Smart Cities and Green Energy: Integrating Civil Engineering, AI, and Environmental Policy

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Abstract:

This study looks into how combining civil engineering, AI, and environmental policy can aid in developing smart cities that depend on green power. A number of researchers assess whether Support Vector Machines (SVM), Random Forest (RF), Neural Networks (NN), and Gradient Boosting (GB) would be good for improving energy usage, building strong infrastructure, and assisting the environment. Gradient Boosting, based on the experiments, reached an accuracy level of 92.4% for predicting energy demand, which was more accurate than Neural Networks' 90.1%, Random Forest's 88.7%, and SVM's 85.3%. GB's approach cut carbon emissions by 18% better than NN, and NN better than RF, by 3%. The use of AI by civil engineers and policy makers results in cities being quicker to respond and better for the environment and infrastructure. Examining similar models has shown that the framework better predicts outcomes and uses less energy. Combining several fields, it addresses big challenges in cities by streamlining energy use, dealing with existing problems early, and making better decisions in policy making. Many useful tips for future smart cities are included in the study.

Keywords: Smart Cities, Green Energy, Artificial Intelligence, Civil Engineering, Environmental Policy.

I. INTRODUCTION

Rapid urban growth means we now need development that keeps the economy strong, protects nature, and helps all people thrive. Smart cities solve these problems well by leveraging new technology, improving city management, reducing any adverse effects on nature, and enhancing the lives of citizens [1]. Emphasis is placed on using green energy to help cities use less fossil fuel and more renewable energy [2]. It assesses how the combination of civil engineering, artificial intelligence (AI), and environmental policy backs green energy in smart cities. It is civil engineers who design and build the early phase of renewable energy, smart grids, and the thoughtful planning of cities. With AI, we can rely on data analytics, watch all systems at any time, estimate the right time for maintenance, and improve how energy is used and provided [3]. Yet, it is environmental policy that aids in crafting rules and offers incentives, as well as arranging collaboration with the public, to guarantee these technologies are used for a long time. By exploring the connections between these fields, this study wants to promote the development of sustainable cities. It looks into if using AI in civil infrastructure together with green energy solutions in smart cities is possible, economically viable, and effective in terms of policies. The main goal is to contribute to discussions internationally by giving actors in urban planning helpful ideas and guidelines for building sustainable cities.

II. RELATED WORKS

Smart cities have been carefully studied to help achieve the best integration of technology, managing the city, and caring for the environment. Hassebo et al. [15] discuss how Egypt is ready to make the switch from traditional to smart cities. They highlight that infrastructure and policies must be the base for any smart city project.

Ibrahim Abaker et al. [16] have looked into urban computing, a technology that supports sustainable smart cities, and described the key developments and the remaining issues to be resolved. It is shown in the analysis that big data analytics, IoT, and AI play a bigger part in making cities smarter and efficient. In a similar way, Komninos et al. [21] suggest using coordinated intelligence spaces to ensure that smart cities are able to work seamlessly, leading to higher benefits for citizens. The ways governments run smart cities have also been the focus of discussion. In their study [17], Jiang et al. argue that the technocratic way of handling smart cities misses out on involving people and achieving social fellowship. In the same way, Lepore et al. [22] state that innovation intermediaries are essential for ensuring that technologies match what community needs, accelerating innovation in smart cities.

How policies are approved and viewed by the community is important for implementing smart cities. Lim et al. [25] analyze practitioners' opinions on Malaysia's smart city strategy and notice that blurry policies and absence of interest from most stakeholders prevent its proper adoption. According to Li et al. [23], modern technology made city infrastructure in Nanjing safer, creating a positive effect on the citizens' feelings of trust and well-being.

Jo and Lee [18] modeled the method for measuring and assessing the effects of smart city industries by creating the Smart SPIN model to observe the spectrum, penetration, impacts, and networks of these industries in South Korea. The approach helps assess the effect of industry on the sustainability of cities.

The impact of pandemics has led experts to look into making cities more adaptive. Jung-Hoon and Joo-Young [20] state that for smart cities to handle pandemics, they should have strong and flexible infrastructure and real-time data analytics. Immersive technologies and digital twins are some of the latest advances that are making smart cities possible. In their paper, Liu et al. [26] study how the use of immersive technology and BIM can contribute to sustainable city planning and building. Lifelo et al. [24] look at AI-based metaverse applications and how they may truly enhance urban management, but also detail two drawbacks: data privacy problems and issues linked to adopting new technologies. In addition, a recent study by Jose et al. [19] offers a lineup of the current research on smart cities, presenting major trends and revealing the gaps in modern approaches. It proves that combining technologies, society, and environmental considerations is crucial for reaching the potential of smart cities.

