



# Combined Cycle Plant Duct Burner Optimization Using ProcessLink

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- NeuCo has been optimizing processes in coal plants for a long time
- Conversations with friends and customers at Combined Cycle (CC) plants suggested that it could be useful in those as well



# The Project

# Independence Station

- Oswego, NY
- 1000 MW Total Capacity
- 2 x 2on1 CC
- GE Units with STAG 207FA (165 MW) GTs
- Vogt HRSGs and BOP controls
- Duct Burners add 88 MW of capacity
- Sell into the NYISO market
- Started bidding into Regulation Market 4 years ago

# Identified Optimization Opportunities

- Maximize plant capability for high Ramp-Rate (RR) Ancillary Services
  - Started development Jan 2013, deployed in closed-loop in Sept 2013. results evaluated.
- Optimize Dynamics of the Combined Cycle
- Enhance Day Ahead Capability Prediction and Provide Production Analytics
- Detect Analyze and Diagnose Anomalies and Changes
- GT Combustion Monitoring/Tuning
- Power Augmentation Management



# The Tools

# The ProcessLink Platform

## ProcessLink Studio™

Product Installation and Configuration Tools

Application Prototyping Tools

Application Deployment and Maintenance Tools

## End-User Interface

Optimizer Demystification Views

Benchmarking and Analysis Views

Alert Diagnosis and Management

## ProcessLink® Engine

Optimization services

Modeling services

Monitoring services

Neural Networks

Model Predictive Control (MPC)

1<sup>st</sup> Principles Models

AI Expert Systems

Plant I&C Systems Interfaces and Network (OPC, etc)





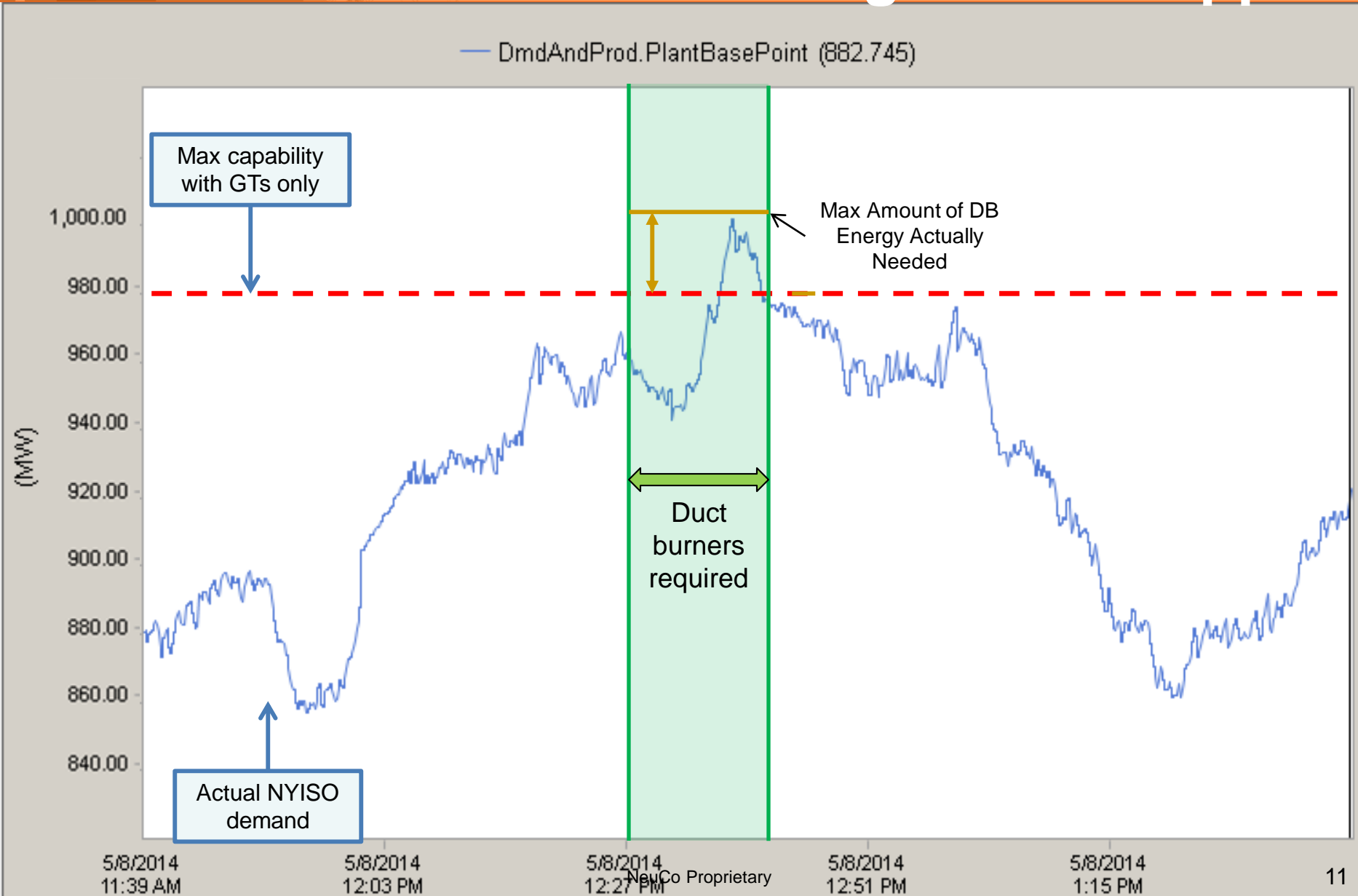


# Maximize Capability for High Ramp-Rate Ancillary Services

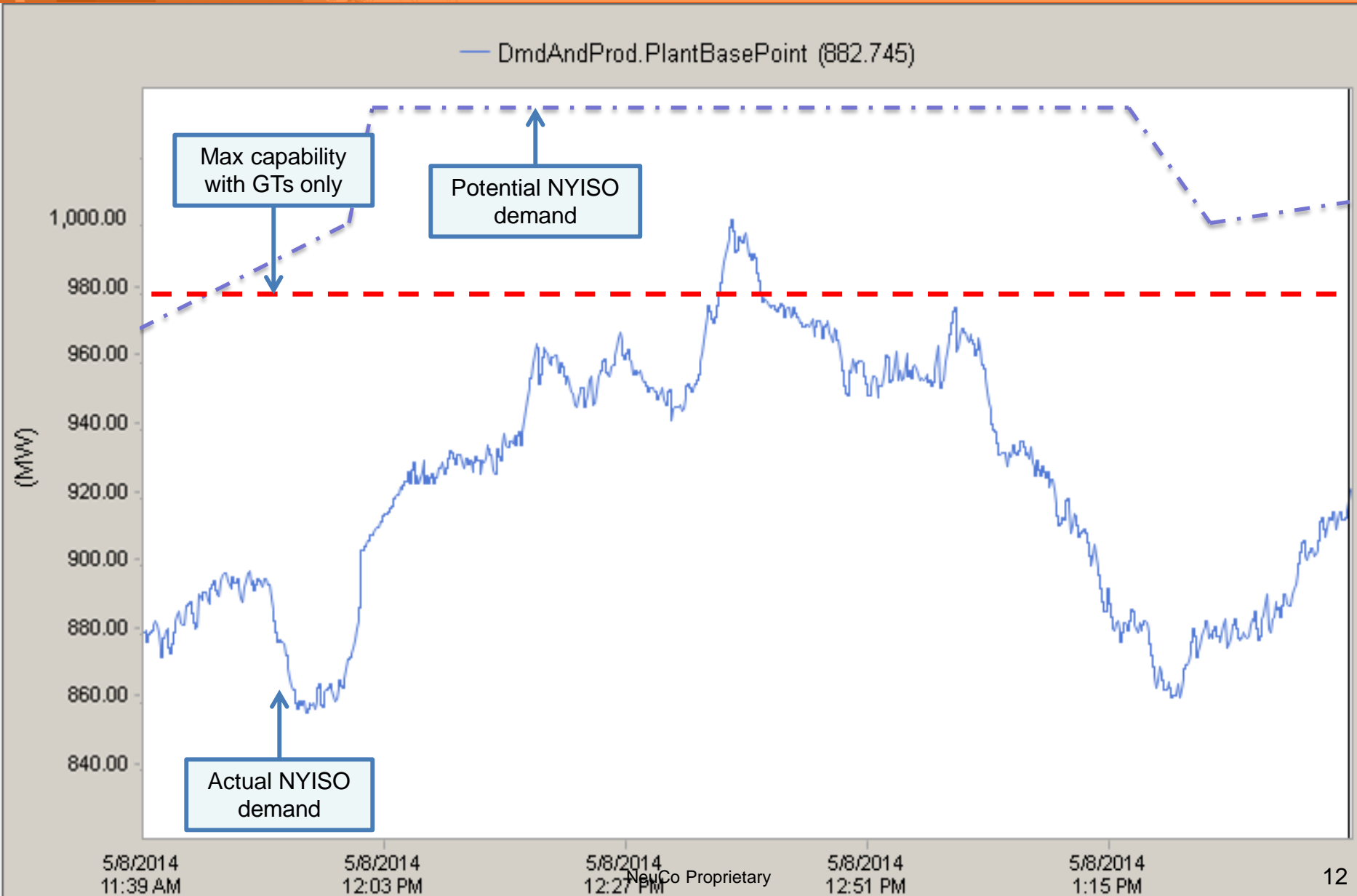
# The Challenge

- For Independence, bidding into the Ancillary Services Regulation Market is believed to have had a substantial positive revenue impact
- They bid 100 MW of ramp at 5MW/min (or 100MW over 20min) up to 1088 (all 1000 GTMW and 88 Duct Burner MW) into the Day Ahead Ancillary Service Regulation Capacity Market
- They can add the Duct Burners to free up some GT capacity in case they are asked to ramp at 5MW/minute all the way to 1088 (or plant max)
- But there is Heat Rate Penalty

