Journal of Autonomous Intelligence (2024) Volume 7 Issue 3
doi: 10.32629/jai.v7i3.1140

ORIGINAL RESEARCH ARTICLE

Classification of cell line Halm machine data in solar panel production factories using artificial intelligence models

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ABSTRACT

A solar energy module consists of solar cells that convert sunlight into electrical energy. The quality of these cells is the most important determinant of panel performance and lifespan. High-quality cells increase energy efficiency and extend panel life. Solar cells are typically composed of crystalline silicon, thin layers, and organic materials. Each material has its own advantages and disadvantages. However, what all cells have in common is that they produce electrical energy when exposed to solar radiation. Solar cells can be classified and ranked. This classification indicates the efficiency and performance of the cell. Solar energy modules are widely used to meet the energy needs of many homes and businesses. Accurately measuring cell performance can improve the overall efficiency of the panel. Therefore, AI (artificial intelligence) modeling offers many advantages in optimizing cell performance. The study yielded several benefits associated with modeling solar panel cells with artificial intelligence. Some of the benefits derived from this research are: Improved efficiency, Error detection and correction, Reduced maintenance costs, predictability, Increased production. These advantages demonstrate that AI modeling can help optimize solar panel cell performance.

Keywords: artificial intelligence; machine learning; solar energy; pv-photovoltaic; energy quality; sigma principle

ARTICLE INFO

Received: 14 August 2023
Accepted: 15 September 2023
Available online: 4 January 2024

1. Introduction

Python is a powerful tool for analyzing panel cell quality parameters. Below are some of the effects Python provides for panel cell quality parameter analysis[1,2].

Data processing and analysis: Python offers a rich data science ecosystem for manipulating, cleaning, and analyzing data. Easily perform tasks such as loading datasets, fixing missing values, creating statistical summaries, visualizing data, and exploratory data analysis.

Machine learning model: Python offers a wide variety of machine learning libraries and tools. These libraries provide different types of models (linear regression, decision trees, random forests, gradient boosting, etc.) that can be used to predict or optimize panel cell quality parameters. Common machine learning libraries for Python include scikit-learn, TensorFlow, and PyTorch.

Deep learning model: Python is also great for developing deep learning models. Leverage libraries such as TensorFlow, Keras, PyTorch, and MXNet to implement deep neural network architectures and deep learning algorithms. These models can be used to analyse and predict complex relationships between panel cell quality parameters.

Data visualization: Visualization libraries for Python help you visualize your data in meaningful and effective ways. Libraries such as Matplotlib, Seaborn, and Plotly allow you to create a variety of charts such as line charts, column charts, scatter plots, histograms, and heat maps. This will help you better understand the panel cell quality parameters and visualize the results.

Optimization and hyperparameter tuning: A Python optimization library can be used to optimize the panel cell quality parameters. You can apply advanced optimization techniques (genetic algorithms, annealing, etc.) to improve model performance through hyperparameter tuning.

Python's data analysis, machine learning, deep learning, visualization, and optimization capabilities provide a powerful platform for analyzing and improving panel cell quality parameters. However, this process can be complicated and requires expertise. When using Python in your application, it is important to collect the right dataset, choose the right model, and evaluate the results carefully.

2. Materials and methods

There are some steps to develop an artificial intelligence model using Python to improve solar panel cell parameters. In this study, here is the general roadmap[3–6].

Data collection: The first step is to collect a dataset on the factors that influence the panel cell parameters. This dataset should include cell properties (efficiency, stability, etc.) and relevant parameters (material quality, cell design, manufacturing process, etc.).

Data preprocessing: We need to preprocess the captured dataset. This means cleaning the dataset for missing values, scaling, transforming categorical variables, and optionally performing feature engineering. It is important that the dataset is prepared in a model-compliant manner.

Model selection: You have to choose an AI model. There are several types of models that can improve the parameters of solar panel cells. For example, you can evaluate different types of models such as linear regression, decision trees, random forests, support vector machines (SVM), and deep learning models (deep neural networks).

