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PREDICTION OF OPTIMAL BATTERY CAPACITIES FOR SOLAR ENERGY SYSTEMS

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ABSTRACT

Solar energy using photovoltaic cells is a highly feasible solution for modern renewable-powered residential buildings in terms of cost reduction of utility bills. The installation of solar PV systems and the (BESS) battery energy resource is the most popular energy cost minimization solution and will continue to increase rapidly. The size of the battery depends on the various energy profile factors and load profile factors. The energy profile factors include Annual energy consumption, Accumulated Energy, Energy Utilization from Grid, and Energy Injected into the grid. And the load profile factors are Average Load, Peak Load, Median Load, and Rated Photovoltaic power. The project aims at predicting the battery size by analyzing a dataset comprising the above-mentioned energy profile factors and load profile factors using machine learning techniques. Optimal sizing of the BESS is an essential prospect for nZEBs. Currently, the price of BESS is very high; therefore, in many countries, governments and grid operators offer several incentives to consumers. However, the cost of BESS is also expected to drop in the coming years. For classification, the project employs two distinct classifiers: Gaussian Naive Bayes (GNB) and Bernoulli Naive Bayes (BNB). By applying these classifiers within a supervised learning framework, the project leverages statistical methods to iteratively improve prediction accuracy

KEYWORDS: *Bernoulli Naive Bayes, Gaussian Naive Bayes, Prediction, Solar PV systems,*

I. INTRODUCTION

Prediction of battery size by analysing a comprehensive dataset that includes both energy profile and load profile factors, using advanced machine learning techniques to derive insights and classify data patterns effectively. Energy profile factors consist of metrics such as annual energy consumption, accumulated energy, energy utilization from the grid, and energy injected back into the grid, which provide a detailed picture of energy flows [1]. Load profile factors, including average load, peak load, median load, and rated photovoltaic power, reflect the load behaviour and demand characteristics. Together, these features offer a holistic view of the energy usage and generation patterns, which serve as inputs for predicting battery size. For classification, the project employs two distinct Naive Bayes classifiers: GNB and BNB

The Gaussian Naive Bayes classifier assumes a Gaussian distribution of continuous variables, comparing neural activations to the means and variances across different stimulus conditions, enabling it to produce a condition label with respect to battery size. This method is particularly effective for data that follows a normal distribution, making it suitable for continuous-valued features like energy and load profiles. The Bernoulli Naive Bayes classifier, on the other hand, is ideal for binary-valued data, applying Bernoulli distribution assumptions to variables that are either present or absent [2]. It's particularly effective for Boolean or categorical data, and here it enhances predictive performance on certain binary factors within the dataset. By applying these classifiers within a supervised learning framework, the project leverages statistical methods to iteratively improve prediction accuracy. This approach allows the machine learning models to make informed classifications or predictions regarding battery size by recognizing and categorizing specific patterns and relationships within the energy and load data. The integration of these classifiers offers flexibility in handling a mix of continuous and binary features, which aids in robust battery size prediction, benefiting applications in energy storage and grid management systems [3].

1.1 Problem statement

The sizing of batteries in a residential solar system is currently quite complex and homeowner-unfriendly. Therefore, this project seeks to bridge that gap by developing a user-friendly machine learning tool that analyses homeowner data for prediction of the optimal battery size, thus improving decision-making while maximizing efficiency for residential solar power. The growing popularity of residential solar power systems creates a demand for a user-friendly tool to optimize battery sizing. This project bridges this gap by developing a machine learning-based tool for homeowners. The tool leverages readily available data on photovoltaic installations and domestic load profiles to predict the ideal battery capacity for each unique system. This homeowner-centric approach empowers users with data-driven insights, maximizing efficiency, minimizing energy waste, and ultimately promoting informed decision-making regarding battery storage for their solar power systems. Machine learning algorithms have shown promising results in prediction [4].
The increasing popularity of residential solar power systems is thus in need of a user-friendly tool optimizing the size of the battery. This project fills the gap by developing a tool based on machine learning for the homeowner to compute the optimal battery capacity for every unique system through available data about photovoltaic installations and domestic load profiles.

This homeowner-centric approach empowers users with data-driven insights, maximum efficiency, minimal loss of energy, and ultimately sophisticated decision-making regarding battery storage for their solar power systems [5].

1.2 Outcome of the Research

This project will develop a predictive model that predicts optimal capacities of batteries to be used in solar energy systems, basis the energy and load profile factors. This would capture key patterns in energy use and demand through using Gaussian and Bernoulli Naive Bayes classifiers so that proper sizing of a battery is ensured. This method will further optimize storage, save waste, depend less on the grid, and saves all costs incurred by oversized and undersized batteries. By enhancing the efficiency of solar energy storage, the model supports environmental sustainability goals in the form of higher adoption of renewable energy. Its adaptability also assists the grid operators in achieving a stable grid through integrating distributed energy resources.

