



FEP

FACULDADE
DE ECONOMIA
UNIVERSIDADE
DO PORTO

Unsupervised learning for fault detection in solar photovoltaic systems

Ana Rita Moreira Rodrigues

Dissertation

Master in Modelling, Data Analysis and Decision Support Systems

Supervised by:

PhD Bruno Miguel Delindro Veloso

PhD Maria Isabel Pinto Preto

2024

Acknowledgments

I would first like to thank my internal supervisor, Professor Bruno Veloso, for all the endless support, patience, and inspiring words. During this journey, we walked side-by-side with a common goal, and you motivated me to do better, learn more, think critically about my work, and organize my thoughts. There are no words to thank you enough.

I want to express my gratitude to *Enlitia* for the opportunity to work hands-on with a company that offers solutions for a more sustainable future; it certainly made my experience more fascinating. To my external supervisor, Isabel Preto, thank you for your insightful guidance during these months, your availability, and for providing me with all the resources I needed to continue my work.

To my dear colleagues at Accenture, Rosa and Gonalo, I want to express my deepest gratitude. Your understanding and kind words have been a source of strength for me. I am truly fortunate to have you as my team members, always.

For all the help in these past two years, I want to thank my colleagues at FEP. You made my academic experience memorable, and I wish you many success.

My beloved friend, Maria, your emotional support healed me through the good and bad times. Thanks for believing in me.

I would also like to thank my parents for encouraging me and reassuring me of my worth throughout all these years. Thank you for being a safe haven, all your efforts made me who I am today. I am grateful for you.

Lastly, my partner, Andr , who motivates me daily to be a better person and a more capable professional, thank you for all the great advice, good times, and tireless orientation. You were the one who motivated me to go on this adventure. Your love and support mean more than you know. Back then, you were counting on me. Now I can say I am the one counting on you.

Abstract

This dissertation applies unsupervised learning techniques to enhance fault detection in solar photovoltaic systems. The inherent complexity and variability of these systems' data make traditional supervised learning approaches challenging due to the scarcity of labeled anomaly data in real-world scenarios.

The methodology encompasses a detailed and rigorous analysis of historical inverter-level data from solar photovoltaic systems. After meticulous data cleaning and preprocessing steps, one year of data without anomalies was used to train and tune a Long Short-Term Memory model (LSTM), a Deep Learning model that handles the dependencies and relationships of data over time. In the second phase, a pre-selected set of anomalous data was input for the parameterized model, whose reconstruction errors were employed on threshold configuration. The anomaly scores above the established limit were considered faults on the testing set. Later, Explainable Artificial Intelligence techniques, like SHapley Additive exPlanations (SHAP), were implemented to extract the most important features of detected anomalies.

This study not only underscores the importance of advanced data-driven techniques in managing and optimizing renewable energy resources but also provides practical recommendations for their implementation in solar photovoltaic systems. This offers a tangible pathway to enhance the reliability and efficiency of solar energy systems, inspiring the transition towards more sustainable energy systems.

Keywords: Time Series; Anomaly Detection; Long Short-Term Memory; Predictive Maintenance; Deep Learning; Solar Photovoltaic Systems; SHapley Additive exPlanations; Machine Learning; Unsupervised Learning

Resumo

Esta dissertação aplica técnicas de aprendizagem não supervisionada para melhorar a detecção de falhas em sistemas fotovoltaicos solares. A complexidade inerente e a variabilidade dos dados destes sistemas tornam os métodos tradicionais de aprendizagem supervisionada desafiantes devido à escassez de dados devidamente rotulados em cenários do mundo real.

A metodologia engloba uma análise detalhada e rigorosa dos dados históricos ao nível de inversor de sistemas fotovoltaicos solares. Após meticulosas etapas de limpeza e pré-processamento de dados, o equivalente a um ano de dados sem anomalias foi usado para treinar e otimizar um modelo de Memória de Curto e Longo Prazo (LSTM), um modelo de Aprendizagem Profunda que capta as dependências e relações dos dados ao longo do tempo. Na segunda fase, um conjunto pré-selecionado de dados só contendo anomalias foi inserido no modelo parametrizado, cujos erros de reconstrução foram utilizados na configuração do threshold. Cada pontuação de anomalia atribuída às instâncias de teste que ultrapasse o limite definido é considerada uma falha. Mais tarde, técnicas de Inteligência Artificial Explicável, como as Explicações Aditivas de Shapley (SHAP), foram implementadas para extrair as características mais importantes das anomalias detetadas.

Este estudo não só sublinha a importância de técnicas avançadas baseadas em dados na gestão e otimização de recursos energéticos renováveis, mas também fornece recomendações práticas para a sua implementação em sistemas fotovoltaicos solares. Isto oferece um caminho tangível para melhorar a fiabilidade e eficiência dos sistemas de energia solar, inspirando a transição para sistemas de energia mais sustentáveis.

Palavras-chave: Séries Temporais; Detecção de Anomalias; Memória de Curto e Longo Prazo (LSTM); Manutenção Preditiva; Aprendizagem Profunda; Sistemas Solares Fotovoltaicos; Explicações Aditivas de Shapley; Aprendizagem Automática; Aprendizagem Não Supervisionada

Contents

Acknowledgements	ii
Abstract	iii
Resumo	iv
1 Introduction	1
1.1 Motivation	1
1.2 Problem Description	2
1.3 Dissertation Structure	4
2 Literature Review and Related Work	7
2.1 Data Simulation	7
2.1.1 Online Simulation Models	7
2.1.2 Experimental Simulations	8
2.1.3 Effects on the I-V Curves	8
2.2 Machine Learning for Anomaly Detection	9
2.3 Deep Learning for Anomaly Detection	11
2.4 Threshold Determination in Anomaly Detection	15
2.5 Evaluation Metrics in Anomaly Detection	17
2.6 Explainable Artificial Intelligence for Anomaly Detection	20
3 Methodology	21
3.1 Business Understanding	22
3.2 Data Understanding	23
4 Data Preparation	27
4.1 Data Preprocessing and Feature Engineering	27
4.2 Exploratory Data Analysis	28
5 Modeling	33
5.1 Detection Layer	33
5.1.1 LSTM-Autoencoder	33
5.1.2 Hyperparameter Tuning	34
5.1.3 Threshold Configuration and Anomaly Detection	35
5.2 Explanatory Layer	36
6 Results	39
6.1 Performance Evaluation	44

7	Conclusion	47
7.1	Final Remarks	47
7.2	Recommendations	48
7.3	Limitations and Future Work	49
	Bibliography	51
A	Appendix	i
A.1	Methodology	i
A.2	Data Preparation	ii
B	Appendix	iv
B.1	Results	iv

Glossary

2T Two-stage Thresholding. 16

A Ampere. 8

AC Alternating Current. xi, 3, 4, 10, 23, 24, 27, 29, 30, 34, 41, 44, 45

ADAM Adaptive Moment Estimation. 34, 47, 48

AE Autoencoder. xi, 12–15, 20, 34, 35

AI Artificial Intelligence. 7, 11, 20, 47, 50

AMRules Adaptive Model Rules. 14, 15

ANN Artificial Neural Networks. 4, 10, 11, 13, 34, 47

API Application Programming Interface. 33

AUC Area Under the Curve. 19, 44

CAE Convolutional Autoencoder. 12, 13, 15

CCC Current Carrying Conductors. 3

CFFSM Code-based Fast Fault Simulation Model. 7

CFSFDP Clustering by Fast Search and find of Density Peaks. 13

CNN Convolutional Neural Network. 11, 12, 15

CSP Concentrated Solar Power. 22

CV Cross-Validation. 10

DC Direct Current. xi, 3, 4, 23, 24, 29–31, 41, 43, 48, 49

DeepLIFT Deep Learning Important Features. 20

DL Deep Learning. 5, 7, 11, 15, 19, 20, 33, 44, 47

DM Data Mining. 21

DNN Deep Neural Network. 12, 15, 36

DT Decision Tree. 10, 11

EL Ensemble Learning. 11

FCM Fuzzy c-means. 10

FDD Fault Detection and Diagnosis. 4, 7, 9, 11, 25

FPR False Positive Rate. 17–19, 49

GAN Generative Adversarial Network. 13, 15

GBSSL Graph-based Semi-Supervised Learning. 11

GHI Global Horizontal Irradiance. xi, 23, 27, 34, 41, 43–45

GTI Global Tilted Irradiance. 27, 43

ICFFSM Improved code-based Fast Simulation Mode. 7

IoU Intersection over Union. 19

IQR Interquartile Range. 16, 35, 36, 41, 49

KNN K-Nearest Neighbors. 10

KPIs Key Performance Indicators. 2

kWh Kilowatt-hour. 22

LIME Local Interpretable Model-agnostic Explanations. 20

LOF Local Outlier Factor. 17

LPF Low Pass Filter. 49

LR Logistic Regression. 9, 11

LRP Layer-wise Relevance Propagation. 20

LSTM Long Short-Term Memory. iv, xi, xii, 14, 15, 19, 20, 33–35, 39–41, 47, 48

MA Moving Averages. 2, 11

MAD Median Absolute Deviation. 16

MAE Mean Absolute Error. 48

ML Machine Learning. 2, 4, 5, 7–11, 15, 17, 36, 47

MLP Multilayer Perceptron. 10

MOGAAL Multiple-Objective Generative Adversarial Active Learning. 13, 15

MPP Maximum Power Point. 9, 23

MSE Mean Squared Error. xi, 40, 48

MSLE Mean Squared Logarithmic Error. 48

PCA Principal Component Analysis. 11

PLA Power Loss Analysis. 4

PRM Polynomial Regression Model. 20

PRO Per-region Overlap. 19

PSBO Partial Shading with the Bypass Diode Open-Circuit Fault. 9

PSSC Partial Shading with the Bypass Diode Short-Circuit Fault. 9

PV Photovoltaic. 1–4, 8, 10, 14, 22–24, 29, 30, 47–49

PVS Photovoltaic System. xi, 2–5, 8, 9, 11, 13, 22, 24, 30, 31, 45, 47–49

ReLU Rectified Linear Unit. 33, 47

RMSE Root Mean Squared Error. xi, 8, 10, 20, 35–37, 41, 42, 48

RNN Recurrent Neural Network. 13

ROC Receiver Operating Characteristic. xii, 19, 44

SAE Stacked Autoencoder. 13, 15

SCD Short-circuit with the Degradation Fault. 9

SDM Single-Diode Model. 8

SHAP SHapley Additive exPlanations. xii, 20, 36, 37, 43, 44, 47

SSA Singular Spectrum Analysis. 20

STC Standard Test Conditions. 13

SVM Support Vector Machine. 9, 10

t-SNE t-distributed Stochastic Neighbor Embedding. xi, 13, 40, 41

TPR True Positive Rate. 19

TWh Terawatt-hours. 1

VAE Variational Autoencoder. 13, 15, 20

VRA Variational Recurrent Autoencoder. 14

W Watts. 1, 23, 31

List of Figures

1.1	Direct Current (DC) and Alternating Current (AC) sides of the Photovoltaic System (PVS). Image Source: SFPE	3
1.2	Classification of faults in DC and AC side of PVS (Madeti & Singh, 2017) . .	3
1.3	Classification of different fault detection techniques (Madeti & Singh, 2017)	4
2.1	I-V characteristic curves (red) and P-V (blue). Image Source: ResearchGate .	8
2.2	Normalized I-V curves of different faults under different ambient conditions (Liu et al., 2021)	9
2.3	Framework of proposed 2-D CNN approach (Aziz et al., 2020)	12
2.4	Structure of an Autoencoder (AE) (Seghior, Abbas, Chouder, & Rabhi, 2023)	12
2.5	Architecture of a CAE (Fu et al., 2021)	13
2.6	Structure of a Long Short-Term Memory (LSTM) Network (Appiah, Zhang, Ayawli, & Kyeremeh, 2019)	14
3.1	CRISP-DM Diagram (Hotz, 2018)	21
3.2	AC and DC variations on 01-01-2021 for Inverter 2	24
3.3	AC and DC variations on 01-01-2021 for Inverter 7	24
4.1	Meteorological variables evolution through 01-01-2021	27
4.2	Meteorological variables evolution over time	28
4.3	Header data of Inverter 7	28
4.4	Inverters' Correlation Matrices	29
4.5	June and December's Heat Maps of Mean Irradiance per Hour and Day of the Month	30
4.6	Inverters' Irradiance-Power Curves	30
4.7	Comparison between variables of both inverters	31
4.8	Inverters' Efficiency curves	31
5.1	Unsupervised Anomaly Detection - System Architecture	33
5.2	Examples of anomalous periods for both inverters, when AC Power does not follow the same pattern as Global Horizontal Irradiance (GHI)	34
6.1	Model Loss (Mean Squared Error (MSE)) - Training phase [Inverter 2] . . .	40
6.2	Model Loss (MSE) - Training phase [Inverter 7]	40
6.3	2D t-distributed Stochastic Neighbor Embedding (t-SNE) of LSTM Layer Activations	41
6.4	Boxplot of Root Mean Squared Error (RMSE) [Inverter 2]	41
6.5	Boxplot of RMSE [Inverter 7]	42

6.6	Distribution of faults for both inverters	42
6.7	Comparison between power, irradiance, reconstructed irradiance, and reconstruction loss. The periods where the occurrence of anomaly is more evident are highlighted.	43
6.8	SHapley Additive exPlanations (SHAP) Waterfall plots for both inverters . .	43
6.9	Receiver Operating Characteristic (ROC) curves for both inverters	44
A.1	Q-Q Plots for Inverter 2	i
A.2	Q-Q Plots for Inverter 7	ii
A.3	Pre-determined efficiency curve of SUNNY CENTRAL 500HE inverters. Source: SMA	ii
A.4	Yearly Heat Map of Mean Irradiance per Hour and Day of the Month	iii
B.1	LSTM Design for both Inverters	iv

List of Tables

2.1	Literature Review on Threshold Determination Techniques	15
2.2	Literature Review on Evaluation Metrics for Unsupervised Anomaly Detection	18
3.1	Description of the original variables	23
6.1	Best Hyperparameters for Inverter Models	39
6.2	Evaluation Metrics	45

Chapter 1

Introduction

1.1 Motivation

According to the *United Nations* (n.d.), renewable energy is derived from natural sources and restored at a higher rate than consumption. Examples include wind, solar, ocean, and geothermal energies, hydro-power, and bio-energy. Non-renewable sources, also known as fossil fuels (coal, oil, and gas), take millions of years to restock. When burned to produce energy, they “*cause harmful greenhouse gas emissions, such as carbon dioxide*”. One answer for the climate crisis is the transition to green energy since it creates lower gas emissions, reduces costs in most countries, and creates more jobs than fossil sources.

Solar energy is the most common and cheapest form of renewable energy. It can also work in cloudy weather and plays a considerable part in energy mixes of countries with lower sunlight exposure. Solar technologies, such as Photovoltaic (PV) panels, convert sunlight into electrical energy and normally have a lifespan of about 30 years (Nations, n.d.).

Worldwide, about 1289.27 Terawatt-hours (TWh) was generated from solar in 2022. In Europe, the electricity production of this kind was 233.21 TWh, and in Portugal, it was 3.07 TWh (*Solar*, n.d.). At the end of the same year, the world’s installed PV power was 1053115 MWatts (W), representing an annual growth rate of 22.2% and a ten-year growth of 26%. Europe accounts for 22.5% of the whole market, with 236957 MW (annual growth rate of 19.8% and a ten-year growth of 12.4%), and Portugal’s PV installed power (share of 0.2%) was 2536 MW, holding an annual growth rate of 54.1%, and a decade growth of 26.7% (*Renewable energy statistics 2023*, n.d.).

Although taking a small part, Portugal has shown crescent interest in investing in solar energy production. In its report for 2022, *IEA* (n.d.) mentioned that the country’s excellent solar energy availability was responsible for the decrease in energy imports, together with public policies providing financial incentives for this sustainable transition. A new incentive program in 2020, “*Programa de Apoio a Edifícios Mais Sustentáveis*”, further supported installing solar thermal systems - critical drivers for market expansion include regulations on the *Energy Performance of Buildings* – making them more affordable for end-users. In 2019, the legislation established rules for classifying buildings as *Nearly Zero Energy Buildings (NZEB)*. Incorporating solar technologies, including passive house and day-lighting technologies, is encouraged, especially in new buildings, since this integration allows buildings to achieve higher energy performance labels and benefits such as tax reductions. It highlights Portugal’s commitment to leveraging its solar energy potential and the comprehensive approach involving market

incentives, regulatory frameworks, and emphasis on quality and sustainability (Bessa, 2021).

The increasing adoption of solar PVSs for electricity generation underscores the importance of maintaining operational integrity. For a smoother energy transition, it is necessary to build a stable network for consumers to trust and employ new energy production methods. An intelligent way to achieve this is by using Machine Learning (ML) rather than resorting to physical relocation or employing other more costly and unstable processes. This research is motivated by the need for reliable, automated fault detection mechanisms to ensure optimal performance and longevity of solar PVS. Emphasizing the importance of technology in predicting anomalies and establishing tools for control is crucial in this process.

1.2 Problem Description

To get a better understanding of this issue, it is necessary to get a hands-on, real-world case study. For that, this dissertation partners with *Enlitia*. In this subsection, we contextualize the company’s corporate mission, its challenges, objectives, and its current methodology. Moreover, it is given a context on the PVS components, the type of faults that occur, and ways to detect them.

Enlitia, a *Smartwatt*’s spin-off, is a portuguese services company focused on delivering intelligent solutions for the renewable energy market - primarily international clients such as *EDP Renováveis*, *Galp*, *Ventient Energy*, and *ERG* (Seara.com, n.d.). Its business model configures the arrangement of “*asset performance management and monitoring solutions, empowering the energy industry to thrive in the digital era.*”. By unlocking the power of data, *Enlitia* presents an algorithm ecosystem that maximizes solar and wind energy production and minimizes operating costs. Furthermore, it lets the client control his renewable assets in real time and plan strategic moves (*About - Enlitia*, n.d.).

The energy producers want to maintain optimal PVS performance, with a growing interest in spotting downgrading performance due to faults in real-time or in the long run. Due to that, the company is looking to improve anomaly detection in elements of PV installations - such as PV panels, strings, or inverters - using remote metering data. Moreover, it is essential to define metrics/rules to grant outlier detection and understand its influence on the overall PVS’s performance.

Their methodology for fault detection contemplates two approaches. The first is an adaptation of the dissertation work of Tereso (2021), which developed Key Performance Indicators (KPIs) for PV centrals based on statistical metrics (mean, standard deviation, quantiles). The power predictions are obtained using the Moving Averages (MA) smoothing method and compared with the actual measurements. The other alternative simulates the expected power through a proprietary model, a simple PV power regression. Both methods for outlier identification depend on a limit imposed by the plant operator. A complementary analysis is also conducted with the client’s maintenance reports, from which the latter results are compared.

Despite advancements in monitoring technologies, conventional fault detection methods may fall short in identifying latent and complex issues. A modern solution is needed: unsupervised ML models present a promising avenue to address these limitations and elevate the accuracy and efficiency of fault-detection processes, aligned with *Enlitia*’s value proposition. These techniques offer the potential to uncover subtle deviations in system behavior, enabling proactive maintenance and minimizing downtime.

A PVS is an electricity production resource that converts solar radiation into electricity

(**Figure 1.1**). It comprises PV arrays where solar cells are combined in series to form PV modules - unities that convert solar energy into electric power and can be connected in series or parallel. The next component is the power conditioner, responsible for conditioning the power generated by the PV array for use or storage. Many PVSs include a method for storing energy, typically in the form of battery banks - a storage system. The PV inverter converts the DC produced by the array into AC, the standard form of power used in homes and by the electrical grid. Moreover, the PVS can be connected to the utility grid, either with or without a local load - allowing for the excess power generated to be fed into the grid or for the grid to supplement the power supply when the output is insufficient (AbdulMawjood, Refaat, & Morsi, 2018).

