Advanced Analytics for Energy Policy-Driven Investment Decisions: Integrating Machine Learning with Optimization Techniques in Smart Grids

Zhanghao Chen

Department of Statistics and Data Science
Southern University of Science and Technology, China
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Summary of the Proposal

Under the new energy transition phase of the Chinese government, this proposed research focuses on developing a novel multi-objective decision-making investment framework driven by machine learning methods. This framework is designed to optimize key factors such as cost, reliability, and sustainability in smart grids.

Firstly, key factors including total electricity generation, electricity consumption, and the generation capacities of traditional and renewable energy sources are collected and processed using variable selection methods.

Subsequently, machine learning techniques, including *LSTM* for short-term forecasting and *ARIMA/SARIMA* for long-term predictions, are applied to estimate future scenarios. The short-term forecast for 2030 indicates a significant decrease in the proportion of traditional thermal power generation, with an estimated **394 TWh** output by December 2030. Meanwhile, the long-term forecast for 2060 suggests **a widening gap** between electricity consumption and production, emphasizing the urgency of energy transition.

Thirdly, optimization techniques are of great importance in providing guidance for making optimal investment decisions. We start with the straightforward **single-objective optimization** problem. Our goal is to minimize total costs, which include construction and operational expenses. Considering various types of constraints, a *mixed-integer programming (MIP)* model can be effectively applied here to find a solution.

Furthermore, **multi-objective optimization** can be applied to make decision evaluation more comprehensive. Objectives such as minimizing the total construction period or maximizing the lifespan of facilities can be integrated into the optimization model. Accompanied by the necessary constraints, *Non-Dominated Sorting Genetic Algorithm II (NSGA-II)* can be employed to provide optimal decisions for power investment that encompass multiple conflicting objectives.

1 Introduction

1.1 Background and Motivation

Smart grid is the integration of cutting-edge technologies such as digital technology and information technology into traditional power transmission and distribution systems, with the entire electricity supply chain, including power generation, transmission, distribution, energy storage, and consumption (Nanaki, 2021). From a policy standpoint, the intelligent transformation of the power grid is considered one of the most crucial tasks for the next phase of China's energy system development (Yuan and Zhang, 2014).

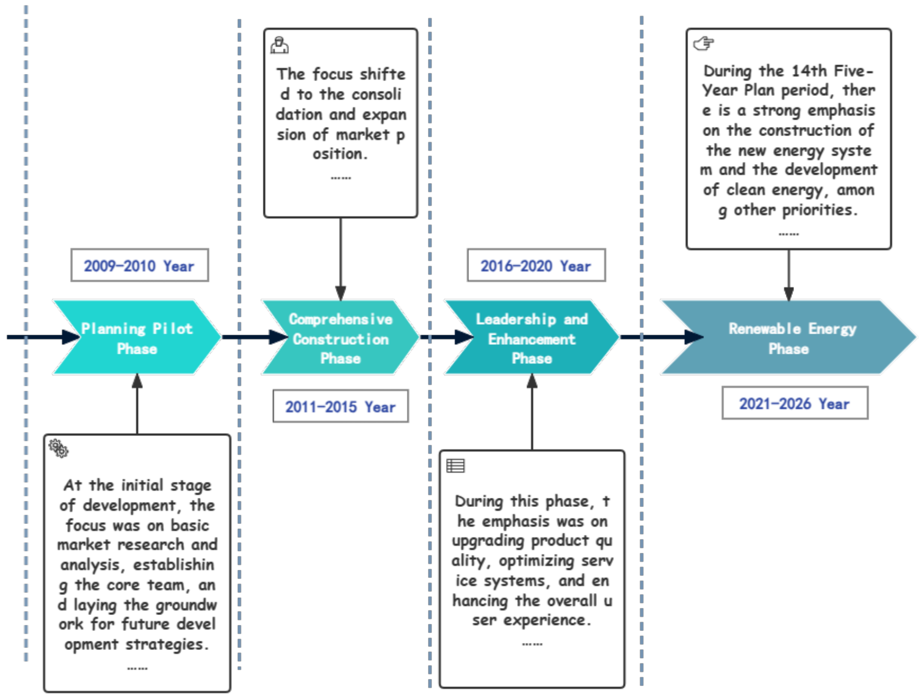


Figure 1: Smart Grid Development Planning Policy of China

In the backdrop of this policy framework and within the context of the big data landscape, how to build a reliable, high-efficient, high-tech and environmental-friendly service system, especially to accurately assess the reliability impact of various technical measures and establish optimal investment decision model for the future distribution network planning, has great theoretical and practical significance. In fact, the investment decision for smart grids has already evolved into a large scale dynamic combinatorial optimization problem (Pournaras et al., 2019).

