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Research Article

Solar Power Generation in Smart Cities Using an Integrated Machine Learning and Statistical Analysis Methods

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Presently, photovoltaic systems are an essential part of the development of renewable energy. Due to the inherent dependence of solar energy production on climate variations, forecasting power production using weather data has a number of financial advantages, including dependable proactive power trading and operation planning. Megacity electricity generation is regarded as a current research problem in the modern features of urban administration, particularly in developing nations such as Iran. Machine learning could be used to identify renewable resources like transformational participation (TP) and photovoltaic (PV) technology; based on resident motivational strategies, the smart city concept offers a revolutionary suggestion for supplying power in a metropolitan region. The sustainable development agenda is introduced at the same time as this approach. Therefore, the article's goals are to estimate Mashhad, Iran's electrical power needs using machine learning technologies and to make innovative suggestions for motivating people to generate renewable energy based on the expertise of experts. The potential of solar power over the course of a year is then assessed in our research study in Mashhad, Iran, using the solar photovoltaic modelling tool. The present idea in this research uses linear regression techniques to forecast utilising artificial neural networks (ANN). The most important factor in sizing the installation of solar power producing units is the daily mean sun irradiation. The amount of power that will be produced by solar panels can be estimated using the mean sun irradiance at a particular spot. A precise prediction can also be used to determine the complexity of the system, return on investment (ROI), and system load metrics. Several regression techniques and solar irradiance-related metrics have been combined to forecast the mean sun irradiation in terms of kilowatt hours per square metre. Azimuth and zenith factors considerably enhance the performance of the model, as demonstrated by the proposed method. The results of this study demonstrate 99.9% reliability rate for ANN model prediction of the electrical power usage during the summer and winter seasons. Thus, the maximum of power requirement during the hottest and coolest periods can be managed by using the photovoltaic system's renewable power projections.

1. Introduction

All modern nations face three major issues in the twenty-first century: social and economic development, environmental sustainability, and energy management. Additionally, one of the key elements of socioeconomic development for any nation in order to become developed is energy independence [1]. According to the International Energy Agency (IEA), energy production and consumption are currently the main man-made sources of air pollution, which kills 6.5 million people prematurely each year. Technology for reducing air pollution is now widely known, and maintaining clean air is crucial for preserving human health. Air pollution issues remain unresolved in many nations, despite the growing awareness of its importance, and in the coming decades, the hazards to world health will increase. PM2.5 refers to suspended particles with a diameter of 2.5 m or less that come from pollution sources. The small size of the pollution source's particles allows them to get through the lungs and into the alveoli, where they can affect the body's other organs [2]. In accordance with the majority of research, PM2.5 at or below 12 $\mu g/m^3$ is deemed healthy and poses little to no danger of exposure. The air is deemed harmful if the quantity reaches or exceeds 35 $\mu g/m^3$ over the course of a 24-hour period and can be problematic for persons who already have breathing conditions like asthma. As a result, managing and controlling urban air pollution is quite difficult. The ability to sense the climate and the surroundings around the city is essential for a smart city to build a smart environment and enhance the quality of life for its residents.

Among the most popular alternative energy sources being looked after to meet the rising demand for power while reducing carbon footprint and protecting fossil fuels and other environmental assets is photovoltaic technologies. The photovoltaic system uses highly conductive materials to convert solar radiation directly into electrical energy [3]. Every wealthy nation relies heavily on energy for economic growth, but using conventional energy sources pollutes cities more. As a result, the management of smart cities constantly suggests installing a renewable energy system to cut down urban pollution. In order to handle widespread urbanisation, cities must become smarter. They must also find innovative ways to manage energy, raise living standards, and protect the environment while doing so [4]. Solar cookers, solar collectors, solar water heaters and air, solar heat pumps, and solar dryers are just a few examples of the various devices that use SE to do beneficial tasks [5]. Because it allows for the load, or the device's power consumption, to be adjusted to correlate with the projected energy output, the concept of power neutrality provides a novel perspective on how devices ought to be constructed. This is due to the fact that power neutrality makes it possible. The term "energy neutral design" can also be used to refer to "environmentally powered electronics," in which electronic equipment either absorbs or harvests energy from their immediate surroundings and converts that energy into the electricity they need to function properly. Researchers have invested a lot of time in identifying various methods for energy modulation, whether through the scheduling of communications or the scheduling of the device's sensing and processing duties using predictions of energy production. Recent methods are especially pertinent for machine learning techniques since they use Internet-sourced public weather forecasts to feed solar electricity production predictions [6].

There are essentially three types of forecasting methods for PV power generation or solar insolation nowadays. Physical techniques fall under the first group because they can forecast future sun positions and the irradiance that outcomes without using any additional temperature data. Although the prediction of sun position can be important, this method is likely to ignore other pertinent meteorological circumstances. For instance, clouds or rain in the sky impede solar irradiation. Group 2 is analytical measurements, which can be further broken down into traditional approaches and contemporary methods that make use of statistical learning. Numerous trainings have embraced this data-driven strategy for creating PV forecast models as a result of the enormous advancements in analytical learning methods over the previous ten years. Last but not least, hybrid methods combine statistical methods with other techniques like signal processing or optimization algorithms [7]. The work involves evaluating solar radiation forecasting using a variety of machine learning regression models. Particularly, artificial neural networks (ANN) reach a very high level of accuracy. The second thing that we have contributed is the utilisation of sun angles (both azimuth and zenith) in conjunction with weather information. Both the solar azimuth and the solar zenith can be used to represent where the sun is located. The angle that is formed by measuring the direction of the sun counterclockwise from the horizon is known as the solar azimuth. The angle that is obtained by measuring the distance between the local zenith and the line of sight of the sun is known as the solar zenith. We demonstrate how these two perspectives enhance prediction accuracy. In particular, using the weather forecast, we attempt to calculate the mean daily solar energy W/m^2 that a solar plant at a specific site can consume. Figure 1 shows the solar zenith and azimuth angles [8].

