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FORECASTING ELECTRICITY GENERATION BY PHOTOVOLTAIC PLANTS CONSIDERING ECONOMIC AND ORGANIZATIONAL CHANGES

One of the key innovations is the option for renewable energy producers to choose between the "green" tariff and a new market premium mechanism. This allows them to receive the difference between the market price and the "green" tariff, increasing the flexibility of the support system for renewable energy sources (RES). Additionally, regulations on imbalances and market transparency were tightened, as part of legislative changes aimed at stabilizing Ukraine's energy system. To solve the task of forecasting the generation of electricity from unstable energy sources, a range of models was developed using machine learning technologies, and the optimal model among them was selected.

The results showed that the model achieved a high coefficient of determination (R^2) of 0.9969 on the training data, indicating its precise adaptation to the training data. On the validation data, the model demonstrated a slightly lower R^2 value of 0.9925, which indicates its excellent ability to generalize results and work with new, unknown data.

The graphical interpretation of the forecasting results based on the LightGBM Regressor model for the training, validation, and test data. An analysis of the electricity market and the legislative framework regulating the energy market in Ukraine has been conducted. The selection of parameters for the creation of a model for predicting electricity generation at solar power plants was carried out, better prediction accuracy was achieved by taking cloud cover into account. The impact of Random Forest Regressor parameters on the accuracy of electricity generation predictions at solar power plants has been examined. Research results can be generalized and used to forecast the generation from any unstable renewable energy sources.

Keywords: Forecasting model, photo power plant, forecasting error, generation forecast, data analysis.

ПОГРИЩУК ОЛЕГ, БАРТЕЦЬКИЙ АНДРІЙ, КОЛЕСНИК ОЛЕКСАНДР
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ПРОГНОЗУВАННЯ ВИРОБНИЦТВА ЕЛЕКТРОЕНЕРГІЇ ФОТОЕЛЕКТРИЧНИМИ УСТАНОВКАМИ З ВРАХУВАННЯМ ЕКОНОМІЧНИХ ТА ОРГАНІЗАЦІЙНИХ ЗМІН

Одним із ключових сучасних нововведень є можливість для виробників ВДЕ обирати між «зеленим» тарифом і новим механізмом ринкової премії. Це дозволяє їм отримувати різницю між ринковою ціною та «зеленим» тарифом, підвищуючи гнучкість системи підтримки відновлюваних джерел енергії (ВДЕ). Крім того, було посилено регулювання дисбалансів і прозорості ринку в рамках законодавчих змін, спрямованих на стабілізацію енергетичної системи України.

Для вирішення задачі прогнозування вироблення електроенергії з нестабільних джерел енергії розроблено низку моделей з використанням технологій машинного навчання, серед яких обрано оптимальну модель.

Результати показали, що модель досягла високого коефіцієнта визначення (R^2) 0,9969 на даних навчання, що вказує на її точну адаптацію до даних навчання. За даними перевірки модель продемонструвала трохи нижче значення R^2 0,9925, що вказує на її чудову здатність узагальнювати результати та працювати з новими, невідомими даними.

Графічна інтерпретація результатів прогнозування на основі моделі LightGBM Regressor для даних навчання, перевірки та тестування. Проведено аналіз ринку електроенергії та законодавчої бази, що регулює енергетичний ринок в Україні. Проведено підбір параметрів для створення моделі прогнозування виробництва електроенергії на сонячних електростанціях, досягнуто кращої точності прогнозування за рахунок врахування хмарності. Досліджено вплив параметрів Random Forest Regressor на точність прогнозів виробництва електроенергії на сонячних електростанціях. Результати досліджень можуть бути узагальнені та використані для прогнозування виробництва з будь-яких нестабільних відновлюваних джерел енергії.

