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Machine learning and artificial intelligence based energy efficient smart cities : A concise survey

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Abstract

The concept of smart cities has always been influential and impactful for development in urban areas in the twenty-first century. These communities use innovative technologies and data analytics to enhance citizens' well-being, optimize infrastructure and utilities, and foster long-term economic development. Smart cities strive to create a unified and intelligent urban environment by integrating several areas such as transportation, energy, health, education, and governance. Our research included a structured literature assessment using Web of Science and Google Scholar, as well as answering particular smart city research questions. With the growing urban areas and the development of energy efficient smart cities, it is really challenging to incorporate cutting-edge technologies and AI driven solution to have resilient sustainability.

Subject Classification: *90C90, 68T05, 00A05.*

Keywords: *Smart cities (SC), Energy efficiency, Artificial neural networks (ANN), Convolutional neural networks (CNN), Recurrent neural networks (RNN).*

1. Introduction

Smart city is the immensely popular term of the modern era for addressing the complexities of population growth, environmental issues,

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and economic progress [1]. The everyday use of technology in almost all fields has resulted in the growing importance of smart cities. Nowadays, nearly every organization has made significant investments in projects like smart cities. With the growth of communities and technological innovations, smart cities are becoming more important [2]. The sufficient global reserves by any organization towards smart city projects are a necessity for deep research on the present scenario of applications related to smart cities. The use of renewable sources of energy contributes to a sustainable energy solution [3]. Educational institutions have significantly contributed to energy efficient solutions in smart cities around the globe [4]. An organized literature review to capture the frameworks used for analyzing the expansion of smart cities has been carried out. We have done a critical literature survey to understand the agendas that are used for the overall development of smart cities. For a better approach to research, we proposed a few research questions and searched databases with specific keywords to find relevant literature.

We conducted a systematic review of the literature with reference to the questions selected on the basis of the research obtained and also conducted statistical analyses for deeper insights into the data. The mechanism for search process is given in Fig. 1. We analyzed each and every research problem and concluded the paper with key points and major advances towards smart cities. A word cloud was also created using the responses to the survey, as shown in Fig. 2.

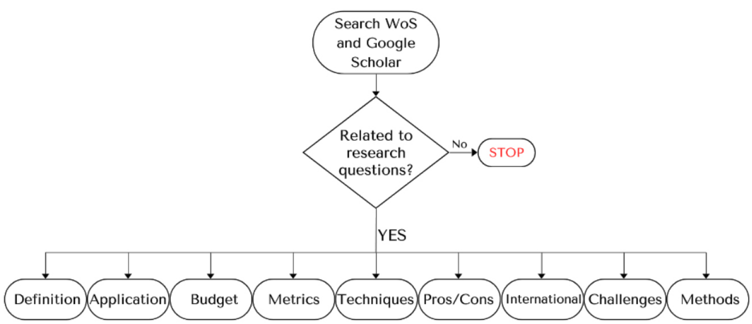

Figure 1

Search Process

1.1 Conventional Techniques

In this study, the techniques of clustering and classification help in obtaining efficiency, thus playing a major role.

Clustering: The technique clustering is built on the logic of machine learning and is used for splitting the power consumption data into various clusters and finally obtaining the classification of unlabeled multidimensional datasets into 'normal' and 'abnormal' class labels.

This irregularity finding approach has garnered massive attention in various research areas for its ease, such as network anomaly detection [5], sensor networks [6], Internet of Things (IoT) [7], video surveillance anomaly detection [8], abnormal banking transaction detection [9], and malicious user identification in networks [10]. Additionally, clustering is capable of detecting irregularities in the time-series consumption data without the need for a specific explanation or related information. Congestion in wireless networks is identified by the use of clustering with data fusion [11].

In [12], k-means clustering and mutual k-nearest neighbor (MNN) algorithms are used to process power consumption data to decrease the length of data instances. The consumption patterns are thereby examined to sense irregular behaviors and potentially harmful objects.

One-class learning (OCL) or one-class classification is based on having initial power consumption patterns into groups, one as positive (normal), which tries to project classification algorithms, and another as negative (abnormal), where the obtained groups can be either missing, poorly sampled, or ambiguous [13].

