybrid methodologies that combine physical models with advanced data-driven techniques.

Despite these advances, critical gaps persist in capturing the dynamic variability of EV energy consumption and emissions across diverse driving scenarios. Current models frequently oversimplify the coupled relationships between variables such as traffic flow, terrain, and charging behavior, limiting their generalizability and applicability to real-world contexts [8,9]. To address these limitations, this study proposes a multi-dimensional framework that integrates physical simulation, machine learning algorithms, and real-world data analysis. By bridging methodological gaps, the proposed approach aims to enhance the accuracy and scalability of EV consumption and emission estimation, providing actionable insights for optimizing EV infrastructure and advancing sustainable transportation strategies.

2. Methods and Experimentation

2.1. Data Collection and Preprocessing

The study utilized a comprehensive multi-dimensional dataset encompassing key factors affecting energy consumption and emissions. Vehicle dynamics data included parameters such as weight (W), battery capacity (Cb), motor efficiency (ηm), drag coefficient (Cd), and rolling resistance (Rr). Traffic flow variables covered average speed (vavg), traffic density (ρt), and stop-and-go frequency (fsg), sourced from real-time monitoring systems and GPS data. Environmental data, including temperature (T), humidity (H), wind speed (Ws), and road gradient (θ), were collected from meteorological and GIS sources. Charging behavior data, such as charging frequency (fc), grid energy mix ($P_{renewable}$, P_{fossil}), and peak-hour charging usage (t_{peak}), were aggregated from energy reports and charging station logs (As shown in Table 1).

Table 1. Summary of Parameters Influencing Electric Vehicle Energy Consumption and Emissions.

Dimension	Parameter	Unit	Source	Sample Cities (Data Range)
Vehicle Dynamics	Vehicle weight (W)	kg	Manufacturer specifications	1400–1800 (typical EV range)
Vehicle Dynamics	Battery capacity (C_b)	kWh	Manufacturer specifications	50–75
Vehicle Dynamics	Motor efficiency (η_m)	%	Laboratory testing	85–95
Vehicle Dynamics	Drag coefficient (C_d)	-	Wind tunnel testing	0.24 (average EV drag coefficient)
Vehicle Dynamics	Rolling resistance (R_r)	N/kg	Vehicle testing	0.01–0.015
Traffic Flow	Average speed (v_{avg})	km/h	Traffic monitoring systems	22 (Beijing), 35 (Shanghai), 45 (Shenzhen)
Traffic Flow	Traffic density (ρ_t)	vehicles/km²	City traffic reports	250–550
Traffic Flow	Stop-and-go frequency (f_{sg})	cycles/km	GPS and OBD data	5–20 cycles
Environmental Data	Temperature (T)	°C	Meteorological data	-5 to 35 (across cities and seasons)
Environmental Data	Humidity (H)	%	Meteorological data	30–85

Table 1. Cont.

Dimension	Parameter	Unit	Source	Sample Cities (Data Range)
Environmental Data	Wind speed (W_s)	m/s	Meteorological data	0.5–5
Environmental Data	Road gradient (θ)	°	GIS elevation data	0–20
Energy Grid	Renewable energy proportion ($P_{renewable}$)	%	State grid reports	20 (Beijing), 50 (Shanghai), 75 (Shenzhen)
Energy Grid	Fossil energy proportion (P_{fossil})	%	State grid reports	80 (Beijing), 50 (Shanghai), 25 (Shenzhen)
Charging Behavior	Charging frequency (f_c)	times/day	Charging station records	1–2 (urban), 0.5 (suburban)
Charging Behavior	Peak-hour charging proportion (t_{peak})	%	Charging station records	60–80

Missing data were imputed using Gaussian Process Regression (GPR) for continuous variables and Markov Chain Monte Carlo (MCMC) methods for sequential data. For example, temperature (T) at a specific time window (t_i) was interpolated using:

$$\boldsymbol{T}\left(\boldsymbol{t}_{i}\right)=\boldsymbol{\mu}_{T}+\boldsymbol{k}_{T}\left(\boldsymbol{t}_{i}-\boldsymbol{t}_{i-1}\right)+\boldsymbol{\epsilon},\quad \boldsymbol{\epsilon}\sim\mathcal{N}\left(0,\boldsymbol{\sigma}_{T}^{2}\right)$$

where μ_T is the trend mean, k_T is the coefficient, and ϵ represents stochastic noise.