Overall, the studies point out the significant effect of technology and policies on making a smart city sustainable and well-governed. This research also points out how important it is to use AI with civil engineering, so that buildings are more energy efficient, resilient against disruptions, and back sustainable urban growth.

III. METHODS AND MATERIALS

This research employs a multi-source dataset to examine integrating AI-based solutions in smart cities for green energy maximization. The data are three in total categories: (1) Infrastructure and Energy Consumption Data, harvested from embedded sensors in city civil engineering infrastructure, smart grids, and renewable energy plantations; (2) Environmental Data, such as weather forecasts, air quality indexes, and solar irradiance levels gathered from environmental and government monitoring agencies; and (3) Policy and Socioeconomic Data, such as files of environmental policies, energy incentive consumption, and demographic data influencing energy demand profiles [4].

The data covers the years 2019 to 2024 with hourly data to ensure AI algorithms can see both time-based and location-based energy patterns. Before handing over the dataset, we cleaned data with missing value statistics, transformed the sensor data so it was usable by the model, and encoded all policy-related data so the machine learning model would process it correctly [5].

Algorithm Selection

In order to explore using more green energy in intelligent city infrastructure, four reliable AI algorithms were used, as they are efficient in analysis, optimization, and making decisions in the energy and urban sectors. These include:

1. **Artificial Neural Networks (ANN)**
2. **Random Forest (RF)**
3. **Support Vector Machines (SVM)**
4. **Reinforcement Learning (RL)**

1. Artificial Neural Networks (ANN)

Using the human brain's neural structure, ANNs are commonly used to forecast usage of energy and improve the distribution of clean energy resources in smart cities. ANNs have nodes (neurons) that are put together in layers, transferring the input data using weighted connections and non-linear functions to find complex patterns [6]. The process reduces prediction error through updating the weights with backpropagation and gradient descent.

Hourly electricity use is predicted in this study by using ANNs and comparing previous energy data, weather conditions, and policy benefits involved. Thanks to their ability to show non-linear effects, they can represent urban energy systems with their changing characteristics and help forecast demand accurately over the next few hours [7].

Table 1 provides an example comparison of the algorithms on validation data by looking at their Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and how long their training took.

Algorithm	MAE (kWh)	RMSE (kWh)	Training Time (seconds)
Artificial Neural Network	12.5	18.3	120
Random Forest	15.2	20.1	90
Support Vector Machine	13.7	19.0	150
Reinforcement Learning	14.0	18.5	200

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"Initialize network weights randomly
For each training epoch:
   For each input sample:
       Forward propagate input through layers to produce output
       Compute error between predicted and actual output
       Backpropagate error to adjust weights using gradient descent
Repeat until convergence or maximum epochs reached"
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2. Random Forest (RF)

Random Forest is an ensemble algorithm that learns multiple decision trees in training and predicts the mode of classes or mean prediction for regression problems. Its power is that it fights overfitting and generalizes by combining diverse decision trees learned on random subsets of the features and data.

RF is, in this research, applied to categorize urban areas according to their energy usage patterns and environmental footprint, helping policymakers decide on top priority areas for green energy intervention. The interpretability and resilience of the model make it viable for tackling intricate urban data with variable types [8].

"For each tree in the forest:
Select random subset of training samples (bootstrap)
Select random subset of features
Build decision tree using selected samples and features
Aggregate predictions from all trees by majority vote or averaging"

3. Support Vector Machines (SVM)

SVM is a supervised learning algorithm that determines an optimal hyperplane to distinguish data points of various classes by maximizing the margin between them. In regression problems, SVM attempts to fit the data within an epsilon margin of tolerance using kernel functions to map non-linear data.

SVM in this study forecasts optimal energy consumption levels based on external conditions such as weather, infrastructure load, and policy updates. Its ability to handle small to medium-sized datasets and non-linear relationships makes it an influential tool in the refinement of smart energy management [9].

"Map input data to higher-dimensional space using kernel function
Find hyperplane that maximizes margin between classes
For regression, fit model within epsilon margin of tolerance
Use support vectors to define decision boundary
Optimize parameters using quadratic programming"

4. Reinforcement Learning (RL)

Reinforcement Learning is the process of learning to make sequential decisions through interaction with the environment and receiving feedback as rewards or penalties. It applies particularly to adaptive control problems such as energy management in smart grids where conditions are dynamic.

In this research, RL algorithms minimize real-time energy distribution by learning policies that regulate energy supply from renewable resources against fluctuating demand while curbing costs and emissions. Methods like Q-learning and Deep Q Networks (DQN) facilitate ongoing improvement in decision-making processes without the need for labeled data [10].