Model training: You can use Python to train a model of your choice on your dataset. A suitable algorithm and training process must be used to enable the model to learn from the training data set. A training process is performed to optimize the model parameters and best learn the characteristics of the dataset.

Model evaluation: I need to evaluate the performance of the trained model. To do this, use another test dataset and compare the model's predictions to the actual values. You can evaluate model success using various metrics (RMSE, R-squared, etc.).

Model improvements: Enhancements may need to be made as needed to improve model performance. This may include steps such as fitting model hyperparameters, collecting more data, or using more complex models. You can retrain your model by improving it using a feedback loop.

These steps provide a general guide to optimizing solar panel cell parameters using artificial intelligence models in Python. However, AI modelling is a complex process and its implementation may require special skills and experience. Furthermore, careful data collection and accurate model selection are essential to obtain reliable results.

In this study, the steps shown in **Figure 1** were applied[7,8].

Figure 1. Analog model of speech wave.

Data collection of Halm machine and choice of method: In the cell line production factory, the data of the Halm machine, which makes cell quality classification, and the outputs that give its final quality, were collected by providing data from four different lines.

Data collection: The data used in this study were collected by Kalyon PV Güneş Enerji Üretim AŞ via an MES system with IOT located in a factory named Halm on the cell production line. This study used his 5000 data set containing machine inputs for four production lines.

Data cleaning: The data cleaning step detects outliers and noisy values. Such data adversely affects model success and should be removed from the dataset. Removed 102 records to prevent data handling discrepancies where the error type was not recognized and the error value was not read from the machine. His 5000 data items used in this study were reviewed and the BIN_Comment output processed.

3. Results and discussion

The visual output of the lost data in the BIN_Commend tab of the work done is attached. Working with noisy data in Python is an important topic for data analysis and machine learning projects. Noisy data usually occurs due to inaccurate measurements, missing values, outliers, or other problems with the accurate representation of the data set. Dealing with and correcting such data can increase the reliability of your analysis results and learning algorithms. A compilation was made on the use of machine learning and artificial intelligence techniques in the field of solar energy[3–8].

In **Figure 2** is shown that if the analysis is performed without cleaning the noisy data, the deviation in the graph expresses how the noise in the data set may inadvertently affect the analysis results. Bias indicates how much the results differ from the real-world situation. This bias can lead to inaccurate conclusions, erroneous predictions, and misleading interpretations.

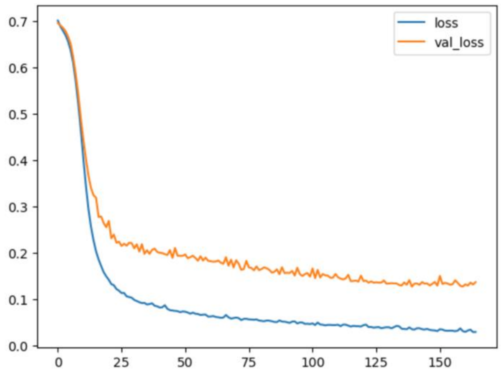

Figure 2. Graph of lost data in the BIN_Commend.

Noisy data represents random or unwanted fluctuations in the data set. These fluctuations can occur due to measurement errors, missing data, outliers, or other problems in data collection processes. Therefore, cleaning noisy data helps the analysis produce more accurate and reliable results.

At the end of a study carried out to eliminate the effect of this loss through artificial intelligence modelling, the final result was presented using new data and an improved process to demonstrate the correct effect of the BIN_Commend line along with the elimination of the quality parameter loss is shown.

In **Figure 3** is shown that after cleaning the data, you can interpret the results. Identify issues that cause noisy data and consider how these issues might impact analysis results. Also consider how reducing or eliminating noise can have a positive impact on analysis results.

