

**Interdisciplinary role of statistics in energy consumption prediction
within smart grid big data analytics**

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Abstract

The study of energy consumption in buildings is crucial due to environmental and financial impacts. Smart metering is suggested to improve energy efficiency, but predicting electrical consumption accurately remains challenging, considering various factors. To tackle this, we propose a Multi-objective Golden Eagle Optimization (MGE) based Hybrid Deep Dynamic Convolutional Fuzzy Network (HDDCFN) method. This approach optimizes

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algorithm parameters and prediction models using multi-objective optimization, considering historical usage and weather conditions. The research is conducted using Matlab.

Subject Classification: 68T07.

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I. Introduction

Over the last decade, urbanization has surged, drawing people to Smart Cities for their advanced amenities. Residential energy consumption has risen due to urbanization, technology, and increased comfort needs. SG play a vital part in ensuring reliable and economical power for Smart Cities, transforming physical infrastructure into digital systems [1]. These grids improve efficiency and reliability by minimizing outages and introducing self-healing capabilities. Smart Grids utilize smart meters and advanced metering infrastructure (AMI) to measure energy consumption, generating vast amounts of high-velocity data. Big data technologies have the potential to revolutionize utility providers' capabilities, enabling a better understanding of customer energy consumption patterns, demand forecasting, outage prevention, and energy optimization [2][3]. Researchers are developing energy management systems using big data approaches to predict energy demand and supply consistently. Creating models to analyze smart meter data and predict energy consumption is crucial. This study proposes energy-efficient big data analytics for residential smart grid metering systems. It develops a time-series model for historical energy consumption and meteorological conditions, storing results in a database. It introduces the Multi-objective Golden Eagle Optimization (MGE)-based Hybrid Deep Dynamic Convolutional Fuzzy Network (HDDCFN) for energy consumption prediction, optimizing algorithm parameters and prediction models. The study validates the system's performance measures and includes sections on existing research, proposed techniques, results, and conclusions with suggestions for future work.

II. Related work

Ensuring responsible and efficient energy consumption practices is increasingly vital in today's power system. The author of [4] proposed an intelligent data mining methodology for analyzing energy time-series

data, achieving short-term hourly prediction accuracy of 81.89% and long-term prediction accuracy ranging from 72.81% to 81.89%. In [5] the author introduced EvoHyS, integrating statistical and machine learning approaches, enhancing accuracy with Mean Squared Error (MSE) evaluation. Also [6] developed a smart energy consumption analysis system, focusing on managing energy usage without extra costs and utilizing IoT and Big Data in various sectors. The [7-9] presented a temporal and spatial-based ensemble forecasting model using clustering algorithms and LSTM and GRU units for high forecasting accuracy. In [10] the author proposed a spatio-temporal visual analytic technique for urban energy consumption patterns, while Fatema, Israt, and colleagues suggested a single complete LSTM for energy forecasting. Also [11] developed a hybrid model combining CNN and BLSTM for precise energy consumption forecasting. Further [12-16] conducted a comparative examination, finding that ConvLSTM combined with BiLSTM performed the best [17][18]. Traditional ML [19] algorithms are prone to local minima traps, and neural networks often face complexity and overfitting issues.

III. Proposed methodology

The proposed model, depicted in Figure 1, comprises data pre-processing, training/testing, prediction, and optimization phases. Figure 2 shows the flowchart of the proposed methodology. It starts by

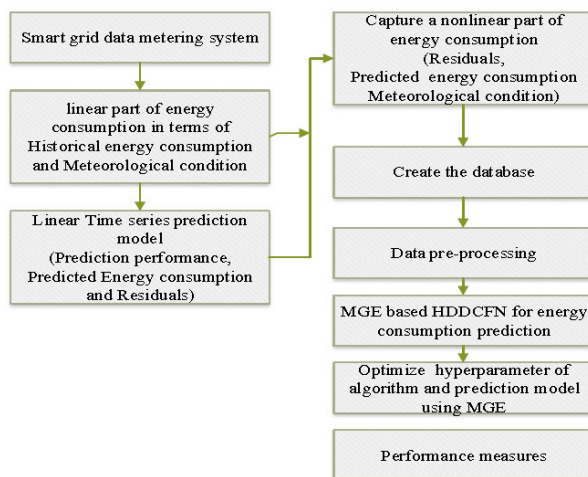


Figure 1
Proposed methodology

constructing a linear component for energy consumption prediction based on historical and meteorological factors, followed by integrating nonlinear aspects for database creation to ensure accuracy. A novel prediction model, MGE-based HDDCFN, is developed and evaluated using test and training sets. Training employs a hybrid deep learning algorithm, with hyperparameters optimized using the MGE method to enhance performance. Performance measures validate the effectiveness of the research.