However, traditional approaches have shown limitations in handling the vast and diverse datasets generated by smart grid systems. Conventional algorithms often fall short when it comes to the simultaneous optimization of multiple conflicting objectives and may not effectively deal with the uncertainties inherent in real-time smart grid data. For example, an unexpected drop in wind energy could prompt these systems to inefficiently deploy backup resources, causing financial and operational inefficiencies (Initiative et al., 2012).

Given these challenges, it is crucial to explore more advanced methodologies that can handle these complexities. This proposal aims to develop a hybrid approach that combines (a) variable selection to identify the most critical factors for smart grid construction; (b) machine learning (ML) to forecast future trends and conditions; (c) multi-objective (MO) optimization to balance various goals, such as minimizing costs while maximizing reliability and sustainability. As a result, the following literature overview focuses on recent advances in this area.

1.2 Literature Review

Significant research efforts have been expended on the development of hybrid method for decision-making systems in smart grids. In this section, research advancements in the above mentioned three tasks are summarized.

Feature selection identifies the key factors affecting smart grid performance and investment results by reducing high-dimensional data elements from energy consumption, weather, and market trends. Qadir et al. (2021) utilized a feature selection technique with a linear regression model and achieved a hybrid PV–wind renewable energy system with mean squared error (MSE) of 0.000000104, mean absolute error (MAE) of 0.00083, and an R^2 of 99.6%. Ahmad et al. (2015) in their study enhanced a day-ahead load forecasting (DLF) model with a new feature selection module, achieving a remarkable 97.11% accuracy and outperforming existing FS + ANN-based models by 38.50% in terms of speed.

Machine learning plays a vital role in the digital transformation of smart grids. The study conducted by Ahmad and Chen (2018b) focuses on short-term load forecasting (STLF) using deep learning regression and AdaBoost. For medium-term and long-term energy demand forecasting in smart grids, Ahmad and Chen (2018a) implemented both an ANN model with nonlinear autoregressive exogenous multivariable inputs and a multivariate linear regression model. Additionally, in the context of the increasing presence of renewable energy sources in the global electric energy grid, various machine learning models, such as Bayesian approaches and Markov Chain models, have been widely employed (Maatallah et al., 2015; Wang et al., 2015, 2019). Furthermore, electricity prices are closely intertwined with investments in the electric grid, and Lago et al. (2018) introduced a novel deep learning framework for forecasting electricity prices. These studies collectively highlight the significant role of machine learning in enhancing various aspects of smart grid management and decision-making.

Multi-objective (MO) optimization technology allows decision-makers to discover balanced and optimal solutions that account for multiple conflicting objectives. In the research conducted by Alzahrani et al. (2023), a non-dominated genetic sorting algorithm (NSGA-II) model was developed to optimize objectives related to pollution emissions, operation costs, and loss of load expectation (LOLE). In another study by Li et al. (2018), they introduced a hierarchical day-ahead Demand Side Management (DSM) model and computed a Pareto optimal set of solutions. As a result, the utility can achieve reductions in operational costs and the peak-to-average ratio, while customers can lower their electricity bills.

2 Research Methodology

Overall Research Objective

- *How can we leverage machine learning to develop an optimization model that integrates key forecasts to guide efficient and sustainable decision-making in smart grids?*

To accomplish this overarching objective, the research is subdivided into three sub-tasks, as outlined in the introduction section. In this section, a detailed exposition on these three tasks will be presented.