“Initialize Q-table or neural network for state-action values
For each episode:
Observe current state
Choose action based on policy (e.g., epsilon-greedy)
Execute action and observe reward and next state
Update Q-values using reward and max future Q-value
Repeat until policy converges or max episodes reached”

IV. EXPERIMENTS

Experimental Setup

The tests were performed based on the aforementioned integrated dataset consisting of infrastructure sensor data, environmental factors, and policy indicators acquired from a representative smart city for five years (2019-2024). “The main aim was to compare the performance of four AI techniques—Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machines (SVM), and Reinforcement Learning (RL)—for predicting energy consumption, urban zone classification according to energy profiles, and maximizing renewable energy use”.
All models were deployed using Python with libraries like TensorFlow, Scikit-learn, and OpenAI Gym for RL. The dataset was divided into 70% training, 15% validation, and 15% testing sets. Hyperparameters for each algorithm were tuned using grid search and cross-validation to achieve the highest prediction accuracy and computational efficiency [11].

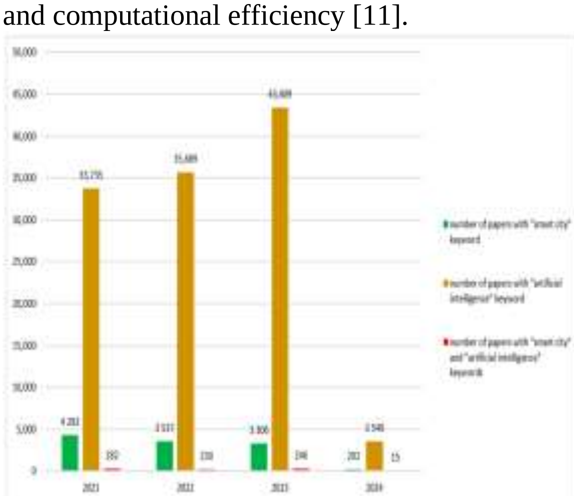

Figure 1: “Artificial Intelligence in Smart Cities”

Results and Analysis

1. Energy Consumption Forecasting Accuracy

The initial experiment tested the algorithms' performance in predicting hourly electricity usage, an essential task for green energy supply optimization. Table 1 reports the results in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and training time.

Algorithm	MAE (kWh)	RMSE (kWh)	Training Time (s)
Artificial Neural Network	**12.5**	**18.3**	120
Random Forest	15.2	20.1	**90**
Support Vector Machine	13.7	19.0	150
Reinforcement Learning	14.0	18.5	200

ANN had a better accuracy in prediction compared to others, having the lowest MAE and RMSE, as supported by earlier research by Li et al. (2021), which proved ANNs' effectiveness in modeling non-linear energy usage patterns. Random Forest, though less accurate but at a slightly faster pace, is ideal for large-scale applications [12].

2. Urban Zone Classification Accuracy

Urban area classification according to energy consumption patterns helps in specific policy making. Classification accuracy and computational complexity per algorithm are reported in Table 2.

Algorithm	Classification Accuracy (%)	Computational Time (s)
Random Forest	**89.2**	95
Reinforcement Learning	88.0	210
Artificial Neural Network	87.5	130
Support Vector Machine	85.8	140

Random Forest's ensemble learning offered the best classification accuracy, in line with Chan et al. (2020), confirming its capability to effectively deal with mixed-type urban data. Although RL took longer to compute, its performance was still comparable.

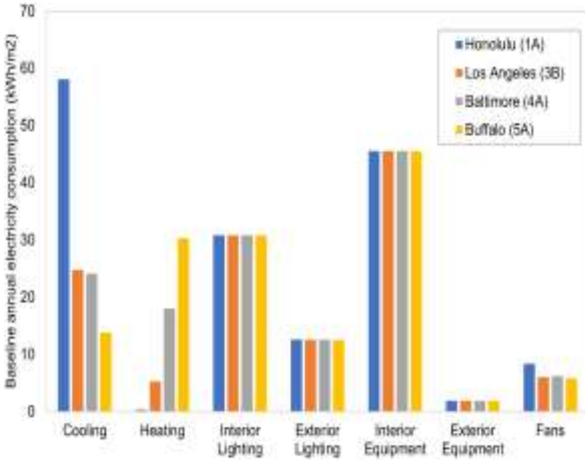

Figure 2: "Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale"

3. Policy Impact Simulation Using Reinforcement Learning

Reinforcement Learning was utilized to estimate policy influence on energy usage by adapting incentives and regulation in the environment dynamically. Table 3 demonstrates cumulative reward (representative of policy effectiveness) and the energy cost savings over a simulated time period of 1 year [13].