# Optimal Use of Duct Burners for Regulation Support

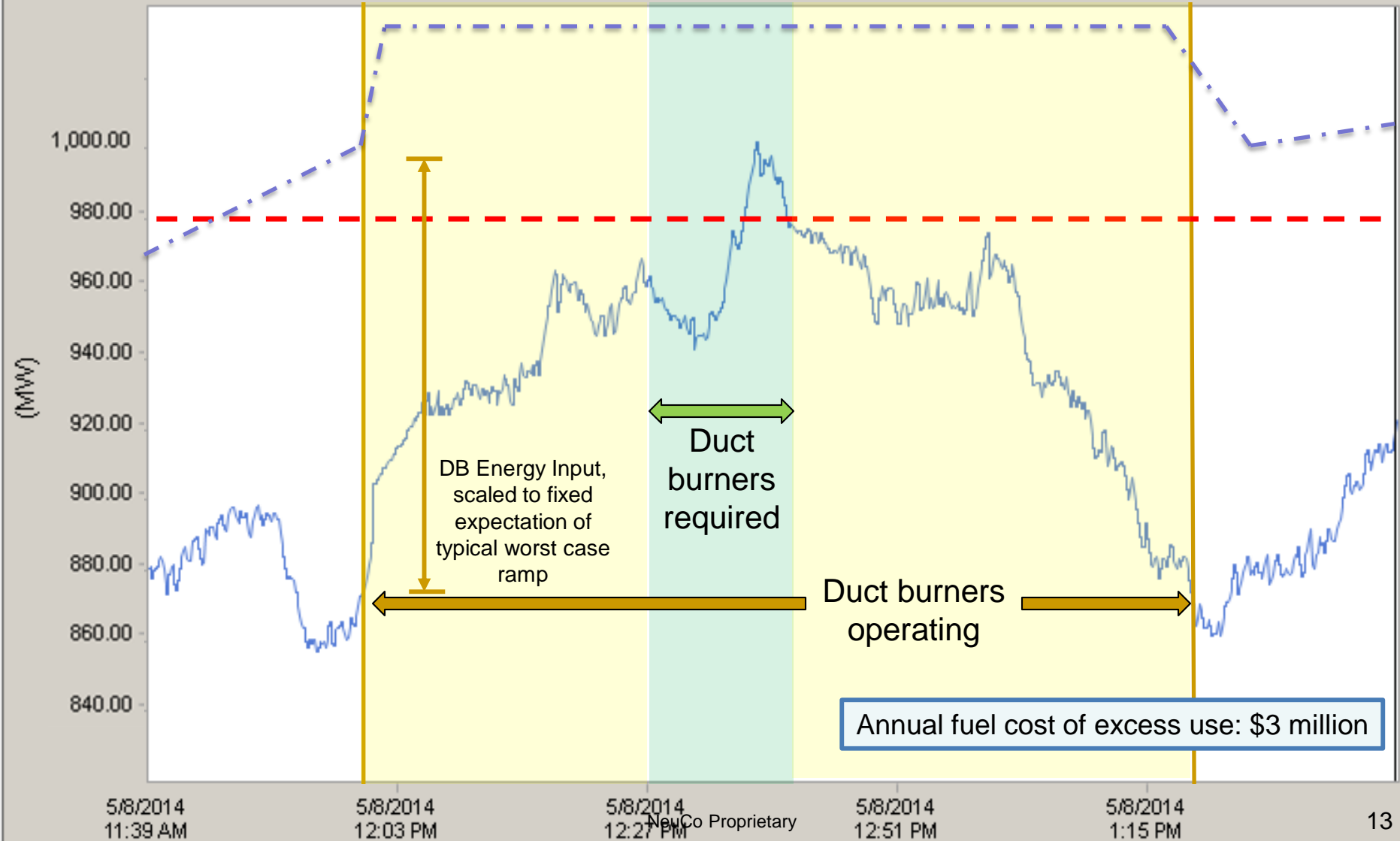


# Predicting Peak Output



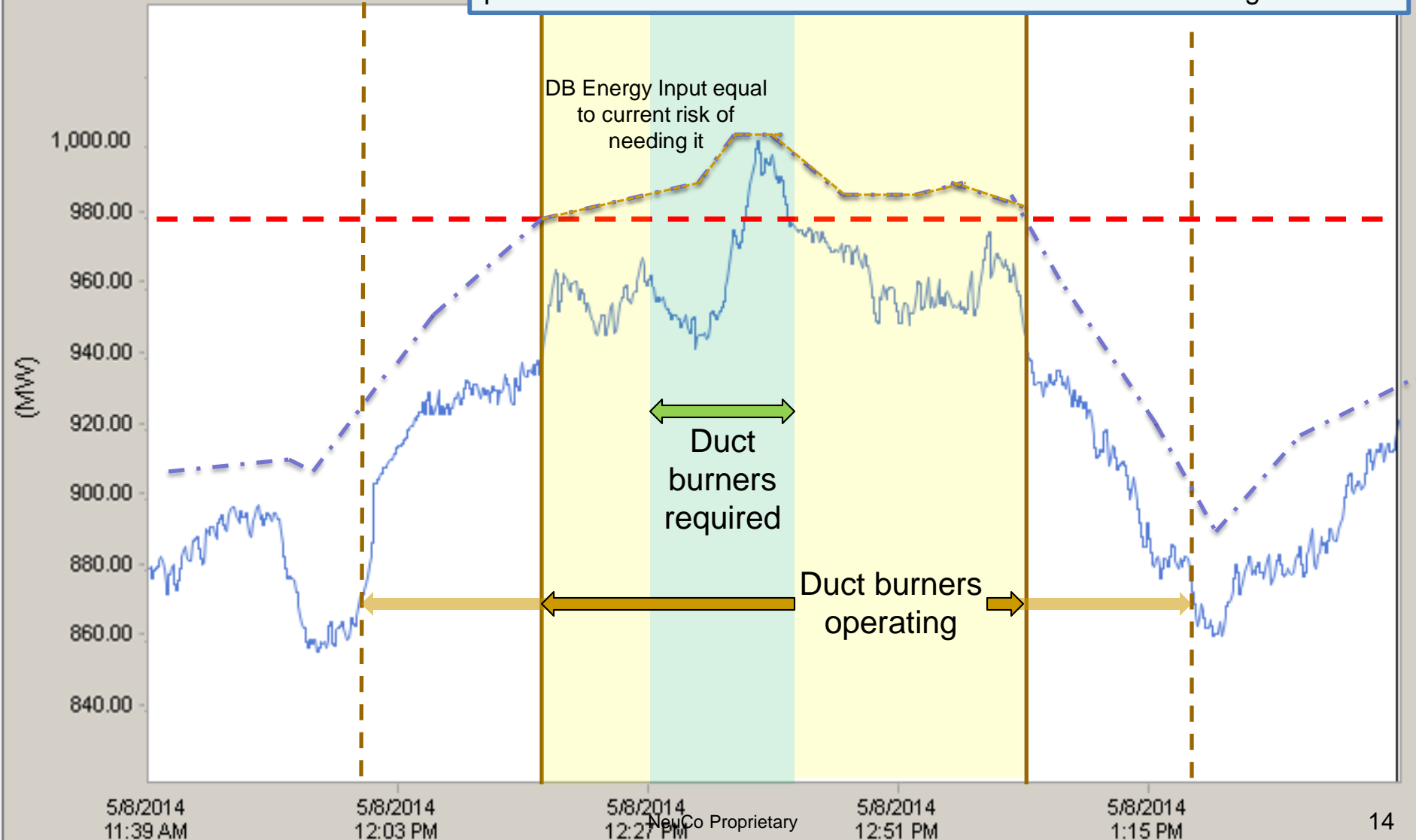
# Duct Burner Management Before Optimization

