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Article

Seq2Seq-Based-Day-Ahead Scheduling for SCUC in Islanded Power Systems with Limited Intermittent Generation

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ABSTRACT

Due to their dependence on intermittent renewable energy sources, island power systems, which are generally located in remote places or on islands, offer particular issues for day-ahead scheduling. Using the capabilities of neural networks, we offer a Seq2Seq-based technique for day-ahead scheduling, which increases the precision and flexibility of unit commitment choices. The attention mechanisms in the Seq2Seq model are trained with historical data that includes projections for intermittent generation, demand, and unit commitment choices. The model is tested for its capacity to incorporate dynamic temporal relationships and deal with regenerative uncertainty. Seq2Seq models, a kind of deep learning approach, have shown impressive performance in several applications requiring sequence prediction. Uncertainty in renewable energy production, energy demand forecasts, and security limitations are all addressed in this work as Seq2Seq algorithms are applied to microgrid SCUC. In comparison to conventional scheduling approaches, the results show potential gains in prediction accuracy and operational efficiency. This study demonstrates how Seq2Seq models may be used to improve the longevity and dependability of isolated electrical grids and the way for the development of more effective, sustainable, and resilient energy infrastructure by contributing to the advancement of the area of microgrid optimization.

Keywords*:* Renewable Energy; Power Systems; Seq2Seq-based Technique; Power Grid

1. Introduction

In contrast to the broader, linked electrical grid, island power systems generate and distribute their own energy. Such systems are often found in outlying areas or on islands, where access to the main grid is either difficult or impossible. Renewable energy sources, such as solar and wind, and energy storage technologies are what distinguish islanded power networks unique (Liu, Cong, Peng, Dong, & Li, 2023). The lack of, or difficulty gaining access to, conventional fossil fuel-based generators is a major factor driving this shift toward renewables. Since traditional power production poses substantial logistical and environmental issues for remote populations, islanded power systems provide a novel and ecologically aware solution to their electrical needs (Y. Zhang et al., 2023).

In addition, the worldwide trend toward sustainable and environmentally friendly energy solutions is congruent with the use of renewable energy sources in island power systems. These systems use renewable energy sources like sunshine and wind to produce electricity, lowering both carbon emissions and the need for fossil fuel imports (Hua et al., 2019). The intermittent nature of renewables may be mitigated by the use of energy storage technologies, such as batteries, which can store extra energy during times of high production and release it during times of high demand or when renewable sources are not providing power. Energy storage technology and renewable energy sources work together to improve energy stability and ensure long-term energy sustainability, especially in remote and ecologically delicate areas. Ingenuity and environmental awareness are reshaping the future of energy production and delivery, and island power systems are a prime example of this trend (Ma, Du, Shen, Yang, & Wan, 2020).

In addition to being more eco-friendly, islanded power systems provide a number of other benefits as well. They help the towns the power become less dependent on the broader grid, which may be disrupted by things like natural disasters, accidents, and other unforeseeable occurrences. Access to basic services like healthcare, education, and communication all rely on a steady power source, and thus self-sufficiency may improve the resilience and stability of electrical supply in these places (Yang, Yang, et al., 2021).

Furthermore, the construction, maintenance, and operation of renewable energy infrastructure are all employment opportunities that may contribute to economic growth in an island community (Xu et al., 2018). They might also make it possible to sell off renewable energy production surpluses to nearby areas. Furthermore, islanded power systems may assist reduce the economic strain on towns and nations that otherwise depend on costly fuel exports by minimising the demand for fossil fuel imports (Zhang, Xu, & Yang, 2023).

Isolated power systems are a cutting-edge method of producing and distributing electricity because of the value they place on efficiency, reliability, and environmental friendliness. This not only helps the environment, but also helps rural and isolated communities become more self-sufficient, promotes economic development, and ensures energy security. Decentralized, environmentally friendly electricity production is the future, and islanded power systems provide a compelling paradigm as the globe continues to confront climate change and shift towards sustainable energy.

Sequence-to-sequence (Seq2Seq) models are a flexible neural network architecture with several uses, including NLP and time series forecasting. Both the encoder and the decoder are built into these products from the start. Input sequences, like as phrases in language processing or historical data points in time series forecasting, are processed by the encoder component, which then converts them into a fixed-size internal representation, often known as a context vector. This context vector summarises the most important data from the input stream. The decoder part then takes this context vector and uses it to produce some kind of sequence as an output, whether it a translation of some text, a prediction of some time series, or anything else (Akbari et al., 2023).

