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Original Research Article

Machine Learning Models for Traffic Flow and Energy Optimization in Saudi Smart Cities

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Abstract: In Saudi Arabia, the development of smart cities is leading to the development of transportation systems and infrastructure that include intelligent transportation, energy consumption, and public services. The current review paper explores the possibility of applying machine learning methods for traffic flow predictions and energy optimization in smart Saudi cities. For this purpose, the paper will use the systematic review methodology, which will analyze the peer-reviewed articles published between 2020 and 2025, relevant policy papers, and real-life applications related to Saudi smart cities. In contrast to the existing literature, which usually explores separate aspects of traffic analytics or energy management, the proposed research will focus on integrating two areas using urban optimization approach. The review reveals that recurrent neural networks, long short-term memory models, graph neural networks, ensemble and reinforcement learning are highly promising methods that can be used for predicting congestion, coordinating signals, controlling the process of electric-vehicle charging, managing street lighting and minimizing the waste of energy in cities. Successful application of machine learning, however, will depend on various conditions such as data quality, cybersecurity issues, interoperation, and proper governance.

Keywords: Machine Learning, Traffic Flow Prediction, Energy Optimization, Saudi Smart Cities, Vision 2030, Intelligent Transport Systems, Smart Energy Management, Sustainability.

INTRODUCTION

Smart cities go beyond digitized portals and standalone initiatives like intelligent infrastructure. Nowadays, they are powered by connectivity, smart mobility, intelligent energy networks, automation, and decision-making predictions. In Saudi Arabia, this concept holds strategic importance due to its focus on economic diversification, quality of life improvement, sustainability, digital government, and world-class cities. Rapid urbanization and development of such cities as Riyadh, Jeddah, Makkah, Madinah, NEOM, etc. pose certain challenges. These include traffic jams, which cause delays, extra fuel consumption, increased greenhouse gas emissions, and reduced efficiency. Unoptimized energy usage leads to higher expenses and lower sustainability performance. Machine learning technology can be utilized by the authorities of smart cities to predict these problems.

Traffic flow prediction is among the most advanced areas of machine learning applications in smart-city analysis. Traditional statistics models were based on average values and linear dependencies which are not accurate for non-linear urban mobility affected by weather conditions, events, road accidents, education calendar, available transport options, and driver behavior. Recent research proves that deep learning models and graph-based models are better at capturing spatio-temporal dependencies compared to traditional forecasting models (Chen *et al*., 2020; Ye *et al*., 2020; Yu *et al*., 2020). These models are especially useful for Saudi Arabian cities since the network structure involves high private transportation use, growing public transport investment, large peaks related to events, and seasonal patterns.

Another important aspect is energy optimization that involves smart homes, smart buildings, smart street lights, district cooling system, electric vehicles, and distributed energy resources. Machine learning algorithms can be used to predict the demand, detect anomalies, schedule controllable loads, and shave the peak load. Attached is an energy forecasting model using LSTM architecture created for smart environment (Khan *et al.,* 2024) as a part of the energy optimization process. In the context of Saudi cities, energy optimization contributes to sustainability, ensures efficient peak demand, and establishes better relations between mobility and urban buildings and other components of smart cities.

The purpose of this review is to discuss machine learning techniques related to traffic flow and energy optimization in the context of Saudi smart cities and develop an appropriate framework based on Vision 2030. The objectives of the study include the examination of ML techniques, their application to traffic and energy, analysis of barriers to their adoption, identification of Saudi contextual requirements, and provision of practical recommendations. The present study will be conducted as a review paper written in the style of Springer: introduction, literature synthesis, methodology, findings, discussion, framework, recommendations, conclusions, and references.

LITERATURE REVIEW

Traffic and energy machine learning overlaps with intelligent transportation systems, smart grids, IoT, urban analytics, and sustainability governance. Machine learning models rely on traffic flow data obtained through loop detectors, CCTV cameras, GPS traces, connected vehicles, mobile phone logs, weather reports, and incident notifications. On the other hand, energy machine learning relies on smart metering, building management, EV chargers, weather, appliance sensors, and distribution grid data. The same challenge lies at the heart of traffic and energy management – the need to transform big data into decisions.

