

Innovative technologies for building climate-resilient cities in Asia and the Pacific

AI-driven high-performance data analytics for climate-resilient smart cities and energy systems

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Abstract

Smart cities require AI-driven solutions to enhance climate resilience, energy sustainability, and adaptive urban management. This paper explores the role of artificial intelligence (AI), big data, high-performance computing (HPC), and edge computing in improving renewable energy forecasting, climate adaptation, and AI governance. Case studies demonstrate advancements in solar and wind energy forecasting, showcasing adaptive model selection, attention-based learning, and hybrid deep learning techniques for enhanced predictive reliability. The findings highlight the potential of AI-driven smart grids and governance frameworks in optimizing energy efficiency. Future research should focus on integrating edge AI for real-time decision-making, improving scalable AI architectures, and developing standardized governance frameworks to ensure sustainable, efficient, and climate-resilient smart cities in an increasingly urbanized world.

Introduction

Climate change poses significant challenges to urban environments, requiring cities to adopt resilient, adaptive, and sustainable solutions. (Kandt and Batty 2021; Yigitcanlar, Butler, et al. 2020; Mehmood et al. 2024; Kashef, Visvizi, and Troisi 2021). The rapid expansion of smart cities, driven by advancements in artificial intelligence (AI), big data analytics, high-performance computing (HPC), edge computing, and high-performance data an-

alytics (HPDA), offers an opportunity to enhance urban sustainability, optimize energy management, and improve climate resilience. (Janbi, Katib, and Mehmood 2023; Mehmood et al. 2023; Alahmari et al. 2023; Javed et al. 2022; Majeed et al. 2021) (see Figure 1 for a layered architecture of technology-driven smart cities (Janbi et al. 2020), further elaborated in Section 5). AI-driven predictive modelling, real-time data analytics, and autonomous decision-making enable cities to mitigate climate risks, manage renewable ener-

gy integration, and improve infrastructure efficiency. (Yigitcanlar, Mehmood, and Corchado 2021; Alkhatat and Mehmood 2021; Kandt and Batty 2021; Alahmari et al. 2023; Herath and Mittal 2022). However, integrating these technologies at scale necessitates robust governance frameworks, energy-efficient computational architectures, and climate-aware urban policies. (Alsaigh et al. 2024; Mehmood et al. 2025; Yigitcanlar et al. 2021).

This paper explores the technological foundations and AI-driven strategies for climate resilience in smart cities. It examines how big data and HPC facilitate large-scale environmental modelling, AI, machine learning (ML), and deep learning (DL), enhance energy forecasting, and enables real-time climate adaptation through edge computing. Special emphasis is placed on renewable energy forecasting, a critical factor in reducing fossil fuel dependence and ensuring stable energy grids.

To illustrate these concepts, the paper presents four case studies demonstrating AI applications in renewable energy forecasting and governance. These studies build on our work in AI-driven energy forecasting and governance, covering SENERGY, an AI-driven model selection tool for solar energy forecasting. (Alkhatat, Hasan, and Mehmood 2022) (Section 7), an attention-based deep learning approach for solar power generation forecasting (Almaghrabi et al. 2024) (Section 8), a hybrid deep learning model for wind energy forecasting (Alkhatat, Hasan, and Mehmood 2023) (Section 9), and an AI governance framework for smart energy systems (Alsaigh, Mehmood, and Katib 2023) (Section 10).

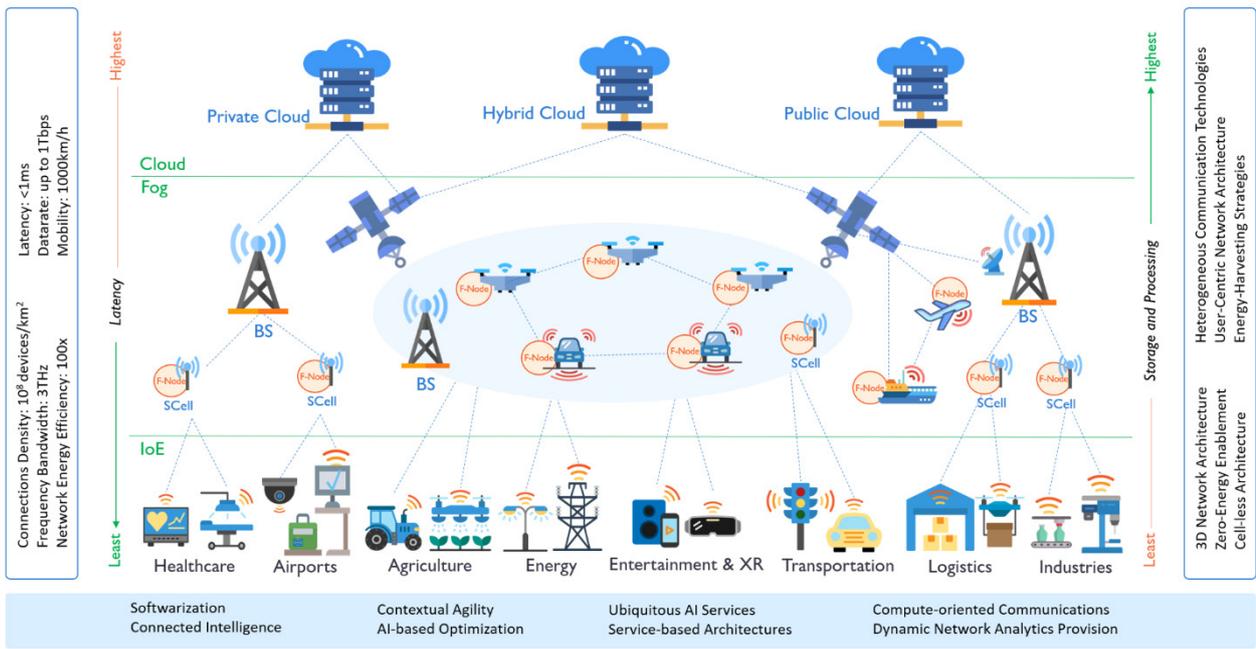


Figure 1: Smart city architecture enabled by edge computing and 6th Gen Networks (Janbi et al. 2020)

The following sections provide a structured exploration of these topics, starting with the evolution of smart cities (Section 2) and their reliance on AI (Section 4), followed by discussions on big data and HPC (Section 3), AI-driven forecasting techniques (Section 6), and the role of edge computing (Section 5). The case studies further demonstrate AI applications in solar and wind energy forecasting as well as governance, culminating in a discussion on key challenges and future directions for AI-powered climate resilience in smart cities (Section 11).

Technologies shaping climate-resilient smart cities

The shift from traditional cities to smart, climate-resilient cities is driven by the need for sustainability, adaptive infrastructure, and AI-driven decision-making (Yigitcanlar, Butler, et al. 2020; Mehmood et al. 2024). Unlike conventional cities, which rely on centralized, reactive systems, smart cities leverage real-time data, AI, and automation to optimize energy use, enhance resilience, and mitigate climate risks. (Alotaibi et al. 2020; Schrotter and Hürzeler 2020). AI enables predic-

tive urban planning, disaster preparedness, and environmental monitoring, making cities more adaptable to global challenges. (Son et al. 2023).