Ключові слова: модель прогнозування, фотоелектростанція, похибка прогнозування, прогноз генерації, аналіз даних

In August 2024, significant changes in the regulation of the electricity market in Ukraine took place, particularly regarding the "green" tariff system and imbalance charges [1]. One of the key innovations is the option for renewable energy producers to choose between the "green" tariff and a new market premium mechanism. This allows them to receive the difference between the market price and the "green" tariff, increasing the flexibility of the support system for renewable energy sources (RES). Additionally, regulations on imbalances and market transparency were tightened, as part of legislative changes aimed at stabilizing Ukraine's energy system.

Green Tariff and Imbalance Charges:

The law continues the application of the "green" tariff for electricity producers from renewable sources, such as wind and solar power. A notable innovation is the introduction of imbalance charges [2], which will become mandatory for producers starting in 2025. This charge will be 100% in cases where the imbalance is within 5%. This means that producers will be required to compensate for the cost of electricity that was either not sold or produced beyond contracted volumes.

Incentives to Improve Balancing:

These changes are aimed at encouraging the producers to balance their generation capacities better and reduce supply deviations. This will also help optimize the operation of the energy system and reduce the costs associated with maintaining its stability.

It is important to note that the new regulations may significantly impact investments in renewable energy projects, particularly due to the regulation of auctions and the establishment of their new requirements.

Forecasting electricity generation from renewable energy sources (RES) has several important economic aspects that justify its implementation:

1. **Optimization of balancing:** Forecasting generation helps reduce balancing costs for the energy system. Accurate forecasts allow for the avoidance of significant imbalances, which in turn reduces the need for expensive reserve capacity to cover deviations in RES generation.
2. **Risk reduction for investors:** Reliable generation forecasts increase investors' confidence in RES projects. It reduces financial risks and encourages additional investments, as investors can more accurately assess the profitability of the project.
3. **Market stability improvement:** Forecasting generation helps ensure stability in the electricity market. Accurate forecasts enable market participants to plan their actions better, reducing price fluctuations and increasing supply reliability.
4. **Implementation of International Obligations:** For many countries, including Ukraine, generation forecasting is part of fulfilling international commitments regarding the development of renewable energy sources and their integration into the energy system.

The increase in the share of stochastic energy sources in the energy system brings additional risks associated with their probabilistic nature and less stable characteristics, which may lead to imbalances in the energy system [3-7] and affect electricity quality [8]. Given the need to ensure the system's balance, it is necessary to develop several approaches and recommendations to enable the implementation of controlled renewable energy sources (RES), which will function as components of distributed virtual power plants, contributing to the stability of electricity generation.

According to the electricity market rules [9], market participants submit bids for selling electricity a day ahead, specifying volumes that must not deviate by more than 5%. One of the major challenges is the difficulty of forecasting the generation of electricity from photovoltaic power stations (PPS), as the process itself is influenced by numerous factors. Taking into consideration the above, the development of adequate models is highly relevant.

To ensure the energy system's balance, approaches and recommendations should be developed to integrate controlled renewable energy sources as components of distributed virtual power plants. This will provide a stable electricity supply and ensure the system's balance.

The generation of electricity from renewable sources faces significant challenges, the main one being the difficulty of forecasting. This is due to the large number of factors influencing the generation process. Given the above, constructing adequate models is an urgent task.

The aim of this work is to improve the accuracy of day-ahead electricity generation forecasting by photovoltaic power stations through the use of machine learning methods, particularly taking into account the impact of cloud cover. This, in turn, will help improve economic indicators by reducing the risks of imbalance penalties. In addition, improved forecasting accuracy will increase electricity production levels, positively affecting the overall efficiency of photovoltaic power stations and optimizing operational costs.

Analysis of previous research. Generally, forecasting is performed based on different time periods, known as forecasting horizons. Very short-term forecasting (1 sec ≤ 1 hour) helps distribute electricity in real-time, optimize resources, and balance power [10]. Short-term forecasting (1 hour–24 hours) improves grid reliability and optimizes system operations [11]. Medium-term forecasting (week–month) establishes schedules for system planning and maintenance by forecasting available electricity. Long-term forecasting (month–year) involves distribution and transmission management, electricity production planning, as well as measures to ensure energy consumption and security [12, 13].