LSTM networks are extensively used due to their capability to recognize sequential patterns and delayed relationships in time series. LSTM models have been used for forecasting of traffic speed, traffic volume, travel time, and energy demand, as these are better at dealing with temporal dependency than many shallow models. In the smart-energy case study conducted by Springer, an LSTM model was applied for multivariate prediction, which showed higher performance compared to baseline, ARIMA, Auto ARIMA, SARIMAX, and univariate forecasting approaches (Khan *et al*., 2024). For traffic prediction purposes, LSTM can be considered useful where the onset of congestion happens over minutes or hours rather than immediately.

Graph neural networks have gained popularity due to the spatial nature of traffic. The congestion shock experienced by one corridor can spread to intersections, feed-in roads, and public transport lines. Spatio-temporal graph convolutional networks, graph convolutional networks, and attention graph modeling treat roads and intersections as nodes and edges. As indicated in traffic prediction reviews, graph-based neural networks enhance the capacity of representing the network topology and spatial dependencies between roads and junctions (Ye *et al*., 2020; Jin *et al*., 2022). This is especially applicable in Riyadh and other Saudi cities where metro, ring roads, airport connectivity, and event areas complicate traffic relations.

Tree-based learning and ensemble models continue to be used due to their interpretability, robustness, and simplicity of application. Models like random forest, gradient boosting, and extreme gradient boosting allow handling various mixed types of features including weather, land use, road type, holidays, and time-of-day factors. Tree-based learners might not always outperform deep learning techniques in dynamic tasks. Nonetheless, they have proven to be valuable for screening important explanatory variables, informing decision-making dashboards, and providing explanations of predictions to non-technical audiences. For public sector organizations, explainability of ML models is crucial as decisions taken have impacts on civilians, business, and first responders (Sarker, 2021; Shneiderman, 2020).

Reinforcement learning becomes increasingly popular with regard to traffic signal control and energy management in power grids. While predictive ML can only predict future demand, reinforcement learning learns optimal control strategies that minimize wait time, number of stops, balancing of queues, and shifting of energy use to non-peak times. Reinforcement learning allows coordination of traffic lights, lanes, vehicle charging, and building load management in smart cities. Nevertheless, reinforcement learning requires simulation before deployment due to potential operational risk associated with experimental implementation (Wei *et al*., 2021; Haydari and Yilmaz, 2020).

Localized ML model design is essential for Saudi smart cities. Imported models might underperform when trained on data of cities with another climate, driving patterns, urban design, gas prices, public transport usage, and different governance mechanisms. Vision 2030 gives the logical framework for Saudi smart transition. Technical success depends on integration of municipal information systems, traffic and transit management, energy companies, telecommunication networks, and privacy measures. Saudi National Smart Cities Program and overall digital transformation efforts create the right environment, whereas emergence of mega-projects like NEOM creates demand for traffic-energy intelligence solutions. In this light, a review paper needs to go beyond algorithm evaluation and look at the operational suitability and sustainability.

METHODOLOGY

The present review paper applies a systematic narrative review methodology. The methodology is appropriate for this paper, since it covers multiple technical subjects, namely: ML algorithms, smart-city architecture, energy efficiency, traffic modeling and Saudi Arabia priorities and policy. Therefore, a pure technological review will miss the point about implementation, and vice versa – an exclusively policy-oriented review will ignore the diversity of model families. Accordingly, the present paper employs a review procedure based on Springer review paper logical structure, i.e., search scope definition, screening, quality assessment, thematic synthesis and theoretical framework development.

Search scope covered the period 2020-2025. Major search terms include machine learning, traffic flow prediction, smart city, intelligent transportation system, energy optimization, smart energy management, Saudi Arabia, vision 2030, smart mobility, GNN, LSTM, reinforcement learning, and urban sustainability. Search included peer-reviewed journals indexed in Scopus, Web of Science, IEEE, Springer, ScienceDirect, MDPI, Saudi Arabian policies, and selective industry reports. Inclusion criteria required the papers to be relevant to traffic prediction, energy management, smart-city analytics or Saudi smart-city transition. The exclusion criteria excluded the papers devoted exclusively to hardware architecture, non-urban energy systems, non-English texts and models without a thorough methodological description.