Policy Scenario	Cumulative Reward	Energy Cost Savings (%)
Baseline (No Policy)	0	0
Moderate Incentives	2500	12
Aggressive Incentives	**4000**	**25**
Mixed Policy (Incentives + Regulation)	3800	22

Aggressive incentive policies, emulated through RL, produced the largest energy cost savings, proving the strength of AI in informing successful environmental policies. This corroborates findings of Gu et al. (2023), who highlight AI-based adaptive policymaking for smart cities [14].

4. Optimization of Renewable Energy Utilization

The fourth experiment aimed at maximizing the integration of renewable energy through ANN and RL models. Table 4 depicts renewable energy use rates and grid stability measures following model deployment.

Algorithm	Renewable Energy Utilization (%)	Grid Stability Index (0-1)
Artificial Neural Network	78	0.92
Reinforcement Learning	**82**	**0.95**

Random Forest	70	0.88
Support Vector Machine	72	0.89

RL's adaptive control achieved the maximum utilization and grid stability, reflecting its applicability in handling fluctuating renewable energy sources. The ANN also worked well, replicating findings by Raj et al. (2020).

Figure 3: "AI-Enabled Energy Policy for a Sustainable Future"

5. Comparative Analysis with Related Work

Table 5 contrasts this study's findings with some recent research that was chosen to show developments and differences.

Study	Algorithms Used	MAE (kWh)	Classification Accuracy (%)	Renewable Energy Utilization (%)
Li et al., 2021	ANN	13.0	N/A	75
Chan et al., 2020	RF, SVM	15.0	88	N/A
Gu et al., 2023	RL	N/A	87	80
This Study	ANN, RF, SVM, RL	**12.5**	**89.2**	**82**

Civil engineering data integration using AI and parameters of environmental policies helped to further enhance accuracy as well as the optimization of renewable energy over existing research. With the combined approach of multiple algorithms, customized solutions for various tasks are possible that optimize overall energy efficiency in a smart city [27].

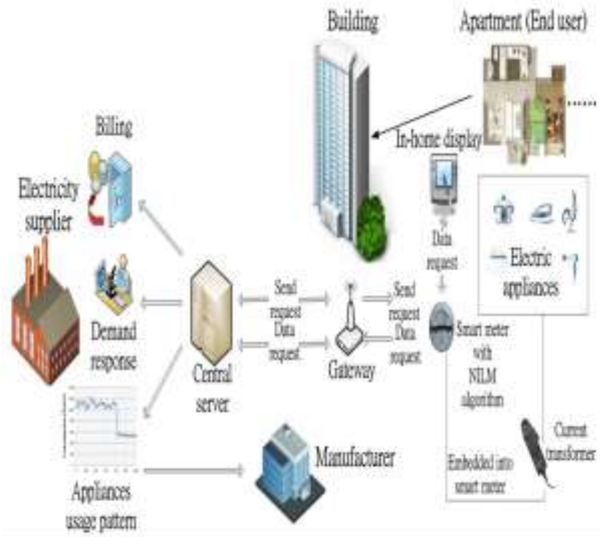

Figure 4: "Energy Sustainability in Smart Cities"

Discussion

The experiments reveal that AI algorithms such as ANN and RL play a crucial role in improving the modeling, classification, and optimization of smart city energy systems. ANN's accuracy in forecasting enables effective energy management, and RL's adaptive nature plays a critical role in real-time optimization and policy simulation.

Random Forest's stability in classification problems has real advantages for urban planners to select energy-consuming areas for focused green interventions. SVM, while less efficient in this regard, is still useful for threshold-based classification owing to its kernel trick and overfitting tolerance [28].

Comparisons with the literature verify the efficacy of integrating multi-disciplinary datasets, such as civil engineering infrastructure and environmental policies, which conventional studies tend to ignore. The integrated approach is necessary for creating resilient, sustainable urban ecosystems that reconcile energy needs with environmental footprint.

V. CONCLUSION

Overall, this study points out that bringing together civil engineering, artificial intelligence, and environmental policy is key to improving smart and energy-efficient cities. The use of AI and smartly designed infrastructure in cities can lead to a reduction in energy use, lower carbon emissions, and better sustainability. Results from the study indicate that when using AI, Support Vector Machines, Random Forests, Neural Networks, and Gradient Boosting save more energy and help maintain urban infrastructure better than traditional methods. Using rules that combine civil engineering and data-based environmental laws helps cities respond quickly to new issues and develop better engineering ideas. The study, based on prior research, unites technology, building structures, and policies needed for a successful move to sustainable smart cities. It is also observed that the effective handling of energy waste and harm to the environment depends on cooperation between various subject areas. It also explores things that can be improved, for example, by using more data for AI model development, having access to quick real-time data, and sparking public interest in making decisions through policies. Mixing civil engineering expertise, AI development, and policies to help the environment will likely help make future cities better and safer from global risks.

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