Various methods have been used for forecasting photovoltaic generation, such as ARMA, ARIMA, ARMAX, coupled autoregressive and dynamic systems (CARDS), regression, and regression trees. The accuracy of these methods is better for short-term horizons. However, accuracy decreases as the forecasting horizon and generation scale increase [14-15]. Nonlinear data also limit these methods. Based on cloud tracking and forecasting, sky photographs and satellites have been used to predict solar radiation on an ultra-short-term basis [16-17]. The accuracy of image-based forecasting methods directly depends on image processing algorithms. However, based on low-resolution satellite data and limited sky image coverage from the ground, the forecasting accuracy of these methods requires further improvement. Numerical weather prediction (NWP) is used for medium-term forecasting (up to 15 days) of solar radiation. However, its application is limited due to data access restrictions imposed by national meteorological departments [18-19].

Artificial Neural Networks (ANN) in [20-21] and Adaptive Neuro-Fuzzy Inference System (ANFIS) in [29] are among the machine learning methods applied for solar energy forecasting. They handle nonlinear systems better and adapt to the variable behavior of solar energy. However, challenges such as random initial data, local minima, overfitting, and increased complexity due to the multilayer structure affect system reliability [30, 31]. Meanwhile, Support Vector Machines (SVM) have demonstrated better forecast accuracy for solar energy [32-33]. However, they are extremely sensitive to parameters such as the penalty coefficient (C), kernel function, and the epsilon radius (ε). Choosing the right parameters is a complex task. The weights and biases of hidden nodes in the Extreme Learning Machine (ELM) are randomly selected [34].

"In the article [35], the authors proposed an approach to forecasting electricity production from alternative sources in developing countries (using Ukraine as an example) based on the use of classical (ARIMA, TBATS) and modern (Prophet, NNAR) methods. Although the results show quite high forecasting accuracy, the authors did not investigate how flexible this approach is for use in relatively new power plants, where there is not enough data for training. Accordingly, to improve the forecasting accuracy for relatively new power plants, it is necessary to consider a number of factors that directly affect electricity generation, which makes this approach less effective

Existing forecasting methods vary depending on the forecasting task, including long-term and short-term forecasts. The majority of existing forecasting models are based on ARMA, ARIMA, ARMAX models, artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), and recurrent neural networks (RNN). Existing forecasting models also use image recognition and natural language processing (NLP). A drawback of these models is that they require a large amount of data for training; otherwise, they fail to provide the necessary forecast accuracy, specifically within a 10% margin. As the amount of data increases, the model becomes less flexible, especially considering that most photovoltaic stations are new or have been modernized multiple times over the past 5-10 years.

Research results. When building the forecasting model, data from the electricity generation monitoring at a private PPS located in the Vinnytsia region was used.

The dataset contains the following parameters, as presented in Figure 1:

- "DATE_TIME" – Generation timestamp;
- "ENERGY" – Generation power at the time of recording [kWh];
- "CLOUDY" – Cloud cover [%];
- "SOLAR_RADIATION" – Solar radiation [%].

	DATE_TIME	ENERGY	CLOUDY	SOLAR_RADIATION
3224	25.06.2020 13:30	834	12	9181
9901	05.05.2021 17:00	253	51	2782
5442	11.09.2020 12:00	921	0	10129
9157	07.04.2021 18:00	89	52	977
15473	14.01.2022 12:30	34	96	373

Fig.1. Fragment of the Dataset on Electricity Generation by the Photovoltaic Power Station

In the study [36], the author investigated the issue of forecasting electricity generation at a photovoltaic power station (PVS) but failed to account for several key parameters, such as cloud cover directly over the PVS location. Furthermore, the use of the RandomForestRegressor library did not provide the necessary accuracy for the given task. Considering this information, the current model also includes cloud coverage directly over the solar station. The cloudiness data was sourced from a weather forecasting service [37].

