A Repository for Global Daily Load and Solar Profiles

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***Abstract*—Existing synthetic grid repositories typically provide only nominal load values without time-series behavior, and when temporal data are available, they are largely limited to Western regions such as the United States and Europe. This paper addresses this gap by creating an accessible repository of daily load and solar generation profiles for underrepresented regions, with a focus on scalable, data-efficient modeling approaches. To create a repository of load profiles, we first conduct an extensive search for all sources with existing load profiles, then approximate load profiles for countries lacking data. We utilized inputs such as population, gross domestic product, climate, industrial infrastructure, and solar contribution to train a neural network that generates daily load profiles for all countries with missing load profile data. We also store solar generation profiles that are generated using the PVWatts®Calculator simulation model. Ultimately, this paper describes the steps involved in creating a repository of load and solar profiles for all non-Western countries to enable multi-period simulations and applications, thus advancing synthetic grid research in these regions.**

***Index Terms*—Synthetic Power Grids, Load Profile Modeling, Solar Generation Modeling, Normalized Solar Profiles, Time-Series Data, Data-Scarce Regions, Grid Modeling and Analysis**

I. Introduction

Power grid test cases are crucial tools for advancing algorithmic research, informing public policy, and supporting education [1]–[3]. While research into creating realistic synthetic grid models has advanced significantly, many synthetic grids have been developed for Western countries, such as the United States and European countries [4]. Conversely, the developing world lacks synthetic grids and, with them, the ability for researchers to model and analyze power grids in a global context. To the best of our knowledge, the only publicly available spatially geolocated synthetic grids for countries outside of the United States and Europe are available for Ghana [5], South Korea [6], Singapore [7], and Saudi Arabia [8].

Beyond the synthetic grid itself, load profile data is also very difficult to obtain. While data such as total annual energy consumption are tracked by large organizations and are often publicly available [9], very few countries publish their actual hourly demand curve. For example, US organizations such as the California Independent System Operator (CAISO) publish daily demand forecasts, which are available on a day-to-day basis [10]. Furthermore, the European Network of Transmission System Operators for Electricity (ENTSO-E) has published an open-source data repository containing daily load and solar profiles for all European countries, dating back to 2015 [11]. However, no such repository exists for non-Western countries. Thus, unlike in the Western world, where this data is recorded, documented, and openly available, the same cannot be said for many developing countries. This lack of reliable sources for the daily load and solar profiles adds a further layer of complexity to research on synthetic grid development and its applications in these regions.

This paper addresses the gap in accessible energy data between Western and non-Western countries by creating a *repository of realistic daily load and solar generation profiles* for underrepresented countries. This repository was developed by combining exhaustive Internet-based data collection, machine learning techniques, and simulation-based methods to provide a centralized and scalable source of representative load and solar profiles for countries outside the United States and Europe, where such data have been limited or unavailable.

The hourly time series data for a country's daily electricity load can be highly erratic, varying from day to day. It is highly dependent on human behavior, climate, economic and industrial infrastructure, demographics, etc. [12]. Due to many factors, the best source of data is actual load measurements. These data form the basis of all profiles provided in this study, and we build on them using additional predictive techniques for regions where such quantitative data are not available. By collecting existing data and creating daily load profiles for countries missing data, research such as creating synthetic grids, grid planning and expansion, and renewable energy integration is more easily accessible. Solar energy generation profiles, on the other hand, are more predictable. Their patterns are inherently dependent on geographic location, atmospheric conditions, and the time of day of the specific solar generation unit. Consequently, solar generation exhibits a highly predictable daily pattern governed by Earth's rotation and solar geometry. This predictability makes solar modeling both feasible and important for capturing realistic grid behavior.

The remainder of the paper is organized as follows. Section II describes the process for obtaining, analyzing, and processing real load profiles. Section III describes our method for generating synthetic load models, and Section IV presents a methodology for compiling solar generation profiles across various regions. Finally, Section V concludes this paper.

