ANALYSING THE ELECTRICITY LOAD AND PRODUCTION BY MEANS OF DIFFERENT MACHINE LEARNING METHODS: A CASE STUDY OF A MG SYSTEM

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Abstract: Renewable energy is a promising solution to combat the scarcity of electricity, particularly in isolated and rural areas. Microgrids (MG) can be employed for installing systems with different energy sources, such as renewable energy components and conventional energy sources like utility grids or grid-connected inverter systems. The amount of energy produced by renewable sources depends on their location, which has implications for energy production. This research aims to explore MG and their challenges for efficient operation. The study discusses various AI models used by researchers to mitigate problems associated with MG planning. Additionally, the paper presents a case study based on the most beneficial ML tool like clustering to gain insights into an existing MG system. The paper also delves into the issues related to PV, a connected distributed energy resource (DER), such as forecasting, and predictive management to reduce maintenance costs, and how AI tools can address them. Furthermore, forecasting methods such as LSTM and GRU models are discussed because of the stochastic nature of PV production.

Key words: micro-grid, renewable energy, machine learning, cost reduction, excess energy reduction.

1. INTRODUCTION

Microgrids were first introduced in 2001 by Bob Lasseter [1]. Microgrids should, in theory, be continuously linked to the utility grid, allowing any surplus energy from the microgrid to be sent to the primary grid and any energy shortfall in the microgrid to be met by the utility grid. The significant components of MG included DERs, power converters [2], energy storage, loads, master controller, intelligent switches, protective devices, communication, control, and automation systems [3, 4]. In microgrid (MG) systems, three distinct control architectures have been developed: centralized, decentralized, and distributed. In a centralized architecture, one main controller oversees and communicates with all other components. In contrast, a decentralized architecture features multiple individual controllers, each managing specific parts of the system independently [3-6]. AI-powered tools can help determine the production from DER, such as photovoltaic (PV) systems. The use of AI-powered tools can help to check the output data and find valuable insights to reduce operational costs and ensure stability [7-9].

This research provides an overview of Microgrids (MG), their challenges and related areas. Before and after installing an MG, it's crucial to consider and analyze factors such as the load pattern, as well as energy production from photovoltaic (PV). The study identifies critical weather parameters for electrical production of PV systems connected to form an MG. Additionally, the research explores how machine learning (ML) tools based on AI can help identify demand, predict valuable insights from data, and plan for the extension of an MG within PV systems.

3. CONTRIBUTION OF AI TOOLS IN MG

In this section, the role of AI tools in addressing the challenges faced by MG is discussed based on the literature. In [12], the researchers discussed the role of AI in MG planning. The method compared the actual grid with an artificial intelligence-generated grid design. The author considered the demand and the model trained with a neural network over time. NN-based algorithms can be implemented mainly in MG's three hierarchical control layers [11]. An NN-based model was deployed to overcome the issues of voltage and frequency disturbances [11]. In a study [13], a Generalized regression neural network (GRNN) model proposed. The researchers used a database to test its efficiency than the MSE error between the two graphs was calculated.

In [14], an article was published presenting an unsupervised deep anomaly detection framework designed to identify anomalies in a system based on data. In terms of fault detection Artificial Neural Networks (NNs) are mainly used to learn the normal operating conditions of the system and detect incipient faults by monitoring the real-time data. In 2019, research was published based on predictive maintenance analysis in a PV plant [15].

Artificial Neural Networks (ANNs) based model proposed for improving the 24h-ahead solar PV power production predictions [16]. Real-Time Energy Management of a Microgrid using Deep Reinforcement Learning has also been modeled by the author(s) in [17]. Forecast of solar irradiance, ambient and cell temperature, and their relationship with predictive maintenance models have been discussed in [32]. The department of computer science at Aalto University used a deep learning model as a reference for convolutional neural networks (CNN) to monitor photovoltaic panel operation [18]. The convolutional unit layers were implemented in Fault diagnosis of PV panels also monitored by researchers [19].

