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A Holistic Approach to Power Systems Using Innovative Machine Learning and System Dynamics

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Abstract: The digital revolution requires greater reliability from electric power systems. However, predicting the growth of electricity demand is challenging as there is still much uncertainty in terms of demographics, industry changes, and irregular consumption patterns. Machine learning has emerged as a powerful tool, particularly with the latest developments in deep learning. Such tools can predict electricity demand and, thus, contribute to better decision-making by energy managers. However, it is important to recognize that there are no efficient methods for forecasting peak demand growth. In addition, features that add complexity, such as climate change and economic growth, take time to model. Therefore, these new tools can be integrated with other proven tools that can be used to model specific system structures, such as system dynamics. This research proposes a unique framework to support decision-makers in dealing with daily activities while attentively tracking monthly peak demand. This approach integrates advances in machine learning and system dynamics. This integration has the potential to contribute to more precise forecasts, which can help to develop strategies that can deal with supply and demand variations. A real-world case study was used to comprehend the needs of the environment and the effects of COVID-19 on power systems; it also helps to demonstrate the use of leading-edge tools, such as convolutional neural networks (CNNs), to predict electricity demand. Three well-known CNN variants were studied: a multichannel CNN, CNN-LSTM, and a multi-head CNN. This study found that the multichannel CNN outperformed all the models, with an R^2 of 0.92 and a MAPE value of 1.62% for predicting the month-ahead peak demand. The multichannel CNN consists of one main model that processes four input features as a separate channel, resulting in one feature map. Furthermore, a system dynamics model was introduced to model the energy sector's dynamic behavior (i.e., residential, commercial, and government demands, etc.). The calibrated model reproduced the historical data curve fairly well between 2005 and 2017, with an R^2 value of 0.94 and a MAPE value of 4.8%.

Keywords: smart grids; machine learning; peak demand; optimization; system dynamics

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1. Introduction

The digital revolution requires greater reliability from electrical power systems; this is an issue that is becoming more prevalent due to rising consumer demand and the increasing use of electric vehicles (EVs). As a result, leaders in the energy sector struggle to manage the energy industry more efficiently and sustainably, especially as they recover from the COVID-19 pandemic. Energy planners use deterministic planning, stochastic optimization, robust optimization, simulation, and electricity forecasting to support the transition to smart grids. While robust optimization is well established as a technique for improving decision-making under conditions of uncertainty [1], the computational complexity of these problems grows as smart grids continue to move forward, adopting more renewable energy scenarios. The main challenge is to model the large uncertainty space (i.e., demand growth and renewables forecast errors) while simultaneously providing flexible computational time for real-time operation and multi-year power plant investments.

In this era of big data and uncertainty, machine learning is shifting from traditional to a more data-driven optimization of smart energy systems. For example, Jahangiri et al. [2] presented an interpretable machine learning model that is based on unsupervised learning to understand the impact of different policy inputs such as the carbon tax, the capital cost of wind, and annual demand growth on the decarbonization of the Canadian electricity system. While the model offered reduced computational time, it could not accurately capture the variations across regions when exploring a broader design space. Zhao and You [3] presented a novel robust optimization framework that was integrated with data-driven machine learning techniques to support "New York State's renewable transition planning under uncertainty". The study concluded that under the full scenario, offshore wind power could become a major energy source towards the end of the decarbonization pathway. In their study [4], Dehghani et al. recently demonstrated the importance of including the power plants' lifetime as a factor in the generation expansion planning problem, guided by a deep learning model to predict annual peak demand growth. Later, Zhao and You extended their work in [3] by introducing a novel robust optimization framework that integrated multiple machine learning techniques to provide more realistic transition pathways for New York [5]. Machine learning based on clustering techniques was used as a first step to reduce the model, making it less computationally demanding. Similarly, the study found that offshore wind, hydro, and utility solar power could dominate the transition planning [5].

Experts' insights and a literature review revealed a major concern for the energy industry. Energy firms face challenges in predicting and managing peak demand growth more sustainably in the long term; the resiliency of smart grids is now being impacted by extreme weather events, as well as the greater demand imposed by electrification in end uses (i.e., cooling, heating, and transportation). For example, Skiles et al. [6] provided a broad perspective of the evolution of peak demand growth for the Electric Reliability Council of Texas (ERCOT), explaining how energy planners could be better prepared based on the lessons learned from the events of February 2021 that left millions of consumers without power. The study emphasizes that cold weather, extreme weather events, and the increasing adoption of heating electrification could represent significant challenges for managing the winter peak demand in the future. Moreover, Chen et al. [7] evaluated the sensitivity of peak demand growth to climate change impacts across several regions in China, with eastern China being the most sensitive to high temperatures due to the demands of air conditioning penetration.

This paper is an extension of our previous work in [8,9] by providing a holistic framework that can support the actual decision-making needs of the energy industry. Most importantly, a decision-making tool is needed that can assist energy managers with the critical decisions related to day-to-day operations, while enabling them to closely manage and respond to peak demand growth more effectively in the long term. The novelty of this work brings together advances in the machine learning and system dynamics fields, integrated through a data-driven framework and validated with a case study regarding the Republic of Panama to support forecasting. This case study was essential for comprehending the challenges that power systems face and how the industry should be organized in the future. The major contributions of the investigation thus presented are as follows. First, this research presents a holistic framework that is validated with a case study that considers different dimensions such as the stakeholders, the power industry (e.g., Siemens Energy), the Panama experts' opinions, and the literature review to understand the real challenges that are faced by the energy industry.

Most importantly, this work is a predictive tool that can help energy managers to react faster to critical peak demand periods before they occur. First, this research seeks to identify and test state-of-the-art machine learning methods, guided by a system dynamics scheme, to provide a more robust forecast analysis. Second, this research provides a mapping of how one-dimensional (1D) convolutional neural networks (CNN) can address complex problems in the energy industry, such as predicting peak demand. Furthermore, this study allows researchers and other interested people to see how different modeling approaches, such as CNN, can target this challenging problem by facilitating a sophisticated feature extraction scheme that conventional machine learning methods cannot accomplish. This paper is organized as follows: Section 2 introduces an extensive literature review, conducted with the keywords of machine learning, deep learning, CNN, electricity forecasting, and peak demand growth. In addition, the research gap was also discussed through a conceptual map that helps to visualize the relationships among the key areas studied. Section 3 provides a high-level overview of the decision-making framework and demonstrates the integration of the system dynamics and machine learning models. Section 4 introduces the case study, while Section 5 shows the implementation of the framework in the case study. Lastly, Section 6 presents our conclusions.

2. Literature Review and Research Gap Analysis

Different models have been suggested in various academic publications for predicting electricity demand. These models can be grouped into four primary classifications: regression models, time series models, machine learning models, and deep learning models. A handful of studies in the literature aimed to improve electricity forecasting models. To improve long-term electricity consumption forecasting in Saudi Arabia, Almuhaini and Sultana [10] compared machine learning algorithms with a well-known statistical model. Significant features related to electricity consumption were investigated, such as population, gross domestic product (GDP), imports, and refinery oil. The study confirmed that a machine learning model based on nonlinear autoregressive networks with exogenous inputs (NARX) provided the highest accuracy and was reliable, with a mean absolute percentage error (MAPE) of 0.3219 and an R^2 value of 99.6%.

Liu and Li [11] tested the performance of three models based on backpropagation neural networks, multiple linear regression, and support vector machines to predict electricity consumption in the United Kingdom (UK). The study revealed that all the models overestimated the energy demand using the test set. The reason behind this was the slow economic decline of the UK in the period 2005–2019, which affected the training of the models. The authors suggested incorporating other economic indicators besides GDP that had a stronger correlation with electricity demand. Stamatellos and Stamatelos [12] suggested feed-forward neural networks for predicting electricity demand 24 h in advance for the Greek electricity system. The models incorporated important features such as the daily heating demands and cooling degree days in Athens, a representative location. The model performed reasonably well on a test set encompassing 12 months in 2022, with a mean value for a MAPE of 3.66%. Aswanuwath et al. [13] boosted the training of an ANN, using a similar day selection approach to predict electricity demand in Thailand. An appropriate decomposition method was used to capture the seasonality of the data. The results demonstrated the model's potential to handle normal days with a MAPE of 2.8%, while requiring a low computational cost. Moreover, Chaturvedi et al. [14] recently attempted to predict the monthly peak demand for India by presenting a comparative assessment of various time series and machine learning models, such as the seasonal auto-regressive integrated moving average (SARIMA), long short-term memory (LSTM), and Prophet, a model developed by Facebook. Unfortunately, all the models severely under-predicted the monthly peak demand, with the Prophet model delivering a high MAPE of 3.3% on a test set covering the two years between April 2017 and March 2019.

Khan et al. [15] presented enhanced machine learning models that were based on SVM and CNN to support electricity forecasting in smart grids, using a big data set from ISO-NE. A feature selection and extraction scheme were implemented to reduce the computational complexity. Despite the significant effort allocated to improving the models, the performance of the CNN slightly increased, with an accuracy of 88.1%. Similarly, Aslam et al. [16] evaluated a hybrid CNN-GRU model to predict the electricity demand of residential buildings using a big data set covering eight years of data from ISO-NE. In addition, the model was guided by a novel coronavirus herd immunity optimization that was introduced for fine-tuning the hyperparameters. As a result, the model achieved 92% accuracy without overfitting due to the robustness of the model, with more convolutional layers considered. Jin et al. [17] attempted to predict the monthly peak demand for a city in China by developing a hybrid LSTM and backpropagation neural network (BPNN) scheme that separately extracts the relevant features related to peak demand, such as meteorological and economic indicators. The model is constantly updated by the BPNN, which continues to feed in future information to improve predictive performance. Nonetheless, a constraint of this study was the limited amount of yearly data available to train the model adequately. Wood et al. [18] evaluated the performance of LSTM for predicting daily electricity demand, using data sets from six different load sectors, such as hotels, EV charging stations, residential premises, etc. While the model's training was relatively stable, LSTM could still not overcome the vanishing gradient problem. Alsharekh et al. [19] focused on improving short-term electricity forecasting through a residual CNN that was guided by a multilayered LSTM to learn sequential information. The model significantly improved accuracy on a residential benchmark data set, with an R^2 of 0.97 and a MAPE of 2.45%. Finally, Mounir et al. [20] found that an electricity forecasting model based on empirical mode decomposition (EMD) and bidirectional LSTM was the most suitable choice for predicting household energy consumption.

The literature review showed that energy planners require more accurate forecasts to help support decision-making at different smart-grid energy management levels. With the rapid development of smart grids, utilities need to project future scenarios for peak demand and the growth of energy consumption to support the long-term expansion of power grids. However, the literature review demonstrated that forecasting electricity demand in the long term is challenging, due to the uncertainties and dynamic complexities of power system operations and the stakeholders involved. The impact of these uncertainties (i.e., weather, economics, etc.) is significant in terms of grid reliability. The main gap in the literature was that only a few studies were conducted on forecasting electricity peak demand in the long term, despite its growing importance, as shown in Table 1. Furthermore, these models still need more confidence to support decision-making in a broader context. For example, in a previous study [14], all the models severely under-predicted monthly peak demand in India, suggesting that these models require further improvement.

Table 1. Literature review and research gap analysis.