Data and AI serve as the foundation of smart cities, enabling evidence-based decision-making. (Yigitcanlar, Kankanamge, et al. 2020; Alomari, Katib, Albeshri, Yigitcanlar, et al. 2021). The integration of IoT sensors, satellite imagery, and HPC facilitates climate modelling, energy forecasting, and smart grid optimization. (Döscher et al. 2022; Abbasi et al. 2025; Yigitcanlar, Butler, et al. 2020). AI-driven simulations have improved urban flood prediction, water resource management, and renewable energy forecasting, reducing reliance on fossil fuels. (Groves et al. 2015; Xiang et al. 2021; Q. Huang et al. 2013; Yigitcanlar et al. 2022). However, the increasing use of urban data raises concerns about privacy, cybersecurity, and regulatory compliance, requiring strong AI governance frameworks. (Alsaigh et al. 2024; Yigitcanlar et al. 2021; D. Chen, Wawrzynski, and Lv 2021).

AI has also revolutionized urban governance, enhancing policy-making, infrastructure planning, and autonomous monitoring. (Alomari, Katib, and Mehmood 2023; Yigitcanlar, Butler, et al. 2020). Digital twins, AI-powered vir-

tual replicas of cities, allow for climate impact simulations, traffic flow optimization, and energy efficiency planning. (Sivarethinamohan and Reddy 2024; Aloupogianni et al. 2024). Cities such as Singapore (X. Liu, Gou, and Yuan 2024; Zhan, Hwang, and Krishnankutty 2024), Zurich (Schrotter and Hürzeler 2020), and Amsterdam (Lohman et al. 2023) employ digital twin technology for sustainability efforts (Faliagka et al. 2024; Shahat, Hyun, and Yeom 2021).

AI-driven energy management improves sustainability by forecasting energy demand and integrating renewables. (Almaghrabi et al. 2024; Alkhatyat and Mehmood 2021; Alkhatyat, Hasan, and Mehmood 2022; 2023). In healthcare, AI optimizes resource allocation and public health monitoring, helping cities adapt to climate-related health risks. (Alotaibi et al. 2020; Alomari, Katib, Albeshri, and Mehmood 2021; Alswedani, Mehmood, and Katib 2022; Alswedani et al. 2023; Verma 2022).

Despite its advantages, AI-driven smart cities face challenges in data privacy, cybersecurity, and ethical governance. Addressing these issues through robust AI policies and regulatory frameworks is essential for equitable, sustainable urban development.

Big Data and high-performance computing in climate-resilient cities

Big data and HPC are fundamental to processing vast and complex datasets in smart cities. (Arfat et al. 2020a; 2020b; Usman et al. 2022). Big data refers to the massive volume of structured and unstructured data generated from IoT sensors, climate monitoring systems, energy grids, and urban infrastructure. (Cesario 2023; Bhattarai et al. 2019; Taherdoost 2024). It enables data-driven decision-making through real-time analytics and predictive modelling. (Kandt and Batty 2021). HPC, on the other hand, provides the computational power needed to process and analyse these large datasets efficiently, running advanced simulations, deep learning models, and large-scale AI applications (Alomari, Katib, Albeshri, Yigitcanlar, et al. 2021; Alomari, Katib, Albeshri, and Mehmood 2021). While traditionally separate, big data and HPC are increasingly converging to enable HPDA, providing real-time insights for climate resilience and urban sustainability (Usman, Mehmood, and Katib 2020; Usman et al. 2022; Elia, Fiore, and Aloisio 2021).

In smart cities, HPC accelerates climate modelling. (Döscher et al. 2022; Wang et al. 2021), energy forecasting (Abbas et al. 2025; Rodriguez et al. 2021), and disaster prediction (Bates 2021; Hori et al. 2018), allowing urban planners to implement proactive adaptation strategies. AI-powered climate risk assessment models utilize HPC to analyse weather patterns, predict extreme events such as floods and heatwaves, and optimize water resource management. (Groves et al. 2015; Xiang et al. 2021; Q. Huang et al. 2013). In the energy sector, HPC-driven AI models improve renewable energy forecasting, optimize smart grids, and enhance power distribution, reducing reliance on fossil fuels. (Parizad and Hatziaodoniu 2022; Rodriguez et al. 2021).

However, the integration of HPC and big data presents challenges, particularly regarding high energy consumption, scalability, and data privacy. (Gilman et al. 2024; Haoyang Liu and Zhai

2025). The computational demands of AI-driven smart cities necessitate energy-efficient HPC architectures, incorporating green computing techniques, workload optimization, and edge AI solutions to reduce reliance on centralized infrastructure. (Usman et al. 2022). Addressing these challenges will be crucial for ensuring scalable, sustainable, and climate-resilient smart cities. (Mehmood et al. 2020; 2023).

AI, Machine Learning (ML), and Deep Learning (DL)

AI encompasses a broad range of technologies that enable machines to perform tasks typically requiring human intelligence. A key component of AI is ML, which allows systems to learn from data and improve their performance over time. ML could be categorized into supervised, unsupervised, and reinforcement learning (RL) (Janiesch, Zschech, and Heinrich 2021).

Supervised ML models learn from labelled datasets where both input and output data are provided. This approach is widely used in classification and regression tasks, such as image recognition, medical diagnostics, and financial forecasting. Common supervised learning algorithms include support vector machines, decision trees, random forests (RF), and linear regression models. (Taye 2023). In contrast, unsupervised ML models identify hidden patterns in unlabelled data. These models are useful for clustering and association tasks, such as customer segmentation and anomaly detection. Clustering algorithms include K-means, mean-shift, and principal component analysis (PCA), while association rule learning relies on techniques including Apriori and FP-growth (Pichler and Hartig 2023). RL mimics trial-and-error learning, allowing models to interact with an environment and optimize their actions based on rewards or penalties. RL is widely used in robotics, self-driving cars, and game-playing AI. A key algorithm in this field is Q-learning (Morales 2020).

The development of artificial neural networks (ANNs), inspired by the human brain, has led to major advancements in ML. An ANN consists of an input layer, multiple hidden layers, and an

output layer, where connected nodes (neurons) adjust their weights through learning. As ANNs evolved into deeper architectures, the field of DL emerged. (Prasad, Naicker, and Tyagi 2021). DL models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have revolutionized AI applications requiring large, high-dimensional data processing, such as image recognition, speech processing, and predictive analytics. (S. Dong, Wang, and Abbas 2021). CNNs are highly effective in computer vision tasks, using convolutional and pooling layers to detect features and patterns in images. (Trask 2019). RNNs, designed for sequential data, excel in natural language processing and time-series forecasting. Advanced variants, including long short-term memory (LSTM) and gated recurrent units (GRU), help overcome the vanishing gradient problem. (Ilya Sutskever 2013).

Other DL architectures have expanded AI's capabilities. Autoencoders (AEs) are useful for data compression and anomaly detection, while variational autoencoders (VAEs) allow for generating diverse variations of input data. (Gensler et al. 2016). Generative adversarial networks (GANs) produce realistic synthetic data, with applications ranging from image generation to data augmentation. (Khodayar, Wang, and Manthouri 2018). Transformer models, a breakthrough in natural language processing, leverage self-attention mechanisms to process text more efficiently than traditional RNNs (Q. Chen et al. 2019). Hybrid DL models combine multiple architectures to enhance performance in complex tasks. In renewable energy applications, DL models are frequently integrated with traditional ML or physical models to improve forecasting accuracy. For more insights into DL and its uses in renewable energy, see (Alkhatat and Mehmood 2021; Forootan et al. 2022).

