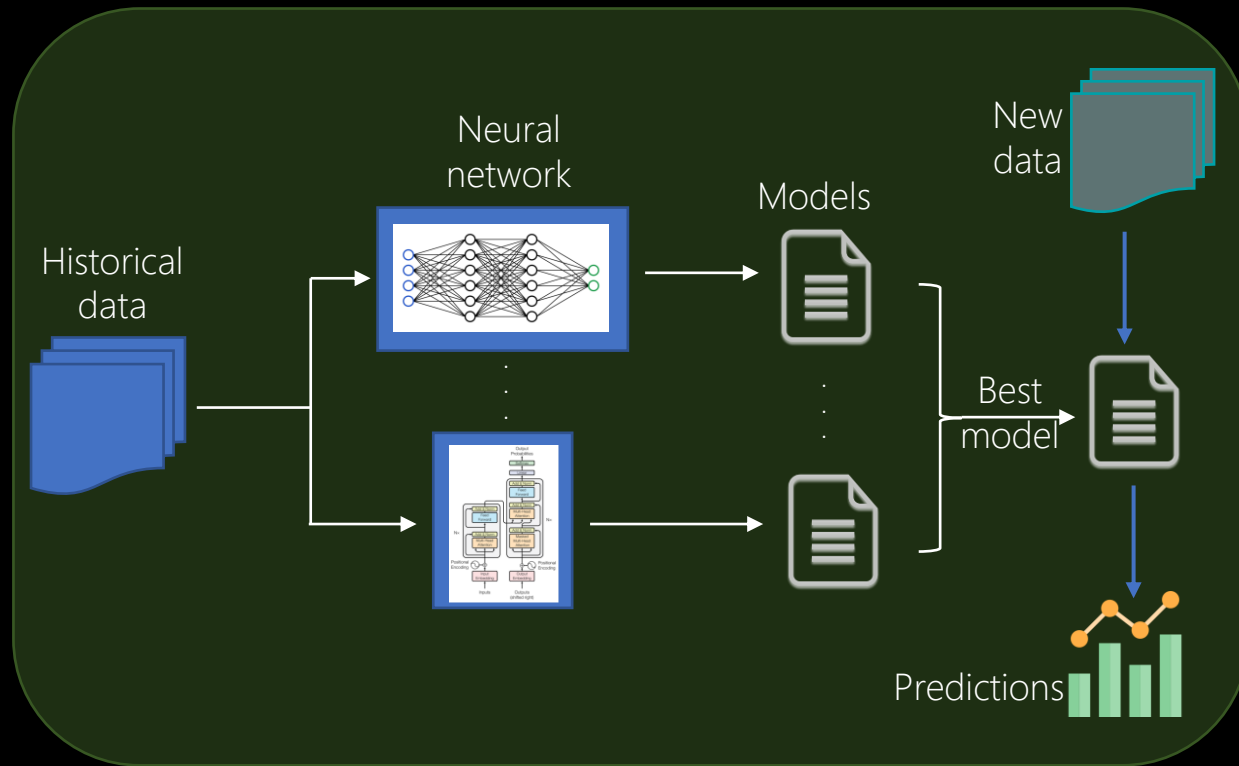


Outline

- FCR-N Market price forecasting
- IEC 104 & REST API for Virtual Power Plants
- Asset capacity forecasting - Photovoltaics / Solar Panels
- Asset capacity forecasting - Building Automation
- Energy Consumption forecasting
- MLOps for FCR-N market forecasting

Prediction with Neural network



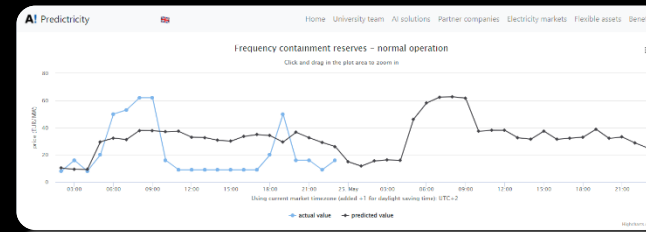
An aerial photograph of a white wind turbine situated in a large, brown, harvested field. A dirt road curves around the turbine. The text "FCR-N Market price forecasting" is overlaid on the left side of the image.

*FCR-N Market price
forecasting*

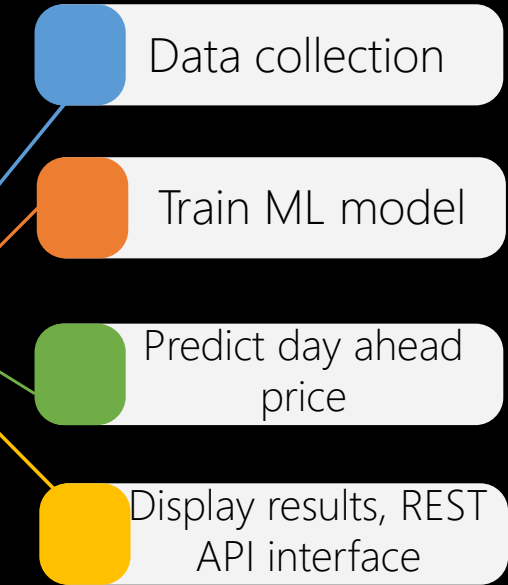
FCR-N Market price forecasting

Previous work & background

- Previous work:
 - Researched the best model
 - Web UI , REST API & Running on CSC
- Current scope:
 - Increase accuracy
 - Automate ML lifecycle

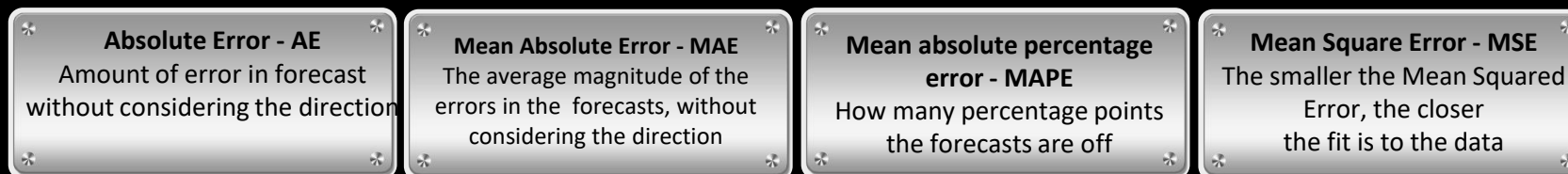


FCR-N market price forecasting



“In machine learning, performance metrics (Error measures) are used to compare the trained model predictions with the actual (observed) data from the testing data set”

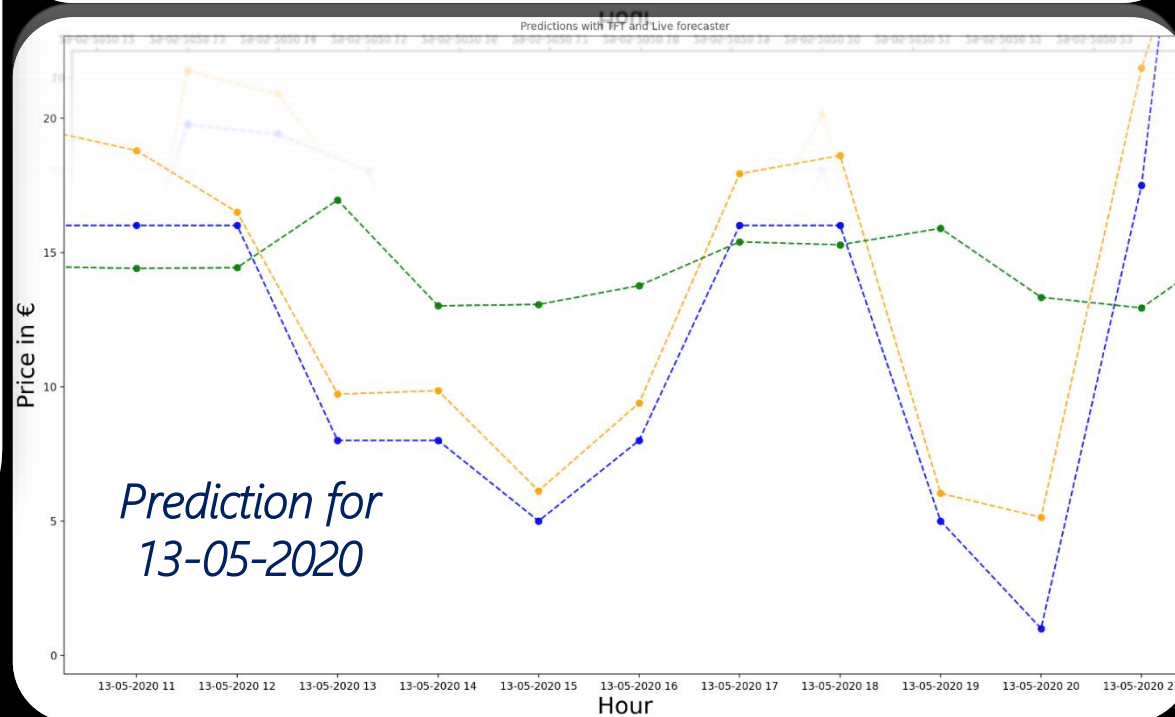
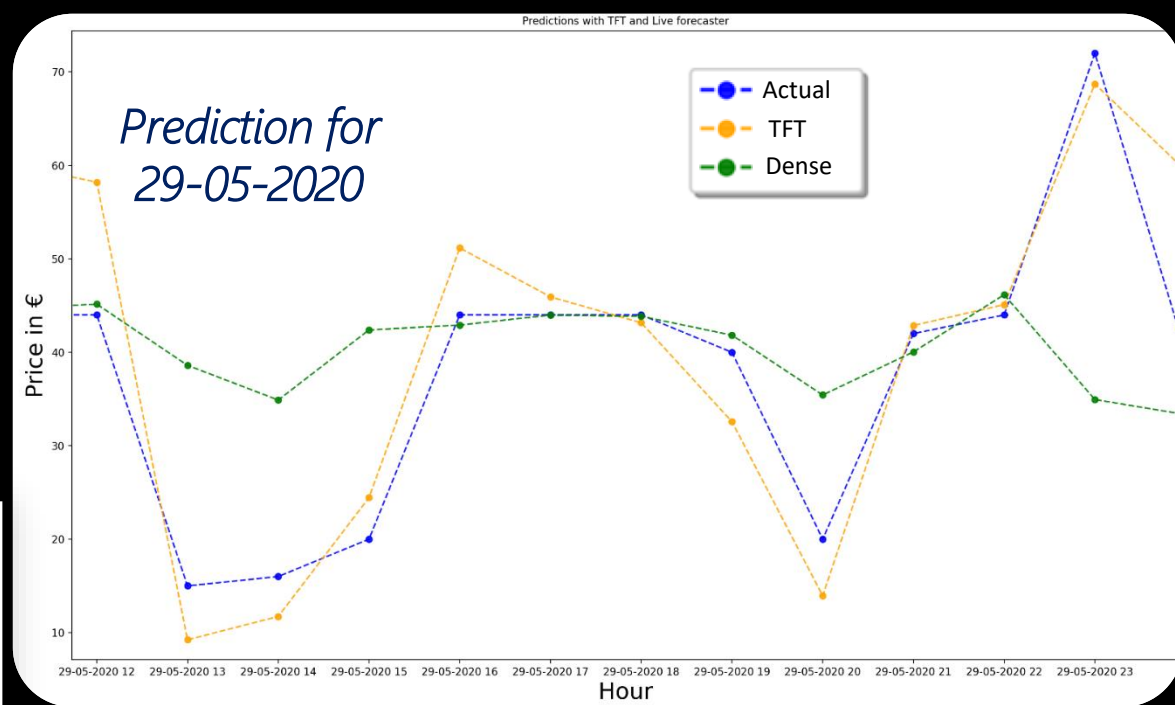
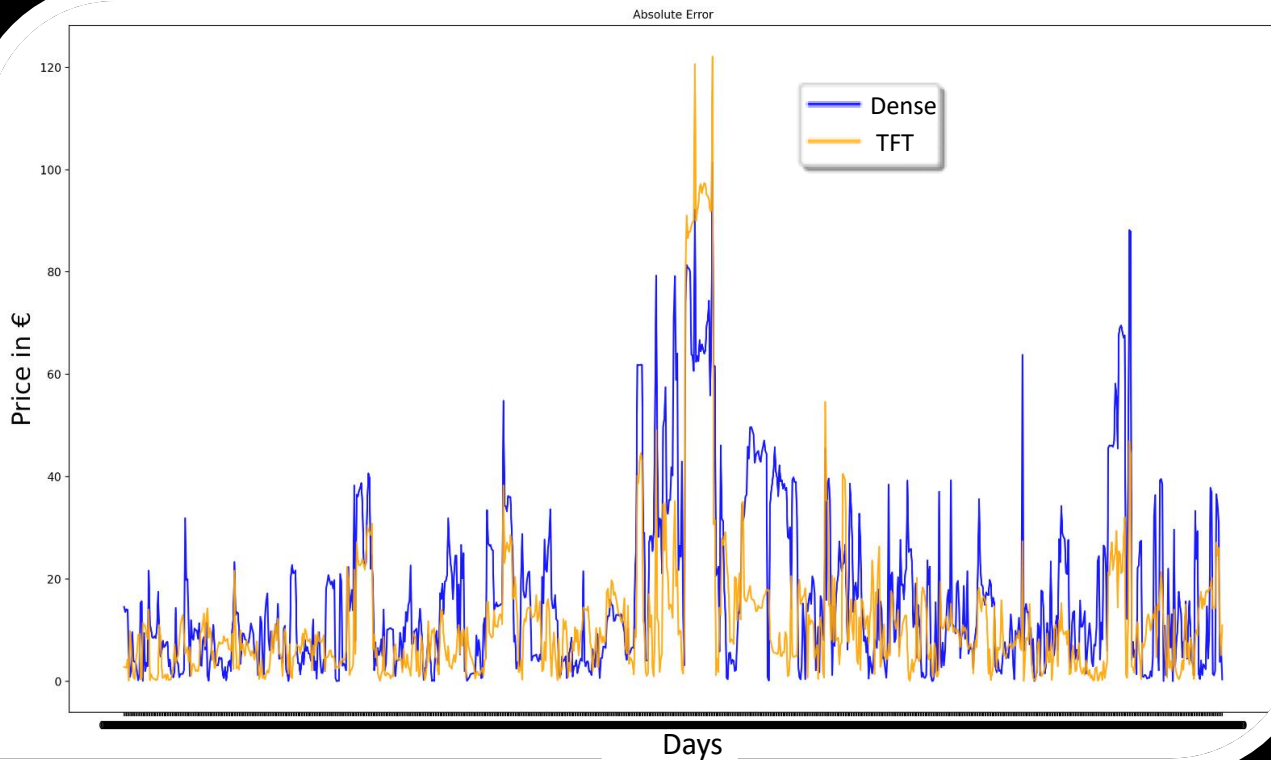
Different error metrics