II. Load Profile Modeling

In this section, we detail the steps involved in generating realistic load profiles for different regions across the world. We

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TABLE I
BREAKDOWN OF COUNTRIES IN OUR SEARCH SPACE BY REGION

Region	**Number of Countries**
Latin America & Caribbean	34
Sub-Saharan Africa	43
Middle East & North Africa	17
Europe & Central Asia	10
South Asia	7
East Asia & Pacific	24
Total	135

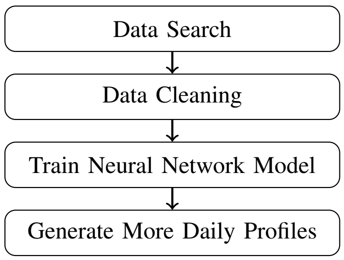

Fig. 1. Overview of the proposed profile generation framework.

discuss the data collection steps, the processing of this data, and how we handle discrepancies across the various sources.

A. Search Space and Methodology

First, we establish the search area of interest. Our goal is to obtain national load profiles for underrepresented regions. This means the load profiles obtained have to be at the national/country level only, excluding individual commercial building demands, microgrids, small town- and village-level demand profiles, etc. Secondly, since we are focusing on non-Western grids, we are primarily considering countries in South and Central America, Africa, the Middle East, and Asia. This leaves us with 135 countries, defined by the World Bank map [13], after excluding several disputed territories. A breakdown by region is provided in Table I and the entire methodology used to derive the load profiles for all these countries is shown in Figure 1.

B. Data Search and Collection

A comprehensive search for daily electric load profiles was conducted for all 135 countries. For a given country, an ideal result would be a publicly available, representative load profile from a trusted source, obtained via real-time measurements. This data could be in the form of a dataset or graph, providing clear national load values (either normalized or not). Out of 135 countries, we initially found data that could be used for 99 of them. Most data sources were drawn from research papers published on IEEE Xplore, ResearchGate, and ScienceDirect (e.g., [14]–[16]). Multiple datasets were also collected from reports published by national energy agencies [17], and the International Energy Agency (IEA) [18]. Figure 2 visualizes the results of the search conducted and the analysis done in Section II-C. The results of this search showed that there were countries missing data on every continent searched. However, Sub-Saharan Africa is the region missing the most data, with 62.7% of countries lacking data.

The majority of the collected data was graphical (i.e., plots showing hourly variation over a 24-hour period) [18], although there were also tables and heat maps [19]. Most of the data came from measurements conducted over a 24-hour period, while some datasets provided synthetically generated data. The complete list of load profile sources can be found in [20].

C. Challenges with Data Sources

The data collection step faced several challenges beyond the lack of existing data in many countries. We discuss them in this subsection.

1) Smaller Geographical Regions: Some research papers specifically examine small rural village test cases [21]. Although these sources provide daily load graphs, they do not adequately capture national-level demand variation. This is because these rural areas do not have much industrial or commercial load; it peaks in the mornings and evenings, when people are at home most often, while the load plummets during working hours. Although these are good datasets for the areas in which they wrote the paper, the goal of this project is to obtain a daily electric load representative of the entire country. Therefore, unless the rest of the country lacks any kind of industrial or commercial infrastructure, these datasets are not considered a good representation of the whole country. For this reason, data from sources explicitly focused on rural areas or small villages were removed from the dataset.

2) Outdated Load Profiles: Another challenge relates to the time of collection. For some countries, the most recent available data dates back to the 2010s [22]. This posed the question of whether this data would still be valuable to other researchers. In instances where more recent data were found, older data were not used. However, in situations where there was no recent source, the older data were the best available and therefore still included in our repository.