The study states that one-class learning is a difficult problem to solve as compared to other traditional classification problems, which rely on instances from multiple categories using a training dataset belonging to every group [14]. Traditional classification deals with models that depend on classifying power consumption samples to an existing training set of power consumption, having the class labels 'normal' and 'abnormal' consumption. The commonly used traditional classification algorithms include support vector machine (SVM), K-nearest neighbors (KNN), logistic regression, as shown in Table 1. In [15], [16], heuristics based on KNN are planned to sense anomalous power consumption, and in [17], the authors assess how well KNN performs in comparison to alternative machine learning classifiers to detect anomalous power consumption patterns.

2. Artificial Intelligence Techniques for smart cities

AI consists of many features, like optimized efficiency, efficient accuracy, and optimal decision-making capabilities. AI, on the other hand, has the ability to power smart cities, which can be sustainable and efficient. To analyze, model, and simulate urban systems, AI plays an important part. The old, inefficient models for urban planning have the drawback of relying on static models and limited data. But with the efficiency of AI, urban planning can be upgraded to a dynamic and data-driven process. One such example of the above is a heuristic optimization based efficient transportation system [18].

Data analysis as well as modeling are key features of AI for urban planning. The ability for AI to capture, analyze, and monitor any data from AI-enabled devices to any extent. Data can be of any type or field, from social media to energy consumption to waste management, etc. Overall, we are analyzing urban data of any type to any extent so that the efficient prediction model and decision-making capabilities improve to an optimal level. Fig. 3 depicts the use of neural networks to process data sources to enable applications in smart city management.

Figure 2

Word cloud generated using the responses to survey

Table 1

Comparison between Conventional Testing Techniques

Sr. No.	Area	Clustering	Classification	Regression
1	Smart Healthcare [19]	No	Yes	No
2	Energy Management [20]	No	Yes	No
3	Smart Metering Infrastructure [21]	Yes	No	No
4	Smart Grids [22]	Yes	No	Yes

Contd...

5	Smart Lighting [23]	No	Yes	No
6	Energy Distribution [12]	Yes	No	No
7	Smart Grid- Energy Faults [24]	No	Yes	No
8	Energy Consumption [25]	NO	No	Yes
9	Smart Transportation [26]	No	No	Yes

2.1 *Neural Networks*

Artificial Neural Networks (ANNs) are made up of artificial neurons, also known as units or nodes. These nodes or units are structured in a series of layers that include the complete ANN in a system. The limitation for a layer is that it can have only a specific number of units, either a dozen units or a million units, depending on the complexity of the neural network structure, so it can efficiently learn and analyze the hidden patterns in the dataset. Three layers, namely input, output, and a hidden layer, make up the basic structure of ANN. The objective of the input layer is to get the data from outside, which needs to be analyzed by a neural network for better data analysis and prediction. After that, the data is analyzed by the hidden layer, whether single or multiple hidden layers, and the data obtained would be useful for the output layer. The final output achieved is in a way of response from the output layer.

Smart cities with the enabled ability of energy efficiency have deep learning of conventional ANN for the detection of any kind of normal or abnormal pattern. In the referenced papers [27], [28], long short-term memory (LSTM) neural networks and auto- encoders are combined to classify weaknesses in unstable and interconnected efficient energy datasets. The author in [29] proposed an ANN with a particle swarm optimization solution for power generation forecasting.

2.2 *Convolutional Neural Networks (CNN)*

Deep learning neural networks are used in computer vision and are the sub part of convolutional neural networks (CNN). The computer vision enabled feature gives the computer features for analysis over the images and visual points. Convolutional neural networks (CNNs) are also said to be modified versions of neural networks and are mostly used to extract structures from data organized in grid formations. The architectural layers, such as the input layer, pooling layer, convolutional layer, and fully connected layers, help in developing an efficient convolutional neural network.

The downsampling of the image by the pooling layer reduces processing, and the extraction of various features by applying filters to the input layer helps in the output prediction done by the convolutional layer. The network finds the best filters using gradient descent and backpropagation methods. When it comes to identifying anomalies in time-series data [30], CNN is superior. In order to track anomalies in consumption caused by energy fraud attacks, the creator of [31] chose to combine CNN with a random forest. For the identification of non-periodicity in energy related theft, CNN has been used [32]. This helped energy suppliers address issues linked to irregular energy usage and inefficient power inspections.