A global grid generally uses technology to supply services and deal with urban concerns. Among other things, a smart city seeks to improve social services, encourage sustainability, and give its citizens a voice. Regarding what it means to be a "smarter city" as well as how to continue with that specific development, the emphasis of each "smart" urban design varies [9]. The system consists of solar PV modules (also known as solar cells), a power inverter, and a net metre, and they are fed into the power grid and used in metropolitan areas. Household appliances (23 percent), water heating (13 percent), lighting (11 percent), refrigerator (8 percent), space heating, and air conditioning (A/C) all use energy (45 percent). Industrial utilisation is shown in Figure 2 [10].

These are the main steps of the suggested study, in order. The first step is to collect the essential energy usage information from Mashhad, Iran's main electricity hub. The gathered data undergoes additional processing and analysis in order to uncover certain statistical tendencies. The second

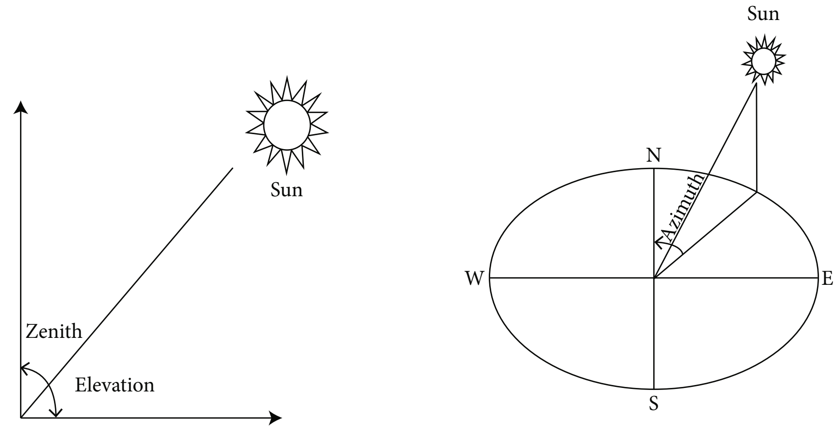

Figure 1: Solar zenith and azimuth angles.

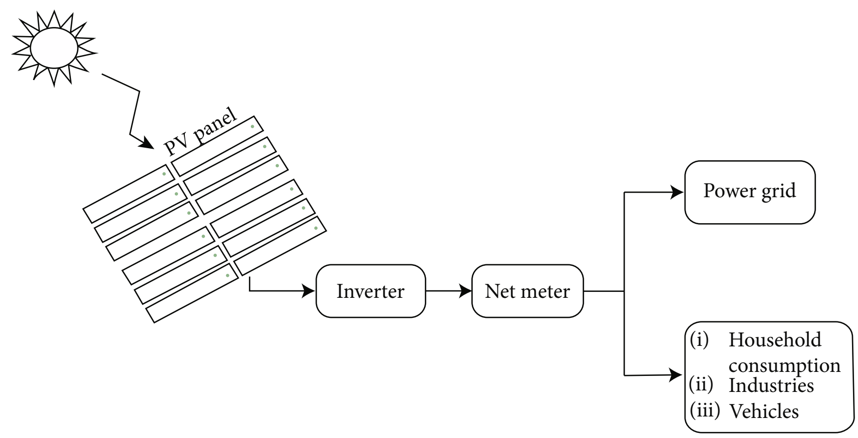

Figure 2: Smart city solar energy generation system.

stage entails running PV simulations using the application of gird PV systems. Then, final section emphasizes on developing a megacity incentive algorithm utilising the TP idea. In the fourth step, an ANN with linear regression appraisal is used for socioeconomic evaluations. To assess the approach for future energy management in urban areas, the fifth phase entails developing scenarios [11].

2. Related Works

Photovoltaic (PV) generation volatility has presented electric utilities with a number of management and operation issues. Grid operators should be aware of the performance of their asynchronous and synchronous generators in order to deliver power in a secure and reliable manner either a day or an hour in advance. During any unforeseen situations, it aids them in controlling the grid stability, frequency response, and inertia. This analysis makes an effort to offer both short- and long-term forecasts for renewable power generation based on machine learning. The researcher utilises Alice Springs, one of Australia's physically renewable power regions, and took into account a wide range of environmental factors. The study is aimed at analyzing a variety of machine learning approaches, such as long short-term memory with decision tree regression, polynomial regression, support vector regression, multilayer perceptron regression, and random forest regression. For both normal and unclear scenarios, several comprehensive comparative analyses were undertaken, and it was discovered that random forest regression performed significantly enhanced for database. Using a variety of performance criteria, the effect of data analysis on prediction accuracy is also examined. The work could assist grid operators in planning the time-ahead generation uncertainty and selecting a suitable PV power forecasting technique. Python is used for the forecasting along with a number of library functions like scikit-learn, Keras, pandas, and NumPy. Due to a lack of data, this study was unable to evaluate its performance using forecasted weather values, which could have negatively impacted predicting performance in real-world applications [12].

Utilising a variety of machine learning techniques, short-term solar power forecasting is frequently employed in sustainable energy integration and power source management. However, selecting the appropriate machine learning models and data properties can be challenging. This study develops a methodology for statistically evaluating several models and feature selection methods, and it identifies the best model and feature combination for forecasting short-term solar power. More specifically, the methodologies use random forest, artificial neural network, and excessive gradient boosting (XGBoost), and the machine learning techniques use feature significance and principal component analysis (PCA). All potential combinations of these feature selection and machine learning algorithms are created and evaluated for solar power forecasting. For Hawaii, US, solar power forecasting, the ideal selection of characteristics and machine learning methods are discovered. The results of the tests indicate that the gradient boosted approach, with features chosen by the PCA method, is superior to the other strategies in terms of effectiveness. Building simpler (weaker) prediction models successively is how gradient boosting gets the job done. Each model in the sequence makes an attempt to anticipate the error that was caused by the model that came before it. Because of this, the algorithm has a propensity for quickly becoming overfit. The framework can be used to select the best machine learning approaches for relatively quick solar power prediction, using the simulation results as a baseline for comparison. Short-term solar activity forecasts have not commonly used the boost and spontaneous forest models [13].