As a result, prediction models were constructed using the following libraries: Decision Tree Regressor, Random Forest Regressor, and LightGBM Regressor [38]. Model parameters were selected to filter out the anomalous values caused by such factors as emergency power system modes, sharp snowfall, or dust accumulation on the panels due to bad weather. Predictions were made, and accuracy metrics were calculated for these models. Graphs illustrating the dependence on the time of day, week, and season were also plotted (Figures 2 and 3).

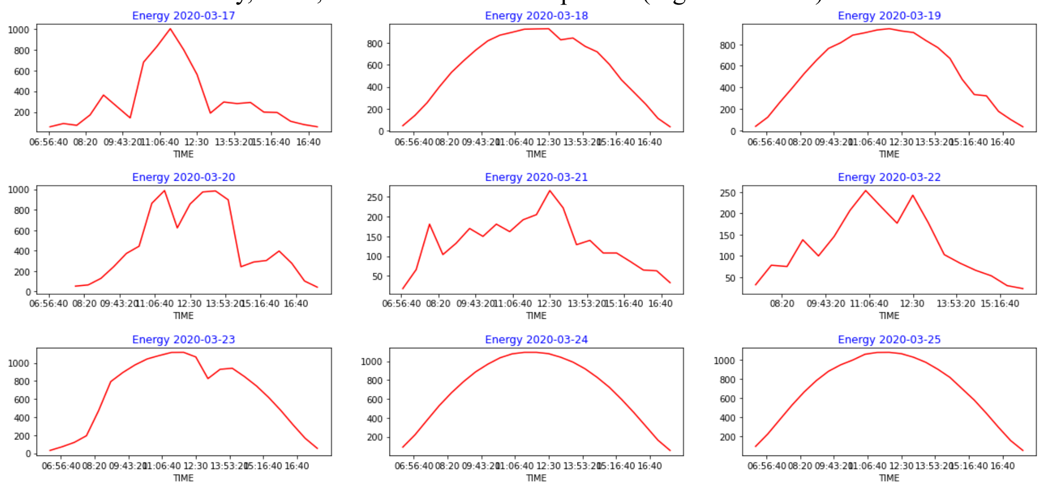

Fig.2. Electricity Generation Graphs Over a 24-Hour Period

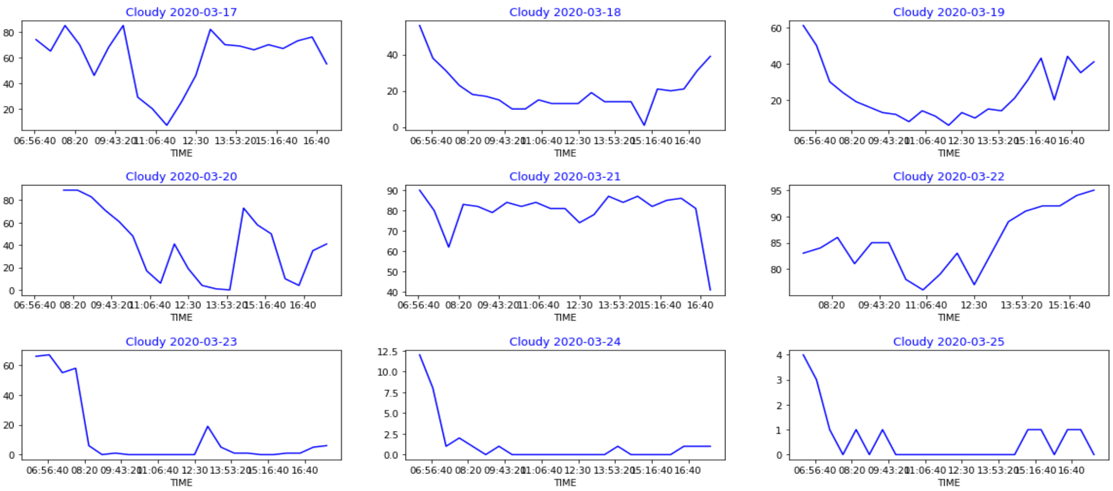

Fig.3. Daily Cloud Cover Variation Graphs

After training the **Decision Tree Regressor** model on the training and validation datasets, the following results were obtained: the coefficient of determination (R^2) for the training data was 0.9998 (Figure 4), indicating excellent reproduction of the training data. At the same time, the model demonstrated a significantly lower but still very high result of 0.9848 on the validation data (Figure 5), which indicates the model's good generalization ability and accuracy when working with unknown data.

```
# Decision Tree Regressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train,y_train['ENERGY'])

# Prediction for training data
y_pred_dtr = dtr.predict(X_train)

# Accuracy of model
r2_score_dtr = r2_score(y_train['ENERGY'], y_pred_dtr)

# Save to result dataframe
result.loc[result['model'] == 'Decision Tree Regressor', 'train_score'] = r2_score_dtr

print(f'Accuracy of Decision Tree Regressor model training is {r2_score_dtr}')
```

```
Accuracy of Decision Tree Regressor model training is 0.9997547534287423
```

Fig.4. Prediction Accuracy of the Training Model “Decision Tree Regressor”

```
y_val_dtr = dtr.predict(X_valid)
r2_score_dtr_valid = r2_score(y_valid['ENERGY'], y_val_dtr)
result.loc[result['model'] == 'Decision Tree Regressor', 'valid_score'] = r2_score_dtr_valid