2. LITERATURE REVIEW

Background and motivation of the introduction the research background relates to the development of an optimized model for sizing residential solar battery systems to address the state-of-the-art challenge in realizing accurate prognostication of battery capacity for better energy efficiency and reduction of dependency on the grid. This research primarily articulates a problem statement regarding the need to have readily available data-driven tools for guidance by homeowners in bringing savings and sustainability. The use of technology available with machine learning should focus on designing intuitive and effective solutions for residential solar energy storage.

Few researchers explored the optimization of energy storage schedules for batteries in photovoltaic (PV) grid-connected near Zero EnergyBuildings (nZEBs) using linear programming techniques. This study addresses the critical challenge of enhancing energy efficiency and reducing operational costs in nZEBs by strategically managing the storage and usage of solar-generated electricity. Through the implementation of a linear programming model, the research demonstrates how optimal battery scheduling can significantly improve the energy performance of PV systems in grid-connected buildings.

The European Environment Agency (EEA) on climate change provides an extensive analysis of climate data, greenhouse gas emissions, and the environmental impacts of climate change, highlighting key findings and trends within the European context (European Environment Agency, 2019). The paper by Ahmadiahangar et al. (2020) introduces a battery sizing tool for nearly Zero Energy Buildings (nZEBs), using data on energy consumption, solar irradiance, battery performance, building specifications, and grid electricity prices to optimize battery capacity and enhance energy efficiency [3].

Jawad et al. (2021) propose a robust optimization technique to minimize energy costs in cloud data centers, utilizing datasets that include energy consumption, workload patterns, electricity prices, server performance metrics, and environmental factors. This study contributes to the field by addressing the critical issue of energy efficiency in cloud computing, providing valuable insights and methodologies for reducing operational costs [6].

Huo et al. (2021) conduct a comprehensive analysis and optimization of external Venetian blind shading systems for nearly zero-energy buildings (nZEBs) across different climate regions in China. Their study draws upon datasets encompassing regional climate data, building energy consumption patterns, shading device specifications, building characteristics, and simulation results, contributing valuable insights into enhancing energy efficiency and thermal comfort in nZEBs [7]. Few researchers examined the design feasibility of a net-zero energy neighborhood in Qazvin, drawing upon datasets encompassing energy consumption patterns, renewable energy potential, building characteristics, cost data, and environmental factors. This study contributes valuable insights into the potential for sustainable urban development and energy self-sufficiency in the region.

3. METHODOLOGY

Current sizes of batteries for residential solar systems come with significant problems in making choices of storage capacity, including the dimensioning thereof, such as high costs and low efficiency. The paper further discusses the most recent developments in machine learning techniques that have increased the accuracy in predicting the optimal size of batteries. Lastly, the survey indicates and discusses ongoing research on the integration of data-driven approaches to enhance energy efficiency and reliability in residential solar applications [8]. It has provided the rationale for the project focus: to develop a machine-learning-based battery sizing tool. The modules developed and integrated by the project form a predicting tool for determining the size of residential solar energy systems' battery, thus making proper predictions. The predictions made by the tool are also accurate and reliable because there will be light on issues among the parties involved [9].