Ref.	Electricity Forecasting for Smart Grid Management			Limitations/Future Work
	Short-Term Forecast	Peak Demand Forecast	Long-Term Energy Consumption	
[10]			✓	The authors will extend their work to improve the models for forecasting electricity consumption in the residential sector of Saudi Arabia.
[11]			✓	The limited data could not adequately train the model to forecast annual energy consumption for the UK.
[12]	✓			Incorporating weather parameters such as air humidity and wind speed will be considered in the future.
[13]		✓		Future research directions include applying hyperparameter optimization techniques.
[14]		✓		All the models underpredicted by far the monthly peak demand for India.
[15]	✓			The proposed models will be optimized using heuristic methods and more work will be conducted on long-term forecasting.

Table 1. *Cont.*

Ref.	Electricity Forecasting for Smart Grid Management			Limitations/Future Work
	Short-Term Forecast	Peak Demand Forecast	Long-Term Energy Consumption	
[16]	✓			The models will be tested on commercial loads and price data sets.
[17]		✓		A limitation of this study was the need for annual data for training the model.
[18]	✓			Future work will consider more complex model structures.
[19]	✓			Future work will consider investigating the performance of the models in other domains, such as renewable power prediction.
This paper	✓	✓	✓	

In addition, Figure 1 presents a co-occurrence network that visually represents the relationships between key areas such as electricity demand, machine learning, peak demand, peak load, and forecasting. The conceptual map was created using VOSviewer version 1.6.19 (https://www.vosviewer.com/ (accessed on 14 May 2023)), a tool for constructing and extracting important terms from the scientific literature. The map consists of four main clusters, which represent groups of terms that are closely related. For example, the main cluster (green) is labeled "electricity demand". This cluster includes forecasting methods, hybrid models, and short-term electrical load. The second cluster (yellow) is labeled "machine learning". This cluster represents the great domain of machine learning, including important terms such as the Internet of Things (IoT), data analytics, artificial intelligence, and big data, which are key concepts for advancing smart grids.

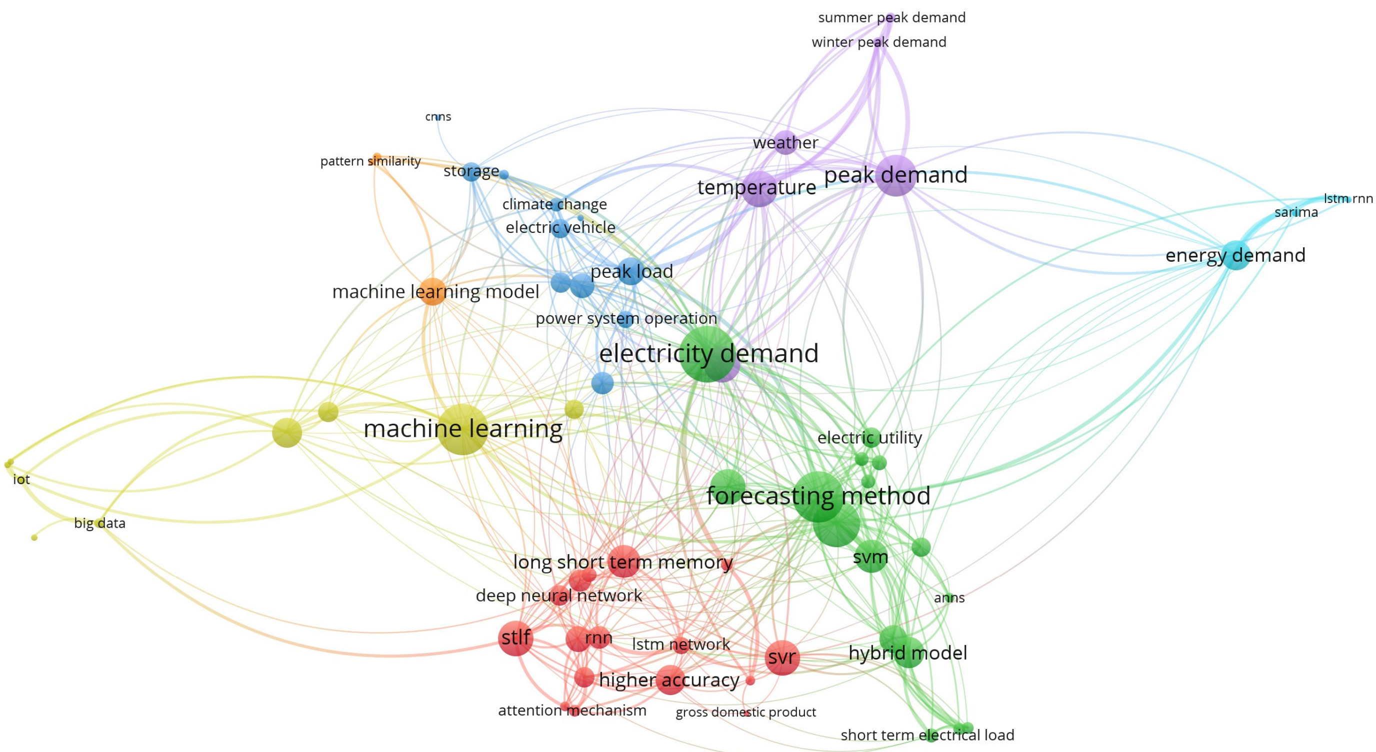

Figure 1. Relationships among electricity demand, machine learning, forecasting, peak load, and peak demand with the co-occurrence of literature review graphs.

The third cluster (blue) is labeled “peak load”. This cluster includes important terms such as energy storage, climate change, electric vehicles, and power system operation. Therefore, it became evident that numerous challenges will emerge since EVs are expected to be integrated on a larger scale, imposing a greater demand for electricity with more notable peaks. For example, a study by Benysek et al. [21] found that a moderate level of EV penetration of 20% could significantly contribute to a peak demand growth of 43% in California, USA, while in the Netherlands and Belgium, it could represent a 54% and 56% increase, respectively. This has motivated more researchers to evaluate how EVs could participate in shifting the load from peak to off-peak periods. Finally, the fourth cluster (purple) is labeled “peak demand,” which is also closely related to the third cluster (“peak load”). This cluster includes terms that characterize peak demand, such as weather, temperature, summer peak demand, and winter peak demand. Therefore, this cluster helps us to understand how peak demand is evolving due to climate change, with many regions, such as Texas, now experiencing a higher winter demand than anticipated [6], with the resulting implications for managing this wider gap between summer and winter demand.

3. Decision-Making Framework

This section introduces the heart of the study, the framework. Decision-making is quite challenging in the context of power systems management. Energy managers must make critical decisions concerning the day-to-day grid operations while ensuring that their long-term outcomes do not impact their consumers. Furthermore, decision-making depends on the decision time frame (planning horizon). For example, decisions about scheduling power plants, fuel purchases, and energy transactions in the real-time electricity markets must be considered in relation to a short period (hours to weeks).

In contrast, decisions about investment in and the retirement of power plants are planned for more than ten years ahead. The integration of decision-making involving short-term operations and long-term investment is quite challenging; this is addressed in the literature using multistage stochastic and robust optimization. However, these are large-scale problems that are computationally difficult to solve, due to the number of scenarios and constraints that must be considered. Long-term expansion plans, also known as integrated resource planning, must guide policymakers and stakeholders in managing the future transition of power systems. To develop and revise these plans accordingly, electric companies first predict future scenarios (pessimistic, moderate, and optimistic) regarding peak demand and the growth of energy consumption, based on the historical data and future indicators (i.e., economic growth, weather, and demographic projections) [8] to determine the requirements for them to be able to meet future demand. By forecasting demand, energy planners can calculate the generation capacity required to meet future demand while complying with environmental policies. In addition, it serves as an essential input for generation expansion plans, to help answer the questions of where, how many, and when new investments in power plants will be needed. Almazrouee et al. [22] stated that long-term forecasting is the most critical horizon since it involves strategic and costly decisions.

In addition, the energy industry is now on the edge of a new era, facing numerous challenges to meet increased security, reliability, and interoperability requirements. More than ever, energy leaders are being challenged to provide more realistic decarbonization pathways to accelerate the energy transition, amid global energy market uncertainty. In addition, the COVID-19 pandemic has introduced more uncertainty to the energy industry, raising concerns about current practices and the regulatory framework that has been put in place. As a result, energy leaders have realized that they can only partially depend on coal for electricity, forcing them to rethink their strategies and revise their long-term expansion plans accordingly. A recent study from the International Energy Agency (IEA) emphasized that new approaches will be needed to guarantee a secure supply of electricity, which will require several phases such as updating energy policies, adding new flexibility sources (e.g., energy storage, and microgrids), and redesigning market structures [23]. However, this is quite challenging since stakeholders still need to understand the complexity of the future energy environment and learn from past failures to prepare for change.

Most importantly, stakeholders must identify the most optimal investment in terms of energy sources to ensure sustainable operations. Many countries have set ambitious renewable targets and are undergoing a gradual but complete coal phase-out along their renewable transition pathways. Despite their increasing efforts to accelerate renewable energy investments, the gap between what is required and what is implemented continues to grow, according to the International Renewable Energy (IRENA) World Energy Transitions Outlook 2023 [24]. In addition, numerous studies can be found in the literature that attempt to model more realistic scenarios with a higher renewable energy contribution. Murugesan et al. [25] introduced a general energy framework to model the least-cost technology pathways as a way to achieve Australia's ambitious renewable energy targets. The study found that Australia could decarbonize the power system by 2039 through the extensive adoption of renewable energy technologies and the increasing uptake of EVs. Arent et al. [26] provided an interesting perspective into the opportunities and challenges of decarbonizing the US energy economy; they examined key factors such as the implications of energy storage, the decarbonization of transportation, and hydrogen readiness. Verástegui et al. [27] attempted to model the decarbonization pathways for Chile between 2030 and 2040. They found that stricter decarbonization scenarios will impose a greater demand on flexibility requirements, such as using technologies based on concentrated solar power with a large storage capacity.

This framework sets a starting point for understanding where power systems currently stand and begins to close in on the significant challenges that they face. Initially, we identified a need for a framework to help support the actual decision-making needs of large-scale power systems. The literature review revealed that most studies were focused on short-term reliability. Another significant gap in the literature was that only some studies analyzed the problem of peak demand growth in the long term, despite this being an important research topic that needs to be addressed as soon as possible. After these gaps were analyzed, the research idea was further refined to investigate whether a hybrid modeling approach could support energy managers in their decision-making process. Therefore, this research proposes a data-driven forecasting framework that considers different dimensions to support the energy managers' decision-making process. Through a complete analysis of the energy supply chain, incorporating stakeholders, the power industry (e.g., Siemens Energy), experts' opinions, and the literature review, we found that energy managers need to include three main forecasts to support decision-making for power systems management, comprising short-term, peak demand, and energy consumption forecasting. Short-term forecasting deals with predicting the demand from one hour to a week ahead. This can benefit short-term decisions, such as fuel purchasing, trading in the electricity market, and the economic dispatch of power plants while providing real-time grid monitoring and security against general power outages. Peak demand forecasting supports such decisions as planning the reserve margin to balance supply and demand during critical demand periods and investment in and the retirement of power plants over an extended period, generally of more than 10 years. Furthermore, forecasting energy consumption can help energy managers to understand what end-use sectors are consuming more energy and determine energy efficiency strategies that can be implemented to reduce the energy losses incurred throughout the distribution and grid operations.

At the core of this framework is a model for predicting monthly electricity peak demand, which will help to address the identified research gaps. Initially, we realized that only a few studies analyzed the problem of peak demand growth in the long term. However, energy planners need to manage peak demand growth more closely and sustainably as the demand for electricity increases. A broad, high-level view of the decision-making framework is shown in Figure 2, demonstrating how the objectives will be met.