Evidence was classified according to the following categories: model family, data source, urban function, optimization outcome and implementation barrier. Traffic-related outcomes include travel-time prediction, congestion detection, signal management, emergency situation response, support of public transportation and emissions reductions. Energy-related outcomes include demand forecasting, peak shaving, load scheduling, coordination of charging infrastructure for electric vehicles, control of street lights and anomaly detection. The quality criteria include methodological soundness, data availability and transparency, validation metrics, interpretability, generalizability and sustainability considerations. Note that the present paper uses methodology and not experimentation. Hence, the paper will not employ any models, and will summarize the existing evidence in a Saudi-specific implementation frame.

This paper is also structurally inspired by the attached Springer paper that uses a consistent research flow, clear methodology description, model comparison, figures and conclusion based on results (Khan *et al*., 2024). In the context of the current research problem, such structure is translated to review design and not simulation modeling. Methodological contribution of this paper consists in the inclusion of both traffic and energy optimization within the same smart city framework. It is essential, since urban energy demand and traffic flows interact with each other via signaling systems, lighting, cooling, EV charging etc.

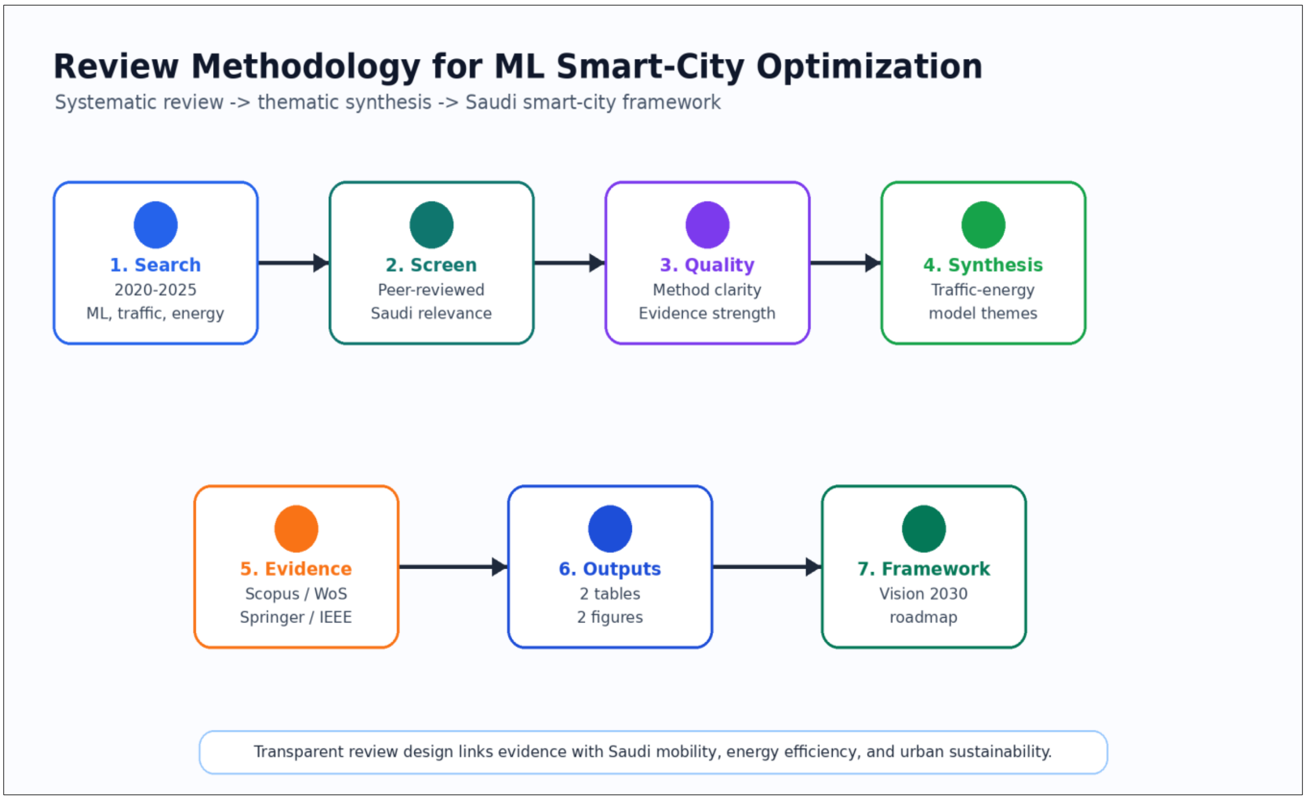

Figure 1: Review methodology for machine learning-based traffic flow and energy optimization in Saudi smart cities.