3) Data Volume Disparities: The variation in data quality and type across the various sources posed another major challenge. Some data sources used averages, others provided data for many seasons or over many days, and some gave data from a single day. For our purposes, an ideal data source would be one that uses averages since we seek to create a generalized representation of the country as a whole rather than from a specific time period. When datasets were collected across multiple months, we selected data from April, as spring months offer more consistent weather conditions than the extremes of winter or summer [23]. When data across multiple days were available, the middling dataset was used to create a more averaged result.

To represent the nationwide average, it was most difficult to generalize from data corresponding to a single day. For example, if a country typically has a warmer climate but the data was collected on the coldest day of the year, the data probably is not the best overall representation of the country. As a result, the ultimate problem is that there is no way to tell whether that day is the best representation when there are

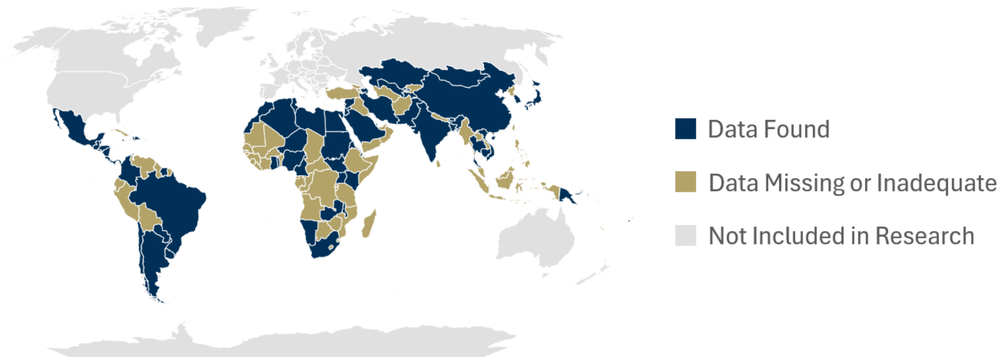

Fig. 2. Geographic representation of countries where data were found via extensive searching versus countries where data need to be approximated.

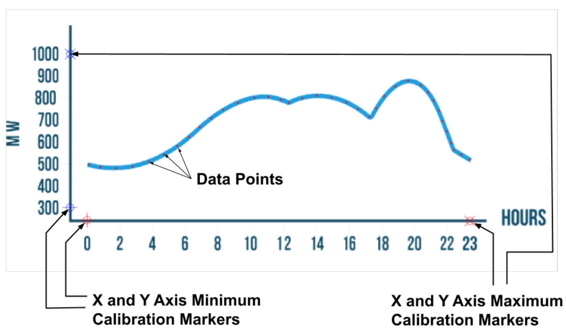

Fig. 3. Graph of El Salvador's load profile [17] being analyzed by GRABIT.

no other sources. In these cases, we sought additional data sources that might be more accurate; however, if none were found, we used the data from a single day, as it was the best available.

D. Processing and Analysis

After analyzing the 99 identified data sources and accounting for the aforementioned challenges discussed in Section II-C, 66 publicly available data sources were deemed the best representation of the respective country's daily load profile. We take two further steps in our data processing and cleaning stage.

1) Image to Dataset Conversion: Most of the data obtained was presented in graphical form, showing the variation in load (in MW) over the 24-hour period. The majority of these graphs lacked clear labels and elements that would have made them easy to convert into numerical form. To address this issue, we utilize the GRABIT package in MATLAB to extract the data [24]. GRABIT allows a user to upload images, calibrate the x- and y-axes based on image labels, and place points on the graph. It then uses the axes calibration data and the placed points to provide the user with a dataset of all points. This enabled us to convert the digital graphs into numerical datasets. Figure 3 shows an example of how this works using the load profile graph for El Salvador [17].

2) Normalization of Load Profiles: With rapid industrialization, growing populations in many countries, and the affordability of new renewable generation technologies, it is unsurprising that electricity demand has increased in recent years [25]. To make these graphs accurate, accessible, and applicable to whatever research needs arise, we decided to create normalized datasets.