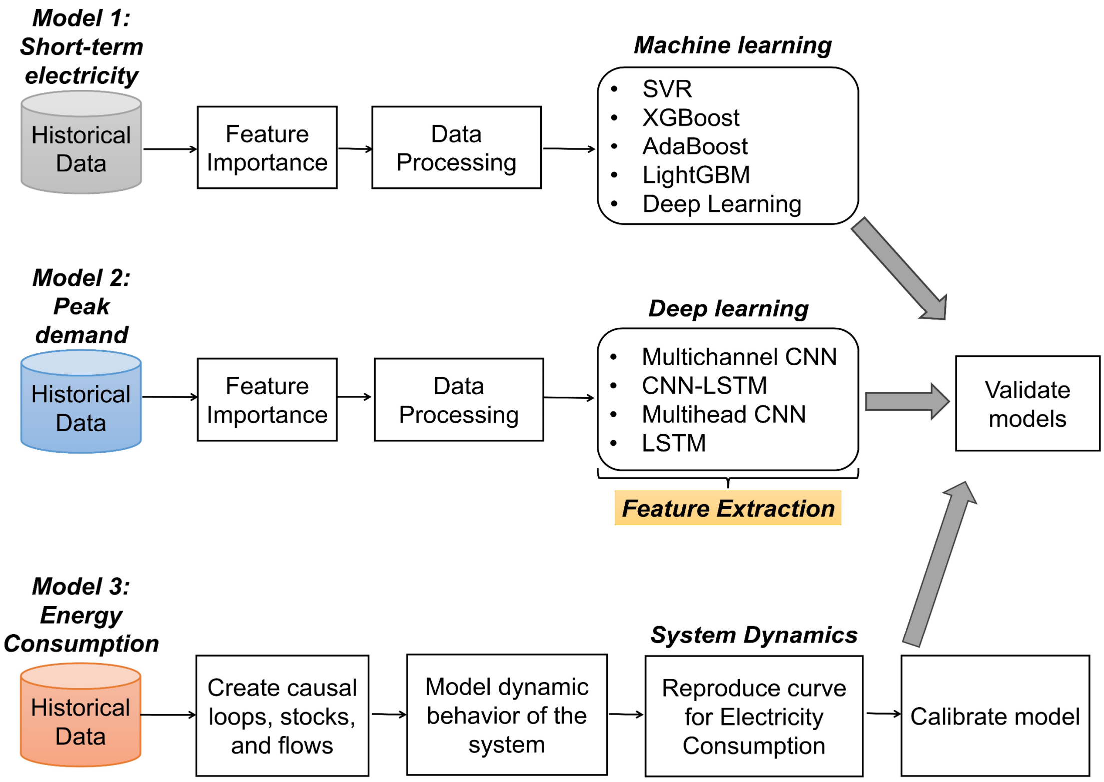

Figure 2. A high-level overview of the decision-making framework.

3.1. Deep Learning Models

3.1.1. Convolutional Neural Networks

Convolutional neural networks (CNNs) are a type of deep learning that has revolutionized the computing landscape, enabling computers to quickly interpret and derive information from a vast amount of digital data, such as images and videos. The evolution of CNN has been widely investigated in terms of depth, computational power, feature extraction, and spatial mapping to support emerging areas [28]. CNNs were initially introduced for image recognition but have now branched out to other applications, such as time series forecasting, human emotion recognition, remote sensing, medical image analysis, video compression, etc. Thus, CNN has received increased attention for leveraging data with diverse spatial, temporal, and spectral patterns. One problem in feedforward neural networks is that each neuron in the first layer is connected to all the neurons in the next layer, resulting in more parameters that need to be learned. CNN addresses this problem through two main concepts, parameter-sharing and local connectivity. Therefore, the weights are shared by all the neurons across the feature map space, which segment the regions with similar local features. Different CNN variants have been proposed for electricity time series forecasting, such as a temporal CNN, graph CNN [29], and residual CNN. Two-dimensional CNNs are also becoming popular for processing image-based time series data [30]. While these methods are gradually becoming more established, improving the generalization and predictive performance of models is still a major area of concern in deep learning. Therefore, ensemble models based on CNN are a new promising research area that has received more attention in a handful of studies [31–33].

The architecture of a CNN consists of convolutional layers, nonlinearity, pooling layers, and fully connected layers. The first layer of the CNN is the convolutional layer, which receives inputs such as time series data, images, video, or audio. The convolutional layer consists of constructive filters that perform convolutional operations as they slide over the data, generating feature maps. These maps provide a more detailed representation of the extracted features that are relevant to predicting the output. The filter size will determine the quality of the features that are extracted. Next, a pooling layer is applied to retain only the dominant features. The max-pooling layer, for example, takes the maximum value of each patch in the feature map, as shown in Figure 3.

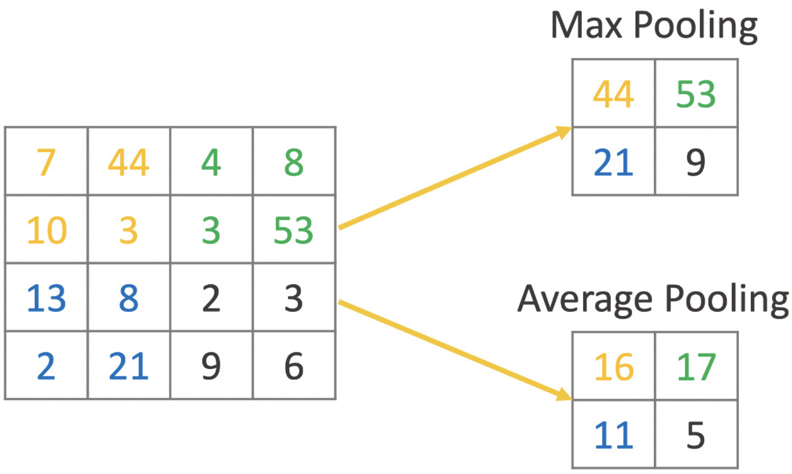

Figure 3. Example of a max-pooling layer in a CNN.

3.1.2. Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) has quickly become the state-of-the-art method of choice in many applications. Hochreiter and Schmidhuber introduced LSTM to help them overcome the vanishing gradient problem found in RNNs. LSTM consists of memory blocks with a unique feature known as the cell state, which helps them improve their memory capacity by introducing a gate. This feature makes them appealing for modeling problems with long-term dependencies, such as speech recognition, stock market prediction, text generation, etc. LSTM has greatly helped Google to improve its machine translation. The main component of the LSTM is the cell state that runs throughout the top layer, which stores the information learned from previous time steps. This information is updated at each step using three main gates, which control what information should be added or removed from the cell state. These gates comprise the forget gate, the input gate, and the output gate.

3.2. Machine Learning Models

3.2.1. Random Forest

Random forest (RF) is a popular machine learning model that is used extensively for classification and regression tasks. RF consists of an ensemble model that combines multiple decision trees, known as classifiers or estimators. Each decision tree is trained on a random subset of n samples of the training data set, using a bagging technique. In bagging, a decision tree can be trained more than once using the same sample. RF also involves feature sampling, where only some input features are selected to split the trees at each decision node successively. Therefore, only some of the training set's features ($m < M$) are used as predictors. This process ensures that the trees are slightly correlated with one another. Finally, the average of all the predictions of the decision trees is calculated, resulting in the final output. Figure 4 demonstrates the first decision tree node of the RF model that has been proposed for predicting hourly electricity demand, with a maximum depth of 2. As observed, the electricity demand from the previous week was determined to be the most important feature to split the first decision node.

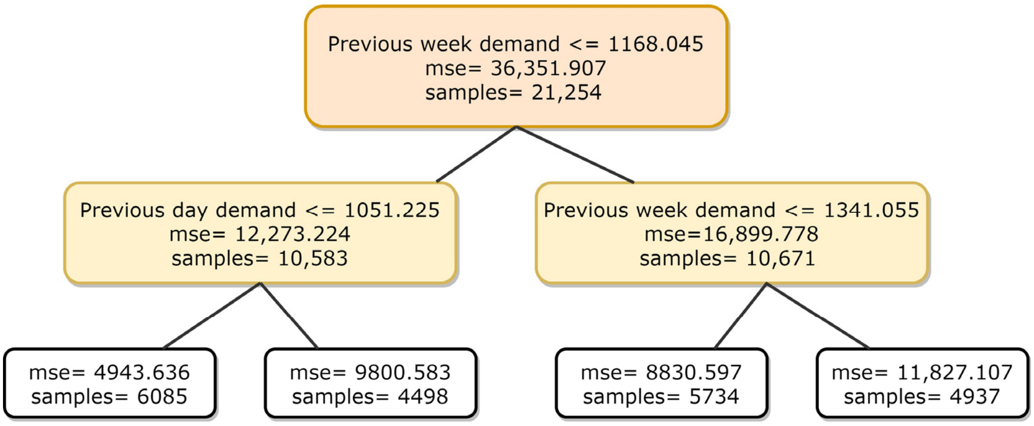

Figure 4. First decision tree node of the RF model for predicting hourly electricity demand.

3.2.2. Adaptive Boosting (AdaBoost)

AdaBoost is another popular machine learning algorithm that attempts to train an ensemble of "weak learners" to create a strong learner. AdaBoost consists of one-level decision trees, referred to as stumps, whereby one split is created based on a single input feature; therefore, these are considered weak learners. The AdaBoost algorithm starts by initializing the weight vector, where the same weights are assigned to each sample of the training data set. For each iteration, more weight is assigned to those instances that were incorrectly predicted or classified via an oversampling technique, so that the subsequent model can focus more attention on them, boosting the performance of the base learners.

3.2.3. Light Gradient Boosting Machine (LightGBM)

LightGBM is a stable gradient-boosting framework introduced by Microsoft [34] to address the challenges of training high-dimensional data sets. The framework has been successful in tabular data competitions. The LightGBM algorithm computes the histogram of gradients to determine the most optimal decision tree split, which helps to accelerate the training process. The LightGBM has many advantages, such as parallel and distributed learning, low memory usage, and feature sparsity. In addition, open-source libraries such as DASK-ML and Apache Spark support training the LightGBM.

3.3. System Dynamics

System dynamics represent a simulation tool that helps experts from academia and industry to model the complex problems that arise in business and in the supply chain. The tool is based on systems thinking, which uses a holistic approach to analyze the interrelated parts of a system and how systems evolve. This approach is extensively used in engineering management and is employed as a guide for leadership. According to Sterman [35], the dynamic behavior seen in systems arises because they are constantly changing; they present strong interactions among components, are nonlinear, and are governed by feedback. Sterman indicated that humans have difficulties making decisions in a dynamic world because "we use mental models that are static, narrow, and reductionist".

Therefore, system dynamics can help us to understand how changes in one variable can produce different outcomes for the system as a result of "cause" and "effect" relationships. Most importantly, it can help us to understand how our decisions affect the system's state. However, these models are not easy to build for several reasons, such as the lack of accurate data and of the skills needed to build reliable models. Forrester introduced system dynamics at the Massachusetts Institute of Technology in 1956. There was a significant breakthrough when Forrester worked with managers at General Electric (Boston, MA, USA) and noticed a problem with employment instability. Since then, system dynamics has taken shape and has been applied to many areas such as workforce management, defense, inventory management, the prevention of cyberattacks, modeling pandemics, etc. However, system dynamics has mainly been used for improving policy design.

