HeatCast

Kognitive Energiesysteme

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Temporal Fusion Transformer (TFT) were investigated to be used in time-series forecasting for several use cases in the energy context within the Competence Center for Cognitive Energy Systems. The project **HeatCast** evaluated whether TFT are suitable to forecast electricity and hot/cold water consumption of a manufacturing plant.

These forecasts offer the possibility to adjust the control of electricity and hot/cold water consumption resulting in reduced electricity and cooling water consumption and thus lower CO_2 emissions. This study shows a comparison of forecasts computed with both Extreme Learning Machines (ELMs) and TFT.

TFT (Temporal Fusion Transformer)

- Based on the principles of Transformer Networks and optimized for time-series forecasting
- Additional to NWP forecasts, known future information such as day-of-week, time-of-day, the position of the sun, and production targets can be incorporated into the forecast -> temporal patterns can be better identified
- In addition to the heterogeneous utilization of input data, the TFT also offers the possibility of
  - multiple-horizon forecasts and
  - probabilistic forecasts.

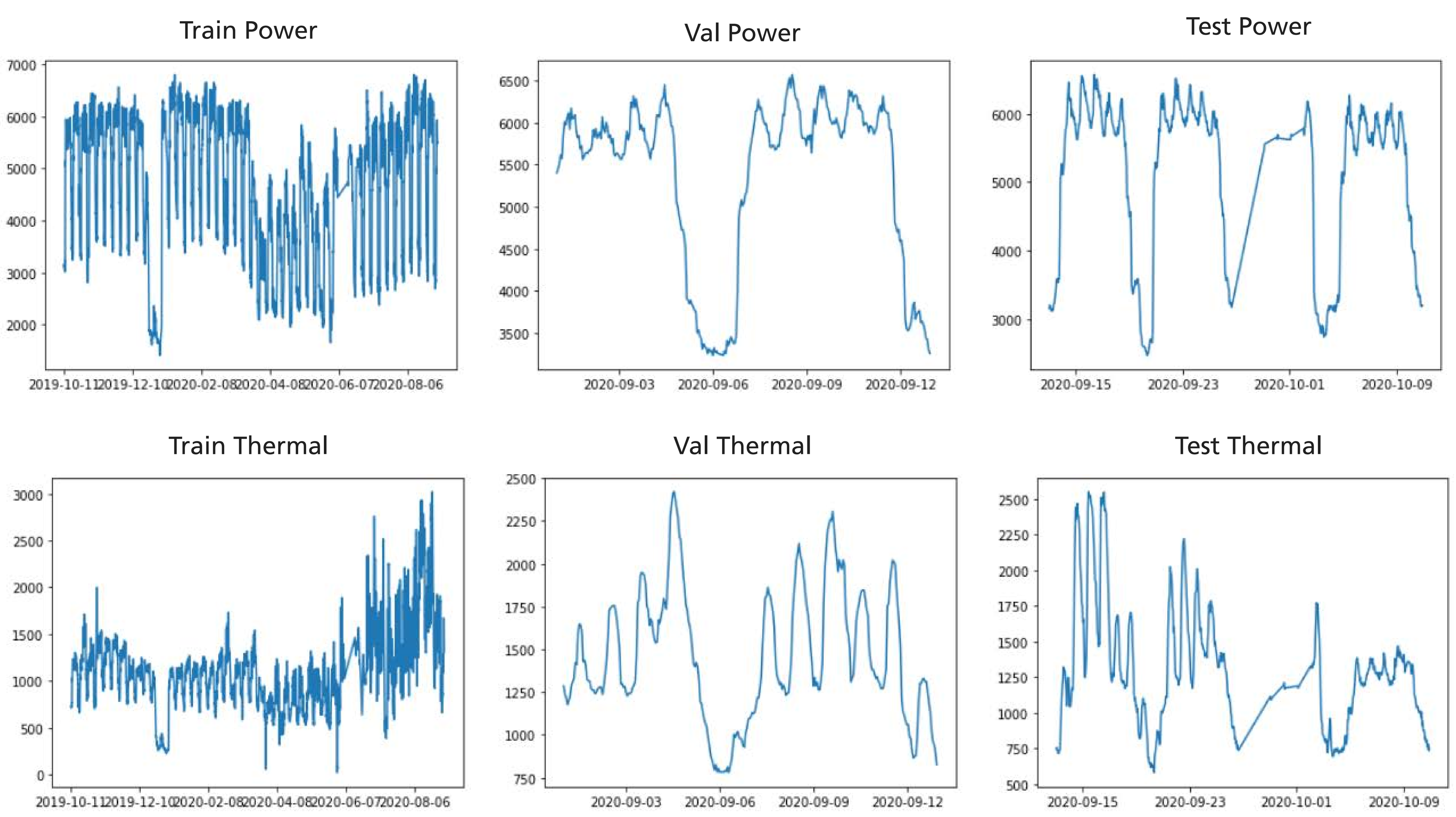

Figure 1: Plotting of time series.
Target data: training, validation and test period for power (top) and heat consumption (bottom)