In terms of predictive control, [20] analysed the Maximum Power Point Tracking (MPPT) based on a Model Predictive Control (MPC) approach in MG is determined by the MPPT algorithm. Techniques such as Principal Component Analysis (PCA) and biplot are executed in a PV output case study, where energy production consequences have been analysed [21]. Time series analysis strategies can also produce output by examining measurable patterns in variable time based on historical data. Thus, it might deliver predictions using this strategy: Power, Irradiance, and Excess Energy [22].

There is also conventional method to predict, fault investigation such as MLP (Multilayered Perceptron). As an Infrared Thermography-Based Technique used which detects thermal state of power substation components into “non-defect” and “defect” classes [23]. There are also challenges in MG, voltage, and frequency control [24]. The developed multilayer perceptron (MLP) model [25] was considered the parameters to maintain the dynamic behaviour of the controller in an MG. In the figure below, we can see MG issues and the tools used to solve them.

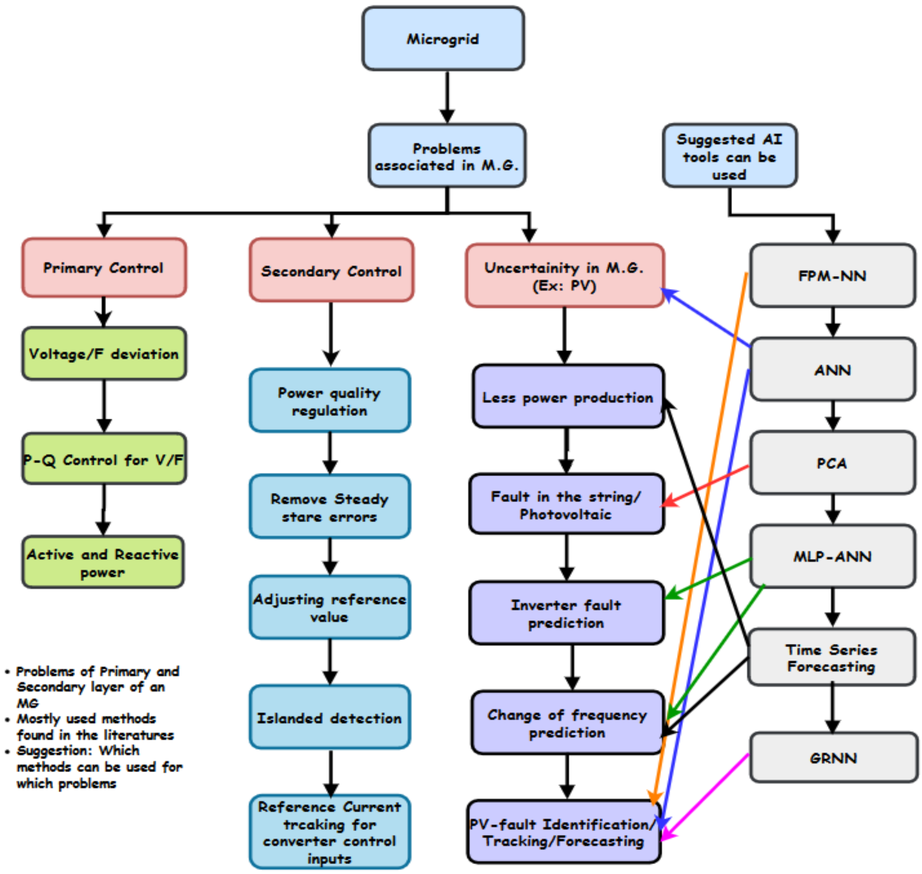


Fig 1. The proposed algorithm to solve the issues in MG is based on literature.

4. CASE STUDY

Based on the literature, the most used AI algorithm is ML algorithm. There are also different techniques like MPC, FCS-MPC control techniques that have been found form literature. According to the literature, ANN was the most used method in MG problems.