Low-power electrical energy producing units can be connected to the grid by using solar energy and other renewable energy sources (wind, hydro, etc.). The opportunity to divide existing distribution networks into smaller units or micro-grids that are self-sufficient and sustainable for shorter or longer periods is offered by the novel idea of distributed energy generation. Enhanced customer energy supply and effective energy use are both achievable in a setting with a smart grid, especially while the primary grid is down. The method to determine a rooftop PV system's potential power capacity in a smart city is presented in this study. Solar-powered generation units and the potential for serving existing loads will receive special consideration. The findings of a theoretical study on the promising applications of PV solar energy for the supply of power in several Serbian cities are provided as a case study. PV generation can lower electricity bills for PV system owners and dramatically lower CO_2 emissions from thermal power plants. A backup from the major public grid is necessary due to the unequal distribution of the electricity produced during the day and its sometimes limited availability during the winter [14]. Using clean, renewable solar power as your main source of energy and selling surplus power to the utility via net metering are just two of the many advantages of installing a grid-tied solar power system with battery backup, commonly known as a "hybrid solar system."

To meet the challenging goals for reducing greenhouse gases outlined in the 2015 Paris Agreement, the power generation industry must undergo a significant transformation. For the purpose of determining spot power prices, it is necessary to decrease uncertainty regarding supply and, in the case of renewable power, demand. In this work, a context-based approach for forecasting the production and consumption of energy in buildings is proposed and evaluated. It focuses on a home that has solar panels and an energy storage device. Evaluating the efficacy of stride predictors, Markov chains, and their incorporation into hybrid predictors is an additional step that must be taken in order to simulate the development of the relationship between the demand for and supply of energy. Markov chains are a useful tool for calculating the likelihood of a certain event taking place by modelling the event as a transition from one state to another state or as a transition from one state to the same state that it was in previously. Each of these techniques forecasts electrical power using historical data. The purpose is to identify the best approach and its ideal configuration that can be incorporated into an intelligent energy management system (perhaps based on hardware). Such a system's function is to coordinate and modify electricity production and consumption through forecasting in order to boost self-consumption and ease demand on the grid. Studies on real-world datasets have shown that a Markov chain with an electricity generation record of 150 values, a structure of single energy distribution value, and an intermission size of 1 is the highest reviewed predictor. Slow converging, instability, and vibration throughout training are some of its drawbacks [15].

The advanced energy domain is one of the trickiest areas of future study in smart urban. Important issues in optimization, the provision of intelligent, flexible networks, and sophisticated computational tools and approaches all call for additional study. When it comes to supporting future global growth in the face of resource depletion and climate change, renewable is a significant resource. In order to meet these higher criteria, artificial intelligence (AI) offers new rules for regulating the operations. In order to address the numerous challenges that will impede the sector's growth and resilience, it is required to improve the architecture of the power infrastructure as well as the deployment and production of RE. This study looks at the advantages of current advancements in the application of AI to the real estate industry in a European nation. The effectiveness of the transformation of RE from gross inland usage to final energy usage within the power sector, its effects on the composition of reliable energy by source (solar, wind, biomass, etc.), the productivity increases in the tertiary sectors especially in comparison to the economy at large as well as its similarity with infrastructure investment, and the possible ramifications of the implementation of AI for RE towards upcoming urban research were all examined by researchers. The establishment of a conceptual framework for appreciating the role of AI in the RE sector in Europe is the major goal of this research. A discussion of the consequences for possible future study on smart cities and proposed research goals is another audacious addition to this work. The broad use of RE still faces significant challenges. These relate not just to the required technology but also to the formulation of policies and factors that should be discussed in subsequent research [16].

Solar energy is produced worldwide using photovoltaic (PV) systems. Due to the intermittent output power of PV systems and their strong reliance on environmental conditions, solar power sources are erratic in nature. Irradiance, humidity, PV surface temperature, and wind speed are only a few of these variables. It is essential to properly foresee the renewable energy deployment highly uncertain in photovoltaic systems. Forecasting solar energy is essential for an utility grid's supply chain management. Given that solar energy is climate-dependent and unpredictable, this forecast is extremely complex and difficult. In this study, it is addressed how various environmental conditions affect the output of the PV system. The effectiveness of artificial neural network- (ANN-) based multiple regression and prediction models is investigated with regard to certain parameters. Both the correlation-based feature selection (CSF) and the relief approaches are used in the decision-making process. Features that have a high correlation are more linearly dependent, and as a result, they virtually always have the same influence on the variable they are attempting to predict. In comparison to the ANN model, all other strategies that were discussed are inadequate. Because of how variable and unpredictable the weather is, it is challenging to forecast how much electricity solar PV systems will generate [17].

Monitoring monthly energy demand is necessary for metropolitan power systems to run smoothly. Various artificial intelligence-based forecasting models have been presented and have shown to work well, but they need a large enough training dataset. Because just one data point is produced per month in the case of monthly forecasting, it is difficult to gather enough data to build models. With the aid of transfer learning techniques, this data shortage can be reduced. This research proposes a novel transfer learning-based monthly electric demand forecasting method for a city or district utilising comparable data from other cities or regions. In order to do this, we gathered five kinds of monthly electric load data from 25 Seoul districts as well as numerous external data, including calendar, demographic, and weather information. Then, using the data acquired from the datasets and the information available for the target city or district, similar data were chosen by manipulative the coefficient correlation, and the chosen data were used to build a forecasting model. The model was then adjusted using the goal data. Through a number of studies, we thoroughly compared our model to other well-liked machine-learning strategies in order to show its efficacy. Some of the findings are reported. Compared to the basic DNN, the prediction performance increased while employing transfer learning [18].