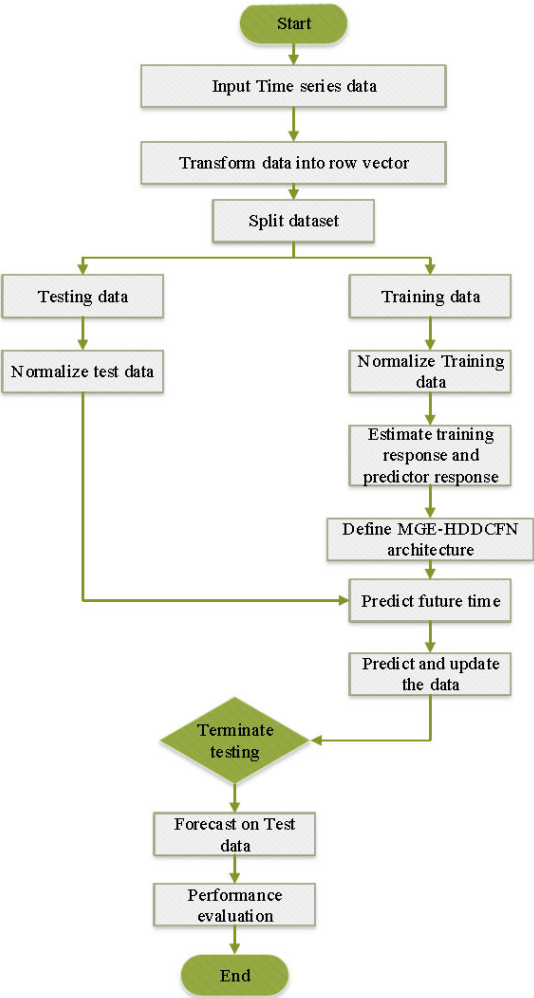


Figure 2
Flowchart of the proposed methodology

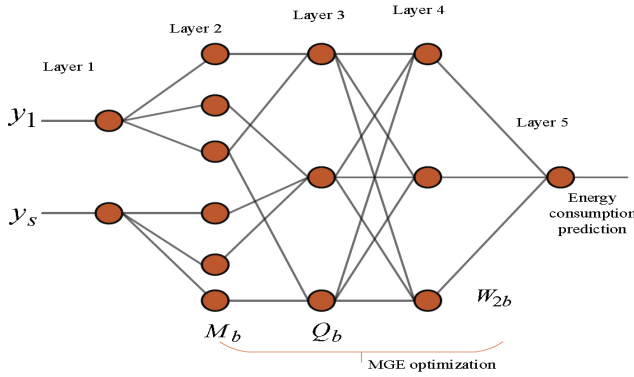


Figure 3

Structure of the MGE-HDDCNN method

- Proposed algorithm

Figure 3 illustrates the new MGE-HDDCNN structure, utilizing Deep CNN to run a fuzzy system based on the TSK model.

- GE optimization

The GE algorithm combines hunting and encircling behaviors to select parameters. Initialize the HDDCFN algorithm's settings and prime number parameters randomly. The HDDCFN algorithm prioritizes selecting the best fitness.

IV. Result and discussion

The experimental design of the suggested research project is described in this section. MATLAB is employed as a general-purpose language in this research study to carry out a number of tests.

- Dataset Description

Data from ENTSOE and Red Electrica Espana were used for consumption and generation stats and settlement pricing. Open Weather API provided weather data for major Spanish cities. Training, validation, and testing sets were separated from the dataset, with performance analysis conducted on weekdays and weekends.

- Performance analysis

The total hourly load curve is illustrated in Figure 4. The observation shows the overall load curve of the energy efficiency SG system.

