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Supply and Value Estimation of Electricity in Smart Grids using Convolutional Neural Networks and Big Data Analytics

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Abstract

Electrical power systems are evolving into more intelligent and green frameworks. These tendencies have several beneficial outcomes, including the active engagement of consumers in power marketplaces. Nevertheless, the resultant consumption-side flexibilities induce significant demand variations, complicating the maintenance of power equilibrium and dependability inside smart grids (SG). Users may modify their power consumption behaviors in SG due to electricity pricing and subsidies. This leads to prices that may deviate from the original pricing structure. Predicting electricity supply and value is essential for SG's dependability and ecological viability. The use of big data analytics (BDA) for predicting has emerged as a prominent study area due to the substantial volume of data created and stored in the SG setting. With enhanced awareness of pricing and demand, power consumers may optimize their load management effectively. This research employs a Convolutional Neural Network (CNN) and BDA for SG Supply and Value Estimation of Electricity (SVE). Consequently, the proposed model uses many variables to forecast prospective energy usage and value metrics. The configuration of variables is essential since the efficacy of the prediction model is contingent upon these values.

Keywords: Smart Grids, Convolutional Neural Network, Big Data Analytics, Supply, Value Estimation.

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Overview of the Research

Electricity, as a critical amenity, plays a key role in a nation's economic and social growth. Given the increasing and variable global power requests, it is essential to identify usage trends and volumes to maintain dependability and enhance power efficiency. SGs were launched in 1998 to facilitate the efficient integration of multiple energy sources and regulate the movement of energy from generating to demand locations via electric networks (Mostafa et al., 2022). Contemporary generation, transfer, distribution, and usage methods facilitate monitoring client behaviors and activities inside a power system (Lepolesa et al., 2022).

The use of wireless communication in an electrical system produces substantial data volumes. Moreover, installing detectors and analogous components for ecological monitoring produces a substantial volume of information daily. The decreased costs of storage devices allowed service providers to archive this data daily. These records include a diverse array of data, expanding fast each day. The mere accumulation of extensive data is futile if no valuable insights are derived from it, rendering it unbeneficial (Lazaropoulos & Leligou, 2023). BDA has emerged as a prominent subject for academics seeking to optimize its advantages. Likewise, experts are using big data associated with SG to enhance the SG's effectiveness, dependability, and consistency while also promoting ecological sustainability. Scholars have suggested models for predicting and anticipating demand, pricing, energy production, and faults and abnormalities in energy systems using BDA (Aslam et al., 2021). Using such frameworks may significantly enhance the productivity of the contemporary SG.

The primary objective of SG is the amalgamation of technological innovations that facilitate interaction and data sharing between energy consumers and utility providers. Both market players seek to optimize advantages via active engagement in energy administration solutions. Their advantages are significantly contingent upon the precise supply forecasting and the power cost. Scholars diligently engage in this domain, using BDA with predicting algorithms (Javaid et al., 2021).

To attain the above objectives, Supply Side Administration (SSA) offers a framework that enhances a generation system's dependability, equilibrium, and stability. Due to load changes and limited control over the supply side, sustaining this equilibrium is a complex endeavor, particularly as the prevalence of green and dispersed power production escalates (Sarker et al., 2021). Additionally, SSA routinely monitors demand in peak and off-peak periods and implements various rules and rewards to regulate power usage. A critical component of SSA is supply and value predicting, which is used to anticipate future power demands. These projections may roughly anticipate future demands over various time frames. The prediction of supply and value also guarantees an equilibrium between power availability and customer demand.

Supply and Value Estimation of Electricity in Smart Grids

The generation of data constitutes the preliminary phase. It aggregates data from several sources, including MG, smart structures, electronic meters, electric vehicles, and factories. Information is unrefined and generated in substantial volumes. The subsequent significant advancement pertains to the prospective retention of this information. The information may be retained in storage facilities or cloud computing environments. Data preparation is a crucial phase in acquiring data for use. This procedure will eliminate vast amounts of data, discern essential attributes, exclude outliers, and convert the data for utilization in various analytical methods. The subsequent phase involves acquiring pertinent information using sensing and data mining strategies.