Once all available datasets were converted to numerical form, we normalized the data by dividing each point by the dataset's mean. The decision to normalize the data using the mean was made because data on yearly energy consumption in most countries are publicly available [9]. The yearly consumption can then be used to calculate the average energy consumption per hour (MWh) every day. This can then be used as a multiplier for the dataset, yielding an accurate daily electric load based on that year's energy consumption. This process enables the datasets to be used in future years as total energy usage changes.

III. Generation of Synthetic Load Profiles

The process discussed in the prior section identified datasets for 66 of the 135 countries, leaving 69 missing accurate, usable data. For countries where no data was available, created our own data to provide a baseline profile until accurate load profiles become publicly available. We train a deep neural network on the data discussed in Section II-B, along with data from other European countries, and predict load profiles for countries for which no data were available. The rest of this section describes the reasoning behind this approach, the neural network's structure and characteristics, and its performance in predicting load profiles.

A. Preliminary Considerations

Our first approach was to analyze whether geographic location played a substantial role in a country's daily load profile. This would allow using the profile of one country as a proxy for neighbors whose load profiles were unavailable.

Initial analysis indicated that this method was unlikely to be a viable option. For instance, consider the normalized

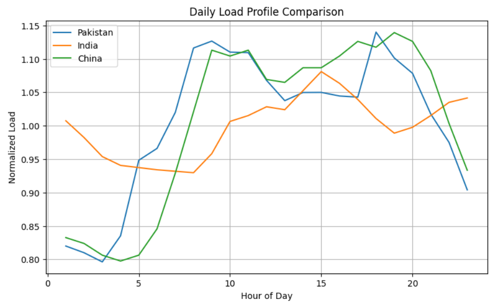

Fig. 4. Graph of normalized daily load curves for Pakistan [20], India [20], and China [20], which shows a significant difference despite close geographic proximity.

load data for India, China, and Pakistan shown in Figure 4. While all three countries share borders, their daily load curves differ. Pakistan and China have similar curves; however, when compared with India's daily load profile, they differ significantly. India has two dips when China and Pakistan are near their peak values. At midday, when China and Pakistan have a dip, India hits its peak. India is an outlier compared to China and Pakistan, but because it is difficult to predict what countries will be outliers, this confirms that it is difficult to predict the load based on geography alone. Another issue with this method is evident in Figure 2, where groups of countries in Central and West Africa lack data on load profiles. Consequently, using geographical approximations is more difficult because there is less data available within those clusters of countries.

B. Determining Factors

Beyond geographic location, several other factors shape a country's electricity demand profile over the course of a day. The timing of the peaks and troughs, the maximum deviation from the average, and the steepness of the curve are determined by various factors. To accurately characterize a country's profile, we determine which factors to use and feed them into a deep neural network. A crucial characteristic of these factors is that they had to be publicly available and broadly applicable across all countries. There were five factors that met these parameters and served as inputs to our neural network, which predicts the 24-hour demand profile of any country.

1) Population – The total number of individuals living in a specific country. Population has often been shown to be a good indicator of electricity demand, making this a potential determinant of the daily load profile [26].
2) Gross Domestic Product (GDP) – The total value of all finished monetary goods and services produced in a country. This acts as an economic health indicator and could serve as an indication of industrial and commercial activity during the day, consequently affecting national load profiles [27].
3) Köppen Climate Classification – This identifies 5 different climate types (tropical, arid, temperate, continental, and polar) using temperature, humidity, precipitation, and seasonality statistics [28].
4) Industrial Infrastructure – To find a metric that would account for industrial infrastructure, we used the percentage of value that industry added to that country's GDP. This shows how reliant a country's economy is on industrial infrastructure [27].
5) Percentage of Solar – The percentage of power generated from solar panels. This accounts for the possible presence of a duck curve [29].

