

Machine Learning Methods for Automated Fuel Cell Monitoring

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Introduction

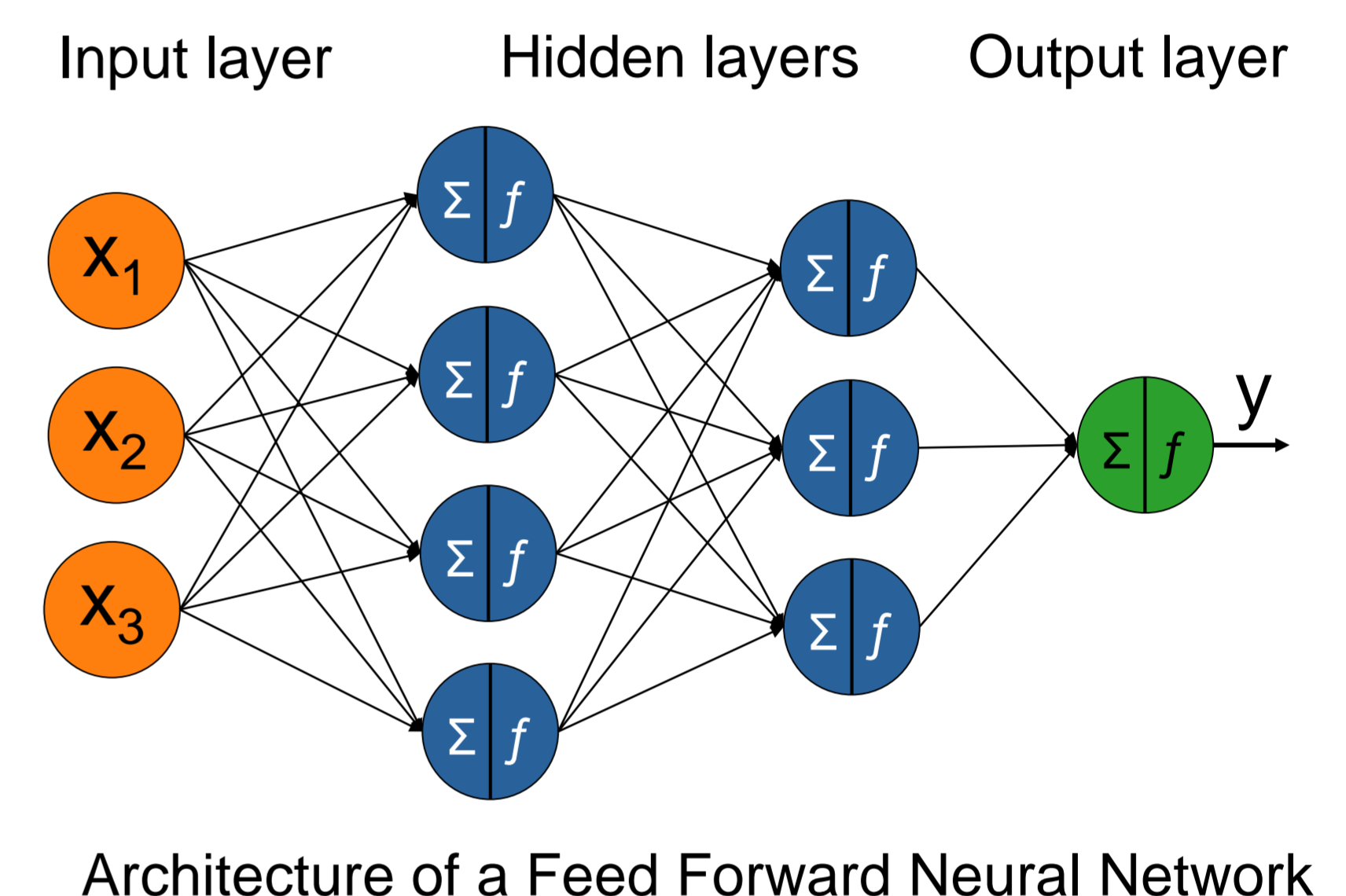
- Fuel cells on test stations are monitored using constant alarm thresholds
- Detection of errors with little or delayed impact on the fuel cell's performance is impossible due to widespread operation range
- Too sensitive alarm thresholds may interrupt tests, especially during transient operation