Albin, under the supervision of Forrester, provided several critical steps for building good system dynamics models. The first step is conceptualizing the model, which starts with defining the purpose of the system, identifying key variables, and drawing the causal loop diagrams to frame, examine, and understand the system's basic structure. Next, the modeler must determine if the feedback loops reinforce (+) or balance (−) the causal loop diagrams. The second step is translating the causal loop diagrams into stock and flow diagrams. Stock and flow diagrams provide a higher-level representation of the system. They enable the modeler to visualize the flow of accumulated information over time through differential equations instead of from static causal loop diagrams. In this step, empirical data are needed to construct the model, and the constant parameters must be defined. The third step is to simulate the model and test the model's behavior and sensitivity to changes in the value of the parameters. The final step involves calibrating the model with historical data to validate it and build confidence.

4. Case Study

Panama has a complex power system with many stakeholders involved, such as energy suppliers, transmission companies, and distribution companies, aiming to deliver electricity to its consumers reliably and cost-effectively. As of March 2023, the three main distribution companies EDEMET, ENSA, and EDECHI (Panama City, Panama) provide electricity services to 1,259,462 clients, according to the National Authority of Public Services. The Panama Canal has hugely contributed to the country's economic growth and is one of the largest commercial trading platforms in the world. Given its global presence and free trade zones, Panama has become one of the most attractive countries in the world for tourism. The Panama Tocumen Airport is one of the busiest airports in the world, serving as a hub between South America, the Caribbean, and North America. Panama also has a rapid transit system, known as the Panama Metro, which serves Panama City and connects the north and east sides of the metropolitan area. Panama has many power plants installed, each with different operating costs and technological capabilities. As of 2023, Panama has a total of 3978 MW of capacity installed, which is distributed in the following manner: hydroelectric (1844 MW), gas (381 MW), biogas (8.1 MW), carbon (300 MW), bunker (454 MW), diesel (196 MW), wind (336 MW), and photovoltaic (457 MW) power sources. Therefore, Panama has started to rely more on combined cycle power plants that are based on natural gas, which produces fewer emissions than coal. Wind and solar energy also have a huge advantage in terms of producing zero emissions. The first solar power plant was installed in 2013, with a capacity of 2 MW; from then onward, the number of solar and wind power plants that have been installed is still growing.

Moreover, Panama has many businesses and large commercial centers that are located in metropolitan areas; they use large air conditioning systems which are energy-intensive. However, researchers are yet to determine what factors contribute to the growth of demand. According to the basic studies conducted by the Panama transmission company ETESA (Panama City, Panama), the entrance of two mega-state projects, the Panama Metro Line 1 extension and the first phase of a water treatment plant, have created more pressure on the grid in recent years. These fundamental studies indicate that demand will continue to increase as more projects are being considered, such as expanding the airport and adding new lines to the Panama Metro. In addition, the Panama Metro started its operations at the beginning of April 2014. Therefore, this scenario creates more pressure on energy managers, who must now manage a more complex system.

5. Implementation of the Framework, with a Case Study

5.1. Data Collection

Data collection was necessary to validate the framework developed in Section 3. Data were collected by approaching the various organizations in Panama that provided the relevant information. In addition, other data were publicly available. As a result, the models were developed and validated using different sources of information, as demonstrated in Table 2.

Table 2. Data collected for the case study.

Model	Data Collected	Source
Short-term Electricity Forecasting	Hourly electricity demand Temperature Relative humidity	Dispatch Center of Panama Authority of Panama Canal Authority of Panama Canal
Peak Demand Forecasting	Monthly peak demand Commercial consumption Monthly economic indicator Residential consumption Large client consumption Minimum temperature Maximum temperature	Dispatch Center of Panama Institute of Statistics and Census Institute of Statistics and Census Institute of Statistics and Census Institute of Statistics and Census Authority of Panama Canal Authority of Panama Canal
Long-term Energy Consumption-Forecasting	Population by age group Death rate by age group Number of houses Number of clients per sector Energy sales per sector Energy losses	Institute of Statistics and Census Institute of Statistics and Census Secretary of Energy of Panama Authority of Public Services Authority of Public Services Secretary of Energy of Panama

First, we collected data on the peak demand, shown by month and year, between 2004 and 2020; the data were sourced from the National Dispatch Center of Panama [36] to gain a better perspective of the evolutionary growth of peak demand. As observed in Figure 5, the peak demand has increased significantly over the past few years, reaching 1961 MW in 2019. The highest demand recorded was 1969 MW, which occurred in March 2020, just before the COVID-19 pandemic started to impact the power system's operations.

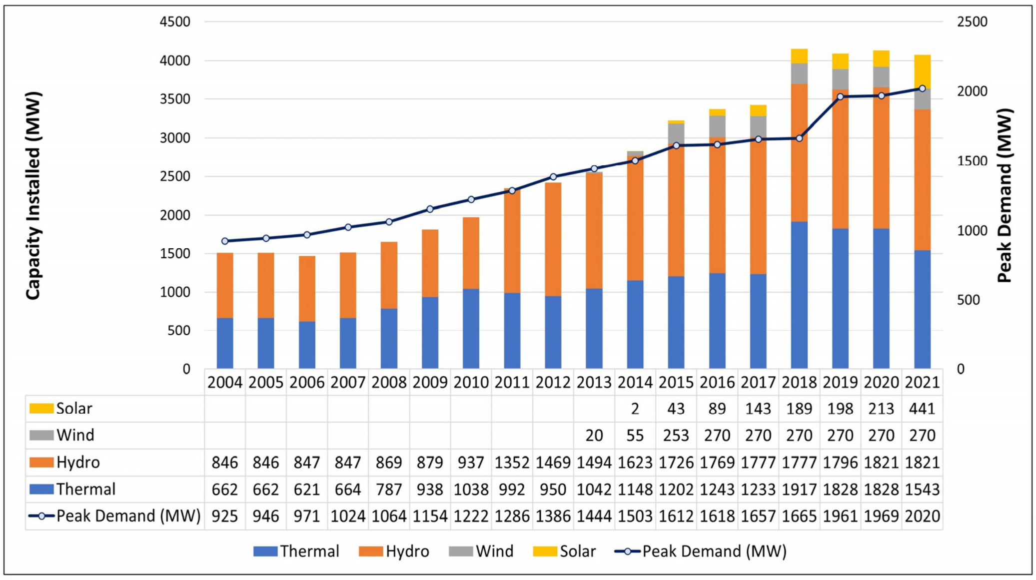

Figure 5. The generation capacity installed to meet the yearly peak demand growth, recorded between 2004 and 2021.

Panama has invested in providing significant generation capacity to meet peak demand, as part of the country's long-term expansion plan. Electricity demand is met using a diversified energy mix that includes hydro, thermal, and renewable power plants, as shown in Figure 5. As of 2019, the generation capacity currently installed is around 4000 MW, which exceeds the peak demand by far. Therefore, Panama's power system has high flexibility to meet electricity demand, especially during critical periods. According to experts from the transmission company, the probability of an energy deficit is very low; therefore, current projections do not foresee energy shortages. However, only some of the demand at peak times is supplied with renewable sources since the participation of thermal generators is required, which have higher operating costs than are seen for renewables. Therefore, experts believe that demand will move closer to the installed generation capacity by around 2030–2034.

In addition, monthly data on peak demand were collected between 2004 and 2020, as shown in Figure 6. The COVID-19 pandemic had a significant impact on Panama's electricity system. As did many other countries, the government of the Republic of Panama declared a state of emergency. In addition, it implemented extensive travel restrictions, beginning on 16 March 2020, closing the republic's borders to other countries and prohibiting the entry of foreigners as a mitigation strategy against the pandemic. Many businesses and offices had to shut down due to the quarantine measures in place, forcing consumers to work from home. As a result, the lowest demand reported was 1461 MW in April 2020. However, electricity demand is now increasing as businesses return to normality.

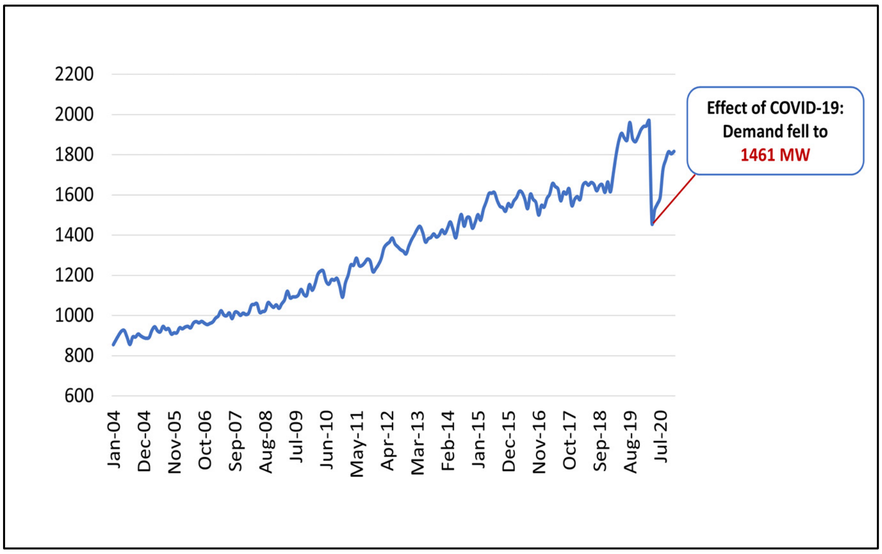

Figure 6. Effect of the COVID-19 pandemic on Panama's monthly peak demand growth, from 2004 to 2020.

The second step involved collecting historical data on hourly electricity demand, temperature, and relative humidity. The National Dispatch Center of Panama provided historical data on electricity demand from January 2016 to October 2019. These data originate from the commercial sensors that are located at the interconnection points linking them with the generators to record hourly electricity consumption. Weather factors such as temperature and humidity are also essential for predicting electricity demand. As the temperature increases, due to global climate change, more businesses and residential customers will need to use air conditioning systems, driving more demand. Humidity is also key since these appliances consume more electricity during hot and humid seasons. For this study, weather data were provided by the Panama Canal Authority for the same period, 2016–2019. The Panama Canal Authority is responsible for the operation and management of the Panama Canal. It collates hydrometeorological information (monthly rainfall, lake elevation) and weather data from different meteorological stations, which are essential for managing the Panama Canal operations. Therefore, temperature and humidity data were collected from the meteorological station Corozal Oeste, which is located at the perimeter of Panama City.

The third step was to collect data such as demographic indicators to reproduce the pattern of growth in energy consumption between 2005 and 2017. Therefore, indicators such as population and the death rate according to the age group were collected from the National Institute of Statistics and Census between 2004 and 2018. In addition, data were also collected on the number of electricity clients and energy sales per class service between 2005 and 2017. These data were publicly available from the National Authority of Public Services website, which contains historical reports of the total number of clients and energy sales per distribution company.

5.2. Feature Importance

The next step of our data analysis was to identify the most important features for capturing peak demand growth. Therefore, eight features were identified for building the model, including economic indicators (i.e., the monthly economic activity index), weather-related features, the peak demand from previous months, and the consumption in megawatt hours (MWh) of three main energy sectors in Panama, which include their residential, commercial, and large clients. Data for each feature were collected monthly from 2004 to 2019 from different sources, as shown in Table 2. First, the Panama Canal Authority provided historical daily temperature and relative humidity data. Then, we obtained the maximum and minimum temperatures for each month according to the daily temperature. Next, data on monthly economic indicators and the power consumption of the main energy sectors were collected from the National Institute of Statistics and the Census of Panama. The large clients represent consumers who can purchase electricity at freely agreed prices or who benefit from regulated rates. These clients include hospitals, manufacturing sites, and private companies. A list of the companies that are considered large clients in Panama includes Cemento Bayano, Gaming & Services de Panamá S.A., Gold Mills, Green Tower Properties, Hospital Punta Pacífica, Nestle Fabrica de Los Santos, and Nestle Fabrica de Nata. In our previous work [8], the SelectKBest method was used to determine which features contribute the most substantially to peak demand growth. The SelectKBest feature selection method is a tool from the Scikit-learn library that removes all the features except those with the highest scores. After the features were ranked, the top three features identified were: monthly economic indicator, residential consumption, and large client consumption, while the categorical variables of month and temperature (minimum and maximum) had the lowest score.

