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Forecasting Solar Power Generation in Energy Markets

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Contents

1. Introduction

Importance of accurate forecasting

- ✓ Forecasting solar power is inherently difficult, due to the **unpredictable meteorological factors** involved.
- ✓ The unpredicted flow of PV power into the power grid can adversely affect the **stability** and the scheduling of the power grid and cause significant **economic losses**.

1. Introduction

Two factors leading to increased demand

- ✓ **Political commitments** according to global agreements (Paris Agreement). In order to achieve greater penetration and adoption, solar power must become more reliable and predictable, leading to an increased need for enhanced forecasting.
- ✓ **Liberalization of electricity markets**. Producers are pledging their estimated energy production for the next day, in the Day-Ahead market. If the prediction is flawed the system must use another energy source to compensate for the deviation. A penalty fee is required from the producer to cover the costs of the system.

1. Introduction

Process summary

An ANN is designed and trained with historical meteorological data and power generated. The model is benchmarked against a linear regression model, a moving average and the persistence model.

Economic Evaluation

The ANN model will be evaluated in an energy market framework based on the imbalance fees generated from the model’s forecasting errors.

2. Literature review

Classification of models

- Forecasting Techniques Based on Historical Data
  - Persistence Model
  - Physical Models
  - Statistical Models
    - ARMA
    - ARIMA
    - Regression
    - Exp. Smoothing
  - Machine Learning Models
    - ANNs
    - ELM
    - SVM
  - Hybrid Models

3. Methodology

Data

The data were derived from three sources:

- ✓ **The Hellenic National Meteorological Service**. Meteorological observations recorded by the Tatoi weather station.
- ✓ **Copernicus Atmospheric Monitoring Service**. Atmospheric observations regarding different measures of solar radiation.
- ✓ **www.pvouput.com**. Daily power generated, as uploaded by the PV plant operator. The PV plant examined is located in the area of Oropos in East Attica.

3. Methodology

Feature selection

Stepwise Regression is used to assess the influence of each meteorological variable to the power generated from the PV plant before introducing them to the model.

Input meteorological variables to the ANN model

Input Variables	Description
Cloud Coverage	Average daily cloud coverage.
Low Cloud Coverage	Average daily cloud coverage in the lower atmosphere.
Rainfall	Average daily rainfall, derived from the weighted average of the hourly rainfall.
Clear sky GHI	Clear sky global irradiation on horizontal plane at ground level.
GHI	Global irradiation on horizontal plane at ground level.
BNI	Beam irradiation on mobile plane following the sun at normal incidence.

3. Methodology

ANN model - Data preparation

Data were split into training, validation and test sets:

- ✓ 1/1/2018 to 14/4/2021 were used for training (80% for training and 20% for validation).
- ✓ 15/4/2021 to 31/12/2021 were used for testing.
- ✓ The data rescaled using the min – max scaling approach.

3. Methodology

ANN model

- ✓ The input layer receives 7 input variables: the 6 meteorological parameters on day *t-1*, and the power generated on day *t-1*. The output layer produces the forecasted PV power on day *t*.
- ✓ An expanding window approach will be used for the recursive generation of one-step ahead forecasts.
- ✓ The number of neurons that constitute the hidden layer was based on a simple “trial and error” process. The architecture with the **best validation performance** was chosen.

3. Methodology

ANN model – Model Parameters

- ✓ Fully interconnected multilayer feedforward network
- ✓ Error measure: **Mean Squared Error** (MSE)
- ✓ Training algorithm: **Bayesian Regularization**
- ✓ Units: 7-16-1
- ✓ Transfer – activation function: Linear – Sigmoid

Benchmark models

- ✓ Persistence Model
- ✓ 3-day Moving Average
- ✓ Multiple linear regression model

4. Results

Statistical evaluation

Error results of models

Model	RMSE	NRMSE	MAE	R	σ
Regression	**12.7265**	**15.31%**	9.8256	**0.8696**	**12.729**
ANN	13.0743	15.72%	**9.7394**	0.8608	13.076
Moving Average	15.0330	18.08%	10.6407	0.8156	15.056
Persistence	15.7189	18.90%	10.2998	0.8106	15.748