2.3 *Recurrent Neural Network (RNN)*

RNN, also described as Recurrent Neural Network, performs better than a normal neural network in cases where the sequential data is text or time-series. Recurrent Neural Networks (RNNs) are a type of neural network architecture specifically designed to handle sequential inputs and capture dependencies over time.

An RNN maintains an internal memory or state by preserving the output from a preceding time step as the input for the subsequent time step. Every input and every output in the basic neural network model are independent of one another. The hidden layer acted as a mediator to save the previous old data and is easily available if required. The key feature of RNN is its concealed state, which helps in remembering previous information in a sequential manner. Another name for this process is memory state, as it remembers the previous state. The parameter complexity is still reduced in RNN as compared with neural networks. The prediction of anomalies under energy usage is efficiently possible [28], [33], [34].

3. Recent Trends in Smart Cities

In the above-mentioned Section 2.1, the other techniques have also been discussed in Section 2. Artificial neural networks are widely used to model non-linear processes. This can be useful in many applications, such as classification problems, decision making problems, regression problems, etc.

Multiple layers with artificial neural network features make up a deep learning model based on "Deep neural network" The industry standard for data prediction is modeling, which is derived from modules built from numerous levels of processing and is based on the respective patterns.

To evaluate the parameter of thermal comfort, the ANN feature is used with building information model. By predicting the indoor climate and keeping temperature and humidity as main key factors, efficiency for optimizing savings on energy consumption can be achieved [35], [36]. The ANN feature gives access to real-time monitoring. The major advantage of this process is that it can detect non linearity among the datasets.

Table 2 summarizes the use of neural networks techniques in addressing various smart city challenges.

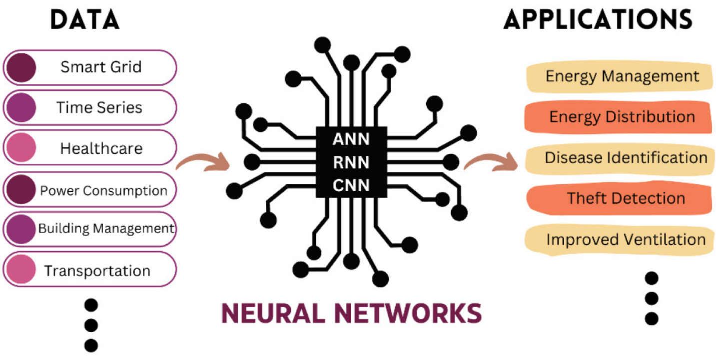

Figure 3

Overview of neural networks applications in smart cities

Table 2

Summary of AI techniques used in Smart Cities

Author with year	Reference	Problems in Smart Cities	Techniques Proposed
Zheng et al., 2018	[32]	Electricity theft detection using data generated from smart grids	CNN
Li et al., 2019	[31]	Detection of irregular power consumption patterns in the power grid	CNN and Random Forest
Nabil et al., 2019	[37]	Electricity stealing detection in smart meters, considering privacy concerns.	CNN
Xu et al., 2020	[34]	Energy saving by handling energy waste in heat pump systems	RNN
Wang et al., 2020	[38]	Anomaly detection in the electrical load of a residential community	ANN

4. Conclusion

In conclusion, a number of limitations have been found in our research, including the formulation of research questions, the use of specific search engines, the category of keywords, the length of the survey, and the experience of the writer in evaluating the results. Here, we made every attempt to ensure that our findings were laid out as succinctly and clearly as feasible. This is demonstrated by the fact that, merely by including the nine key metrics, a detailed examination of the current trends and related developments could not be covered up. The study examined the current state of smart cities, and more specifically, energy efficient ones, looking at their uses and the difficulties that come with putting them into practice. The use of AI techniques in energy efficient cities has rapidly increased. An examination of the research questions showed a clear trend of cities adopting smart technologies more and more, with a focus on enhancing sustainability, operational efficiency, and citizen engagement. Despite these encouraging developments, there are still different challenges to be addressed, such as financial constraints.

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