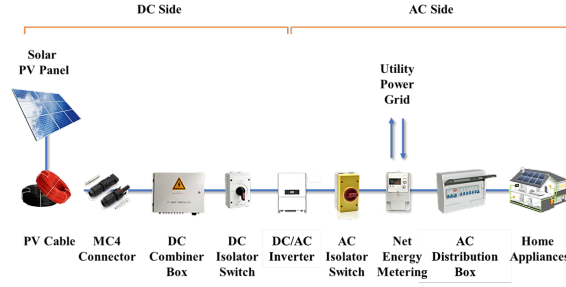


Figure 1.1: DC and AC sides of the PVS. Image Source: SFPE

Most studied faults occur on the PV array (**Figure 1.2**). Open-circuit results of disconnection on a PV string, causing high-frequency noise and a rapid decrease in current and voltage outputs (risk of fire hazards). Short circuits happen on unintended connections between two points in a PVS, potentially life-threatening. Mismatch faults are divided into temporary ones caused by particle accumulation or shading on the PVS surface, and damages and deterioration of materials cause permanent ones (Liu et al., 2021). Besides ground (unintentional low impedance path between Current Carrying Conductors (CCC)), bypass diode, arc, and bridging faults, it is essential to mention the asymmetrical anomalies of two categories: line-to-line (the unintentional connection between two nodes of the PV array) and line-to-ground (one conductor drops to the ground or contacts the neutral conductor). On the AC side, the most critical one is inverter failure, resulting from high thermal and mechanical stress on power switches (Madeti & Singh, 2017).

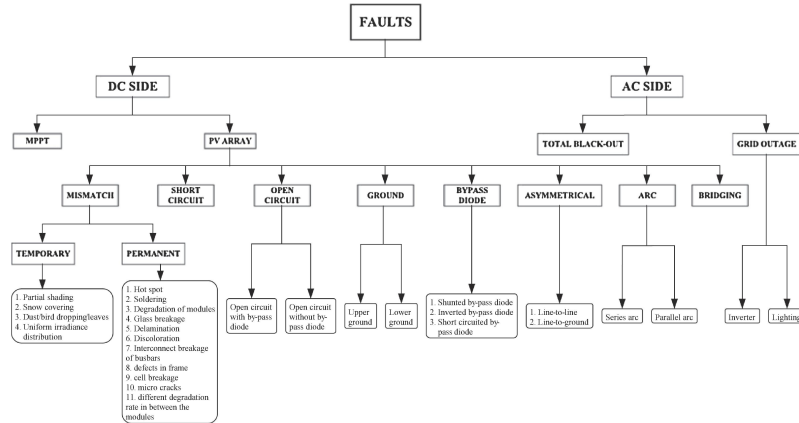


Figure 1.2: Classification of faults in DC and AC side of PVS (Madeti & Singh, 2017)

According to the literature, various ways exist to execute Fault Detection and Diagnosis (FDD), most of them on the DC side (**Figure 1.3**). Infrared thermograms detect and locate defects (hot spots) by analyzing the temperature characteristics of a PV module. This method is expensive, and its high-resolution infrared imager is unsuitable for small-scale PVSs. Deviation calculations between the theoretical working current, voltage, power (obtained through a mathematical model), and the measurements are also a great tool. A fault threshold is set to classify the deviations for FDD, but multiple ones can be used for fault classification. However, it can be challenging to identify various fault types and determine the threshold since fewer fault examples mean low accuracy levels (Liu et al., 2021). Electrical and Performance Analysis are techniques that analyze electrical signals and performance data to identify deviations indicative of faults. Include the analysis of current-voltage (I-V) characteristics, Power Loss Analysis (PLA), and statistical approaches like analysis of variance (ANOVA) for detecting faults in PVSs. A simpler but unsophisticated way is to do regular visual checks to detect mechanical or electrical deficiencies in PV modules. Others employ ML applications by leveraging advanced ML algorithms to analyze complex data patterns and predict potential faults. Lastly, some electric protection devices are recommended, and, in some cases, combining various methods to enhance fault detection capabilities is helpful (AbdulMawjoood et al., 2018). On the AC side, the model-based techniques, like signal processing, and model-free approaches, like ML models, such as Artificial Neural Networks (ANN), are very popular (Madeti & Singh, 2017).

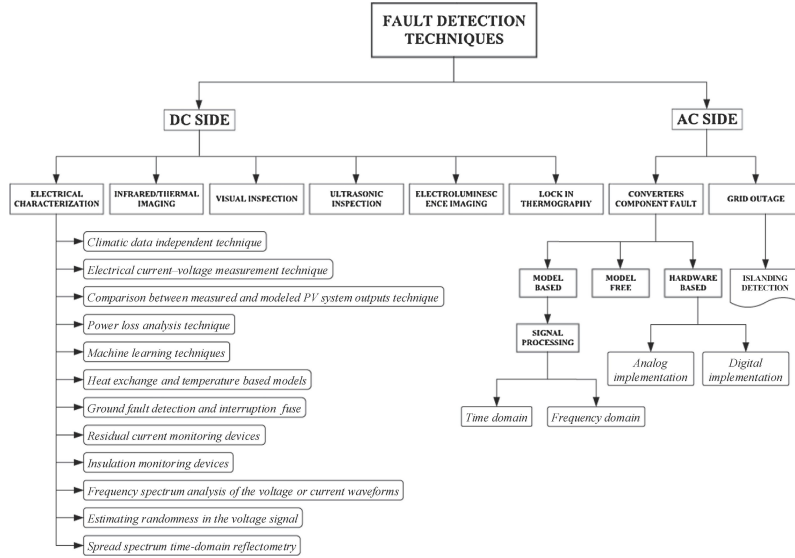


Figure 1.3: Classification of different fault detection techniques (Madeti & Singh, 2017)

1.3 Dissertation Structure

The dissertation endeavors to construct a predictive fault detection model based on historical inverter-level data. It aims to provide theoretical insights and practical recommendations for implementing fault detection in solar PVSs in sustainable energy infrastructure. To provide a clear direction for the research, the following primary research question was posed:

- **How can we detect anomalies on PVSs using unsupervised learning methods, such as ML and Deep Learning (DL)?**

This question explores the effectiveness of unsupervised learning techniques in identifying unusual patterns or malfunctions in PVS without the need for labeled training data.

This thesis is organized into several sections. **Chapter 2** delves into the Related Work, providing an overview of unsupervised ML and DL techniques for fault detection, threshold determination, and data explainability, as found in the literature. **Chapter 3** presents the proposed methodology, a review of the business context of *Enlita*, and a comprehensive exploration of key concepts necessary for understanding the problem. The Data Preparation steps, including exploratory analysis and data preprocessing, are detailed in **Chapter 4**. **Chapter 5**, titled Modeling, outlines the DL model used for anomaly detection. The results will be discussed in a separate section (**Chapter 6**), ending with a Conclusion (**Chapter 7**) about the proposed recommendations and future work.

Chapter 2

Literature Review and Related Work

This chapter presents previous findings of other authors, focusing on their methodology to answer the same research question. In the end, analyzing different techniques of FDD is expected to extract valuable knowledge for the following steps to take in this dissertation.

Usually, the anomaly detection experiments follow a typical ML pipeline - a training (Data Preprocessing, Modeling, and Evaluation) and a testing phase, where the predictions are made. Regarding the data frame alterations, most papers opt to include new layers of information, whether by adding satellite data, temperature sensors, or image devices. However, the choice of the models to fit and transform divides authors: some stick to traditional ML models with or without ensemble methods, while others prefer DL, sometimes by combining both.

2.1 Data Simulation

Although all have a straightforward course of action, they face a similar limitation - a lack of data. Collecting sufficient and clear evidence of fault for predicting future events is difficult. Due to that, many authors included an additional step - data simulation. Some created online simulation models, and others conducted experimental simulations.

2.1.1 Online Simulation Models

In past research, circuit-based simulation software was limited due to poor portability and computational efficiency. Code-based Fast Fault Simulation Model (CFFSM) could only simulate three fault types (short circuit, partial shading, and increased series resistance).

To overcome these handicaps, many authors used tools to simulate I-V and P-V (power-voltage) curves under normal and faulty conditions. Liu et al. (2021) developed an Improved code-based Fast Simulation Mode (ICFFSM), whose parameters were extracted from measured I-V curves using Nature-inspired Artificial Intelligence (AI) algorithms¹. Seghiour et al. (2023) performed a co-simulation between MATLABTM and PSIMTM, with the One Diode Model (ODM) as a reference, as well as Chao, Chiu, Li, and Chang (2011), that employed the

¹Utilized to model the collective behavior of natural social swarms (honey bees, bird flocks, and ant colonies) by performing tasks essential for their survival cooperatively through interacting together in particular behaviors.

same software to simulate islanding² detection. Aziz et al. (2020) opted for a *Simulink* model to generate I-V curves.

These studies plotted the simulated curves against the measured data to assess the model's accuracy. Liu et al. fitted the functional relationship between model parameters and environmental factors in different seasons. In their turn, Seghior et al. decided to organize the features based on the plant operating status. After both introduced some noise to replicate the measured data, obtaining a mean RMSE of 0.0893 Ampere (A) and 0.011 A, respectively, when crossing the information.

However, due to the degradation phenomenon in the long-term operation of the PV array, it is necessary to update the parameters periodically. Otherwise, the performance of the model output will deviate from the actual output state of the PV array.

2.1.2 Experimental Simulations

Voutsinas, Karolidis, Voyiatzis, and Samarakou (2023) used a year's worth of irradiance and temperature data for the modeling training phase, most of it through Single-Diode Model (SDM) to simulate PV cell operation and create a dataset for the ML algorithm. The faults were manually induced, obtaining deviations in the voltage inferiors to 10 mV, and the corresponding ones in the current were less than 100 mA.

Zhao, Ball, Mosesian, De Palma, and Lehman (2015), Zhao et al. (2015) and Momeni, Sadoogi, Farrokhifar, and Gharibeh (2020) proposed experimental setups that simulated a small-scale grid-connected PVS and two-diode model, respectively. This included collecting normal and intentionally created experimental PV faults to transform into initial labeled data.

Basnet, Chun, and Bang (2020) focused on studying the PVS operation characteristics during the winter season when the I-V curves of certain faulty states resemble normal states. Various datasets were collected during the season under wide environmental conditions for experimental verification, where anomaly data was generated by making several intentional faults in the circuit of the PV array.

2.1.3 Effects on the I-V Curves

Both simulation methods underline the influence of different faults on the shape of I-V curves (**Figure 2.1**).

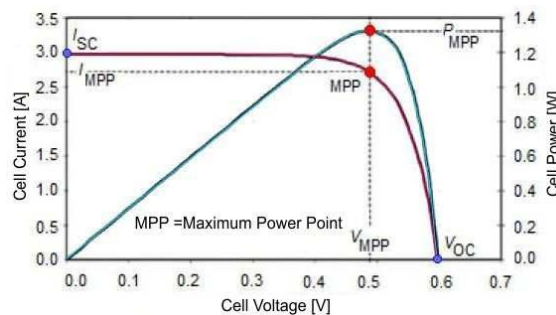


Figure 2.1: I-V characteristic curves (red) and P-V (blue). Image Source: ResearchGate

²Islanding is a phenomenon that happens when the system loses its stable reference power supply, preventing it from detecting the problem and cutting the power (Zhao et al., 2012).

Based on the study of Liu et al., for instance, regarding short-circuit faults, it is possible to observe that as the degree of short-circuit increases, the open-circuit voltage and maximum power decrease significantly. On degradation faults, motivated by series resistance increase, the slope of the I-V curve between the Maximum Power Point (MPP) and the open-circuit point changes, and the maximum power is reduced. When partial shading occurs, it distorts the I-V curves - the higher the irradiance reduction, the lower the current at the curve's inflection point (**Figure 2.2**).

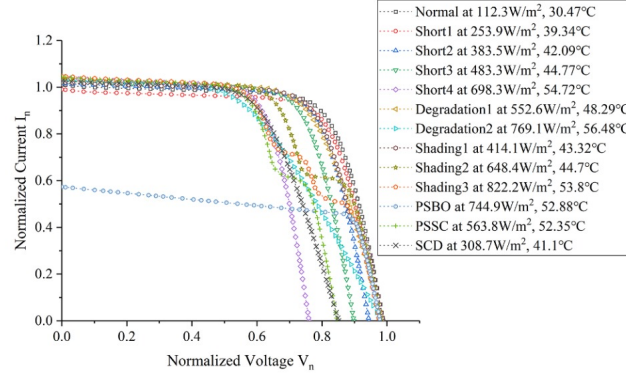


Figure 2.2: Normalized I-V curves of different faults under different ambient conditions (Liu et al., 2021)

Regarding concurrent faults, like Partial Shading with the Bypass Diode Open-Circuit Fault (PSBO), a significant reduction of the short-circuit current and the maximum power of the I-V curve is observed. On the other side, open-circuit voltage is reduced on Partial Shading with the Bypass Diode Short-Circuit Fault (PSSC), and the I-V curve is distorted. Lastly, when the configuration of the Short-circuit with the Degradation Fault (SCD) changes, the slope of the I-V curve between the MPP and the open-circuit point changes, and the open-circuit voltage is reduced.

2.2 Machine Learning for Anomaly Detection

AbdulMawjood et al. (2018) cited the critical aspects of ML, praising its ability to learn on its own and automatically, overcoming the typical limitations of the traditional FDD methods. As a fact, ML methods can be used not only for detecting faults but also for classifying them based on their nature and characteristics. The author divided the types of ML algorithms into two main categories: (1) Supervised Learning, where the algorithm learns to predict the output from the input labeled data, and (2) Unsupervised Learning, which tries to learn the structure and patterns from the data since there are no labels.

The studies focused on fault detection and prediction in photovoltaic systems elaborated by Voutsinas et al. (2023) and Jufri, Oh, and Jung (2019) utilized Logistic Regression (LR) and Regression combined with Support Vector Machine (SVM), respectively. SVM builds hyper-planes (defined by the kernel function) that are equally separated into classes of objects. Due to that, this supervised learning algorithm is well-known for its ability to identify the abnormal condition of a PVS.

Both only considered daylight time, discarding certain hours after sunset and before sunrise. The regression models predicted the expected power generation under solar irradiance, which the latter used to feed the SVM. Overall, Voutsinas et al. (97.11%) achieved more accurate results than Jufri et al. (94.64%). Hyperparameter tuning allied to Cross-Validation (CV) enhanced the performance of the models through the reduction of over-fitting and generalization.

Bognár, Loonen, Valckenborg, and Hensen (2018) went further and predicted local shading with the help of a system constituted by a grey-box model and SVM. The grey-box fitting process only admitted PV data under undisturbed, well-defined operating conditions. Its power predictions generated labeled training data for the SVM shade model in the second step. The ratio between measured and simulated AC power was a threshold (0.8) for classifying whether an instance is locally shaded.

A Decision Tree (DT) consists of root and internal nodes labeled with attribute test conditions, whose terminal nodes are, for this problem, normal or fault. After removing outliers and missing values and choosing low inter-correlation but high correlation with the class-label attributes, Zhao et al. (2012) found that increasing the tree size will make the model more complex and accurate. The proposed DT model shows high accuracy in fault detection (up to 99.98%) and fault classification (up to 99.8%) on the test data.

Regarding clustering algorithms, Zuniga-Reyes et al. (2021) and Zhu, Lu, Yao, Dai, and Hu (2018) implemented the K-Nearest Neighbors (KNN) and GK-Fuzzy c-means (FCM), respectively. Including a data normalization³ step is crucial to extracting fault sample features more effectively because it eliminates the nonlinear influence of irradiation and temperature changes on the photovoltaic output.

The FCM algorithm, an unsupervised clustering method, groups fault samples based on how closely they relate to cluster centers using Euclidean distance, just like KNN. However, FCM's standard approach does not account for non-linear data traits and often gets trapped in local minima. To address this, the Gaussian kernel function is integrated. This function transforms the samples to a higher-dimensional space, enhancing their features for better clustering performance. Comparing the two studies, the most sophisticated approach gave better results: an overall accuracy of 92.48%, depending on the fault type. In comparison, KNN showed effectiveness greater than 90%, whereas there is a slightly lower detection certainty in anomalous conditions with locations very close to each other.

An ANN typically comprises an input layer, various hidden layers, and an output layer, all containing neurons equipped with activation functions. These networks operate like parallel processors and efficiently manage complex systems. Their standout feature is the rapid approximation of non-linear functions, achievable even without strict normality or independence in the input data.

Markovics and Mayer (2022) focused on photovoltaic power forecasting. They emphasized data preprocessing, like removing nighttime data and normalizing inputs. A wide range of ML models was employed, and non-linear models like Kernel Ridge and Multilayer Perceptron (MLP) were the most effective. The research highlighted the importance of input selection over model selection, with tuned models showing a RMSE reduction of 13.1%. Chao et al. (2011) developed an extension neural network for differentiating power quality interference from islanding operations. Their model was supervised and leveraged the extension distance for data analysis. Basnet et al. (2020) investigated fault detection using MLP and

³All data are dimensionless numbers between 0 and 1 (Zhu et al., 2018).

probabilistic ANN. They encoded categorical variables and normalized data, split the dataset, and used categorical cross-entropy as the loss function. Their results indicated high accuracy, with significant variance in data across seasons.

Ensemble methods also can analyze I-V curves from normal and faulty photovoltaic conditions. In their 2022 study, Mellit and Kalogirou explored a variety of ML models like LR, DT, and Random Forest, alongside ensemble learning models such as Hist Gradient Boosting and AdaBoost. The study emphasized the importance of data preprocessing, feature extraction, and dimensionality reduction using Principal Component Analysis (PCA). The results showed varying accuracies across models, with ML models performing well in detection (between 67.82% and 80.86%), while Ensemble Learning (EL) methods like stacking and voting exhibited distinct accuracy levels (81.73%).

Lastly, Graph-based Semi-Supervised Learning (GBSSL) is another alternative to answer the research question. This model uses graph theory principles, representing data points as nodes and connections as weighted edges. It leverages the proximity of data points, allowing labeled data to spread their labels to nearby unlabeled points, aiming for a cohesive classification across the network. Zhao et al. (2015) developed a GBSSL to detect dangerous line-to-line faults in PVS, which processed normalized data and employed a MA filter to reduce noise. It used current and voltage inputs to output references for short-circuit current and open-circuit voltage. The results demonstrated that due to low training costs, self-learning capabilities, and effective data visualization, the model can achieve 100% accuracy in fault detection and classification. Momeni et al. (2020) also applied a GBSSL model to locate faults, using limited labeled data and achieving high accuracy (between 96.56% and 100%) with different normalization techniques.

2.3 Deep Learning for Anomaly Detection

Nevertheless, ML is limited: feature extraction relies on expert experience and lacks automation; artificial feature extraction ignores potential features; and shallow network structures can not effectively learn non-linear characteristics of I-V curves (Liu et al., 2021).

DL is a ML in AI that mimics the workings of the human brain in processing data and creating patterns for use in decision-making. It is a form of ML that uses neural networks with many layers. These networks can learn unsupervised from unstructured or unlabeled data (Goodfellow, Bengio, & Courville, 2016). The success of DL-based FDD hinges on the ability to extract and represent features from data effectively. This includes real-time changes, phase changes, trend changes, and faulty modes (Liu et al., 2021).

Aziz et al. (2020) and Seghiour et al. (2023) utilized advanced neural network methodologies for photovoltaic system analysis, albeit with different approaches. Aziz et al. focus on deep 2-D Convolutional Neural Network (CNN)s to analyze scalograms derived from PVS data, highlighting the CNN's ability to manage noise and classify faults with notable accuracy. A CNN typically consists of convolutional, pooling, and fully connected layers. The convolutional layer creates feature maps from input data, the pooling layer reduces the data size, and the fully connected layer, often with a softmax function, classifies data based on learned time-frequency patterns, eliminating manual feature engineering. In this study, a CNN model using error-backpropagation was trained with a pre-trained AlexNet to minimize classification errors and extract key features (**Figure 2.3**). It achieved 73.53% accuracy in fault detection and tested on noiseless and noisy data to demonstrate noise resilience. The dataset was split

70-30 for training and testing, with this process repeated multiple times for validation.

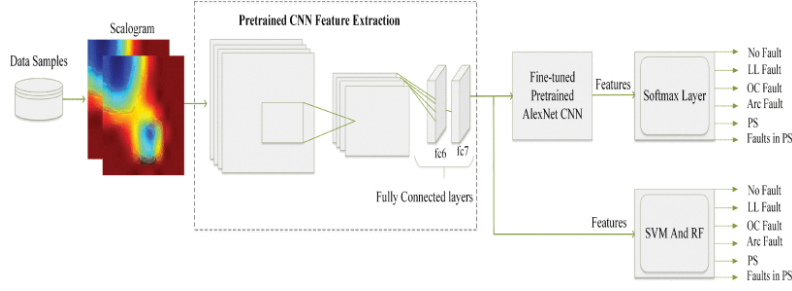


Figure 2.3: Framework of proposed 2-D CNN approach (Aziz et al., 2020)

In this softmax function (**Equation 2.1**), x_i represents a feature map input value, e is the base of the natural logarithm, and K is the total number of classes in the classification problem.