FCR-N Market price forecasting

Dense vs TFT

- Data sources: Fingrid, Finnish Meteorological Institute, Calendar features
- Dense (Three-layer classic NN) = Old model.
- TFT (Temporal Fusion Transformer) = Current research model



FCR-N Market price forecasting

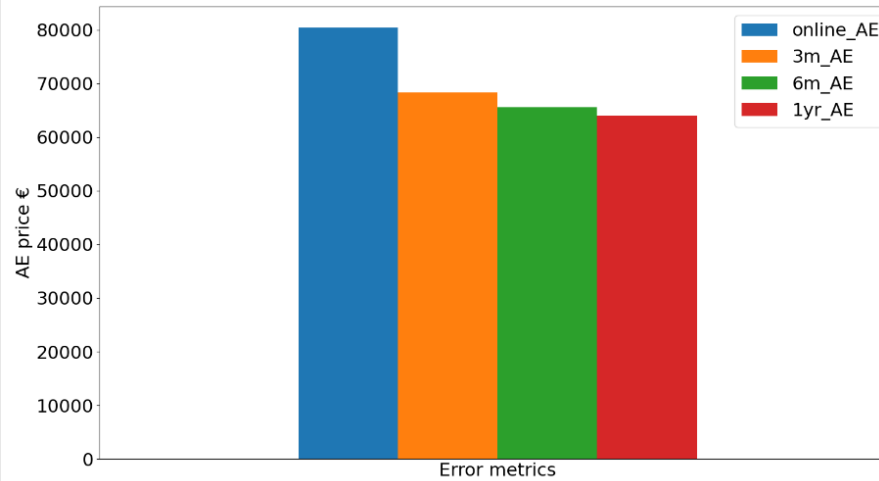
Dense vs TFT

- Error Comparison
- Four metrics
- Three different training periods for TFT
 - 3 Months – 3m
 - 6 Months – 6m
 - 1 Year – 1yr
- Similar result for 2020 and 2022
- TFT performs better than existing model

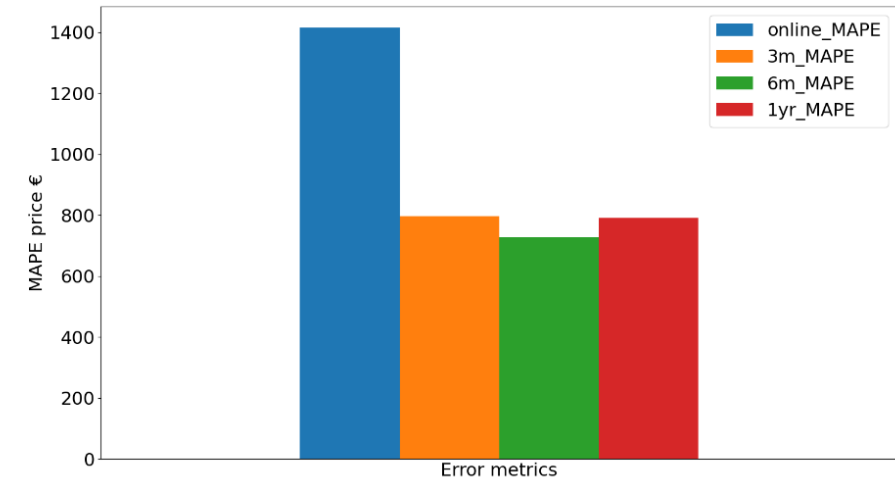
Online – Using Dense NN & running on CSC
3m,6m,1yr – Using TFT on Triton for 3m, 6m and 1yr historical data respectively

2021 Metrics

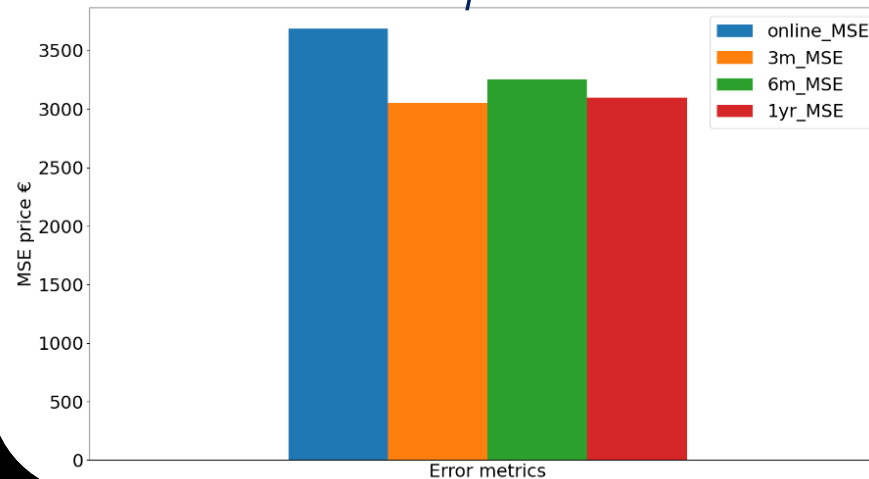
Absolute Error



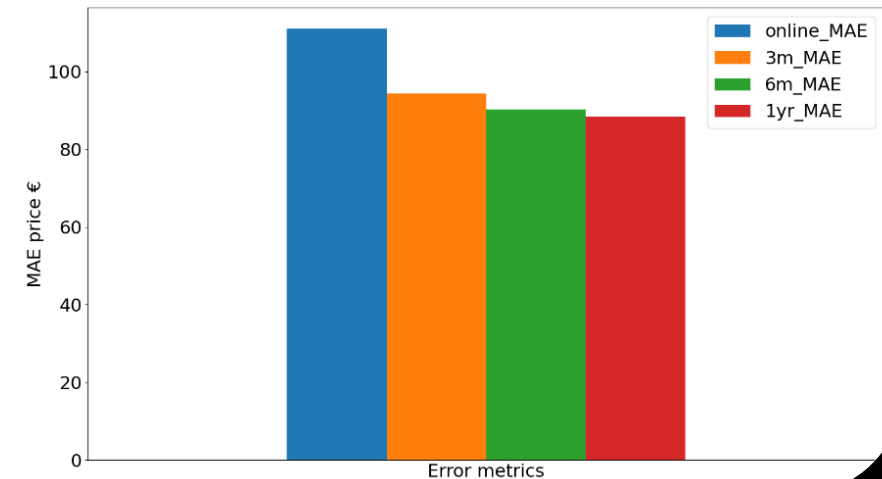
Mean Absolute Percentage Error



Mean Squared Error



Mean Absolute Error



An aerial photograph of a white wind turbine situated in a large, brown, harvested field. A dirt road curves around the turbine. The text 'IEC 104 & REST API for Virtual Power Plants' is overlaid on the left side of the image.

*IEC 104 & REST API for
Virtual Power Plants*

IEC 104 & REST API for VPP

Background

- VPP:
 - Manage energy resources that are not co-located (DER)
 - Lack of research: Cloudification & multi-tenancy
 - Need: Interoperability via cloud computing
- IEC 60870-5-104 (IEC 104)
 - Well-established standard for telecontrol in automation applications
- IEC 104 Role:
 - VPP interoperability & Cloudification.
 - Third-party integration (as SaaS clients)
 - Internet of Things-enabled Distributed Energy Resources
 - Electricity market information systems

Interfacing Third Party Cloud Services to a Virtual Power Plant

Publisher: IEEE

Cite This

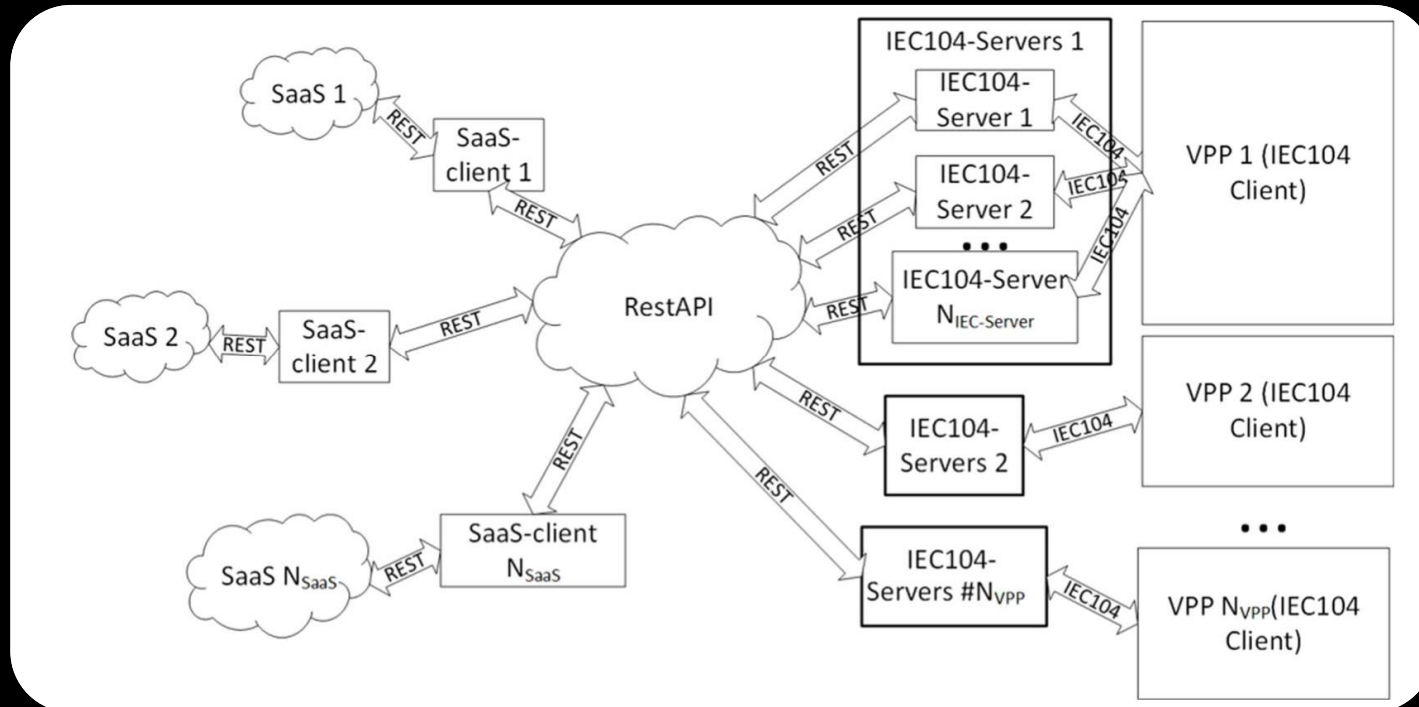
PDF

Rakshith Subramanya ; Seppo Sierla ; Matti Yli-Ojanperä ; Henri Makkonen ; Mahdi Poura...