Edge computing for smart cities: extending cloud and fog architectures

Edge computing is a distributed computing paradigm that brings computation and data storage closer to the

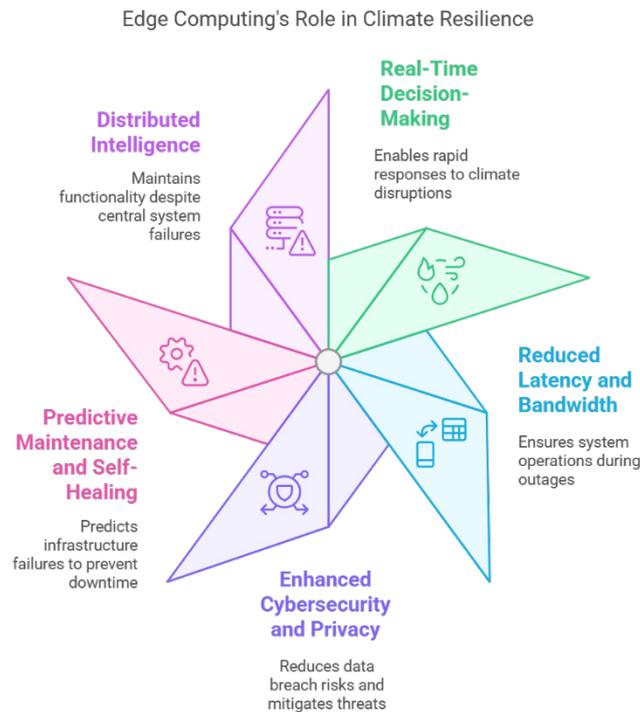


Figure 2: The role of edge computing in climate resilience

source of data generation, reducing latency and improving real-time processing capabilities (Janbi, Katib, and Mehmood 2023; Janbi et al. 2022). Unlike traditional cloud computing, where data must travel to distant data centres for processing, edge computing distributes computational load to localized nodes. This approach minimizes delays and bandwidth usage, improves security and privacy by keeping sensitive data local, and reduces reliance on internet connectivity (Singh and Gill 2023). Figure 1 illustrates a smart city architecture enhanced by edge computing, showing how different computing layers work together to optimize connectivity and processing across urban environments (Janbi et al. 2020). At the top, the cloud layer provides centralized storage and high computational power but with increased latency. In the middle, the fog computing layer brings processing closer to end devices, enabling faster responses. At the bottom, the edge layer comprises Internet of Everything (IoE) devices such as mobile devices, autonomous vehicles, drones, smart traffic lights, and other connected technologies, powering var-

ious smart city applications, including healthcare, airports, agriculture, energy, entertainment & XR, transportation, logistics, and industries. This illustration highlights how edge computing decentralizes processing, reducing dependence on distant cloud data centres and enabling real-time, intelligent urban infrastructure, which can make smart cities more efficient, adaptive, and sustainable.

Similarly, these features of edge computing can play an important role in enhancing climate resilience (see Figure 2). By processing data closer to its source, edge computing can enable real-time decision-making for critical systems, such as smart grids, transportation networks, and emergency services, to remain operational during climate disruptions. (Minh et al. 2022; Gill et al. 2025). Moreover, localized data processing can ensure continued services despite central system failures as services are distributed across multiple devices. (Shinde, Hemanth, and Elhoseny 2023). Edge computing combined with distributed intelligence can also support predictive maintenance and self-healing infrastructure,

helping to prevent system failures before they occur, thereby reducing downtime and improving reliability. (M. Dong et al. 2021; Jin et al. 2022). Additionally, it can enhance cybersecurity and privacy by reducing reliance on centralized cloud systems and minimizing the risk of large-scale data breaches. (Cao et al. 2020; Gill et al. 2025). Keeping sensitive data localized reduces exposure to cyber threats while ensuring compliance with data protection regulations. This is particularly important for climate monitoring systems, emergency response networks, and energy grids, where secure and private data handling is essential. Furthermore, edge computing can contribute to renewable energy resilience by optimizing solar energy forecasting and defect detection in solar cells, improving the sustainability of power generation. (Venitourakis et al. 2023). Overall, edge computing can strengthen climate resilience by ensuring operational continuity, reducing latency, enhancing privacy and security, and providing localized, intelligent responses to environmental challenges, making smart cities more robust.

Applications for edge computing for climate resilience span a variety of industries, including smart grids, transportation networks, water and waste management, telecommunications infrastructure, and healthcare systems, improving efficiency and adaptability in the face of climate change. Smart grids can benefit from edge computing integrated with AI to balance energy loads, incorporate renewable energy sources, and prevent blackouts during extreme weather (Minh et al. 2022). Transportation networks leverage edge computing for real-time traffic management, autonomous vehicle operations, and railway monitoring, ensuring mobility during climate-related disasters such as floods and earthquakes (Arthurs et al. 2022; Bhambri and Khang 2025). Water and waste management systems can utilize edge computing to monitor water quality, detect leaks, and predict flood risks in real-time, enabling swift responses to protect water supplies and mitigate cascading impacts on urban populations (Amesho et al. 2024; Ren, Zhu, and Wang 2022). Telecommunications infrastructure can integrate edge computing to maintain communication networks during natural disasters, enhancing 5G and 6G networks with AI to dynamically manage bandwidth, optimize traffic flow, and sustain mission-critical communications during peak loads or severe storms (Letaief et al. 2022; Park et al. 2019). Healthcare systems can also benefit from edge computing through real-time patient monitoring and disaster response, which is crucial during climate-induced health crises such as heat waves and floods (Hartmann, Hashmi, and Imran 2022; Abdellatif et al. 2019).

In Asia and the Pacific region, the resilience of urban infrastructure and essential services are further challenged by the intensifying climate threats the region faces, including typhoons, floods, rising sea levels, and extreme heat waves. (Nunn et al. 2024; Prizzia and Levy 2018). As cities in the region become more digitally connected, the role of edge computing in enabling real-time, localized responses to climate-induced disruptions will become increasingly critical. By enabling adaptive, real-time, and decentralized decision-making, edge computing can

strengthen climate resilience across Asia and the Pacific, ensuring that cities remain operational, secure, and efficient in the face of escalating climate challenges. As the region continues to urbanize, integrating edge AI with smart city applications will be key to building sustainable, future-proof urban environments capable of withstanding climate-induced disruptions.

Renewable energy forecasting for climate-resilient smart cities

Renewable energy forecasting plays a crucial role in ensuring grid stability, energy market efficiency, and climate resilience. While various forecasting techniques apply to multiple renewable energy sources, such as solar, wind, and hydro, this section focuses on solar energy forecasting due to space constraints. Some methodologies and challenges discussed here are also relevant to other forms of renewable energy, though each source has unique forecasting requirements.

Solar power generation forecasting and climate resilience: The variability of solar power presents a challenge for renewable energy integration, as photovoltaic (PV) systems depend on fluctuating weather conditions (Zhang et al. 2015). Unlike fossil-fuel power plants that provide a steady energy output, solar generation varies daily and seasonally. Accurate forecasting helps grid operators balance supply and demand, prevent voltage fluctuations, and minimize reliance on fossil fuel reserves, reducing carbon emissions. Energy storage systems, such as lithium-ion batteries and pumped hydro storage, are key to mitigating solar power intermittency. However, they are costly and require precise management. Forecasting enables optimized charging and discharging schedules, improving storage efficiency and cost-effectiveness (Suberu, Mustafa, and Bashir 2014). Climate resilience planning also benefits from forecasting, particularly for extreme weather events such as hurricanes, heat waves, and wildfires, which disrupt energy generation and grid operations. (Nyan-

gon 2024). Reliable forecasts allow utilities to take preventive measures, such as disconnecting solar arrays before storms or deploying mobile storage solutions. In electricity markets, supply-demand balance dictates energy pricing. In high solar penetration regions, forecasting enables producers to predict output and bid efficiently in electricity markets. (Da Silva, Ilić, and Karnouskos 2013). It also supports power purchase agreements (PPAs) and grid feed-in mechanisms, ensuring stable pricing and minimizing financial risks for investors.