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^K e^{x_j}} \quad (2.1)$$

Seghiour et al., on the other hand, employ AEs for feature extraction followed by a Deep Neural Network (DNN) for fault detection and classification, achieving high efficiency under noisy conditions. AE are neural networks that aim to replicate their input. They have two components: an encoder that maps inputs to a latent space and a decoder that reconstructs the input from this space (**Figure 2.4**). Their training involves adjusting parameters to minimize a loss function, which ensures the output closely matches the original input. This process evaluates the accuracy of the reconstruction (Pereira & Silveira, 2018).

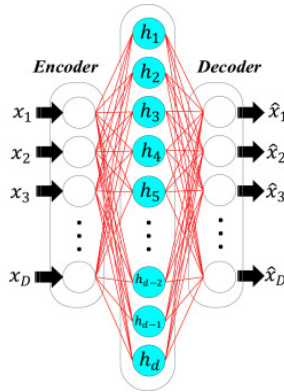


Figure 2.4: Structure of an AE (Seghiour et al., 2023)

The modeling involved using five AEs for unsupervised feature extraction, one for each metering variable. The extracted features were reintegrated with target classes to train the DNN. The technique, tested against classical AN in noiseless and noisy environments, achieved a 99.9% efficiency rate in noisy conditions, although with some misclassifications.

Both studies demonstrate the strength of neural networks in handling complex data, with Aziz et al. emphasizing CNNs for noise resilience and Seghiour et al. using AE and DNN for effective feature extraction and classification.

Other experiments, such as Fu et al. (2021), used Convolutional Autoencoder (CAE) for sky image processing, applying both 2-D and 3-D convolutional operations. In the study,

the CAEs comprise convolutional and transposed convolutional layers for feature processing (**Figure 2.5**). 2-D convolutional kernels are used for basic spatial feature mapping, while 3-D convolutional kernels provide more detailed spatiotemporal feature extraction at the cost of increased computational demand. The CAE-based sky image prediction model effectively processes input image sequences through an encoder and a bottleneck layer. Then, a decoder utilizes this processed information to predict future frames.

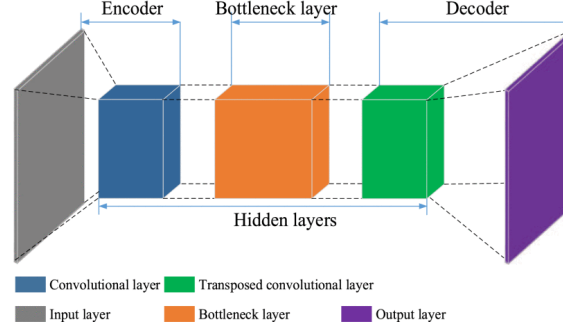


Figure 2.5: Architecture of a CAE (Fu et al., 2021)

Results showed that the models of the CAE outperformed the traditional methods, especially with shorter output times. Both 2-D and 3-D CAEs performance was similar, but 2-D models excelled in specific scenarios, indicating that increased complexity does not always yield better performance. The most effective CAEs were those with five and three hidden layers.

Liu et al. (2021) employed Stacked Autoencoder (SAE) for feature extraction and fault diagnosis in PVs. The preprocessing in this study involved transforming I-V curves to Standard Test Conditions (STC) and normalizing data to reduce environmental influences and numerical disparities. The modeling comprised SAE for feature extraction and t-SNE for dimensionality reduction and visualization. Also, Clustering by Fast Search and find of Density Peaks (CFSFDP) was chosen, and the fault was diagnosed through membership function analysis. The model demonstrated an average accuracy of 98.3%, with specific challenges in accurately diagnosing certain fault types, particularly under varying irradiance conditions.

Hempelmann et al. (2020), as usual, prepared data from May to August 2019, including photovoltaic plant performance and local weather conditions, through normalization, outlier removal, and synchronization between weather and monitoring data. Various models were used, including linear models, proximity-based models, and ANN like AEs, Variational Autoencoder (VAE)s, and Multiple-Objective Generative Adversarial Active Learning (MOGAAL). MOGAAL, a model based on Generative Adversarial Network (GAN) employs multiple generator networks to create anomalies. It utilizes a discriminator network trained with real data to generate and learn the characteristics of anomalies.

This process allows the final discriminator to detect anomalies in the data effectively. Neural networks performed better in detection rates (percentage of correctly identified anomalies in all the cases labeled as faults), with AEs having the highest overall rate (74.55%). The VAE was most effective in fault detection (92.06%), and MOGAAL excelled in shade detection (91.60%). Future work focuses on enhancing accuracy through feature engineering and testing combinations of models (Hempelmann et al., 2020).

In this field, time series is the most used type of data. Due to that, Recurrent Neural Network (RNN), an ANN designed to handle time-dependent data, is very popular, introducing

a memory concept to track past information. However, it presents a vanishing gradient problem (exponentially fast decreasing gradient norm to zero). It occurs when inputs from much earlier in the sequence affect the network's output at a given time step. LSTM networks were developed to effectively address this constraint to maintain and process information over longer periods (Figure 2.6) (Pereira & Silveira, 2018).

Pereira and Silveira (2018) developed an anomaly detection model using a Variational Recurrent Autoencoder (VRA) with Bi-LSTM and attention mechanisms. The model, trained on non-labeled time-series data, includes reconstruction and anomaly detection stages. Since the LSTMs can still not integrate information from future instants of time, the Bi-LSTM was proposed - it processes inputs in both directions - with an attention mechanism focusing on relevant data. Anomaly detection is based on the reconstruction score, with higher errors indicating anomalies. The model successfully learned seasonal data patterns and differentiated between normal and anomalous data, evidenced by attention maps. The study faces challenges in conventional evaluation due to unlabeled data and aims to extend to a multi-class framework.

Appiah et al. (2019) and Ribeiro et al. (2023) both utilize LSTM networks, but with different applications and methodologies. Appiah et al. focuses on feature extraction from PV array data for fault classification using LSTM networks, achieving high accuracy in noiseless (between 99.03% and 100%) and noisy conditions (between 97.66% and 99.23%). Their approach includes standardization, grid-search hyperparameter tuning, and softmax regression for classification (**Figure 2.6**).

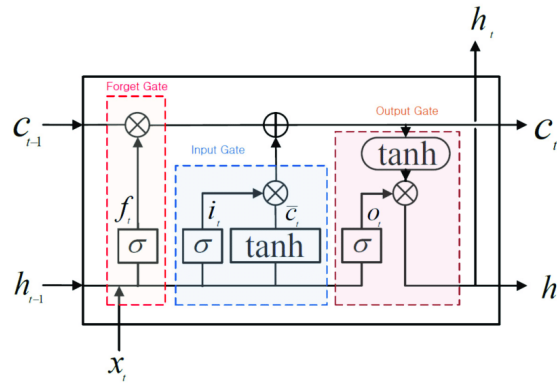


Figure 2.6: Structure of a LSTM Network (Appiah et al., 2019)

Ribeiro et al. employ a dual-layered LSTM-AE networks for fault detection. The first layer detects anomalies using reconstruction error thresholds (0.8), while the second layer employs Adaptive Model Rules (AMRules) for a detailed explanation. Chebyshev-based sampling methods (**Equation 2.2**), ChebyUS⁴ and ChebyOS⁵, address data imbalance, optimizing training efficiency and model accuracy. The approach effectively balances memory usage and predictive capability, demonstrating an advanced, nuanced method for fault detection in photovoltaic systems.

⁴The Chebyshev-based under-sampling method selectively trains the model with incoming examples based on Chebyshev's probability. It uses a random number in the range $[0, 1]$, and if this number is greater than or equal to the calculated (Ribeiro et al., 2023).

⁵Chebyshev-based over-sampling method is designed to balance data streams by specifically increasing the representation of rare cases in imbalanced data (Ribeiro et al., 2023).

The Chebyshev’s probability is written as follows:

$$P(|X - \mu| \geq k\sigma) \leq \frac{1}{k^2} \quad (2.2)$$

In the comparison of the two sampling strategies, ChebyUS + AMRules and ChebyOS + AMRules, the former produces a more concise set of rules. Still, it is less effective in predicting normal cases than the latter. ChebyOS + AMRules, while potentially yielding better predictions, requires more training time than standard AMRules, whereas ChebyUS + AMRules is noted for its faster processing. This highlights a trade-off between rule set compactness and predictive accuracy in different sampling methods.

The most effective DL models in this domain can handle complex data structures, feature extraction, and noise effectively, being highlighted in this sub-chapter. CNNs excel in handling complex data and noise. AEs, especially when paired with DNNs, are effective for feature extraction and noise handling. CAEs and SAEs show promising image processing and fault diagnosis results. VAEs and GANs, like MOGAAL, are noted for their proficiency in anomaly detection. Lastly, LSTMs are recognized for their ability to process time-dependent data efficiently.

2.4 Threshold Determination in Anomaly Detection

Reiterating the relevance of establishing suitable thresholds to distinguish between normal and anomalous instances, especially after accurately modeling and completing the training phase, is crucial for successful anomaly detection. This literature review highlights the cutting-edge methods for threshold determination, categorized into parametric statistical modeling, nonparametric statistical modeling, ML-based thresholds, and adaptive and dynamic thresholds, all of which are highly relevant to our field (**Table 2.1**).

Table 2.1: Literature Review on Threshold Determination Techniques

Types of Thresholds	Thresholds	Authors
Parametric Statistical Modeling	k-Sigma ($T = \mu + k \cdot \sigma$)	(Laptev, Amizadeh, & Flint, 2015)
		(Bergmann, Batzner, Fauser, Sattlegger, & Steger, 2021)
		(Yang, Rahardja, & Fränti, 2019)
Nonparametric Statistical Modeling	p-Quantile Threshold	(Bergmann et al., 2021)
	Statistical Profiling using Histograms	(Chandola, Banerjee, & Kumar, 2009)
	Highest Reconstruction Error	(Xu, Jang-Jaccard, Singh, Wei, & Sabrina, 2021)
		(Bergmann et al., 2021)
Machine Learning-Based Thresholds	Previous knowledge	(Munir, Siddiqui, Dengel, & Ahmed, 2019)
	Density distribution	(Laptev et al., 2015)
	Max-Area Threshold	(Bergmann et al., 2021)
Adaptive and Dynamic Thresholds	Sample and "band" Thresholds	(Dhiman, Deb, Muyeen, & Kamwa, 2021)
		(Poornima & Paramasivan, 2020)

• Parametric Statistical Modeling

Parametric statistical modeling is a fundamental approach to anomaly detection. It is predicated on the assumption that normal data instances occur in high-probability regions of a stochastic model, whereas anomalies manifest in low-probability regions. This methodology

is especially effective when the data is assumed to follow a Gaussian distribution, allowing for precise and interpretable threshold settings.

The k-Sigma threshold is a parametric technique that leverages statistical properties such as the mean and standard deviation inherent in Gaussian distributions (**Equation 2.3**).

$$T = \mu + k\sigma \quad (2.3)$$

Laptev et al. (2015) and Bergmann et al. (2021) stated k-Sigma as a common outlier detection technique in quality control, which involves classifying data instances more than 1.5σ from the mean (μ) as outliers, where σ is the standard deviation. Moreover, severely isolated data points fall within the 3-Sigma range ($\mu \pm 3\sigma$ range encompasses 99.7% of data instances).

Yang et al. (2019) presented four techniques based on the box-plot rule, a straightforward statistical outlier detection method that uses summary statistics: minimum, lower quartile (Q1), median, upper quartile (Q3), and maximum.

The Interquartile Range (IQR) is defined as $Q3 - Q1$. Observations beyond $1.5 * IQR$ below Q1 or above Q3 are considered anomalies. This range, containing 99.3% of data, is analogous to the 3-Sigma rule for Gaussian data. Unfortunately, the standard deviation and Q3 are increased by the outliers, and consequently, the threshold tends to be set up too high, and several faults are missed.

To overcome this issue, a similar method, the Median Absolute Deviation (MAD), was proposed as a more robust thresholding method to reduce the impact of outliers. However, its effectiveness diminishes when outliers constitute more than 50% of the data, causing the median to fall within the outlier range.

Other approaches, like Clever Standard Deviation (Clever SD), iteratively removes one outlier at a time, recalculating the standard deviation until no outliers remain within the range of $\mu \pm 2.5\sigma$. However, this method can excessively remove normal points. Two-stage Thresholding (2T) improves robustness by cleaning noisy data before recalculating thresholds - Clever SD is a specific case of 2T, iterating until convergence with single outlier removal. It can also apply other techniques like MAD and IQR, removing outliers that exceed a preliminary threshold and then updating the threshold accordingly.

Bergmann et al. (2021) computed the p-Quantile Threshold, based on the entire distribution of validation anomaly scores, to detect anomalous structures in natural image data. It selects a threshold with a percentage p of validation, usually 95%, where pixels are classified as anomaly-free.

• Nonparametric Statistical Modeling

Nonparametric statistical modeling offers a flexible approach to threshold determination, particularly well-suited for datasets that do not adhere to predefined distributions.

One of the simplest and most effective nonparametric techniques is histogram-based modeling (Chandola et al., 2009). This method involves creating a histogram to profile normal data by dividing it into bins. Each bin represents a range of values that the normal data can take. A new data instance is checked against these bins during the testing phase. It is considered normal if it falls within one of the predefined bins; otherwise, it is classified as anomalous.

Another option is to consider a maximum threshold equal to the maximum value of all occurring anomaly scores on the validation set. As warned by Xu et al. (2021) and Bergmann et al. (2021), this is a very conservative approach.

Authors like Munir et al. (2019) also highlighted the possibility of establishing a limit based on previous knowledge about the time series particularities through combinations of parameters. This trial-and-error approach can be very subjective and, in most cases, unsuitable for real-world problems.

- **ML-Based Thresholds**

ML-based thresholds represent a sophisticated approach to anomaly detection, leveraging advanced algorithms to identify outliers within complex datasets.

One notable method is the Local Outlier Factor (LOF), which operates on local density. This technique assesses the density of a data point by considering its nearest neighbors and their distances. By comparing the local density of an object to that of its neighbors, LOF can identify regions of similar density and pinpoint data points with significantly lower density as outliers. This approach is particularly effective in detecting anomalies in datasets with varying density distributions, offering a powerful tool for nuanced and accurate anomaly detection (Laptev et al., 2015). Similarly, Bergmann et al. (2021) employed the Max-Area Threshold to consider the spatial location of image pixels, setting a threshold by allowing connected components on validation images to remain within a predefined maximum area. This prevents the anomaly detector from falsely identifying single defects as anomalies based solely on their area.

- **Adaptive and Dynamic Thresholds**

Adaptive and dynamic thresholds are crucial for effective anomaly detection in environments where data characteristics change over time. One significant application of adaptive thresholds is in wind turbine gearbox anomaly detection. Due to the unique behavior of each segment in a time series during turbine operation, a static threshold often fails to capture local anomalies, leading to false alarms and potentially catastrophic failures. An adaptive threshold creates a band beyond which the presence of a data sample is considered an anomaly. This band varies for different segments of a univariate time series. According to Chebyshev's inequality, the value of λ determines the percentage of samples falling outside the $\mu \pm \lambda\sigma$ band. For a segment with k samples, if a sample exceeds the threshold, it is labeled as anomalous; otherwise, it is labeled normal (Dhiman et al., 2021).

On the other hand, dynamic thresholds are essential in systems where parameters vary due to physical factors such as time and seasonal changes, as seen in wireless sensor networks. Static thresholds can lead to high False Positive Rate (FPR) because they do not account for these variations. Instead, dynamic thresholds adjust based on recent data. For example, a sliding window approach might use the most recent 40 samples to calculate the threshold, ensuring that the threshold adapts to the latest data trends and reduces false alarm rates (Poornima & Paramasivan, 2020).

By the end of this section, one can make a sustained choice on which model to implement and how to design the whole system architecture for fault detection based on the threshold selected.

2.5 Evaluation Metrics in Anomaly Detection

Assessing the performance of anomaly detection models requires various metrics to evaluate their effectiveness thoroughly. In summary, the evaluation metrics discussed in the liter-

ature can be grouped into performance metrics, spatial accuracy metrics, and computational efficiency metrics (**Table 2.2**).

Table 2.2: Literature Review on Evaluation Metrics for Unsupervised Anomaly Detection

Type of Evaluation Metric	Evaluation Metric	Authors
Performance Metrics	Accuracy	(Xu et al., 2021)
		(Dhiman et al., 2021)
		(Laptev et al., 2015)
	False Positive Rate	(Bergmann et al., 2021)
	F1-Score	(Xu et al., 2021)
		(Munir et al., 2019)
		(Dhiman et al., 2021)
		(Laptev et al., 2015)
	Recall	(Xu et al., 2021)
		(Dhiman et al., 2021)
	Precision	(Xu et al., 2021)
		(Dhiman et al., 2021)
		(Bergmann et al., 2021)
	ROC/AUC	(Ergen & Kozat, 2020)
		(Xu et al., 2021)
		(Goldstein & Uchida, 2016)
		(Munir et al., 2019)
Spatial Accuracy Metrics	Intersection over Union (IoU)	(Bergmann et al., 2021)
	Per-region overlap (PRO)	
Computational Efficiency Metrics	Training Time	(Laptev et al., 2015)
	Model Size	

• Performance Metrics

Accuracy is the most well-known performance metric, which measures the proportion of correctly identified anomalies and normal instances. Various authors, such as Dhiman et al. (2021), Laptev et al. (2015), and Xu et al. (2021), have employed accuracy as a primary metric in their evaluations and highlighted its importance in assessing model performance (**Equation 2.4**).

In the equation, TP is the number of True Positives, TN is the number of True Negatives, FP is the number of False Positives, and FN is the number of False Negatives.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2.4)$$

The FPR represents the proportion of normal instances incorrectly classified as anomalies (**Equation 2.5**). Bergmann et al. (2021) extensively used this metric to evaluate the rate of false alarms generated by their models.

The FPR is given by:

$$\text{FPR} = \frac{FP}{FP + TN} \quad (2.5)$$

Recall, also known as sensitivity or True Positive Rate (TPR), measures the proportion of actual anomalies correctly identified (**Equation 2.6**). Xu et al. (2021) and Dhiman et al. (2021) are examples of authors who have utilized recall in contexts where the cost of missing anomalies is high.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2.6)$$

Precision (positive predictive value) represents the proportion of identified anomalies that are true anomalies (**Equation 2.7**). Xu et al. (2021), Dhiman et al. (2021), and Bergmann et al. (2021) have utilized precision to provide a detailed assessment of their models when the cost of false positives (false alarms) is high.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2.7)$$

The F1-score, a harmonic mean of precision and recall, provides a single metric to evaluate the trade-off between those metrics (**Equation 2.8**). Munir et al. (2019) employed this metric to evaluate their DL-based approach for time series anomaly detection, along with underscoring the importance of selecting appropriate thresholds and time window sizes for optimizing model performance. Furthermore, studies by Xu et al. (2021), Dhiman et al. (2021), and Laptev et al. (2015) proved the effectiveness of the F1-score in summarizing model performance in a single value.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2.8)$$

The ROC curve plots the TPR against the FPR, and the Area Under the Curve (AUC) quantifies the model’s overall ability to distinguish between anomalies and normal instances. Ergen and Kozat (2020) used them to evaluate their LSTM-based anomaly detection model, emphasizing the importance of these metrics in capturing the trade-offs between different types of errors in unsupervised settings. Xu et al. (2021), Goldstein and Uchida (2016), and Munir et al. (2019) have also employed AUC as a robust metric for evaluating model performance, especially in imbalanced datasets.

- **Spatial Accuracy Metrics**

For object detection and segmentation tasks, spatial accuracy metrics like Intersection over Union (IoU) and Per-region Overlap (PRO) are crucial. IoU measures the overlap between the predicted anomaly region and the ground truth, while PRO averages the performance over each connected ground truth component. Bergmann et al. (2021) demonstrated the use of these metrics in evaluating anomaly detection in image data, providing a comprehensive evaluation framework that considers both pixel-level and region-level performance.