Duct burners were turned on when GT IGV angle  $> 74^\circ$

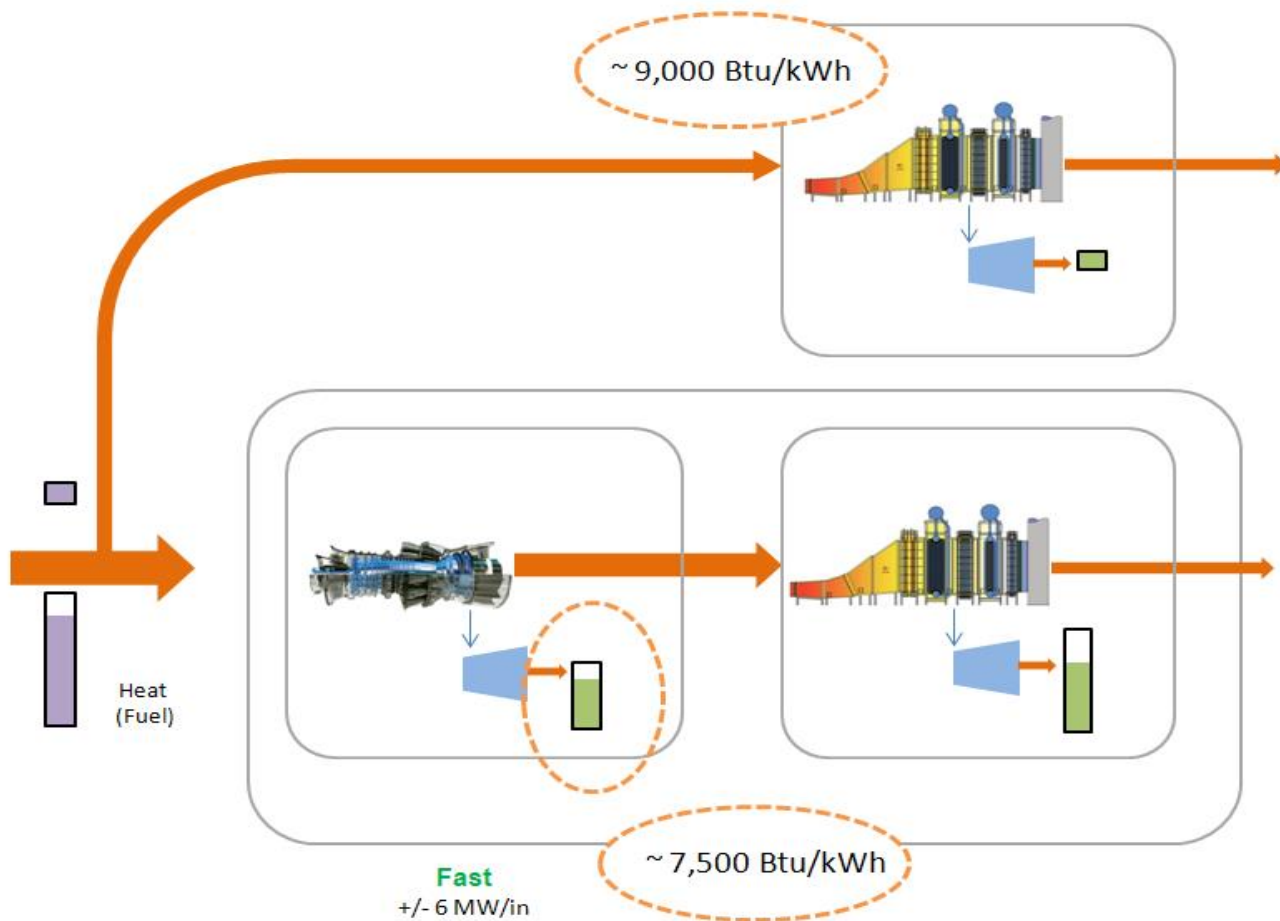


# Duct Burner Management After Optimization

Duct burners were turned on when predicted 30 minute max demand > 980 MWs and GT IGV angle > 74°



# HR vs. Ramp Rate Readiness

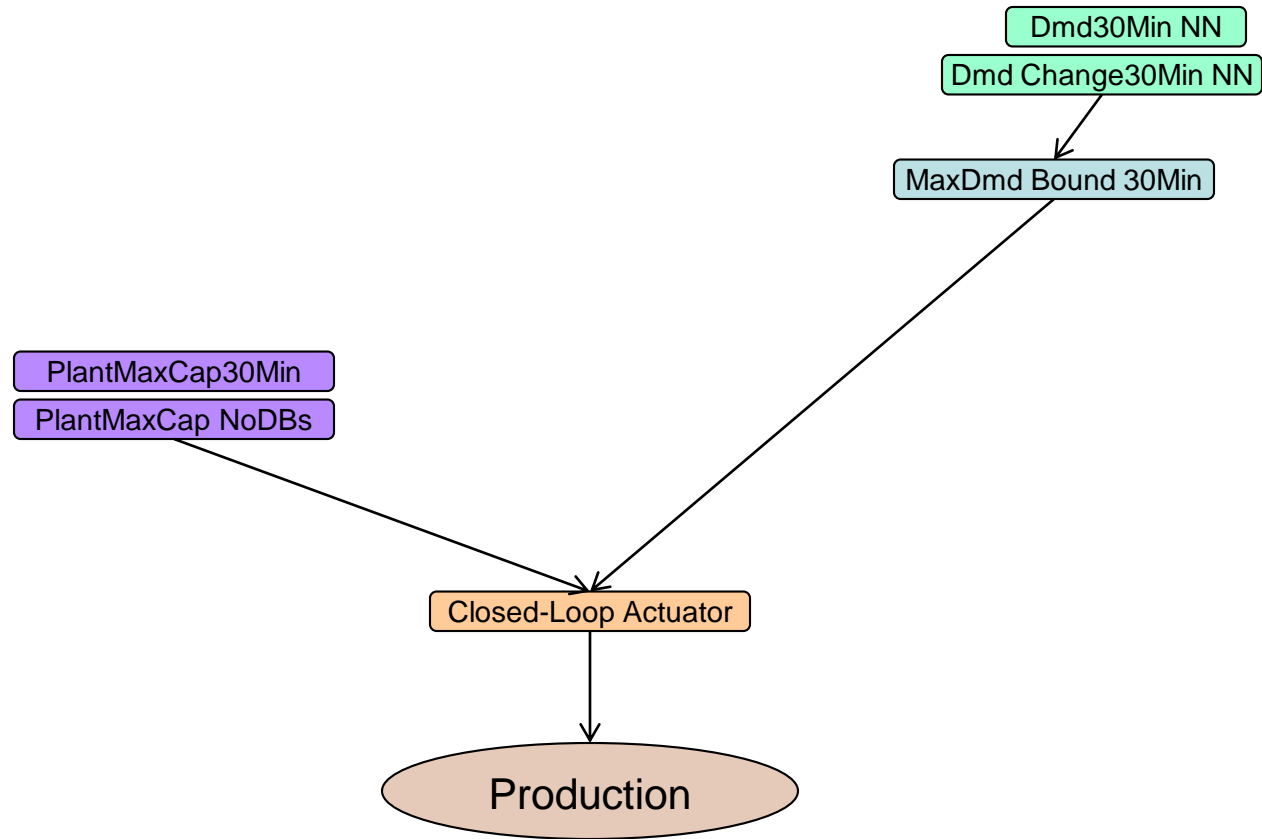


# How The Optimizer Works

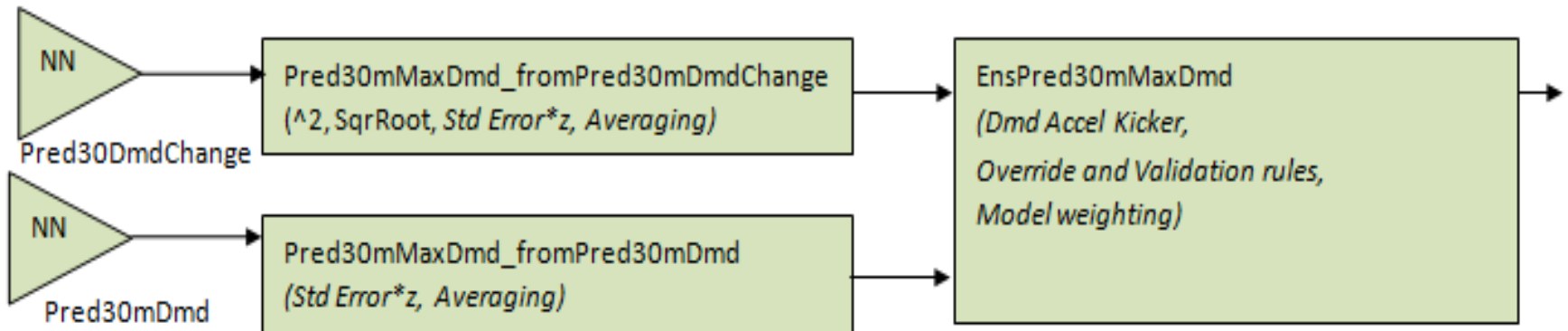
- Predicts maximum likely demand over the next 30 minutes
- Adds only enough Duct Burner fuel to offset shortfall in case of maximum likely demand
- Uses dynamic modeling to avoid over-shooting and under-shooting
- Predicts true combined cycle capability without duct burners in 30 minutes given current state and history
- Enables users to specify how certain they want to be that they'll meet demand