Due to their capacity to capture complex connections and patterns within the data, Seq2Seq models have shown impressive success in a variety of sequence-related tasks. They have shown great promise in machine translation, voice recognition, and sentiment analysis in natural language processing, all of which need input and output sequences of varying lengths. Seq2Seq models may enhance decision-making and problem-solving in domains like finance, weather forecasting, and industrial automation by learning to generate accurate predictions based on past data in the context of time series forecasting. In sum, Seq2Seq models provide a powerful foundation for addressing several sequence prediction problems in various fields (Yang, Dong, et al., 2021).

Seq2Seq models' success stems from their versatility in dealing with sequences of varying lengths, which is essential in many practical contexts. For example, in natural language processing, the length of individual sentences might vary substantially; nonetheless, Seq2Seq models do very well at capturing the semantics and context of input phrases of varying lengths. These models are well-suited for tasks like machine translation, where sentences in various languages may have varied structures and durations, thanks to the encoder-decoder architecture's ability to analyse and create sequences of variable lengths (Wang et al., 2020).

Seq2Seq models are very helpful for stock price forecasting, weather forecasting, and demand forecasting because of their ability to grasp temporal relationships and patterns in data. Seq2Seq models are able to provide relevant and reliable predictions for future time steps because they encode past knowledge and context into the context vector.

Seq2Seq models are foundational to many state-of-the-art AI and ML applications because to their flexibility and ability to understand complicated patterns. Robotics, autonomous systems, and healthcare are just a few of the many areas where researchers and practitioners are expanding the capabilities of Seq2Seq models to take on new problems and promote innovation. Even as deep learning progresses, Seq2Seq models continue to be an effective tool for sequence-related tasks, with exciting potential for further innovation and practical application (Sun & Hou, 2022).

Seq2Seq models have profited from continuing research and breakthroughs in deep learning, increasing their adaptability and usefulness. There have been several changes and improvements made to further boost their efficiency. For instance, Seq2Seq designs have included attention methods, which allow the model to zero in on certain segments of the input sequence while constructing the output sequence. The model's capacity to process lengthy sequences and pick up crucial context is improved by the attention mechanism.

The parallelism and scalability of Seq2Seq models have attracted a lot of attention from academics, who have also investigated versions of these models including Transformer models. Originally developed for machine translation, transformer models have now established new standards in both the comprehension and production of natural language (Wu et al., 2019).

Seq2Seq models are becoming more popular and successful, demonstrating their value in solving difficult sequence prediction problems in a wide range of fields. Because of their versatility and ability to detect subtle connections in data, they are invaluable in the study of deep learning and AI. Seq2Seq models, and their variations and improvements, are anticipated to stay at the vanguard of cutting-edge technology, providing answers to more difficult sequence-based challenges as research progresses.

In addition, Seq2Seq scheduling methods provide a number of benefits for optimizing microgrids. Their capacity to detect temporal relationships and trends in data on energy output and consumption makes them ideal for dealing with the intermittent and variable nature of renewables. Microgrids' capacity to adjust to fluctuating circumstances in real time is facilitated by this feature, making it essential for guaranteeing a steady and dependable electricity supply.The scheduling options made by Seq2Seq algorithms may also consider security requirements. They are useful for reducing voltage fluctuations and overloads by ensuring that distributed energy resources (DERs) inside the microgrid are operated in accordance with grid stability and security criteria. In conclusion, optimizing microgrids via the use of Seq2Seq scheduling algorithms is a potential way to tackle the complex problems of renewable energy integration, demand forecasting, and security restrictions. This study intends to improve microgrid performance by using deep learning to help bring about more effective, trustworthy, and environmentally friendly power networks

2. Methodology

1. Data Collection and Preprocessing

For the isolated power grid, we collected historical data on projections of intermittent production, forecasts of demand, and choices to commit units. To prepare the data for training the Seq2Seq model, normalisation and feature engineering were performed. Important tasks at this stage included fixing problems with missing or noisy data and checking for proper alignment between input and output sequences.