- **Computational Efficiency Metrics**

Evaluating the computational efficiency of anomaly detection models involves metrics like training time and model size. These metrics are essential for practical applications where computational resources and time are constrained. Laptev et al. (2015) discussed the importance of these metrics in their work on scalable anomaly detection frameworks.

Overall, the evaluation metrics are applicable across various problems, showcasing their versatility and usefulness in assessing the model’s performance.

2.6 Explainable Artificial Intelligence for Anomaly Detection

Traditional DL models have proven to be highly effective in identifying anomalies, but their "black box" nature poses a significant challenge: they provide little to no insight into why a particular data point is flagged as anomalous. Explainable AI addresses this challenge by making these models more transparent, explaining the results generated, and helping users understand and trust their decisions. Nevertheless, the more complex the AI model is, the more difficult it is for Explainable AI to interpret (Hwang & Lee, 2021).

Many authors have included explicative components in their models, like Nguyen, Low, Lim, Chan, and Divakaran (2019), who developed a Gradient-based Explainable VAE for Network Anomaly Detection. It calculates the gradients of the VAE's objective function concerning each feature of the data point, then analyses how the reconstruction error changes when a feature is slightly varied. If the reconstruction error changes significantly with a small variation in a feature, that feature is likely contributing to the anomaly. This sensitivity indicates that the feature at its current value is abnormal because it strongly influences the model's ability to reconstruct the data point accurately.

In their turn, Kieu et al. (2022) decided to quantify the explainability of AE-based outlier detection methods, proposing two types of scores. The first is the Polynomial Regression Model (PRM)-based Explainability Score, which utilizes a PRM to approximate the no-faulty time series. The aim is to find the smallest polynomial order N such that the RMSE between the reconstructed time series and the PRM approximation is below a certain threshold. The second approach is Singular Spectrum Analysis (SSA)-based Explainability Scores: SSA decomposes the time series into components representing trends, seasonality, and noise. The top- N components are then used to reconstruct the time series, and the RMSE between this reconstruction and the original no-faulty time series is calculated. For both scores, the smallest N achieving an RMSE below the threshold signifies higher explainability.

Other studies preferred SHAP, a unified approach connecting game theory with local explanations. It provides additive feature attribution, enabling a clear understanding of how each feature contributes to anomaly detection (Hwang & Lee, 2021). Alternatively, Local Interpretable Model-agnostic Explanations (LIME) also helps identify the most relevant features by approximating a complex model with a simpler one locally around an anomalous data point (Morichetta, Casas, & Mellia, 2020).

Lastly, Layer-wise Relevance Propagation (LRP) is another method that assigns relevance scores to features by backpropagating through the model, which turned out to be particularly effective with LSTM models, as it reveals the contribution of each feature at every timestep (Patil, Wadekar, Gupta, Vijan, & Kazi, 2019). Similarly, Deep Learning Important Features (DeepLIFT) decomposes the output prediction by backpropagating contributions of all neurons in the network to input features. This method compares neuron activations to a reference activation, assigning contribution scores based on the difference (Shrikumar, Greenside, & Kundaje, 2019).

In conclusion, Explainable AI transforms how anomaly detection models are perceived and utilized by providing transparency and insights into the decision-making process. As the field advances, integrating this kind of method in anomaly detection will continue to play a critical role in various domains, ensuring models are accurate but also interpretable and trustworthy.

Chapter 3

Methodology

The CRISP-DM methodology, described in the article "*CRISP-DM: Towards a Standard Process Model for Data Mining*", is a comprehensive and structured approach for Data Mining (DM) projects (**Figure 3.1**).



Figure 3.1: CRISP-DM Diagram (Hotz, 2018)

It comprises six phases:

1. **Business Understanding:** focuses on understanding the project's objectives and requirements from a business perspective, then translating this knowledge into a data mining problem definition.
2. **Data Understanding:** initial data collection, proceeding with activities to explain the data, identify quality problems, discover insights, or detect interesting subsets for hypotheses.
3. **Data Preparation:** activities to construct the final dataset from initial raw data, including data cleaning, construction of new attributes, and data transformation for modeling tools.
4. **Modeling:** selecting and applying various modeling techniques, attuning their parameters to optimal values, and meeting specific data formats' requirements.
5. **Evaluation:** models built in the previous phase are thoroughly evaluated to ensure they meet the business objectives. This stage includes reviewing the construction steps and deciding on the use of data mining results.

6. **Deployment:** the final phase where the knowledge gained is organized and presented so the customer can use it.

Each step consists of a set of generic tasks that are applicable across different data mining projects. The methodology emphasizes the need for a standardized approach to make data mining projects more reliable, repeatable, and efficient, regardless of the industry or technology used - precisely what is needed for this project (Wirth & Hipp, 2000). Nevertheless, some of the structure might be changed according to the needs and specifications of the dissertation.

3.1 Business Understanding

Business understanding is the first step in the CRISP-DM framework and involves thoroughly comprehending the solar energy industry, its drivers, and its significance. In addition to the global context described in this section, from the client's perspective, the significance of this issue is tied not only to the profitability of the equipment but also to the operational aspects, such as team allocation. This is important not only for maximizing their portfolio value but also for managing technical and logistic operations while ensuring potential economic advantages.

The trend for renewable capacity additions is upward, motivated by the global energy crisis and policy support, such as the *Paris Climate Accords* and the *UN sustainable development goals* (Maka & Alabid, 2022). However, it still contributes a minor share of total electricity demand (4.5% of worldwide power production), dominated by non-renewable sources (*Global Market Outlook For Solar Power 2023 - 2027 - SolarPower Europe*, n.d.).

The traditional utility's value proposition includes producing and delivering electricity for a fixed price per Kilowatt-hour (kWh), which means that the more energy consumed, the better. Many companies participate in third-party decentralized power generation (ideal for the energy transition acceleration process), developing new revenue models. To maintain their competitiveness, they apply different sales strategies. One is decoupling, which recovers fixed costs from the electricity sold. They also introduced flat rate tariffs by charging a fixed price regardless of the energy consumed and dynamic pricing - which has a fixed price per kilowatt hour but applies a flexible price according to the wholesale price of electricity (Richter, 2012).

Usually, the business model of *Enlitia's* clients configures four phases: the generation (1); transmission (2), transport of electricity at high voltage via the transmission grid; distribution (3), when the energy goes to the distribution network; and supply (4) when it arrives to the supply point and is sold (Richter, 2012). Furthermore, there are two kinds of solar energy applications: Concentrated Solar Power (CSP) and solar PVS. In CSP systems, the sun's rays are concentrated using mirrors to heat a fluid and transform the steam into electricity by powering a turbine. PV devices, or solar cells, directly convert sunlight into electricity (Maka & Alabid, 2022).

The solar market has immense potential, and its cost leadership will continue to capture a larger share of investors compared to other power generation technologies and, consequently, more likely to lead the global energy transition, being the fastest growing one (followed by wind). Solar power dominated the global power generation added capacity in 2022, with 66% of the RES (new renewable capacity). This technology holds twice the capacity installed by the other renewable technologies, showing its prominence (*Global Market Outlook For Solar Power 2023 - 2027 - SolarPower Europe*, n.d.).

The main factor attributed to this success is the significant cost reduction over the past ten years. Nevertheless, in the past two years, the COVID-19 pandemic and the Shanghai lockdown implied severe disruptions in global supply chains, leading to price escalations due to increased shipping costs. The war in Ukraine also led to inflationary pressures, especially on raw materials like poly-silicon, which is essential for solar panel construction. These conditions resulted in the first increase in solar PV’s Levelized Cost of Electricity (LCOE) after a decade. At rest, with the escalated production capacity, the upgrade of supply chains, and the post-pandemic economic recovery, one can anticipate that things will return to normal levels (*Global Market Outlook For Solar Power 2023 - 2027 - SolarPower Europe*, n.d.).

According to the International Energy Agency (*Solar*, n.d.), solar PV’s installed power capacity is prepared to surpass coal by 2027, becoming the leading player in the world. When it comes to cumulative solar PV capacity, it is expected to triple, growing by almost 1500 GW over the period - annual additions are expected to increase every year for the next five years (Institute, n.d.).

Renewable energy business models depend highly on the regulatory framework, so policymakers influence the energy transition for a sustainable future (Richter, 2012). In the years to come, the growth in PV energy consumption will need to continue and even scale up to follow the Net Zero Emissions by 2050 scenario and other international climate agreements, representing an excellent opportunity for companies (*Solar*, n.d.).

3.2 Data Understanding

Enlitia provided historical multivariate time series data containing metering information for two inverters (model SMA 500HE11), located on a South European PV park. Each included the corresponding inverter’s DC and AC current, voltage, and power measurements every 15 minutes from 01-01-2021 00:00:00 to 13-07-2023 09:00:00, even though some days are missing. The datasets contain 6 variables, 88524 instances for inverter 2 and 88531 instances for inverter 7. The AC current and voltage variables are empty, as determined by the inverter’s technical specifications, configurations, and setup (**Table 3.1**). It was also optional to include an extra column, GHI¹, but it was purposely excluded to prioritize sources specializing in meteorological data for more precise measurements. Regarding the data behavior, the computation of the inverters’ Q-Q plots for each variable showed that they do not follow a Normal Distribution, as is evident in the **Appendix A.1**.

Table 3.1: Description of the original variables

Variable	Unity of Measure	Presence of Null Values
ac_power	Watts (W)	No
ac_voltage	Volts (V)	Yes
ac_current	Ampere (A)	Yes
dc_power	Watts (W)	No
dc_voltage	Volts (V)	No
dc_current	Ampere (A)	No

PV cells and panels will produce the most electricity when directly facing the sun (MPP). Due to that, during the day, the power generated depends on the Earth’s rotation movement.

¹GHI is the total irradiance from the sun on a horizontal surface on Earth (Solargis, 2024).

The inclination and orientation of the PVS influence the energy produced. For instance, east-facing PV panels will have maximum generation partway through the morning, knowing the sun rises in the east, and west-facing arrays tend to produce the most electricity part-way through the afternoon (NEA, 2021).

On the day represented in **Figures 3.2 and 3.3**, a marked increase in AC Power is observed, reaching its zenith ² during the midday hours—a pattern commonly associated with solar energy generation. This trend, consistent across both inverters, indicates synchronous peak production periods. Similarly, DC Power mirrors the trajectory of AC Power, ascending to a maximum concurrently. Such parallelism is anticipated, given that DC Power constitutes the immediate output from the photovoltaic panels before its conversion to AC Power. Fluctuations in DC Voltage and Current are noted throughout the daily cycle, with the current exhibiting more significant variability. A noteworthy simultaneous reduction in DC Voltage occurs at the point of peak power generation for both AC and DC, potentially indicative of intrinsic behaviors of the inverters or the solar array’s operational efficiency when subjected to maximal energy production.

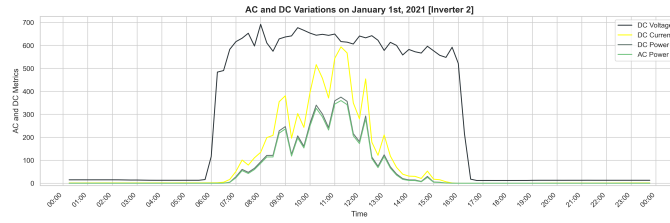


Figure 3.2: AC and DC variations on 01-01-2021 for Inverter 2

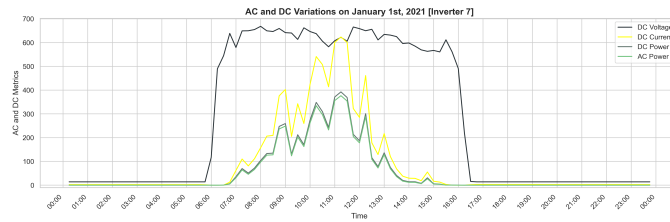


Figure 3.3: AC and DC variations on 01-01-2021 for Inverter 7

While the overall power generation trends may appear similar, a closer examination reveals nuanced differences in the contour of the curves, the precise timings, and the intensities of the peaks and valleys. These variations, which could be attributed to many factors, underscore the complexity of our analysis. Disparities in inverter efficiency, solar panel positioning, the presence of shading, and other operational considerations all contribute to these unique patterns.

Besides that, one needs to consider the impact of seasonality on solar energy generation. In winter, the daily number of sun hours is reduced compared to summer periods, compromising the performance of the PVS. Weather conditions are also an aspect to consider when making power predictions. For example, cloudy days reduce the available irradiance, meaning less energy production on higher levels of cloud cover. Comparing data regarding the same

²The point on Earth directly overhead for an observer (NASA, n.d.)

period is crucial when proceeding to FDD; therefore, it is essential to search for other sources of information to improve this study.

Chapter 4

Data Preparation

4.1 Data Preprocessing and Feature Engineering

The first step to conduct Data Processing was to check for null values, which only occurred on the AC current and voltage - these two variables were removed since they only contained empty cells. Since the park's climate sensors generate inaccurate and noisy samples, *Solcast*TM was employed as an external source. It delivers updated time series data containing variables such as air temperature measurements, Global Tilted Irradiance (GTI)¹, and GHI, cloud cover, and wind speed for a given geographical location and time. All the code was developed in Python using Jupyter Notebook and tested on a Linux server.

Figure 4.1 showcases a detailed look on weather data. The pattern of GTI rises and falls in a clear, bell-shaped curve, reaching its highest point at midday, which is typical for this solar measurement. Similarly, GHI follows the same daily trend but at consistently lower values, likely due to how the solar panels are angled. The temperature steadily climbs throughout the day, peaking in the late afternoon — a common pattern for daily temperature changes. Meanwhile, cloud cover varies throughout the day, explaining the occasional solar irradiance drops. Contrary to what one might expect, wind speed does not vary significantly throughout the day.

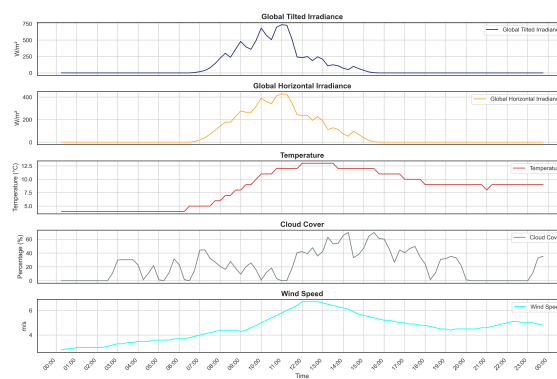


Figure 4.1: Meteorological variables evolution through 01-01-2021

Conversely, **Figure 4.2** provides a broader overview over a more extended period. The GTI and GHI data repeat regularly, indicating the daily sunrise and sunset cycle over a more

¹GTI is the total irradiance from the sun on an inclined surface on Earth (Solargis, 2024).

extended period. The temperature also shows a wave-like pattern, which means daily variation and seasonality, as anticipated in **Chapter 3**. Cloud Cover varies greatly, suggesting shifting weather conditions that affect solar energy production. Lastly, wind speed fluctuates unpredictably, but the peaks are not particularly high; they are within normal ranges and could be tied to specific weather events.

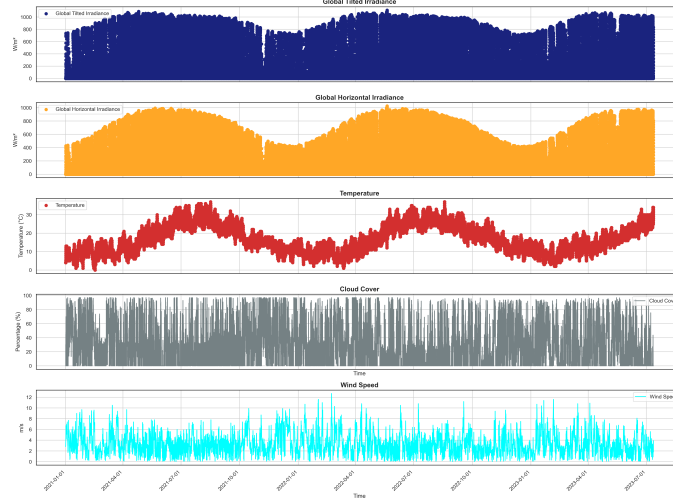


Figure 4.2: Meteorological variables evolution over time

All datasets are time series (**Figure 4.3**). To maintain the information's integrity, the variable containing the moment of measurement was converted to a standard date and time format and set as an index. Then, satellite and metering information were crossed to form a single dataset. Secondly, some data cleaning was performed. Nighttime and the first and last sunlight hours were eliminated to avoid false alarms (Voutsinas et al., 2023). When uploading the *astral* library, the sunrise, sunset, and night times for a given date and location can be calculated - in this case, somewhere in South Europe. Also, all the variables' time zones were synchronized to UTC².

	ac_power	dc_power	dc_voltage	dc_current	temperature	cloud_cover	global_horizontal_irradiance	global_tilted_irradiance	wind_speed
read_at									
2021-01-01 08:30:00+01:00	45.853	50.887	649.800	81.153	5	32.5	71	77	4.2
2021-01-01 08:45:00+01:00	65.987	71.763	654.867	111.027	6	27.1	104	142	4.3
2021-01-01 09:00:00+01:00	97.413	104.095	668.467	157.607	6	20.8	142	226	4.4
2021-01-01 09:15:00+01:00	126.387	133.200	649.600	206.393	7	16.4	178	300	4.4
2021-01-01 09:30:00+01:00	127.773	134.791	646.733	209.393	7	27.9	178	237	4.4

Figure 4.3: Header data of Inverter 7

4.2 Exploratory Data Analysis

Afterward, the relationship between all nine variables was examined to understand interactions determinant for accurate anomaly detection, revealing influential factors and underlying patterns in the time series data. The augmented Dickey-Fuller test (ADF) was chosen to check their stationarity³, ensuring the statistical properties of the time series data remain

²Universal Time Coordinated is the common time standard across the world (Buckle & Hocken, 2024).

³In a stationary process, the mean, variance, and autocorrelation structure do not change over time (NIST, 2024).

constant, which is essential for reliable modeling and forecasting. In all cases, the test statistic was below the critical value, leading to the rejection of the null hypothesis in favor of stationarity (Harris, 1992). Subsequently, Pearson’s correlation was calculated for the variables. The confirmed stationarity ensures that the models provide reliable forecasts and insights, as the underlying patterns remain stable. The similar correlation patterns between the two inverters suggest a consistent environmental impact on solar power generation across different systems within the same locale.

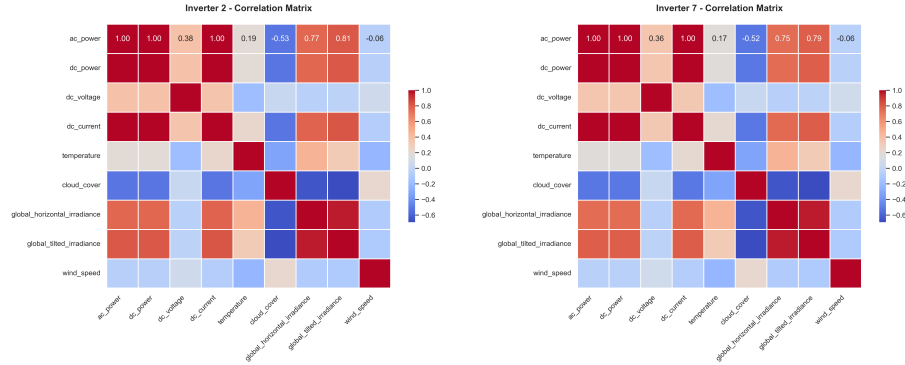


Figure 4.4: Inverters’ Correlation Matrices

The correlation matrix analysis presented in **Figure 4.4** for Inverters 2 and 7 reveals that AC Power and DC Power share a strong positive correlation, indicating a direct relationship between the power output from solar panels and the power delivered after inversion. A moderate positive correlation is observed between DC Voltage and DC Power, suggesting that voltage increases are generally associated with rises in power output, albeit not linearly.

Nevertheless, an inverse relationship is noted between DC Voltage and DC Current, highlighting the electrical property where voltage drops as current increases under certain conditions. The temperature correlates positively with power output, implying that higher temperatures may enhance solar panel efficiency on sunny days. Conversely, the percentage of cloud cover negatively correlates with power generation, aligning with the expected reduction in solar irradiance on cloudier days. Both measures of solar irradiance demonstrate a strong positive correlation with power output, affirming their roles as critical drivers of solar energy production. Wind speed has a negligible linear relationship with power outputs, suggesting other non-linear dynamics are at play.