Methods of solar power generation forecasting: Solar power forecasting methods fall into physical models, non-physical models, and hybrid approaches. Physical models use atmospheric physics to simulate solar irradiance and PV power generation. These models incorporate numerical weather prediction (NWP) systems, where meteorological forecasts are converted into solar energy estimates. However, their accuracy depends on NWP precision, and errors can propagate through the system (Geraldini, Romano, and Ricciardelli 2012). Studies using European Centre for Medium-Range Weather Forecasts data have shown systematic overestimations of PV power output during winter (Lorenz, Heinemann, and Kurz 2012). Bias correction algorithms improve accuracy under cloudy conditions (Lorenz et al. 2011). Non-physical models, or empirical models, analyse historical solar power data using statistical, ML and DL techniques [54]. These methods identify patterns in past data to predict future power generation without relying on atmospheric equations. Traditional statistical models, such as auto-regressive integrated moving average (ARIMA), perform well under stable weather conditions [55], while AI-driven models better handle complex dependencies (Antonanzas et al. 2016). Studies show that support vector regression (SVR) (Awad and Khanna 2015; Shi et al. 2012) and multiple linear regression (MLR) models improve forecasting accuracy when incorporating weather variables (Abuella and Chowdhury 2015). DL models, including ANNs (Abdi, Valentin, and Edelman 1999; Changsong Chen et al. 2011; Rana and Koprinska 2016), CNNs (Gu et al. 2018; Shih, Sun, and Lee 2019;

C.-J. Huang and Kuo 2019), and RNNs (Medsker and Jain 2001), offer superior predictive accuracy. CNNs process satellite imagery and irradiance maps, while LSTM networks capture temporal dependencies in solar power data (du Plessis, Strauss, and Rix 2021; Abdel-Nasser and Mahmoud 2019). Studies have validated AI-based forecasting, such as Shi et al.'s SVR model in China (Shi et al. 2012) and Rana et al.'s study in Australia, where SVR outperformed traditional models (Rana, Rahman, and Jin 2020). Hybrid models integrate physical and data-driven approaches to combine their strengths. For example, Mathe et al. developed a CNN-LSTM hybrid model for Germany, significantly reducing forecasting errors (Mathe et al. 2019).

Challenges in solar power generation forecasting: Despite advancements, data quality, computational efficiency, and model interpretability remain key challenges. Data availability and reliability are concerns, as ML and DL models require high-resolution datasets that are often incomplete in some regions. (Sarmas et al. 2022a). Sensor malfunctions and missing values further degrade model performance, necessitating preprocessing techniques such as normalization and outlier detections. (Almaghrabi et al. 2021). Computational complexity presents another challenge, as deep learning models demand significant processing power, making real-time deployment difficult. (Chunlei Chen et al. 2020). Model interpretability and explainability are concerns since deep learning models often function as black boxes. While traditional mod-

els such as ARIMA provide transparent predictions, DL-based forecasting lacks explainability. Explainable AI (XAI) techniques, such as SHapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), improve transparency. (Hassija et al. 2024; Lundberg and Lee 2017; Ribeiro, Singh, and Guestrin 2016). Generalization across locations is also a challenge, as solar energy generation is climate-dependent. A model trained on desert conditions may not perform well in coastal or mountainous areas. Transfer learning and domain adaptation techniques help improve generalization. (Sarmas et al. 2022b).

Case Study 1: SENERGY- An ML model selection tool for solar energy forecasting

As previously mentioned, Smart cities increasingly depend on accurate solar energy forecasting to ensure grid stability, energy efficiency, and market operations. Due to the variability of weather conditions, forecasting errors can lead to imbalances in energy supply and demand, requiring backup storage or alternative power sources. Addressing these challenges, we developed SENERGY, an AI-based deep learning model selection tool specifically designed for solar energy forecasting (see (Alkhayat, Hasan, and Mehmood 2022) For details). SENERGY improves forecasting accuracy by automatically selecting the best-performing model based

on real-time meteorological data, ensuring adaptability across diverse climate conditions. Unlike conventional forecasting approaches that rely on a fixed model architecture, SENERGY employs an adaptive selection strategy, making it a valuable tool for smart grid management and renewable energy integration.

SENERGY consists of a model prediction engine and a forecasting engine. The prediction engine selects the most suitable deep learning model for a given dataset, while the forecasting engine applies the selected model to generate next-hour global horizontal irradiance (GHI) predictions (see Figure 3 For system architecture). The system was trained and evaluated using meteorological datasets from ten locations across three distinct climate zones, including Saudi Arabia, Canada, and Venezuela. These datasets contain 33 meteorological features, such as forecasting hour, temperature, wind speed, humidity, and solar radiation components. Five deep learning models, LSTM, GRU, CNN, CNN-Bidirectional LSTM (CNN-BiLSTM), and LSTM Autoencoder (LSTM-AE), were tested and evaluated under varying weather conditions (Alkhayat, Hasan, and Mehmood 2022).

SENERGY's forecasting engine applies all five models and determines the best-performing architecture dynamically. The LSTM-AE model demonstrated the highest accuracy across climate conditions, leveraging an encoder-decoder structure with two LSTM layers and a dense output layer to capture temporal dependencies

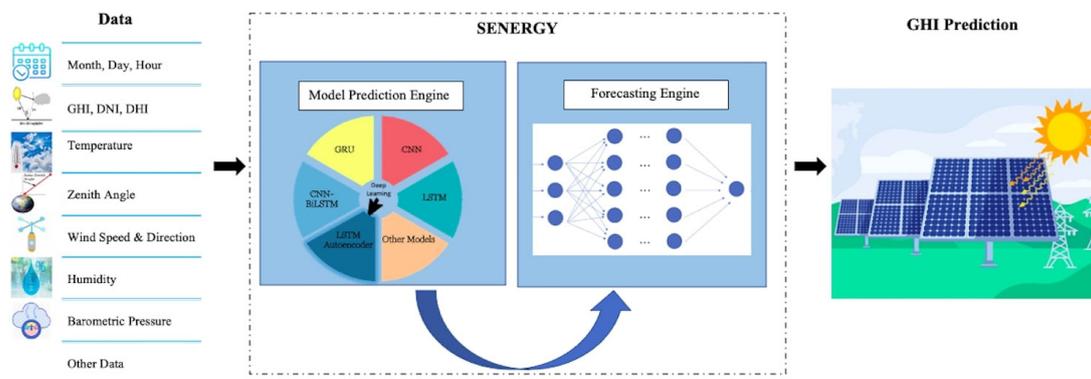


Figure 3: SENERGY framework (Alkhayat, Hasan, and Mehmood 2022)