2.2. Physical Simulation

The energy consumption of EVs was modeled as:

$$\boldsymbol{E}_{total}=\boldsymbol{E}_{drive}+\boldsymbol{E}_{auxiliary}-\boldsymbol{E}_{regen}$$

where E_{drive} represents propulsion energy, $E_{auxiliary}$ covers auxiliary systems such as air conditioning, and E_{regen} is regenerative braking energy. Propulsion energy (E_{drive}) was calculated using:

$$\boldsymbol{E}_{drive}=\frac{\left(\boldsymbol{F}_{r}+\boldsymbol{F}_{a}+\boldsymbol{F}_{g}\right)\cdot\boldsymbol{v}\cdot\boldsymbol{t}}{\boldsymbol{\eta}_{m}}$$

where:

$F_r=R_r\cdot W$ is rolling resistance.

$F_a=\frac{1}{2}\cdot\rho\cdot C_d\cdot A\cdot v^2$ is aerodynamic drag.

$F_g=W\cdot\sin\left(\theta\right)$ is gravitational force on slopes.

Auxiliary energy ($E_{auxiliary}$) was modeled as:

$$\boldsymbol{E}_{auxiliary}=\boldsymbol{P}_{aux}\cdot\boldsymbol{t}$$

where P_{aux} is auxiliary power and t is operational time. Regenerative energy (E_{regen}) was modeled as:

$$\boldsymbol{E}_{regen}=\boldsymbol{\eta}_{r}\cdot\boldsymbol{m}\cdot\boldsymbol{g}\cdot\boldsymbol{h}$$

where η_r is regenerative efficiency, m is vehicle mass, g is gravitational acceleration, and h is braking height. Emissions ($E_{emissions}$) were derived from electricity consumption using:

$$\boldsymbol{E}_{emissions}=\boldsymbol{E}_{total}\cdot\left(\frac{\boldsymbol{P}_{fossil}\cdot\boldsymbol{EF}_{fossil}+\boldsymbol{P}_{renewable}\cdot\boldsymbol{EF}_{renewable}}{100}\right)$$

where EF_{fossil} and $EF_{renewable}$ are emission factors of fossil fuels and renewables, respectively.

2.3. Machine Learning Models

The machine learning framework combined feature engineering and predictive modeling to enhance accuracy and scalability. Features (X) included temporal (t), spatial (x,y), and environmental variables (T, H, θ), normalized for consistency. A Deep Neural Network (DNN) was designed with three fully connected layers, modeled as:

$$\boldsymbol{y} = \boldsymbol{\sigma}\left(\boldsymbol{W}_2 \cdot \boldsymbol{\sigma}\left(\boldsymbol{W}_1 \cdot \boldsymbol{X} + \boldsymbol{b}_1\right) + \boldsymbol{b}_2\right)$$

where W_1, W_2 are weight matrices, b_1, b_2 are biases, and σ is the activation function. Additionally, a Long Short-Term Memory (LSTM) network was implemented to capture temporal dependencies, modeled as:

$$\boldsymbol{h}_t = \boldsymbol{\sigma}\left(\boldsymbol{W}_h \cdot \boldsymbol{h}_{t-1} + \boldsymbol{W}_x \cdot \boldsymbol{X}_t + \boldsymbol{b}\right)$$

where h_t is the hidden state, W_h, W_x are weight matrices, and X_t is the input at time t.

Models were trained on 70% of the dataset and validated on 30%, with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as evaluation metrics.