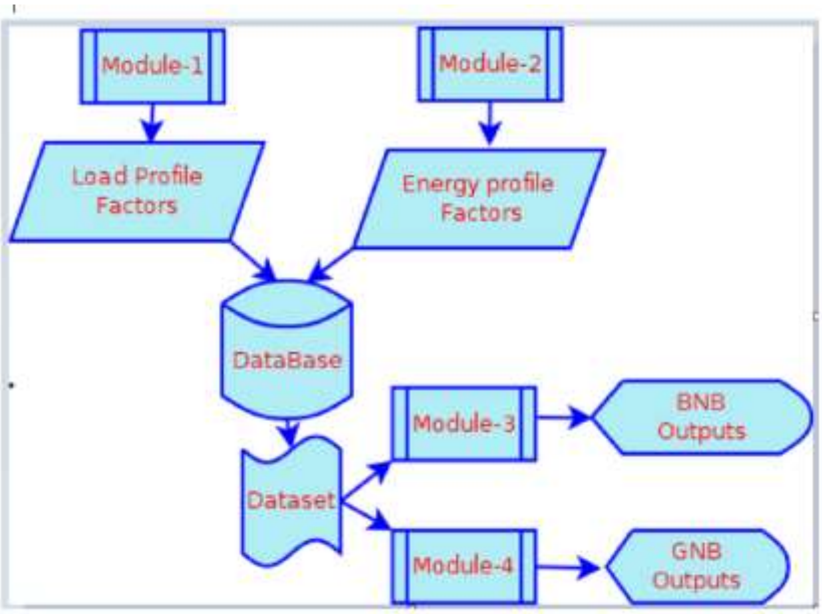

Fig 1: System Architecture

The diagram illustrates system elements and their interactions. The project consists off our main modules: Load Profile Factors Module: Function: Adds load profile factors to the database. Components: User interface, database connection, data validation. Energy Profile Factors Module: Function: Adds energy profile factors to the database. Components: User interface, database connection, data validation. Bernoulli Naive Bayes Classification Module: Function: Runs BNB classification on the dataset. Components: Data preprocessing, classification implementation, result storage. Gaussian Naive Bayes Classification Module: Function: Runs GNB classification on the dataset. Components: Data preprocessing, classification implementation, result storage

3.1 Data Collection

Collect data on factors involving energy and load profiles, such as photovoltaic installations, household energy usage, solar generation, grid usage, and also data points like average load, peak load, and rated photovoltaic power [10]. These data points are highly crucial for developing a good battery capacity forecast.

3.2 Data Preprocessing

Data must be cleaned and preprocessed for it to appropriately handle missing values, normalize features, scale features, and transform categorical data. This gets data ready for the training process of the machine learning model.

3.3 Feature Selection

Identify the most relevant features for predicting battery capacity. This would be done through statistical testing, correlation analysis, or feature importance - the scores would show which factors most strongly influence battery sizing. The model would be either Gaussian Naive Bayes, Bernoulli Naive Bayes, or any other algorithm that fit the characteristic found in their data. They have to choose models that can actually work appropriately and handle continuous and categorical data [11].

3.4 Model Training and Validation

Train selected models on the training dataset and validate them on the validation set to measure their performances [12]. Hyper parameters are fine-tuned using cross-validation techniques or any other effective cross-validation for the 7better accuracy of prediction.

4. EXPERIMENTS AND RESULTS

Results show that machine learning models, especially Gaussian and Bernoulli Naive Bayes classifiers, may predict optimal battery capacities for solar energy systems with high accuracy and are more effective than traditional sizing methods in predicting models for efficiency [13].

4.1 Performance Evaluation Techniques

Collect historical data on how the house has used energy vis-à-vis the photovoltaic panels, which would interact with the grid at different times. Use techniques like regression and decision trees to model and predict the size of the BESS based on energy usage and generation patterns. Perform load profiling to ascertain the peak, average, and typical energy demands of the building [14].

Implement energy management algorithms, for instance, model predictive control or reinforcement learning that can take advantage of forecasted solar generation and energy demand to optimize the charging and discharging schedule of the battery bank. Assess economic feasibility, including probable energy savings, initial investment, and available incentives or subsidies. Most of the key metrics for the analysis of the performance of BESS include self-consumption, self-sufficiency, peak shaving, round-trip efficiency, and battery degradation. Provide lifecycle cost analysis of the equipment, including the resultant maintenance and replacement costs as well as the revenues from any potential grid services. Regulatory compliance should be ensured, and the system should be optimized for both technical performance and economic viability [15].

4.2 Evaluation Steps

- GNB Gaussian naive Bayes classifier is a probability distribution and has the effect of comparing neural activation to the means and variances of activation in different stimulus conditions. The output of the classifier is a condition label [16].
- GNB classifier on the testing data as 86.23. And in the first set, we have given 0 as nothing but a low battery size same as 1 is a medium battery size and 2 is a high battery size
- Bernoulli Naive Bayes. BernoulliNB implements the naive Bayes training and classification algorithms for data that is distributed according to multivariate Bernoulli distributions; i.e., there may be multiple features but each one is assumed to be a binary-valued (Bernoulli, boolean) variable.
- The BNB classifier obtained an accuracy of the BNB classifier on testing data is around 36.3013. Here the prediction on the first, second, the third set is 2, and 2 is the high battery size.
- This includes a thorough evaluation of the work carried out and brings out the contributions from the study. The discussion shall logically lead to inferences and conclusions and scope for possible future work.

5. CONCLUSION

This data-driven project, which sets a promising course for the economic use of sun energy, has already reached its research goals, and to some extent is already being used in one or more households. The proper use of the system to be installed, the sizing and size of the battery and even the cost of the total system are considerable in preventing this problem. For solar power producers and especially for battery manufacturers, the project delivers actual insights about consumers' needs and behaviour in housing. This information shapes an efficient manufacturing policy and decreases the amount of excess capacity. Result: products that are both low-cost and longer-lasting in life. In short, this application aimed at preventing waste energy in a responsible way, and the contribution made toward energy efficiency and further energy conservation. Reducing their energy consumption and smart energy storage solutions are a way to contribute to a faster global transition to the use of renewable sources of energy, paving the way for a greener, more sustainable future.

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