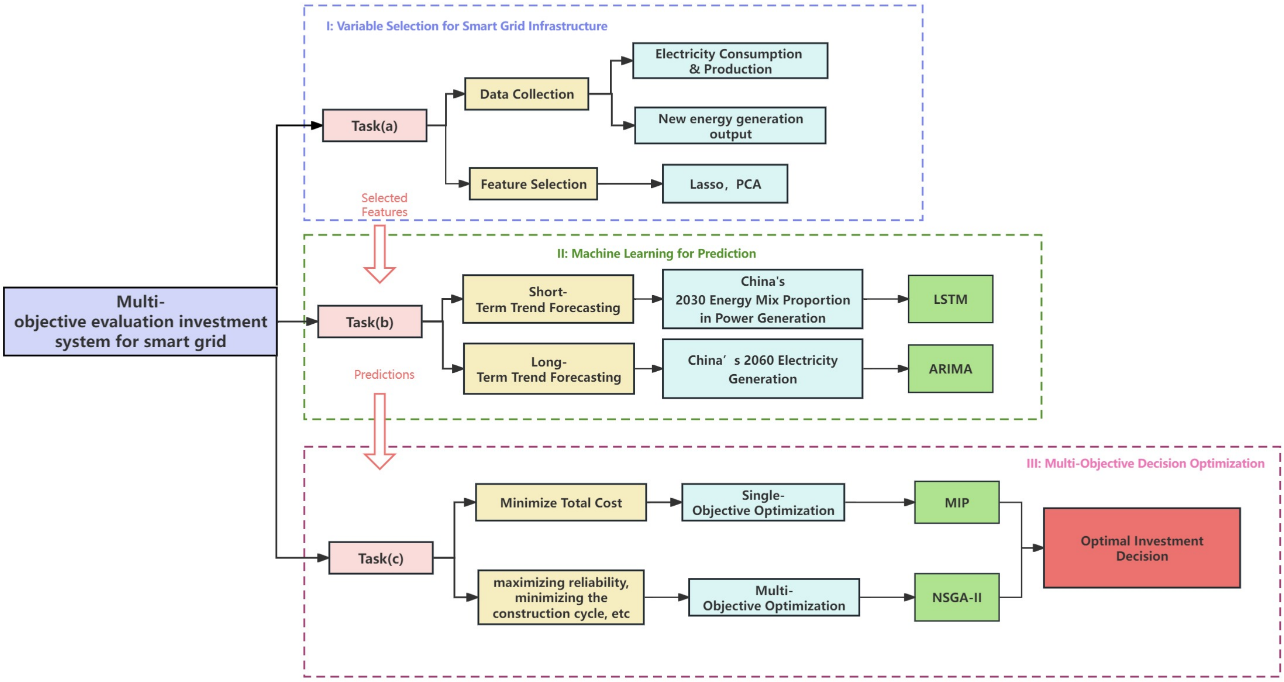


Figure 2: Overall research framework

Task (a): Data Collection and Variable Selection for Identifying Key Factors in Smart Grid Infrastructure

For Task (a) in identifying crucial factors in smart grid infrastructure, the research encompasses a thorough review, pinpointing three vital areas: Electricity Demand Forecasting, Renewable Energy Output Forecasting, and Electricity Price Forecasting. Firstly, the sources of data related to these three areas will be clarified.

The data for this study is sourced from the National Bureau of Statistics of China, including China's electricity production spanning from 1986 to 2023, electricity consumption metrics, new energy generation statistics, and electricity pricing, etc.