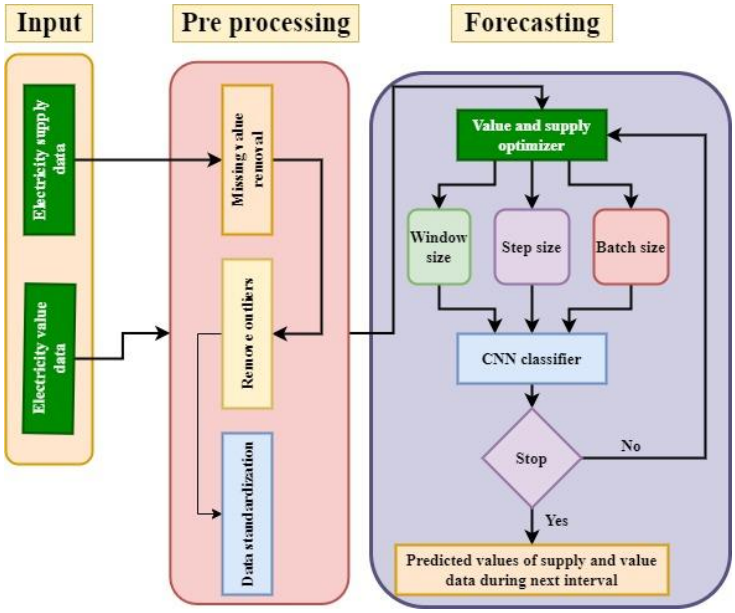


Fig. 1: Architecture of SVE using CNN

Fig. 1 shows the SVE model employed with BDA using the CNN framework. It has the following stages:

Input

The necessary data for the forecast is gathered at this step. This model utilizes two datasets: electricity supply and value statistics from (Amjady & Daraeepour, 2009). The database comprises information collected hourly. Publicly accessible data has been used to replicate the results. The research employs a variety of elements related to supply and value estimates as input factors. The growing number of input factors complicates the model and necessitates additional resources and technology for efficient prediction. Tests are also accessible with a single predictive input factor. These systems use historical values of input variables to predict potential trends. Consequently, the most reliant factors that fulfill the fundamental criteria of the method have been used in the proposed model. The subsequent phase is data preparation, followed by the data acquisition step.

Pre-processing

Data pre-processing is a data mining method that converts raw data into a suitable and comprehensible format. The data derived from the real world has a deficiency in cohesiveness, contains errors, is inadequate, and lacks unambiguous behavior. Consequently, we must convert this data into a comprehensible format before its use. Strategies for data preparation must be used on the initial information to attain the purpose. Data is subjected to several cleansing and optimization processes throughout the pre-processing stage:

• The initial step is to filter the information from noisy data. The missing values noise has been smoothed, and data inconsistencies have been addressed by filling or deletion from the dataset.

Conflicts among data are resolved, diverse formats are combined, and anomalies have been removed. Conversion of information is crucial in standardizing variables within the same timeframe to enhance comparability.

• Data is reduced by eliminating extraneous or duplicate information during the data compression phase.