- Integration with Siemens Virtual Power Plant (VPP).
- Used for: Data imports from VPP and perform forecasts on the data.
- **Publication:**
<https://ieeexplore.ieee.org/document/9640200>

IEC 104 & REST API for VPP

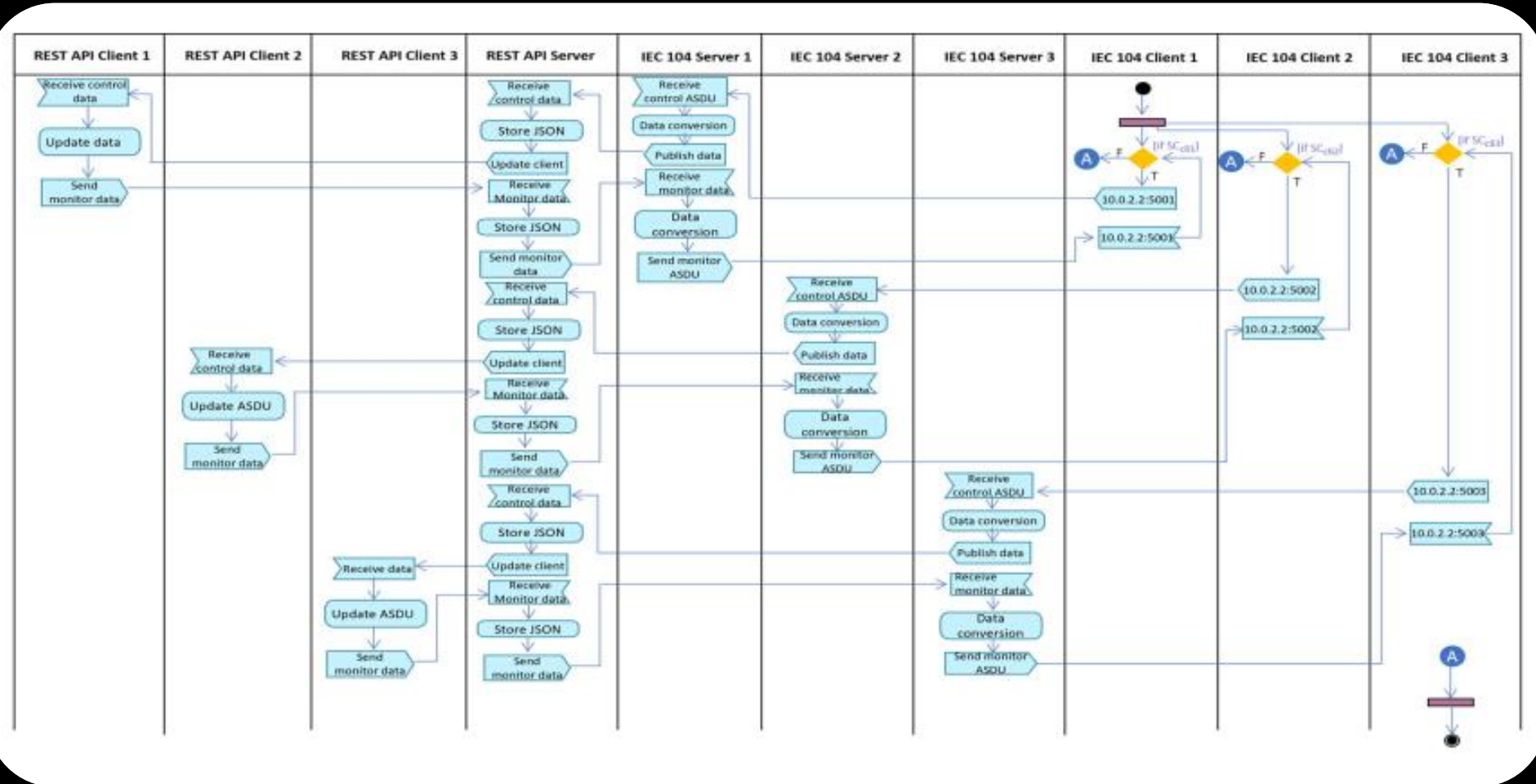
Architecture




- Smart grid: VPP interfacing via IEC-104
- Software as a Service – SaaS architecture
 - IEC 60870-5-104 / 104
 - REST (Representational State Transfer)
 - APIs (Application Programming Interfaces).
 - Multitenancy (For scaling)
 - SaaS clients: Connected to assets like photovoltaic panels / EV charging stations via the REST API

IEC 104 & REST API for VPP

Multitenant Architecture Implementation



- Multiple SaaS (REST API) clients
- Multiple IEC 104 Clients
- Single REST API server
- Both monitor and control signal communication
- Security: Request authentication

An aerial photograph of a white wind turbine situated in a large, brown, harvested field. A dirt road curves around the turbine. The text 'Asset capacity forecasting' and 'Photovoltaics / Solar Panels' is overlaid on the left side of the image.

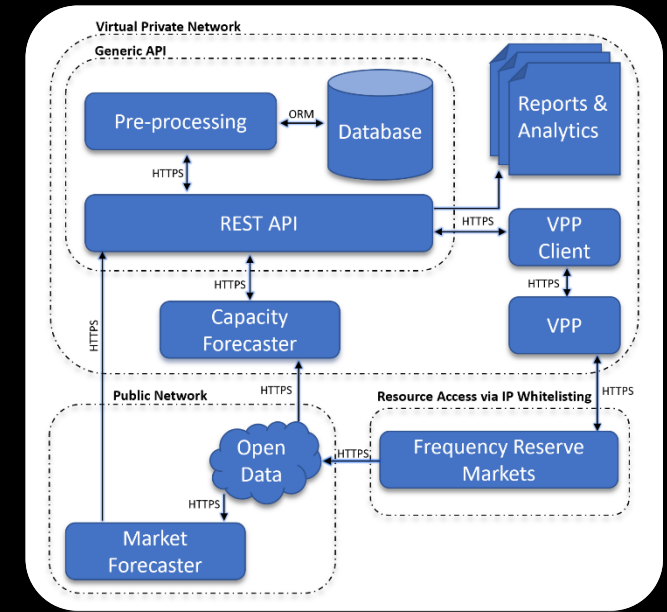
Asset capacity forecasting

Photovoltaics / Solar Panels

Asset capacity forecasting : PV

Sello usecase : Introduction

- Penetration of Photovoltaic (PV) power generation in PFR (Primary Frequency Reserves).
- For VPP, asset capacity forecast is useful due to the minimum capacity of one bid in the PFR markets.
- PV data is collected from Siemens VPP for forecasting.
- Dense model (Three-layered classical neural network).
- Data sources: Finnish Meteorological Institute, Calendar features
- Publication: <https://www.mdpi.com/1996-1073/14/5/1242>



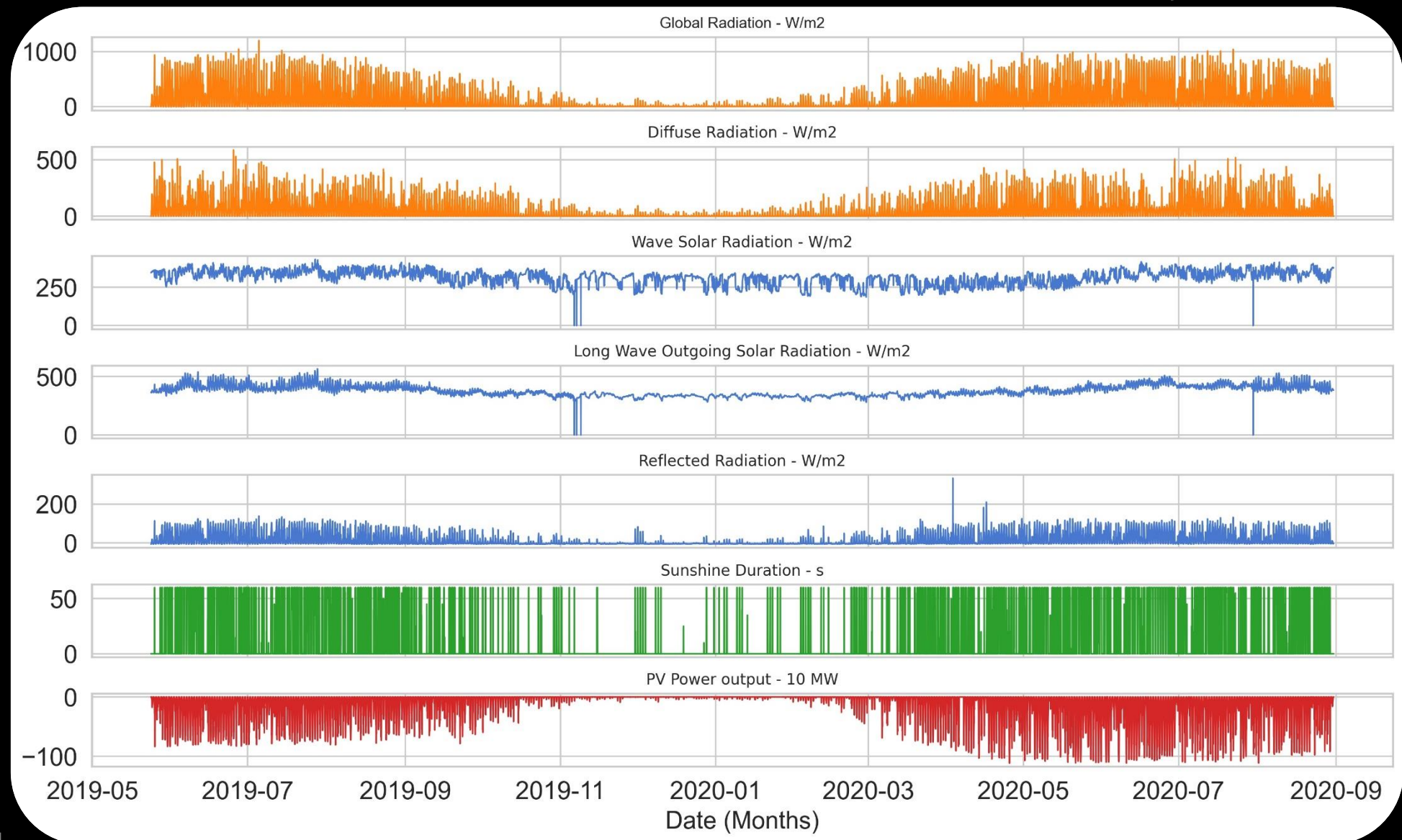
A Virtual Power Plant Solution for Aggregating Photovoltaic Systems and Other Distributed Energy Resources for Northern European Primary Frequency Reserves

by Rakshith Subramanya ^{1,*}, Matti Yli-Ojanperä ¹, Seppo Sierla ¹, Taneli Hölttä ¹, Jori Valtakari ² and Valeriy Vyatkin ^{1,3,4}

Asset capacity forecasting : PV

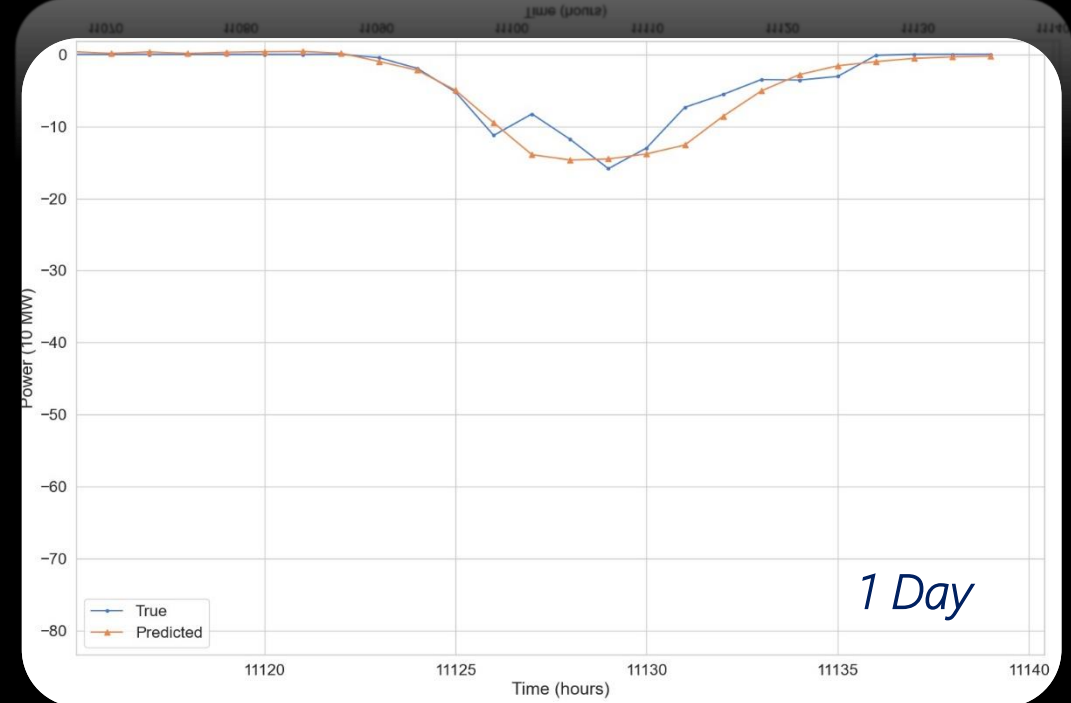
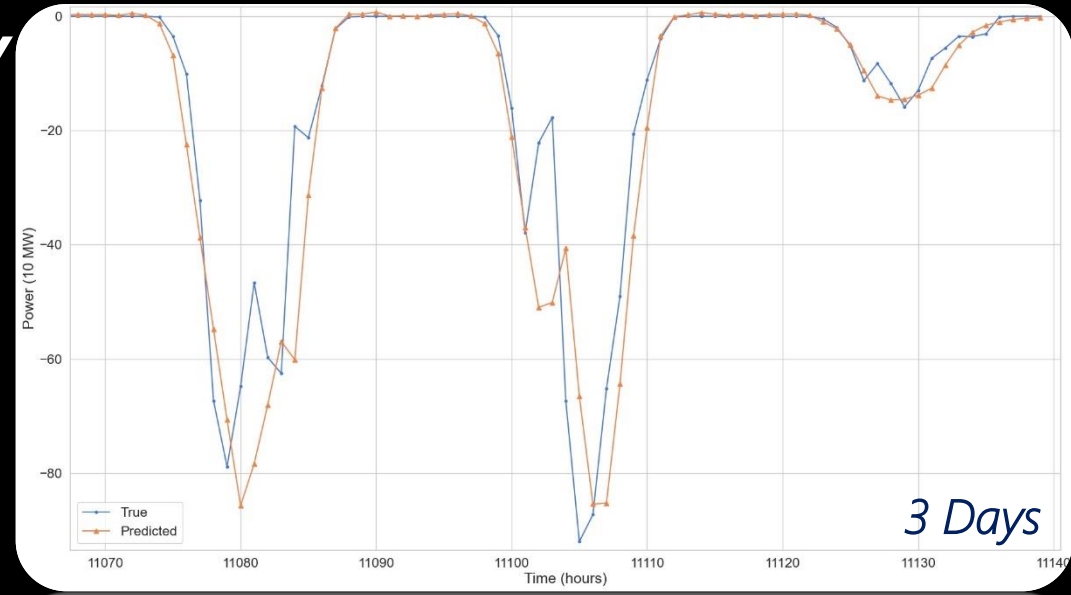
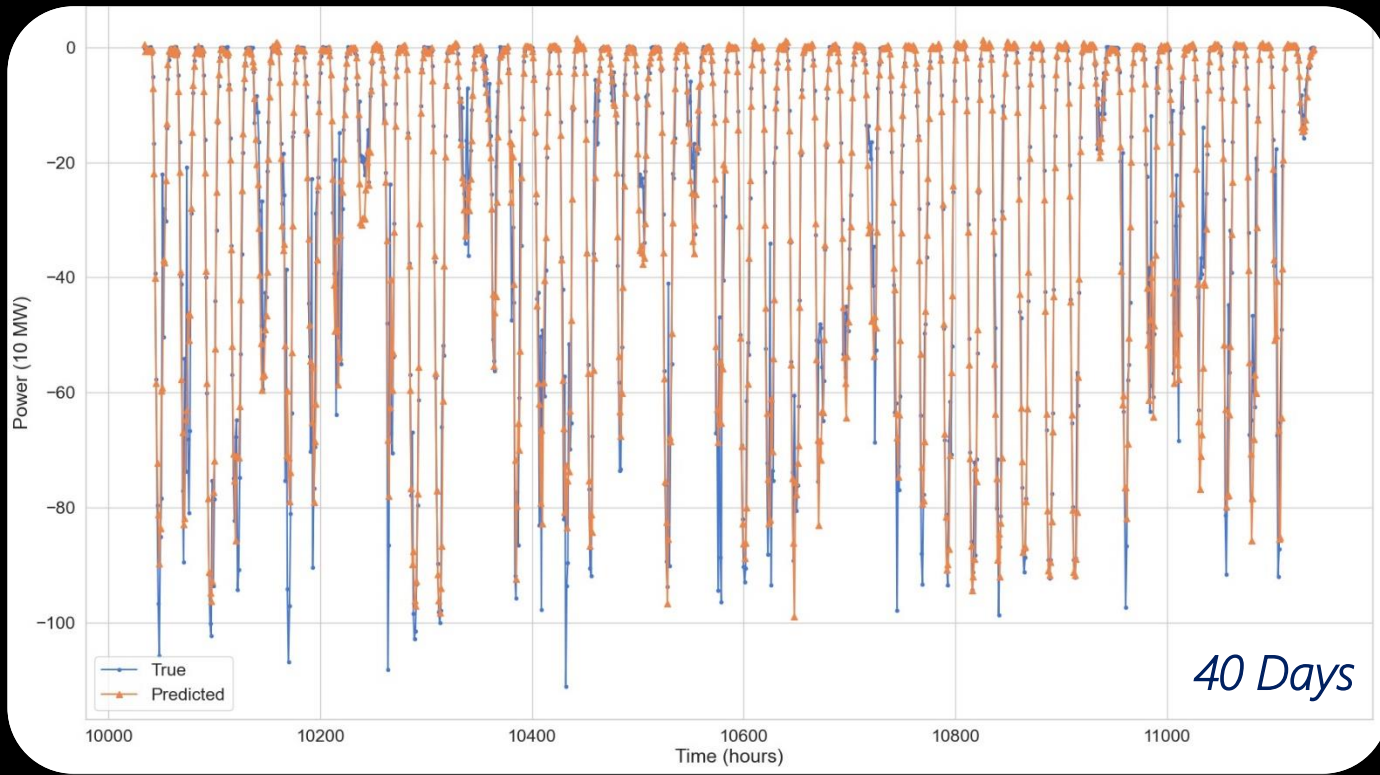
Sello usecase