A feature selection process was also conducted to understand which variables were significant for predicting hourly demand. Therefore, ten input features were examined in terms of predicting demand. The correlation heatmap tool was used to visualize how each feature correlated with hourly electricity demand, as demonstrated in Figure 7. For example, the heatmap shows that electricity demand is strongly correlated with the following variables: the hourly load on the same day of the previous week (0.89) and the hourly load of the previous day (0.8). Temperature shows a moderate relationship (0.69).

5.3. Data Preprocessing

Data preprocessing and cleaning were necessary to ensure more efficient model training. First, all the data collected for the respective models were merged into a CSV file format and uploaded to the Jupyter Notebook using Python 3.7.6. Then, the entire data set was split into training and test sets, without shuffling the data. Table 3 shows how the data were partitioned. The second step consisted of normalizing the data between a scaling range of 0 and 1. An additional step was required for the deep learning models, CNN and LSTM, to define the input shape (batch size, timesteps, and features) to feed into the models since they needed to receive a three-dimensional tensor. Finally, the data were maintained in their original format for the machine learning models.

Table 3. Data partitioning into a training set and test set for the respective models.

Models	Training Set	Test Set
Short-term Electricity Forecasting	1 January 2016–25 January 2019	26 January 2019–31 October 2019
Peak Demand Forecasting	January 2004–September 2016	October 2016–December 2019

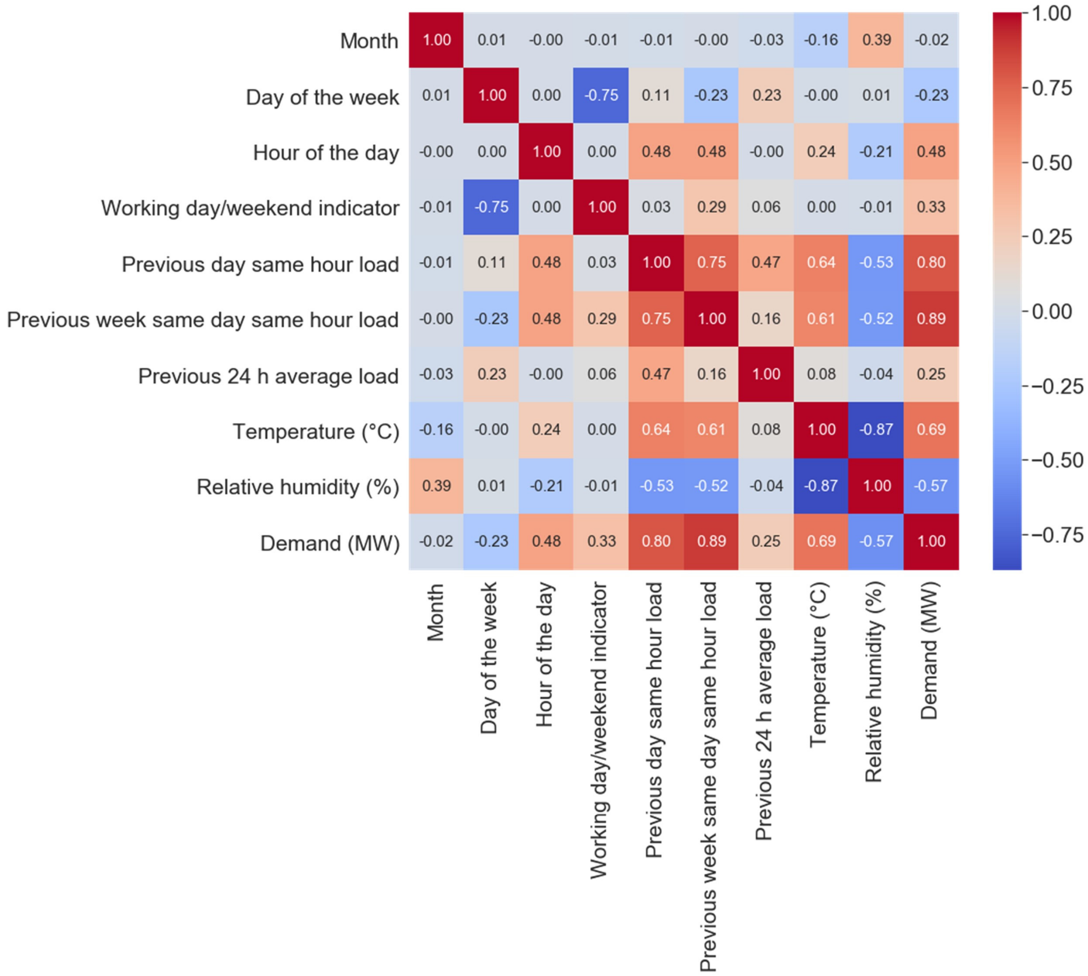

Figure 7. Correlation heatmap.

5.4. Building and Training of Machine Learning Models

5.4.1. Peak Demand Forecasting

Once the data were preprocessed and transformed, the next step of this study consisted of building and training the CNN and LSTM models. The models were built and trained in Python 3.7.6. The architecture for each of the models is demonstrated below. Initially, only four input features were considered for predicting month-ahead peak demand, based on a rigorous feature selection process that was previously conducted in [8]. These features comprise the categorical variable month, residential consumption, large client consumption, and the peak demand figures from the previous three months.

Multichannel CNN

The multichannel CNN consists of one main model that processes each input feature as a separate channel while retaining the relevant information from all the features extracted into one feature map. The CNN starts with a convolutional layer that generates several feature maps. Next, a max-pooling layer reduces the feature maps' dimensions. Then, a flattened layer outputs the information as a vector, which is then passed through a dense layer. Figure 8 shows the plotted graph for the multichannel CNN model. As can be observed, the model starts with a convolutional layer with the input shape (3, 4), which means that the model receives three previous time steps consisting of four input features.

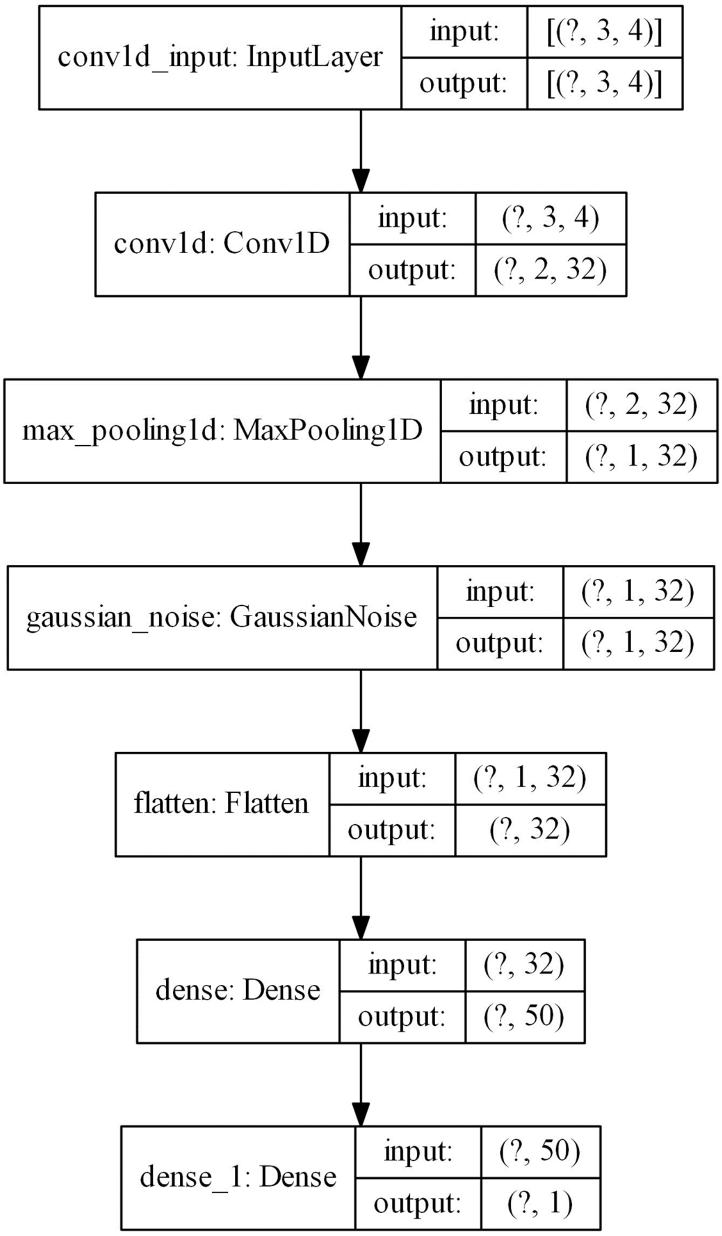

Figure 8. Multichannel CNN model.

CNN-LSTM

The first layer of the CNN-LSTM model consists of a convolutional layer that applies 32 filters to extract those features related to peak demand. A max-pooling layer is then applied to downsize the feature maps. Finally, the features extracted are further transformed by an LSTM layer, which models the sequential patterns. Figure 9 shows the sequential plot graph of the CNN-LSTM.

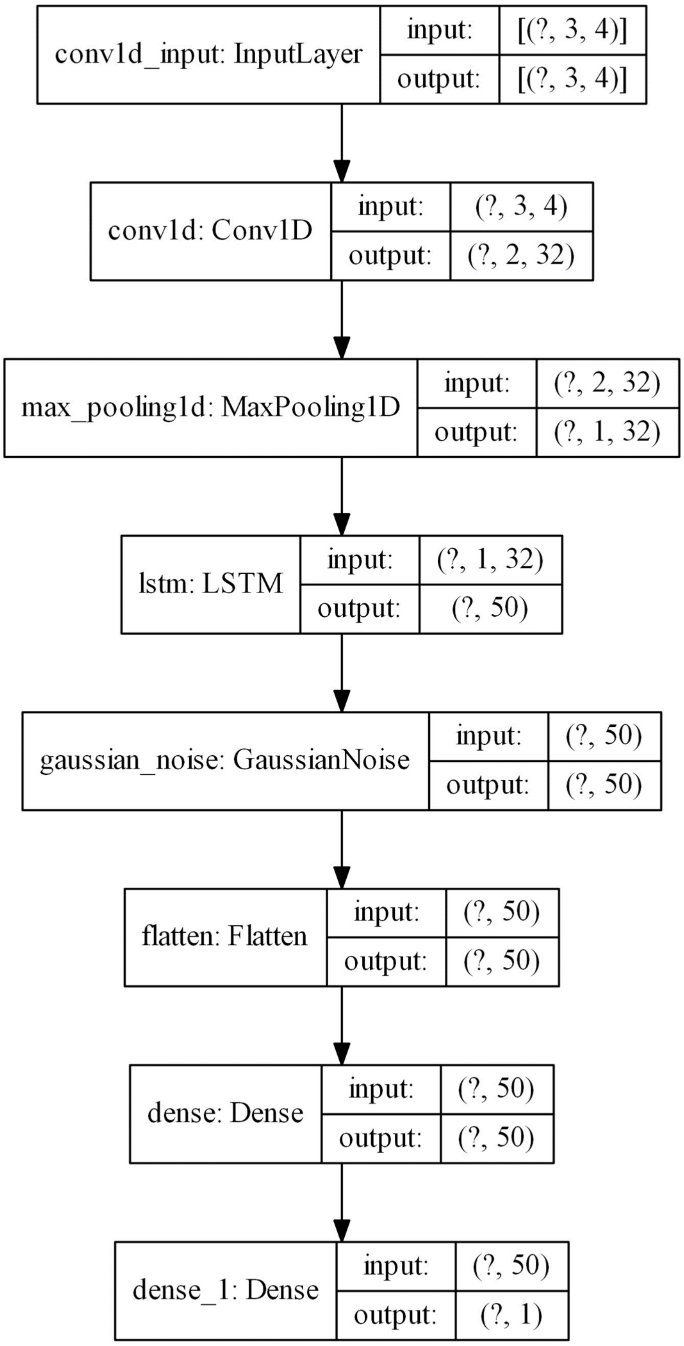

Figure 9. CNN-LSTM model.