3. Data Collection and Data Mining

A systematic approach for the Iranian city of Mashhad was completed as part of this programme. The studied region has commercial and touristic land uses and is Iran's second megacity. There are 3 million people living in the Iranian city of Mashhad, which is situated in the country's northeast. Throughout the analysis, MATLAB 2018 and SPSS 19 software were used to examine the fluctuations in electrical power consumption utilising data mining and statistical methodologies. For the year 2019, all data were acquired from the Mashhad Distribution Electrical Energy Company's consumption management division. The energy consumption discrepancies based on the energy utilisation regimes for the peak winter and peak summer consuming months (December and July, respectively), which are illustrated in Tables 1 and 2 with Figures 3 and 4, were examined using computational methods. For the trend analysis in the adopted mathematical techniques, machine learning systems that is multilayer perceptron artificial neural network and histogram methodologies are combined with descriptive statistics like histogram approaches and metrics like average, sample variance, mean, and frequency distribution. In relation to the winter season, summertime electrical power use has been higher. Principals must undertake an efficient power consumption peak management during the summer due to rising power consumption [11].

Table 1: Power consumption of Mashhad, Iran, in summer.

Bin	Freq	Cumulative value
40000	6	150%
35000	10	115%
30000	10	90%
25000	10	78%
20000	10	56%
15000	10	23%
10000	10	5%

4. Proposed System

The number of urban populations is expected to increase by 75% by 2050, driving up the cost of thoughtful, sustainable environments that offer residents a high quality of life. The emergence of smart cities is the result of this. A smart city will integrate technology, government, and society in order to improve particular elements, such as smart energy, smart economics, smart transportation, building automation, smart industry, sustainable cities, and representative democracy. The full dataset is first collected, and then, it is further processed using the ANN model shown in Figure 5. The present study estimated the amount of solar radiation coming from all around the globe by using ANN in combination with a technique called linear regression. You may determine whether or not there is a linear connection between the predictor, descriptive, or criteria variable and the response or outcome variable by using the technique of linear regression. The basic nature of linear regression makes it easy to grasp and explain, and it may be regularised to prevent overfitting. In addition, employing stochastic gradient descent to incorporate fresh data into linear models makes it simple to keep these models current. The parameters include location, longitude, elevation, and the day of the week. The duration, average outside temperature, stress at departmental levels, air velocity, and moisture levels. The prediction simply included one production: the expected global weekly sun radiation. Based on the lowest absolute percentage inaccuracy, the shortest RMS, and the highest linear correlation coefficient, the optimal approach and precise ANN model were chosen. Then, the relative error percentage rate for the present job was calculated and contrasted it with other similar mechanisms.

Table 2: Wintertime power use in Mashhad, Iran.

Bin	Freq	Cumulative value
40000	10	120%
35000	15	95%
30000	15	70%
25000	15	58%
20000	15	36%
15000	15	13%
10000	15	2%

Almost no studies have been done on the application of an energy production gathering system that focuses on the ANN-based linear regression model that captures economic circumstances, according to a complete assessment and critical evaluation of the studies that have been gathered. Given this gap in the state of the art, the following are the main goals of the current research, and Figure 6 illustrates the suggested system's flowchart. Data mining is used to identify patterns in the electrical energy use at homes in Mashhad, Iran. The construction of a drive mechanism for TP power generation in a contemporary metropolis, the modelling of a solar energy installation in the recipient's residence, and the use of scenario wizard were computed to assess the vulnerability of future outcomes.

4.1. Photovoltaic Simulations. The power generation was used to simulate photovoltaic platforms in residential energy consumptions, and the input data for the calculations described in overall results of experiments are shown. Modelling has been done using the meteorological data from Mashhad, Iran's mean irradiance. This image specifically depicts the irradiance that the panels received throughout the course of a day. The irradiation was evidently received from 8 AM to 6 PM, with the highest irradiation in Iran City happening at 12 PM. the possibility of obtaining sunshine from various horizons in Mashhad, Iran. According to the analysis's findings, between 11 AM and 12 PM, the 0° horizon receives the most sunshine on average. Furthermore, Mashhad, Iran's regular home use and its pattern of electricity usage. Particularly, current intensities and voltages that are approximately 10 A and 50 V have been used to achieve usage patterns for lamps, TVs, laptops, digital phone, and household solar panels. Whenever the output was larger than 2 kilowatt, it was demonstrated that the inverter's maximum effectiveness was almost 100%. To put it another way, as soon as the power hits 2 kilowatt, the efficiency of converting radiation to electrical signal begins to rise. The calculations for the electricity production in Mashhad, Iran, are finally displayed using the research approach based on the integration of ANN, photovoltaics, and regression analysis.

4.2. Implementation of ANN Using Linear Regression. The ANN model's construction is essential for determining the amount of solar radiation on a global scale because there is no radiation from the sun factors impacting in situ. This ANN model will enable the successful utilisation of a considerable amount of available ecological renewable power for a wide range of real applications. The ANN structure is composed on three tiers. Typically, there are 3 parts: one or more unseen units, an output neurons, and an input layer that accepts data from gathering sources that are beneficial for establishing connections between the receiver and transmitter layers via processed unit neurons. A design of a machine learning algorithm can calculate the value of a result after being trained on a given set of inputs. A feed-forward network ANN model with 3 layers with a quadratic output layer activation function and a tangent sigmoid hidden state activation function was built in MATLAB version 2018 for the current analysis. Out from the following nine factors, location, elevation, period, season, average atmospheric air temperature, mean station level pressure, mean wind velocity, and mean humidity levels, one, monthly average global solar irradiance, was predicted as an output. This provides a list of the training settings with each of the four methods used in the current study [19].

The disruptive innovation theory can be used to explain the developing technologies that are characterised by growing AI incorporation as new market leaders in the real estate sector. When faced with various kinds of technical and market change, dominant players' actions are elucidated by disrupting improvement as a management theory. A type of mathematical model known as an artificial neural network (ANN) mimics the function of a biological neuron. This technique for nonlinear modelling is effective. Multilayer perceptron (MLP), a neural network with a fully connected topology, is an early ANN architecture. In essence, MLP has a strong track record and is frequently used. Many brand-new ANN architectures are currently being developed. The primary architectural types used in this paper are ANNs with linear regression methods. Animal neurons' functionality serves as a model for artificial neural networks (ANN). A neuron is a type of processing unit that performs activation as well as output and input. Although there are other ANN versions, we employed the straightforward feed-forward neural network with back-propagation for this work. The ANN receives the weather characteristics as inputs and predicts the solar power as the output shown in Figure 7.