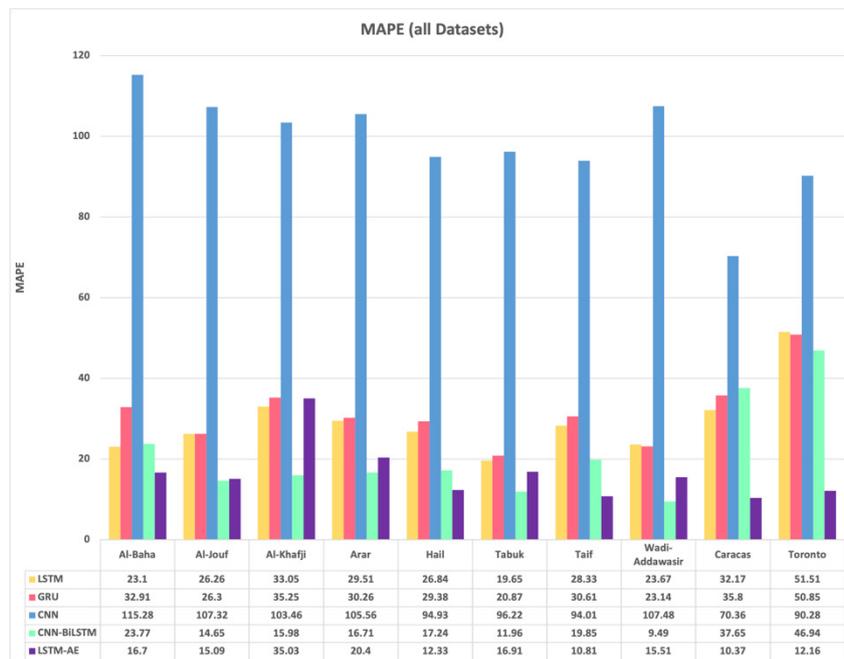


Figure 4: MAPE results of 5 models for next-hour GHI forecasting (Alkhayat, Hasan, and Mehmood 2022)

and improve sequence learning. To automate model selection, an LSTM-based classifier was trained on a merged dataset from all ten locations, assigning the optimal model based on historical performance. The classifier achieved an 81% classification accuracy and was optimized for binary selection between LSTM-AE and CNN-BiLSTM, which outperformed other models in most cases. The mean absolute percentage error (MAPE) results confirm that these two models provide superior forecasting accuracy (Figure 4).

By dynamically adapting to changing weather conditions, SENERGY represents a major advancement in AI-driven renewable energy forecasting, improving the efficiency and reliability of smart grid operations. The tool reduces dependence on static forecasting methods and enhances energy resilience by enabling more reliable solar energy predictions. Beyond solar forecasting, SENERGY’s approach is scalable to wind energy predictions, smart grid optimization, and energy load forecasting. Future enhancements could expand the selection of candidate models, incorporate multi-criteria decision-making based on computational efficiency, and integrate real-time optimization techniques.

Case Study 2: Attention-based interpretable predictions for solar power generation forecasting

As stated earlier, smart cities increasingly rely on AI-driven energy forecasting models to ensure grid stability and optimize renewable energy integration. Solar power, despite its advantages in sustainability, presents significant forecasting challenges due to its dependence on fluctuating weather conditions. Addressing these challenges, we developed the Multidimensional Dynamic Attention (MDA) model, specifically designed for solar power generation forecasting (see (Almaghrabi et al. 2024) for details). MDA enhances prediction reliability and interpretability by dynamically identifying key meteorological variables influencing solar power output at different time horizons. These insights assist grid operators, policymakers, and energy analysts in making informed decisions for efficient energy management.

Forecasting solar power generation is complex due to the non-stationary and multivariate nature of the data. Solar energy production depends on various

meteorological variables, including solar irradiance, wind speed, cloud opacity, and temperature, each exhibiting changing influences over time. Many existing forecasting models rely on static attention mechanisms, which fail to capture these dynamic dependencies, leading to limited interpretability and reduced accuracy. The MDA model overcomes this limitation by introducing a dynamic representation learner that adjusts attention weights over time, allowing for more flexible and explainable predictions. (Almaghrabi et al. 2024).

MDA was evaluated on solar power generation data from New South Wales (NSW) and Queensland (QLD), Australia, spanning January 2019 to November 2021. The dataset includes aggregated PV power output and multiple meteorological features collected from weather monitoring stations. These features include solar irradiance metrics, atmospheric conditions, and environmental factors, all recorded at 30-minute intervals. The model architecture consists of two main components: the Multidimensional Dynamic Attention Layer (MDAL), which captures temporal and variable dependencies, and the Task Learner (TL), which generates the final solar power predictions (see Figure 5).