We have conducted a study to evaluate the potential of machine learning (ML) tools using data from the TwInSolar Consortium Work Package: WP4 – A smart microgrid in a tropical island by the University of La Reunion [34]. Several datasets were used to gain a deep understanding, including load profile data for different campuses such as IUT_load, ESIROI_SEASOI, and CROUS_load data. The IUT_load data combines the data from Dpt. 1, 2, 3, 4, and Enerpos building. Some buildings are already equipped with PV, including ESIROI_PV, ENERPOS_PV, and Dept 1_2_PV data. An ML approach was employed to analyze their MG consolidated data to determine the potential load patterns and behavior of

PV productions. The load and PV data were utilized for forecasting based on historical data and PV production analysis based on meteo data, which was collected from the weather station [34].

The use of ML models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) has been considered for forecasting approaches. GRU and LSTM are types of recurrent neural networks (RNN) that are preferred due to their better mechanism in handling long-term dependencies. The CROUS_load, ESIROI_SEASOI_Load, IUT_load, ESIROI_IUT2_HVAC, ESIROI_PV, ENERPOS_PV, and Dpt_1_2_PV data were trained for forecasting.

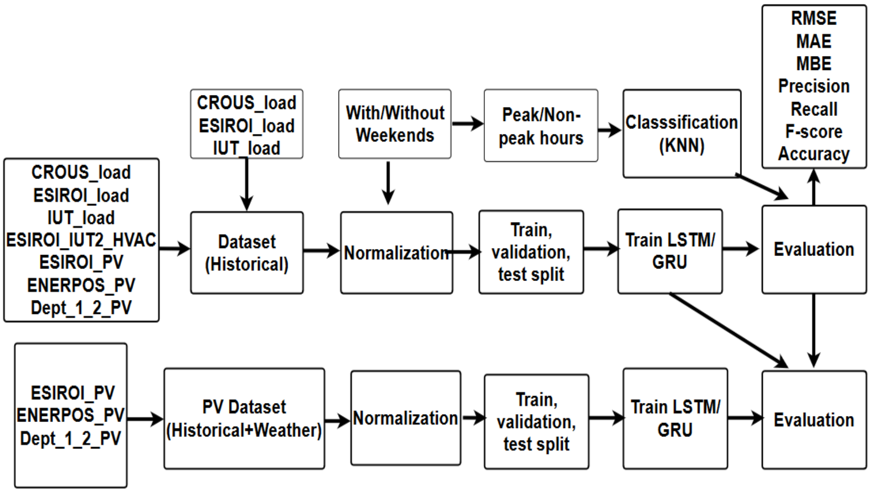
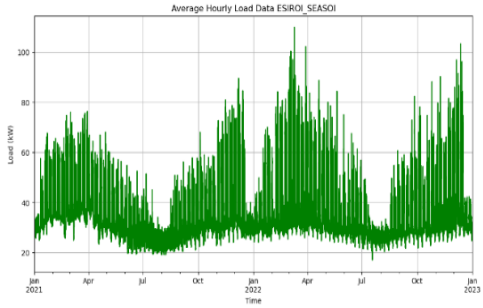


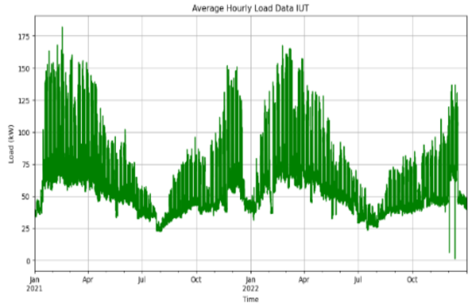
Fig 2. The structure of the research (with 3 different steps to analyzing the data).