Objective

- Development of machine learning based approaches to monitor the operation and testing of fuel cells stacks on test stations

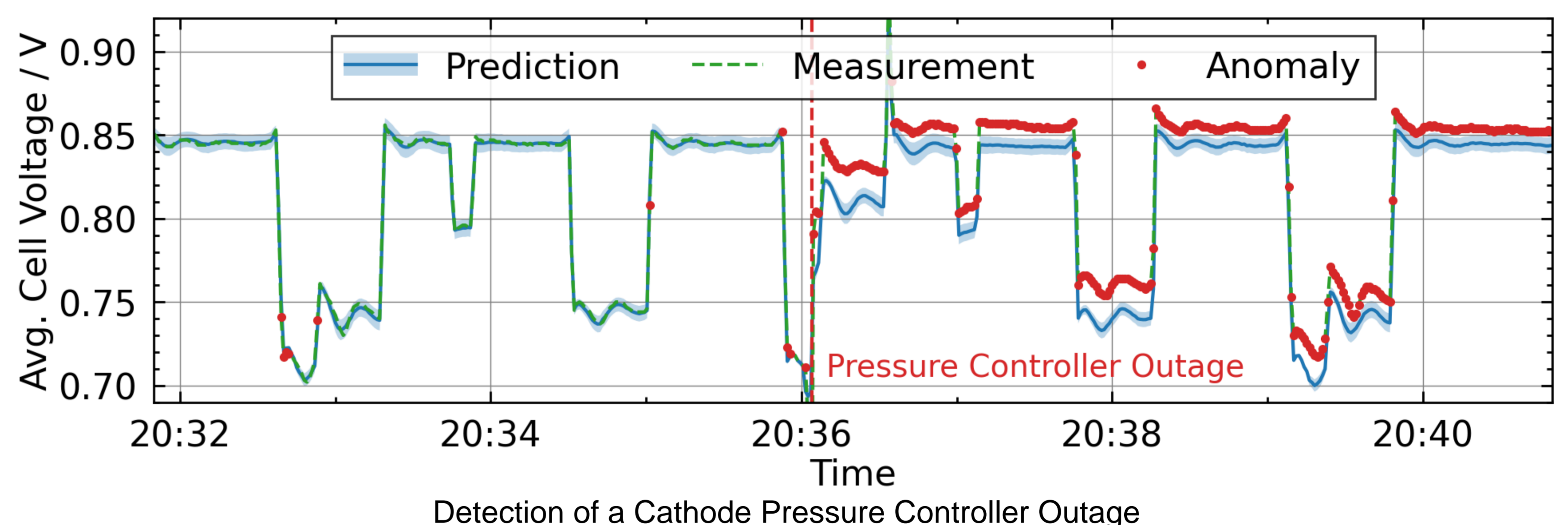
Approach

- An Artificial Feed Forward Neural Network (FF-NN) as shown on the right is trained as a fuel cell model to predict the stack's cell voltage based on current, stoichiometry, anode & cathode gas temperature & pressure, dew point, coolant flow & temperature
- A second FF-NN is trained as an error model (assuming a Gaussian error) to estimate the fuel cell model's prediction confidence using the same input parameters
- The deviation of the predicted and the measured cell voltage in relation to the confidence is a probabilistic indicator for anomalies in the measurement