Regression, curve fitting, and prediction are just a few of the many tasks that artificial neural networks (ANNs) can perform. In this study, models for forecasting solar radiation are developed using artificial neural networks. A machine learning program's basic building element, the neurons, creates the response via a frequency response. Each input is multiplied by a weight, which serves as a link between the intake and the neuron and among the various layers of neurons. In the final stage, the neuron employs a frequency response to obtain the result. The benefit of ANN approaches is that they offer a concise solution for multivariable problems while requiring less computer work and no prior knowledge of mathematical calculations between the parameters.

4.3. Linear Regression. Linear regression is the most fundamental and well-liked regression approach (LR). The link

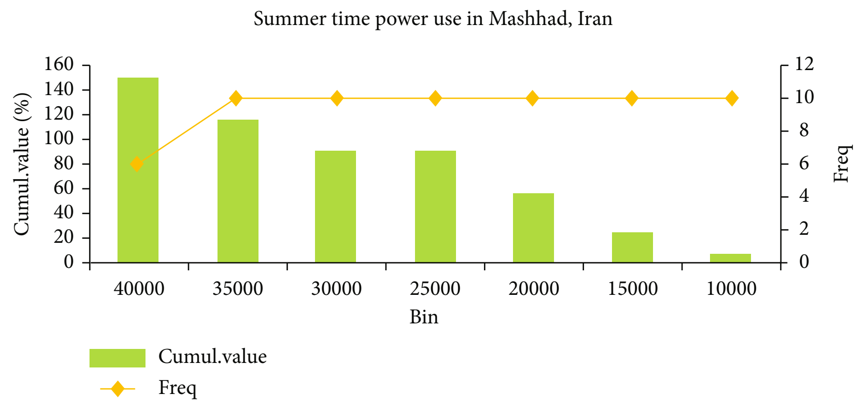

Figure 3: Summertime Mashhad city power consumption histogram.

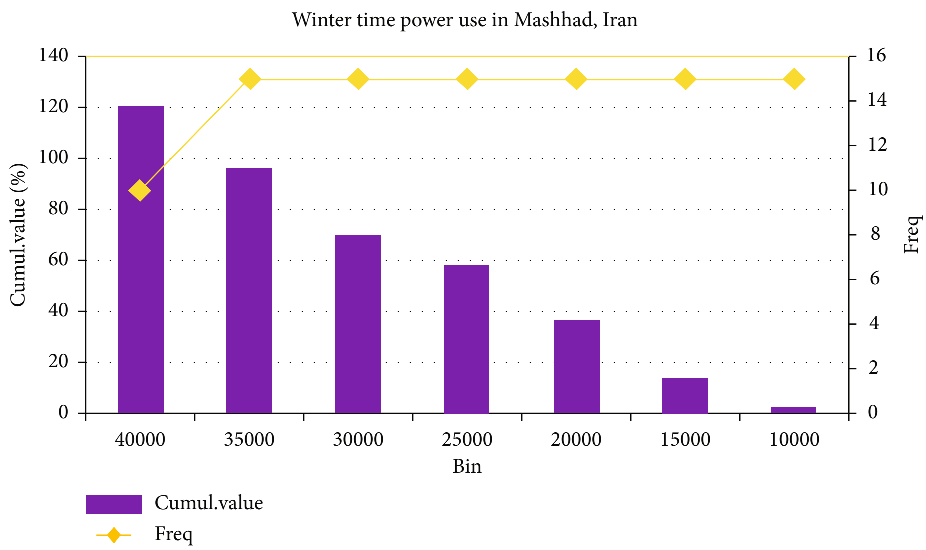

Figure 4: Wintertime Mashhad city power consumption histogram.

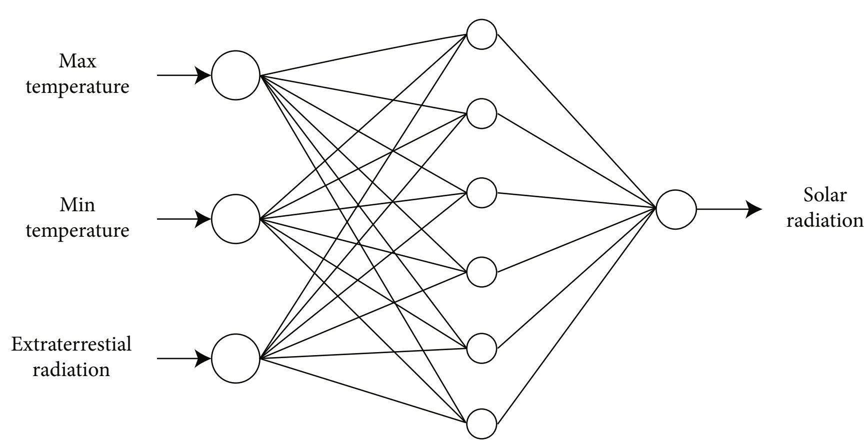

Figure 5: Diagrammatic representation of the ANN model used in this work.

between the dependent and independent variables is represented using future direction, and the unknown model parameters are estimated from the data using the statistical method. To estimate the parameter values, one can either solve a set of linear equations or utilise an iterative technique like linear regression. Regression analysis can be performed using a variety of techniques and algorithms, and applications can be made using specialised software like SPSS, SAS, SIMCA, STATISTICA, STATGRAPHICS, and NCSS. The least squares method is the most popular regression