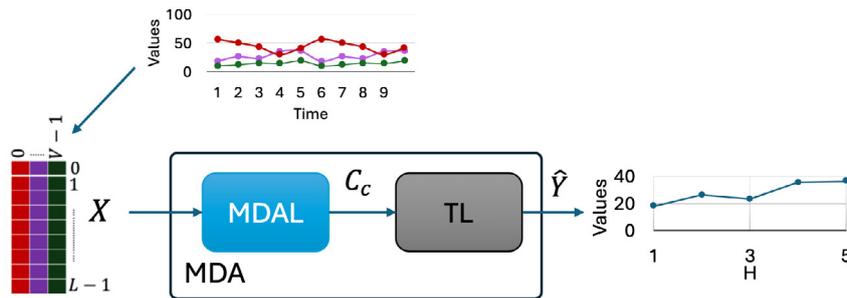


Figure 5: MDA Model

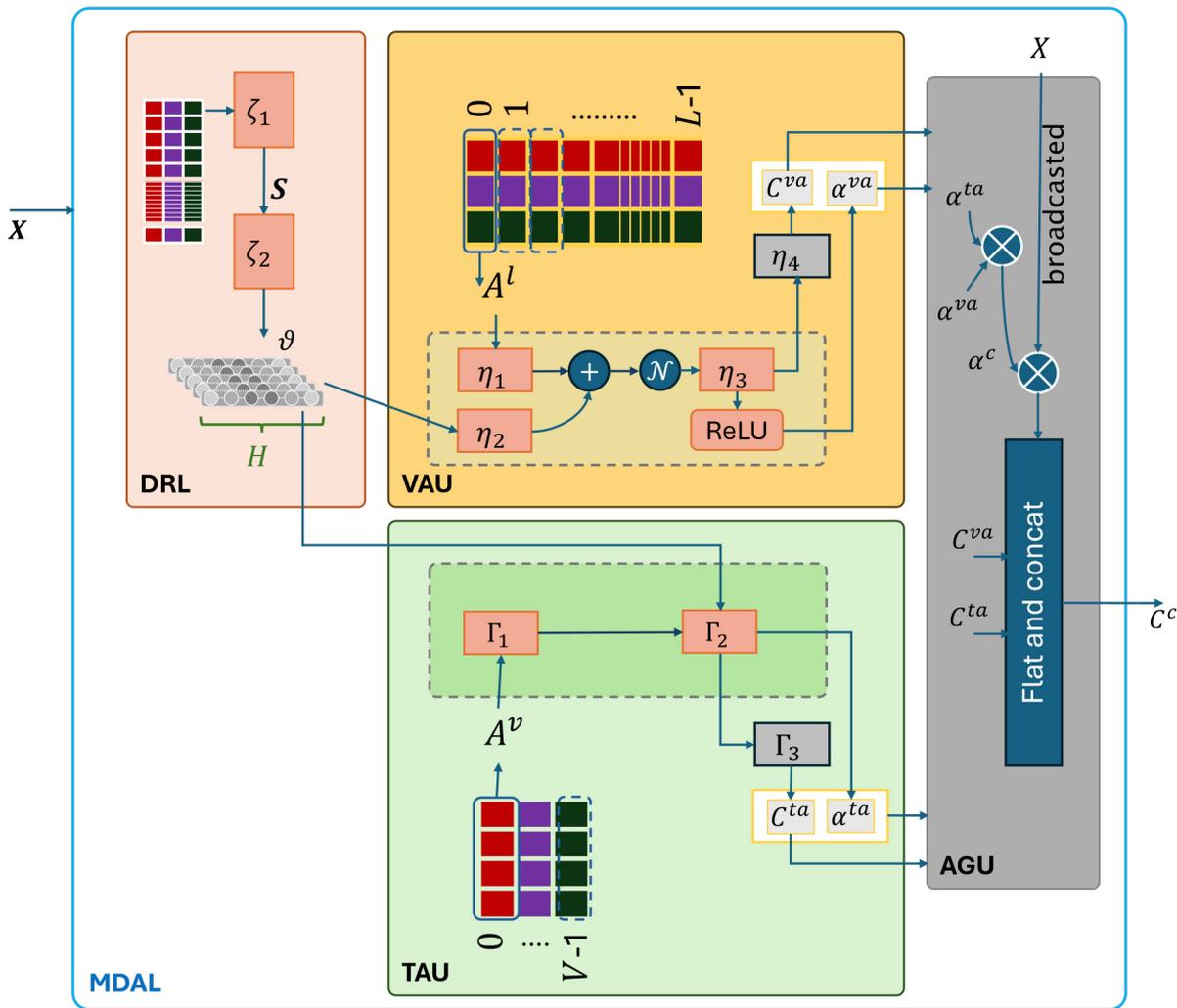


Figure 6: Architecture Diagram of MDAL

MDAL introduces three key mechanisms: the Dynamic Representation Learner (DRL), which adjusts feature importance dynamically over time; the Variable Attention Unit (VAU), which assigns relevance scores to different meteorological features at each time

step; and the Temporal Attention Unit (TAU), which adjusts feature importance across different prediction horizons (see Figure 6). We implemented two architectural variants: MDA_{par} , which processes variable and temporal attention in parallel, and MDA_{seq} , which

refines attention weights sequentially, allowing dependencies to evolve dynamically (Almaghrabi et al. 2024).

MDA demonstrated superior forecasting performance and interpretability compared to baseline models. Figure 7 illustrates feature importance over dif-

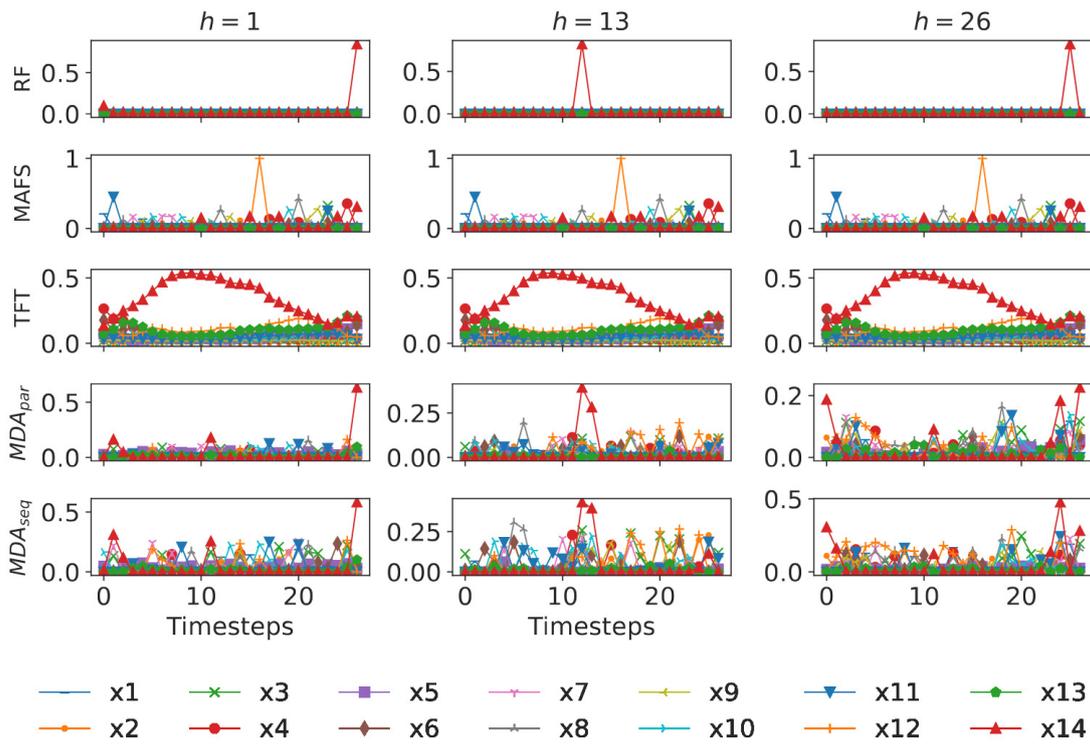


Figure 7: Lagged variables importance in NSW at different horizons (h)

ferent forecasting horizons, highlighting the most influential meteorological variables affecting solar power generation in NSW. The MDA variants (MDA_{par} and MDA_{seq}) consistently outperformed traditional models such as RF, Moving Average Forecasting Systems (MAFS), and Temporal Fusion Transformers (TFT). The MAPE results confirm MDA’s ability to adaptively capture evolving feature dependencies (see Figure 7 for performance comparison).

A major advantage of MDA is its explainability. Unlike conventional deep learning models that function as black-box predictors, MDA provides interpretable insights, allowing energy analysts and grid operators to understand how specific weather variables influence solar power generation over time. This interpretability is critical for developing energy management strategies, helping stakeholders anticipate variations in solar power availability and take proactive measures to maintain grid stability.

The MDA model advances solar power forecasting by offering both high predictive accuracy and interpretability. By dynamically adjusting feature im-

portance across time horizons, MDA provides a scalable and explainable solution for smart city energy management. These insights support climate resilience initiatives by enabling smarter grid planning, improved renewable energy integration, and more reliable solar power forecasting.

Case Study 3: A hybrid DL-based wind energy forecasting across three climates

Wind energy plays a crucial role in smart city sustainability, but its high variability and nonstationary nature make forecasting challenging. Unlike solar power, which follows predictable diurnal cycles, wind speed is influenced by complex atmospheric and meteorological conditions, requiring advanced AI-driven forecasting models. Single DL models have demonstrated superior performance compared to traditional statistical methods in wind energy forecasting (Abualigah et al. 2022; Bali, Kumar, and Gang-

war 2019). However, hybrid models that integrate DL with decomposition techniques have shown higher forecasting accuracy than standalone DL models (Deng et al. 2020; Hui Liu et al. 2019). Addressing these challenges, we developed a hybrid DL model combining Variational Mode Decomposition (VMD) and LSTM networks for next-hour wind speed forecasting (see (Alkhatay, Hasan, and Mehmood 2023) for details). This approach improves accuracy by decomposing wind speed time series into multiple components, allowing LSTM networks to extract relevant patterns more effectively. The model was tested across three distinct climate zones, hot desert (Saudi Arabia), tropical (Caracas, Venezuela), and cold temperate (Toronto, Canada), to assess its robustness in climate-resilient smart grid planning.

The hybrid model consists of two main stages. First, VMD decomposes wind speed data into four subseries, each capturing distinct frequency components. Second, four separate LSTM models are trained to predict next-hour wind speed, with each model focusing on a specific decomposed subseries.