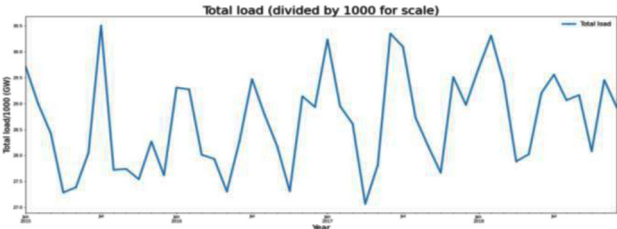


Figure 4
Total hourly load curve

Figure 5 displays Hourly load and apparent temperature, illustrating consumption patterns driven mainly by households and services.

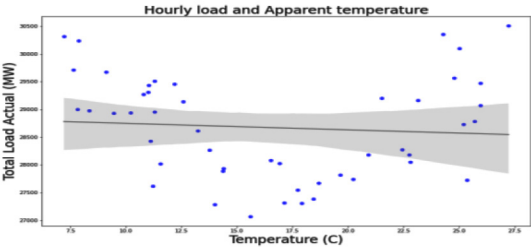


Figure 5
Hourly load and apparent temperature

The use of electricity for heating is restricted to a few service segments and high-income homes.

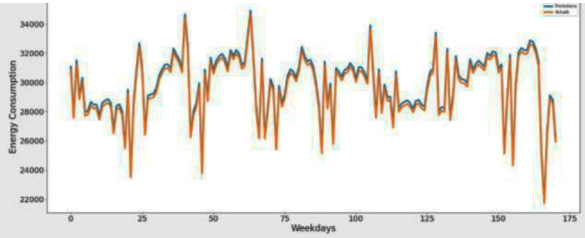


Figure 6
Load forecast for week day

Figures 6 and 7 depict hourly power demand trends for weekdays and weekends from 2015 to 2019.

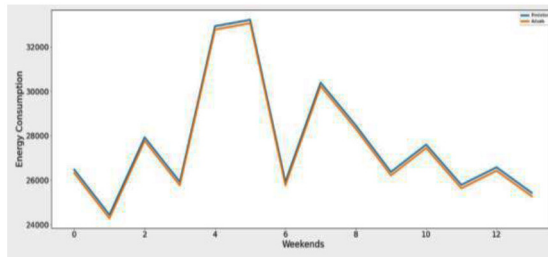


Figure 7

Load forecast for weekend day

The observation underscores the substantial disparity in power usage between weekdays and weekends, with significantly lower demand during weekends due to reduced activities. This forecast promises notable utility cost savings and enhanced facility utilization. Simulation results, along with metrics in Table 1, elucidate the suggested model's performance. It was trained and evaluated on unbiased data, using MAE and RMSE values for assessment.

Table 1

Elucidate the suggested model's performance Top of Form

Metrics	Weekday	Weekend
MAE	0.15	0.24
MSE	0.2	0.27
RMSE	0.43	0.76
Correlation (R)	0.842	0.861
Coefficient of Determination (R^2)	0.932	0.926

R^2 is a correlation coefficient that measures how well the prediction models performed. The correlation between the actual and expected values is greater the higher the R^2 value. In both situations, weekdays and weekends, the R^2 value for power demand is over 0.9, showing a significant connection between actual and expected values.

- Comparative analysis

In Table 2, the effectiveness of the suggested approach and the traditional approach are compared.

Table 2
Comparison of performance measures using various approaches

Parameter	Algorithm	MAE	MSE	RMSE	R	R ²
Weekday	EvoHyS[17]	4.02	1.20	12.05	0.76	0.9
	LSTM-GRU [18]	5.44	0.310	2.669	-	-
	LSTM [19]	50.96	-	67.35	-	0.62
	Proposed	0.15	0.2	0.43	0.84	0.93
Weekend	EvoHyS[17]	3.05	1.05	23.05	0.682	0.90
	LSTM-GRU [18]	3.769	0.340	2.695	-	-
	LSTM [19]	31.5	-	31.5	-	0.59
	Proposed	0.24	0.27	0.76	0.861	0.92

The suggested model achieves the highest R2 values of 0.932 for weekdays and 0.926 for weekends.

V. Conclusion

This research presents a new deep learning framework for energy-saving decisions, vital due to increasing electricity use. Using advanced forecasting techniques, it optimizes energy consumption with high precision. Results, analyzed using MATLAB, demonstrate superior performance over existing methods. Future work includes refining the model for different climates and expanding to city-level energy estimates for improved accuracy.

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