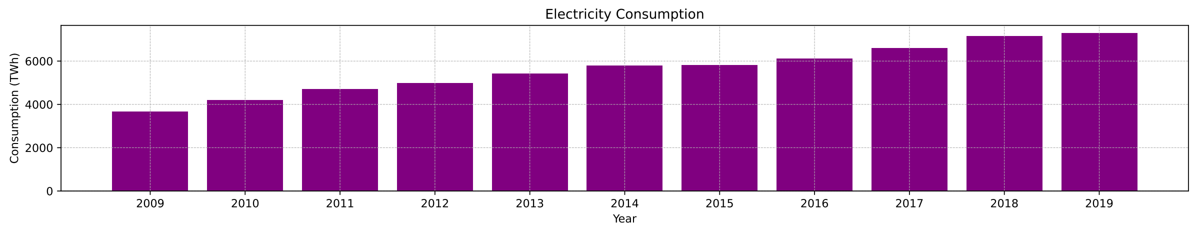


Figure 3: Electricity consumption in China from 2009 to 2019

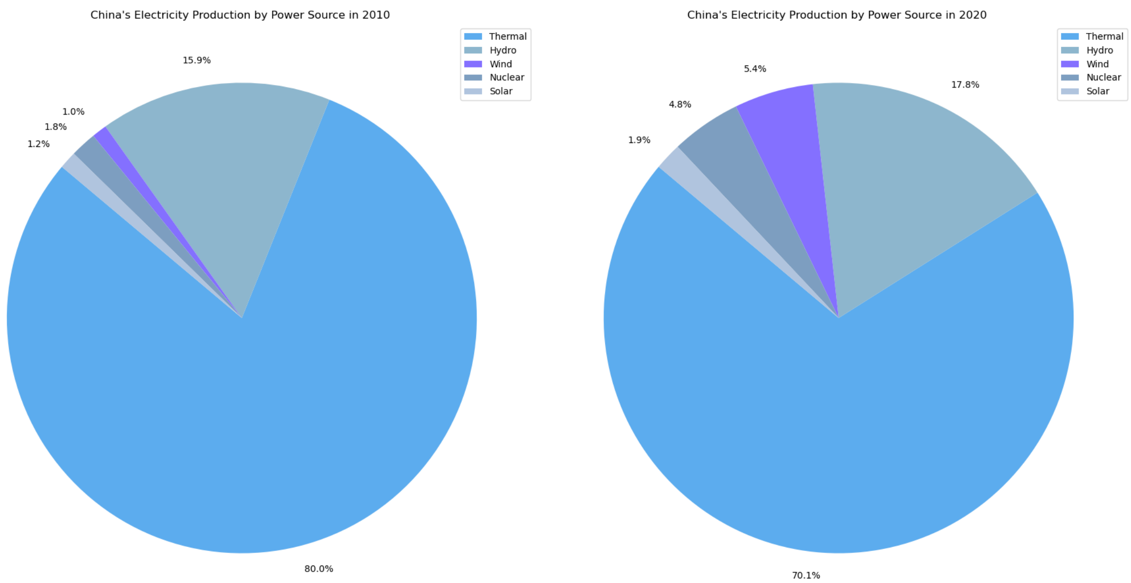


Figure 4: The proportion of power generation in China, with the left image representing 2010 and the right image representing 2020

From Fig.3 and Fig.4, it can be seen that China's electricity consumption experienced an unprecedented near-doubling over the decade from 2009 to 2019. At the same time, in alignment with global sustainability trends and national new energy policies, there was a discernible shift away from traditional thermal power generation, which saw a reduction in its share by 10%. Correspondingly, the proportion of new energy generation increased, with a substantial growth in wind, nuclear, and hydroelectric power sources.However, with such a significant growth in electricity consumption and production, the per capita electricity cost of residents in 36 cities in China remained relatively stable at 53 RMB per 100 kilowatt hours from 2010 to 2020, further highlighting the crucial role of renewable energy generation.

After getting this data, it is feasible to employ it for both short-term and long-term forecasting of future trends. The data collected thus far is annualized. Nevertheless, if the subsequent research necessitate further resolutions, such as monthly or even daily data, the amount of data would be very large. In such circumstances, it is necessary to use Feature Selection Method to filter the data. Lasso Regression and Principal Component Analysis (PCA) are two common methods for variable selection. Fonti and Belitser (2017) and Shlens (2014) provide an overview of how to these methods in detail.

In summary, Task (a) is focused on obtaining the most critical features within the smart grid, conducting data collection and variable selection to prepare the dataset, which will then serve as the foundation for the ensuing machine learning predictions in Task (b).

Task (b): Machine Learning Using Selected Variables for Smart Grid Prediction

In Task (b), the main focus is on using machine learning to make predictions about the future trends. This research will take a look at how much electricity will be produced by different methods (like traditional thermal power and newer green sources), how much electricity China will generate and use, and how the cost of electricity might change. Predictions for both short-term and long-term periods will be conducted to assist China in formulating energy policies and making decisions on smart grid investment.

Short-Term Trend Forecasting: LSTM for China's 2030 Energy Mix Proportion in Power Generation

First of all, this study plans to make short-term predictions on the energy transformation of China's smart grid in 2030. The forecasting objectives comprises the total electricity generation, as well as the output from various energy sources including Thermal, Hydro, Nuclear, Wind, and Solar power. The capacity of newly added power generation equipment will be also considered, aiming to evaluate whether the country will have successfully undergone an energy transition. These insights are intended to offer strategic guidance for investments in China's smart grid infrastructure, such as which power generation methods should be prioritized for investment.

Neural networks have strong capabilities for processing nonlinear data. Neural networks are characterized by large parameter dimensions, strong versatility, and the use of nonlinear activation functions in each layer, thus enabling the model to have good adaptability to processing under nonlinear data. Long Short Term Memory Network (LSTM) is an extension and development of Recurrent Neural Networks (RNN). Based on ordinary RNN, one unit is added to each neural unit in the hidden layer, thereby making RNN has long-term memory function.

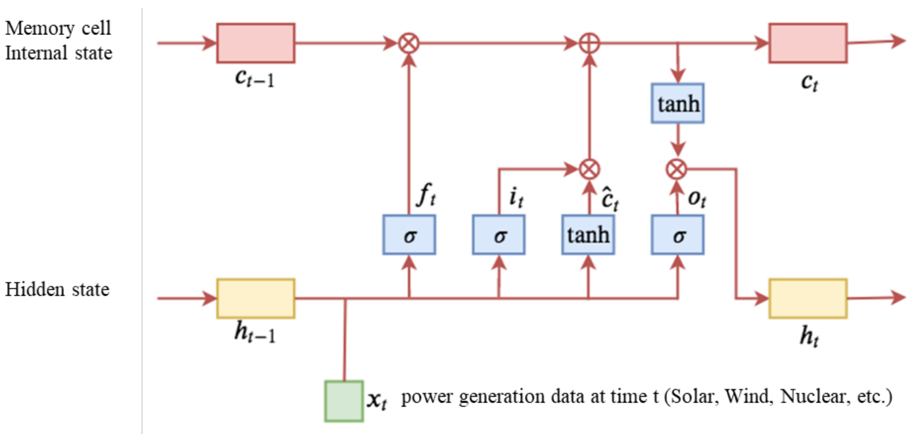


Figure 5: Internal structure of LSTM neural network storage unit.