Multi-Head CNN

A multi-head CNN model consists of four sub-CNN models that process each input feature separately. Therefore, a feature map is produced for each input. The results of each model are concatenated and then pass through the dense layers. Figure 10 depicts the plot graph for the multi-head CNN model. As observed, each submodel receives an input shape of (3, 1), meaning that the previous three months with one input feature represent the sequence of this model.

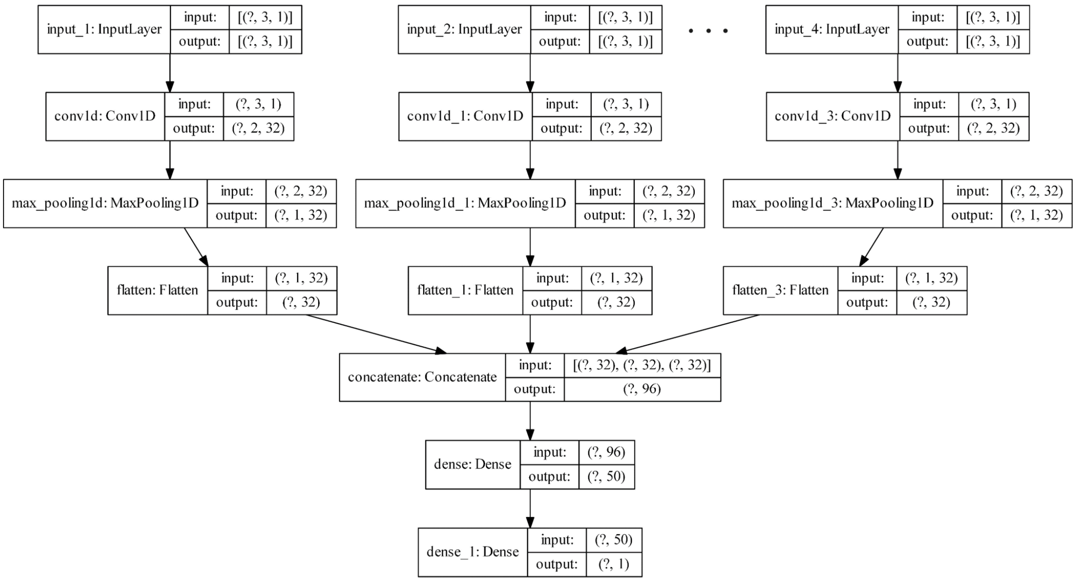

Figure 10. Multihead CNN.

LSTM

The final model consists of two LSTM layers comprising 50 hidden units each, which will process the data to learn the sequential patterns. First, the model receives an input shape (3, 4) similar to that of the CNN models. Then, the transformed data are passed through the LSTM layers, as shown in Figure 11.

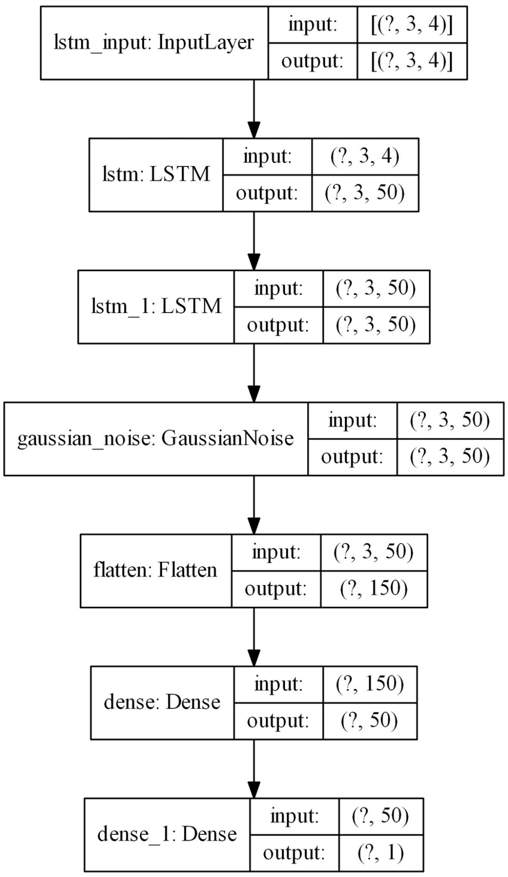

Figure 11. LSTM model.

5.4.2. Short-Term Electricity Forecasting

Several machine and deep learning models were compared and evaluated to measure their capacity for predicting short-term electricity demand. The machine learning approaches considered were: AdaBoost, SVR, XGBoost, random forest, and LightGBM. Moreover, the deep learning methods included deep learning regression and Bi-LSTM. This study explored how well the Bi-LSTM model performs in making multi-time-step predictions 24 h in advance. Table 4 presents the architecture for the models.

Table 4. The architecture of the machine learning models.

Models	Parameters	Parameter Value
SVR	Kernel	Radial basis function
	Regularization parameter (c)	0.1
	Degree	3
XGBoost	Learning rate	0.1
	Maximum depth of trees (max_depth)	3
	Number of trees (n_estimators)	100
	n_jobs	1
AdaBoost	Number of trees (n_estimators)	100
	Learning rate	0.01
	Loss	linear
RF	Number of trees (n_estimators)	100
	min_samples_leaf	1
	min_samples_split	2
LightGBM	Learning rate	0.1
	Maximum depth of trees (max_depth)	−1
	Number of trees (n_estimators)	100
	n_leaves	31

The following hyperparameters were considered when building the deep learning models: the activation function, the learning rate, the number of dense layers, the hidden units, the batch size, and the epochs. The structure used for building the deep learning model using Knime is shown in Table 5. A neural network with a three-layer architecture and 95 hidden units in each layer was considered to learn nonlinear patterns efficiently. Moreover, the network captured the relationship between the input features and the output (demand). The number of epochs considered in the training phase was 500, in small batches of 50 units. The optimizer used was the stochastic gradient descent algorithm, adjusting to a learning rate of 0.01.

Table 5. Model architecture for deep learning.

Dense Layers	Number of Hidden Neurons	Activation Function	Optimization Algorithm	Batch Size	Epochs
3	95	ReLU	Stochastic Gradient Descent	50	500

The structure of the Bi-LSTM model is shown in Figure 12. The model consists of three Bi-LSTM layers of 70 hidden units each, followed by a dense layer. In total, 500 epochs were considered during the training process. In addition, small batches of 30 units were considered. The previous 48 h of electricity demand, with seven input features, represents the model's input sequence.

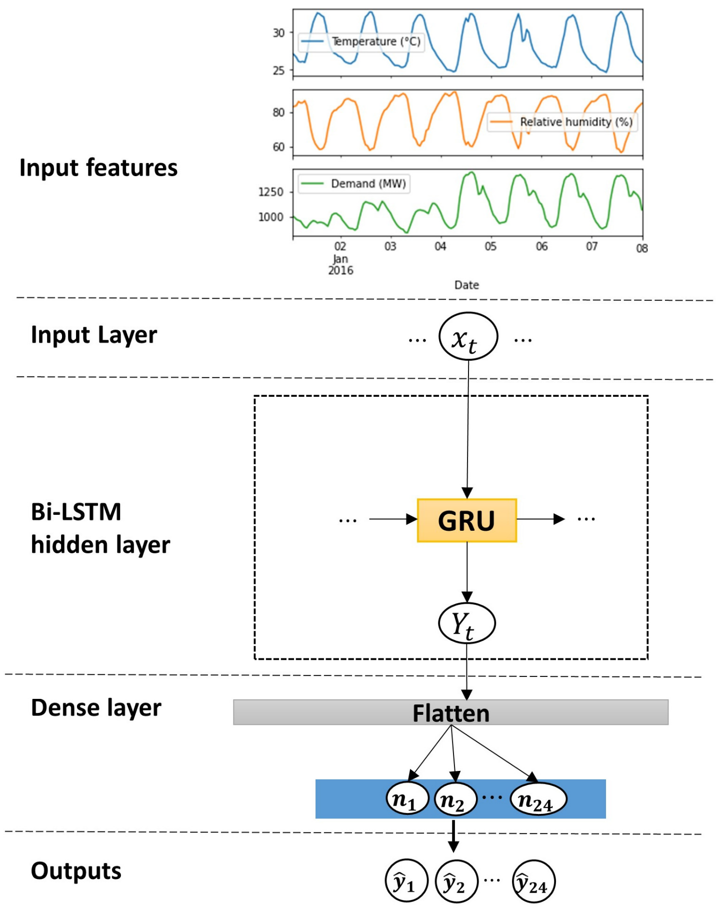

Figure 12. Bi-LSTM model for predicting hourly demand.

5.5. System Dynamics Model for Long-Term Energy Consumption

The field of system dynamics has been receiving increased attention from academia and industry for quite some time. Ford [37], for example, presented an impressive body of work on how system dynamics can provide strategic guidance for utilities, consultants, and policymakers to improve resource planning in the energy industry. In [37], Ford modeled a weak point that presented itself among the US energy utilities faced with financial problems due to the energy crisis at the beginning of the 1970s. The major problem was that utilities had to cut back on constructing new power plants, due to the ongoing high coal and natural gas prices. More recently, Laimon et al. [38] applied a system dynamics approach to model possible scenarios for the development of the energy sector in Australia by examining the implications of fossil fuel dependency, energy prices, and carbon dioxide emissions. Gu et al. [39] also used system dynamics to address major concerns about the effect of China's rapid urbanization growth on future energy demand requirements. The authors highlighted the urgency with which China should transition toward a low-carbon development scenario to ensure sustainable urbanization growth. One of the greatest challenges that Panama is facing is how to plan for future energy demand. Increasing globalization has changed the direction of the country's economy. It has made it necessary to modernize and strengthen Panama's energy supply structure in response to new global trends and the demands of its consumers. Therefore, the National Secretary of Energy of Panama must regularly meet with regional planners to develop comprehensive plans on how they will meet future energy requirements. Their mission is to provide a comprehensive energy policy within the current constitutional framework to guarantee a competitive, high-quality, and environmentally sustainable supply of energy resources. The main mission is to establish and promote energy policymaking, to address the following objectives:

- Guarantee the security of supply;
- Promote the rational and efficient use of energy and electrical energy;
- Promote the use of energy in a sustainable way;
- Support in the implementation of regional electrical interconnection;
- Comply with the mitigation of and adaptation to climate change.

The National Secretary of Energy has invested more funds into reducing the country's emissions by depending more on hydroelectric, natural gas, renewable wind, and solar power. Figure 13 shows the total electricity generated by energy sources in gigawatts/hour (GWh). In 2021, 60.1% of the electricity produced came from hydroelectric sources, 11.5% from natural gas, 3.3% from bunker, 16.4% from carbon, 3.8% from wind power, and 4.2% from solar energy.