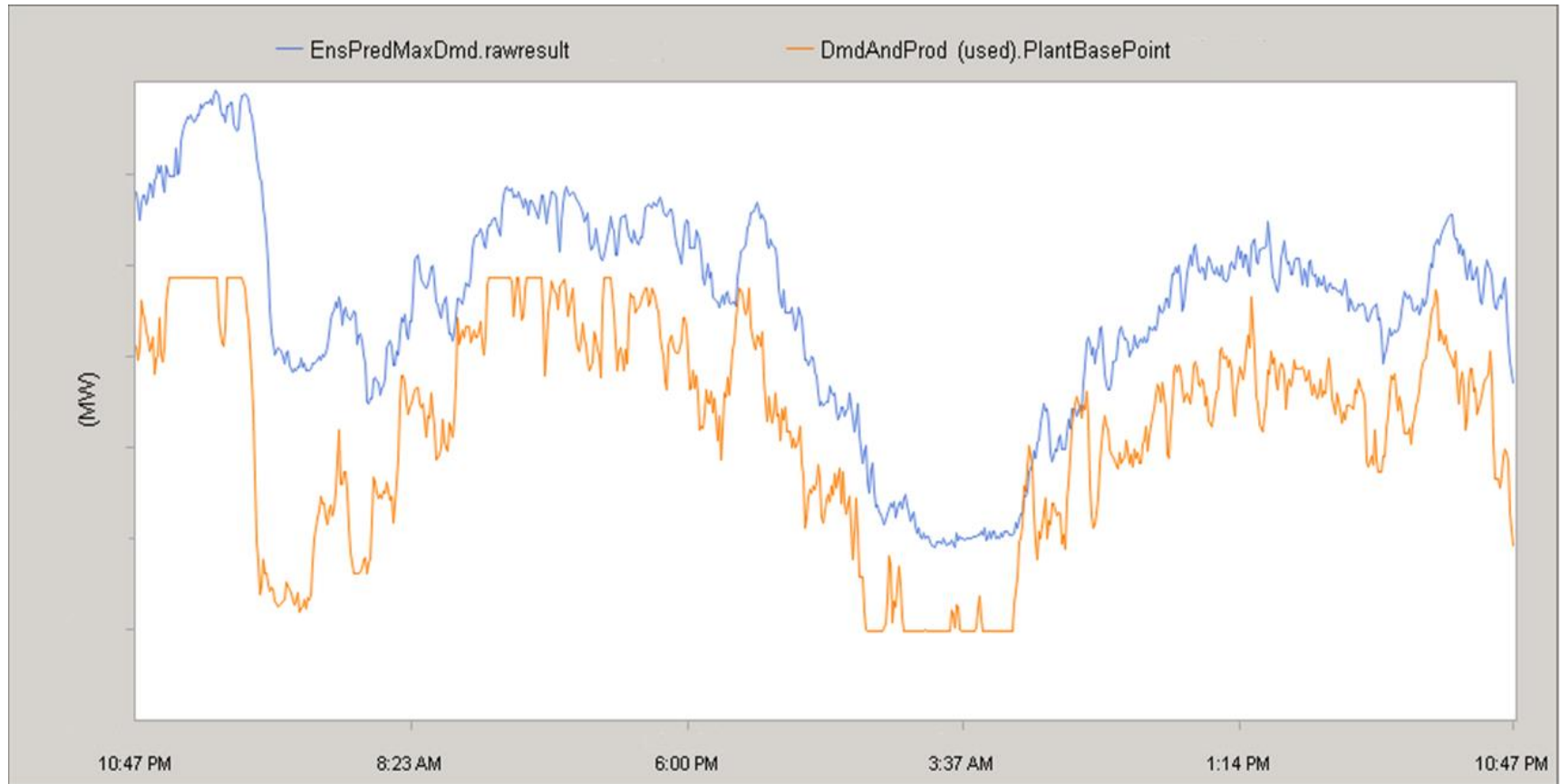
# Application Evolution



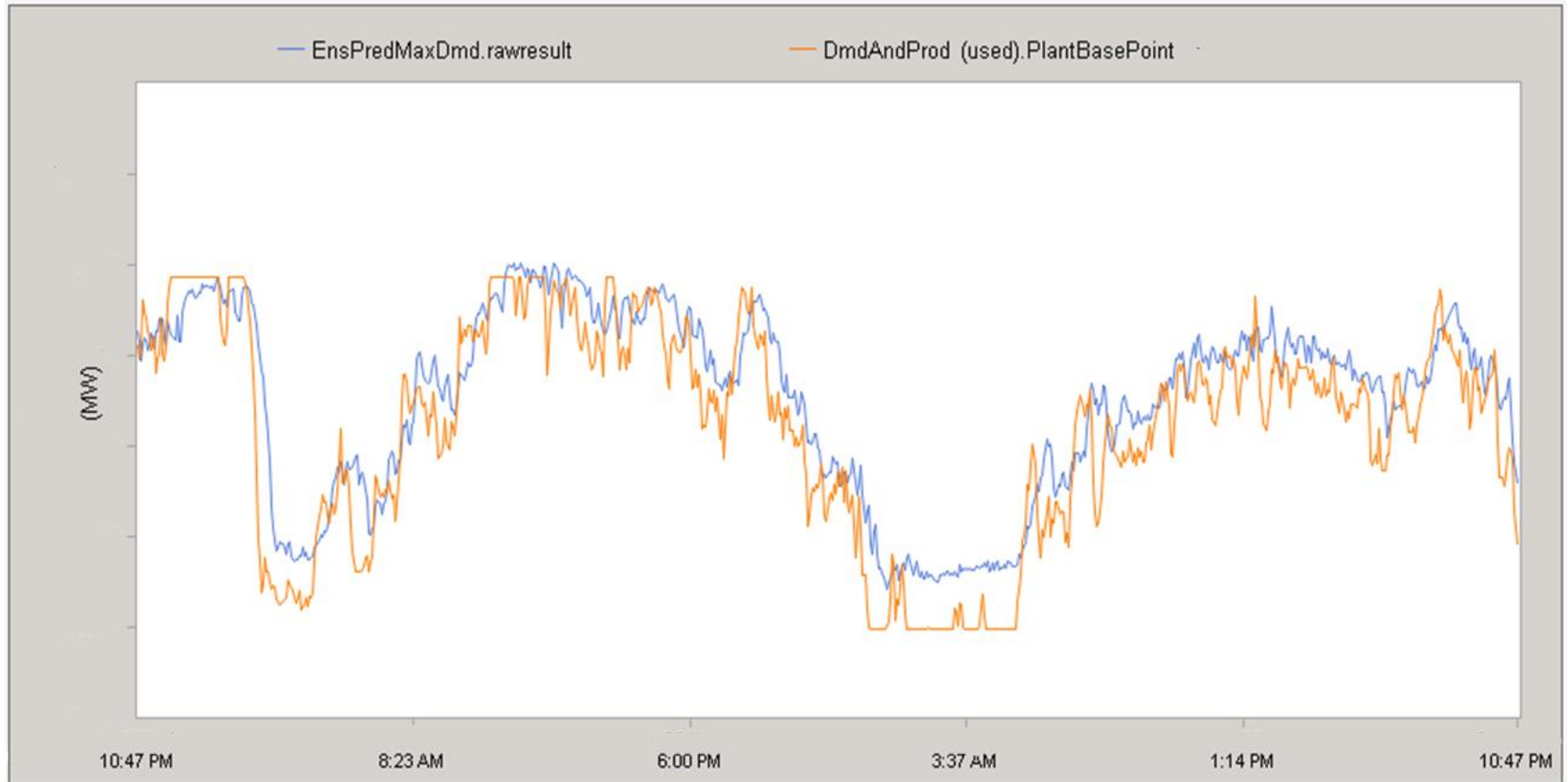
# Max Thirty Minute Demand Predictor (Model Ensemble)