Data used for prediction



Asset capacity forecasting: PV

Sello usecase - Prediction results



Negative capacity: Adjustable curtailable power production.

An aerial photograph of a white wind turbine in a rural landscape. The turbine is positioned in the center-right of the frame, with its three blades extending horizontally. The surrounding area consists of brown, harvested fields and a dirt road. The text is overlaid on the left side of the image.

Asset capacity forecasting
Building Automation

Asset capacity forecasting : Building Automation

Sello usecase – Building Automation

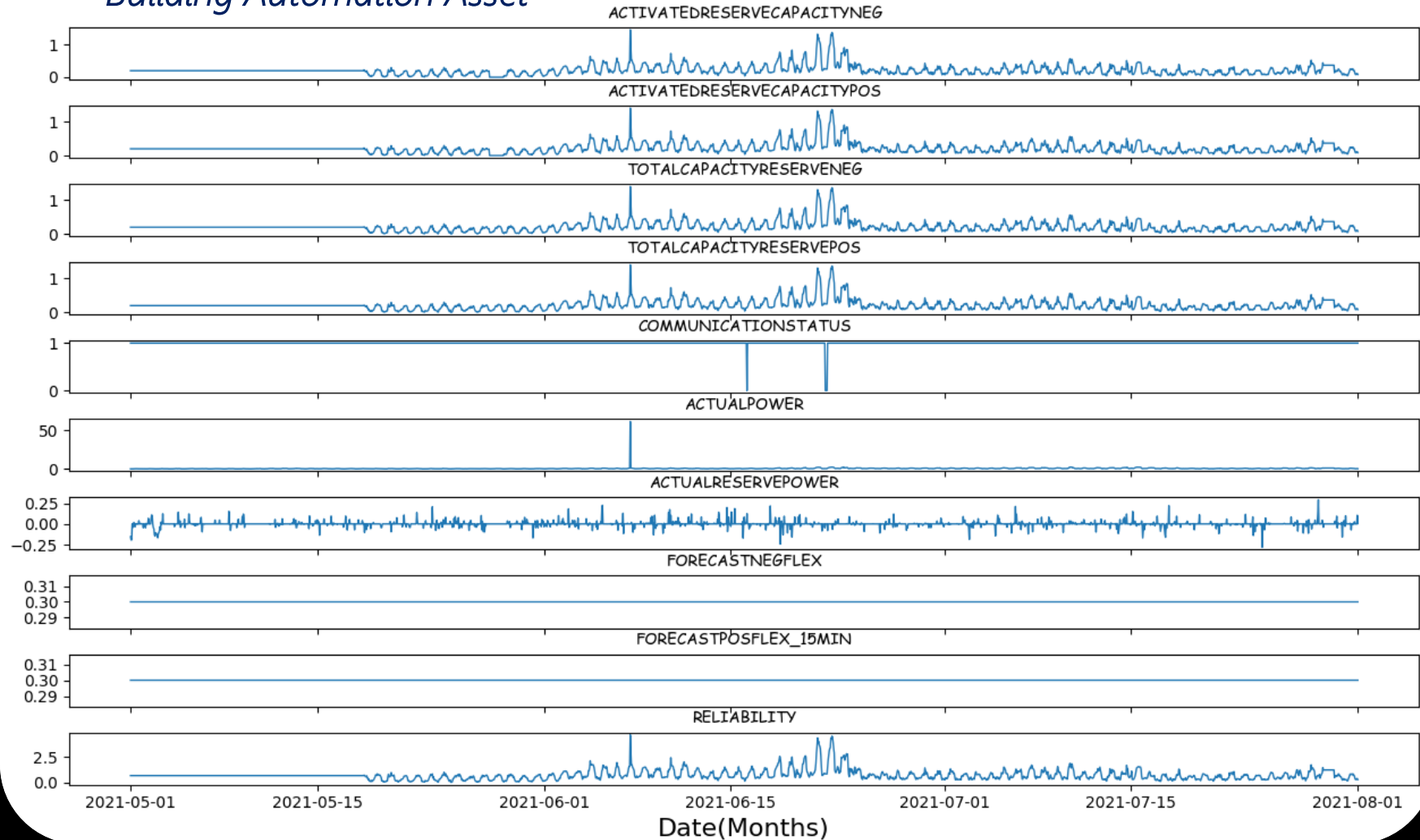
- Forecasting different asset capacities:
 - Building automation
 - Diesel generation
 - Battery storage
- Asset data is collected from Siemens VPP for forecasting.
- Data Sources:
 - BuildingAutomation data + Calendar features + Fingrid features (FCR) + Mall operating hours.
 - Researched with previous PV data for increasing accuracy.
- Auto Machine Learning (AutoML) is used for determining the optimal learning parameters.
- Types of networks used:
 - Three-layered classical neural network - Dense
 - Convolutional Neural Networks - CNN
 - Temporal Fusion Transformer - TFT

Asset capacity forecasting

Sello usecase – The data

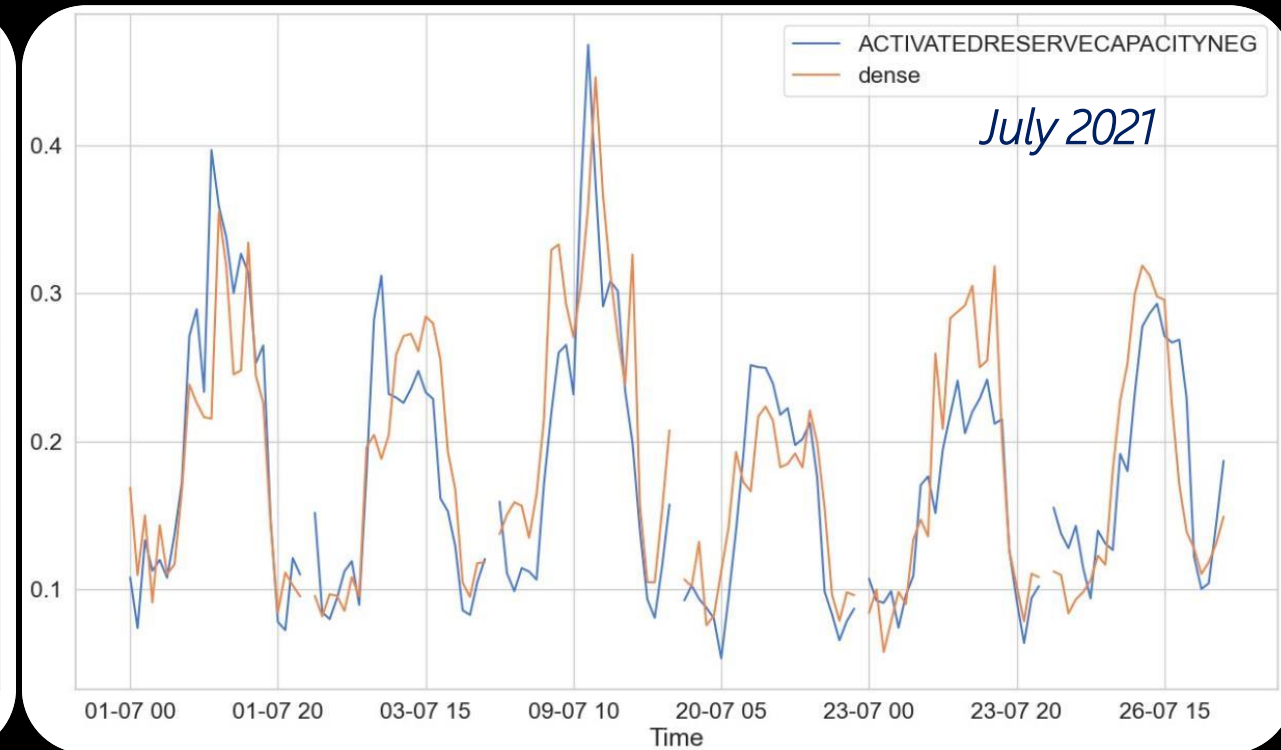
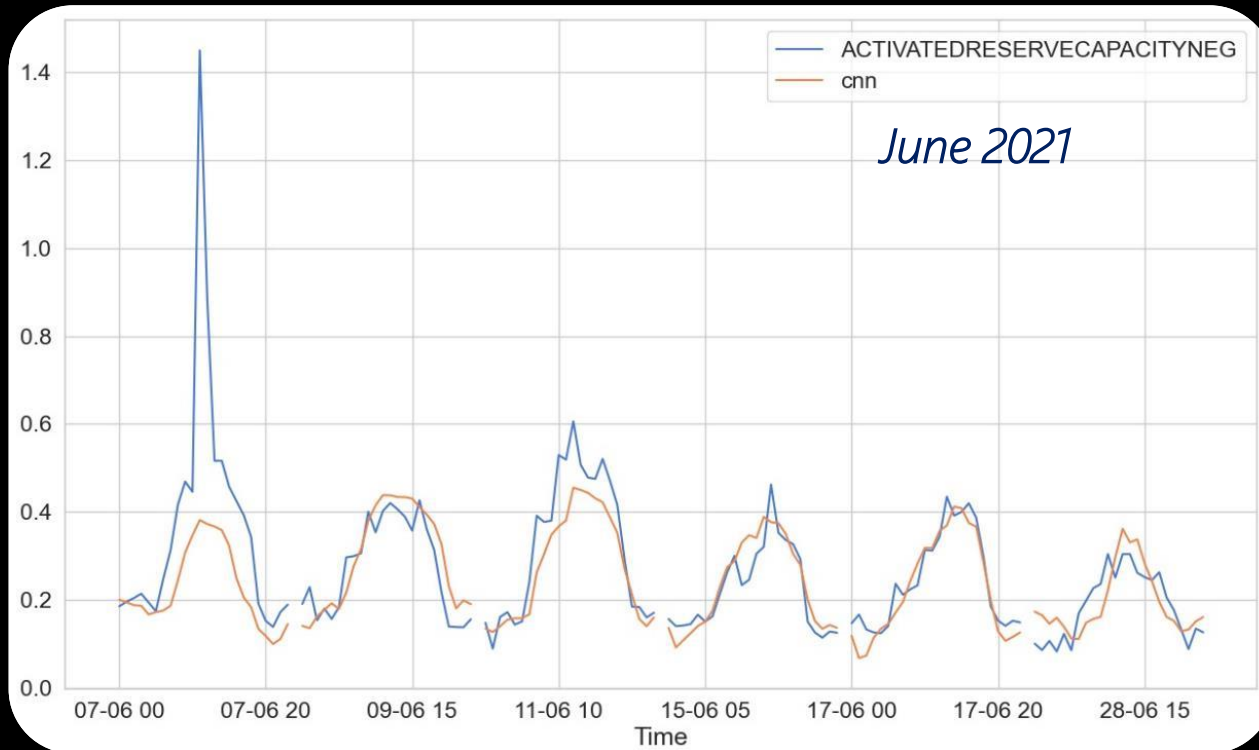
../data/data3/buildingautomation/BA0521_0721_data3_1hr.csv