Forecasting

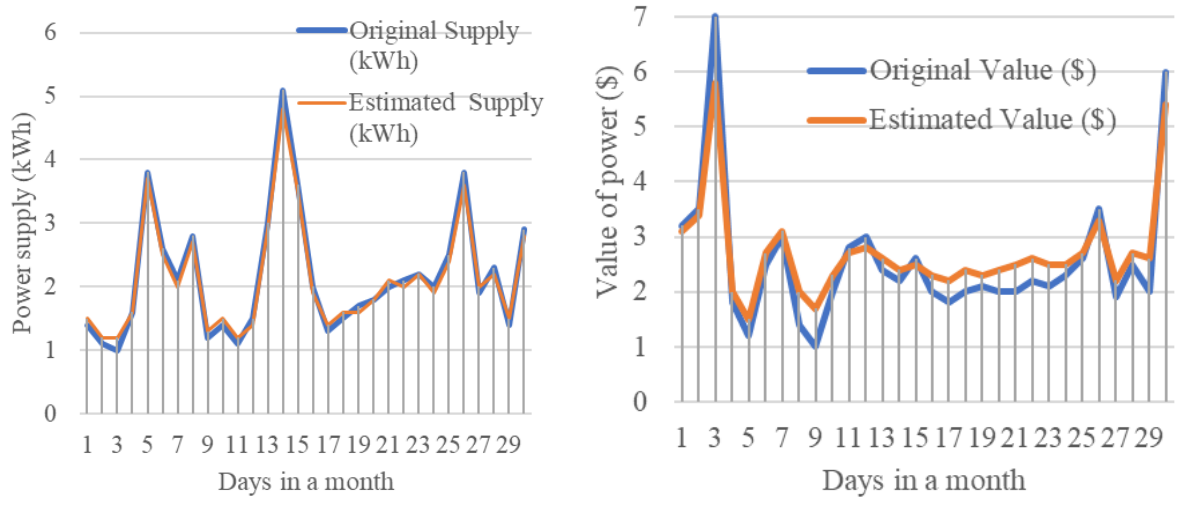
A crucial activity in smart grids is the supply and value estimation (SVE) of electricity, which gauges the precise electricity supply-demand equilibrium and the economic value of electricity in different nodes in the grid. One of the most advanced techniques is enhancing this capacity for deep learning models, such as CNNs, which were initially developed for image processing but are now widely used for structured time series and spatial-temporal data in smart grids.

CNNs possess the required features to perform more effectively in this scenario since they can capture local features and patterns in huge datasets. Regarding Smart Grids, data regarding electricity consumption, generation, and pricing can be arranged in multi-dimensional matrices akin to images, with each dimension representing time, location, or

type of energy source. Using convolutive layers, CNN can recognize intricate relations and patterns that are difficult for traditional models to capture. For example, CNNs can associate peak demand times with pricing and those time-flow.

Simulation Results and Outcomes

The simulations were conducted with an Intel Core i7 CPU with 16 GB of RAM and a 64-bit Python 3.6 operating system. The standard simulation software is Matlab. The present section examines the simulation results about anticipated supply levels and power values.



(a) Supply (b) Value

Fig. 2: SVE analysis using CNN and BDA

A comparison between actual and estimated electricity supply over 30 days is illustrated in Fig. 2 (a). The estimates from the CNN integrated with BDA procedures were consistent with the original supply figures. Notably, most predicted values are estimated to be lower and upper bounded by ± 0.1 – 0.2 kWh, indicating model accuracy. The model estimation also captures peak values like 5.1 kWh (Day 14) and 3.8 kWh (Days 5 and 26). This reliability underscores the remarkable capabilities of CNN and BDA in capturing temporal dependencies and fluctuations of underlying electricity supply dynamics, enabling these frameworks to function optimally within real-time SG systems for control and operational strategy formulation. In Fig. 2(b), the actual and estimated monetary values ($) depicting electricity consumption over the span of a month have been observed. It can be noted that the estimations achieved through the BDA-enhanced CNN model provided accurate representations of daily value fluctuations. Most estimates also seem to follow the actual values within a reasonable margin of error (approximately 0.1–0.4). Estimates for some days, such as Day 3 and Day 30, had slightly higher variances (1.2 and 0.6, respectively), likely due to anomalies or peak consumption fluctuations due to real consumption patterns.

Conclusion

This research employs a CNN and BDA for Supply and Value Estimating Electricity (SVE) in SG. Consequently, the proposed model uses many variables to forecast prospective energy usage and value metrics. The configuration of variables is essential since the efficacy of the prediction model is contingent upon these values. Notably, most predicted values are estimated to be lower and upper bounded by ± 0.1 – 0.2 kWh, indicating model accuracy. The model estimation also captures peak values like 5.1 kWh (Day 14) and 3.8 kWh (Days 5 and 26). The overall predictive trend seems to agree with the historical data, thus proving that the CNN and BDA architectures have commendable accuracy for estimating the cost implications of electricity consumption in SG.

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