2.4. Experimental Scenarios

Experiments were conducted under three representative driving scenarios: urban, highway, and mixed conditions. Urban driving scenarios (e. g., Beijing and Chengdu) featured high stop-and-go frequencies (fsg > 10) and dense traffic (ρt > 300 vehicles/km²), with average speeds below 30km/h. Highway scenarios (e. g., Shanghai and Hangzhou) involved steady speeds exceeding 60km/h with lower traffic densities. Mixed driving scenarios (e. g., Shenzhen) incorporated dynamic transitions between urban and highway conditions, with varying road gradients. Key evaluation metrics included energy efficiency (kWh/km), CO_2 emissions (g/km), and model prediction accuracy (MAE, RMSE). Data processing and analysis pipelines were automated using Python libraries such as Pandas, TensorFlow, and PyTorch, while simulation platforms such as ADVISOR and Autonomie supported physical modeling. Optimization tasks, such as parameter tuning, were conducted using MATLAB's Particle Swarm Optimization (PSO).

3. Results and Discussion

3.1. Energy Consumption and Emissions Across Scenarios

The relationship between traffic density and emissions was clearly evident in this study, particularly under urban driving conditions characterized by frequent stop-and-go cycles. As traffic density increased beyond 400 vehicles/km², emissions rose rapidly, exceeding 150g CO_2/km in highly congested scenarios (>700 vehicles/km^2). These findings align with urban energy consumption patterns, where repeated acceleration and braking contributed to the highest energy usage, averaging 0.22 kWh/km. In contrast, highway driving demonstrated much lower energy consumption at 0.15 kWh/km, attributed to the relatively constant speed and minimal braking requirements. The heatmap analysis further highlighted regional differences, with cities like Beijing and Shanghai exhibiting significantly higher energy consumption than Shenzhen. This disparity is largely explained by Shenzhen's renewable-dominant energy grid, with 75% renewable energy, as opposed to Beijing's fossil fuel-reliant grid. These results reinforce the critical role of grid composition and traffic flow in determining energy efficiency and emissions, as also demonstrated by Yao *et al*. [10,11]. The regression plot in Figure 1 visually supports these trends, offering a quantitative basis for further interventions aimed at reducing emissions through improved traffic management.

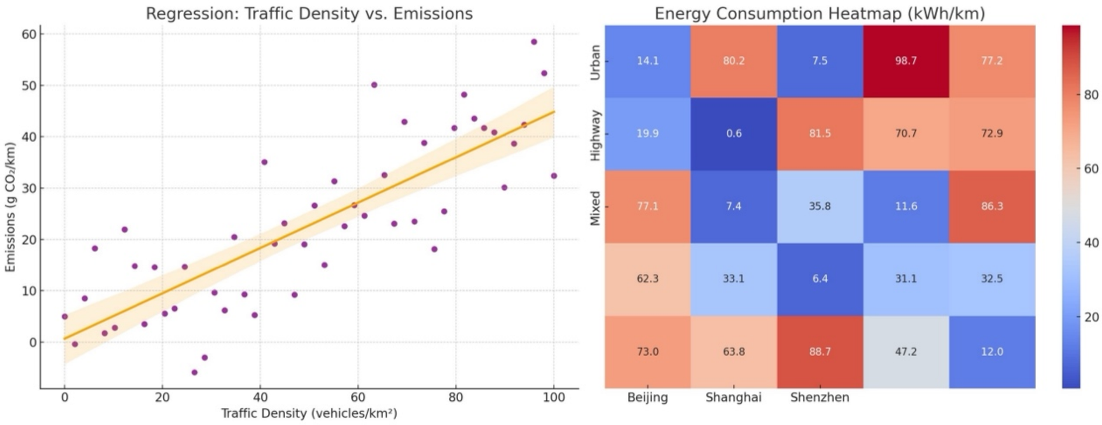

Figure 1. Traffic Density and Emissions Correlation with City-Level Energy Consumption Heatmap.