Algorithm 1 Forward Pass in LSTM Cell

for each time step t in input sequence **do**
  $h_{prev} \leftarrow$ hidden state from previous time step
  $c_{prev} \leftarrow$ cell state from previous time step
  $x_t \leftarrow$ input at current time step

  $f_t \leftarrow \sigma(W_f \cdot [h_{prev}, x_t] + b_f)$ {Forget Gate}
  $i_t \leftarrow \sigma(W_i \cdot [h_{prev}, x_t] + b_i)$ {Input Gate}
  $\tilde{C}_t \leftarrow \tanh(W_C \cdot [h_{prev}, x_t] + b_C)$ {Candidate Values}
  $c_t \leftarrow f_t * c_{prev} + i_t * \tilde{C}_t$ {Update Cell State}
  $o_t \leftarrow \sigma(W_o \cdot [h_{prev}, x_t] + b_o)$ {Output Gate}
  $h_t \leftarrow o_t * \tanh(c_t)$ {Update Hidden State}
end for

When dealing with larger and more complex datasets, especially those exhibiting nonlinear relationships, LSTM models have already demonstrated good performance in many cases.

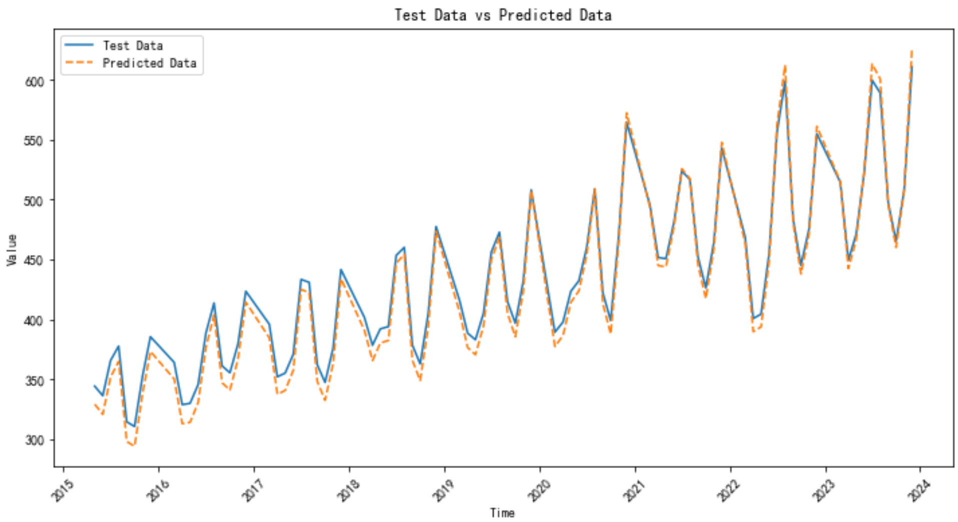


Figure 6: LSTM performs well on the test set

The LSTM model enables the forecasting of electricity generation across various methods (thermal, solar, etc.) for the year 2030. It also facilitates the calculation of the respective proportions of different energy production types. For example, existing results predict that from 2030 to December 1st, traditional thermal power generation will decrease to **394 TWh**, which preliminarily indicates the effectiveness of China's new energy transformation policy. Comparing these forecasts with the data in Figure 4 allows for a direct assessment of the transformation in the energy generation structure, reflecting the progress in the diversification and sustainability of energy sources.

Long-Term Trend Forecasting: ARIMA for China's 2060 Electricity Generation

Autoregressive Integrated Moving Average (ARIMA) model is a commonly used method for dealing with time series problems. Typically, ARIMA models perceive time series data as stochastic processes, effectuating the conversion of non-stationary observations into stationary series through differencing and then using past data relationships to predict future values.

A nonseasonal ARIMA model is classified as an "**ARIMA (p, d, q)**" model, where: AR is "autoregressive" and p is the number of autoregressive terms; MA is the moving average, q is the number of moving average terms, and d is the number of differences (order) made to make it a stationary sequence. The predicted values of observed variables are assumed to be a linear function of past observations and random errors, and the model calculation formula can be expressed as:

$$y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

where,

- y_t and ϵ_t represent the actual value and random error at time t respectively.
- ϕ_i (for $i = 1, 2, \ldots, p$) and θ_j (for $j = 1, 2, \ldots, q$) are model parameters. p and q are model parameters denoting the order of autoregressive and moving average terms respectively (both p and q are integers).