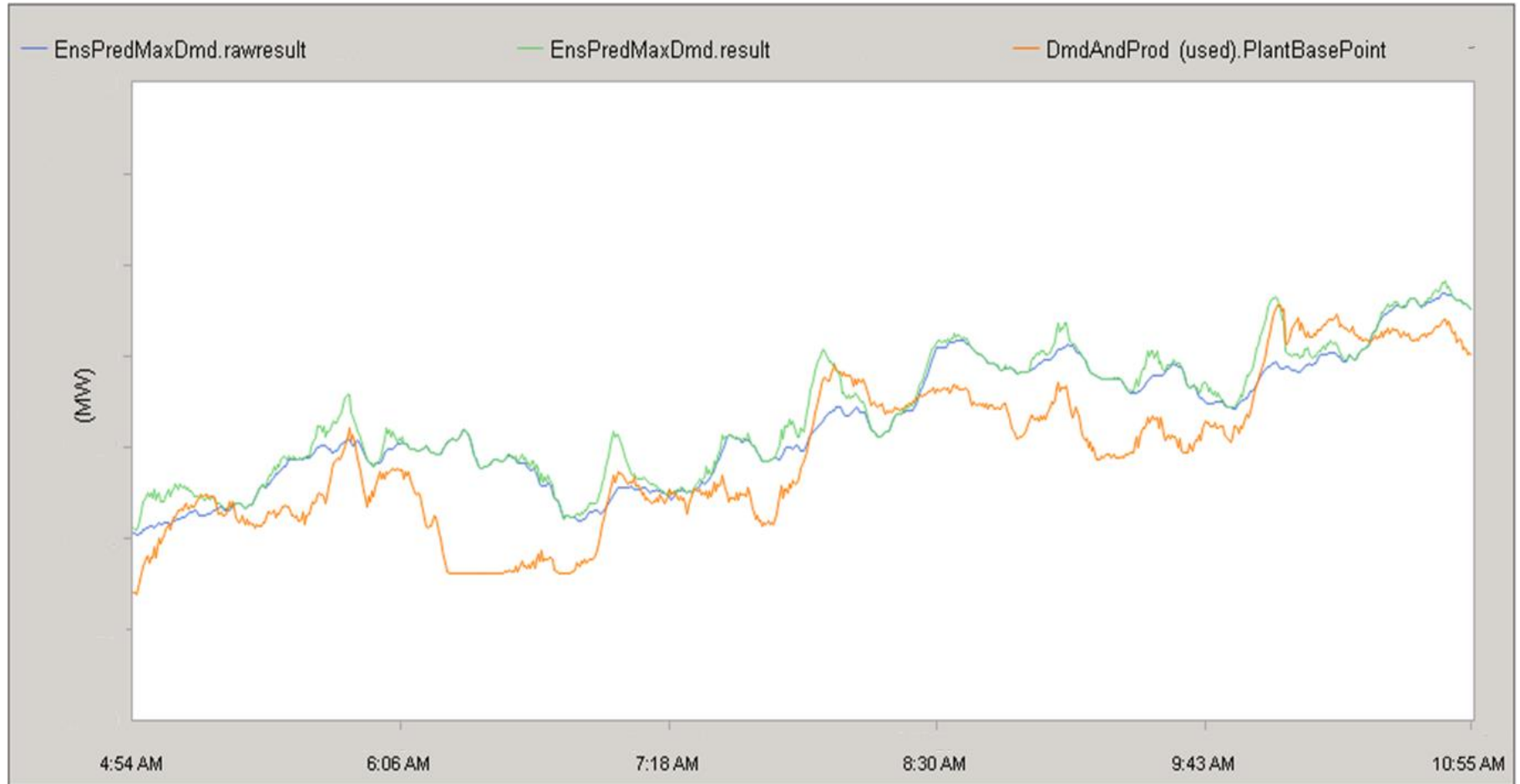
# Max Thirty Minute Demand Predictor (Conservatively tuned)



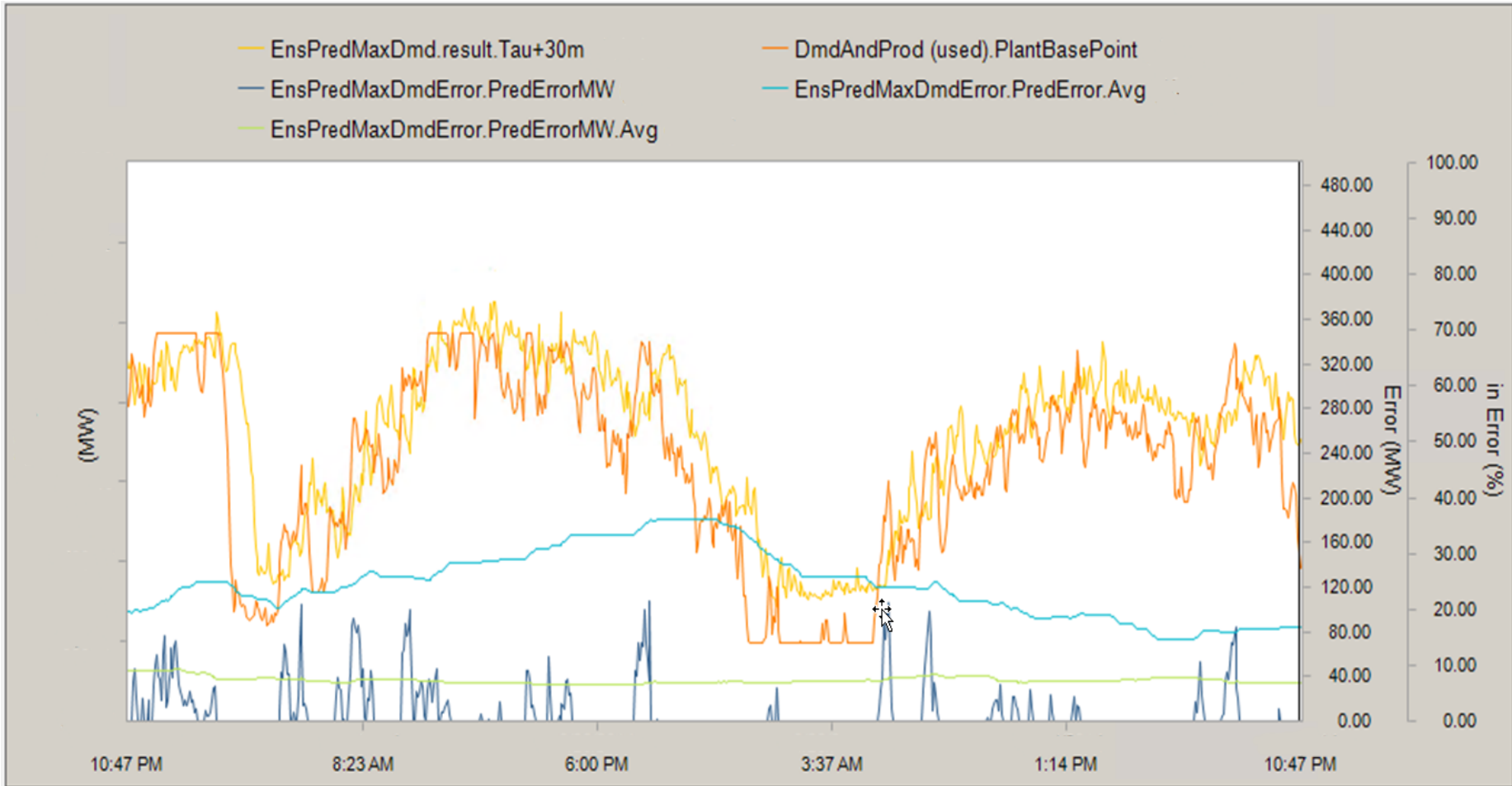
# Thirty Minute Max Demand Predictor (Aggressively tuned)



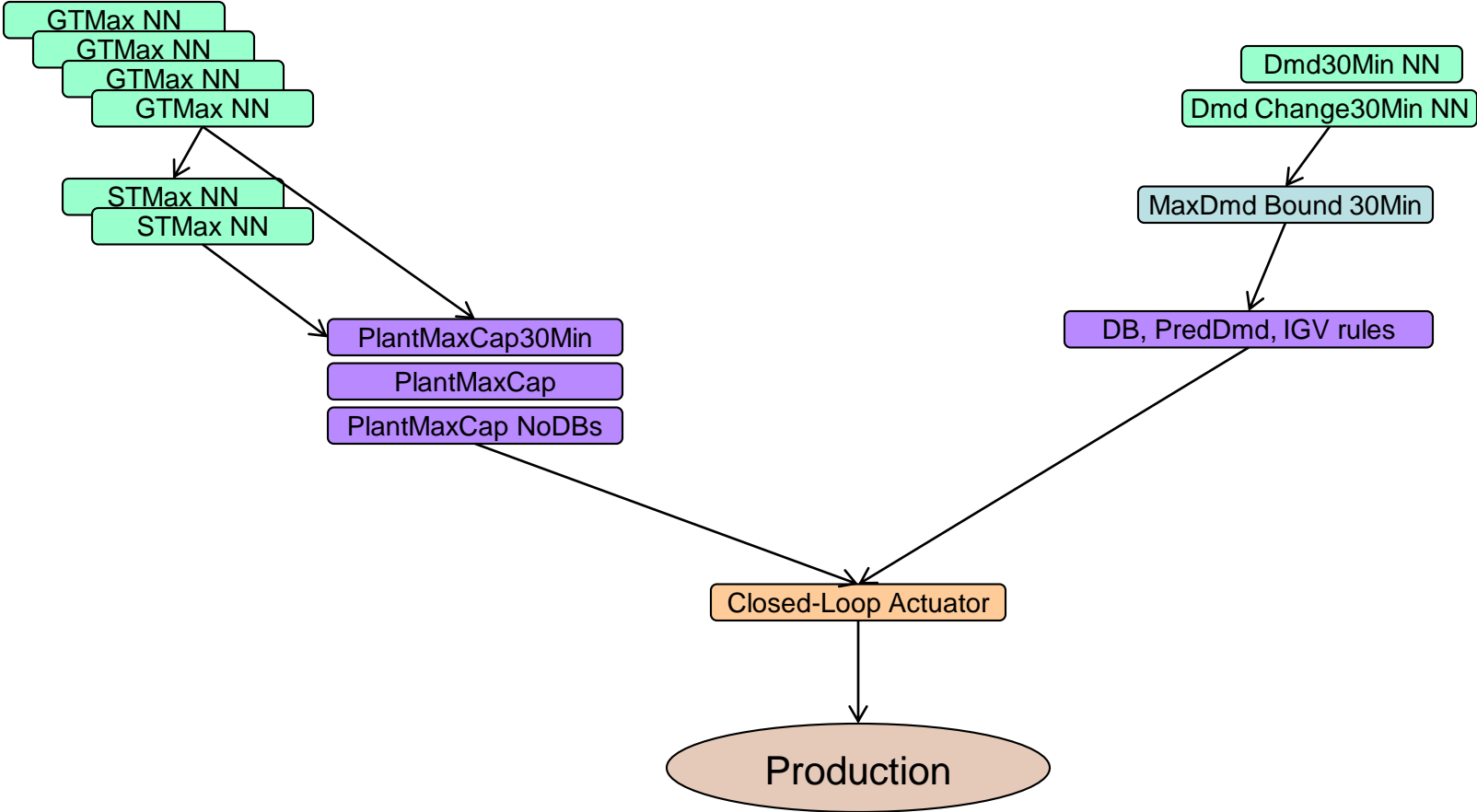
# Thirty Minute Max Demand Predictor (Aggressively tuned + Expert Rules)