Building Automation Asset



Asset capacity forecasting

Sello usecase – Prediction results

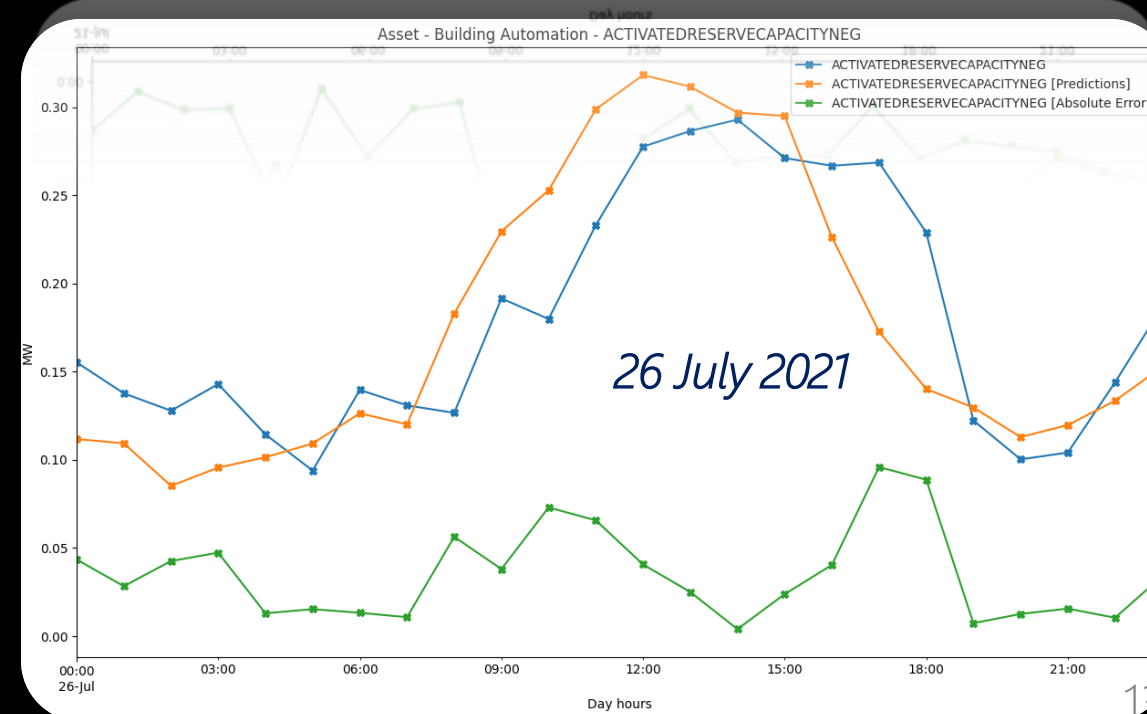
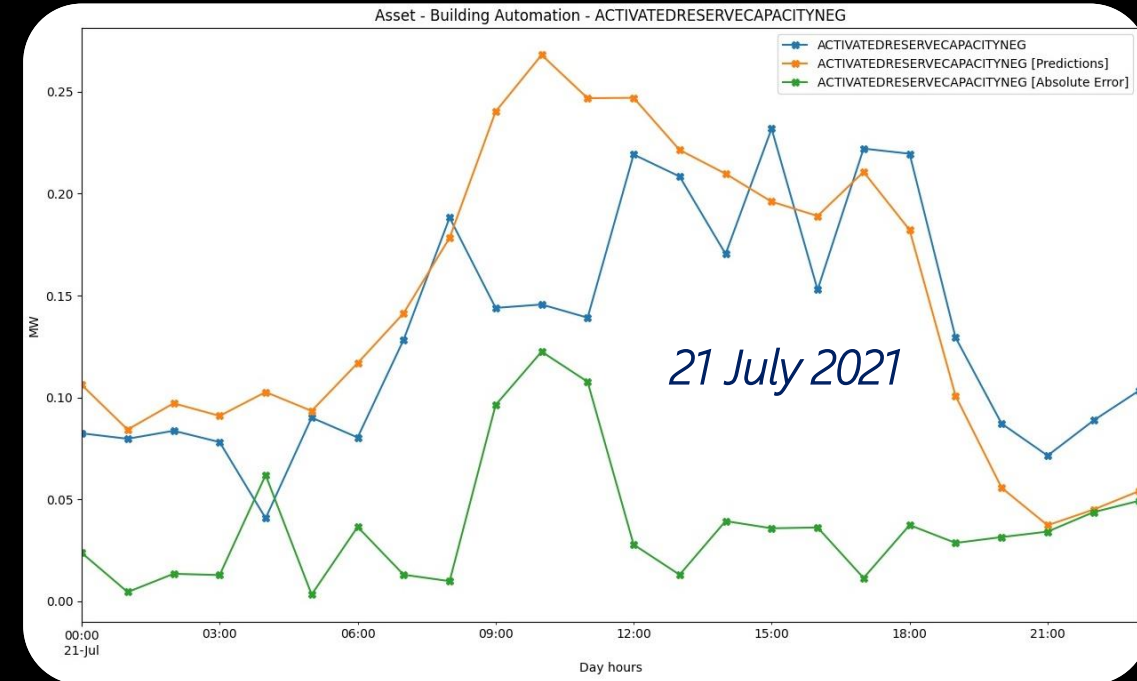
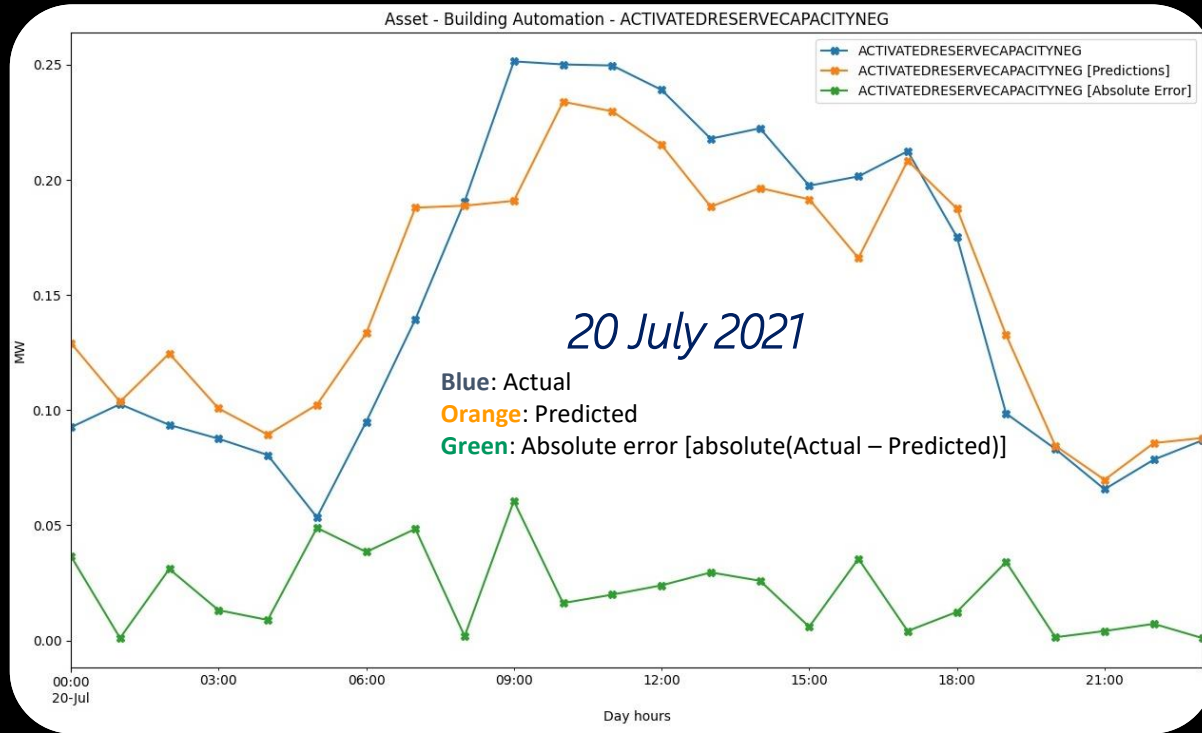


Prediction with CNN Model leads to slightly higher accuracy

Asset capacity forecasting

Sello usecase – Prediction results

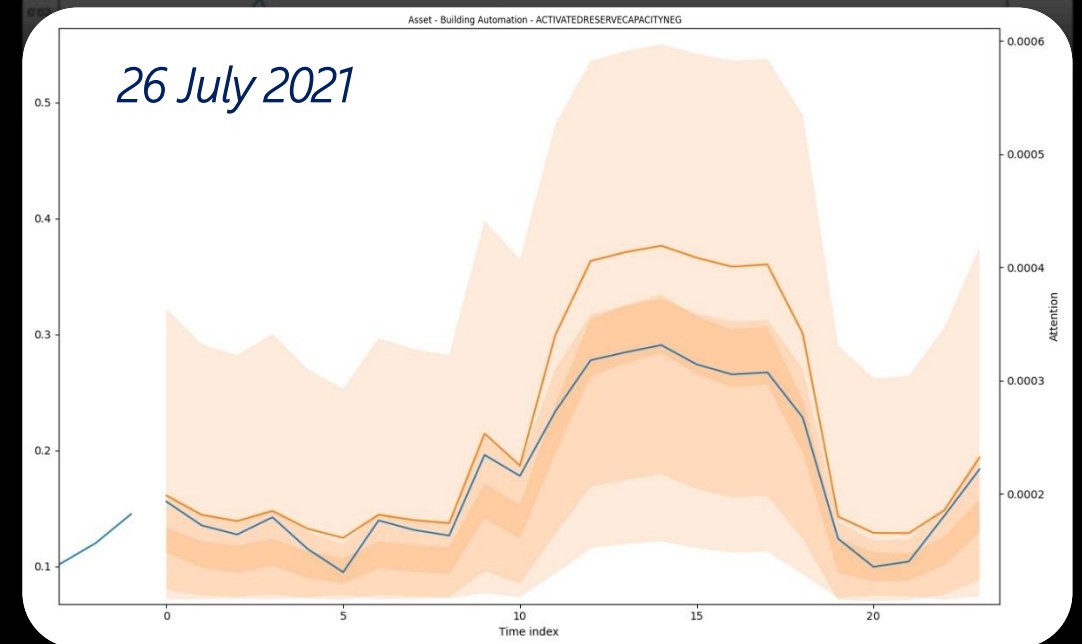
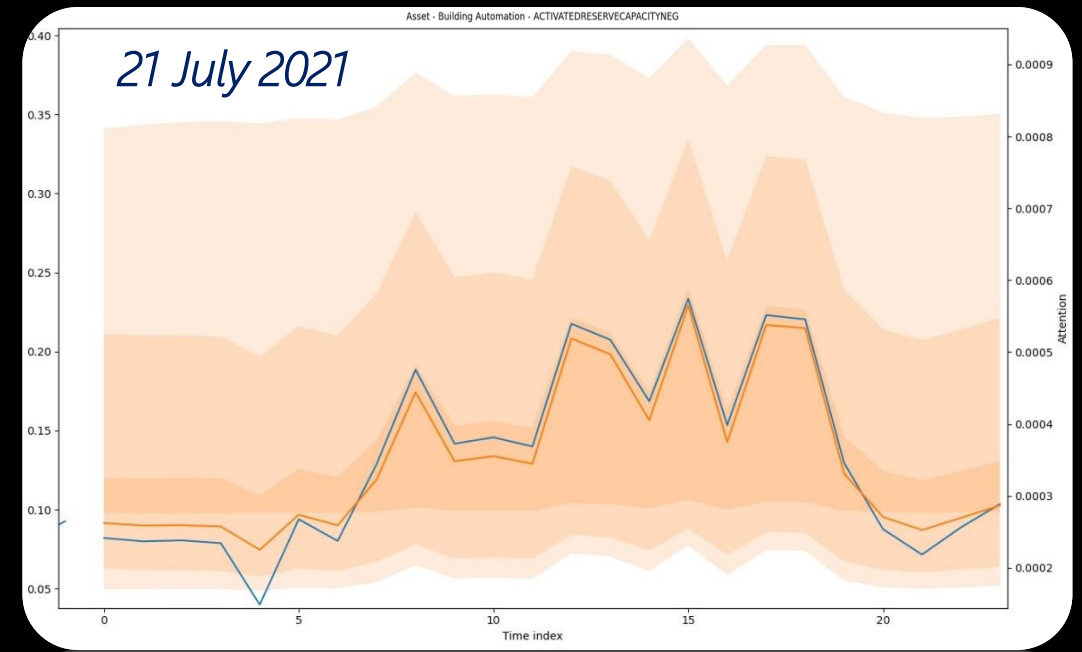
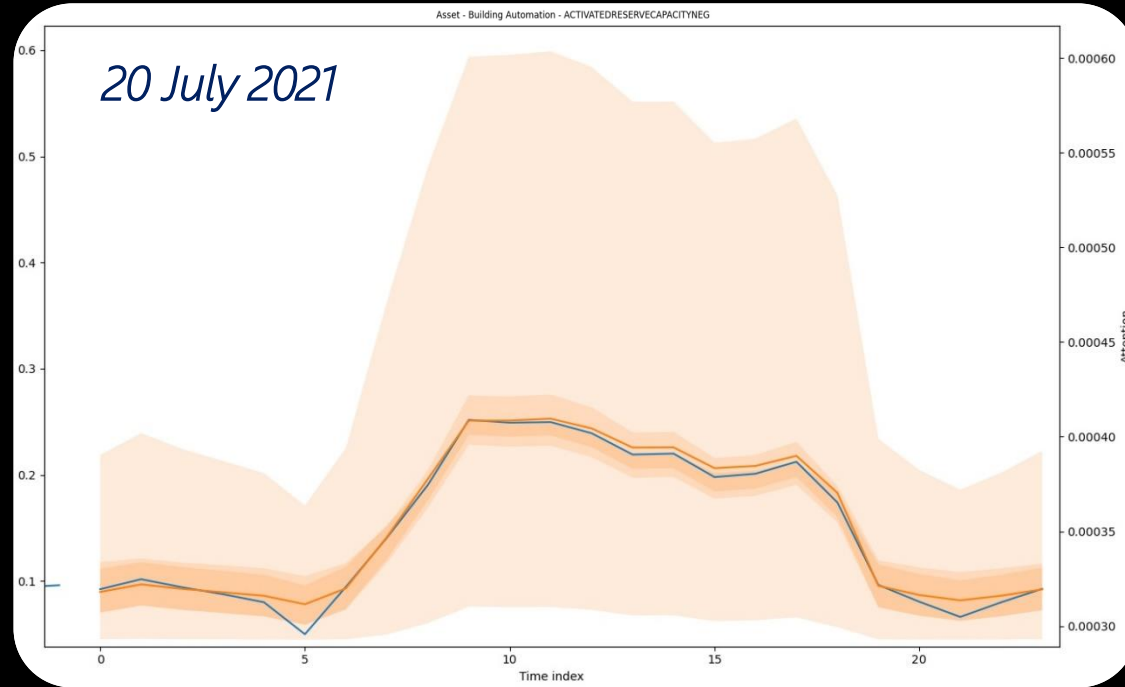
Prediction with CNN Model