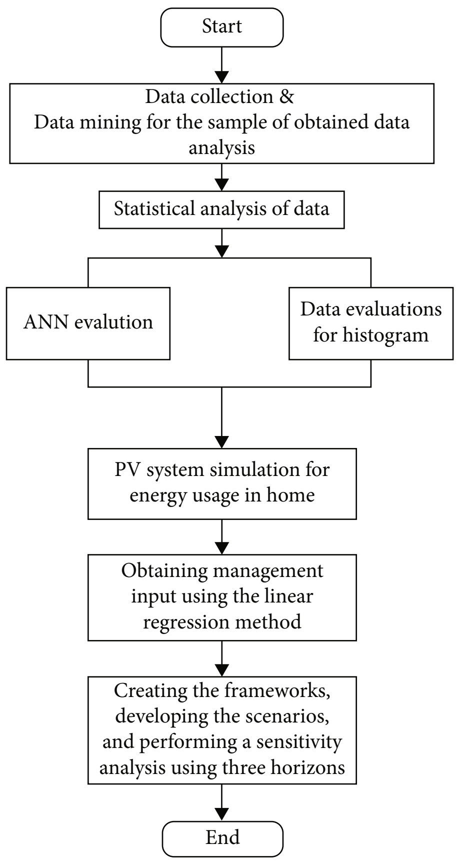

Figure 6: Flow chart of the proposed work.

analysis technique in building energy assessments. Linear regression can be used to identify a proper relationship (model or equation) between the forecast, descriptive, or target variable and the response or outcome variable. Regression analysis using only one dependent variables is known as univariate regression, and regression model using two or more response variables is known as multiple regressions.

For complicated systems like the power use of buildings, linear regression should indeed be viewed as an iterative process in which the outcomes are used to analyze, evaluate, criticise, and perhaps alter the inputs. The multivariate linear regression analysis tries to describe the relation among variables by fitting a linear expression to the dataset. When there are multiple predictor variables, the linear fitting is done while keeping all but one fixed. The presence of a link between a dependent variables and a regression coefficient does not suggest that the predictor variable is the cause of the response variable; rather, it just indicates that the two parameters have a high correlation. For instance, the temperature difference and the heat capacity of the walls both affect the heat flux through the walls, which is what causes the heat flow. In other words, the heat flux is not caused by the thermal conductivity of the walls, although it is strongly correlated with their heat capacity. Using simple linear regression as one of the regression analysis strategies depends on how complex the relationship between the variables is. The approaches for regression analysis are discussed in this section based on the classification in Table 3, which also includes a list of the equations relevant to the approach.

The inaccuracy to account for the discrepancy between the simulated values from Equation (1) and the identified data is represented by the equation of the linear regression form, in which Y is the primary predictor, X is the dependent variables, and α_0 and α_1 are the coefficient vectors or regression variables. In the estimated value form of Equation (1), X is the fitted or predicted value, and estimations of the coefficient of determination are provided. Estimated parameters can be determined for any collection of regression coefficient values that deviate from the observed data, which makes them different from regression coefficients in Equation (2).

$$X = \alpha_0 + \alpha_1 Y + \mathscr{E}, \tag{1}$$

$$\widehat{X} = \widehat{\alpha}_0 + \widehat{\alpha}_1. \tag{2}$$

The instance in which the variables utilised for the regression model correlate to one of the data instances of the actual observations used to identify is referred to as the fitted value.

To forecast solar intensity, first use a linear regression technique. Linear regression is a simple and popular technique for establishing the link between a reliant or responding variable, such as solar activity, and a collection of explanatory variables or forecasters. The regression attempts to minimise the sum of squared error variances between the observed solar radiation and the anticipated solar irradiance by applying a linear function of the prevailing climate metrics. To verify the precision of the forecasts in Table 3, utilise the experimental database for the remaining period of every year. Pay attention to the sun's cross identification root mean square and forecast frequency, which are 150 and 170 kilowatt hours, correspondingly. Figure 8 image illustrates how closely the model matches the projected solar intensity, albeit with minor deviations [20].

5. Results and Discussion

As per prosecution's findings, the annual energy use during the summertime is 1.32 higher than it is during the wintertime. The annual power usage in the summertime is between 25,000 and 30,000 $\mathrm{kW\,h^{-1}}$, according to histograms. All enhance the overall and scenario creation in the current study which are assessed in respect to the set restrictions (25,000–30,000 kWh). Throughout this research, Mashhad city's power consumption was projected using artificial neural network (ANN) time series that could be used to govern smart city initiatives. When compared to other classification and machine learning techniques from the viewpoints of data input and database design, the justification for choosing ANN for this inquiry is related to the versatility of this methodology for estimate of parametric variations over various timescales. In addition, the ANN system showed considerable accuracy for forecasting future energy demand in cities based on past research initiatives. By applying the ANN system for electrical energy data mining, the following objectives are attained:

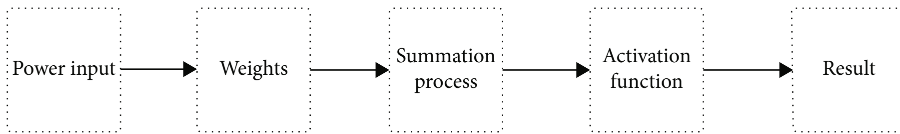

Figure 7: Architecture of ANN.

Table 3: Solar power intensity prediction using linear regression.

Observed	Linear regression
159	255
143	175
132	265
167	245
243	267
324	346
388	432
455	487
576	584
654	785

(i) Energy consumption forecasts for monitoring all Mashhad city electricity installations, including solar, methane, and hydropower ones, during peak demand and busy periods

(ii) On the basis of the predicted energy demand and the forces created by Mashhad's power plants, the energy crisis warning system was activated

(iii) Establishing a pattern for power utilisation and regulating it based on changes in the demand for electrical energy over time while also spotting abnormalities

The power consumption in each anticipated time step can also be linked to a summary of further data regarding the ANN time series characterizations for the machine learning procedure. A multilayer perceptron ANN, an intake ANN, was used to estimate the energy consumption in Mashhad city. The inputs were time-based factors, and the output took the city network's energy demand into account. There was an output layer, a hidden layer with two delays, and ten hidden neurons. An average of 70% of the data were used to train the model, 15% of the data were used to validate it, and 15% of the data were used to test it. It displays the results of calculating energy consumption during the summertime and wintertime, accordingly. The time period during which the full dataset is only once carried forward and reversed through the neural network, taking into account the fact that the created model seeks out the greatest match during the learning process, is referred to as an "epoch." The gradient descent method also necessitates that the model repeatedly pass the original dataset through this kind of neural network. This process is iterative; thus, numerous epochs can be observed. The 11th epoch in this inquiry is when the observed and predicted data are most closely matched. This shows that the eleventh epoch produces the lowest squared error (with a 99 percent accuracy).