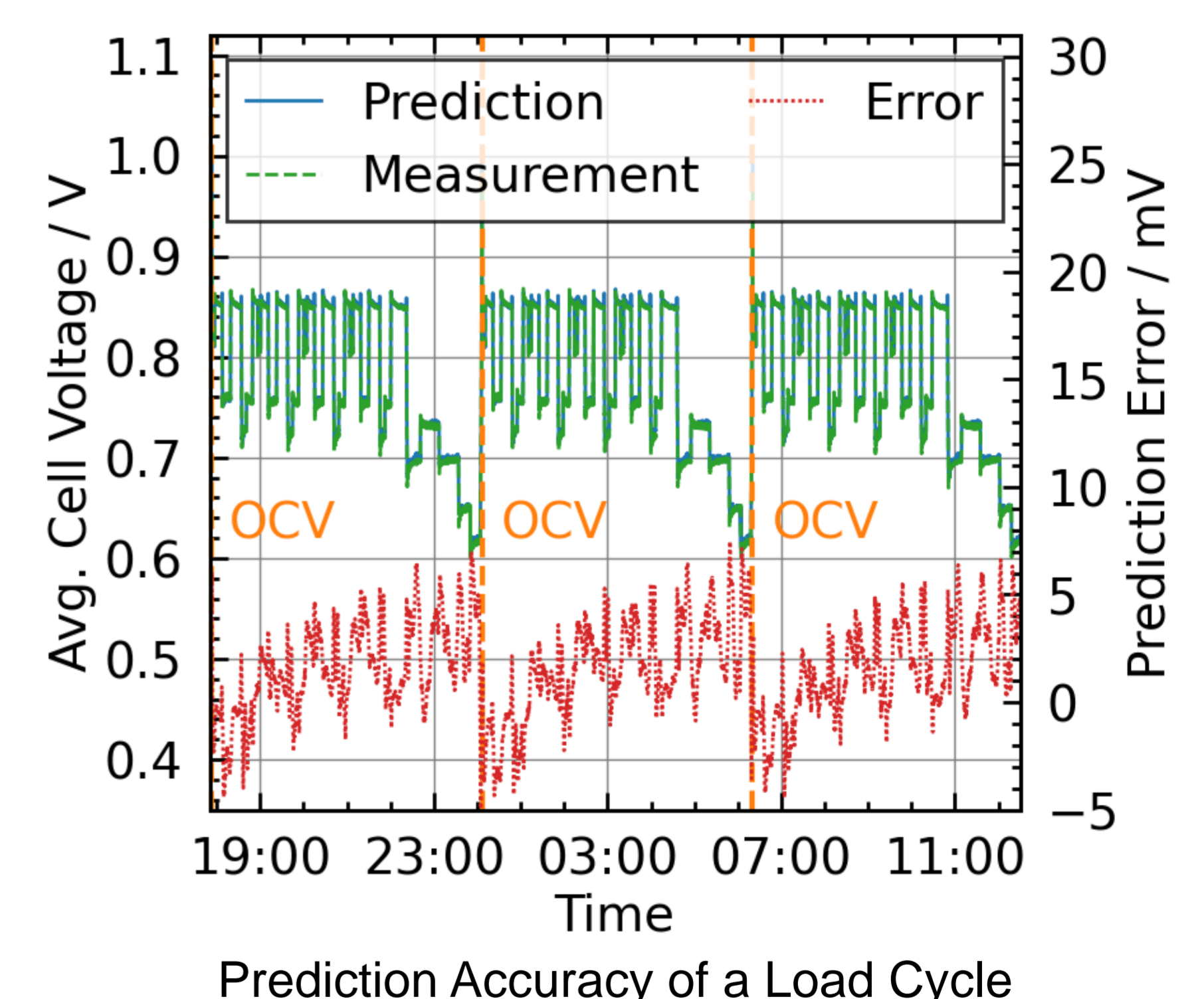
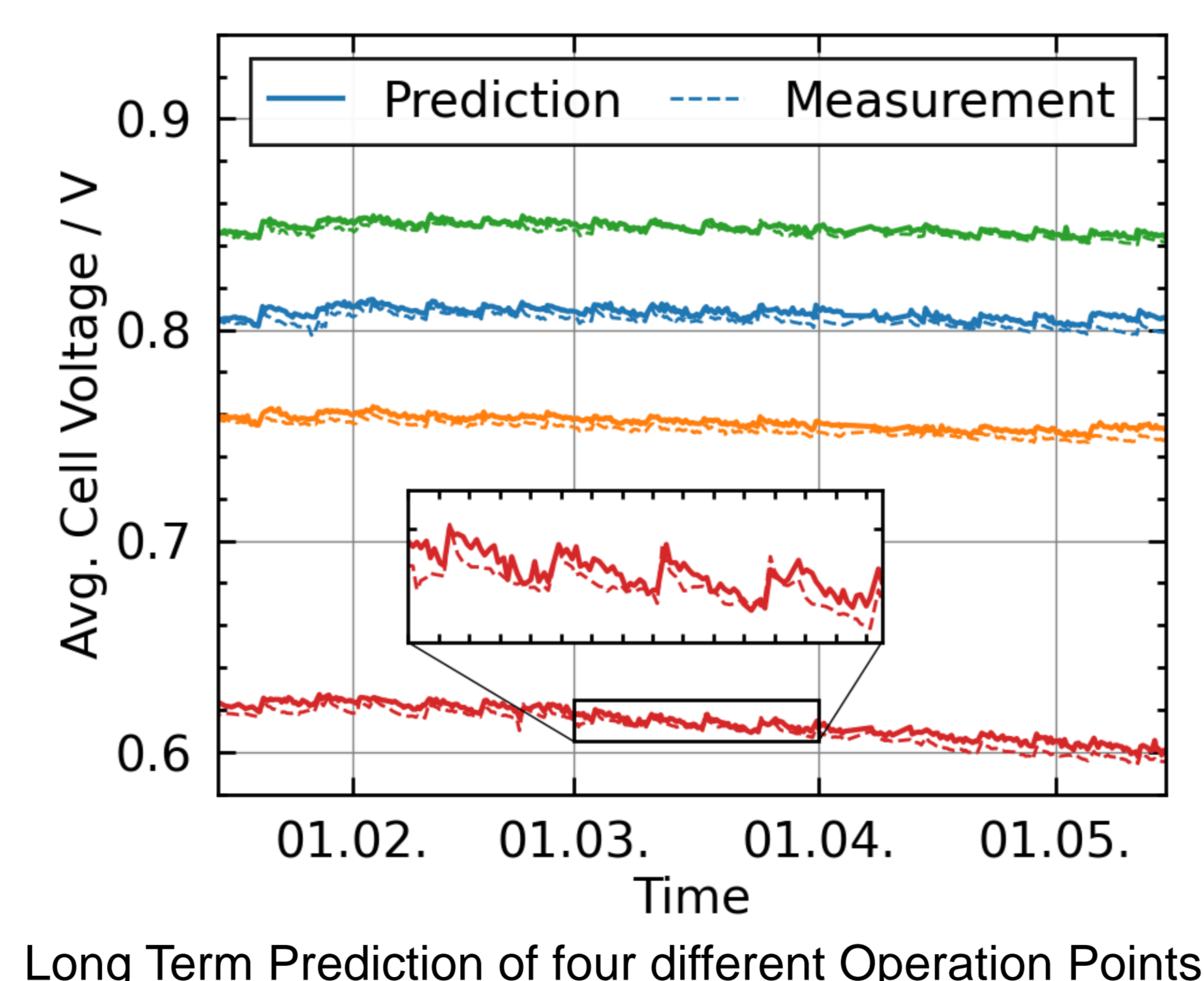
Short Term Prediction

- Anomaly (prediction vs. measurement) due to a temporary pressure controller outage causing a cathode starvation
- 3 h training data, 2.5 mV RMS error
- Anomaly detected with 99.99% confidence
- Singular False-positives on transients



Long Term Prediction

- Additional input features: Operating time, time since last restart and operation point dwell time
- 4300 h training data, 8.4 mV RMS error
- Accurate prediction of reversible and irreversible cell voltage degradation (saw tooth profile in the left plot)
- OCV-recovery is not captured yet (change of error in the right plot)



Conclusion

- During fuel cell stack testing, FF-NN are able to detect errors which were undiscovered with conventional threshold monitoring
- The model must be able to capture four different time scales: overall irreversible degradation, recovery after shutdown, settling time after change of operating conditions and controller oscillations
- FF-NN is able to model time scales if they are parametrized as features, consequently FF-NN must be enabled to learn which events have to be remembered

Outlook

- Introduction of local history as feature
- Investigation of Long Short-Term Memory Neural Networks (WIP)
- Application of clustering methods to monitor operating conditions
- Development of an automated monitoring-framework