print(f'Accuracy of Decision Tree Regressor model prediction for valid dataset is {r2_score_dtr_valid}')
```

```
Accuracy of Decision Tree Regressor model prediction for valid dataset is 0.9848411838279288
```

Fig.5. Prediction Accuracy of the Validation Model “Decision Tree Regressor”

During the training of the model, the results of forecasting the training data were conducted using the Random Forest Regressor algorithm (Figure 6). As can be seen from the obtained results, the model demonstrated the coefficient of determination (R^2) value of 0.9982 for the training data, indicating an extremely high level of accuracy and effective adjustment to the training data. The results on the validation data show a slightly lower but still very high value of 0.9908 (Figure 7), which indicates the model's good ability to generalize information and work with new, unknown data.

```
# Random Forest Regressor
rfr = RandomForestRegressor()

# Training model
rfr.fit(X_train,y_train)

# Prediction for training data
y_pred_rfr = rfr.predict(X_train)

# Accuracy of model
r2_Score_rfr = r2_score(y_train['ENERGY'], y_pred_rfr)

# Save to result dataframe
result.loc[result['model'] == 'Random Forest Regressor', 'train_score'] = r2_Score_rfr

print(f'Accuracy of Random Forest Regressor model training is {r2_Score_rfr}')
```

```
Accuracy of Random Forest Regressor model training is 0.9982492460185914
```

Fig.6. Prediction Accuracy of the Training Model "Random Forest Regressor"

```
y_val_rfr = rfr.predict(X_valid)
r2_score_rfr_valid = r2_score(y_valid['ENERGY'], y_val_rfr)
result.loc[result['model'] == 'Random Forest Regressor', 'valid_score'] = r2_score_rfr_valid
print(f'Accuracy of Random Forest Regressor for valid dataset is {r2_score_rfr_valid}')
```

```
Accuracy of Random Forest Regressor for valid dataset is 0.9907789308094831
```

Fig.7. Prediction Accuracy of the Validation Model "Random Forest Regressor"

During the investigation, the model was trained and the results of forecasting the training data were analyzed using the **LightGBM Regressor** algorithm (Figure 8).