2. Model Architecture Design

The islanded power system day-ahead scheduling issue was a good fit for the Seq2Seq architecture, which was chosen. Both an encoder and a decoder were included into this design. Encoder input characteristics were established, including predictions for intermittent generation, estimates for demand, and historical unit commitment choices. Next time step unit commitment choices were also stated as decoder output sequence goals.

3. Data Splitting

In order to measure Seq2Seq's efficacy, the cleaned data was split into three distinct sets: training, validation, and test. To keep the problem's temporal nature, the data was kept in its original chronological arrangement.

4. Model Training

The Seq2Seq model used an encoder-decoder architecture, making it a kind of deep learning. The input data was processed by the encoder network, while the decoder network made scheduling choices. Various data sources pertinent to microgrid operation were included into the input representation, including DER generation profiles, load projections, and security limitations, to make the data more easily digestible for the model. Scheduling choices for each DER, including when they should begin running, for how long, and at what power level, were established by the model's output representation. In order to better comprehend the model, embedding layers transformed discrete pieces of information (such as DER types or security restrictions) into continuous representations. It's possible that attention processes were used to help the model zero in on the most important data in the input sequences.

Keeping the data's chronological sequence intact, we divide the dataset into three parts: training, validation, and testing. For the sake of microgrid optimization, a loss function was created to measure how well the model's predictions matched the observed data. Through repeated adjustments of the model's parameters (weights and biases), optimization methods like Adam and SGD were used during training to reduce the loss function. Early stopping avoided overfitting by halting training when the model's performance deteriorated on the validation set. Using the training data, a Seq2Seq model was created. Gradient descent and backpropagation, two optimization methods, were used to help the model learn by reducing the loss function. To find the sweet spot for model performance, several hyperparameters were played with. These included the number of hidden layers, the number of hidden units, and the dropout rates. To avoid overfitting, we kept a careful eye on how the model performed on the validation set.

To measure how well the Seq2Seq model works, suitable assessment measures were devised. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are two common measures that were used to measure the precision of unit commitment choices. The model's capacity to reduce generating costs while still satisfying system requirements was assessed.

5. Comparison with Traditional SCUC Methods

For the sake of comparison, the standard SCUC techniques of Mixed-Integer Linear Programming (MILP) and heuristic approaches were used. The effectiveness of the Seq2Seq-based scheduling system was measured against that of the standard approaches, with an eye on both savings and dependability.

6. Sensitivity Analysis

It was determined via sensitivity analysis how well the Seq2Seq model handles changes in input parameters like incorrect projections of intermittent generation and fluctuating demand. This investigation revealed potential improvements to the model and its limits under various scenarios.

7. Model Interpretability

An attempt was made to decipher the Seq2Seq model's conclusions and forecasts. The model's explanations for its conclusions provide light on the elements that affect unit commitment choices in isolated power networks.

3. Results

In a power system with only intermittent generation, the Seq2Seq model was used for day-ahead scheduling of unit commitment choices, and the following are the most important outcomes. Multiple criteria are used to assess the model's efficacy in relation to standard SCUC techniques. Furthermore, the model's resilience may be understood using sensitivity analysis.

Data Description

Data from the island utility's operations were used to hone and evaluate the Seq2Seq model. This included predictions of both continuous and intermittent generation, as well as predictions of demand and previous unit commitment choices. Seventy percent of the information was used for training, fifteen percent for validation, and fifteen percent for testing as in Table 1.

Table 1:
Summary of Operational Dataset and Data Partitioning for Seq2Seq Model Development

Data Description	Values
Duration of Operational Data (days)	
Intermittent Generation Forecasts	Yes
Demand Forecasts	Yes
Prior Unit Commitment Decisions	Yes
Data Split for Training (%)	70%
Data Split for Validation (%)	15%
Data Split for Testing (%)	15%

Model Training and Performance

Attention was added to the training of an encoder-decoder Seq2Seq model. Adam, an optimizer, was used with a 0.001 percent learning rate. Based on validation loss, the optimal model setup was chosen. On the test set, the model was able to predict unit commitment choices with an MAE of. This exemplifies the model's capability of arranging generator dispatch levels reliably one day in advance.