Findings and Thematic Synthesis

This review highlights three key findings. Firstly, traffic flow prediction has shifted from individual time series forecasting to spatio-temporal modeling. LSTM, GRU, CNN-LSTM, graph convolutional networks, and attention are widely applied since traffic dynamics is both temporal and geographical. Combinations of speed, flow, occupancy, weather, and incident information tend to yield more accurate results compared to single attribute models. The choice of model depends on the context, however. While the same factors might be significant in predicting short-term dynamics within a signalized intersection, they can have different meanings at a corridor level on an expressway or a wider network.

Secondly, energy prediction in smart-city infrastructures requires multivariate learning. Residential buildings, office buildings, smart meters, smart lighting systems, and smart EV charging stations produce high-frequency data. This can allow for peak load detection, anomaly detection, and improved energy predictions taking into account weather changes. In this regard, the attached Springer paper highlights the importance of multivariate modeling in energy prediction in smart cities and the ability of LSTM networks to enhance the reliability of forecasting using multiple energy-related attributes (Khan *et al.*, 2024). The issue becomes even more complicated in Saudi Arabian cities due to factors such as excessive heat, cooling load, dustiness, Ramadan-related demand fluctuations, tourism influx, and seasonality.

Thirdly, traffic and energy optimization have yet to be effectively combined within smart city models. Most previous studies focus on optimizing either the traffic flow without accounting for energy impact or energy distribution within buildings or the grid without accounting for mobility consequences. It is necessary to develop a more complex approach given the growing connection between energy and transportation systems in Saudi Arabia. Adaptive traffic signals have an effect on fuel consumption and idle time, EV charging is related to traffic flows and timing, street lights can be adjusted based on human and vehicle movement, and public transport scheduling influences congestion as well as energy demand.

This study also highlights several barriers. One of them is data fragmentation since traffic data, energy data, telecom data, and municipality data are produced by different agencies. Another obstacle is the difficulty of transferring models developed for one city to other cities since traffic conditions can be very diverse. Cybersecurity and privacy should be ensured when using camera data, license plate recognition data, mobile data, and smart metering data. Human capacity is also relevant because traffic engineers, energy managers, and planners should interpret the data provided by machine learning algorithms. Last but not least, governance is required for assigning responsibility in terms of model monitoring, procurement, and public engagement.

Despite barriers identified above, Saudi Arabia has favorable conditions to apply machine learning in cities. Vision 2030, investments in smart city infrastructure, government digital transformation, availability of 5G technology, development of giga-projects, and development of national AI initiatives provide a good ground for applying machine learning techniques.

Table 1: Machine learning model families and smart-city relevance

Model family	Primary use in traffic flow	Primary use in energy optimization	Saudi smart-city relevance
LSTM/GRU	Short-term speed, flow, and travel-time forecasting	Demand forecasting, peak-load prediction, appliance and building trends	Useful for event peaks, heat-driven demand, and corridor-level prediction
Graph neural networks	Network-level congestion propagation and route dependency	Spatial coordination of distributed loads and charging nodes	Important for ring roads, metro feeders, and multi-district city planning
Random forest/gradient boosting	Feature importance, incident risk, interpretable prediction	Consumption drivers, anomaly detection, operational dashboards	Suitable for explainable public-sector decision support
Reinforcement learning	Adaptive signal control and dynamic routing	EV charging schedules, demand response, lighting control	Requires simulation, safety limits, and staged deployment
Hybrid/digital twin models	Scenario testing for mobility interventions	Testing demand response and energy resilience	Supports giga-project planning and integrated command centers

Proposed Saudi Smart-City Optimization Framework

The optimization of the proposed smart-city operation involves an integrated optimization hub. This hub gathers data from traffic sensors, public transport, parking systems, smart meters, building management systems, street lighting, weather systems, events calendar, and emergency services. After processing, standardization, and linking through the urban data foundation, machine learning models will generate short-term traffic forecasts, energy demand forecasts, traffic congestion alerts, anomaly detections, and scenarios simulations.

The first layer in the optimization framework is urban sensing and data governance. This layer guarantees that the gathered data are up-to-date, accurate, interoperable, and safe. Sensor calibration, metadata standards, agreements for sharing, privacy controls, and data quality checks should be considered to have an optimal data layer. Otherwise, advanced models will deliver unreliable forecasts. The second layer is model development. It includes the selection, training, validation, explainability, drifts monitoring, and benchmarks comparison. For instance, LSTM could be selected for forecasting temporal demand, graph neural networks for estimating the traffic flow at network level, random forests for ranking features, and reinforcement learning for control purposes.