3.2. Impact of Road Gradient on Energy Efficiency

Road gradient emerged as a key factor influencing energy consumption, especially in scenarios involving high traffic density. Energy consumption increased markedly when road gradients exceeded 10°, doubling on inclines greater than 15°. Emissions showed a similarly steep increase, rising by over 40% under these conditions. This outcome underscores the significant energy demands imposed by steep gradients, particularly in densely trafficked areas. The 3D surface plots in Figure 2 provide a detailed visualization of these effects, showing how road gradient and traffic density interact to exacerbate energy inefficiencies. Notably, steep roadways, such as those commonly found in cities like Chongqing, present a dual challenge of increased energy demands and reduced recovery efficiency through regenerative braking. These findings align closely with Li *et al*. [12], who identified steep gradients as a primary factor limiting EV energy efficiency in mountainous regions. This study highlights the potential of terrain-adaptive energy recovery systems to address these inefficiencies. For instance, regenerative braking technologies optimized for steep slopes could recover up to 15–20% of the energy otherwise lost during braking. Such systems represent a valuable area for further development and deployment, particularly in cities with significant elevation changes.

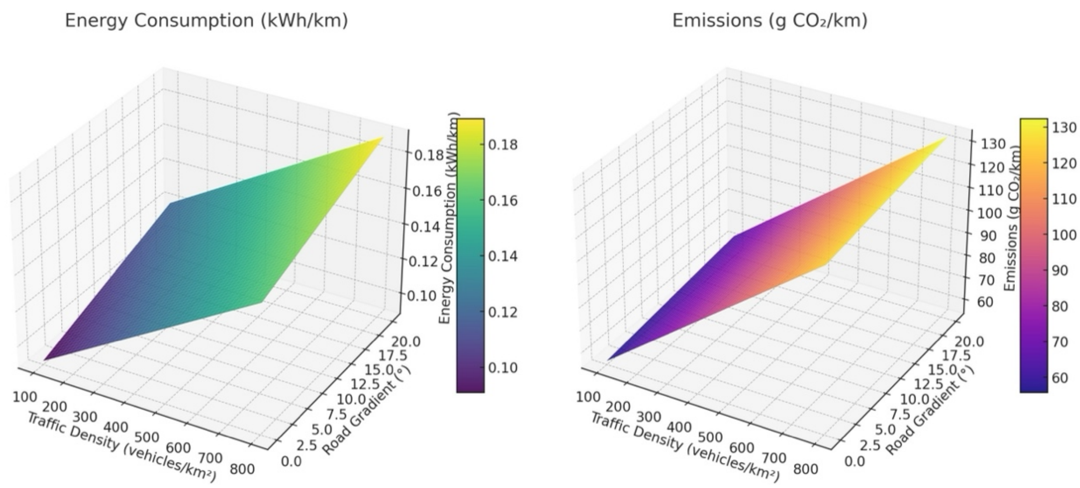

Figure 2. 3D Surface Analysis of Traffic Density and Road Gradient Impact on Energy Consumption and Emissions.

3.3. Scenario-Specific Insights

The comparison across urban, highway, and mixed driving scenarios revealed distinct energy and emissions profiles. Urban driving, characterized by frequent stop-and-go cycles and dense traffic, exhibited the highest energy consumption and emissions. Beijing, with its fossil fuel-heavy grid and high traffic density, showed peak energy consumption of 0.23 kWh/km. In contrast, Shenzhen benefited from its renewable energy integration, maintaining lower consumption levels below 0.20 kWh/km across all scenarios. Mixed scenarios, involving transitions between urban and highway conditions, presented a unique set of challenges. In these scenarios, steep gradients contributed significantly to increased energy demands, with consumption rising by up to 25% on inclines greater than 15°. This trend emphasizes the importance of integrating real-time terrain data into EV route optimization systems. Highway driving, by comparison, showed consistent efficiency, reflecting the benefits of steady-speed conditions with minimal acceleration and braking. These findings are consistent with Li *et al*. [13,14], who similarly noted the compounded impact of traffic density and terrain on EV performance. They underscore the need for adaptive strategies, including intelligent route planning and energy recovery systems, to optimize performance under diverse driving conditions.