Asset capacity forecasting

Sello usecase – Prediction results

Prediction with Temporal Fusion Transformer (TFT) Model



Prediction with TFT Model leads to higher accuracy than CNN

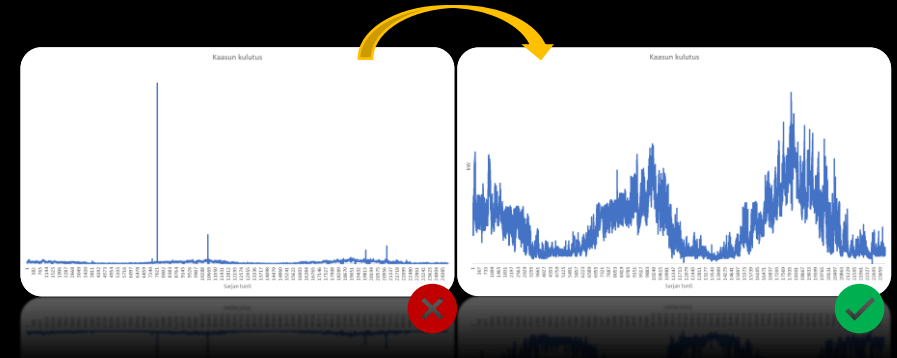
An aerial photograph of a white wind turbine situated in a large, brown, harvested field. A dirt road curves around the turbine. The text "Energy Consumption forecasting" is overlaid on the left side of the image.

Energy Consumption forecasting

Lempäälän Lämpö energy consumption forecasting

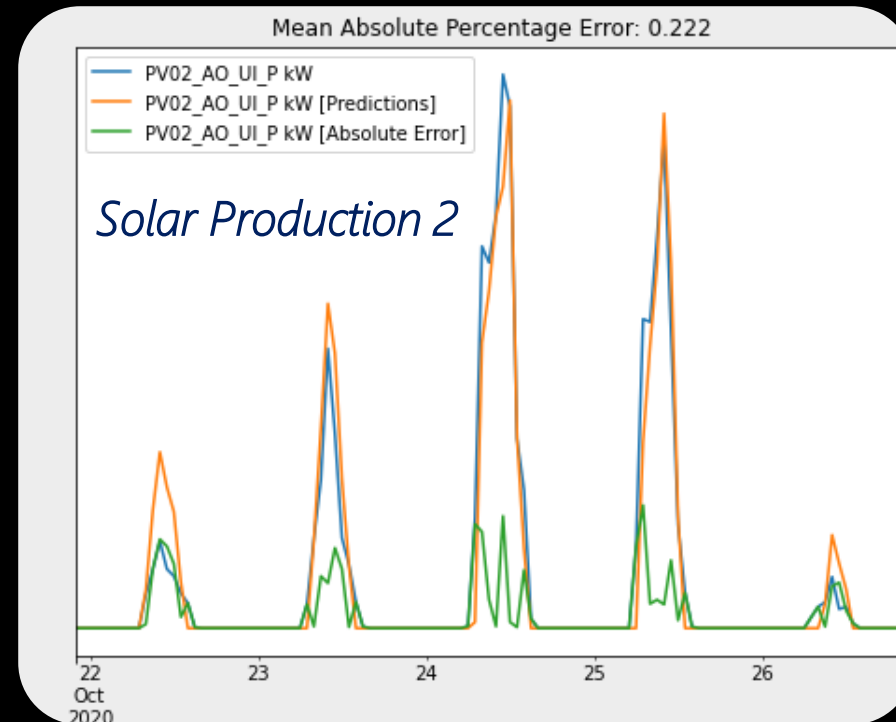
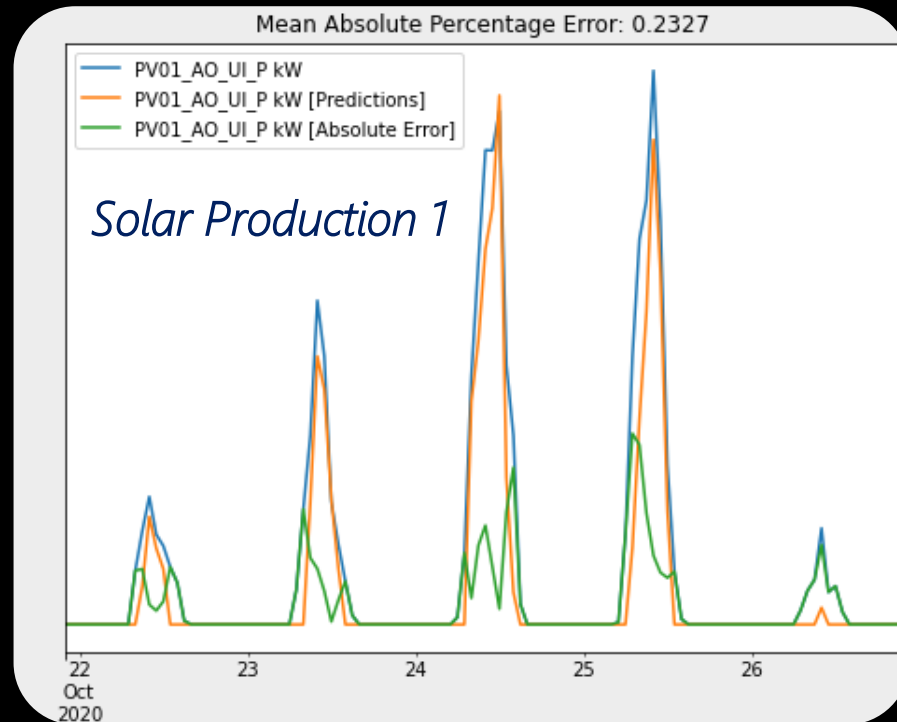
Background

- Prediction of:
 - Solar production
 - 2 Solar power plants
 - District heating consumption
 - Fire station, school, sports hall, service building
 - Electricity consumption
 - Gas consumption
 - Goal was to use AI under the 'Leading energy community' program.
 - Main tasks:
 - Exploratory data analysis - Data Cleaning
 - Fixing: Timestamp, double entries, missing series data, data format.
 - Forecasting using the Dense model (Three-layered classical neural network).



Lempäälän Lämpö energy consumption forecasting

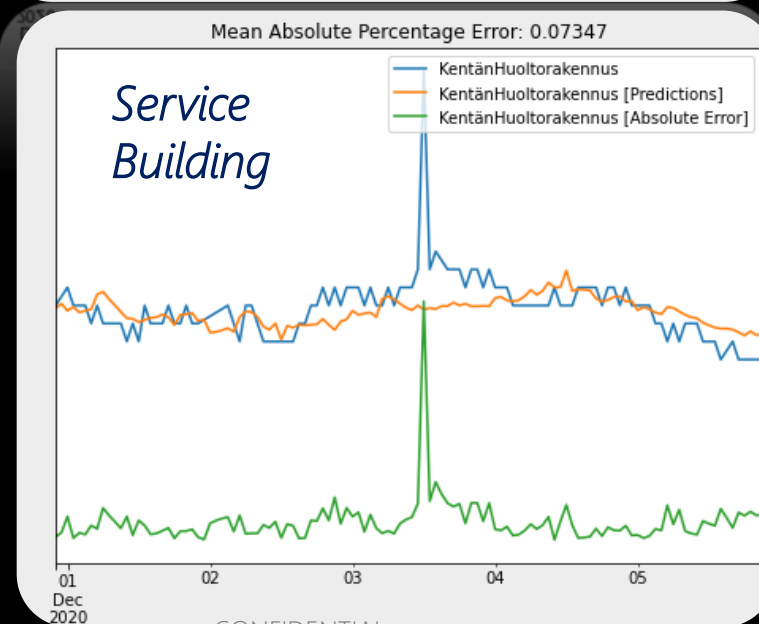
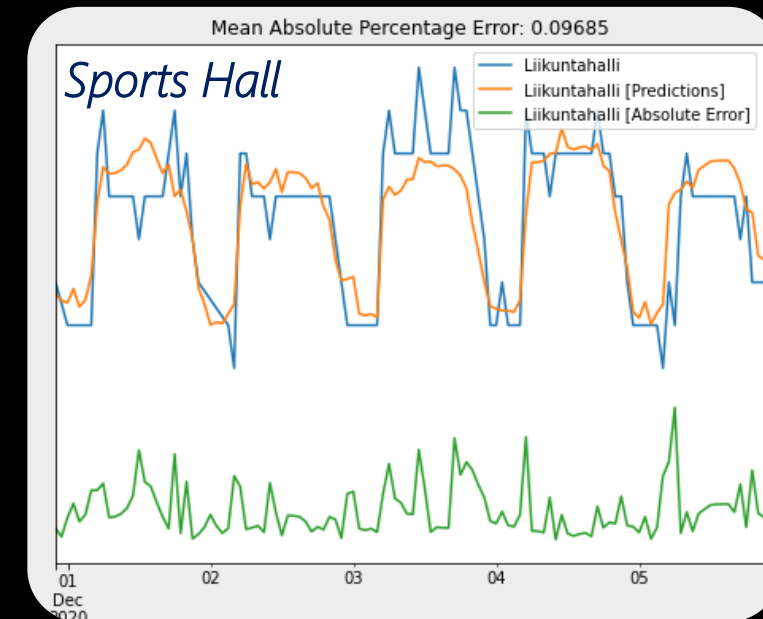
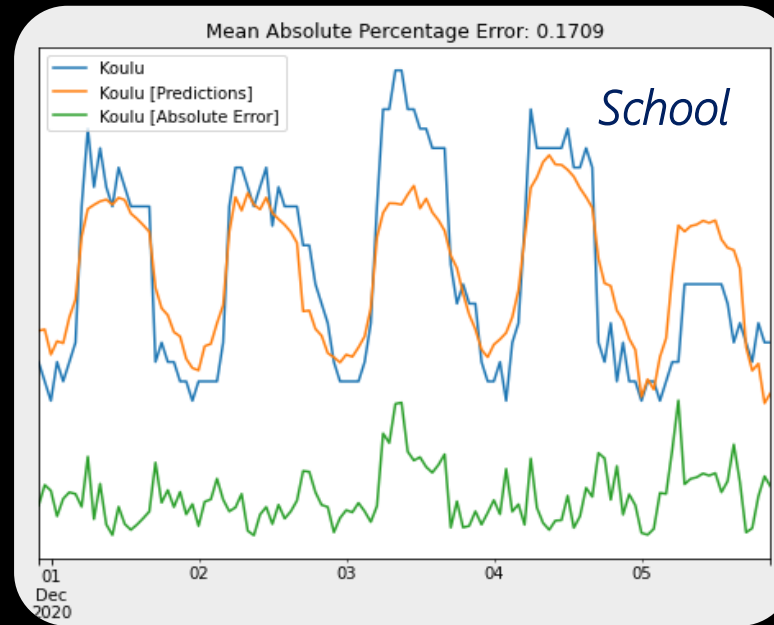
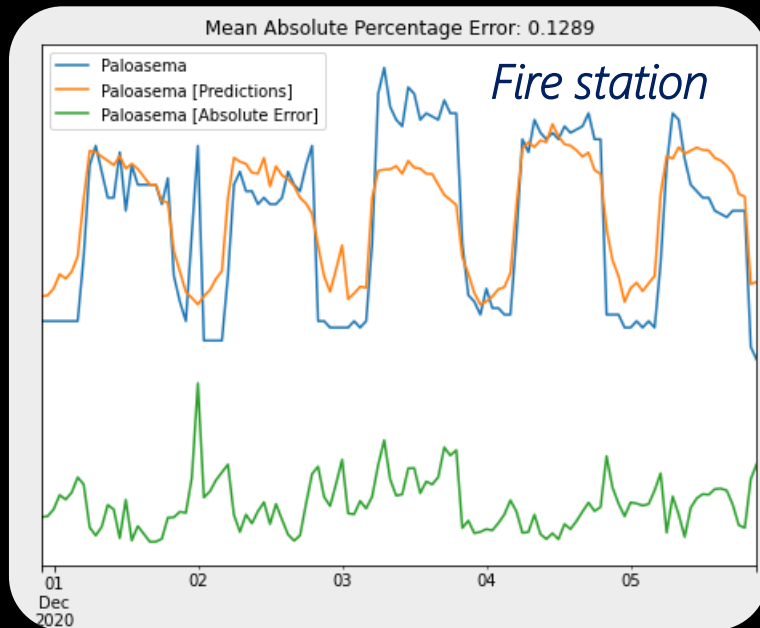
Solar production forecasting