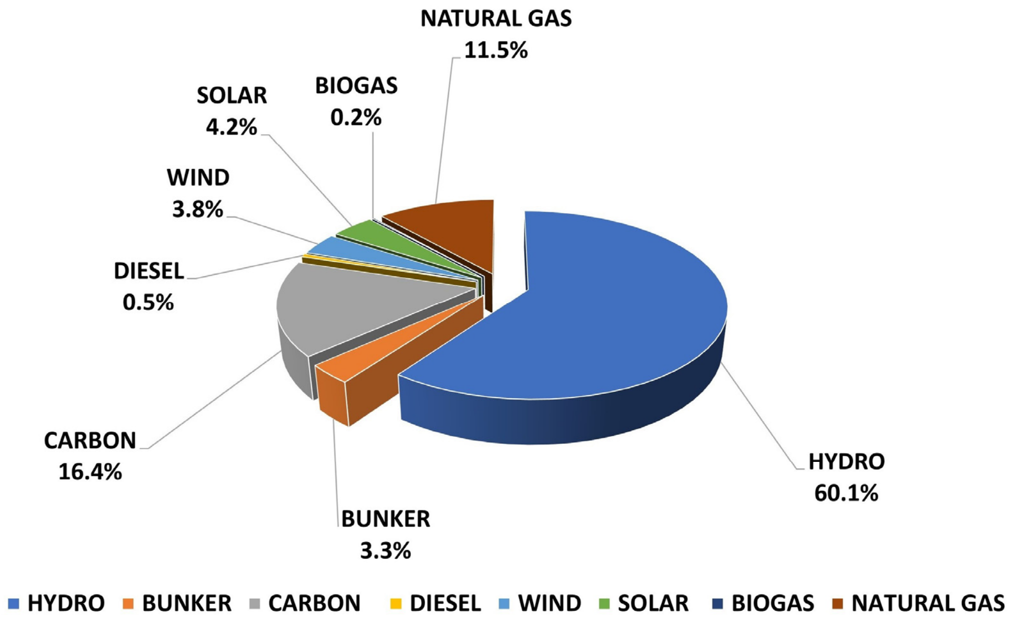

Figure 13. Net energy generated in GWh, shown according to the source.

This research proposes a system dynamics model to predict the growth in energy consumption for Panama, which could guide future energy policymaking. This complex problem requires that it be viewed from a system dynamics perspective to model the energy needs of the different end-use sectors involved (i.e., residential, government, business, etc.). Previous efforts have addressed this problem in the literature using time series and machine learning models. However, these models present limitations in that they cannot capture the dynamic interactions of the system as a whole. The authors of [38] stated that traditional time series and neural networks disregard the integration of different levels of behavior; therefore, they found system dynamics more suitable to model energy sector development. In addition, machine learning models require vast volumes of training data and features to perform well. Therefore, a system dynamics model was built as a first step to reproduce the growth in energy consumption from 2005 to 2017. The model uses a top-down approach; at the top of the model, we simulated the population growth, while at the bottom, we simulated the energy consumption of the end-use sectors.

5.5.1. Population Growth

Population growth is essential for modeling the growth of energy consumption. Many countries are becoming more densely populated and need to be more effective at implementing energy efficiency measures, leading to higher energy consumption. According to the US Energy Information Administration, global energy consumption is rising faster than population due to a possible shift in the economy and the consumer adoption of more energy-intensive appliances. System dynamics has been widely used to model population dynamics. These models include the fertility rate and immigration to reproduce population growth more accurately. Ali et al. [40] used a system dynamics approach to analyze the impact of population growth on the residential housing market in the US. They used a top-down approach to model population growth, based on birth, migration, and death rates. This study's population model was divided into different age groups of 0–4, 5–9, 10–14, 15–19, etc., which are represented as stocks, as shown in Figure 14. Data from the National Institute of Statistics and the Census of Panama were used to build the model. The National Institute of Statistics and the Census present estimates and projections for population growth that are sorted according to the different age groups in Panama. Therefore, population data for 2005 were used as initial values for the stock levels. The aging chain begins with the accumulation of births per year in the 0–4 age group. Then, the age 4 group matures and flows into the next age group, 5–9. The aging chain continues until the last age group, 80 and above. Therefore, the population changes, based on the birth rate and death rate. The population model has 34 differential equations.

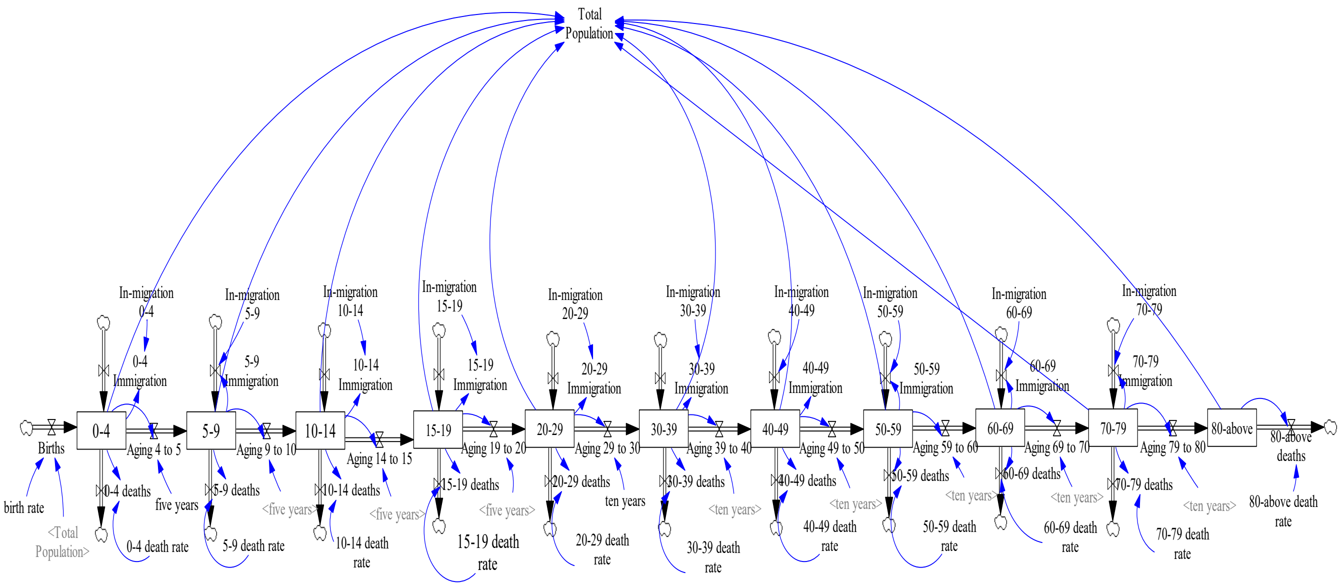

Figure 14. Population growth.

Table 6 provides the values for the constants and initial stock levels for the population model.

Table 6. Parameter values for initializing the population model.

Variable Name	Type of Variable	Parameter/Initial Value
Birth rate	Auxiliary variable	0.0197
80 and above death rate	Auxiliary variable	89.3
0–4	Stock	358,971
5–9	Stock	342,358
10–14	Stock	318,918
15–19	Stock	307,161
20–29	Stock	577,678
30–39	Stock	509,854
40–49	Stock	387,951
50–59	Stock	253,723
60–69	Stock	161,034
70–79	Stock	90,046
80 and above	Stock	43,313
0–4 death rate	Auxiliary variable	3.6

Table 6. *Cont.*

Variable Name	Type of Variable	Parameter/Initial Value
5–9 death rate	Auxiliary variable	0.3
10–14 death rate	Auxiliary variable	0.3
15–19 death rate	Auxiliary variable	0.7
20–29 death rate	Auxiliary variable	1.2
30–39 death rate	Auxiliary variable	1.3
40–49 death rate	Auxiliary variable	2.2
50–59 death rate	Auxiliary variable	4.5
60–69 death rate	Auxiliary variable	10.8
70–79 death rate	Auxiliary variable	27.2
80 and above death rate	Auxiliary variable	89.3

The model estimated that the population would reach 4 million by 2017 (time = 13). The results were compared with the data collected on the National Secretary of Energy population, as shown in Table 7. In 2017, the actual population was 4,098,135. Therefore, we were able to reproduce the population patterns reasonably well.

Table 7. The total population, according to the National Secretary of Energy.

Year	Population
2004	3,122,763
2005	3,168,043
2006	3,213,980
2007	3,260,583
2008	3,307,861
2009	3,355,825
2010	3,661,835
2011	3,723,821
2012	3,787,511
2013	3,850,735
2014	3,913,275
2015	3,975,404
2016	4,037,043
2017	4,098,135

5.5.2. Housing Growth

The next step consists of modeling the housing growth for Panama. This model is adopted from Forrester's urban dynamics model, wherein he attempts to simulate the main internal forces that affect a city's growth, based on its employment level, population, and business growth dynamics. The urban dynamics model presents a more complex structure regarding how house construction is mainly affected by the region's attractiveness, land availability, and housing availability. However, our model only considers some of these factors. Figure 15 presents the system dynamics model for housing growth. The variable "Houses" is modeled as a stock that changes based on house construction. Therefore, it has a reinforcing feedback loop that indicates the building of more houses when needed. House construction is affected by two main variables: the house construction rate and house availability after construction. Therefore, more houses being available means that house construction will slow down.

We compared data from the National Secretary of Energy and the National Authority of Public Services to determine the initial number of houses. According to the National Secretary of Energy, the number of occupied homes with electricity was 659,796, as of 2005. The National Authority of Public Services holds more accurate data on the number of residential clients registered by the distribution companies, which is estimated to be 606,109 for 2005. Therefore, these data were used for the study. The initial value for the house construction rate was set to 0.023, and the average household size was set to 4. The model estimated that by 2017 (time = 13), the number of houses would reach 952,310. Based on the data provided, the actual number of residential clients was 941,769. Therefore, the model estimated the housing growth fairly well. The variable for house construction tends to decline due to the effect of housing availability.

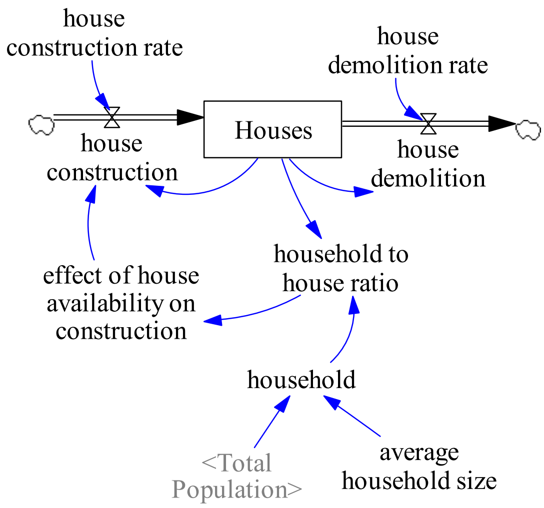

Figure 15. System dynamics model for housing growth.

5.5.3. Energy Demand per Sector

At the bottom of the system dynamics model, we show the stocks and flows that are used to reproduce the energy consumption pattern for each end-use sector from 2005 to 2017. Panama has many electricity clients who are grouped into different categories: residential, industrial, commercial, government, business, and public use. The model also considers the energy losses incurred by the distribution companies. Therefore, to model the energy consumption of each sector by year, it was necessary to gather information on the number of clients per sector (Table 8), the total energy sales per sector, and the average consumption per client per year. The data were collected from the National Authority of Public Services.

Table 8. Number of clients per sector.