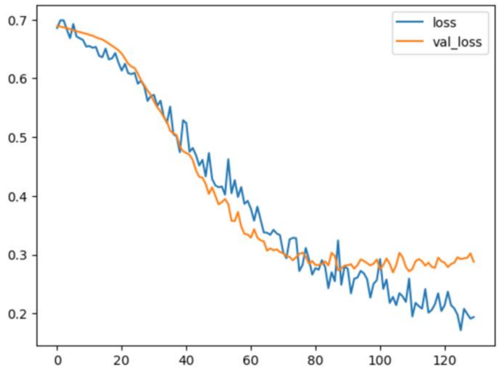

Figure 3. Graph of lost data in the BIN_Commend.

Remember that analysing and cleaning noisy data is an important step in data science and analytics and can increase the reliability of your analysis results.

There are many factors that affect the quality of panel cells. The main factors that affect panel cell quality are:

Semiconductor material quality: Silicon semiconductor material is commonly used for panel cells. The quality of semiconductor materials directly affects electrical performance. Semiconductor materials with high purity and low contamination levels enable more efficient and reliable panel cell manufacturing[9].

Cell design: Interior design and panel cell construction also affect quality. Superior cell design ensures maximum absorption of sunlight and conversion into electrical energy. For example, it is important to design surfaces to reduce reflections or take optical measures to better scatter light indoors[10].

Manufacturing process: The manufacturing process of panel cells has a great impact on quality. A carefully controlled production process ensures consistent and stable cell production. Factors such as the use of high-quality materials, proper cleaning and contamination control, measurement and testing influence the quality of the production process[11].

Durability and stability: The durability and stability of panel cells depend on their ability to withstand long-term use and environmental exposure. Cells must be resistant to environmental influences such as heat, moisture, UV light and mechanical stress. Material selection, coating techniques, and sealing measures are critical to increasing durability and stability[12].

Efficiency: The energy conversion efficiency of a panel cell determines how efficiently it can convert sunlight into electrical energy. Panel cells are more efficient, so they can generate more power. Factors affecting efficiency include material quality, cell design, semiconductor material type, and light management techniques.

4. Conclusion

In recent years, there has been a burgeoning interest in the integration of artificial intelligence (AI) and machine learning (ML) techniques within the domain of renewable energy systems. This growing synergy is evident from the extensive body of research highlighted in the provided references. Researchers such as Alavinasab et al.[13] and Zou et al.[14] have primarily focused on enhancing the accuracy of short-term wind power forecasting using AI and ML models. Thereby facilitating better grid management and resource allocation. Similarly, Pandey et al.[15] conducted a comprehensive review that underscores the manifold applications of AI in renewable energy, highlighting its potential in optimizing the operation and management of various renewable sources.

Furthermore, these technologies have been instrumental in advancing the state of the art in renewable energy integration across various sectors. For instance, Shen et al.[16] explored the application of ML in bioenergy systems, highlighting its role in optimizing biomass conversion processes. Additionally, Wu et al.[17] delved into the applications of AI in geothermal energy, showcasing its efficacy in reservoir characterization and resource assessment. This intersection of AI and renewable energy, as extensively reviewed in the aforementioned references, not only underscores the potential for improved efficiency and sustainability but also emphasizes the need for further research to harness the full spectrum of possibilities in this dynamic field.

These factors are the main parameters affecting the panel cell quality. The photovoltaic industry conducts research and development to continuously improve these factors and develop innovative solutions. The research also supports the operational improvements needed for the five parameters enabled by artificial intelligence algorithms.

Author contributions

Conceptualization, MŞ and İY; methodology, MŞ; software, MŞ; validation, MŞ, DA and İY; formal analysis, MŞ; investigation, DA; resources, İY; data curation, İY; writing—original draft preparation, MŞ; writing—review and editing, DA; visualization, MŞ; supervision, MŞ; project administration, DA. All authors have read and agreed to the published version of the manuscript.

Acknowledgments

I would like to thank Mr. Murat ŞİMŞEK and Mr. Demiral AKBAR, who have always supported Kalyon PV to expand and be comprehensive, with the opportunity to provide this data.

Conflict of interest

The authors declare no conflict of interest.

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