Data Sources : Calendar features, Solar data (From LL)

Lempäälän Lämpö energy consumption forecasting

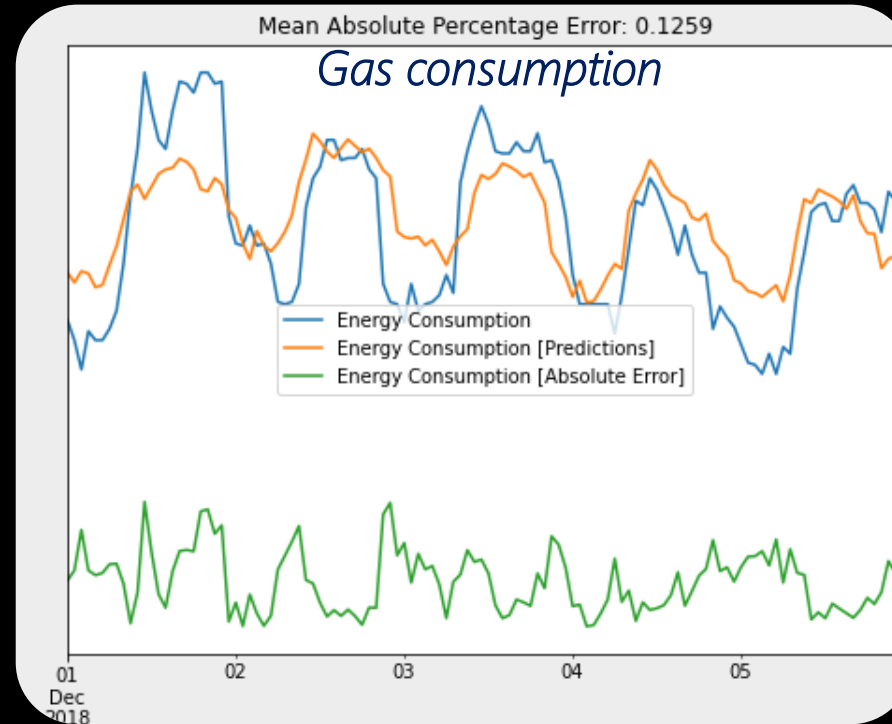
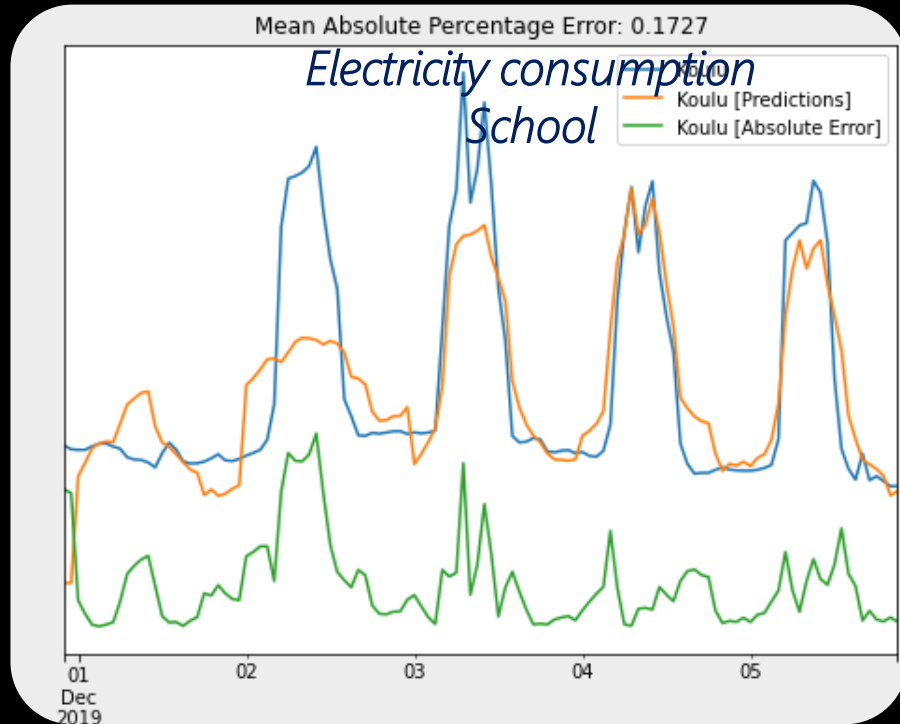
Forecasting District heating consumption



Data Sources : Calendar features, Solar data (From LL), Finnish Meteorological Institute

Lempäälän Lämpö energy consumption forecasting

Forecasting electricity and gas consumption



Forecast Summary

| Asset Type | MAE | MAPE |
|--------------------------------------|--------|--------|
| Solar production Power plant 1 | 33.80% | 23.30% |
| Solar production Power plant 2 | 25.90% | 22.20% |
| District heating School | 15.30% | 17.10% |
| District heating Fire station | 11.70% | 12.90% |
| District heating Sports hall | 9.30% | 9.70% |
| District heating Service building | 7.70% | 7.30% |
| Electricity consumption School | 17.50% | 17.30% |
| Electricity consumption Sports hall | 12.10% | 12.50% |
| Electricity consumption Fire station | 10.70% | 11.20% |
| Gas consumption | 11.70% | 12.60% |

Data Sources : Calendar features, Energy consumption (From LL), Finnish Meteorological Institute

An aerial photograph of a white wind turbine situated in a large, brown, harvested field. A dirt road curves around the turbine. The text "MLOps for FCR-N market forecasting" is overlaid on the left side of the image.

*MLOps for FCR-N
market forecasting*

MLOps for FCR-N market forecasting

Background

- Core ML (e.g., in FCR-N) is only a small part
- ML applications are more experimental in nature
 - Tracking, debugging
- Usually works with other software systems
 - Web applications, Mobile API
- Continuous software engineering practices
- Production: Accessibility, Scalability, Security

1. Reproducible

Must be able to reproduce the predictions with the same model & data to within few % error

3. Collaborative

Must be able to do asynchronous collaboration

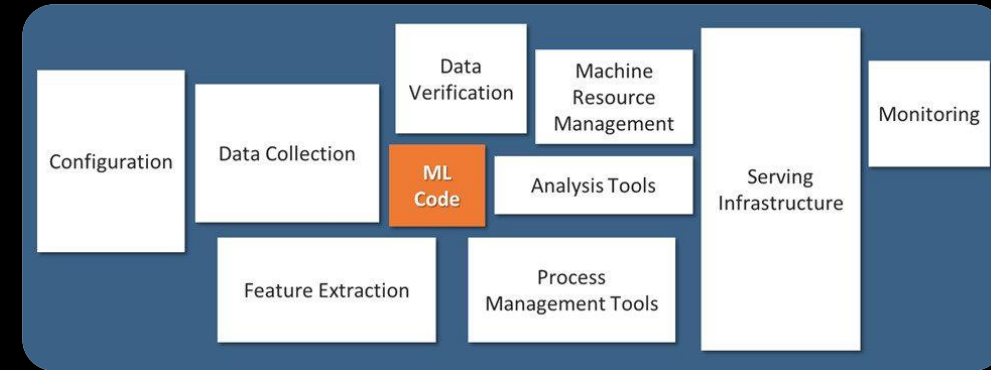
2. Accountable

Must be able to trace back from model in production to its provenance

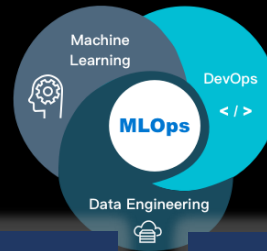
4. Continuous

Must be able to deploy automatically & monitor statistically

Real-world application with ML code



Publication: WIP

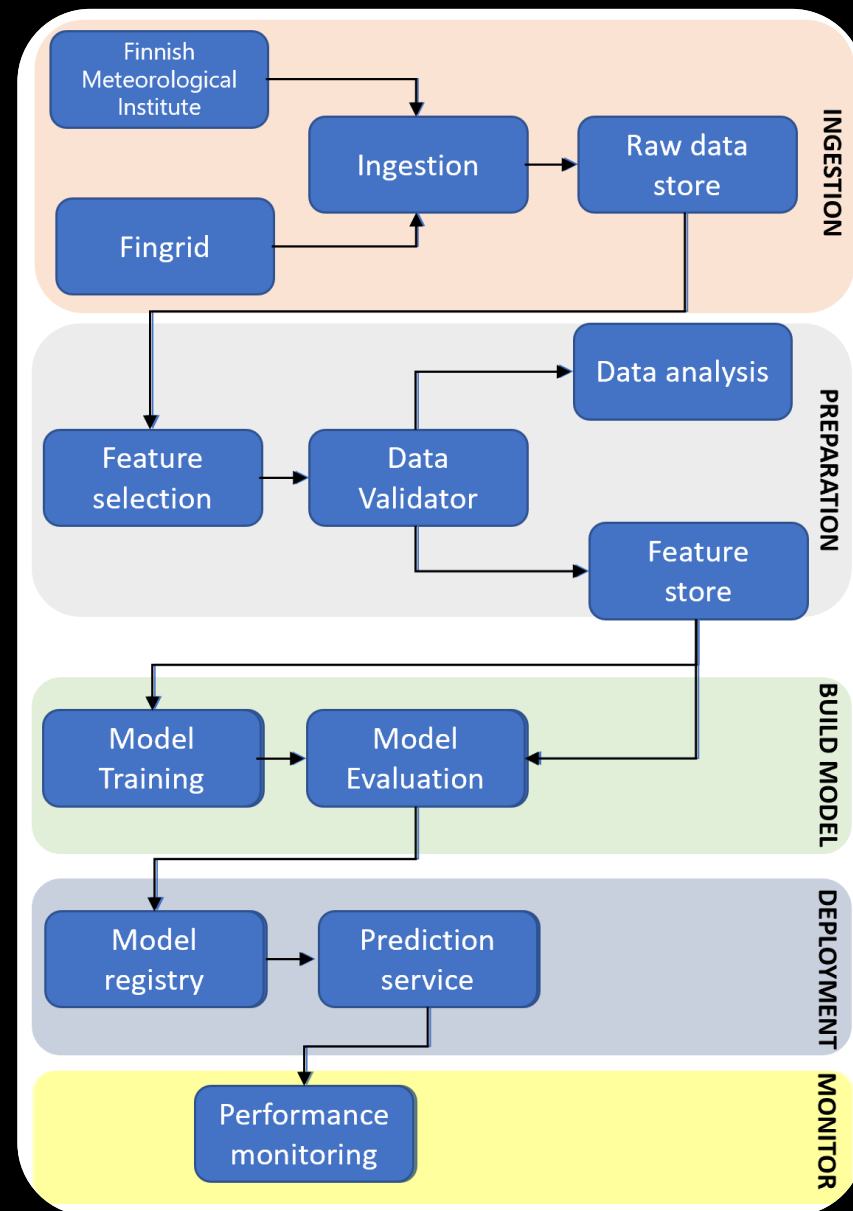
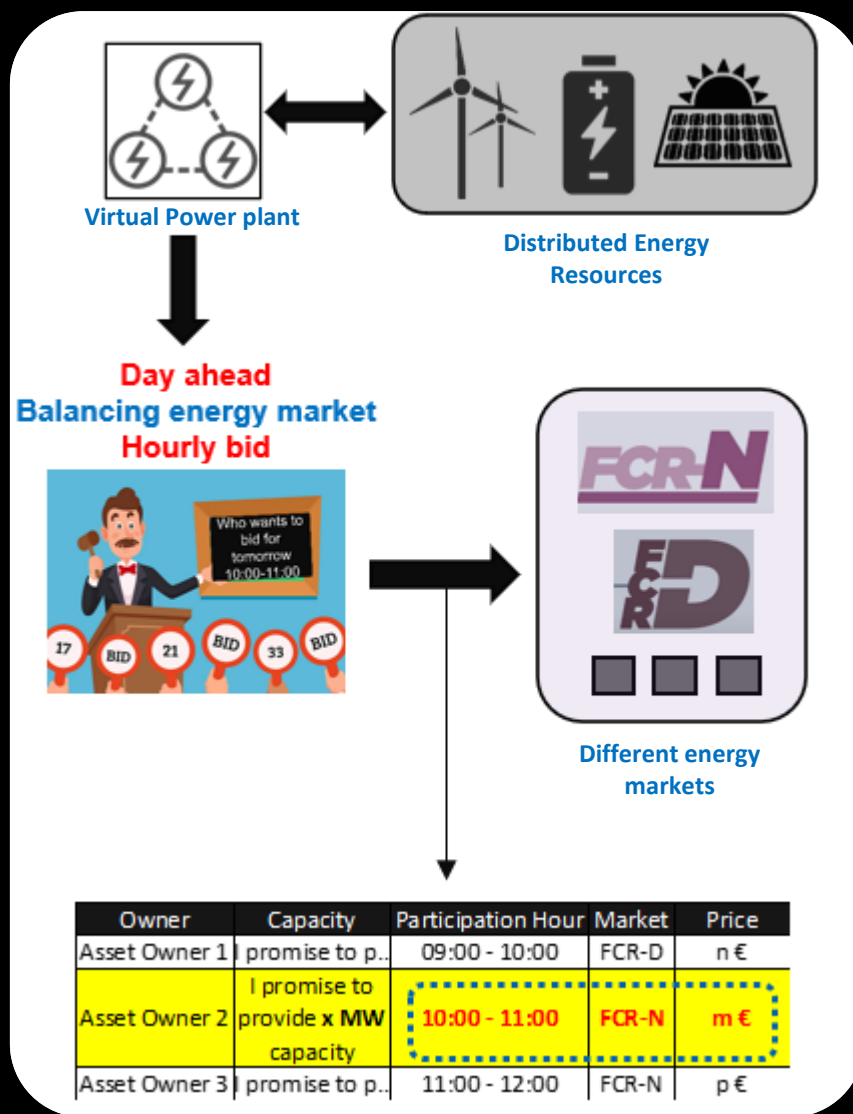