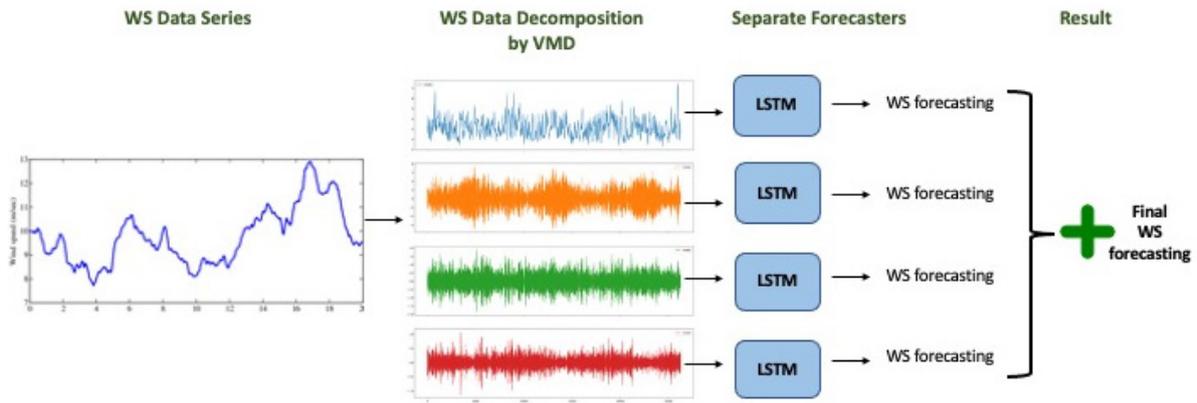


Figure 8: Hybrid model of VMD and LSTM framework (Alkhatay, Hasan, and Mehmood 2023)

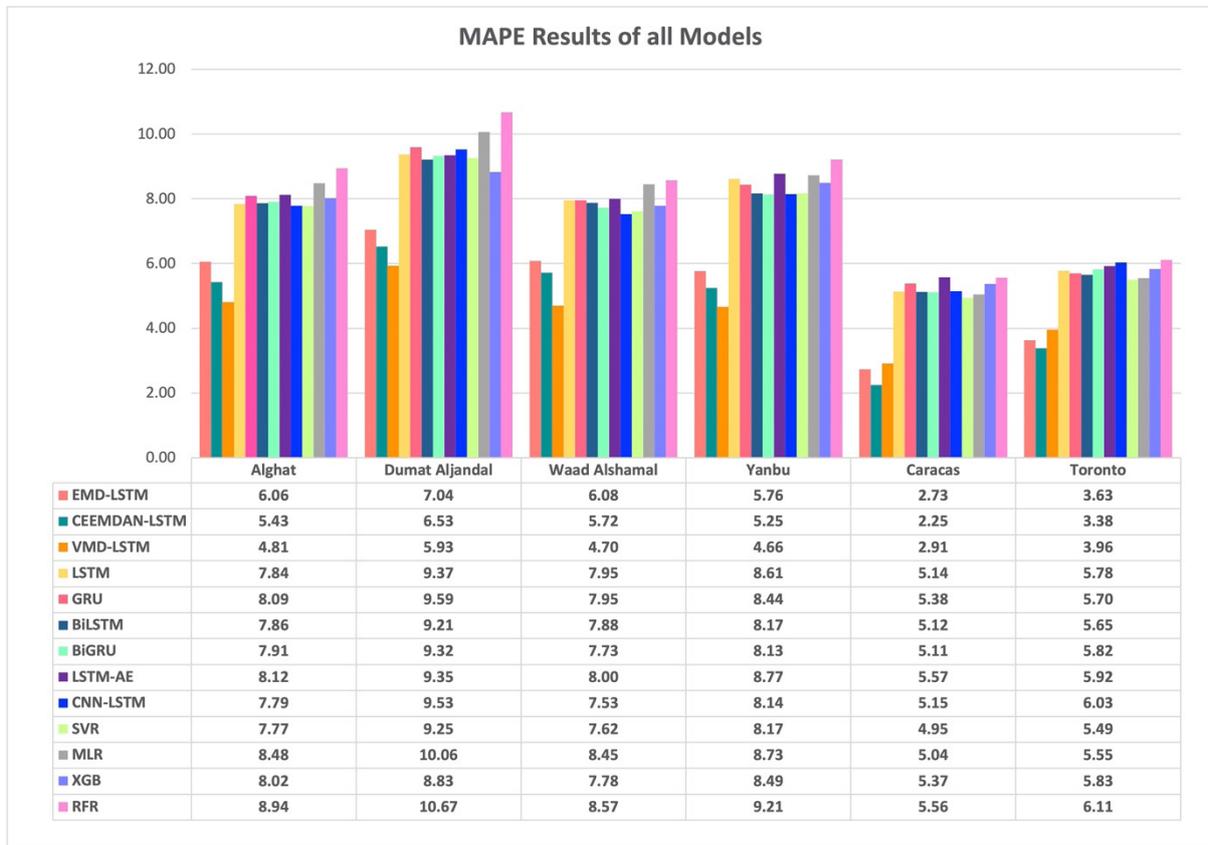


Figure 9: MAPE results of 13 models for WS forecasting (Alkhatay, Hasan, and Mehmood 2023)

The final wind speed forecast is obtained by aggregating the predictions from these models. The LSTM architecture includes two stacked layers with 256 and 128 neurons, followed by two dense layers with 64 and 32 neurons, using TanH activation. The model was trained and evaluated using meteorological datasets from diverse climate zones, ensuring robustness across dif-

ferent atmospheric conditions. These datasets contain 18 meteorological features, including wind speed history, solar radiation, temperature, and humidity. The hybrid model's framework is illustrated in Figure 8.

Performance comparisons against six single DL models (LSTM, GRU, Bidirectional LSTM, Bidirectional GRU, LSTM Autoencoder, and CNN-LSTM) and

four machine learning models (SVR, RF Regression (RFR), Extreme Gradient Boosting (EGB), and MLR) confirmed the superiority of VMD-LSTM. The model outperformed LSTM alone by 39-47% in MAE, RMSE, and MAPE for the Saudi Arabian datasets. In Caracas and Toronto, the best-performing model was CEEMDAN-LSTM, achieving 50-63% improvement over LSTM in Caracas

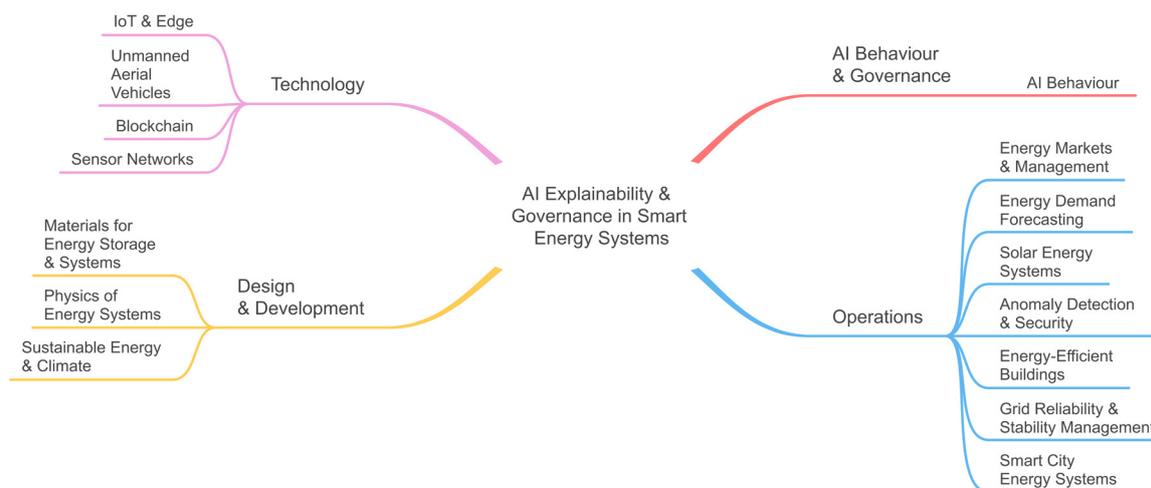


Figure 10: Taxonomy of Parameters for AI Explainability and Governance in Smart Energy Systems (Alsaigh, Mehmood, and Katib 2023)

and 39-42% improvement in Toronto. The MAPE results, illustrated in Figure 9, highlight the importance of choosing decomposition methods based on regional climate characteristics.