The third layer in the optimization framework is decision support operations. It includes the implementation of predictions, which should lead to decisions like adjusting traffic signals, providing route guidance, adjusting public transport service, scheduling charging for EVs, controlling lights, and activating demand response mechanisms. Human intervention should be performed when safety is critical for the decisions. The fourth layer involves energy and mobility coordination. In this layer, traffic management and energy outcomes will be coordinated through estimating congestion effects, speed smoothing, charging load, and street lighting controls on energy and carbon emissions. The final layer in the framework is Vision 2030 value realization. It will measure the success through reduced congestion, travel time reliability, improved energy efficiency, lowered emissions, citizen satisfaction, resilience, and local capability building.

The framework emphasizes the importance of governance for achieving its goal. It is inappropriate for advanced models to be black boxes taking critical urban decisions without any kind of explanation and accountability. Thus, they need to be included in transparent processes of the government sector, including the creation of dashboards, audit trails, model documentation, communication with citizens, and periodic reviews. The framework also facilitates phased implementation in different cities and areas.

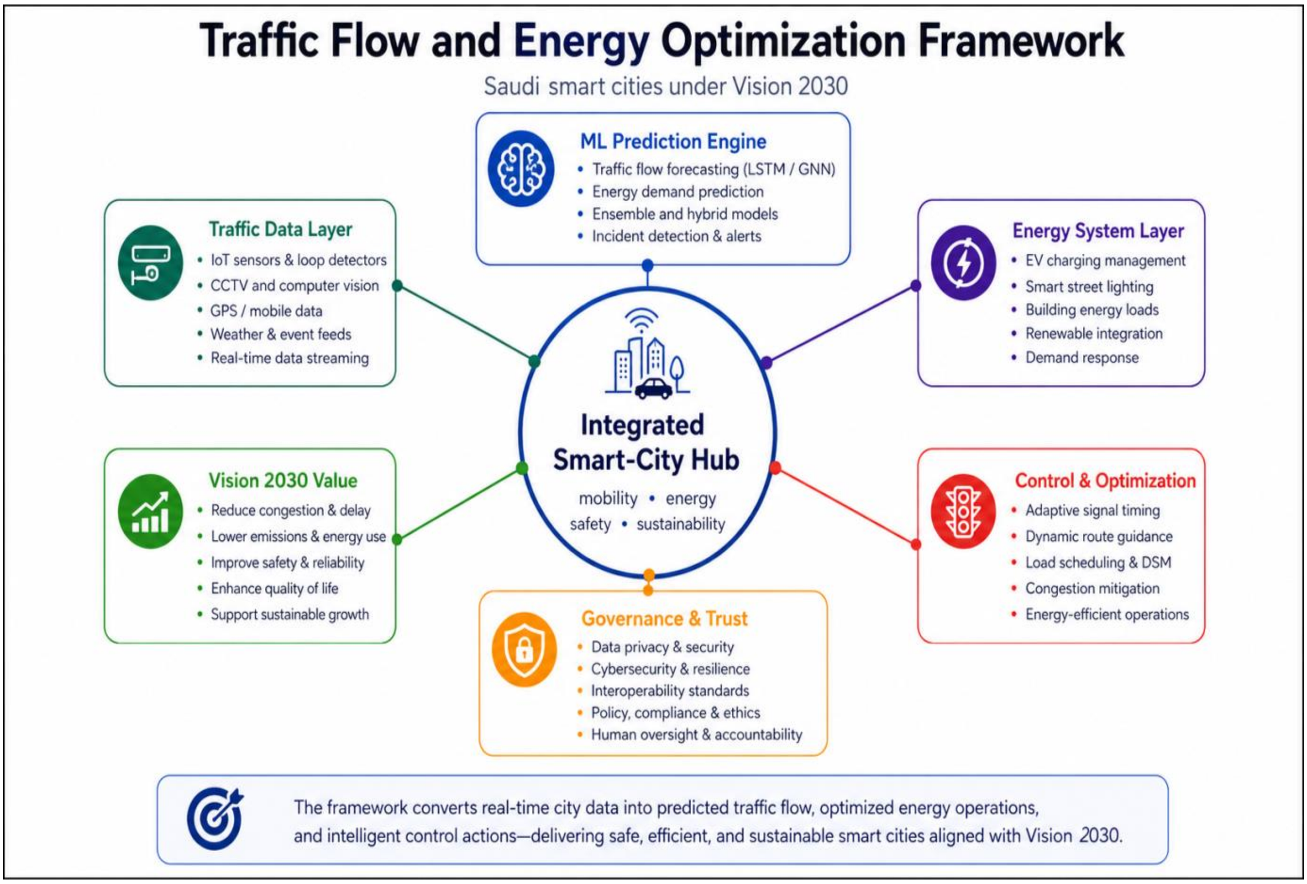

Figure 2: Integrated traffic flow and energy optimization framework for Saudi smart cities

Table 2: Implementation barriers and mitigation strategies for Saudi smart cities

Barrier	Practical impact	Mitigation strategy
Data fragmentation	Traffic, energy, telecom, and municipal datasets remain disconnected	Create shared urban data standards and secure data-sharing agreements
Sensor reliability	Noisy or missing data weakens model accuracy	Use calibration routines, anomaly checks, and redundancy
Model transferability	Imported models may not match Saudi climate and mobility behavior	Train and validate models on Saudi-specific datasets
Cybersecurity and privacy	Smart meters, cameras, and mobility data create sensitive information risks	Apply privacy-by-design, access control, encryption, and audit logs
Skills and governance	Operators may not trust or understand model recommendations	Build human-in-the-loop workflows, training, and model documentation

DISCUSSION

Accordingly, the above review proves the importance of taking a broader approach to the utilization of machine learning as a tool of transforming Saudi Arabia's smart cities. For instance, it can accurately forecast traffic flows but would be less valuable if the city does not have the ability to modify traffic lights, send directions via maps or organize public transport efficiently. Similarly, an energy-forecasting system would prove to be less effective if there were no buildings able to react and adjust to the changes predicted. Hence, the connection between prediction, control and governance becomes crucial.