Specially, If $q = 0$, the model simplifies to a p-order AR model. If $p = 0$, the model simplifies to a q-order MA model. How to choose suitable p and q is crucial in constructing the ARIMA model and determine the accuracy of the model's predictions.

In this study, the average annual power generation in China from 1986 to 2023 is used to predict China's electricity generation in the short term by 2060. The forecast results show that China's power generation and production will approximately maintain a linear growth, reaching **1948.26 terawatt-hours (TWh)** by 2060.

Correspondingly, China's electricity consumption data exhibits pronounced seasonality, indicating that a direct application of the ARIMA model may not be entirely suitable. The Seasonal ARIMA (SARIMA), an enhancement of the standard ARIMA framework, is equipped to tackle such scenarios. SARIMA extends the ARIMA model by introducing additional seasonal terms, allowing it to capture both the short-term dependencies and the seasonality in data. A SARIMA model is typically denoted as **SARIMA(p,d,q)(P,D,Q,s)**, where p, d, q are the non-seasonal parameters the same as ARIMA, and P, D, Q represent the seasonal components. s is the seasonality period.

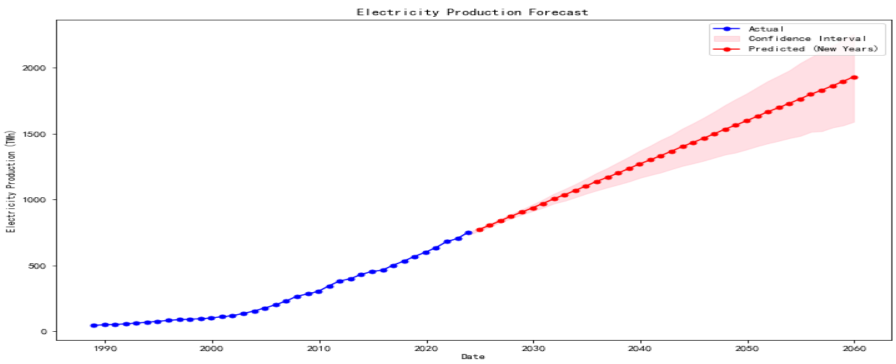


Figure 7: China's 2060 Electricity Production Forecast

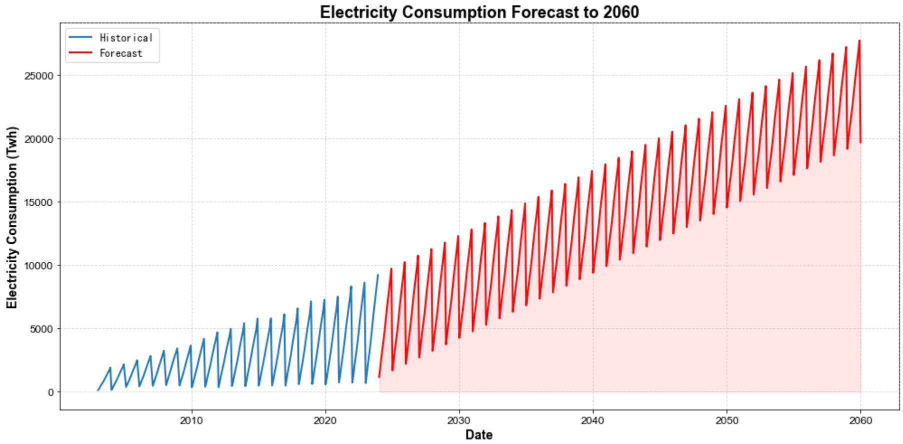


Figure 8: China's 2060 Electricity Consumption Forecast

The consumption data, recorded starting from 2003, is be divided into training and test sets for model development and validation. Data after 2018 is used as the training set. The SARIMAX model fitting results suggest that the best model for forecasting is the **SARIMAX(3,1,0)x(0,1,0,12)**. This model was selected based on its AIC (Akaike Information Criterion) value of 2843.840. The forecasted electricity consumption in January 2060 is **19711.63 Twh**. The forecast results indicate that by 2060, the gap between China's electricity consumption and electricity production is expected to widen further, highlighting the urgent need for an energy transition.

In summary, in Task (b), we aim to forecast the short-term changes in China's power generation structure and the long-term supply-demand dynamics. Current findings indicate that by 2030, the proportion of traditional thermal power generation is expected to decrease, while that of new energy sources will likely increase. Looking further ahead, China's electricity demand is projected to significantly surpass its generation capacity, underscoring the critical importance of energy transition. Furthermore, in addition to LSTM and ARIMA, alternative machine learning models such as Random Forest, XGBoost, LightGBM, among others, can also be employed for prediction, enriching the experimental results.