Furthermore, data can furnish information by highlighting the seasonal variability solar energy systems must accommodate. The heat maps in **Figure 4.5** compare mean solar irradiance across June and December, illustrating the significant seasonal variation in solar energy potential. June’s heat map shows intense irradiance during midday hours, consistent with summer’s extended daylight. In contrast, December’s irradiance is notably lower, reflecting shorter days and a lower sun angle typical of winter. This visual data underscores the seasonal fluctuations in solar power generation, with a peak in potential during June and the lowest level in December. A yearly outlook is presented in **Appendix A.2**.

According to the principle stated by Penn State University, as irradiance increases, the output current and, consequently, the power generated by PV modules also increase. This is because the current produced by a PV cell is directly proportional to the irradiance it receives. In both scatter plots (**Figure 4.6**), a positive trend is evident, where increased irradiance leads

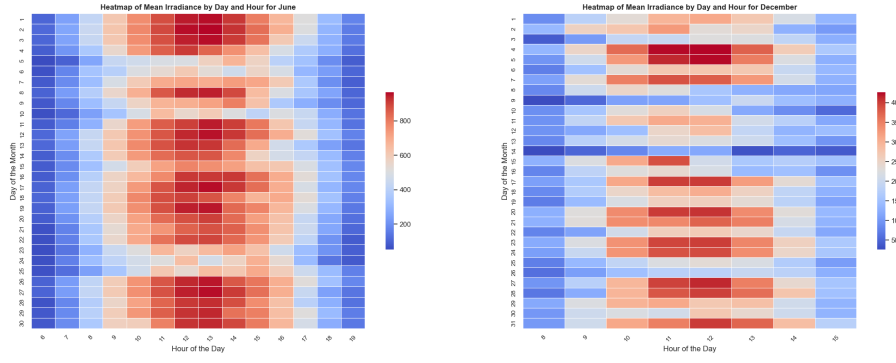


Figure 4.5: June and December's Heat Maps of Mean Irradiance per Hour and Day of the Month

to increased power output, consistent with the expected behavior of PVSs.

However, the dispersion of points, particularly at higher irradiance levels, indicates some variability in the efficiency of each inverter in converting solar energy into electrical power. This variability could be attributed to factors such as the technical characteristics of each inverter, temperature influences, or shading effects. Additionally, the presence of numerous points along the x-axis, where high irradiance corresponds to zero power output, suggests inefficiencies or inverter stoppages. These outliers, where power output is low despite high irradiance, may result from temporary shading, inverter limitations, or instances where the inverter is inactive due to malfunction or intentional shutdown.

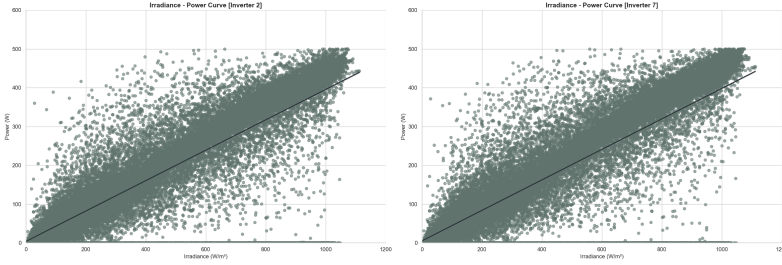


Figure 4.6: Inverters' Irradiance-Power Curves

Lastly, the time series graphs (**Figure 4.7**), with nighttime data removed, show that both solar inverters respond consistently to daylight conditions with similar patterns of power output, irradiance, and temperature, unaffected by wind speed variability. This indicates comparable efficiency and operational behavior during active solar periods.

In Chapter 2, the concept of I-V curves was first introduced to evaluate the performance of PV modules and strings. The literature does not extend it to inverters but uses inverter efficiency curves for the same purpose (Faranda, Hafezi, Leva, Mussetta, & Ogliari, 2015). The efficiency (η) of a given solar inverter is defined by (**Equation 4.1**):

$$\eta \text{ (\%)} = \frac{\text{AC Power Output}}{\text{DC Power Input}} \times 100 \quad (4.1)$$

An inverter efficiency curve graphically depicts the conversion efficiency from DC to AC power across varying output levels. The latter is measured through normalized DC power,

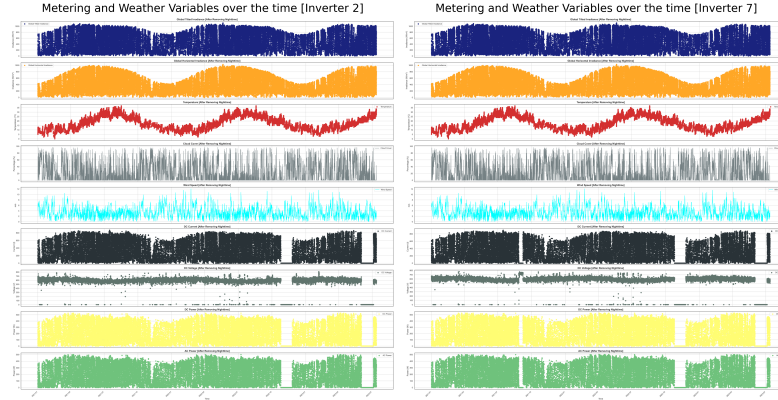


Figure 4.7: Comparison between variables of both inverters

which analyses the performance of the device across different operating conditions by comparing it with the nominal DC power (500 W, given by the manufacturer) (**Equation 4.2**).

$$\text{Normalized DC Power (\%)} = \frac{\text{Actual DC Power}}{\text{DC Power Input}} \times 100 \quad (4.2)$$

Typically, this curve demonstrates a rise in efficiency from low output levels to a peak at mid-capacity, often slightly declining at total capacity. The curve's apex represents the inverter's maximum efficiency point, crucial for optimizing system performance and energy yield in PVSs. It is expected that inverters demonstrate increased efficiency stability at elevated power inputs, which can be seen on the inverters' manufacturer's pre-determined efficiency curve (**Figure A.3**).

Just for visualization purposes, it was computed for both inverters. In the comparative analysis of the efficiency curves for Inverters 2 and 7, distinct operational behaviors are evident under varying load conditions (**Figure 4.8**). Inverter 7 consistently maintains a high efficiency, closely approaching or slightly exceeding 100%. Such efficiencies exceeding the theoretical maximum uncover possible anomalies. In contrast, Inverter 2 exhibits a broader dispersion in efficiency measurements, particularly noticeable at lower normalized DC power percentages. Efficiency fluctuates more markedly, with the lowest values nearing 80%. The variation reduces as the power input approaches full nominal capacity, indicating more stable and efficient operation at higher load levels.

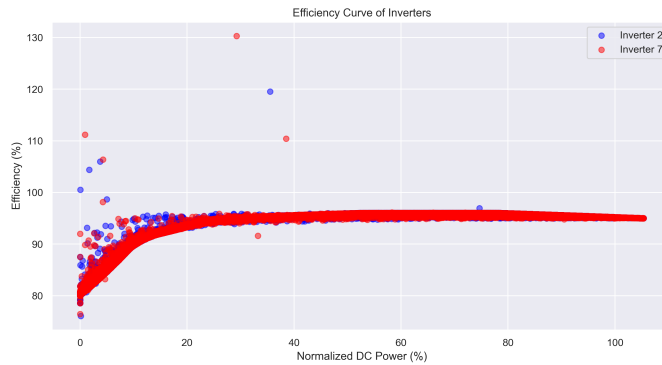


Figure 4.8: Inverters' Efficiency curves

Chapter 5

Modeling

The system architecture splits into two subsections: a detection layer, harnessed by a DL model, and an explanatory player, which scrutinizes the impact of the predictions.

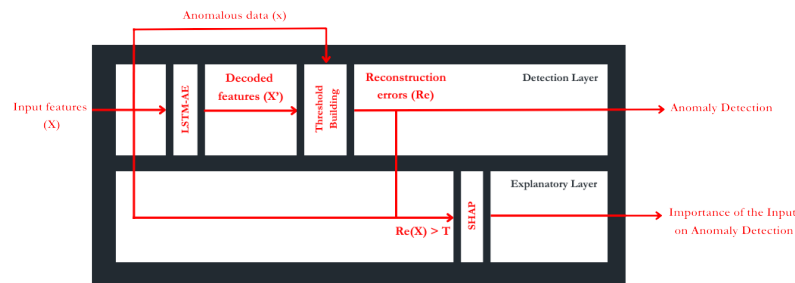


Figure 5.1: Unsupervised Anomaly Detection - System Architecture

5.1 Detection Layer

5.1.1 LSTM-Autoencoder

The LSTM model is the groundwork of the Detection Layer, and it was constructed using *Keras*, a high-level neural networks Application Programming Interface (API), running on top of TensorFlow, an open-source Python library.

The preliminary steps include splitting the data into training and testing sets. As mentioned in Chapter 2, auto-encoders must only be trained on non-faulty instances, as high reconstruction errors are associated with anomalies. The most straightforward way to select adequate examples for training is to inspect discrepancies in the power-irradiance relationship (Chapter 4) - 12067 and 9766 anomalies were found for inverters 2 and 7, respectively. Considering the data's seasonality and the urge to reproduce that effect on the predictions, one year (2021) of non-faulty data was selected to train the model. The two remaining years, including faulty instances, were used to test the model (**Figure 5.2**).

The model starts with an input layer that accepts sequences with a shape defined by the reshaped training data [samples, timesteps, features], suitable for the model.

Regarding the Encoder, the first LSTM Layer consists of 9 units, one for each feature. It utilizes Rectified Linear Unit (ReLU) activation function to introduce non-linearity to the model, helping capture complex patterns in the data. The layer returns sequences, allowing

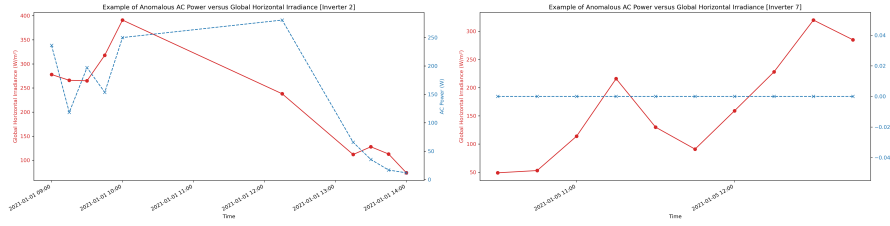


Figure 5.2: Examples of anomalous periods for both inverters, when AC Power does not follow the same pattern as GHI

the next layer to process these sequenced outputs further. L1 and L2 regularization were applied to the LSTM weights to mitigate overfitting. The Elastic Net method, which combines the strengths of L1 (Lasso) and L2 (Ridge) regularization, ensures effective feature selection by eliminating less significant variables and maintains model stability by addressing multicollinearity, thus harmonizing the diverse influences in the dataset (Hastie, Tibshirani, & Friedman, 2009). The regularization strengths are parameterized to allow for tuning during model training, with l1 ranging from 0.0001 to 0.01 and l2 from 0.0001 to 0.1.

The second Layer of the AE has a reduced number of LSTM units to compress the information and was defined as a tunable hyperparameter, ranging from 2 to 8. This flexibility allows experimenting with varying model complexity and capacity levels during hyperparameter optimization phases. The Repeat Vector Layer takes the final state output from the second Layer. It repeats it to reconstruct the original sequence length, bridging the encoder and decoder parts of the AE.

Third and Fourth LSTM Layers mirror the architecture of the encoder, facilitating the reconstruction of the original input sequence for the decoder. The number of units in the Third one matches the tuned units from Layer 2, ensuring symmetry in the model. The Fourth Layer again uses 9 units, aligning with the first LSTM layer to reconstruct the sequence effectively. Nevertheless, the final output Layer independently applies a dense (fully connected) layer to each time step. It has as many units as features in the input data, ensuring the output sequence matches the dimensionality of the input sequence.

5.1.2 Hyperparameter Tuning

The model is compiled with a stochastic gradient descent method, the Adaptive Moment Estimation (ADAM) optimizer, known for its efficiency in handling sparse gradients on noisy problems. The ADAM optimizer's learning rate is adaptively tuned through hyperparameter optimization, with values ranging logarithmically from 0.0001 to 0.01. The clipvalue hyperparameter, set between 0.1 and 1.0, is also incorporated to control the gradient clipping during backpropagation. Gradient clipping is a technique that prevents exploding gradients in Deep ANN, ensuring stable and reliable training by bounding the gradients to a defined range. The loss function is set to mean squared error (MSE), a common choice for regression problems and for training models where the magnitude of prediction errors is squared to emphasize larger errors, which is particularly useful in capturing the performance of time-series forecasting in the context of the AE for anomaly detection.

The Random Search algorithm systematically explored several hyperparameter configurations to optimize the model. The primary goal of this tuning process was to minimize the validation loss, thereby enhancing the model's generalization capability on unseen data. The

tuning was configured to perform 50 trials with 2 executions per trial to ensure robustness in the results. The search process used the training dataset as input and labels due to the AE's nature of learning to reconstruct its input.

Each configuration was trained batch size of 32, strategically set to align with the natural daily solar cycle. This decision is rooted in the observation that there are approximately 8 hours of effective sunlight per day, and with each hour divided into four 15-minute segments, this results in 32 segments per day. An early stopping callback was utilized to halt training if the validation loss did not improve for 32 consecutive epochs. For this reason, a large number of training epochs, specifically 300, were selected. This setup allows the model to train extensively while the callback efficiently halts training when no further improvement in validation loss is observed, ensuring optimal resource utilization without risking over-fitting. Lastly, a standard validation split of 0.2 was utilized, meaning that 20% of the training data is reserved for validation purposes, monitoring the model's generalization ability.

Lastly, the training phase is performed to fit the hyper-parameterized model to the training data and restore the weights from the epoch with the lowest validation loss. Therefore, the model is ready for testing.

5.1.3 Threshold Configuration and Anomaly Detection

High reconstruction errors dictate whether an observation is configured as an anomaly, meaning the choice of a proper threshold is crucial to the study's success. The better way to define it is to feed the final model with anomalous data since it will struggle to reproduce the input by applying the previously mentioned preliminary steps. The LSTM AE model was systematically employed in two distinct phases to enhance its utility in fault detection and anomaly analysis within a comprehensive dataset, including faulty and non-faulty data.

In the first phase, the model was trained and utilized exclusively on a dataset containing only fault instances. This initial application was critical for establishing a normal versus abnormal behavior baseline. The primary objective during this phase was to develop an accurate threshold for anomaly detection. To achieve this, the model predicted the fault-only data, then flattened and reshaped into a two-dimensional format, which is mandatory to fulfill the Neural Network input requirements and simplify the output processing and error calculation. The predictions were compared with the actual data to calculate the RMSE (**Equation 5.1**), due to its sensitivity to outliers, as the squaring of larger error terms has a disproportionately large effect on the sum of squares.

In the RMSE equation, n is the number of observations, y_i is the observed value, and $\hat{y}_i$ is the predicted value.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5.1)$$

For the threshold configuration, three types of thresholds were considered: the 95th percentile, an adaptive threshold, and the IQR. The first one is very restrictive, leaving many faults unreported (low detection rate) and culminating in high operational costs for the client. Regarding an adaptive solution, a limited time frame (3 days) was selected for the periodic computation of the k-Sigma ($k = 1.5$). However, this can be misleading as the anomaly detection depends greatly on the sample considered. For example, if the previous set threshold is too high, the model will struggle to spot more outliers in the next sample. On the other

hand, sequences of anomaly-free instances will smooth the threshold, and the number of false positives will rise. Even though IQR is a simple and static metric, it appeared to be the most suitable configuration for the problem in hands.

Using the distribution of these RMSE values, the first (Q1) and third (Q3) quartiles were computed, and an IQR was determined (**Equation 5.2**). An anomaly detection threshold was established at 1.5 times the IQR above the Q3 (**Equation 5.3**), providing a quantitative criterion to differentiate between typical variations and significant deviations that might indicate underlying issues.

$$IQR = Q3 - Q1 \quad (5.2)$$

$$Threshold = Q3 + 1.5 \times IQR \quad (5.3)$$

In the second phase, the model was applied to a broader test dataset that included both faulty and non-faulty instances. This step was crucial to evaluate the model’s capacity to reconstruct and accurately predict across a mixed dataset, reflecting more realistic operational conditions. The model’s predictions were reshaped, inverse-transformed to their original scale, and rigorously compared against the actual data. The RMSE was again employed to quantify the reconstruction error for each instance. The calculated errors were systematically cataloged in a Data Frame, which also flagged anomalies based on the threshold derived from the fault-only data analysis.

5.2 Explanatory Layer

The absence of transparency and validation in the decision-making processes of ML systems presents a significant drawback. Without clear explanations, it becomes challenging for decision-makers to utilize the outputs of these algorithms effectively. Providing reliable explanations enhances trust among users, aids in pinpointing where models may fail, and reduces obstacles to the adoption of DNNs (“black boxes”) across various fields.

To address these challenges, the proposed explanation method, SHAP, emphasizes linking features with high reconstruction errors to those that significantly influence these errors. Originally developed for game theory to assess the contribution of individual players within a collaborative team, Shapley values have been adeptly repurposed for the domain of ML by quantifying the importance of features in a prediction model (**Equation 5.4**). They evaluate how various features influence the model’s output, accounting for the magnitude and direction of each feature’s contribution. Positive contributions indicate a feature’s role in predicting activity, while negative values suggest a feature detracts or contributes towards inactivity (Rodríguez-Pérez & Bajorath, 2020).

The importance of feature i by Shapley values¹ is given by:

$$\phi_i = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|!(|N| - |S| - 1)! [f(S \cup \{i\}) - f(S)] \quad (5.4)$$

This method ensures that the explanation model matches the output of the original model, that features not present in the input have no impact, and that the importance assigned to any

¹In the equation, $f(S)$ corresponds to the output of the model to be explained applied to a reduced set S of features, and N corresponds to the set of all features (Rodríguez-Pérez & Bajorath, 2020).

feature increases if the model relies more heavily on it (Antwarg, Miller, Shapira, & Rokach, 2020).

The Explanatory Layer's initial block, the class ('initiator'), is designed as a custom regression estimator. Upon initialization, the class accepts an already trained 'model' parameter. The primary operation of the class occurs when incoming data is first scaled using 'MinMaxScaler' to normalize the features and then reshaped to fit the model's input requirements. Post prediction, the method calculates the RMSE by comparing the flattened version of the predicted output against the original data, serving as a quantitative measure of prediction accuracy. Furthermore, the class is integrated with the SHAP library - an instance is used with SHAP's Explainer to analyze the impact of different features on the prediction errors. The Shapley values are computed for anomalies detected in the data, and a waterfall plot is generated to visualize these explanations, providing insights into which features most significantly influence the model's predictions. This detailed analysis aids in understanding model behavior and enhances the transparency of the predictive process, a critical aspect of predictive modeling in applied settings.

Chapter 6

Results

This chapter presents and discusses the results obtained following the methodology explained previously.

After an extensive hyperparameter tuning, the most optimal set was identified. This set was then used to construct the optimized model and finalize the design of the LSTM for each inverter, as detailed below (**Table 6.1**).

Table 6.1: Best Hyperparameters for Inverter Models

Hyperparameter	Inverter 2	Inverter 7
'L1_reg'	0.0011	0.0001
'L2_reg'	0.0001	0.0201
'L2_units'	6	8
Learning Rate	0.0015	0.0004
Clip Value	0.5	0.1

Both have similar architectures but different second-layer output units: the one from Inverter 2 has 6 units, and the correspondent on Inverter 7 has 8 units, suggesting a slightly higher capacity to capture information or patterns from the input data (**Appendix B.1**).

The key distinction between Inverter 2 and Inverter 7 lies in their hyperparameters. Inverter 2's slightly higher L1 regularization rate may result in a more sparse model, enhancing feature selection. Conversely, Inverter 7's significantly higher L2 regularization prevents overfitting by penalizing larger weights. The lower learning rate in Inverter 7 promotes a more conservative approach to weight updates, which is ideal for stable convergence. Additionally, the lower clip value in Inverter 7 indicates a stricter control on update magnitudes, potentially mitigating gradient exploding issues.

Regarding the learning phase, Inverter 7's model is tailored for environments where consistent performance is critical. In contrast, Inverter 2's model is configured to be more responsive, allowing for faster adaptation to changes. This distinction in learning approaches underscores the models' adaptability, stability, and suitability for different operational environments.