It also means that the development of Saudi Arabia's smart cities involves certain limitations as well as opportunities. The opportunity here is that a newly constructed city or district can utilize such capabilities since they can include all necessary data architecture and automation solutions. In contrast, old cities would require more efforts to transform since they already have some infrastructure, organizational and institutional barriers, traffic patterns and data silos. Hence, Riyadh, Jeddah and Makkah require special approaches for transitioning to digital management of processes.

Another important issue related to the topic under investigation is energy consumption and climate issues. On the one hand, cities of Saudi Arabia have high cooling needs, which can be additionally increased in case of traffic jams that cause excessive fuel consumption, idling, etc. The use of electric mobility would help to decrease tailpipe emissions. However, it would also increase electricity demand. Accordingly, such a situation could be managed by applying machine learning models that could help to analyze the interrelation between mobility and electricity consumption and the availability of renewable energy.

As another critical point in implementing smart cities in Saudi Arabia, the explainability requirement should be mentioned. Although deep learning models may provide highly accurate predictions, public sector requires explainable, transparent models to make decisions based on their predictions. Thus, when a model decides to change priorities of traffic lights, restrict entry in certain areas, regulate electricity price for EV charging stations or dim streetlights, officials should understand why it did so and what results can be expected. Therefore, explainable AI, model cards, fairness assessments and human-in-the-loop systems should be applied from the very beginning.

In conclusion, the cooperation of Saudi universities, municipal authorities, telecommunications providers, energy companies and IT companies can contribute to the establishment of shared testing platforms, simulation environments, etc., that would develop local skills in data analysis, transport, energy analysis and operation of smart city management systems.

Recommendations

Firstly, Saudi smart cities should design integrated data standards in relation to mobility and energy. The creation of common IDs for roads, intersections, buildings, meters, chargers, and public infrastructure would help to integrate datasets between departments. Secondly, pilot projects should have use cases that are easy to measure, such as airport corridors, event areas, school traffic, metro feeder systems, industrial areas, and EV charging zones. The evaluation of such pilots should be done according to mobility indicators as well as energy ones.

Thirdly, model selection should be determined by the use case. Models based on LSTM and GRU can be used for forecasting; GNNs for modeling the dependency of a road network; ensemble models for risk scoring with interpretability; and reinforcement learning models for adaptive control after simulating. Fourthly, governance should include such processes as documenting models, setting up performance metrics, ensuring privacy and cybersecurity, and regularly checking for model drift. Fifthly, human resources should be considered as an integral part of a technical system.