Year	Commercial Clients	Industrial Clients	Residential Clients	Government Clients
2005	63,669	1347	606,109	8294
2006	66,621	1420	635,975	8376
2007	68,570	1437	659,646	8558
2008	72,903	1475	690,297	8830
2009	71,377	1594	704,139	9191
2010	74,587	1612	724,414	9738
2011	78,346	1612	750,594	10,075
2012	80,783	1624	775,713	10,361
2013	83,105	1688	806,522	10,643
2014	85,897	1799	838,959	10,916
2015	97,536	1835	893,175	11,505
2016	100,628	1859	929,572	11,817
2017	100,866	1820	941,769	11,840

Figure 16 provides an example of the stock-flow diagram for the commercial sector. It can be seen that the total energy consumed by the commercial sector will increase, based on the growth of the stocks labeled “commercial clients” and the “average consumption per commercial client”.

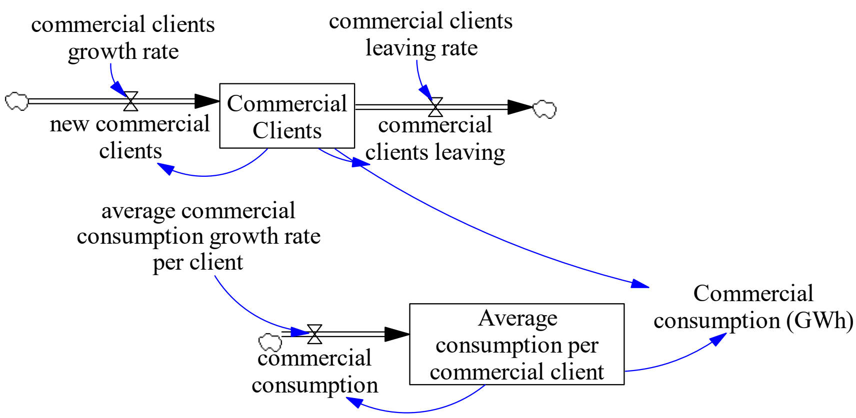

Figure 16. Stock-flow diagram of the commercial sector.

Figure 17 demonstrates the initial electricity consumption curve reproduced for the period from 2005 to 2017, in which electricity consumption increased from 6073.85 GWh to 10,684.8 GWh.

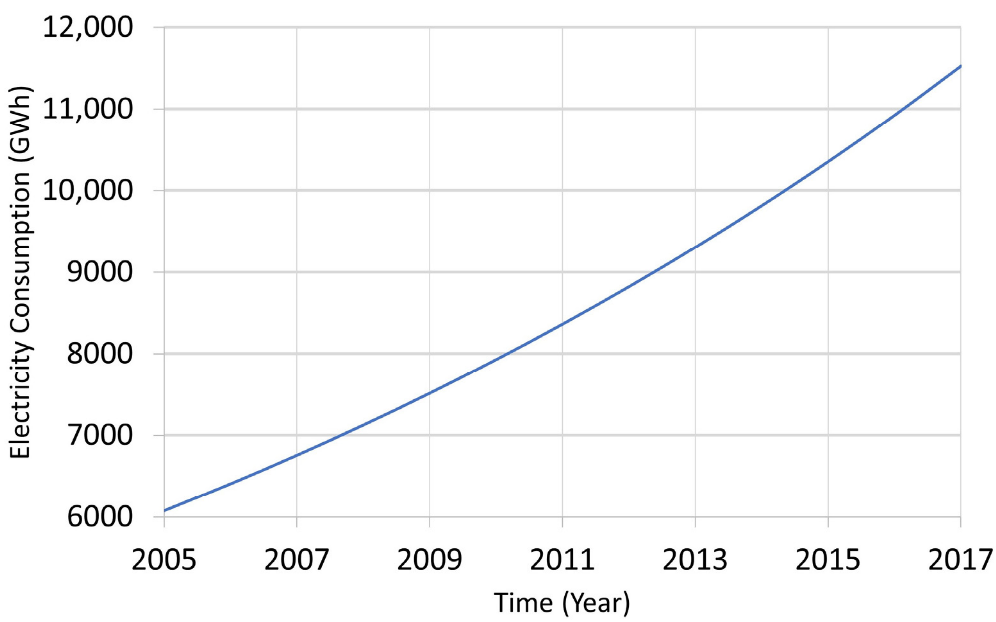

Figure 17. The initial electricity consumption curve was reproduced for the period from 2005 to 2017.

5.5.4. Calibration of the Model

Once the model was structurally complete and it simulated the system correctly, we proceeded to calibrate the model. Calibration is the most important step for validating the integrity of a system dynamics model. Calibration is an optimization process that identifies the optimal parameters that best fit the historical data curve. The first step was to select the variable to be calibrated, "Electricity Consumption". Therefore, data on electricity consumption were collected from 2005 to 2017 from the National Secretary of Energy of Panama to help the model to fit the historical data better; the initial curve is reproduced in Figure 17. Figure 18 shows a flowchart of the calibration process.

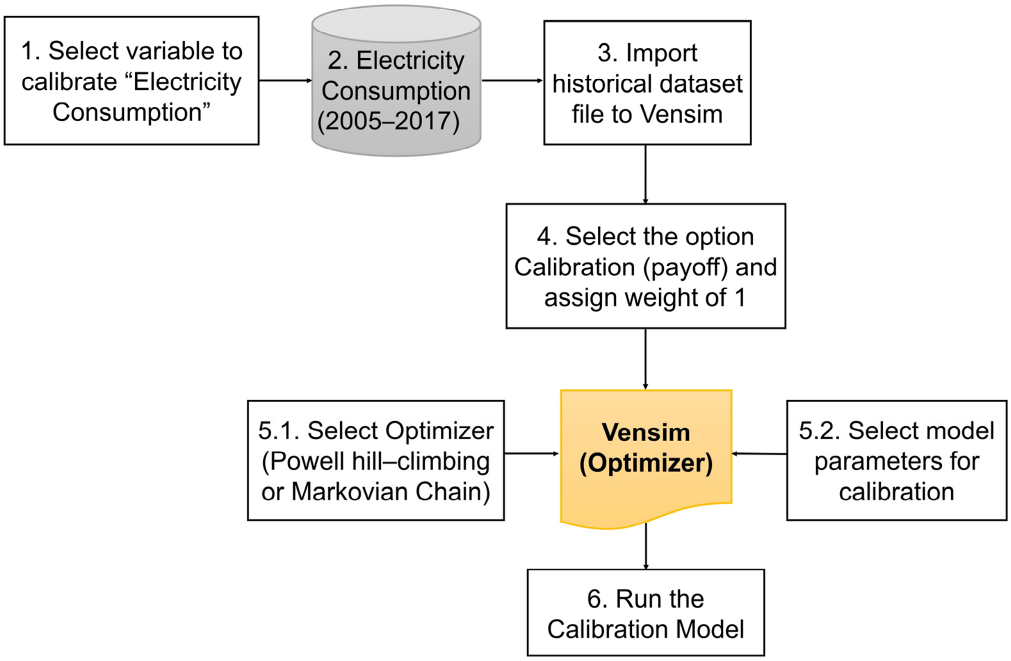

Figure 18. Flowchart of the calibration process for the system dynamics model using Vensim.

As shown in Figure 18, the third step involves importing the historical data set file into Vensim. Once the data set is successfully imported, the fourth step involves selecting the payoff type. Vensim's optimizer offers model calibration and policy optimization. The payoff defines which variable you are trying to fit into the calibration. In this case, the variable "Electricity Consumption" was selected. The fifth step is followed by selecting the optimizer and the model parameters that are to be optimized. First, the Powell hill-climbing algorithm was selected. Powell hill-climbing is a heuristic method based on a local search strategy. This algorithm improves its calculations iteratively by exhaustively searching along a single direction within the parameter space until it converges onto a local optimum solution. The Powell hill-climbing model has an advantage over the Markovian chain Monte Carlo simulation, in that it can provide appropriate solutions much faster since it is based on a local search. In addition, each parameter's minimum and maximum bounds were defined. Four parameters were selected as the initial step: the average commercial consumption rate per client, the commercial clients' growth rate, the average growth rate of industrial consumption per client, and the growth rate for industrial clients. The model reproduces the historical data fairly well between 2005 and 2017, with an R^2 value of 0.94 and a 4.8% value for MAPE.

Once the model was calibrated, we used it along with the optimization parameters thus obtained to predict the energy consumption for 2018 and 2019 and compare them with the actual values. For both years, the model overestimated the energy consumption. For 2018, the model predicted that the energy consumption value would reach 10,966 GWh, while for 2019, the model estimated this value to be 11,465 GWh.

6. Conclusions

This methodology addressed the following two main research questions, which will help to fill the research gap: (1) Is there a way to capture the complex features that affect monthly peak demand? (2) Which state-of-the-art methods are the most effective for predicting monthly peak demand? We first collected the monthly historical data on peak electricity demand from January 2004 to December 2019, to address these two research questions. The data played a significant role in understanding Panama's efforts to modernize and strengthen its grid over the years, to respond to new global trends and the demands of its consumers by investing in more reliable energy sources, such as natural gas, wind, and solar power. This data originates from the SCADA systems, which generate data at 15-minute intervals. In addition, collecting data on electricity consumption for the different sectors and economic indicators (i.e., the monthly economic activity index) was also essential and used information publicly available on the National Institute of Statistics and the census. A deep learning framework was proposed, in which we investigated 1D CNN and LSTM for predicting monthly peak demand. The CNN was mainly used for feature extraction, while LSTM was used to learn the sequential patterns. The CNN models consisted of three different architectures that have been widely studied in the literature: the multi-channel CNN, CNN-LSTM, and multi-head CNN. The results for these models are provided in Table 9.

Table 9. Comparison of the three CNN variants, versus LSTM.

	Test Data Set			
Model	**R^2**	**MSE**	**MAPE (%)**	**MAE**
Multichannel CNN	0.92	1271.65	1.62	27.86
CNN-LSTM	0.50	7731.80	3.76	65.54
Multihead CNN	0.81	2940.98	2.30	40.17
LSTM	−0.52	23,654.8	5.7	103.27

The input layer of the models received four input features, comprising the three previous timesteps: the categorical month, "large clients" consumption, residential consumption, and the peak demand from the previous three months. The models were trained for 1000 epochs and were then evaluated on a separate test set. We found that the multichannel CNN outperformed all the models, with an R^2 of 0.92, an MSE of 1271.65, a MAPE of 1.62%, and a MAE of 27.86. However, the model reasonably followed the peak demand pattern but could not successfully predict the highest peaks seen in August and December 2019, severely underestimating them. Therefore, the input features could only partially capture the peak demand growth for these months. The implication of this finding is significant as it provided a basis by which to understand what other features and data need to be collected.

Lastly, this methodology addressed another important research question related to the case study: Can a system dynamics approach allow us to model complex dynamic interactions to reproduce the growth of energy consumption in the long term? We found that the system dynamics model reproduced the historical data fairly well between 2005 and 2017, with an R^2 value of 0.94 and a MAPE of 4.8%. Once the model was calibrated, we ran the model to predict energy consumption for 2018 and 2019 and compare them with the actual values. For both years, the model overestimated the energy consumption. For 2018, the model predicted the energy consumption value to reach 10966 GWh, while for 2019, the model estimated this value to be 11,465 GWh.

The authors plan to perform more implementations of this hierarchical framework in other case studies in Latin America. Panama represented an excellent case study due to its flexibility, integration, size, data collection/availability of records, and growth in renewables. Such cases in North America are possible but are addressed from the viewpoint of regional utilities.

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