The results demonstrate that hybrid AI models effectively handle complex, nonstationary time series data, making them valuable for wind energy forecasting in diverse climates. The success of VMD-LSTM suggests that decomposition-enhanced DL models could be extended to solar and hydroelectric power forecasting, further improving smart grid resilience. Future research could explore alternative decomposition techniques, optimize hybrid architectures for real-time deployment, and integrate these models into edge computing frameworks to enhance AI-driven renewable energy forecasting in climate-resilient smart cities.

Case Study 4: AI explainability and governance in smart energy systems

Smart energy systems integrate renewable energy sources, decentralized grids, and intelligent automation to enhance sustainability and efficiency (Ceglia et al. 2020; Serna Torre and Hidalgo-Gonzalez 2022; Ashworth 1990). However, as AI plays an increasing role

in energy forecasting, grid optimization, and power distribution (López Santos et al. 2022; Sun et al. 2022), its lack of transparency and governance raises concerns about trust, accountability, and regulatory oversight (Zhao et al. 2021; Nitzberg and Zysman 2022). As stated earlier, AI models often function as black boxes, making it difficult for stakeholders to interpret decisions, which can hinder public trust and policy enforcement (Castelvecchi 2016). While AI-powered smart grids enhance efficiency and resilience (Abdel-Razek et al. 2022; Hussain, Bui, and Kim 2019), they also introduce challenges related to bias, security vulnerabilities, and compliance with energy regulations, necessitating governance frameworks that ensure fair, explainable, and trustworthy AI systems (Phillips et al. 2021; Przhedetsky 2021; Nitzberg and Zysman 2022; Volkova et al. 2022). AI governance has become crucial with the increasing number of worldwide regulations on data protection, privacy, and AI, including the EU AI Act (European Union 2024), General Data Protection Regulation (GDPR) (European Union 2016), U.S. Blueprint for an AI Bill of Rights (The White House 2022), China’s Personal Information Protection Law (PIPL) (China Briefing Team 2021), and others.

Addressing these challenges requires a systematic understanding of AI governance in smart energy systems, identifying key parameters that shape

transparency, regulatory compliance, and decision accountability. To contribute to this effort, we conducted a comprehensive review of AI governance in energy systems by analysing 3,568 papers from the Scopus database covering research of over five decades, focusing on emerging governance frameworks, explainability techniques, and policy gaps (see (Alsaigh, Mehmood, and Katib 2023) for details). By adopting a data-driven DL-based big data analytics approach, the study identified 15 key governance parameters and classified them into four overarching themes: AI Behaviour and Governance, Technology, Design and Development, and Operations (see Figure 10). AI Behaviour and Governance covers AI responsibility, ethics, legal compliance, and bias mitigation (Volkova et al. 2022; Nitzberg and Zysman 2022; Niet, van Est, and Veraart 2021). Technology includes AI applications in IoT, edge computing, blockchain, and sensor networks to enhance security and efficiency (Haseeb et al. 2022; Nemer et al. 2022; Yang et al. 2022; Kolangiappan and Kumar 2022). Design and Development focuses on XAI, sustainable energy system designs, and interpretable machine learning (IML) techniques for energy optimization (Lee et al. 2020; Du, Pablos, and Tywoniuk 2021; D’amore et al. 2022; L. Huang and Ling 2020). Operations addresses AI-driven energy forecasting, market regulation, anomaly detection, and grid stability,

ty management (Sun et al. 2022; Luo et al. 2021; Xie, Ueda, and Sugiyama 2021; Ardito et al. 2022).

Our study also revealed significant gaps in AI governance research, where studies often focus on narrow AI aspects such as fairness and transparency while neglecting broader governance issues such as accountability, cybersecurity, and compliance with energy market regulations. A key challenge in AI-driven energy management is ensuring interpretability in decision-making, particularly for energy demand forecasting, grid stability assessments, and renewable energy availability predictions (Gao and Yu 2021). The complexity of AI models in smart energy systems makes it difficult for stakeholders to understand how decisions are made, assess reliability, and ensure regulatory compliance.

To address these challenges, explainability techniques such as SHAP and LIME have been introduced to improve transparency in energy forecasting models (Pinson, Han, and Kazempour 2021; Tsoka et al. 2022). However, these methods are applied inconsistently, limiting their effectiveness across different energy applications. Furthermore, research on integrating cybersecurity and AI trustworthiness in energy systems remains underdeveloped, increasing the risk of adversarial attacks, data poisoning, and algorithmic manipulation (Bhattacharjee, Islam, and Abedzadeh 2022). Feature importance analysis and visualization techniques have been explored to enhance AI transparency (Pinson, Han, and Kazempour 2021; Tsoka et al. 2022; Ardito et al. 2022), but explainability remains a major barrier to regulatory compliance and stakeholder trust.

Key governance challenges include bias mitigation in AI decision-making, cybersecurity risks in AI-powered energy grids, and the absence of clear legal standards for AI accountability in energy markets (Bhattacharjee, Islam, and Abedzadeh 2022; Bhattacharjee, Madhavarapu, and Das 2021; Niet, van Est, and Veraart 2021). Bias in energy forecasting models is often due to skewed training datasets, necessitating fairness-aware AI techniques to

ensure equitable energy distribution (Liao et al. 2016; Spinelli et al. 2022). AI security risks, such as adversarial attacks and manipulation of energy trading algorithms (Figueroa, Wang, and Giakos 2022; Samy et al. 2021), require the development of robust cybersecurity frameworks. Regulatory gaps must be addressed by establishing policy-driven AI governance to enforce algorithmic accountability and compliance with industry standards.

These findings have significant implications for AI adoption in smart cities as they transition to sustainable energy ecosystems. Ensuring AI transparency, cybersecurity resilience, and regulatory compliance is critical for the long-term success of AI-powered energy systems.

Conclusion and outlook

AI, big data, HPC, and edge computing are transforming smart cities, enabling climate resilience, energy sustainability, and real-time decision-making. This paper explored how these technologies enhance renewable energy forecasting, urban climate adaptation, and AI governance, emphasizing the importance of scalable, adaptive, and explainable AI models. The presented case studies demonstrated AI-driven approaches for solar and wind energy forecasting and governance, showcasing how model selection, attention-based learning, and hybrid deep learning techniques improve prediction accuracy and reliability. These advancements support efficient energy management, grid stability, and climate adaptation in urban settings.

Despite progress, challenges remain in AI explainability, computational efficiency, and ethical governance. The complexity of deep learning models requires improved interpretability to ensure trust in AI-driven decision-making. Additionally, scalability and energy-efficient AI architectures are critical as cities increase reliance on HPC and edge computing. Addressing data privacy, regulatory compliance, and AI fairness is also crucial in developing sustainable, equitable smart cities. Future research should focus on integrating edge AI for decentralized re-

al-time processing, allowing for localized climate adaptation strategies and smart energy management. Advancing hybrid AI architectures for energy forecasting, improving energy-efficient AI deployments in edge environments, and establishing standardized AI governance frameworks will be essential. As urbanization accelerates, advancing AI-driven climate resilience strategies through intelligent, decentralized, and adaptive systems will be key to ensuring sustainable and efficient smart cities.

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