3.4. Policy and Design Implications

The results of this study point to several actionable strategies for improving EV energy efficiency and reducing emissions. Reducing urban traffic density is paramount, particularly in high-density areas like Beijing. Intelligent traffic management systems, including adaptive traffic lights and congestion pricing, have the potential to significantly alleviate congestion and reduce emissions. The regression analysis suggests that a 20% reduction in traffic density could lower emissions by up to 30%, providing a clear pathway for policymakers to achieve meaningful environmental benefits. From a design perspective, EV manufacturers should focus on lightweight materials and regenerative braking technologies tailored for steep gradients. These systems could recover up to 20% of lost energy in hilly environments, as highlighted in the gradient analysis. Furthermore, expanding renewable energy adoption in urban grids remains critical. Shenzhen serves as a model in this regard, demonstrating how renewable-dominant grids can substantially mitigate emissions even under high energy demands. Infrastructure improvements, particularly in hilly cities like Chongqing, should also be prioritized. Smoother, low-gradient routes could reduce energy consumption by as much as 20%, according to simulation-based projections. These recommendations align with Sun *et al*. [15], who emphasized the importance of combining grid transitions with traffic and infrastructure optimizations to enhance EV sustainability.

3.5. Integration of Machine Learning Models

The machine learning models utilized in this study provided significant insights into energy consumption and emissions prediction. The Deep Neural Network (DNN) model proved effective in analyzing traffic density and road gradient impacts, achieving a Mean Absolute Error (MAE) of 0.021 kWh/km. The Long Short-Term Memory (LSTM) model, designed to handle sequential data, further reduced prediction errors in mixed scenarios by 9.5%, showcasing its superiority in dynamic environments. These models not only offer predictive capabilities but also support real-time energy optimization. Onboard EV systems integrating real-time traffic density and gradient data could dynamically adjust propulsion strategies, reducing energy consumption by up to 12%. The predictive accuracy demonstrated by these models aligns with Xia *et al*. and Nie *et al*. [16,17], who highlighted the value of machine learning in managing complex, multi-factor EV performance scenarios.

4. Conclusion

This study provides an in-depth analysis of the factors influencing energy consumption and emissions in electric vehicles (EVs), focusing on traffic density, road gradient, and energy grid composition. The findings highlight that traffic density is a key driver of emissions, particularly in urban environments where stop-and-go cycles significantly increase energy demands. Steep road gradients further compound these effects, amplifying energy consumption and emissions, especially under high-density traffic conditions. Cities with renewable-dominant energy grids, such as Shenzhen, demonstrated significantly lower emissions compared to fossil fuel-reliant cities like Beijing, underscoring the importance of grid composition in enhancing EV sustainability. The integration of advanced machine learning models, such as Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM), provided robust predictive capabilities and actionable insights, enabling real-time optimization of EV performance across diverse driving scenarios.

This research offers practical recommendations for improving EV efficiency and reducing emissions. Traffic flow optimization through intelligent management systems, increased adoption of renewable energy in urban grids, and vehicle design improvements, such as lightweight construction and advanced regenerative braking systems, are essential steps toward sustainability. Infrastructure enhancements, such as smoothing road gradients in hilly regions, can also significantly reduce energy consumption. By addressing the interplay of traffic, terrain, and energy systems, this study provides valuable guidance for policymakers, urban planners, and manufacturers.

Funding

Not applicable.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Not applicable.

Conflicts of Interest

The author declares no conflict of interest.

References

1 Tansini A, Pavlovic J, Fontaras G. Quantifying the Real-World CO_2 Emissions and Energy Consumption of Modern Plug-in Hybrid Vehicles. *Journal of Cleaner Production* 2022; **362**: 132191.