The ANN forecasting model has the accurateness needed for the forecast of power requirement, according to the results. The created platform can be helpful for time-sensitive motivational activities and megacity management techniques. It is possible to construct motivating methods for solar energy use by utilising ANN time series prediction. It is possible to plan and evaluate energy use. Third, when approaching high periods of energy use, a set of predetermined motivational approaches may be assigned to each period. Households in Mashhad city use an average of 8.2 kW and 11.5 kW of electrical energy per day in the winter and summer, respectively, according to data obtained from the DEEC. Additionally, based on the information that is currently available, residences in Mashhad cities with renewable energy potential are anticipated to be about 90 square metres in size on average. The photovoltaic system model was used in the research to calculate the solar energy potential for 90 m^2. The flowchart shows the annual gains and losses in energy. This picture clearly shows how 21,195 kilowatt hours of renewable radiation are lost annually in a typical residential location. It is important to keep in mind that the dielectric breakdown cabling loss, which is associated with the resistance in the wires, lowers the system's efficiency. In contrast, the light-induced degradation is a capability loss that occurs within a few hours of being exposed to the sun and results in a decrease in performance. Power is lost as heat in the paper insulation of a cable when an electric field is created by the leakage current and the polarity reversal of current in an alternating current supply. This loss becomes more significant as the temperature rises. It has a direct impact on the way a cable functions in the system. Furthermore, it is clear from the simulation findings that the solar energy output is higher in the summer and spring than it is in the winter and fall. The DEEC may find that the study's findings are helpful in lowering peak energy demand given that May, June, July, August, and September frequently have the maximum solar energy potential. It is hard for the expected energy to completely meet the network's needs because solar energy production varies substantially from month to month.

When a PV system is installed in the yard or on the roof of a private residence, peak usage can still be controlled. The solar energy from the collection plane's global irradiation incident has accumulated on the panels. Global irradiation incidence is the term used to describe the solar panels' theoretical ability to absorb sun energy. The incentive algorithm for persuading people to generate solar power during peak hours was created as part of this study by speaking with 40 energy industry professionals. To establish the approach, energy sector experts took part in three sessions that

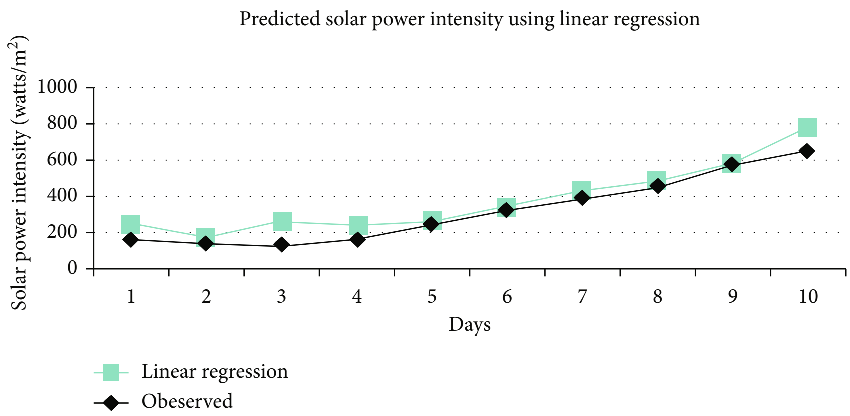

Figure 8: Solar power intensity prediction using linear regression.

Table 4: Solar power availability in Mashhad city.

Months	Temperature (degree Celsius)	Solar irradiation (kWh)
1	2	5540
2	6	9987
3	10	11345
4	16	16780
5	20	19657
6	24	23478
7	28	24456
8	26	21345
9	18	19880
10	14	14231
11	12	8764
12	8	5321

followed one another. Table 4 displays the results of their combined knowledge. At three meetings separated by a month, the announced committee assessed the agreement of the presented recommendations. Additionally, the permitted techniques were established through the linear revision process for the review and involvement of governmental authorities. The outcomes of each round and the TP items being authorized using the LR approach. It is crucial to remember that each approach was developed over the course of three time periods using the 3H technique (short-term, mid-term, and long-term). All approaches for the short (1H) time were built with financial incentives in mind based on the findings. Based on PV system and PV sol-online simulations, Figures 9 and 10 compare the amount of solar energy available and the amount of energy consumed in Mashhad city. The results show that, depending on the time period, Mashhad city's solar energy availability outstrips energy usage by a ratio of 10 or more.

However, the energy demand problem happens every year in several Iranian megacities, particularly Mashhad city, as a result of factors like the availability of water, the number of tourists, and the supply of gas for power plants. Additionally, with the use of particular motivating tactics as a TP in conjunction with optimised domestic energy efficiency, captured power can also be utilised for a variety of urban facilities in modern cities. Based on the findings of this investigation, some novel tendencies as well as some shared directions with prior studies may be seen. An innovative energy design, for instance, was provided to optimise energy use in smart cities. When solar cells and a triboelectric nanogenerator were used in tandem, power production performance improved from 9 megawatt to 28 megawatt per 130 millimetre to 24 millimetre solar panel area on a building's roof. While in the current study, the maximum power consumption in smart cities can be minimised by simply applying solar energy to home roofs and should be accomplished via TP. Furthermore, by implementing motivational citizenship programmes, energy consumption peaks can be managed. Some managers turn to technological solutions, while others place their faith on socioeconomic elements. Recent studies have shown that the second set of options could have more effectiveness in urban management. Various green power generation methods, including independent sustainable microgrids with rooftop solar arrays, micro-hydro turbines, biofuel central heating, aqua-electrolyzers, and power storage, were studied in a separate experiment. The salp swarm algorithm is the foundation of the controlling panel the authors supplied for energy management in urban centres. When electricity is not available, it can be provided by combining CHP with microgrid. On the other hand, by using ANN models to anticipate energy consumption and making modifications to citizen incentive programmes, the existing efforts could even be able to avert the shortage of energy that is now being experienced. The group developed a deep learning model based on LSTM in order to forecast the amount of electricity that would be generated by photovoltaic cells (long short-term memory recurrent neural network). Both the mean absolute error and the mean squared error of the predicted values have decreased as a result of the enhanced long-term memory network's implementation. This approach has the ability to produce short-term predictions of PV power and has the potential to lessen the influence that noise has on predictions of PV power. In this study, ANN computations allowed for the precise prediction of energy use. Additionally, compared to previous methodologies, which usually need time-consuming calculations, the proposed methodology could dramatically slow down computations [10].

