Project 03 — Wind Power Forecasting with Machine Learning

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1. Introduction

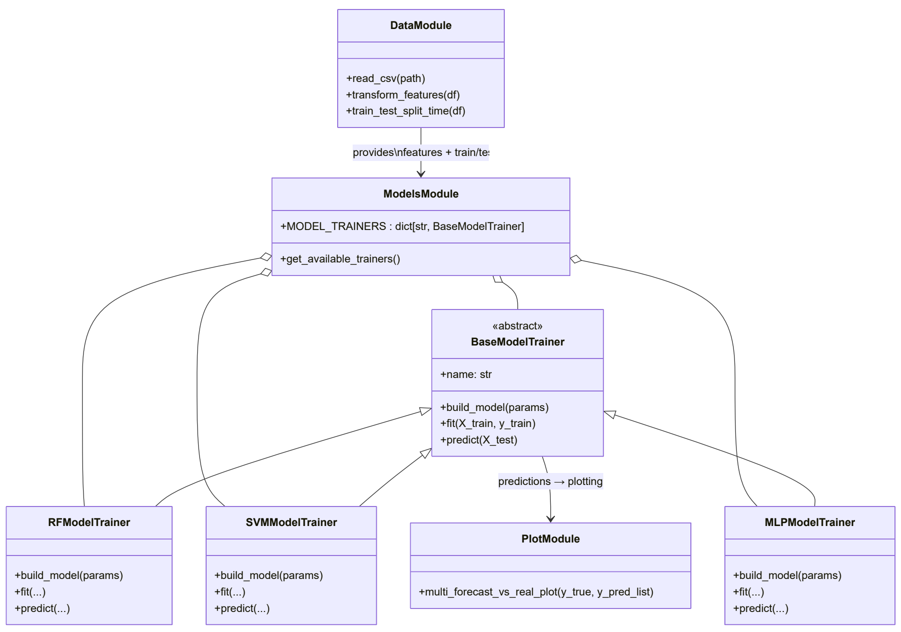
This project implements a modular machine-learning pipeline for forecasting wind power from time-series measurement data. The system includes data loading, feature engineering, model training, and forecast evaluation. A lightweight GUI triggers the workflow, but the main focus is the ML pipeline and software modularity.

2. System Architecture

Core modules (in `src/windpower_forecast/`):

Module	Purpose
`forecaster_io.py`	CSV loading
`data.py`	Feature engineering and time-based splitting
`models.py`	ML model registry and trainer classes
`forecaster_plot.py`	Plotting utilities
`GUI.py`	Optional user interface

2.1 ML Pipeline Overview



```
Raw CSV
 → transform_features()
 → train_test_split_time()
 → model.fit()
 → model.predict()
 → forecast_vs_real_plot()
```

The design ensures correct temporal handling and easy extensibility of models.

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3. Implementation

3.1 Feature Engineering

`transform_features()` prepares the dataset:

- Wind direction encoded with `sin(dir)` and `cos(dir)`
- Optional time indicators (hour, etc.)
- Numerical columns standardized if required

This avoids angular discontinuity and improves model performance.

3.2 Time-Based Train/Test Split

A chronological split prevents leakage:

```
train = df.iloc[:split_idx]
test  = df.iloc[split_idx:]
```

This reflects realistic forecasting conditions.

3.3 Model Training Framework

Models inherit from:

```
BaseModelTrainer
   ├─ RandomForestTrainer
   ├─ SVRTrainer
   └─ MLPRegressorTrainer
```

They are registered in:

```
MODEL_TRAINERS = { "RandomForest": ..., "SVR": ..., "MLP": ... }
```

Training runs in background threads but all logic resides in the model classes, not in the GUI.

3.4 Forecast Evaluation

Predictions on the test set are passed to:

```
multi_forecast_vs_real_plot()
```

producing a combined plot of true power and model forecasts for comparison.