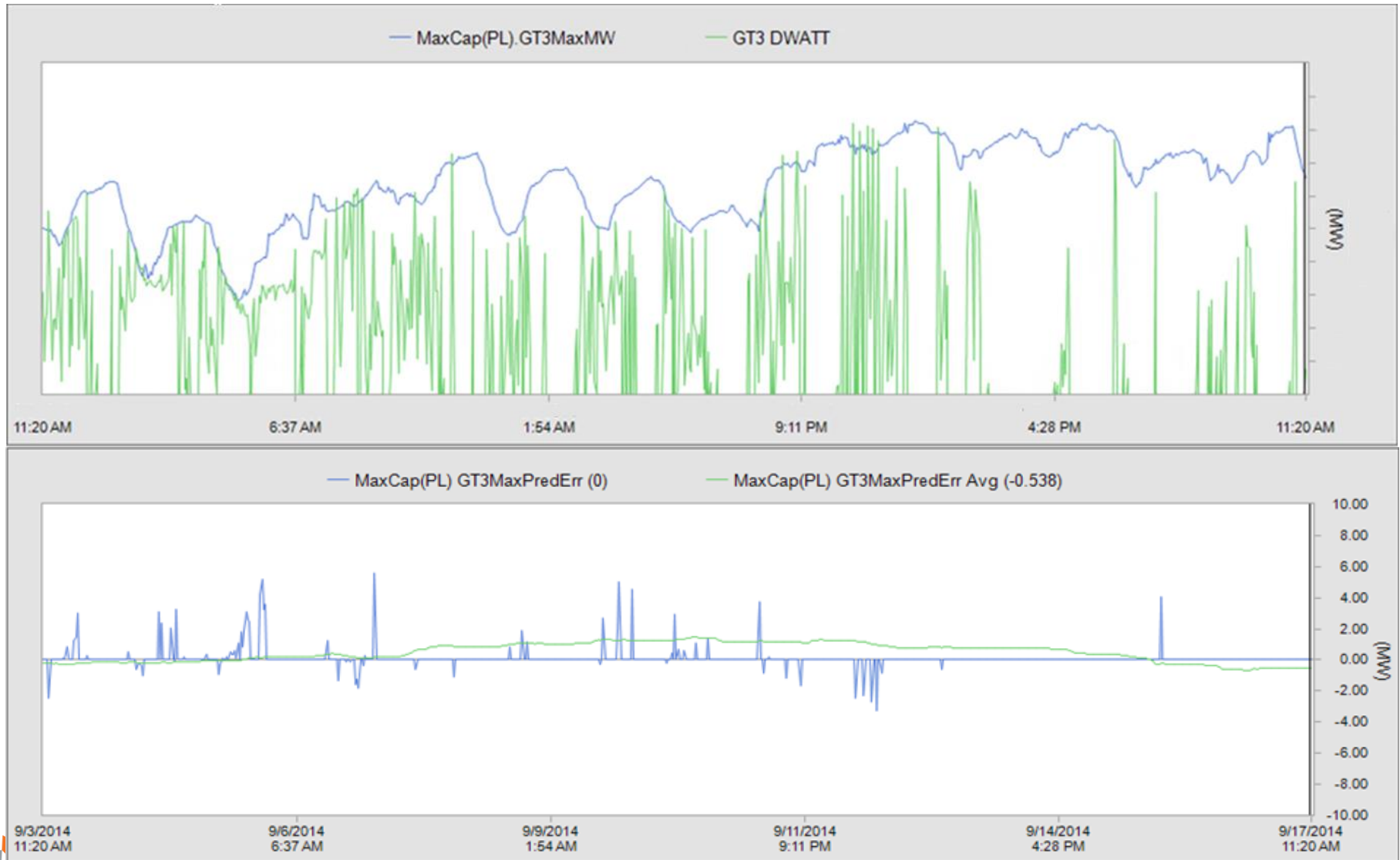
# Thirty Minute Max Demand Prediction Error