C. Neural Network Inputs and Outputs

The inputs to our neural network are population, Gross Domestic Product, climate classification, each country's industrial share of GDP, and the percentage of the country's electricity generation that is solar. The output is a length-24 vector representing the country's daily load profile, normalized to the average. This is visualized in Figure 5.

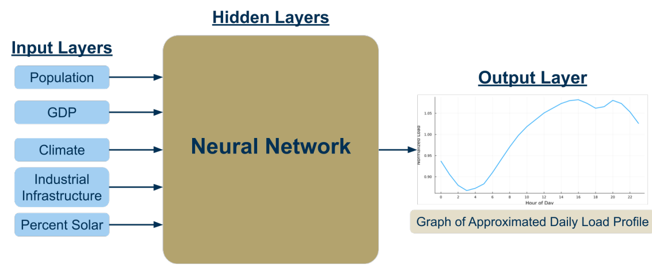

Fig. 5. Visual representation of the neural network created.

Population, GDP, industrial share, and solar generation values can be directly fed into the neural network because they are numeric. Conversely, we use a one-hot classifier to encode the climate classification input for the neural network. We classify countries as Arid, Tropical, Continental, Temperate, Polar, and Diverse, which correspond to the different climate zone designations [28]. Each country has a 1 in the climate category if the majority of the country has that climate. They have a 1 in the Diverse category if the country contains more than three climate types.

All the input parameters are publicly available, thus making them valuable for our purposes. The population, GDP, and industrial share of GDP can all be found in the World Bank Group data repository [30]–[32], while the climate designation for each country was determined using a map created by the Smithsonian Institution [33].

D. Neural Network Parameters and Structure

This neural network takes 34 inputs and outputs 24 data points, one for each hour of the day. It consists of three hidden layers with 128, 64, and 32 neurons. We set the number of epochs to 2000 and the batch size to 8. The Adam optimizer [34] was used with a learning rate of 0.0005. Due to the wide range of input magnitudes, we normalize the population, GDP, industrial share, and solar percentage inputs

TABLE II
SUMMARY OF RESULTS FROM THE LEAVE-ONE-OUT CROSS-VALIDATION OF NEURAL NETWORK PERFORMANCE.

Metric	Value
Mean-Squared Error	0.01732
Mean-Absolute-Error	0.0885
Mean Absolute Percentage Error	9.58%
Within ±5%	40.2%
Within ±10%	69.7%

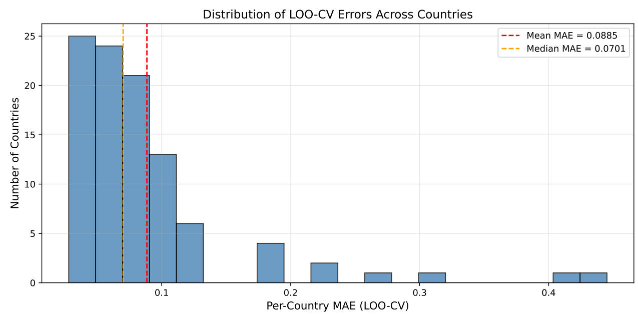

Fig. 6. Neural network performance under leave-one-out validation.

to improve training stability, convergence speed, and overall model performance.

Combining the data from Section II-B with data from European countries yields a total of 99 training samples. This is a relatively small training dataset, which is not ideal. We thus conduct the following performance evaluation.

E. Neural Network Performance Evaluation

To assess the performance of the neural network model, we use leave-one-out (LOO) validation [35]. This method is used to obtain an accurate estimate of the performance of a neural network created with a small dataset, such as ours. This is done by systematically leaving one country's hourly data out of the neural network, then using the neural network to approximate the data that was left out, so it can be analyzed and compared to the actual data.