Table 1. The evaluation result from the LSTM and GRU ML tools

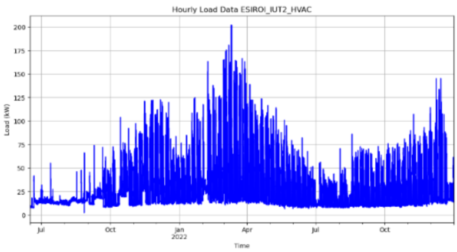
Dataset	RMSE	MAE	MBE	LSTM	GRU
CROUS_load	0.093	0.071	0.031	✓	x
CROUS_load	0.092	0.070	0.029	x	✓
ESIROI_SEASOI_load	0.116	0.088	-0.0053	✓	x
ESIROI_SEASOI_load	0.117	0.089	-0.005	x	✓
IUT_load	0.094	0.064	0.0082	✓	x
IUT_load	0.094	0.064	0.0070	x	✓
ESIROI_IUT2_HVAC	0.130	0.101	0.014	✓	x
ESIROI_IUT2_HVAC	0.126	0.097	0.012	x	✓
ESIROI_PV	0.109	0.092	-0.048	✓	x
ESIROI_PV	0.109	0.093	-0.050	x	✓
ENERPOS_PV	0.110	0.090	-0.035	✓	x
ENERPOS_PV	0.109	0.090	-0.037	x	✓
Dpt_1_2_PV	0.114	0.096	-0.044	✓	X
Dpt_1_2_PV	0.113	0.096	0.044	x	✓



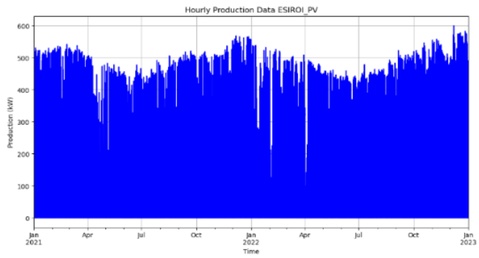
Average hourly load data ESIROI_SEASOI



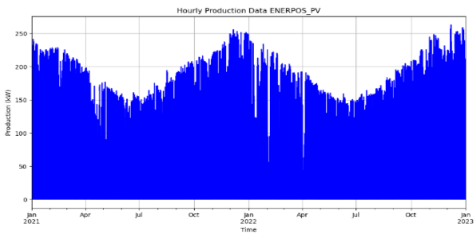
Average hourly load data IUT



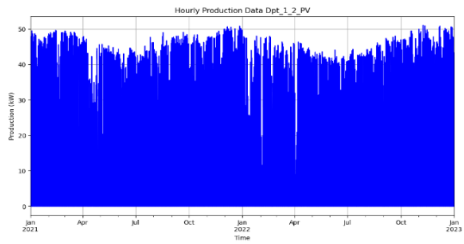
Average hourly load data ESIROI_IUT2



Average hourly prod. data ESIROI_PV



Average hourly prod. data ENERPOS_PV



Average hourly prod. data Dept_1_2_PV

Based on the table provided, the forecasting models which used GRU and LSTM algorithms produced nearly similar results. In MG planning, understanding the load characteristics is crucial to avoid producing excess energy in the absence of feed-in tariffs (FIT). Therefore, we conducted a pattern analysis on the load data, including detailed analysis with and without weekends, to determine the load characteristics. To identify the load patterns, we used a K-means clustering classification model and found that peak and off-peak hours were the most prominent patterns. We then applied the algorithm to all the load data mentioned above.

We have analyzed the pattern of a model with and without results. The model showed us that the result without considering the weekend was better. This is because the data was more normalized, or the predicted value was closer to the actual value. The actual value was obtained from weather stations and sensors, and the consolidated MG data was mostly in real-time.

This information is crucial when planning a new MG or an extension, as an oversized or undersized system can significantly impact both cost and technical performance.