Model Inputs

- Historical heat and power consumption time-series
- NWP parameter (wind-speed and direction, temperature, irradiance, …)
- Lags and leads of parameters
- Known future information
  - Categorical variables (time-of-day, day-of-week, …)
  - Position of the sun
  - Production targets

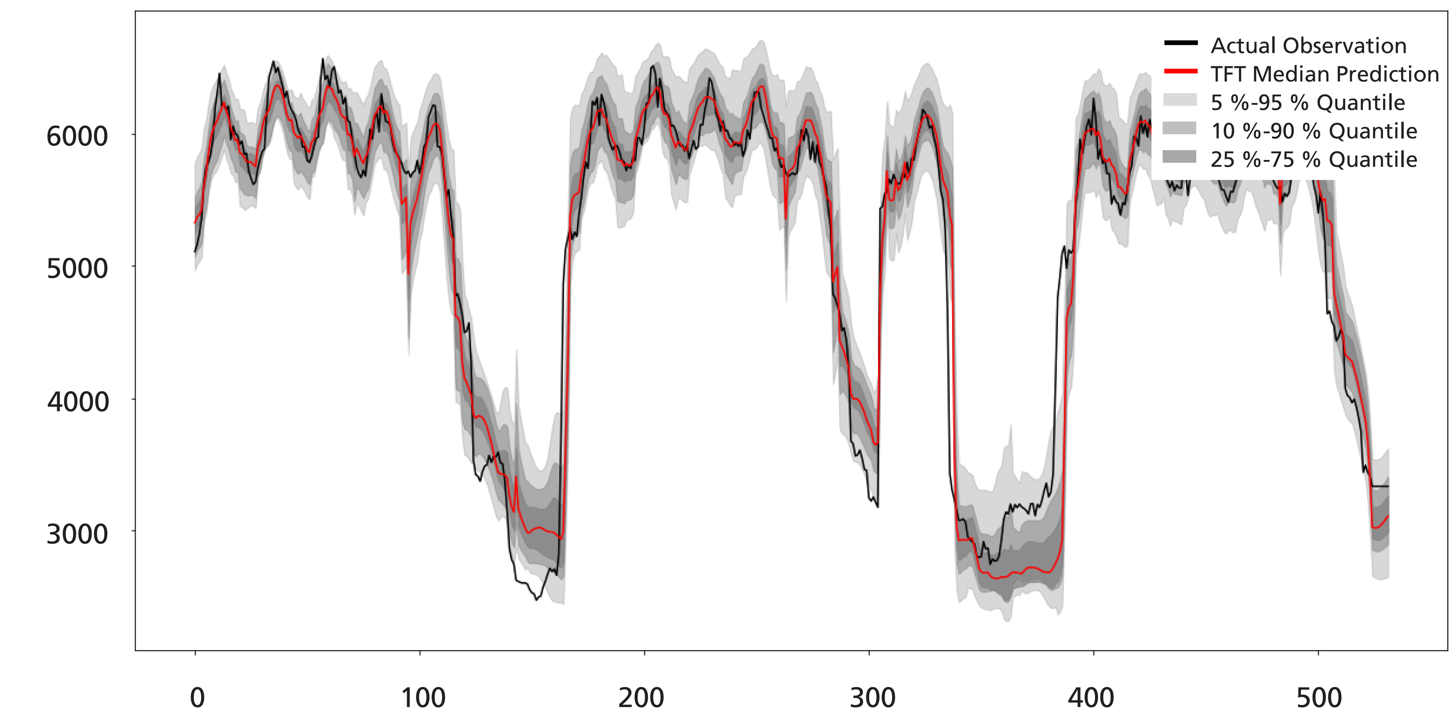

Figure 2: Probabilistic forecast example for power consumption

Results

Performance

- Power demand
  - Performance of TFT a lot better for both MAE and RMSE
- Heat demand
  - ELM and TFT with similar MAE
  - RMSE of ELM lower
- Differences nearly constant over forecast horizon

Feature importance

- Helps to explain the model and analyze the problem
- Helpful to reduce the number of input features
  - Required training period reduced
  - Reduction of training time
  - Better performance

Additional findings

- Multi-horizon forecasting trade-off between model reduction and performance
- Training-time of TFT magnitudes longer (GPU vs. CPU)
- TFT needs a lot of training data
- Probabilistic optimization reduces RMSE in some cases compared to the RMSE optimization
- Probabilistic forecasts reflect uncertainties very well
- Corona restrictions affected production a lot in the spring of 2020; the data could be used nevertheless

Conclusion

The results show that both methods (ELM/TFT) are suitable to forecast electricity consumption, as well as hot/cold water consumption. However, the forecast behavior differs and the methods have both advantages and disadvantages. With the used data at hand, the TFT model can not be recommended without restrictions for all problems within time-series forecasting. But the possibility to examine (to some extent) the feature importance (over time) within the TFT opens up further interesting findings.

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