Moving to the learning phase, in the training configurations for Inverters 2 and 7, both models utilize the Early Stopping callback set at 32 consecutive epochs. Specifically, Inverter 2 is set to train for up to 300 epochs, whereas Inverter 7 may train for up to 1000 epochs, with a batch size of 32 and a standard 20% validation data split. Based on preliminary observations,

Inverter 7 required more fine-tuning to achieve optimal performance, which explains the epoch disparity between the two models.

When observing **Figures 6.1 and 6.2**, one can state a sharp decrease and convergence of the model loss through epochs, indicating that, for both inverters, the model is learning efficiently from the dataset. The initial loss for Inverter 7 starts higher (configured to handle finer nuances in the data) than that for Inverter 2 but decreases to a comparable level. Both models show excellent generalization capabilities, as indicated by the close tracking of training and validation losses. However, Inverter 2 reaches its plateau much quicker, which could be advantageous with limited computational resources or time. The extended training epochs for Inverter 7 without overfitting align with the slower, more cautious approach in weight updates, which might be necessary to maintain stability in more complex scenarios.

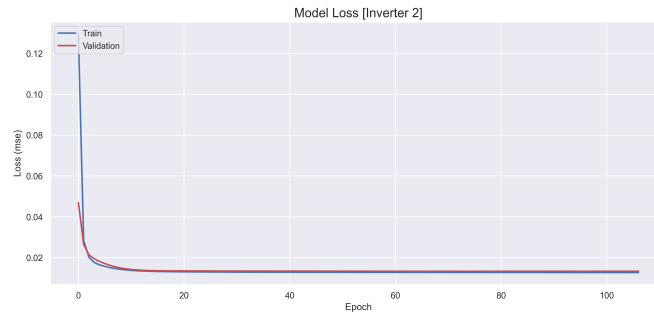


Figure 6.1: Model Loss (MSE) - Training phase [Inverter 2]

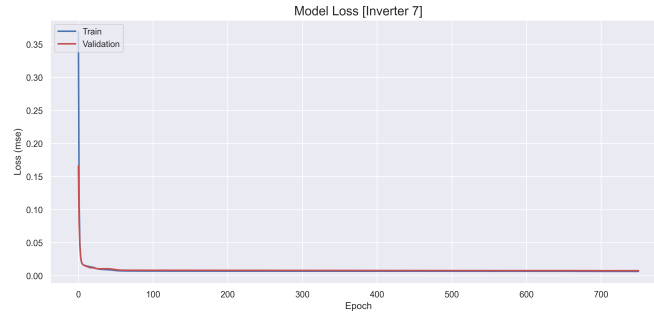


Figure 6.2: Model Loss (MSE) - Training phase [Inverter 7]

Understanding how the encoder compresses and learns patterns in the data is a crucial step post-training. However, the high dimensionality of the latent space makes it difficult. To overcome this handicap, various dimensionality reduction techniques, such as t-SNE, can be employed to visualize the transformations.

The outcomes for the two inverters are very different, as displayed in **Figure 6.3**. The t-SNE plot for Inverter 2 shows a highly structured and continuous latent space with clear, loop-like structures, indicating strong internal correlations and systematic variations within the data. The pathways reveal that the model has learned significant temporal dependencies among the features. Contrary to Inverter 2, Inverter 7's t-SNE plot displays a more dispersed and cloud-like structure with data points spread across the plot without clear paths. With more LSTM units, Inverter 7 can encode a richer representation of the input data, explaining

the more dispersed clustering seen in its t-SNE plot, as the model might be capturing diverse aspects of the data, each represented in different regions of the latent space.

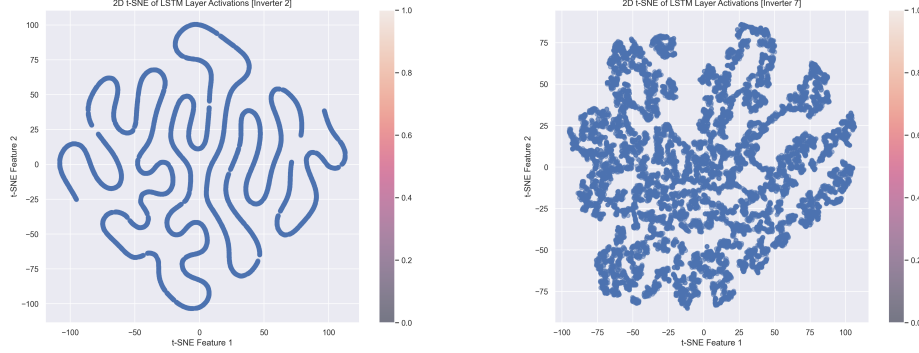


Figure 6.3: 2D t-SNE of LSTM Layer Activations

Following the workflow described in Chapter 5, the anomalous data was fed into the trained model, and the RMSE was computed. The boxplots provided compare the distribution of RMSE across various variables for two different inverters, giving insight into model performance for each variable (**Figures 6.4 and 6.5**).

The RMSE for Inverter 2 exhibits a wide range across variables. Some variables show tight distributions (AC Power, DC Power, DC Voltage), indicating consistent prediction accuracy across multiple observations. In contrast, other variables (such as GHI and wind speed) display a higher RMSE and greater variability, suggesting challenges in accurately predicting these variables. Several variables have outliers with significantly higher error values, particularly variable wind speed. Compared to Inverter 2, Inverter 7 generally exhibits lower RMSE values across all variables, which indicates better overall prediction accuracy and model performance. The spread and median values are more consistent across variables, with fewer showing extreme outliers or variations. This more robust model performs well across different types of data inputs.

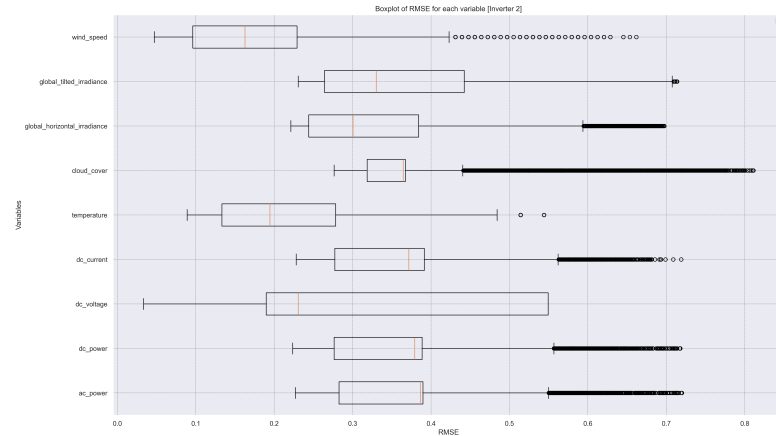


Figure 6.4: Boxplot of RMSE [Inverter 2]

The error dispersion permitted calculating the anomaly threshold through IQR, a more stable and reliable metric under distinct conditions. For Inverter 2, the established threshold

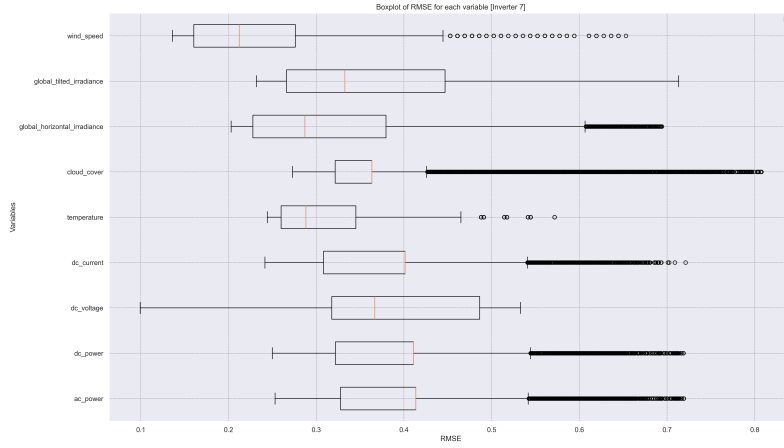


Figure 6.5: Boxplot of RMSE [Inverter 7]

was 0.6279 and for Inverter 7 was 0.6194, a slightly lower value. **Figure 6.6** shows the distribution of detected anomalies on the testing set. If an instance's RMSE is equal or superior to the defined threshold, it is considered an outlier.

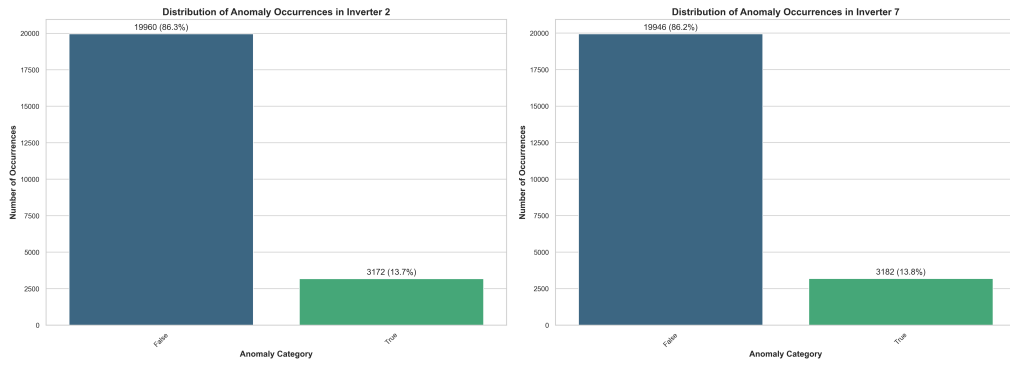


Figure 6.6: Distribution of faults for both inverters

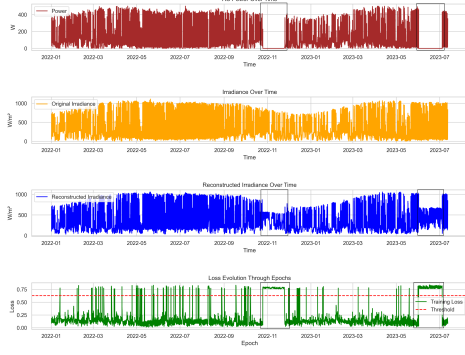
A significant part of the instances, 86.3% and 86.2%, for Inverters 2 and 7, respectively, are classified as non-anomalies, indicating normal operations. A slightly higher number of anomalies are detected in Inverter 7, with 3182 instances (13.8%). These are low values compared to the manual inspection performed and detailed earlier. Still, the gap can be explained by the conservative approach taken - on the minor suspicion, an instance was considered a fault. This marginal increase is due to slight differences in data quality between the two inverters, as expected.

Both inverters show a similar distribution of anomalies since they operate under the same conditions. However, this might also mean that either the model is too sensitive (generating false positives) or insensitive (missing true anomalies). A review of the detection model's parameters or thresholds is a way to overcome the raised concerns.

For a wider prospect, **Figure 6.7** presents the power generated throughout the analysis, the irradiance available for the period, its reconstruction to spot dissimilarities, and the reconstruction errors (accompanied by the respective anomaly threshold). The black rectangles highlight obvious anomalies. Overall, Inverter 7 exhibits more frequent and significant deviations - higher loss spikes and greater variance on the reconstructed irradiance - explained by

the different data quality and model tuning.

Anomaly detection through reconstructed irradiance [Inverter 2]



Anomaly detection through reconstructed irradiance [Inverter 7]

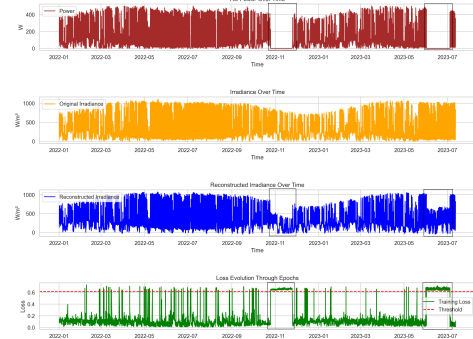


Figure 6.7: Comparison between power, irradiance, reconstructed irradiance, and reconstruction loss. The periods where the occurrence of anomaly is more evident are highlighted.

On the Explanatory Layer of the system architecture, the SHAP model was fed with the flagged anomalies and explained how different features contribute to the anomaly detection.

Waterfall plots present some key components: the base value ($f(x)$) is the average model output over the dataset, which serves as the starting point for the SHAP value calculation; the positive contributions, colored in magenta, are the features that push the model output higher than the base value; negative contributions, colored in blue, are the features that decrease the model output from the base value; and feature values, provided on the left side, which influence the SHAP values (**Figure 6.8**).

Regarding Inverter 2, the SHAP Waterfall plot highlights the predominant role of DC Current as the most significant positive contributor to the model's prediction, followed by wind speed and temperature, indicating their importance in operational assessments. Conversely, GTI and GHI negatively influence the model's output. The final SHAP value of 0.308 suggests a moderate influence from the set of analyzed features on the model's decisions.

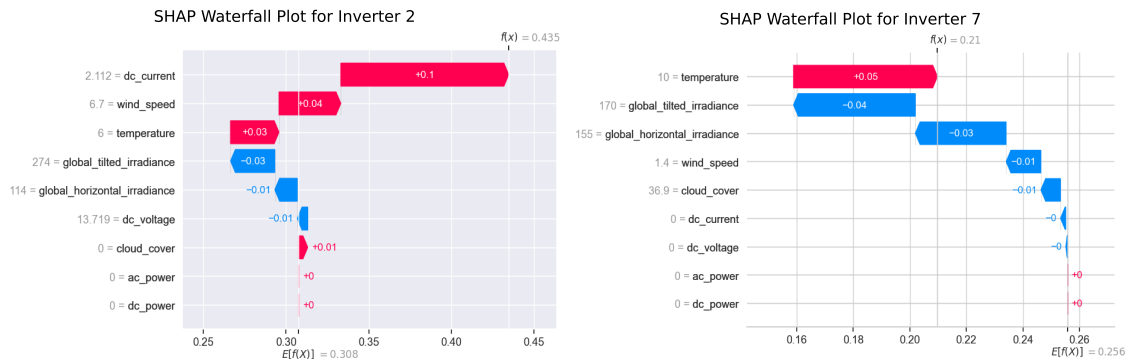


Figure 6.8: SHAP Waterfall plots for both inverters

For Inverter 7, the plot reveals that temperature significantly elevates the model's output, highlighting its positive impact on the predictions. Contrastingly, GHI and GTI exert a strong

negative influence, indicating good performance. The overall lesser final SHAP value of 0.256 compared to Inverter 2 indicates a slightly lower cumulative impact of the features, suggesting a different sensitivity setting in the model's configuration.

6.1 Performance Evaluation

After unveiling the results, it is time to evaluate the proposed model behavior. When dealing with an unsupervised anomaly detection problem, there are no labels to assist the computation of the most common performance metrics.

To address this challenge, the strategy employed involved observing and analyzing how the relationship between GHI and AC Power evolves. Normally, these two variables should exhibit similar patterns due to their inherent correlation, and any significant deviations could indicate a fault. By integrating these observational techniques with the outcomes from the DL system, confusion matrices and ROC curves will be used to evaluate and highlight the model's predictive capabilities.

$$\begin{aligned} \text{Confusion Matrix [Inverter 2]} &: \begin{bmatrix} \text{TN: 15108} & \text{FP: 51} \\ \text{FN: 4852} & \text{TP: 3121} \end{bmatrix} \\ \text{Confusion Matrix [Inverter 7]} &: \begin{bmatrix} \text{TN: 16163} & \text{FP: 38} \\ \text{FN: 3783} & \text{TP: 3144} \end{bmatrix} \end{aligned}$$

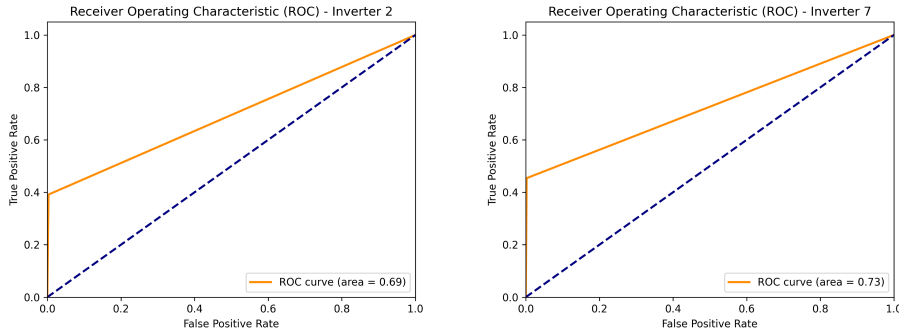


Figure 6.9: ROC curves for both inverters

For Inverter 2, the model correctly identified 15108 instances as non-fault (True Negatives) and 3121 instances as fault (True Positives). However, 51 instances were incorrectly classified as faults (False Positives), and a significant number, 4852 instances, were missed faults (False Negatives).

In the case of Inverter 7, the model demonstrated a similar pattern but slightly better performance in reducing false positives. It accurately predicted 16163 non-fault instances and 3144 fault instances. The model incorrectly predicted only 38 instances as faults (False Positives), but like Inverter 2, it failed to detect 3783 actual faults (False Negatives).

The ROC curves illustrate the performance of the predictive models for each inverter (**Figure 6.9**). For Inverter 2, the ROC curve has an AUC of 0.69, indicating that the model has a moderate ability to distinguish between positive and negative classes. The curve is slightly above the diagonal line, representing better-than-random performance, but still shows significant room for improvement. For Inverter 7, the curve has a slightly higher AUC of

0.73, suggesting a better performance than Inverter 2. The curve for Inverter 7 also demonstrates a better trade-off between the true positive rate and false positive rate but similarly indicates the need for further enhancement to achieve higher accuracy and reliability.

The large number of false negatives can be attributed to the conservative approach of the observational technique used. Any deviation in AC Power over consecutive periods was classified as a fault without additional criteria. This method resulted in a high count of perceived faults for each inverter—a tendency to over-diagnose faults. Conversely, the false positives occurred when the AC Power generated was zero, and the GHI was very low, below 50. The subjective nature of the observational technique did not identify these as faults, whereas the model did. This discrepancy suggests that the model’s predictions were correct, as the power generated should not have been zero even with low irradiance, indicating real issues the observational method missed.

Thereafter, a few performance evaluation metrics were computed to explore the subject more thoroughly (Table 6.2).

Table 6.2: Evaluation Metrics

Metrics	Inverter 2	Inverter 7
F1-Score	0.5601	0.6220
Accuracy	0.7880	0.8348
Precision	0.9839	0.9881
Recall	0.3914	0.4539

For Inverter 2, the accuracy is set at 0.7880, reflecting a relatively high rate of correctly predicting faults and non-faults. The precision metric is quite high at 0.9839, showing that when a fault is predicted, it is very likely to be a true fault. However, the recall is quite low at 0.3914, indicating that a significant number of actual faults are not detected by the model. The F1-Score stands at 0.5601, indicating a moderate balance between precision and recall but suggesting room for improvement in either or both metrics.

In comparison, Inverter 7 shows generally better performance in some areas. Precision remains high at 0.9881, almost similar to Inverter 2, ensuring that most predicted faults are indeed faults. The recall rate for Inverter 7 is 0.4539, which, while still under half, is noticeably better than that of Inverter 2, meaning it captures a higher proportion of actual faults. The accuracy is also higher at 0.8348, indicating that it correctly classifies a greater percentage of the total cases. Lastly, it achieves a higher F1-Score of 0.6220, suggesting a better balance between precision and recall than Inverter 2.

The current baseline, developed by *Enlitia*, is based on a method similar to that proposed by Tereso (2021), with significant adaptations for evaluating the performance of solar PVSs. According to the enterprise, this model did not undergo any quantitative analysis and proved highly inflexible, requiring extensive client customization, which led to undetected underperformance. Although it detects some faulty scenarios, it cannot identify additional issues. Furthermore, the model’s parameterization places a heavy burden on clients. In contrast, the newer, more automated model is considerably more valuable as it can identify more anomalous instances.

Chapter 7

Conclusion

This dissertation has effectively demonstrated how unsupervised learning techniques can significantly enhance fault detection in solar PVSs. By addressing the challenges posed by the inherent complexity and variability of PVS data, this study has validated the utility of advanced ML models, particularly LSTM models, in overcoming the limitations associated with the scarcity of labeled anomaly data in real-world scenarios. Furthermore, applying Explainable AI techniques such as SHAP has provided profound insights into the significant factors influencing the detection of anomalies.