MLOps for FCR-N market forecasting

Usecase

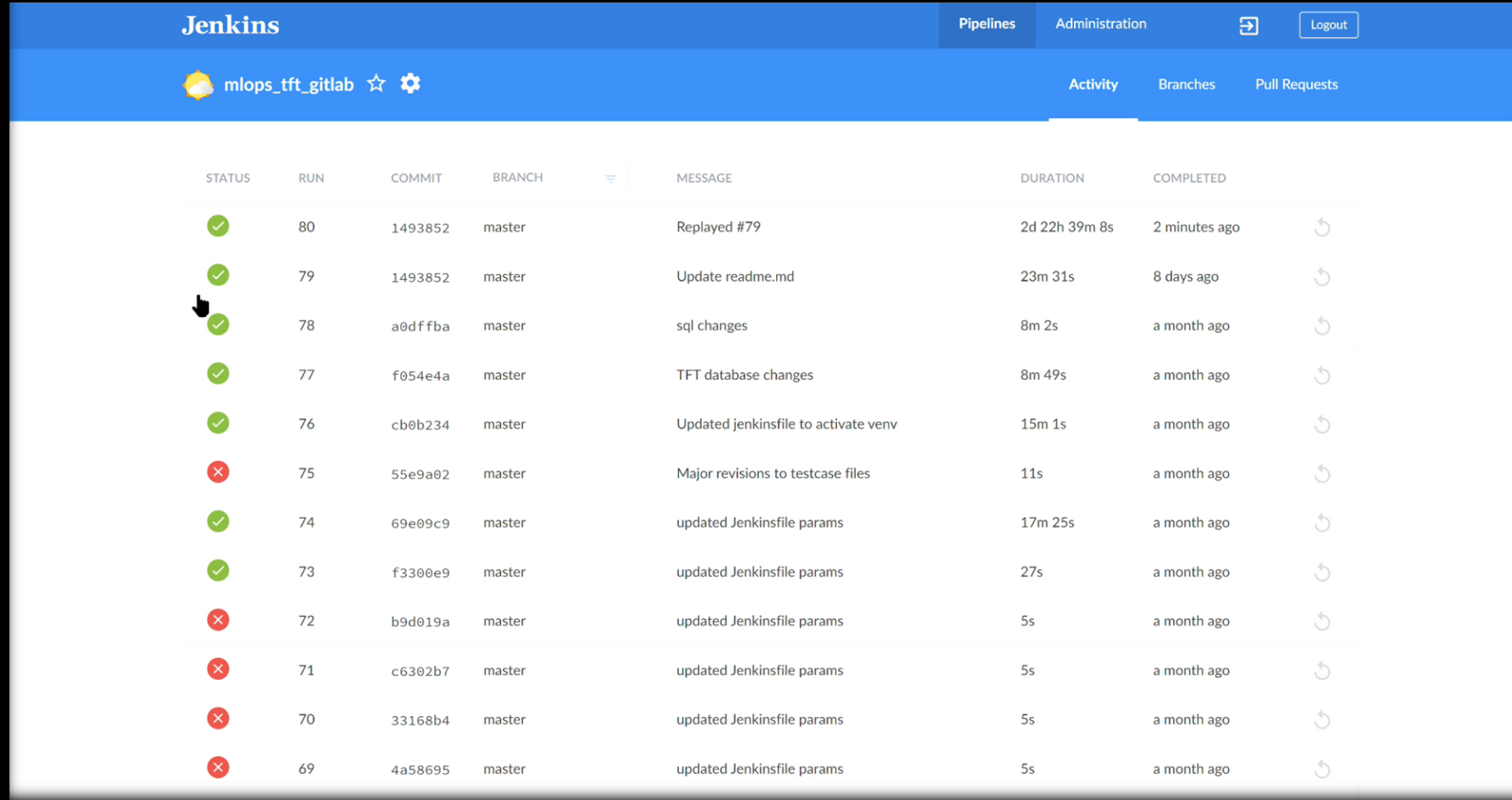
FCR-N market

MLOps pipeline



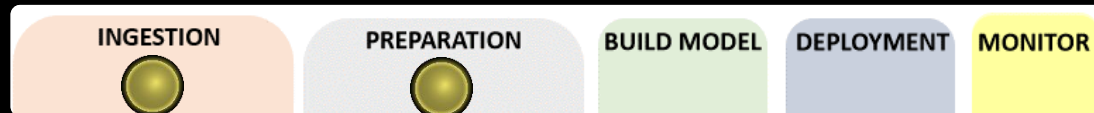
MLOps for FCR-N market forecasting

Ingestion, Preparation



The screenshot shows the Jenkins web interface for a project named 'mlops_tft_gitlab'. The top navigation bar includes 'Pipelines', 'Administration', and a 'Logout' button. Below the navigation, there are tabs for 'Activity', 'Branches', and 'Pull Requests'. The main content area displays a table of pipeline runs with the following columns: STATUS, RUN, COMMIT, BRANCH, MESSAGE, DURATION, and COMPLETED. A mouse cursor is pointing at the third row of the table.

| STATUS | RUN | COMMIT | BRANCH | MESSAGE | DURATION | COMPLETED |
|--------|-----|---------|--------|--------------------------------------|---------------|---------------|
| ✓ | 80 | 1493852 | master | Replayed #79 | 2d 22h 39m 8s | 2 minutes ago |
| ✓ | 79 | 1493852 | master | Update readme.md | 23m 31s | 8 days ago |
| ✓ | 78 | a0dfbba | master | sql changes | 8m 2s | a month ago |
| ✓ | 77 | f054e4a | master | TFT database changes | 8m 49s | a month ago |
| ✓ | 76 | cb0b234 | master | Updated jenkinsfile to activate venv | 15m 1s | a month ago |
| ✗ | 75 | 55e9a02 | master | Major revisions to testcase files | 11s | a month ago |
| ✓ | 74 | 69e09c9 | master | updated Jenkinsfile params | 17m 25s | a month ago |
| ✓ | 73 | f3300e9 | master | updated Jenkinsfile params | 27s | a month ago |
| ✗ | 72 | b9d019a | master | updated Jenkinsfile params | 5s | a month ago |
| ✗ | 71 | c6302b7 | master | updated Jenkinsfile params | 5s | a month ago |
| ✗ | 70 | 33168b4 | master | updated Jenkinsfile params | 5s | a month ago |
| ✗ | 69 | 4a58695 | master | updated Jenkinsfile params | 5s | a month ago |

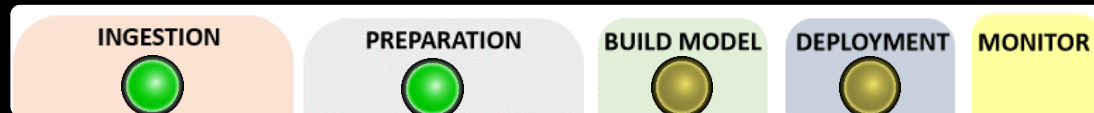


MLOps for FCR-N market forecasting

Build model, Deploy

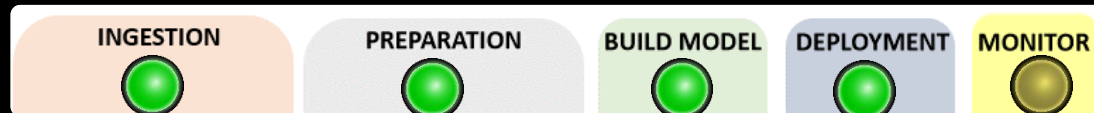
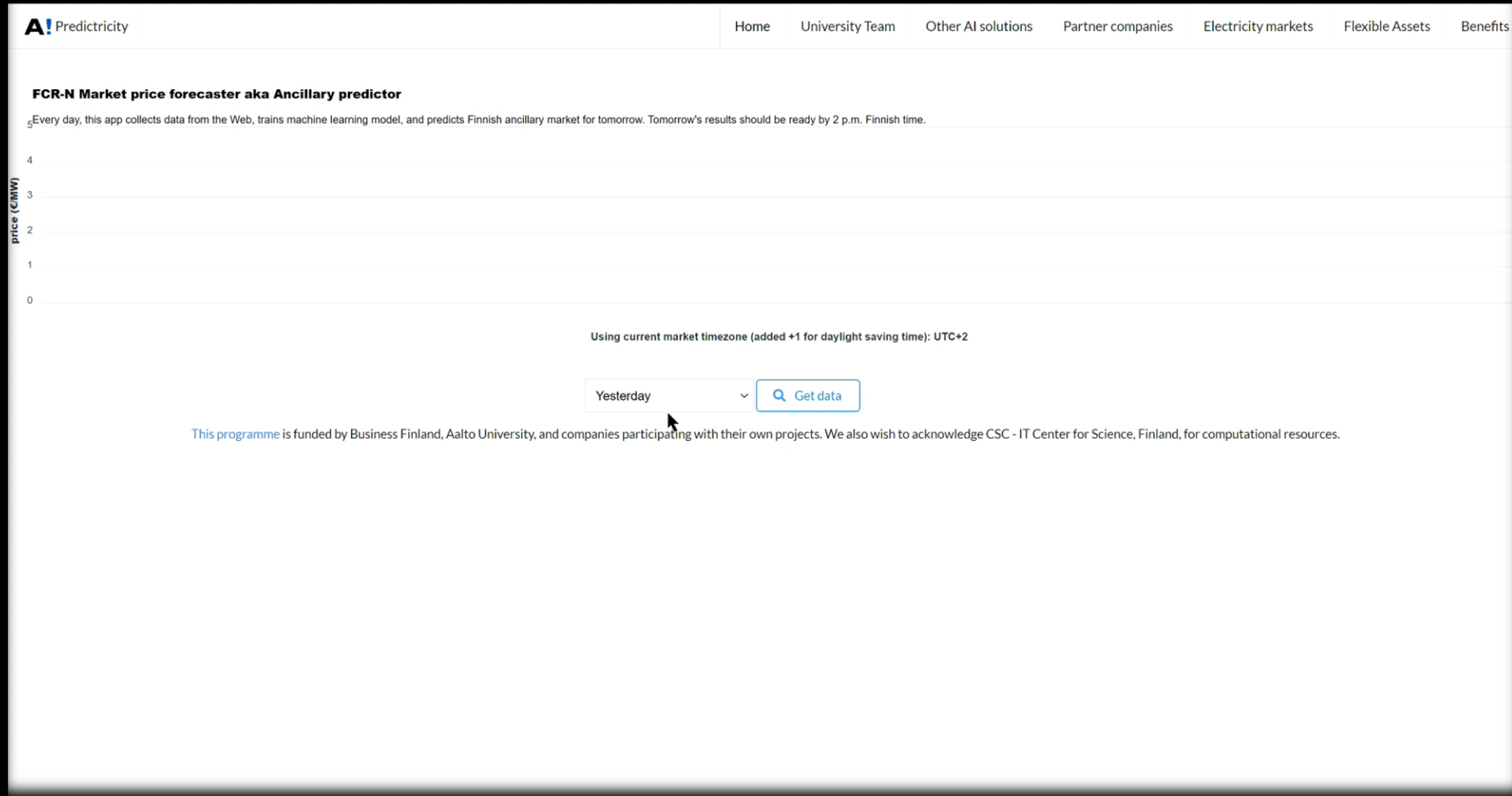
The screenshot displays the mlflow web interface. The top navigation bar includes 'mlflow', 'Experiments', 'Models', 'GitHub', and 'Docs'. The main content area is titled 'From CSC VM' and shows 'Experiment ID: 1'. Below this, there are controls for 'Notes', 'Showing 8 matching runs', and a toolbar with buttons for 'Refresh', 'Compare', 'Delete', 'Download CSV', and a 'Start Time' dropdown. A search bar contains the query 'metrics.rmse < 1 and params.model = "tree"'. Below the search bar is a table of runs with columns for 'Start Time', 'Duration', 'Run Name', 'User', 'Source', 'Version', 'Models', 'best_score', 'restored_epoch', and 'sto'. The table lists 8 runs, with the first five having a 'best_score' and the last two having a 'sto' value of '-'. A 'Load more' button is visible at the bottom of the table.

| | Start Time | Duration | Run Name | User | Source | Version | Models | best_score | restored_epoch | sto |
|--------------------------|-------------|----------|----------|----------------|--------------|---------|---------|------------|----------------|-----|
| <input type="checkbox"/> | 2 days ago | 3.3min | - | jenkins | tft_forecast | 149385 | pytorch | 1.564 | 0 | 1 |
| <input type="checkbox"/> | 7 days ago | 7.8min | - | jenkins | tft_forecast | 149385 | pytorch | 1.774 | 3 | 4 |
| <input type="checkbox"/> | 25 days ago | 4.3min | - | jenkins | tft_forecast | a0dffb | pytorch | 1.964 | 1 | 2 |
| <input type="checkbox"/> | 1 month ago | 7.1min | - | jenkins | tft_forecast | f054e4 | pytorch | 1.707 | 3 | 4 |
| <input type="checkbox"/> | 1 month ago | 7.1min | - | jenkins | tft_forecast | cb0b23 | pytorch | 1.659 | 3 | 4 |
| <input type="checkbox"/> | 1 month ago | 0.8s | - | Rakshith Su... | tft_forecast | 69e09c | - | - | - | - |
| <input type="checkbox"/> | 1 month ago | 2.4s | - | Rakshith Su... | tft_forecast | 69e09c | - | - | - | - |
| <input type="checkbox"/> | 1 month ago | 9.0min | - | jenkins | tft_forecast | 69e09c | pytorch | 1.847 | 4 | 5 |



MLOps for FCR-N market forecasting

Monitor



Thank you