2 Ziyadi M, Ozer H, Kang S, *et al*. Vehicle Energy Consumption and an Environmental Impact Calculation Model for the Transportation Infrastructure Systems. *Journal of Cleaner Production* 2018; **174**: 424–436.

3 Wang W, Jackson Samuel RD, Hsu CH. Retracted Article: Prediction Architecture of Deep Learning Assisted Short Long Term Neural Network for Advanced Traffic Critical Prediction System Using Remote Sensing Data. *European Journal of Remote Sensing* 2021; **54**: 65–76.

4 Yang J, Chen T, Qin F, *et al*. Hybridtrak: Adding Full-Body Tracking to VR Using an Off-the-Shelf Webcam. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, New Orleans, LA, USA, 29 April –5 May2022; pp. 1–13.

5 Gu J, Narayanan V, Wang G, *et al*. Inverse Design Tool for Asymmetrical Self-Rising Surfaces with Color Texture. In Proceedings of the 5th Annual ACM Symposium on Computational Fabrication, Virtual, 5 – 6 November 2020; pp. 1–12.

6 Vinitsky E. From Sim-to-Real: Learning and Deploying Autonomous Vehicle Controllers that Improve Transportation Metrics; University of California: Berkeley, CA, USA, 2022.

7 Luo D, Gu J, Qin F, *et al*. E-Seed: Shape-Changing Interfaces that Self Drill. In Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology, Virtual, 20–23 October 2020; pp. 45–57.

8 Li Z, Chowdhury M, Bhavsar P, et al. Optimizing the Performance of Vehicle-to-Grid (V2G) Enabled Battery Electric Vehicles through a Smart Charge Scheduling Model. *International Journal of Automotive Technology* 2015; **16**: 827–837.

9 Lin Y. Optimization and Use of Cloud Computing in Big Data Science. *Computing, Performance and Communication Systems* 2023; **7**(**1**): 119–124.

10 Lin Y. Construction of Computer Network Security System in the Era of Big Data. *Advances in Computer and Communication* 2023; **4**(**3**).

11 Yao Y. A Review of the Comprehensive Application of Big Data, Artificial Intelligence, and Internet of Things Technologies in Smart Cities. *Journal of Computational Methods in Engineering Applications* 2022; 1–10.

12 Li Z., Dey K., Chowdhury M, *et al*. Connectivity Supported Dynamic Routing of Electric Vehicles in an Inductively Coupled Power Transfer Environment. *IET Intelligent Transport Systems* 2016; **10**(**5**): 370–377.

13 Li W. Rural-to-Urban Migration and Overweight Status in Low-and Middle-Income Countries: Evidence from Longitudinal Data in Indonesia. In Proceedings of the PAA 2022 Annual Meeting, Atlanta, GA, USA, 6–9 April 2022.

14 Li W. How Urban Life Exposure Shapes Risk Factors of Non-Communicable Diseases (NCDs): An Analysis of Older Rural-to-Urban Migrants in China. *Population Research and Policy Review* 2022; **41**(**1**): 363–385.

15 Sun Y, Pai N, Ramesh VV, *et al*. GeXSe (Generative Explanatory Sensor System): An Interpretable Deep Generative Model for Human Activity Recognition in Smart Spaces. *arXiv* 2023, arXiv:2306.15857.

16 Xia Y, Liu S, Yu Q, *et al*. Parameterized Decision-Making with Multi-Modal Perception for Autonomous Driving. *arXiv* 2023, arXiv:2312.11935.

17 Nie Z, Farzaneh H. Real-Time Dynamic Predictive Cruise Control for Enhancing Eco-Driving of Electric Vehicles, Considering Traffic Constraints and Signal Phase and Timing (SPaT) Information, Using Artificial-Neural-Network-Based Energy Consumption Model. *Energy* 2022; **241**: 122888.