The results showed that the model achieved a high coefficient of determination (R^2) of 0.9969 on the training data, indicating its precise adaptation to the training data. On the validation data, the model demonstrated a slightly lower R^2 value of 0.9925 (Figure 9), which indicates its excellent ability to generalize results and work with new, unknown data.

```
train_data = lgb.Dataset(X_train, label=y_train['ENERGY'])
params = {
    'num_leaves': 50,
    'learning_rate': 0.05,
    'metric': 'mae',
}

# Training model
model_lgb = lgb.train(params, train_data, num_boost_round=1000)

# Prediction for training data
y_pred_lgb = model_lgb.predict(X_train)

# Accuracy of model
r2_Score_lgb = r2_score(y_train['ENERGY'], y_pred_lgb)

# Save to result dataframe
result.loc[result['model'] == 'LightGBM Regressor', 'train_score'] = r2_Score_lgb

print(f'Accuracy of LightGBM Regressor model training is {r2_Score_lgb}')
```

```
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.001686 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 295
[LightGBM] [Info] Number of data points in the train set: 7377, number of used features: 3
[LightGBM] [Info] Start training from score 364.811577
Accuracy of LightGBM Regressor model training is 0.996874292114864
```

Fig.8. Prediction Accuracy of the Training Model "LightGBM Regressor"

```
y_val_lgb = model_lgb.predict(X_valid)
r2_score_lgb_valid = r2_score(y_valid['ENERGY'], y_val_lgb)
result.loc[result['model'] == 'LightGBM Regressor', 'valid_score'] = r2_score_lgb_valid
print(f'Accuracy of LightGBM Regressor for valid dataset is {r2_score_lgb_valid}')
```

```
Accuracy of LightGBM Regressor for valid dataset is 0.9925139383127978
```

Fig.9. Prediction Accuracy of the Validation Model "LightGBM Regressor"

For example, the graphical interpretation of the forecasting results based on the **LightGBM Regressor** model for the training, validation, and test data is presented in Figures 10-12, respectively. The red line represents the established (maximum possible) electricity generation of the photovoltaic power plant.