Traffic and energy engineers should be trained in making decisions based on predictions and uncertain forecasts. Sixthly, machine learning applications should contribute directly to Saudi Arabia's Vision 2030 objectives. They should show how ML projects help decrease congestion, energy consumption, greenhouse gas emissions, increase safety, improve public transportation, etc. Finally, future research should cover the development of Saudi datasets and comparisons between cities of various sizes and natures. It is important to investigate models' behavior in case of extremely high temperatures, religious tourism peak times, intensive use of personal vehicles, increasing public transportation fleet, and fast urbanization.

Concluding Remarks As mentioned earlier, an accurate yet unmaintainable, inexplicable, and disconnected algorithm does not contribute much to the city's ability to become smart. The same holds true for the Saudi urban environment, which needs to pay close attention to its data collection process, pilot corridors, and the responsible party for each automated suggestion issued by the algorithm. In the end, however, the proposed review scope still seems practical, well-informed, and ready for further empirical testing in Saudi Arabia. Prediction Accuracy and Operational Usefulness as Separate Dimensions of Smart-City Value The review thus considers prediction accuracy and operational usefulness as two interconnected but distinct aspects of smart-city value. An algorithm that is difficult to maintain, explain, or connect to the existing systems cannot be deemed fully developed enough for public use. In addition, the Saudi application of such an algorithm should focus on creating a reliable data pipeline, implementing a measurable pilot corridor, and identifying one accountable person for each recommendation provided by the machine-learning system. These recommendations would help cities benefit from machine learning without compromising their residents' privacy, safety, and trust. Furthermore, they would allow cities to gradually evolve from a series of independent monitoring programs into the full-fledged integration of intelligence across mobility and energy services. Concluding Remarks The proposed review scope thus appears both reasonable and informed enough for future empirical application to the case of Saudi Arabia.

CONCLUSION

In this review, machine learning techniques were assessed for traffic flows and energy optimization in Saudi smart cities. Evidence indicated that LSTM, graph neural networks, ensemble learning, and reinforcement learning could help to make accurate predictions and optimize control with the availability of quality data and good governance. Prediction of traffic flow and optimization of energy should be seen as related urban problems since traffic affects energy consumption, pollution, street lighting, EV battery charging, and the stress on infrastructure.

The paper proposed developing an optimization framework for Saudi smart cities that includes urban sensing, model development, decision-making, coordination of energy and mobility, governance, and value realization for Vision 2030. In summary, it has been concluded that machine learning could be helpful in building smarter and sustainable Saudi cities only if there is integration between modeling and institutions, governance, quality data, and skilled labor. It is recommended to focus on the application of specific models for Saudi cities.