The evaluation of the research's effectiveness is performed using a confusion matrix, which includes essential parameters such as true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). From these parameters, validity metrics like Accuracy, Recall, F1-score, and Precision can be derived. The formulas for these metrics are as follows:

Accuracy = (TP+TN)/(TP+FP+TN+FN)

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F-score = 2* (Precision * Recall)/ (Precision +Recall)

Table 2. Classification report of load pattern analysis using K-means clustering

Dataset	Precision	Recall	F1-score	Support	Accuracy	Peak hours	Weekends
CROUS_load	0.71	0.49	0.58	730	0.66	✓	✓
CROUS_load	0.76	0.67	0.71	521	0.73	✓	x
ESIROI_SEASOI_load	1.00	0.38	0.56	730	0.81	✓	✓
ESIROI_SEASOI_load	1.00	0.52	0.69	521	0.84	✓	x
IUT_load	1.00	0.27	0.42	730	0.79	✓	✓
IUT_load	1.00	0.36	0.53	521	0.80	✓	x

The final part of the research is focused on comparing the forecasting models. The first case did not consider any weather data, while the second case included the meteo data from the weather station as input parameters. The output results show that considering weather data as input parameters improves the accuracy of the forecasting model. LSTM and GRU were trained on each PV dataset merged with weather data. Here is the evaluation summary for the test set.

Table 3: Evaluation report of forecasting analysis using meteo data combined with PV production data

Dataset	RMSE	MAE	MBE	LSTM	GRU
ESIROI_PV+Meteo	0.1047	0.0864	-0.0439	✓	x
ESIROI_PV+Meteo	0.1051	0.0856	-0.0417	x	✓
ENERPOS_PV+Meteo	0.1085	0.0867	-0.0341	✓	x
ENERPOS_PV+Meteo	0.1065	0.0867	-0.0032	x	✓
Dpt_1_2_PV+Meteo	0.1077	0.0881	-0.0303	✓	✓
Dpt_1_2_PV+Meteo	0.094	0.064	-0.0292	x	

As we discussed earlier, both LSTM and GRU models have the primary advantage of capturing long-term dependencies. Our research outcomes demonstrate that these models can effectively identify patterns within historical data without the need for additional data. We evaluated the performance of these models using root mean squared error, mean absolute error, and mean bias error as our metrics, and we conducted the evaluations using a hold-out test set. Our results indicate that there was no significant improvement when we used both historical load data and weather data compared to using only historical load data. However, we must note that our evaluation was based on a scaled (0-1) test set. Moving forward, we plan to explore the following areas:

- Evaluating the model performance on the original scale could provide more insights, such as the effect of incorporating weather data in the prediction tasks.

- Since our dataset only consists of 731 days, we couldn't use a very large training set. By adding synthetic data to the training set using the synthetic minority over-sampling technique, we may be able to improve the performance of the models on unseen data/test sets.
- In all of our experiments, we used a sequence length of 5. However, using a more extended sequence length could potentially improve the model performance, as both LSTM and GRU can capture long-term dependencies.

5. CONCLUSION

In this research, we have seen the usefulness of different prediction models in terms of energy production scheme identification which are significant in energy production. Different operating modes of MG have also been discussed.

Mostly ML algorithms can be helped in MG and decision making, such as energy production, fault analysis, reducing the forecasting error, etc. Several models can also help design a better system before the installation process based on the installed system and its historical data. Based on the finding, we can conclude our research as follows:

- As the connected resources play an essential role in the production, for that reason, the component fault can be identified by using models such as CNN, ANN, NN based MLP models.
- Forecasting can also give us an overview such as identifying PV Irradiation, production.
- Clustering analysis can also identify the pattern of the load characteristics and PV production over the time.

This kind of models has limitations also such as:

- These applications rely on historical data or information to predict the future fault (grid connected-Islanded mode)
- It requires good accuracy for the prediction process, and it is challenging to identify which model will suit which problem identification.

The research focused on data analysis of an MG system considering all the limitations and primarily using PV sources. It provides an overview of the issues associated with the system and its connected resources. To further develop the system, future work could use the collected data to design new MG systems where no RE sources exist, by using optimization tools. Additionally, optimization algorithms could be used to determine potential influence compared to ML models, and data could be leveraged to enhance the accuracy of the analysis.

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Data has been collection from the University of La Reunion and TwinSolar. The University was the source of all information regarding the case study and data preparation. The date is available in internet as an open-source data.

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Remark:

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