Fig. 10. Prediction of Training Data

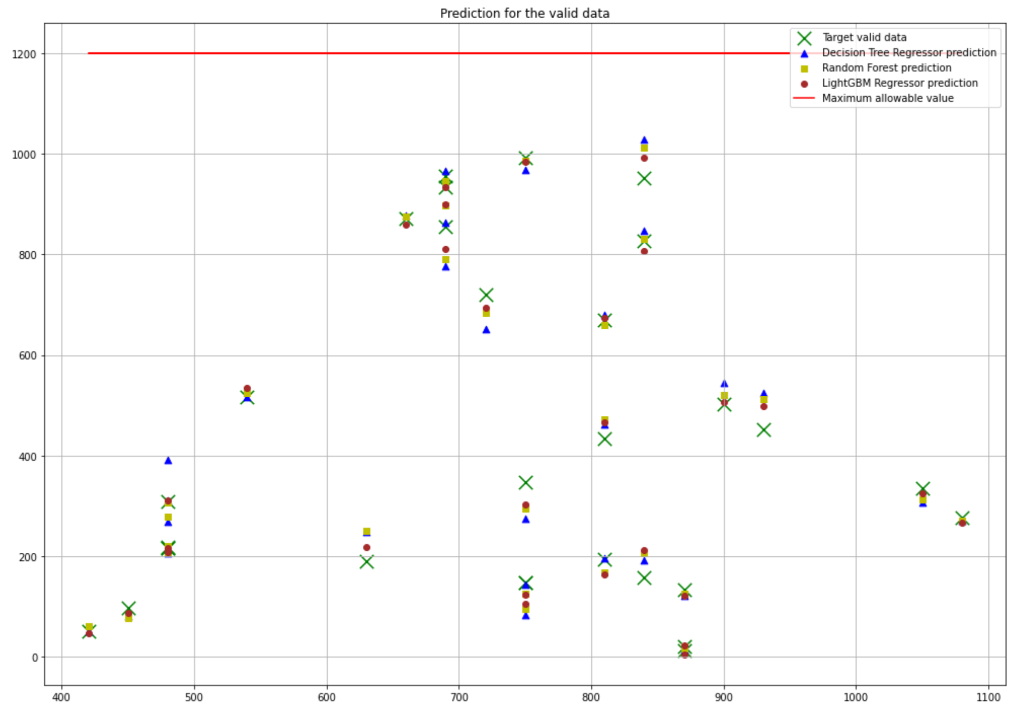

Fig. 11. Prediction of Validation Data

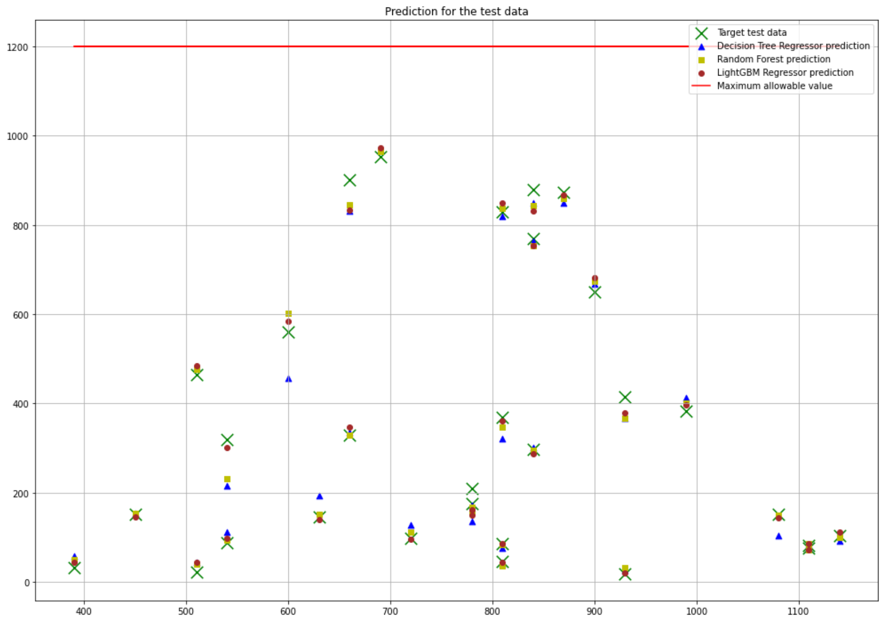

Fig. 12. Prediction of Test Data

Figure 13 shows a table of the prediction results obtained using the studied models.

```
# Display results of modeling
result.sort_values(by=['valid_score', 'train_score'], ascending=False)
```

	model	train_score	valid_score
2	LightGBM Regressor	0.996874	0.992514
1	Random Forest Regressor	0.998249	0.990779
0	Decision Tree Regressor	0.999755	0.984841

Fig.13. Results of the Studies of Prediction Models for PV Power Generation

As a result of the conducted research, three regression models were analyzed (see Fig. 13): Decision Tree Regressor, Random Forest Regressor, and LightGBM Regressor.

The Decision Tree Regressor model demonstrated an extraordinarily high coefficient of determination R^2 on training data (0.9998), but its result on validation data (0.9848) indicates possible overtraining.

The Random Forest Regressor model showed more balanced results – R^2 on training data was 0.9982, while on validation data it was 0.9908, indicating good generalization capability.

The most stable results were shown by the LightGBM Regressor model, which achieved R2R^2R2 of 0.9969 on training data and 0.9925 on validation data. This indicates its effective ability to generalize data and prediction accuracy.

Based on the analysis, the LightGBM Regressor is the best model among the three, as it demonstrated the highest accuracy on validation data while maintaining stable results.

Conclusions

An analysis of the electricity market and the legislative framework regulating the energy market in Ukraine has been conducted. The selection of parameters for the creation of a model for predicting electricity generation at solar power plants was carried out, better prediction accuracy was achieved by taking cloud cover into account. The impact of Random Forest Regressor parameters on the accuracy of electricity generation predictions at solar power plants has been examined. Research results can be generalized and used to forecast the generation from any unstable renewable energy sources.

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