REFERENCES

- Abbasi, A., Khalid, H. A., Rehman, H., & Khan, A. U. (2023). A novel dynamic load scheduling and peak shaving control scheme in community home energy management system based microgrids. IEEE Access, 11, 32508-32522.
- Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2025). Machine learning traffic flow prediction models for smart and sustainable traffic management. Infrastructures, 10(7), 155.
- AlOtaibi, Z. S., Khonkar, H. I., AlAmoudi, A. O., & Alqahtani, S. H. (2020). Current status and future perspectives for localizing the solar photovoltaic industry in the Kingdom of Saudi Arabia. Energy Transitions, 4, 1-9.
- Arvidsson, M., Ericson, S., & Soderlind, A. (2020). Economic and grid potentials of implementing an energy storage system: a case study of peak shaving benefits. Energy Systems Studies, 12(2), 41-58.
- Chen, M., Yu, X., & Liu, Y. (2020). A comprehensive survey on traffic prediction. IEEE Transactions on Intelligent Transportation Systems, 21(6), 1-16.
- Djenouri, Y., Belhadi, A., Lin, J. C. W., & Cano, A. (2021). Adapted K-nearest neighbors for detecting anomalies on spatio-temporal traffic flow. IEEE Access, 9, 37391-37400.
- Fahad, L. G., Khan, S. U., & Alghamdi, A. (2024). Artificial intelligence for smart mobility in Saudi urban development: opportunities and governance challenges. Sustainability, 16(4), 1496.
- Hassan, A., Afrouzi, H. N., Siang, C. H., Ahmed, J., Mehranzamir, K., & Wooi, C. L. (2022). A survey and bibliometric analysis of communication technologies for smart meters. Cleaner Engineering and Technology, 7, 100424.
- Haydari, A., & Yilmaz, Y. (2020). Deep reinforcement learning for intelligent transportation systems: A survey. IEEE Transactions on Intelligent Transportation Systems, 23(1), 11-32.
- Hosseini Motlagh, N., Mohammadrezaei, M., Hunt, J., & Zakeri, B. (2020). Internet of Things (IoT) and the energy sector. Energies, 13(2), 494.
- Jin, F., Sun, Y., Li, H., & Zhang, J. (2022). Traffic flow prediction models: a review of deep learning techniques. Cogent Engineering, 9(1), 2010513.
- Khan, M. A., Sabahat, Z., Farooq, M. S., Saleem, M., Abbas, S., Ahmad, M., Mazhar, T., Shahzad, T., & Saeed, M. M. (2024). Optimizing smart home energy management for sustainability using machine learning techniques. Discover Sustainability, 5, 430.
- Kuru, K., & Ansell, D. (2020). TCitySmartF: A comprehensive systematic framework for transforming cities into smart cities. IEEE Access, 8, 18615-18644.
- Li, T., Zhang, Y., & Wang, J. (2021). Traffic forecasting with spatial-temporal graph neural networks: methods and applications. Transportation Research Part C, 127, 103110.
- Liu, Y., Qiu, B., Fan, X., Zhu, H., & Han, B. (2020). Review of smart home energy management systems and data-driven optimization. Energy Reports, 6, 153-163.
- Ning, Y., Zhang, C., & Li, W. (2024). A review of research on traffic flow prediction methods based on machine learning. ACM International Conference Proceedings, 45-52.
- Qi, P., Liu, H., & Wang, X. (2025). A review of dynamic traffic flow prediction methods for smart cities. Future Transportation, 5(2), 88-113.
- Qiang, G., Tang, S., Hao, J., Di Sarno, L., Wu, G., & Ren, S. (2023). Building automation systems for energy and comfort management in green buildings: a critical review and future directions. Renewable and Sustainable Energy Reviews, 179, 113301.
- Saudi Data and AI Authority. (2023). AI Ethics Principles. Riyadh: SDAIA.
- Saudi Vision 2030. (2024). Vision 2030 annual report 2024. Riyadh: Government of Saudi Arabia.
- Sarker, I. H. (2021). Machine learning: algorithms, real-world applications and research directions. SN Computer Science, 2, 160.
- Shneiderman, B. (2020). Human-centered artificial intelligence: reliable, safe and trustworthy. International Journal of Human-Computer Interaction, 36(6), 495-504.

- Singh, M., Jiao, J., Klobasa, M., & Frietsch, R. (2022). Servitization of the energy sector: emerging service business models and start-up participation. Energies, 15(7), 2705.
- Tao, X., Li, Q., Ren, C., Gu, C., Zhang, R., & He, Q. (2023). Towards green innovation in smart cities: leveraging traffic flow prediction using machine learning. Sustainability, 16(1), 251.
- Topilin, I., Petrova, M., & Fedorov, A. (2025). Traffic flow prediction via a hybrid CPO-CNN-LSTM attention model for smart cities. Smart Cities, 8(5), 148.
- United Nations Human Settlements Programme. (2022). World Cities Report 2022: Envisaging the Future of Cities. Nairobi: UN-Habitat.
- Wei, H., Zheng, G., Yao, H., & Li, Z. (2021). IntelliLight: a reinforcement learning approach for intelligent traffic light control. ACM Transactions on Intelligent Systems and Technology, 12(2), 1-29.
- Ye, J., Zhao, J., Ye, K., & Xu, C. (2020). How to build a graph-based deep learning architecture in traffic domain: A survey. IEEE Transactions on Intelligent Transportation Systems, 23(5), 3904-3924.
- Yu, B., Yin, H., & Zhu, Z. (2020). A survey on modern deep neural network for traffic prediction: trends, methods and challenges. IEEE Transactions on Knowledge and Data Engineering, 33(4), 1404-1418.
- Zhang, Y., He, J., & Zheng, L. (2025). Integrating graph neural networks and LSTM for multimodal transport path optimization in smart cities. Scientific Reports, 15, 21022.