The performance results from training our neural network and testing with leave-one-out cross-validation are summarized in Table II and visualized in Figure 6. The results show that the neural network model performs fairly well with the presence of some significant outliers. The majority of the predictions have a Mean Absolute Error (MAE) of less than 0.1, which is unitless because it was calculated from normalized values. Notable outliers in the LOO histogram are China (0.33), the Netherlands (0.41), Bosnia (0.32), Suriname (0.27), and Haiti (0.26). These countries have load profiles that are unusual relative to others in their climate group, so the model struggled when they were withheld. Ideally, both MAE and Mean-Absolute Percentage Error (MAPE) values would be as small as possible, but this is challenging given the limited amount of input data. For our purposes, an MAPE of less than 10% (meaning that the predicted values, on average, were off by less than 10%) was considered reasonably accurate.

F. Load profile Repository

The daily load profiles for all countries are now publicly available in a fully open-source repository[1]. This repository contains data for 157 countries, 99 of which were published in various sources, and 58 of which were approximated using a neural network.

IV. SOLAR GENERATION MODELING

Unlike load modeling, obtaining solar generation profiles is much more straightforward. Solar generation is more predictable and can be easily determined by physical principles. Solar output at any location depends on the sun's position in the sky, which changes throughout the day. During nighttime hours, solar output is zero. After sunrise, the output increases until peaking around midday. After that, the output decreases as the sun moves toward sunset.

Even though the total amount of solar energy can vary between locations, the overall shape of the curve remains similar for regions at similar latitudes. This is because the timing of sunrise peak generation and sunset is controlled by geographic position rather than local system conditions. As a result, regions close in latitude often exhibit very similar solar generation patterns. This allows for multiple simulation tools to provide adequate solar generation profiles.

The solar profiles in our repository are developed using one of these tools, called PVWatts® Calculator, an online simulator that estimates the energy production of grid-connected photovoltaic (PV) systems worldwide. It allows homeowners, small building owners, installers, and manufacturers to easily develop performance estimates for potential PV installations[2]. This tool was developed by the National Laboratory of the Rockies, and its reliability has been validated in prior studies, making it widely accepted in both academic and industry contexts [36], and thus a strong candidate for this application.

The model inputs include geographic coordinates, system capacity, panel orientation, and default system loss assumptions. The resulting output includes hourly AC power generation, annual energy production, and capacity factor metrics. For simplicity, we store a representative daily load profile, normalized to each country's values, in our repository. We normalize over the maximum or the rated capacity of the solar unit. We define the representative day as the average over the course of the year; however, for more detailed modeling, the user can obtain a more detailed simulation from the PVWatts® website.

V. CONCLUSION

This paper addresses the challenge of limited time-series data in synthetic grid test cases, particularly for non-Western regions. Existing test cases often provide only nominal load values, limiting their effectiveness for modeling and applications that require multi-period load data. To address this gap, this study developed a framework for consolidating existing

[1]The load profiles can be accessed at https://doi.org/10.5281/zenodo.20695292 and can be visualized https://solarloadprofileatlas.streamlit.app/

[2]The PVWatts® Calculator can be accessed at https://pvwatts.nlr.gov/

data and generating synthetic load and solar generation profiles using scalable, data-driven methods.

For the daily load profiles, the proposed solution combines cataloging available data with load modeling techniques, using a deep neural network to create approximations for countries with missing data. The data collected and created are publicly available in a repository for use by the research community. Additionally, we employ the simulation-based software PVWatts® to obtain representative solar curves for every non-Western country. Ultimately, this repository provides a one-stop location for all global daily load and solar profiles.

Several challenges remain to be addressed in future work. The neural network's results for load profiles were promising. However, there are still a few outliers due to the erratic behavior of load demand in some regions. This raises the need for more real data to be used for both training and validation, ultimately increasing the model's accuracy. Further research on load profiles may be conducted to obtain additional load data, such as year-long profiles that capture monthly and seasonal variations. Over time, as more measured load profile data is published, we will replace any synthetically generated profiles in our repository with the new data. Additional analysis for the solar profiles may also explore hybrid approaches that combine simulation-based models with real-world data to enhance accuracy.

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