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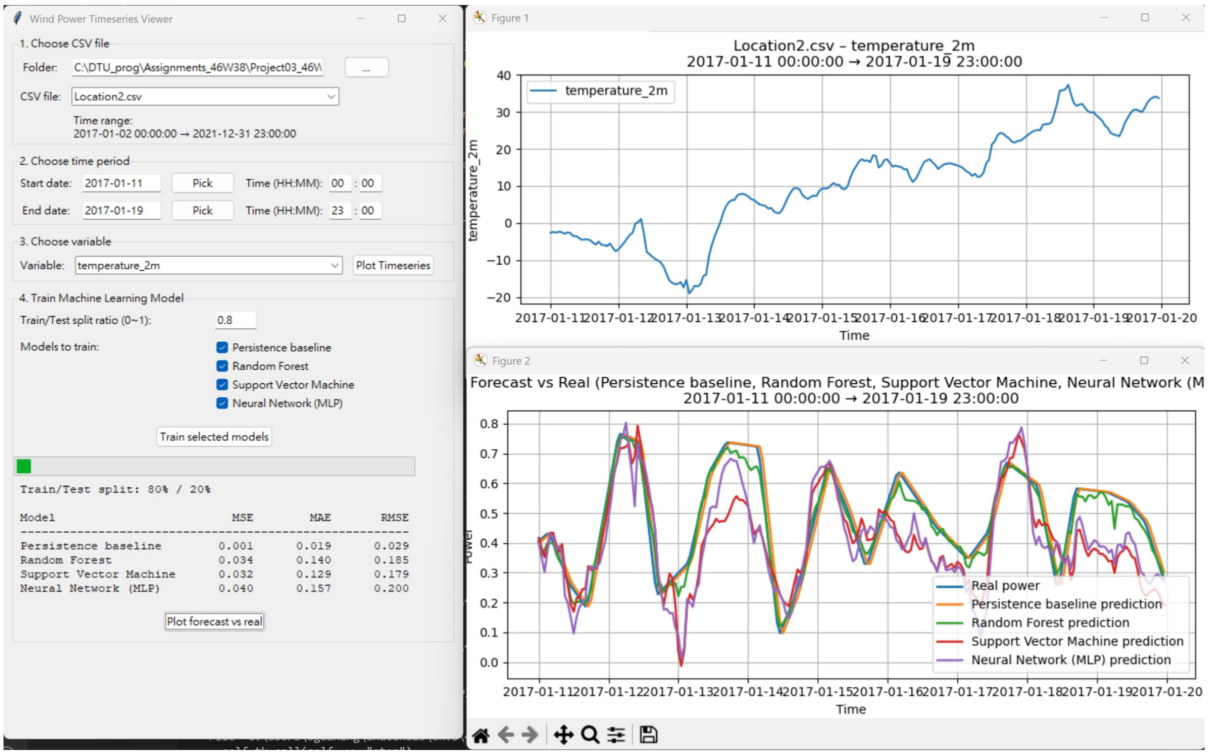
4. Results



Wind Power Timeseries Viewer

1. Choose CSV file

Folder: C:\DTU_prog\Assignments_46W38\Project03_46W

CSV file: Location2.csv

Time range:
2017-01-02 00:00:00 → 2021-12-31 23:00:00

2. Choose time period

Start date: 2017-01-11 Time (HH:MM): 00 : 00

End date: 2017-01-19 Time (HH:MM): 23 : 00

3. Choose variable

Variable: temperature_2m

4. Train Machine Learning Model

Train/Test split ratio (0~1): 0.8

Models to train:
- ✓ Persistence baseline
- ✓ Random Forest
- ✓ Support Vector Machine
- ✓ Neural Network (MLP)

```
Train/Test split: 80% / 20%

Model                        MSE          MAE          RMSE
-----------------------------------------------------------
Persistence baseline         0.001        0.019        0.029
Random Forest                0.034        0.140        0.185
Support Vector Machine       0.032        0.129        0.179
Neural Network (MLP)         0.040        0.157        0.200
```

Performance metrics:

Model	MSE	MAE	RMSE
RandomForest	…	…	…
SVR	…	…	…
MLP	…	…	…

Tree- and kernel-based models generally provide stable results with minimal tuning.

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5. Discussion

Wind-direction vectorization and chronological splitting have strong positive effects on accuracy. RandomForest and SVR produce reliable forecasts under limited feature engineering, while MLP is more sensitive to scaling and hyperparameters. The modular design simplifies future extensions (new models, new features, or external predictors).

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6. Conclusion

The project demonstrates a clear, modular ML forecasting workflow for wind power. The GUI serves only as an interaction layer, while the core contribution lies in the design of the data pipeline, model training structure, and forecast evaluation. The system is extensible and aligned with the goals of the 46W38 Scientific Programming course.