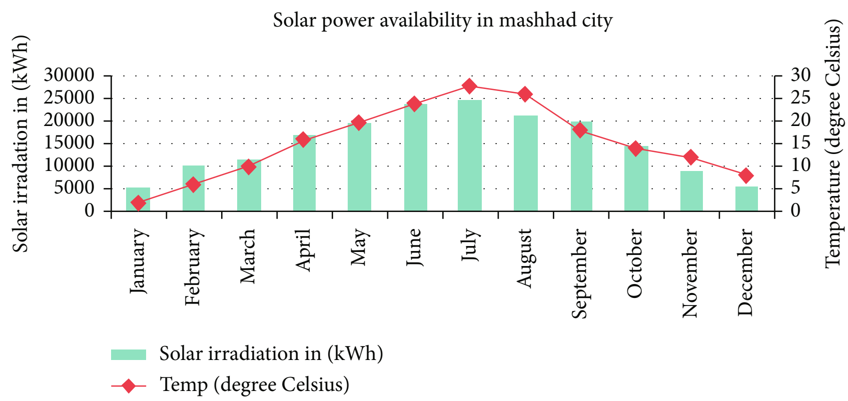

Figure 9: Solar power availability in Mashhad city.

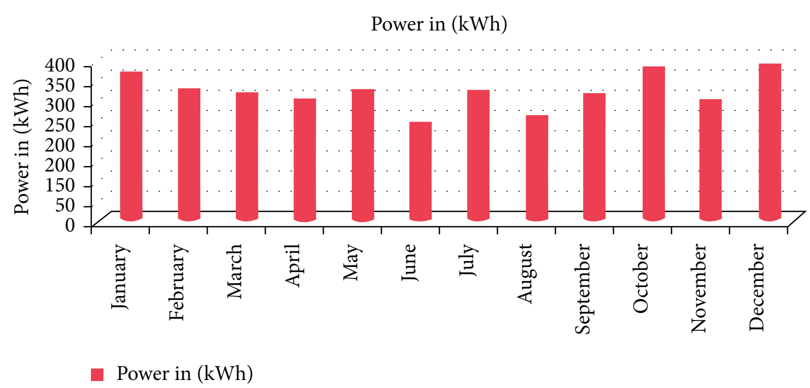

Figure 10: Power utilisation and the mean temperature in Mashhad city is 15.6 degrees Celsius, and the average size of a home is 100 square metres.

6. Conclusion

Energy recovery in metropolises is thought to be a critical concern, especially in developing countries. The amount of renewable energy could fill energy gaps and aid energy systems in managing maximum output in warm locations. Additionally, by using innovative urban organisations and solar energy collection, certain dangers can be transformed into possibilities. In the current work, linear regression was created as a smart system for anticipating energy demand, and machine learning and statistical models were utilised to evaluate Mashhad, Iran's usage of renewable energy. The PV system model was then employed for the research study of Mashhad, Iran, to replicate the distributed solar capacity and demonstrate its role in controlling power consumption requirements. Several implementation solutions for transformative participation (TP) in smart cities were proposed as a result of this study. The findings of this study demonstrated that neural network soft computing could properly predict more than 99 percent of the amount of electricity required to build the continuous surveillance system. The future of Iran's Mashhad city prospective for renewable energy then showed that solar radiations might be used to manage maximum power generation. The proposed model was linked to a photovoltaic system in order to use energy from the sun to fulfil the required energy. The created model also directly combined ANN and photovoltaic simulation, the former of which was used to supply solar resources and the former of which was used to determine electric power levels. The incentive algorithm for persuading people to generate solar power during peak hours was created as phase of this research by speaking with 45 experts in the energy fields. The specialists in the energy sector participated in three meetings that followed each other to design the plan. The approved strategies were created using the linear regression method for the government's review and input. Three temporal horizons were used for the creation of each approach and the LR evaluation. By accurately forecasting daily solar output using these diverse patterns, solar power firms may quickly make up for production deficits and avoid the expensive last-minute purchase of power from the market. This illustrates how machine learning regression approaches, in particular neural networks, can accurately and dependably estimate the average daily solar power. To boost the accuracy of such predictions, it is suggested and established that sun angles (azimuth and zenith) as well as weather and season-specific features be used. It was discovered that all tactics were created with financial incentives in mind for the short-term timeframes. For the mid-term phases, the amount of cost factors was dropped. Over time, these solutions also started to apply to choices for citizenship and growth. It is hoped that these findings will benefit the concerned parties and ease energy management in smart cities. Due to the increasing need for power generation and the depletion of nonrenewable, renewable technologies have attracted the attention of individuals all over the globe. Therefore, thorough research should be done on various energy sources. According to the findings of this study, additional research is needed on some other alternative energy sources like wind energy, biogas, and incinerations. To build an integrated energy resource management framework that may help in accomplishing the aims of smart cities, all these approaches and factors need to be assessed and carefully examined. Considering that new forecasting technologies and machine learning methods are viable options for conducting additional study on achieving the goals of smart cities and can be used for efficient power management as a part of future studies is pointless.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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