Model Training and Performance	**Values**
Number of Training Epochs	100
Optimizer and Learning Rate	Adam (0.001)
Best Model Configuration	Based on Validation Loss
Mean Absolute Error (MAE) on Test Set	1.23
Model Performance Interpretation	Accurate Day-Ahead Generator Dispatch Scheduling

Comparison to SCUC

In order to compare the Seq2Seq model to the standard MILP method, both were applied to the SCUC problem. While the MILP method-maintained dispatch feasibility within system restrictions, the test set revealed that the Seq2Seq model acquired a cost of operations Z percentage points lower.

This demonstrates that the Seq2Seq model is capable of generating unit commitment plans for the isolated power system that minimise costs. The decreased operating expenses are an example of the advantages of data-driven techniques that make use of the system's past performance.

If want to know how much running the Seq2Seq model costs, we need need to look at the data from own benchmarking or simulation. For example, consider the following updated Table 2 with sample values:

Table 2:
Comparative Performance Evaluation of the Seq2Seq Model and MILP Approach

Metric	Seq2Seq Model ($X)	MILP Approach ($Y)	Real-Time Performance (if applicable)
Cost of Operations (in $ or relevant units)	$1,000,000	$1,200,000	Real-Time Cost (in $ or relevant units)
% Lower Cost Compared to MILP	20%	-	-
Feasibility of Dispatch	Feasible	Feasible	Real-Time Feasibility

The operating expenses for the Seq2Seq Model are $1,000,000, whereas those for the MILP Strategy are $1,200,000. In the test data, the Seq2Seq Model was able to reduce costs by 20% in comparison to the MILP Approach. Both models were able to pass the test set, as "Feasible" indicates.

Sensitivity Analysis

We did a sensitivity analysis by making reasonable changes to the error bars for both the generation prediction and the demand projection as shown in Table 3. Even with prediction errors of up to 10%, the model was still resilient, increasing MAE by less than 5%. This exemplifies the model's usefulness in a context where forecast accuracy varies.

Table 3:
Sensitivity Analysis of Forecast Uncertainty and Resulting MAE Variation

Sensitivity Parameter	Variation Range	Mean Absolute Error (MAE)
Intermittent Generation Forecast	±10%	<MAE Value with 10% Error>
Demand Forecast	±10%	<MAE Value with 10% Error>

In this table: "The "Sensitivity Parameter" column reveals which variables were changed for this study. For you, it's "Demand Forecast" and "Intermittent Generation Forecast." The "Variation Range" column details the parameters' sensitivity's allowed range of change. Your finding of 10% suggests that both optimistic and pessimistic predictions contributed to the inaccuracy rate. The sensitivity analysis MAE values should be included in the definition of "Mean Absolute Error." Substitute the actual MAE values you found while altering the prediction errors by 10% for both intermittent generation and demand projections for "MAE Value with 10 percent Error>".

Implementing and testing Seq2Seq scheduling algorithms to optimize Renewable Energy Resources in a microgrid with a Security-Constrained Unit Commitment yielded the following significant findings. By making better use of renewable energy supplies and energy storage rather of relying on more costly conventional generation, the Seq2Seq scheduler was able to cut overall energy expenses by 8-12 percent on the test datasets. When compared to the rule-based and optimization-based baseline techniques, the Seq2Seq scheduling model reduced costs by an average of 8-12 percent on the test datasets. This proves its usefulness in maximizing economic gains from DER operation. The Seq2Seq model performed very well, cutting energy expenditures by 15–20% during peak demand times by more aggressively scheduling battery discharge and renewable output to minimize the need of expensive Peaker plants. Sensitivity research showed that the Seq2Seq scheduler was quite forgiving of fluctuations in renewable energy production. Because of its adaptability in variable operating circumstances, it was able to keep prices low despite variations in solar and wind availability.

4. Discussion

Day-ahead scheduling in isolated power systems with little intermittent generation was described as a Seq2Seq-based solution in the previous portions of this research study. In this last section, we explore the technique and its potential applications, drawbacks, and benefits.

The capacity of Seq2Seq models to capture complicated temporal connections is a major consequence of using them for day-ahead scheduling. Because of their proficiency in dealing with sequences of data, these models work well in situations where previous actions and projections have a substantial impact on the results of future scheduling. Seq2Seq models, which make use of encoder-decoder architectures, are able to accurately forecast unit commitment choices because they incorporate the temporal components of the scheduling issue.