Task (c): Multi-Objective Decision Optimization for Smart Grid Investment

In Task (c) , our goal is to find the optimal decision for grid investment through multi-objective optimization. Since multi-objective optimization is quite complicated, we start by focusing on a single objective and then gradually broaden our approach.

Minimizing total cost is a clear optimization objective. Our goal is to minimize the total cost, which includes the investment cost of new power facilities and the cost of power generation.

$$Z = \sum_{d} \sum_{t} (C_{dt} \cdot I_{dt} + O_{dt} \cdot G_{dt})$$

Here, t can represent various types of power generation technologies, such as thermal power, hydropower, nuclear energy, wind energy, solar energy, as shown in Task (b). d represents the year. The detailed description of each parameter is shown in Table 1.

Table 1: Variables used in the optimization model

Symbol	Description	Unit
G_{dt}	Electricity generated by technology t in year d	TWh
C_{dt}	Cost of investing in technology t in year d	RMB
I_{dt}	Binary decision variable indicating whether to invest technology t in year d	
O_{dt}	Operational and maintenance cost for technology t in year d	RMB/TWh
D_d	Total electricity demand in year d	TWh
Cap_t	Maximum generation capacity for technology t	TWh
R_d	Renewable energy quota requirement for year d	%

Some possible **constraints** for this optimization problem are as follows:

1. **Demand Satisfaction:** For each target year, the total electricity generated by all technologies must at least meet the forecasted demand:

$$\sum_t G_{dt} \geq D_d \tag{1}$$

2. **Generation Capacity Limit:** Each technology's generation cannot exceed its maximum capacity:

$$G_{dt} \leq Cap_t \cdot I_{dt} \tag{2}$$

3. **Renewable Energy Quota:** Ensure that renewable energy accounts for a certain proportion of electricity supply:

$$\sum_{t \in \text{Renewables}} G_{dt} \geq R_d \cdot \sum_t G_{dt} \tag{3}$$

4. **Investment Decision:** The decision to invest in each technology is binary:

$$I_{dt} \in \{0, 1\} \tag{4}$$

This is a typical mixed integer programming (MIP) problem. The standard form of MIP is shown in Equation 5.

$$\begin{cases} \min z = \mathbf{c}^\top \mathbf{x} \\ \text{s.t.} \quad \mathbf{A}\mathbf{x} \leq \mathbf{b} \\ \mathbf{x} \geq 0, \quad \text{some } x_j \text{ are integer} \end{cases} \tag{5}$$

MIP problems are a class of optimization problems that involve both continuous and discrete decision variables. To solve MIP problems, one common approach is the Branch and Bound algorithm. This algorithm solves a series of related linear programming (LP) problems to find the optimal integer solution. It systematically explores branches of the solution space, creating bounds to eliminate regions that do not contain the optimal solution.

In practical grid infrastructure development, besides *cost minimization*, there are often other objectives to consider, such as *maximizing reliability*, *minimizing the construction cycle*, *Maximizing usage time* and so on.

In a multi-objective optimization problem, denoted by $f_i(x)$, $i = 1, \ldots, k$,$k \geq 2$, where x is the design variable set with values $\{x_1, x_2, \ldots, x_n\}$, $e_i(x)$ and $g_j(x)$ represent the constraint functions. The objective functions are divided into h minimization objectives and $k - h$ maximization objectives.

$$
\begin{aligned}
\underset{x}{\text{minimize}} \quad & f_1(x_1, x_2, \ldots, x_n) \\
& \vdots \\
& f_h(x_1, x_2, \ldots, x_n) \\
\underset{x}{\text{maximize}} \quad & f_{h+1}(x_1, x_2, \ldots, x_n) \\
& \vdots \\
& f_k(x_1, x_2, \ldots, x_n) \\
\text{subject to} \quad & e_i(x) \geq 0, \; i = 1, \ldots, r \\
& g_j(x) = 0, \; j = 1, \ldots, s
\end{aligned}
\tag{6}
$$

