MATLAB **EXPO**

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Leveraging AI for Superior PV Energy Predictions: A User-Friendly Approach

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Eaton DERMS Offerings



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Content

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- PV Analytics Methodology
- Results
- App Development
- Summary

Background

Problem Statement:

 Accurate forecasting of photovoltaic (PV) power generation is crucial for efficient grid management and energy planning. However, PV power output is highly variable due to weather conditions, seasonal changes, and geographic location. Traditional forecasting methods often struggle to handle this complexity, leading to suboptimal energy management and increased operational costs.

Proposed Solution:

- Leveraging the AI toolchain of MathWorks, including MATLAB and Simulink, to develop a robust PV power forecasting model. This solution will utilize machine learning (ML) and deep learning (DL) techniques to accurately predict PV power output.
- Improved Accuracy: Leveraging advanced ML/DL techniques enhances the accuracy of PV power forecasts.
- Scalability: The solution can be scaled to accommodate different geographic locations and varying data volumes.
- Efficiency: Better forecasting leads to optimized grid management, reducing operational costs and improving energy efficiency.

Challenges in Implementing a PV Predictions System



4

Use Case

Establishing user-friendly workflow for PV estimation and edge deployment





New Data



- Model Retraining
- PV Estimation

Low Code AI Workflow



Photovoltaic Analytics Methodology

Local Files

2023 ... 18.6938

-2023 ... 19.65572

2022 10 1729

170.5



Acquire / Generate Data





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974.8

974.65 974.5

Video

Databases

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Data Preprocessing

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Preprocess Data

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Feature Engineering

Redundancy check



Feature Engineering

Correlation matrix of the feature

High correlation between two features suggests redundancy.

Why to remove redundant features?

- •Redundant features can cause the model to learn noise instead of the actual patterns
- •Removing redundant features can simplify the model
- •Fewer features mean less computational resources





Feature Engineering

Relevance check





fscmrmr function : Rank features using minimum redundancy maximum relevance (MRMR) algorithm

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Model Training

for	k=	=1:max
x	=	fft(da
У	=	20*log

Train Model



Classification Learner app to try different classifiers and find the best fit for data sets.



Regression Learner app to try different regressions and find the best fit for data sets.



Deep Network Designer app to build, visualize, and edit deep learning networks.



Experiment Manager app to run deep learning experiments to train networks and compare results

The data is divided into training (70%) and testing dataset (30%)

Model Training

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Train Model

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11618

55406

12162

Model Evaluation





Train Model

Matrices	Wide NN	Shallow NN	SVM	GPR	Bagged Tree	Boosted Trees	LSTM	CNN
RMSE	3.94	1.20	5.01	2.09	1.28	1.41	2.19	2.36
R-Squared	0.00	0.91	-0.62	0.72	0.90	0.87	0.69	0.64
MBE	-1.64	0.16	3.14	0.06	-0.36	-0.51	0.52	1.39
MDAE	1.93	0.61	5.29	0.94	0.21	0.23	1.58	1.20
MDAPE	332.40	91.50	544.54	185.05	40.69	39.70	187.01	129.18
SMAPE	132.17	67.74	134.25	95.48	45.00	42.15	97.29	74.24
MAE	2.79	0.84	4.66	1.46	0.65	0.70	1.72	1.71
MAPE	332.04	98.74	894.03	188.51	41.54	35.98	274.98	217.97

App Designer

Building modern, full-featured applications using the rich set of components and custom interactions available in App Designer.



Develop UI App



Create \rightarrow Package \rightarrow Share



PV Analytics Methodology



Develop UI
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Conclusion



Supports end-to-end Workflow

Benefits and opportunities

Faster Time To Market

Ease in Development

Ease in Deployment

Streamlined Documentation

Adherence to Standards / Compliance

Continuous Verification

Way forward







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