The research findings highlight the critical role of unsupervised learning in improving the operational efficiency and reliability of solar PVS. This thesis contributes to the academic field by providing robust fault detection methodologies and aligning with the global push towards more sustainable energy solutions.

7.1 Final Remarks

LSTM networks are crucial for managing sequence data effectively in the context of solar PV fault detection. However, the standard architecture may not always meet the dynamic nature of this task. This section, therefore, presents a structured discussion on a range of design modifications that can be implemented to enhance the model's predictive capabilities, providing a clear road map for the reader to follow.

Activation functions are crucial in ANN, introducing non-linearity that allows the networks to learn complex patterns. The ReLU was used for its simplicity and effectiveness in DL scenarios - it reduces computational overhead and mitigates the vanishing gradient problem. Nevertheless, there are alternatives that could be implemented to upgrade the chosen system architecture regarding the activation function. Softmax is commonly employed in the output layer of classification models, where it converts the outputs into probabilities that indicate class memberships, making it crucial for tasks that require clear distinctions between multiple classes. In contrast, ReLU is utilized primarily in hidden layers to introduce non-linearity, enhancing the model's ability to learn complex patterns. Given their different roles within a neural network, Softmax and ReLU could be used together. To add some complexity, the former could be included to enhance fault classification (Szandala, 2020).

Optimizers play a crucial role in efficiently training ANN, with ADAM being a popular choice due to its standout features: high computational efficiency and minimal memory requirements. When comparing ADAM with other optimizers like the Lion optimizer and

Adamax, distinct differences emerge. The Lion optimizer, for example, is particularly advantageous in resource-limited environments, though its aggressive update strategy may sometimes risk overshooting the minimum. On the other hand, Adamax, a variant of ADAM based on the infinity norm, is less prone to issues with large gradients and is better suited for datasets with noisy or sparse gradients. Unlike ADAM, which rapidly adjusts the learning rate based on the square of gradients, Adamax moderates the learning rate adjustments, providing a gentler approach that might be more suitable in datasets with highly variable gradients (Srivastava et al., 2023).

Lastly, selecting an appropriate loss function directly impacts how prediction errors are calculated and adjusted through learning. Due to its sensitivity to larger errors, the chosen metric, RMSE, is particularly favored in fields requiring precise anomaly detection, such as in solar PVSs. However, other metrics offer different perspectives on error measurement. Mean Absolute Error (MAE) provides a straightforward average of error magnitudes without direction, making it less sensitive to outliers (like Huber loss) compared to RMSE (Hodson, 2022). MSE, similar to RMSE, accentuates larger errors but lacks the interpretability of the latter since it does not express errors in the original data units. Mean Squared Logarithmic Error (MSLE) is advantageous in scenarios dealing with exponential growth where the magnitude of prediction errors does not linearly impact outcomes, making it less suited for systems like solar PV where the precise magnitude of deviations is critical (Istaiteh, Owais, Al-Madi, & Abu-Soud, 2020). Cosine similarity, which measures the angle between predicted and actual data vectors, offers insights into directional accuracy but fails to capture the magnitude of errors, limiting its utility in systems where error size directly affects performance (Hananto, Sulaiman, Widiyanto, & Rahman, 2021).

These are just final remarks to consider during the modeling phase about the LSTM. Regarding hyperparameter tuning, other heuristics than random search, such as gradient-based or Bayesian optimization, could be employed. Using grid search is not encouraged since it ensures that all possible combinations are evaluated. Notably, it is time-consuming and computationally demanding, which can be a significant drawback when working with such large datasets or complex models (Torres, Martínez-Álvarez, & Troncoso, 2022).

7.2 Recommendations

Based on the promising results obtained, several targeted business recommendations can be formulated to significantly boost the operational effectiveness and reliability of solar PVS. Initially, clients should prioritize key factors in maintenance and process optimization. For Inverter 2, it is crucial to closely monitor and maintain DC current within optimal ranges to prevent faults. Similarly, monitoring wind speed and temperature is essential; therefore, implementing Smart Monitoring Systems to provide notifications when these factors deviate from typical patterns could enhance system reliability. This approach is preferable to relying solely on external satellite data. For Inverter 7, optimizing panel angles and cleaning schedules to maximize tilted irradiance absorption is advisable. Additionally, operations should be adjusted preemptively during periods of expected low irradiance to maintain efficiency.

Another recommendation involves refining anomaly detection models by incorporating additional environmental and operational parameters into the feature engineering process and customizing sensitivity settings. Examples of additional parameters include humidity levels, solar panel surface temperature, shading patterns, and inverter load. Given its lower cumula-

tive impact, Inverter 7 may benefit from a more sensitive setting to detect subtle anomalies, such as minor temperature fluctuations or slight deviations in power output.

Finally, advancing predictive maintenance strategies is not just a suggestion but an essential step that requires the active involvement of all stakeholders. This involves scheduling maintenance activities when there is an increased likelihood of faults due to environmental or operational conditions (months of June and November). Additionally, updating systems to adjust operational parameters in real-time based on predictive models that account for the impact of DC current, wind speed, temperature, and irradiance variations could significantly enhance system responsiveness and efficiency.

7.3 Limitations and Future Work

However, it is important to note that the current work is just one step in the continuous process of improving solar PVSs. Further research is still needed to refine these models with real-time data integration and explore the scalability of the proposed solutions across different geographical and operational conditions. This reassurance should instill the readers' confidence about the future of solar PVS optimization.

One limitation of this technique is that it primarily allows for retrospective analysis rather than predictive analysis. The model's capacity for anticipation, or how far in advance it can detect failures, was not evaluated. This means that while the technique is effective at identifying past failures, its ability to predict future issues remains uncertain and untested. Moreover, the low computational capacity of the used devices, along with time constraints, dictated the quality of the hyperparameter tuning process, which can be enhanced in future works.

The main limitation of the developed work is the time-consuming way the training set is chosen, which primarily relies on observational techniques. One possible solution to this drawback is using the *pvl* library in Python, a specialized tool designed primarily for simulating the performance of PV energy systems. It provides essential capabilities for calculating solar positions, estimating clear sky irradiance, and modeling atmospheric conditions influencing solar radiation. In fault detection, for example, *pvl* can simulate expected outputs under ideal conditions, effectively identifying performance discrepancies through statistical tests ($p > 0.05$). Notwithstanding, such a model may struggle under less predictable weather conditions, potentially leading to higher rates of false positives or false negatives. On the bright side, it is insightful for anomaly classification, as various faulty states can be simulated, like shading.

Automated control systems are developed to dynamically adjust settings in response to changes in environmental factors such as wind speed, temperature, and irradiance. These systems are designed to maintain optimal operation of devices or installations without manual intervention, enhancing efficiency and performance through real-time adaptive adjustments (Aghaei, Grimaccia, Gonano, & Leva, 2015). Although *pvl* does not handle real-time data acquisition or device control, it can provide the back-end calculations and forecasts necessary for the control logic in an automated system.

Furthermore, the results proved that simple threshold configurations lead to higher FPR (Yang et al., 2019). In fact, IQR is more effective in addressing Gaussian Distributions, so other options should be explored. Similar to strategies employed in network monitoring, implementing a Low Pass Filter (LPF) in the post-processing phase could reduce the impact of transient spikes in irradiance data, often marked as false alarms - as performed by Ribeiro

et al. (2023). This would help in smoothing out rapid fluctuations in the data, focusing the detection process more on significant trends and outliers that are true indicators of faults.

To conclude, while this work establishes a solid foundation for integrating more AI-driven tools into the renewable energy sector, it is important to acknowledge that it is not without limitations. There is considerable room for improvement and further refinement, which could significantly enhance the sustainability and efficiency of solar energy production.

Bibliography

- AbdulMawjood, K., Refaat, S. S., & Morsi, W. G. (2018). Detection and prediction of faults in photovoltaic arrays: A review. In *2018 IEEE 12th international conference on compatibility, power electronics and power engineering (CPE-POWERENG 2018)* (pp. 1–8). IEEE. Retrieved 2024-01-02, from <https://ieeexplore.ieee.org/document/8372609/> doi: 10.1109/CPE.2018.8372609
- About - enlita. (n.d.). Retrieved 2024-01-02, from <https://www.enlita.com/about>
- Aghaei, M., Grimaccia, F., Gonano, C. A., & Leva, S. (2015). Innovative automated control system for pv fields inspection and remote control. *IEEE Transactions on Industrial Electronics*, 62(11), 7287–7296. Retrieved from <https://doi.org/10.1109/TIE.2015.2468065> doi: 10.1109/TIE.2015.2468065
- Antwarg, L., Miller, R. M., Shapira, B., & Rokach, L. (2020). Explaining anomalies detected by autoencoders using shap.
- Appiah, A. Y., Zhang, X., Ayawli, B. B. K., & Kyeremeh, F. (2019). Long short-term memory networks based automatic feature extraction for photovoltaic array fault diagnosis. , 7, 30089–30101. Retrieved 2024-01-23, from <https://ieeexplore.ieee.org/document/8660399> (Conference Name: IEEE Access) doi: 10.1109/ACCESS.2019.2902949
- Aziz, F., Ul Haq, A., Ahmad, S., Mahmoud, Y., Jalal, M., & Ali, U. (2020). A novel convolutional neural network-based approach for fault classification in photovoltaic arrays. , 8, 41889–41904. Retrieved 2024-01-28, from <https://ieeexplore.ieee.org/document/9018018> (Conference Name: IEEE Access) doi: 10.1109/ACCESS.2020.2977116
- Basnet, B., Chun, H., & Bang, J. (2020). An intelligent fault detection model for fault detection in photovoltaic systems. , 2020, 1–11. Retrieved 2024-01-02, from <https://www.hindawi.com/journals/js/2020/6960328/> doi: 10.1155/2020/6960328
- Bergmann, P., Batzner, K., Fauser, M., Sattlegger, D., & Steger, C. (2021). The mvtec anomaly detection dataset: A comprehensive real-world dataset for unsupervised anomaly detection. *International Journal of Computer Vision*, 129(4), 1038–1059. doi: 10.1007/s11263-020-01400-4
- Bessa, S. S. N. (2021). A framework for policy mix analysis: Portuguese case study on energy poverty. Retrieved 2024-01-05, from <https://repositorio-aberto.up.pt/handle/10216/135054> (Accepted: 2022-09-11T21:29:32Z)
- Bognár, □, Loonen, R., Valckenborg, R., & Hensen, J. (2018). An unsupervised method for identifying local PV shading based on AC power and regional irradiance data. , 174, 1068–1077. Retrieved 2024-01-02, from <https://linkinghub.elsevier.com/retrieve/pii/S0038092X18309873> doi: 10.1016/j.solener.2018.10.007
- Buckle, A., & Hocken, V. (2024). *Utc: Coordinated universal time*. Time and Date AS. Retrieved from <https://www.timeanddate.com/time/aboututc.html> (Accessed: 2024-04-23)
- Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. *ACM*

- Computing Surveys*, 41(3), Article 15. doi: 10.1145/1541880.1541882
- Chao, K.-H., Chiu, C.-L., Li, C.-J., & Chang, Y.-C. (2011). A novel neural network with simple learning algorithm for islanding phenomenon detection of photovoltaic systems. , 38(10), 12107–12115. Retrieved 2024-01-22, from <https://www.sciencedirect.com/science/article/pii/S095741741100399X> doi: 10.1016/j.eswa.2011.02.175
- Dhiman, H. S., Deb, D., Muyeen, S. M., & Kamwa, I. (2021). Wind turbine gearbox anomaly detection based on adaptive threshold and twin support vector machines. *IEEE Transactions on Energy Conversion*, 36(4), 3462–3470. doi: 10.1109/TEC.2021.3075897
- Ergen, T., & Kozat, S. S. (2020). Unsupervised anomaly detection with lstm neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 31(8), 3127–3141. doi: 10.1109/TNNLS.2019.2935975
- Faranda, R., Hafezi, H., Leva, S., Mussetta, M., & Ogliari, E. (2015). The optimum pv plant for a given solar dc/ac converter. *Energies*, 8, 4853–487. doi: 10.3390/en8064853
- Fu, Y., Chai, H., Zhen, Z., Wang, F., Xu, X., Li, K., ... Catalao, J. P. S. (2021). Sky image prediction model based on convolutional auto-encoder for minutely solar PV power forecasting. , 57(4), 3272–3281. Retrieved 2024-01-02, from <https://ieeexplore.ieee.org/document/9399287/> doi: 10.1109/TIA.2021.3072025
- Global market outlook for solar power 2023 - 2027 - SolarPower europe*. (n.d.). Retrieved 2024-01-02, from <https://www.solarpowereurope.org/insights/outlooks/global-market-outlook-for-solar-power-2023-2027/detail>
- Goldstein, M., & Uchida, S. (2016). A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data. *PLOS ONE*, 11(4), e0152173. doi: 10.1371/journal.pone.0152173
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press. (<http://www.deeplearningbook.org>)
- Hananto, A. L., Sulaiman, S., Widiyanto, S., & Rahman, A. Y. (2021). Evaluation comparison of wave amount measurement results in brass-plated tire steel cord using rmse and cosine similarity. *Indonesian Journal of Electrical Engineering and Computer Science*, 22(1), 207–214. Retrieved from <http://doi.org/10.11591/ijeecs.v22.i1.pp207-214> doi: 10.11591/ijeecs.v22.i1.pp207-214
- Harris, R. (1992). Testing for unit roots using the augmented dickey-fuller test: Some issues relating to the size, power and the lag structure of the test. *Economics Letters*, 38(4), 381–386. Retrieved from <https://www.sciencedirect.com/science/article/pii/016517659290022Q> doi: [https://doi.org/10.1016/0165-1765\(92\)90022-Q](https://doi.org/10.1016/0165-1765(92)90022-Q)
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). New York, NY: Springer. doi: 10.1007/978-0-387-84858-7
- Hempelman, S., Feng, L., Basoglu, C., Behrens, G., Diehl, M., Friedrich, W., ... Pfeil, T. (2020). Evaluation of unsupervised anomaly detection approaches on photovoltaic monitoring data. In *2020 47th IEEE photovoltaic specialists conference (PVSC)* (pp. 2671–2674). IEEE. Retrieved 2024-01-02, from <https://ieeexplore.ieee.org/document/9300481/> doi: 10.1109/PVSC45281.2020.9300481
- Hodson, T. O. (2022). Root-mean-square error (rmse) or mean absolute error (mae): when to use them or not. *Geoscientific Model Development*, 15, 5481–5487. Retrieved from <https://doi.org/10.5194/gmd-15-5481-2022> doi: 10.5194/gmd-15-5481-2022
- Hotz, N. (2018). *What is CRISP DM?* Retrieved 2024-01-02, from <https://www.datascience>

- pm.com/crisp-dm-2/
- Hwang, C., & Lee, T. (2021). E-sfd: Explainable sensor fault detection in the ics anomaly detection system. *IEEE Access*, 9, 140470-140485. doi: 10.1109/ACCESS.2021.3119573
- IEA SHC | | *solar heat worldwide*. (n.d.). Retrieved 2024-01-02, from <https://www.iea-shc.org/solar-heat-worldwide>
- Institute, E. (n.d.). *Home*. Retrieved 2024-01-02, from <https://www.energyinst.org/statistical-review/home>
- Istaiteh, O., Owais, T., Al-Madi, N., & Abu-Soud, S. (2020). Machine learning approaches for covid-19 forecasting. In *2020 international conference on intelligent data science technologies and applications (idsta)*. Amman, Jordan. Retrieved from <mailto:othmanistaiteh@gmail.com>, talaowis@gmail.com, n.madi@psut.edu.jo, abu-soud@psut.edu.jo (Computer Science Dept., Data Science Dept.)
- Jufri, F. H., Oh, S., & Jung, J. (2019). Development of photovoltaic abnormal condition detection system using combined regression and support vector machine. , 176, 457–467. Retrieved 2024-01-22, from <https://www.sciencedirect.com/science/article/pii/S0360544219306358> doi: 10.1016/j.energy.2019.04.016
- Kieu, T., Yang, B., Guo, C., Jensen, C. S., Zhao, Y., Huang, F., & Zheng, K. (2022). Robust and explainable autoencoders for unsupervised time series outlier detection. In *2022 IEEE 38th international conference on data engineering (icde)* (pp. 2375–026X). doi: 10.1109/ICDE53745.2022.00273
- Laptev, N., Amizadeh, S., & Flint, I. (2015). Generic and scalable framework for automated time-series anomaly detection. *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1939-1947. doi: 10.1145/2783258.2788611
- Liu, Y., Ding, K., Zhang, J., Li, Y., Yang, Z., Zheng, W., & Chen, X. (2021). Fault diagnosis approach for photovoltaic array based on the stacked auto-encoder and clustering with i-v curves. , 245, 114603. Retrieved 2024-01-02, from <https://linkinghub.elsevier.com/retrieve/pii/S0196890421007792> doi: 10.1016/j.enconman.2021.114603
- Madeti, S. R., & Singh, S. N. (2017). A comprehensive study on different types of faults and detection techniques for solar photovoltaic system. , 158, 161–185. Retrieved 2024-01-09, from <https://www.sciencedirect.com/science/article/pii/S0038092X17307508> doi: 10.1016/j.solener.2017.08.069
- Maka, A. O. M., & Alabid, J. M. (2022). Solar energy technology and its roles in sustainable development. , 6(3), 476–483. Retrieved 2024-01-02, from <https://academic.oup.com/ce/article/6/3/476/6606003> doi: 10.1093/ce/zkac023
- Markovics, D., & Mayer, M. J. (2022). Comparison of machine learning methods for photovoltaic power forecasting based on numerical weather prediction. , 161, 112364. Retrieved 2024-01-02, from <https://linkinghub.elsevier.com/retrieve/pii/S136403212200274X> doi: 10.1016/j.rser.2022.112364
- Mellit, A., & Kalogirou, S. (2022). Assessment of machine learning and ensemble methods for fault diagnosis of photovoltaic systems. , 184, 1074–1090. Retrieved 2024-01-02, from <https://linkinghub.elsevier.com/retrieve/pii/S0960148121017316> doi: 10.1016/j.renene.2021.11.125
- Momeni, H., Sadoogi, N., Farrokhifar, M., & Gharibeh, H. F. (2020). Fault diagnosis in photovoltaic arrays using GBSSL method and proposing a fault correction system. , 16(8), 5300–5308. Retrieved 2024-01-02, from <https://ieeexplore.ieee.org/>

- document/8680674/ doi: 10.1109/TII.2019.2908992
- Morichetta, A., Casas, P., & Mellia, M. (2020). Explain-it: Towards explainable ai for unsupervised network traffic analysis. *arXiv preprint arXiv:2003.01670*.
- Munir, M., Siddiqui, S. A., Dengel, A., & Ahmed, S. (2019). Deepant: A deep learning approach for unsupervised anomaly detection in time series. *IEEE Access*, 7, 1991–2005. doi: 10.1109/ACCESS.2018.2886457
- NASA. (n.d.). *Chapter 2: Reference systems*. Retrieved 2024-04-10, from <https://science.nasa.gov/learn/basics-of-space-flight/chapter2-2/>
- Nations, U. (n.d.). *What is renewable energy?* Retrieved 2024-01-02, from <https://www.un.org/en/climatechange/what-is-renewable-energy> (Publisher: United Nations)
- NEA. (2021). *How much electricity do solar panels produce?* Retrieved 2024-01-11, from <https://www.nea.org.uk/who-we-are/innovation-technical-evaluation/solarpv/how-much-electricity-solar-produce/>
- Nguyen, Q. P., Low, K. H., Lim, K. W., Chan, M. C., & Divakaran, D. M. (2019). Gee: A gradient-based explainable variational autoencoder for network anomaly detection. In *2019 IEEE conference on communications and network security (cns)* (p. 91-99). IEEE. doi: 10.1109/CNS.2019.8802790
- NIST. (2024). *6.4.4.2. stationarity*. Engineering Statistics Handbook. Retrieved from <https://www.itl.nist.gov/div898/handbook/pmc/section4/pmc442.htm> (Accessed: 2024-04-23)
- Patil, A., Wadekar, A., Gupta, T., Vijan, R., & Kazi, F. (2019). Explainable lstm model for anomaly detection in hdfs log file using layerwise relevance propagation. In *2019 IEEE Bombay section signature conference (ibssc)* (p. 1-6).
- Penn State University. (n.d.). *Lesson 8: Solar resource assessment for pv*. Online. Retrieved from <https://www.e-education.psu.edu/ae868/node/877> (Accessed: 2024-04-11)
- Pereira, J., & Silveira, M. (2018). Unsupervised anomaly detection in energy time series data using variational recurrent autoencoders with attention. In *2018 17th IEEE international conference on machine learning and applications (ICMLA)* (pp. 1275–1282). IEEE. Retrieved 2024-01-02, from <https://ieeexplore.ieee.org/document/8614232/> doi: 10.1109/ICMLA.2018.00207
- Poornima, I. G. A., & Paramasivan, B. (2020). Anomaly detection in wireless sensor network using machine learning algorithm. *Computer Communications*, 151, 331–337. doi: 10.1016/j.comcom.2020.01.005
- Renewable energy statistics 2023*. (n.d.). Retrieved 2024-01-02, from <https://www.irena.org/Publications/2023/Jul/Renewable-energy-statistics-2023>
- Ribeiro, R. P., Mastelini, S. M., Davari, N., Aminian, E., Veloso, B., & Gama, J. (2023). Online anomaly explanation: A case study on predictive maintenance. In I. Koprinska et al. (Eds.), *Machine learning and principles and practice of knowledge discovery in databases* (Vol. 1753, pp. 383–399). Springer Nature Switzerland. Retrieved 2024-01-02, from https://link.springer.com/10.1007/978-3-031-23633-4_25 (Series Title: Communications in Computer and Information Science) doi: 10.1007/978-3-031-23633-4_25
- Richter, M. (2012). Utilities’ business models for renewable energy: A review. , 16(5), 2483–2493. Retrieved 2024-01-02, from <https://linkinghub.elsevier.com/retrieve/pii/S1364032112000846> doi: 10.1016/j.rser.2012.01.072
- Rodríguez-Pérez, R., & Bajorath, J. (2020). Interpretation of machine learning models using shapley values: application to compound potency and multi-target activity predictions.