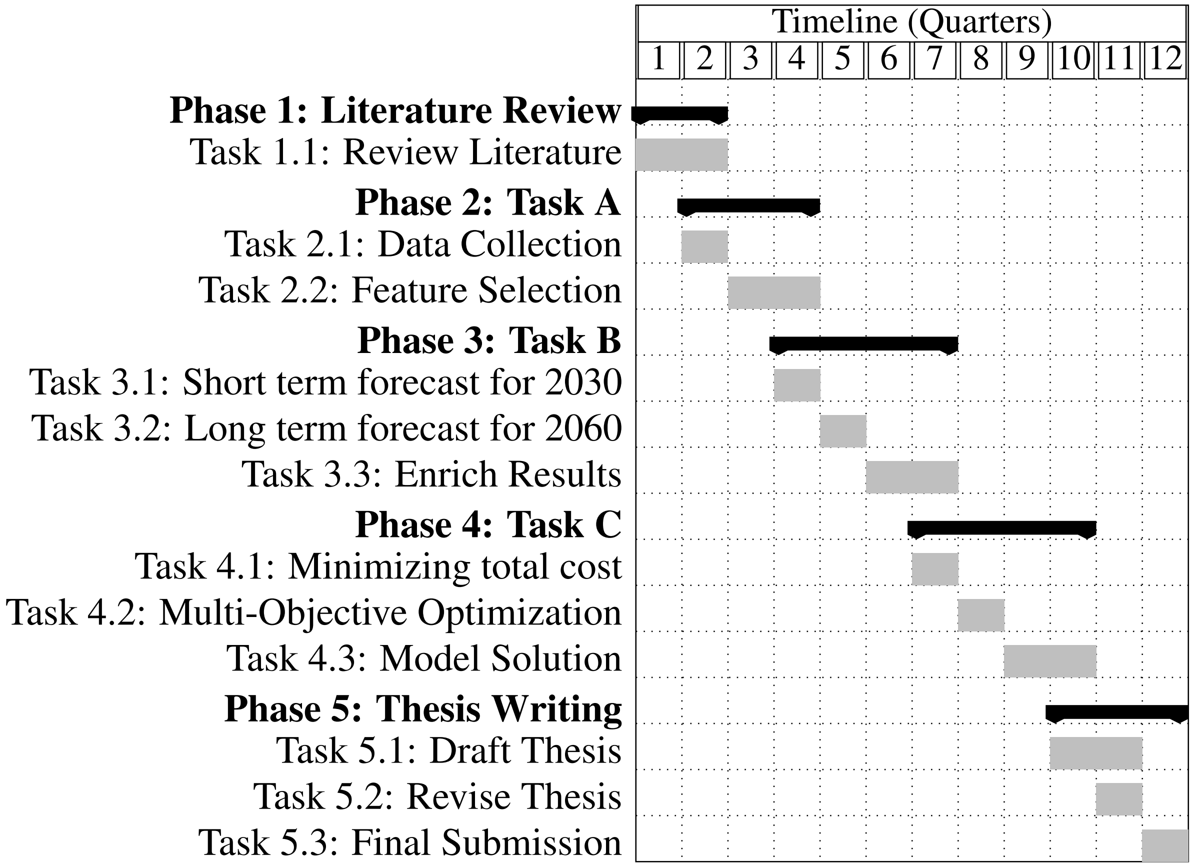
Based on various needs and constraints, a multi-objective optimization model can be developed for power grid investment. **NSGA-II**, or the *Non-Dominated Sorting Genetic Algorithm II*, is a popular method used to solve problems where we have multiple goals to achieve at the same time. When planning investment in the power grid, it can be imagined as attempting to balance different priorities such as cost, reliability, and environmental impact. This algorithm works by efficiently organizing potential solutions into different groups based on how well they perform across all the goals.

3 Experience and Expertise

Throughout my undergraduate studies, I actively participated in the **Mathematical Contest in Modeling** (MCM) and gained extensive experience in mathematical modeling and interdisciplinary projects. I also took part in the Business Artificial Intelligence program at **Nanyang Technological University** (NTU), designing a pneumonia patient image classifier using Convolutional Neural Networks.

During my master's program, I was involved in a joint project with Huawei that centered on timing synchronization within extensive network fibers. I played a key role in devising a novel statistical algorithm aimed at identifying nodes with latency issues. This initiative was recognized with the **Huawei Spark Problem-Solving Award**, and I am presently in the process of co-authoring a paper on our findings. Furthermore, I engaged in a research endeavor titled "***SurfDiff: Enhancing Protein-Ligand Predictions through Initial Pocket Identification and Surface-Aware Ligand Optimization***, with our findings submitted to the prestigious CVPR conference. In terms of programming skills, I am proficient in using research software such as Python, R, Matlab, and Latex, etc.

4 Research Management



5 Conclusion

In summary, this research proposes a decision framework based on machine learning and optimization objectives. In Task (a), important variables such as electricity generation and demand will be screened. Then, in Task (b), machine learning methods will be utilized to predict future trends. Based on the current results, it appears that the proportion of traditional thermal power generation will decrease by 2030, while long-term electricity demand will continue to grow by 2060, resulting in an increasing gap between supply and demand and necessitating energy transformation. In Task (c), single-objective optimization will be initially employed to minimize total cost, followed by considering multi-objective optimization. Finally, comprehensive recommendations for power grid investment decisions will be provided.

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