# Application Evolution

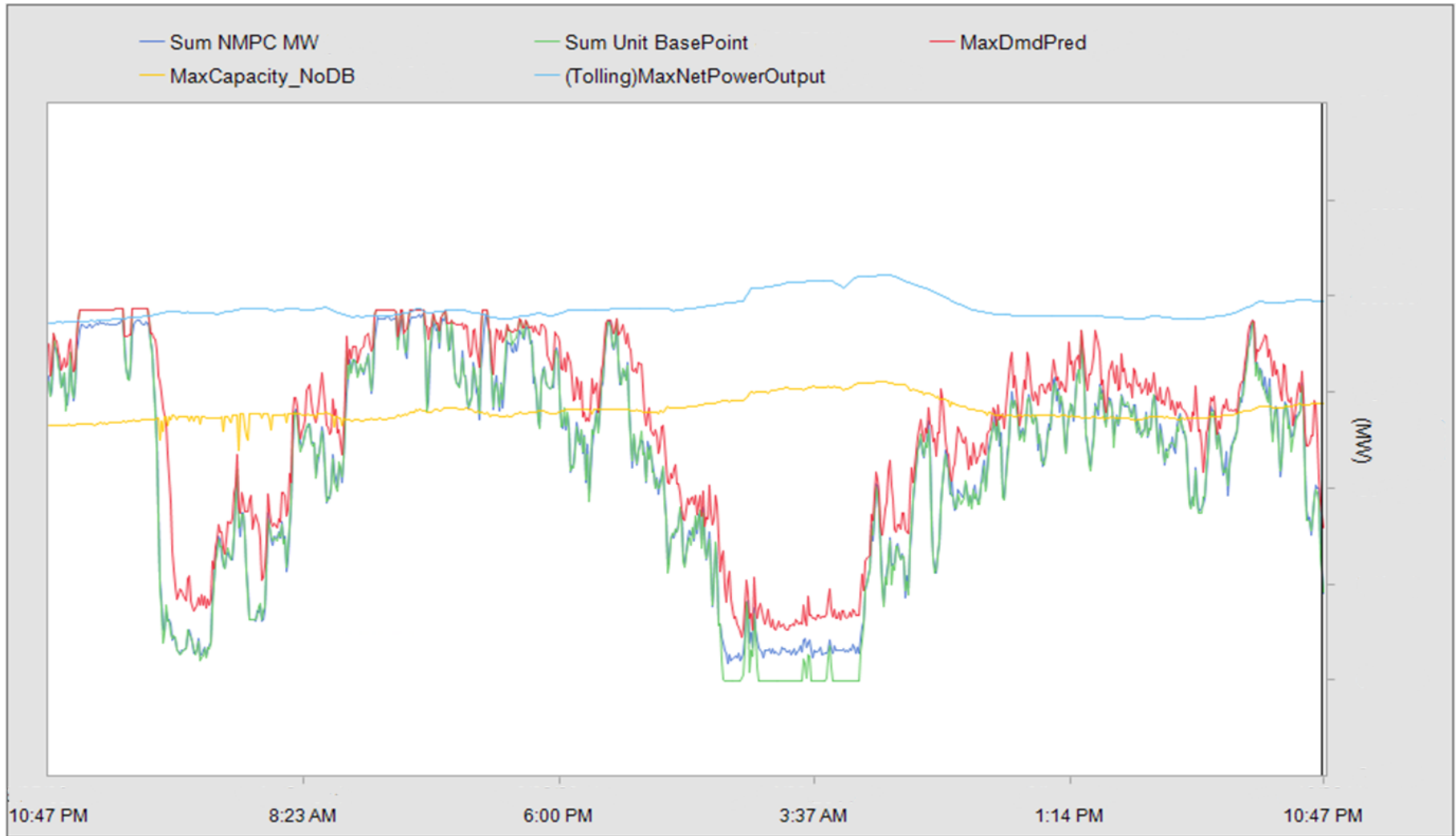


# Neural Model Prediction of GT Max Capability

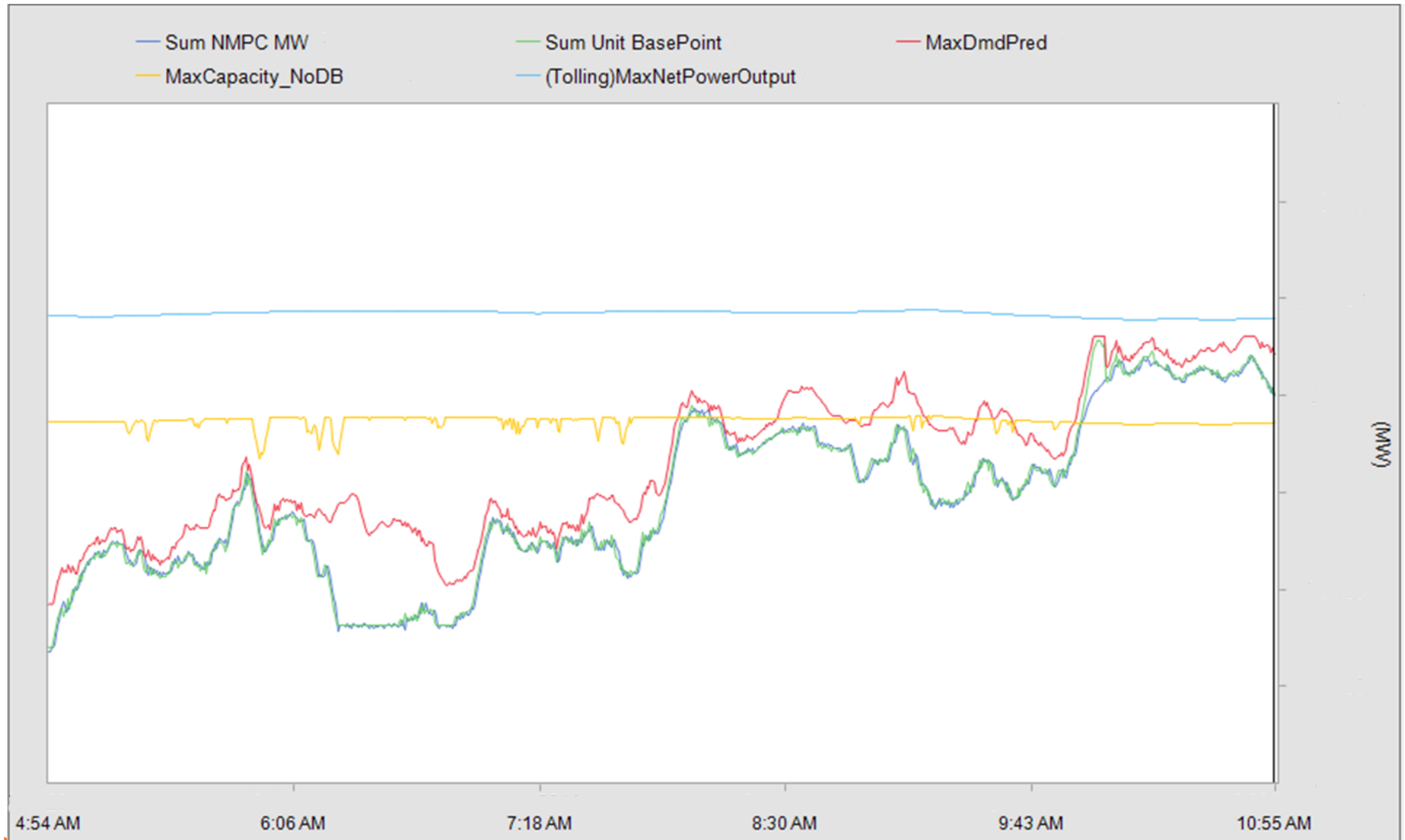




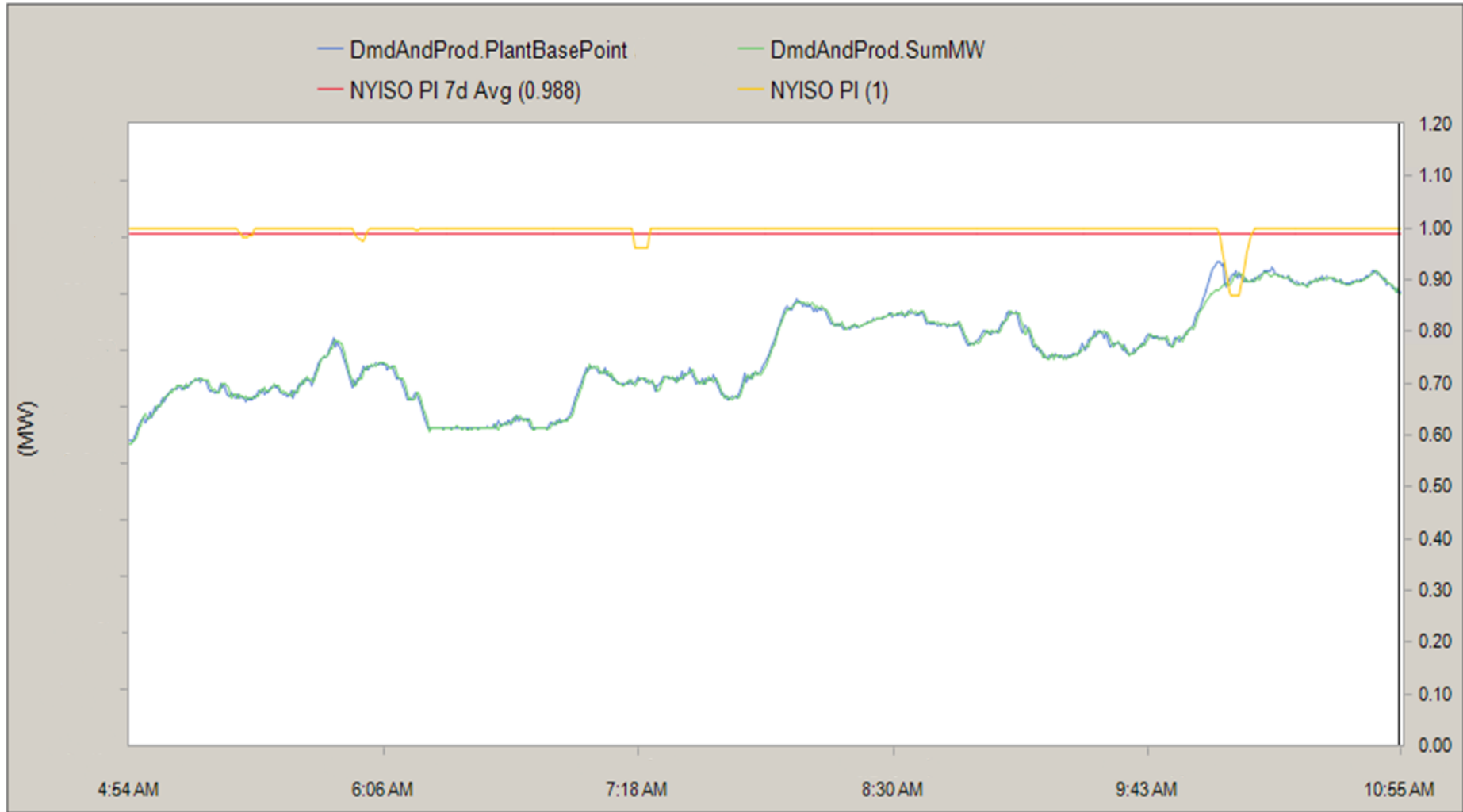
# Max 30 minute Demand and Max Capability Predictions