- Journal of Computer-Aided Molecular Design*, 34, 1013–1026. doi: 10.1007/s10822-020-00314-0
- Seara.com. (n.d.). *InvestPorto*. Retrieved 2024-01-05, from <https://www.investporto.pt/en/news/enlitia-is-the-new-artificial-intelligence-company-dedicated-to-renewables/>
- Seghiour, A., Abbas, H. A., Chouder, A., & Rabhi, A. (2023). Deep learning method based on autoencoder neural network applied to faults detection and diagnosis of photovoltaic system. , 123, 102704. Retrieved 2024-01-02, from <https://linkinghub.elsevier.com/retrieve/pii/S1569190X22001733> doi: 10.1016/j.simpat.2022.102704
- Shrikumar, A., Greenside, P., & Kundaje, A. (2019). Learning important features through propagating activation differences. *arXiv preprint arXiv:1704.02685*.
- Solar*. (n.d.). Retrieved 2024-01-02, from <https://www.iea.org/energy-system/renewables/solar-pv>
- Solargis. (2024). *Solar radiation modeling*. Solargis. Retrieved from <https://solargis.com/docs/methodology/solar-radiation-modeling> (Accessed: 2024-04-23)
- Srivastava, A., Rawat, B. S., Singh, G., Bhatnagar, V., Saini, P. K., & Dhondiyal, S. A. (2023). A review of optimization algorithms for training neural networks. In *2023 international conference on sustainable emerging innovations in engineering and technology (icseiet)* (p. 886-890). IEEE. Retrieved from <https://ieeexplore.ieee.org/document/10303287> doi: 10.1109/ICSEIET58677.2023.10303287
- Szandala, T. (2020). Review and comparison of commonly used activation functions for deep neural networks. *arXiv preprint arXiv:2010.09458*. Retrieved from <https://arxiv.org/abs/2010.09458> (cs.LG) doi: 10.48550/arXiv.2010.09458
- Tereso, I. M. F. (2021). Avaliação de desempenho de produção de centrais fotovoltaicas. Retrieved 2024-01-05, from <https://repositorio-aberto.up.pt/handle/10216/135225> (Accepted: 2022-09-09T19:48:25Z)
- Torres, J. F., Martínez-Álvarez, F., & Troncoso, A. (2022). A deep lstm network for the spanish electricity consumption forecasting. *Neural Computing and Applications*, 34, 10533–10545. Retrieved from <https://doi.org/10.1007/s00521-021-06773-2> doi: 10.1007/s00521-021-06773-2
- Voutsinas, S., Karolidis, D., Voyiatzis, I., & Samarakou, M. (2023). Development of a machine-learning-based method for early fault detection in photovoltaic systems. , 70(1), 27. Retrieved 2024-01-17, from <https://doi.org/10.1186/s44147-023-00200-0> doi: 10.1186/s44147-023-00200-0
- Wirth, R., & Hipp, J. (2000). CRISP-DM: Towards a standard process model for data mining.
- Xu, W., Jang-Jaccard, J., Singh, A., Wei, Y., & Sabrina, F. (2021). Improving performance of autoencoder-based network anomaly detection on nsl-kdd dataset. *IEEE Access*, 9, 140136-140146. doi: 10.1109/ACCESS.2021.3116612
- Yang, J., Rahardja, S., & Fränti, P. (2019). Outlier detection: How to threshold outlier scores? In *Proceedings of the 3rd artificial intelligence and industrial product conference (aiipcc)* (pp. 19–21). ACM. doi: 10.1145/3371425.3371427
- Zhao, Y., Ball, R., Mosesian, J., De Palma, J.-F., & Lehman, B. (2015). Graph-based semi-supervised learning for fault detection and classification in solar photovoltaic arrays. , 30(5), 2848–2858. Retrieved 2024-01-02, from <https://ieeexplore.ieee.org/document/6933939/> doi: 10.1109/TPEL.2014.2364203
- Zhao, Y., Yang, L., Lehman, B., de Palma, J.-F., Mosesian, J., & Lyons, R. (2012). Decision tree-based fault detection and classification in solar photovoltaic arrays. In *2012 twenty-*

- seventh annual IEEE applied power electronics conference and exposition (APEC)* (pp. 93–99). Retrieved 2024-01-22, from <https://ieeexplore.ieee.org/document/6165803> (ISSN: 1048-2334) doi: 10.1109/APEC.2012.6165803
- Zhu, H., Lu, L., Yao, J., Dai, S., & Hu, Y. (2018). Fault diagnosis approach for photovoltaic arrays based on unsupervised sample clustering and probabilistic neural network model. , *176*, 395–405. Retrieved 2024-01-02, from <https://linkinghub.elsevier.com/retrieve/pii/S0038092X18310338> doi: 10.1016/j.solener.2018.10.054
- Zuniga-Reyes, M.-A., Robles-Ocampo, J.-B., Sevilla-Camacho, P.-Y., Rodriguez-Resendiz, J., Lastres-Danguillecourt, O., & Conde-Diaz, J.-E. (2021). Photovoltaic failure detection based on string-inverter voltage and current signals. , *9*, 39939–39954. Retrieved 2024-01-02, from <https://ieeexplore.ieee.org/document/9360819/> doi: 10.1109/ACCESS.2021.3061354

Appendix A

Appendix

A.1 Methodology

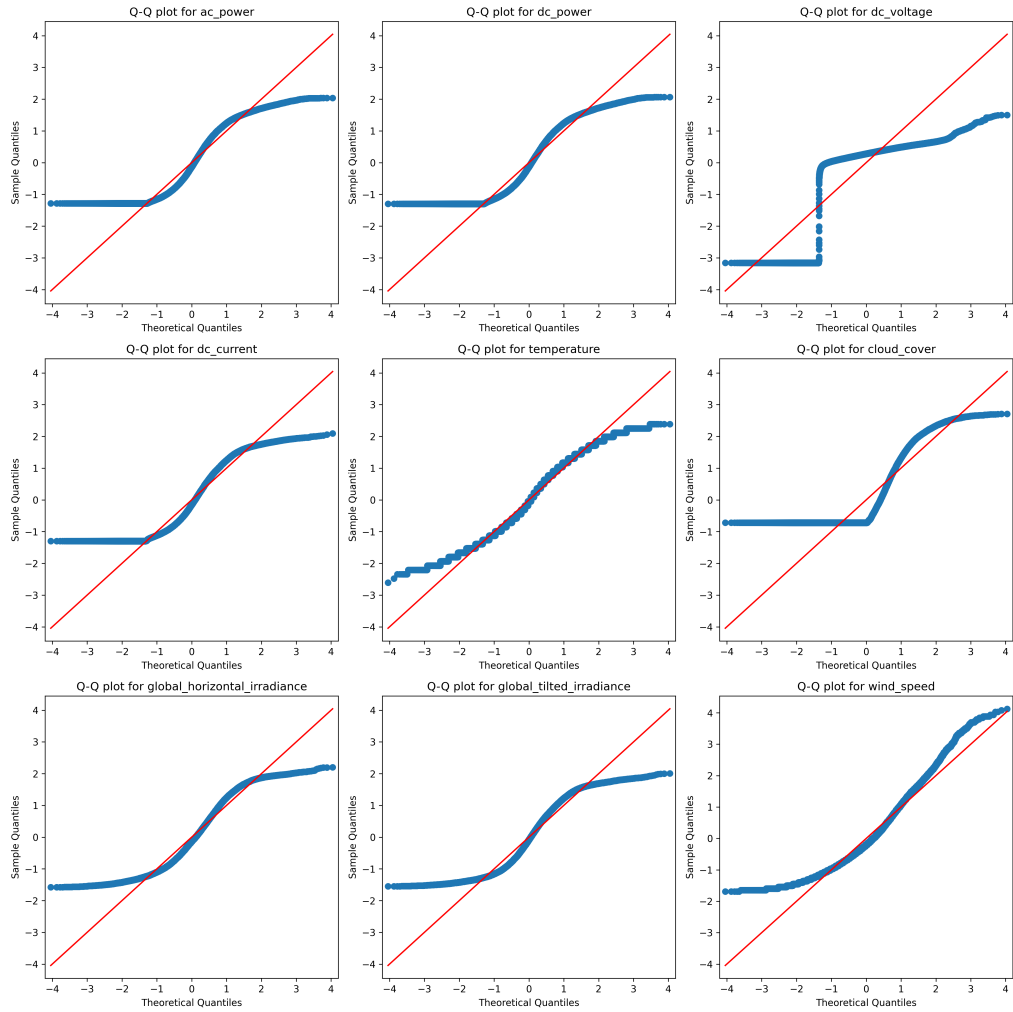


Figure A.1: Q-Q Plots for Inverter 2

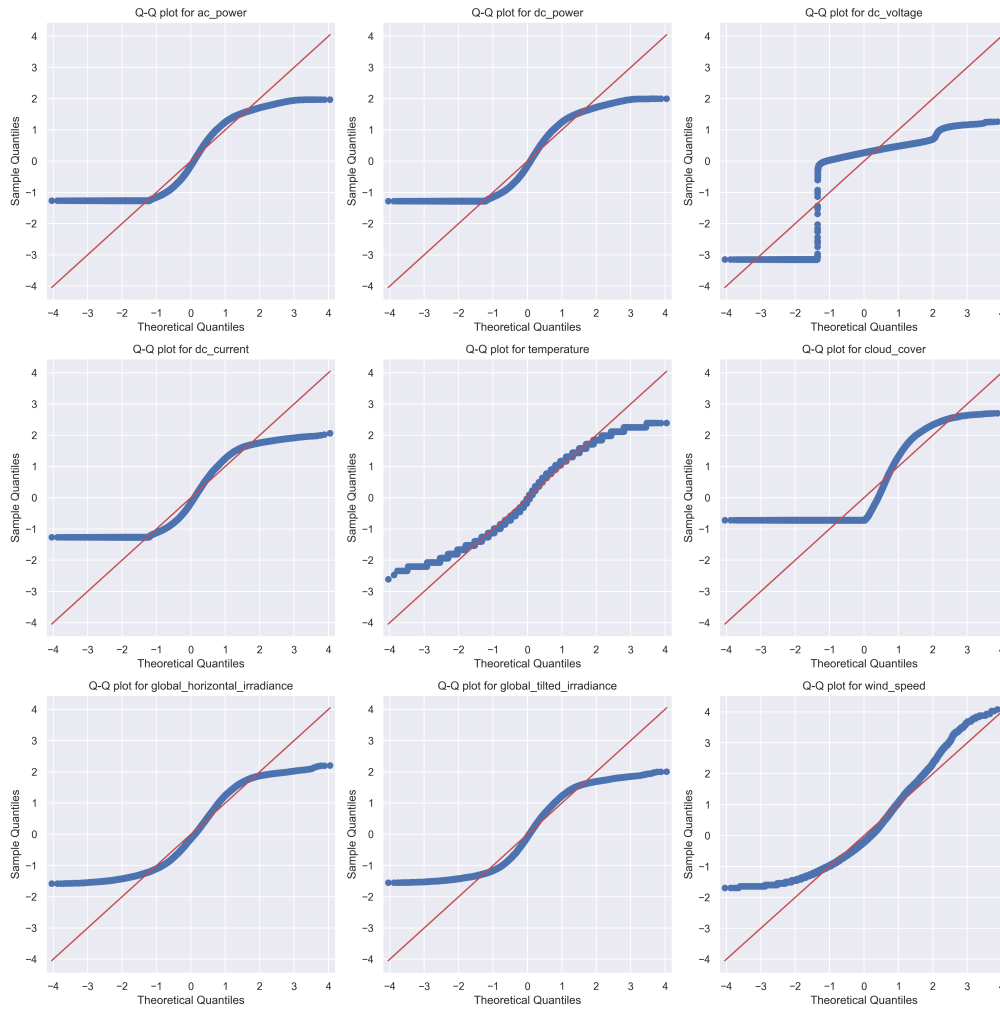


Figure A.2: Q-Q Plots for Inverter 7

A.2 Data Preparation

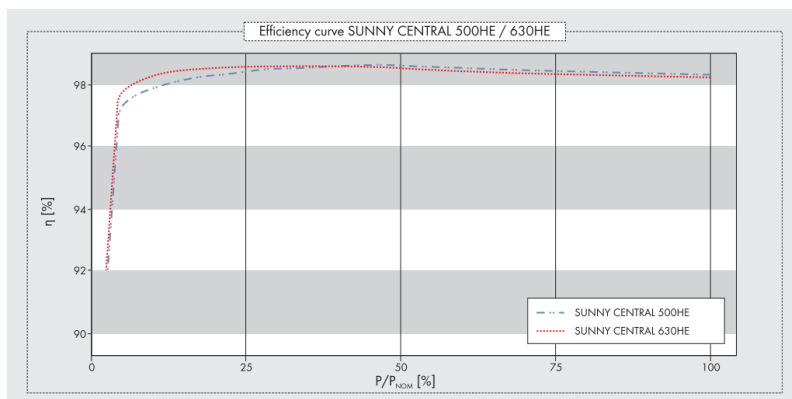


Figure A.3: Pre-determined efficiency curve of SUNNY CENTRAL 500HE inverters.
Source: SMA

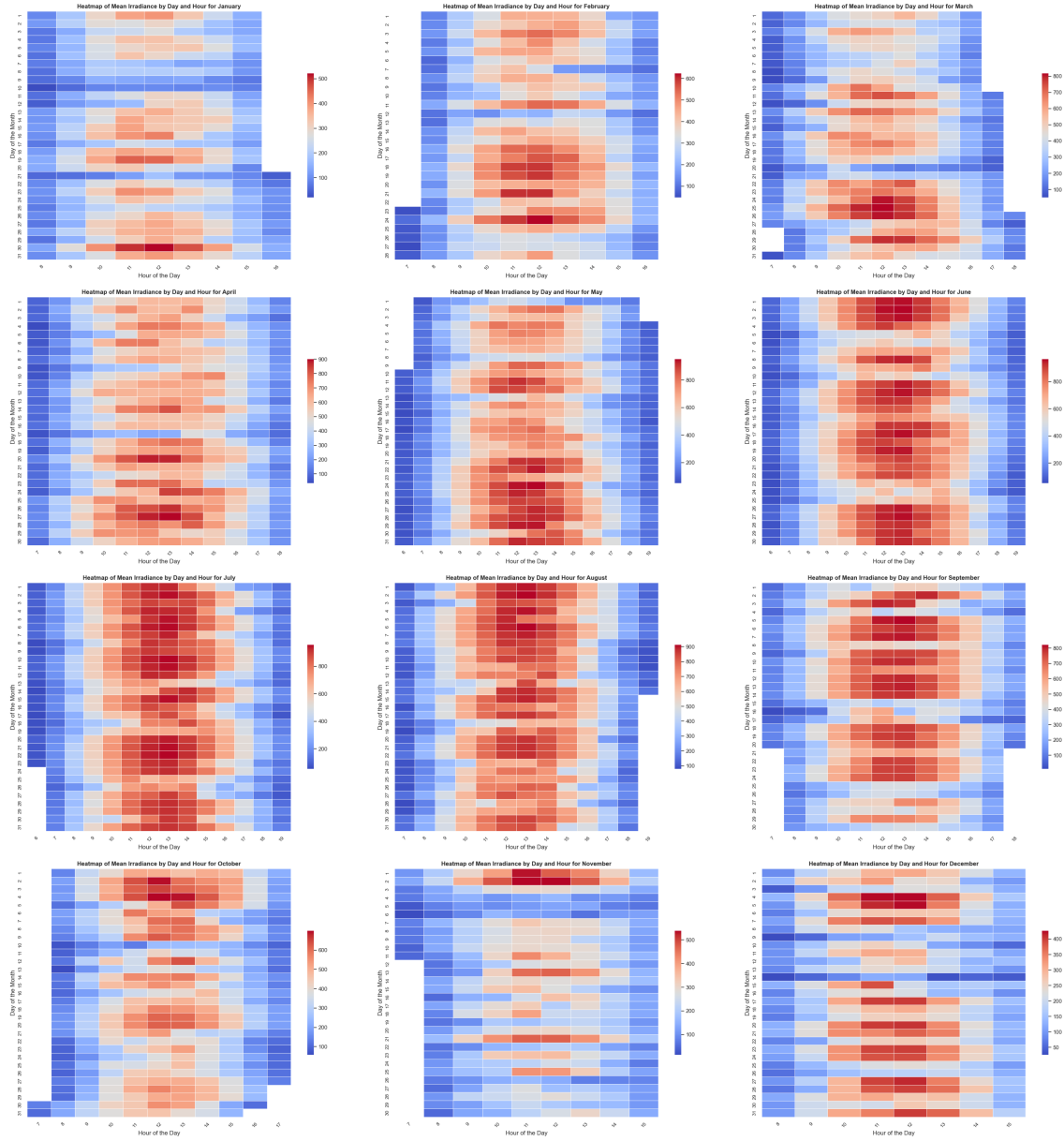


Figure A.4: Yearly Heat Map of Mean Irradiance per Hour and Day of the Month

Appendix B

Appendix

B.1 Results

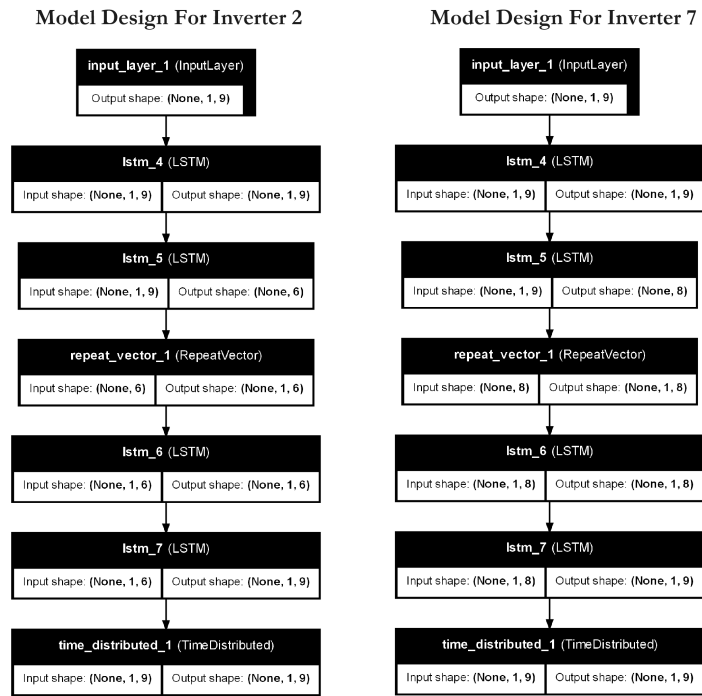


Figure B.1: LSTM Design for both Inverters