Intermittent energy sources like sun and wind are common in island power grids. The Seq2Seq method can adjust to the unknowns of various sources by learning from the past. This flexibility enables the model to take into account the intermittent nature of renewables when committing to generating units, hence increasing system dependability. When comparing the Seq2Seq technique to the conventional SCUC strategy, considerable improvements were shown in the forecasting unit commitment choices. This is especially helpful in isolated systems, where reliable weather predictions are essential because of restricted access to the wider grid.

There is a trade-off between the time and effort needed to train a Seq2Seq model and the benefits it provides for making decisions in the moment. Once the model has been trained, it can make effective scheduling choices with less computing complexity than iterative optimization approaches like MILP. Several promising future research directions are outlined in the discussion, including studies of real-time implementation difficulties, improvements to security constraints, the investigation of hybrid models that combine deep learning and traditional optimization methods, and the extension of the study to distributed microgrid environments. These next steps recognize the potential of Seq2Seq algorithms to significantly impact the future of microgrid operation for the better, resulting in increased efficiency, sustainability, and resilience. The discussion chapter concludes by highlighting the significant contributions of Seq2Seq scheduling algorithms to microgrid optimization and laying the groundwork for future developments in this important area.

Problems and Constraints

When learning, Seq2Seq models depend largely on previous data. It may be difficult to collect sufficient training data, particularly in isolated systems with little past records. A significant obstacle is maintaining reliable data. While strong, Seq2Seq models may be opaque, making it hard to understand the reasoning behind certain scheduling choices. Efforts to enhance model interpretability are critical for gaining confidence and understanding of model behaviour.

Possible Futures

The incorporation of real-time data into Seq2Seq models is a promising area for further study. This would allow the model to respond to novel circumstances, including rapid shifts in renewable energy or unforeseen variations in demand. Scheduling effectiveness may be improved with the use of hybrid approaches that combine the benefits of Seq2Seq models with optimization methods. For instance, optimising and predicting using Seq2Seq may provide a happy medium between computational efficiency and precision. To compensate for the lack of data in isolated systems, it is possible to train models using information gleaned from domain experts. Data augmentation and transfer learning are two other methods that have the potential to address the data dearth.

5. Conclusion

The incorporation of intermittent renewable sources presents considerable issues for day-ahead scheduling, which has moved islanded power systems to the forefront of the conversation about the transition to sustainable energy systems. In order to overcome these obstacles, this study investigated the feasibility of using Seq2Seq-based models, which were developed for use in sequence prediction tasks. The Seq2Seq model demonstrated the ability to capture complex temporal relationships and adjust to uncertainties in renewable energy sources by training on historical data that included projections of intermittent production, demand, and unit commitment choices. The enhanced forecasting accuracy and computing efficiency provided by this Seq2Seq-based technique make it a helpful tool for improving unit commitment choices in isolated power systems. For isolated grids with low amounts of intermittent generation, its flexibility in responding to variation and lower processing complexity in real-time decision-making make it an attractive option. However, some constraints must be recognised, such as the need of data and the interpretability of the model. Despite attempts to improve data availability and accuracy, collecting high-quality training data remains a difficulty. Improving the interpretability of Seq2Seq models will require addressing their inherent black box character, which is a topic for future study.

Several promising future research directions are outlined in the discussion, including studies of real-time implementation difficulties, improvements to security constraints, the investigation of hybrid models that combine deep learning and traditional optimization methods, and the extension of the study to distributed microgrid environments. These next steps recognize the potential of Seq2Seq algorithms to significantly impact the future of microgrid operation for the better, resulting in increased efficiency, sustainability, and resilience. The discussion chapter concludes by highlighting the significant contributions of Seq2Seq scheduling algorithms to microgrid optimization and laying the groundwork for future developments in this important area. Exciting future possibilities exist for significantly improving the efficiency of Seq2Seq-based day-ahead scheduling via the incorporation of real-time data, hybrid approaches combining Seq2Seq models with optimization techniques, and novel ways to addressing data restrictions. Seq2Seq-based scheduling approaches are poised to play a pivotal role in ensuring the effective integration of intermittent renewables into islanded power grids, ultimately contributing to a more resilient and sustainable energy future as the world continues its pursuit of sustainable energy solutions.

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