4. Results

Statistical evaluation

Model RMSE based on season

Model	Spring	Summer	Winter
Regression	**14.425**	**10.390**	13.336
ANN	14.673	11.423	**13.200**
Moving Average	18.137	11.928	14.960
Persistence	18.746	11.288	16.716
Variable	**Standard Deviation**		
Energy	17.219	14.062	15.609

4. Results

Results comparison to Literature

- ✓ Results are consistent with the literature that indicates that ANN outperforms the persistence and moving average models, even at short term horizons in which they are at the peak of their performance (Zhang et al., 2015).
- ✓ Studies also show ANNs, linear and polynomial regressions to have similar performance (Sharma et al., 2018).
- ✓ ANN being outperformed by the persistence model during summer can also be found in Kardakos et al. (2012).

5. Economic analysis

- ✓ In liberalized energy markets, electricity generation sources are utilized based on their marginal cost.
- ✓ The minimal marginal costs combined with special, risk-free RES subsidization schemes that act as incentives for the green energy transition, have led to distorted market prices and wrong economic signals to market actors.
- ✓ To ensure a level-playing field for all generating sources, according to EU, RES producers will be compensated based on market mechanisms and will be subject to imbalance costs.

5. Economic analysis

Model

- ✓ **Day-Ahead Market (DAM)**: Market participants who represent generating resources, have to place a bid for their available generation capacity for the next day. Traders and energy suppliers also place their offers, demanding the available energy.
- ✓ **Balancing Market**: The Balancing Market deals with system imbalances in real-time which are settled by the Transmission System Operator (TSO). The imbalance price is the price of DAM plus a markup which is cost reflective of the expenses incurred by the TSO to provide real time balancing energy to the system.

5. Economic analysis

Model

A simple function is created to evaluate the economic effect of the predictive error of the ANN forecasting model. This function is intended for a solar power producer who commits all their available predicted next-day power output on the Day-Ahead Market.

$$\Pi = \hat{P} * S + e * I$$

where $\hat{P}$ is the predicted output, S the DAM market price, e the forecasting error and I the Imbalance price.

5. Economic analysis

Model

When considering the state of the system (either oversupplied or undersupplied) the concept of opportunity cost arises. Therefore, the function is modified as follows:

$$\Pi_{opportunity} = P * S + e * (I - S)$$

where P is the actual output, S the DAM market price, e the forecasting error and I the Imbalance price.

5. Economic analysis

Results

Producer incomes in the Greek electricity market

Model	Income (€)
Regression	1,593.2
ANN	1,592.9
Moving Average	1,591.6
Persistence	**1,599.7**
Error (-30 kWh)	1,697.0

The **Single Price Imbalance** market allows producers to **profit from being on the opposite direction of the grid.** When the system is oversupplied (as it was during the period examined), producers who produce less than the energy pledged at DAM can acquire the energy they lack in the discounted Imbalance price leading to higher profits.

5. Economic analysis

Dual Price Imbalance Market

In a **Dual Price Imbalance** market, if the energy that the producer injects to the grid surpasses the scheduled one, then the producer is compensated for the excess energy at a price DAM – *c*. On the other hand, if the producer generates less energy than the scheduled one, they must procure the missing energy at a price DAM + *l*. Therefore, in this case the function presented above is modified as follows:

$$\Pi_{opportunity} = \begin{cases} P * S - c * e, when\ e > 0 \\ P * S + l * e, when\ e < 0 \end{cases}$$

$$where, c\ and\ l > 0$$

5. Economic analysis

Dual Price Imbalance Market | Results

Producer incomes in the Greek electricity market

Model	Normalized Income (%)
Regression	88.84
ANN	**88.86**
Moving Average	87.96
Persistence	87.93
Error (-30 kWh)	71.57

These results are in line with both the statistical error measurements presented above as well as with the rationale of the Dual Price Imbalance Market.

6. Conclusion

- ✓ The ANN model can predict the next day's generated PV energy with **greater accuracy** than the persistent model and the moving average.
- ✓ The ANN model and the Multiple Linear regression present similar performances. **ANN generates a lower MAE**, while **Regression generates a lower RMSE**.
- ✓ The economic evaluation in a Single Price Imbalance Market is **not conclusive** in evaluating the models' accuracy.
- ✓ However, in a Dual Price Imbalance Market, the most statistically accurate models lead to **higher incomes** for the solar energy producers.