# Max 30 minute Demand and Max Capability Predictions

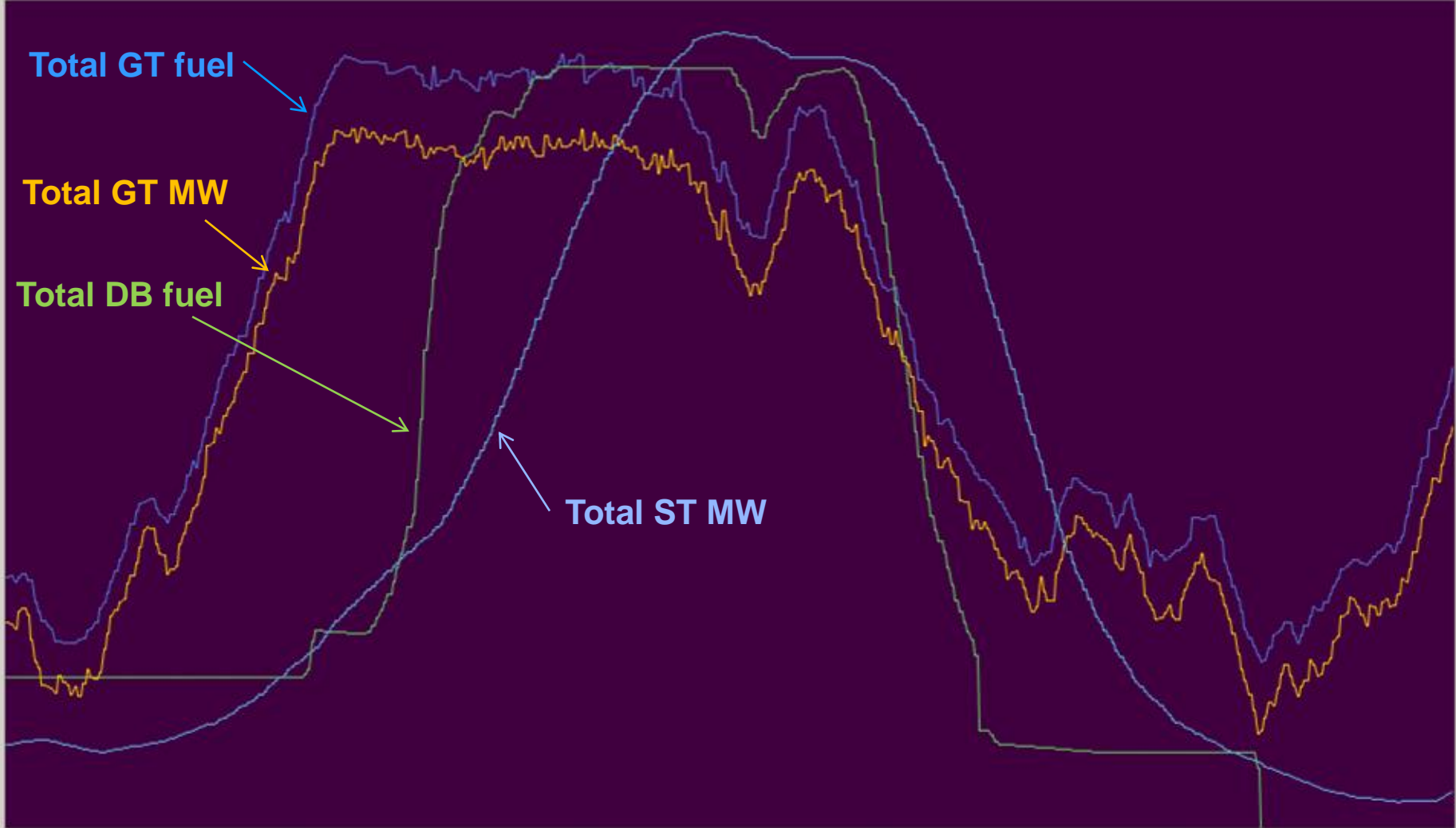


# ISO Regulation Ancillary Services “Performance Index”

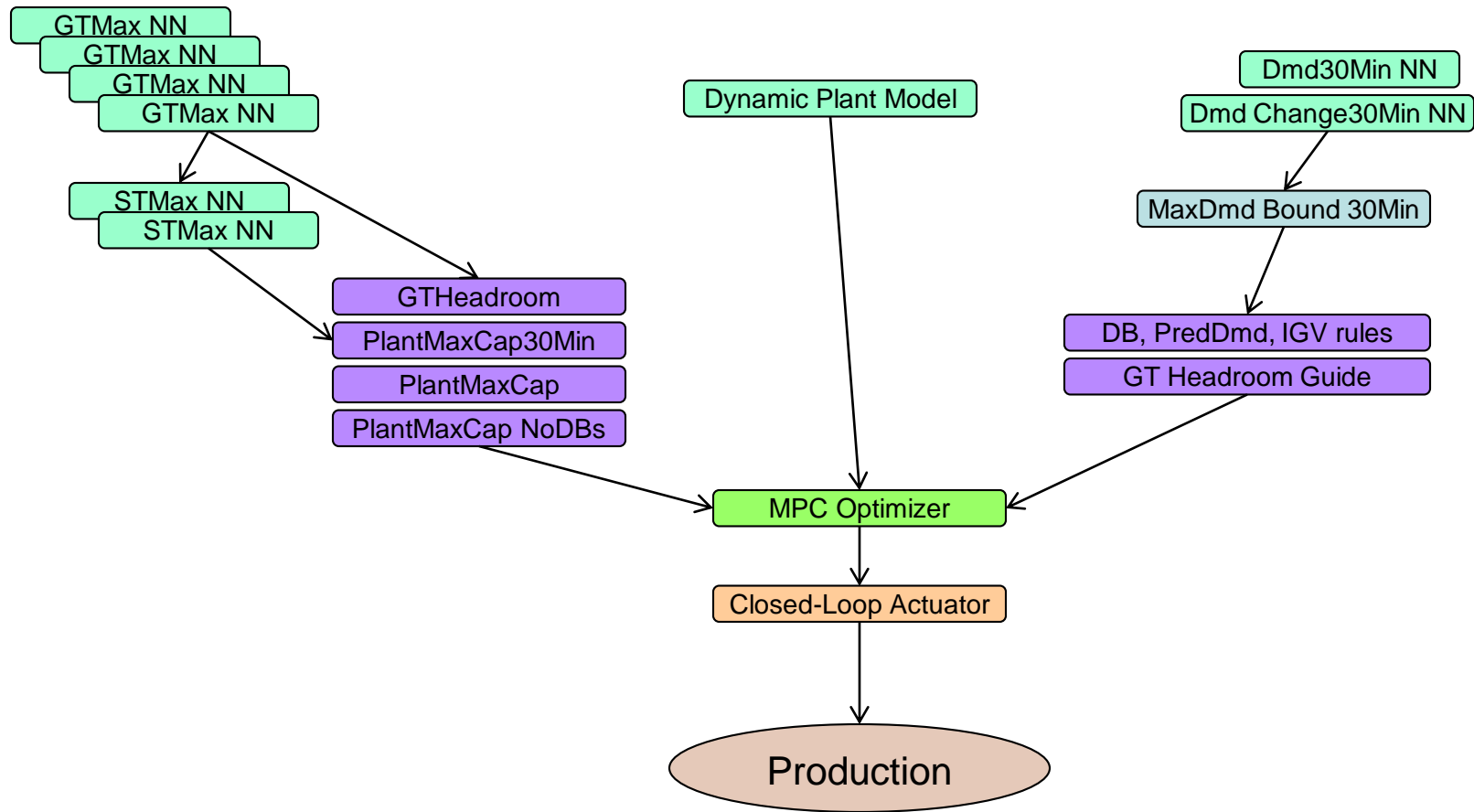


# The Challenge

FuelFlow.TotalGT      FuelFlow.TotalDB  
DmdAndProd.SumGTDWatt      DmdAndProd.SumSTDWatt



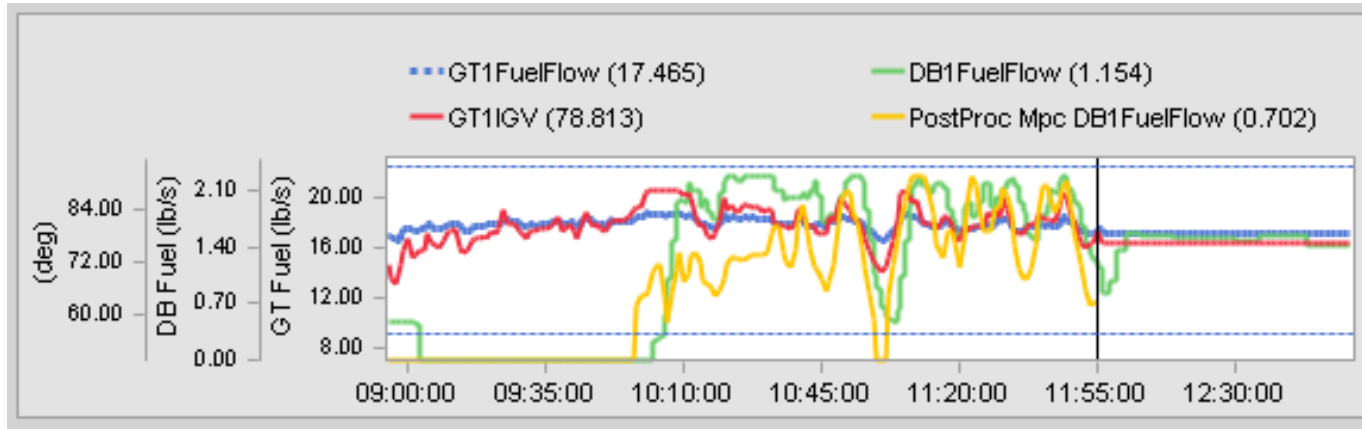
# Evolution



# Closed-Loop MPC Duct Burner Optimizer

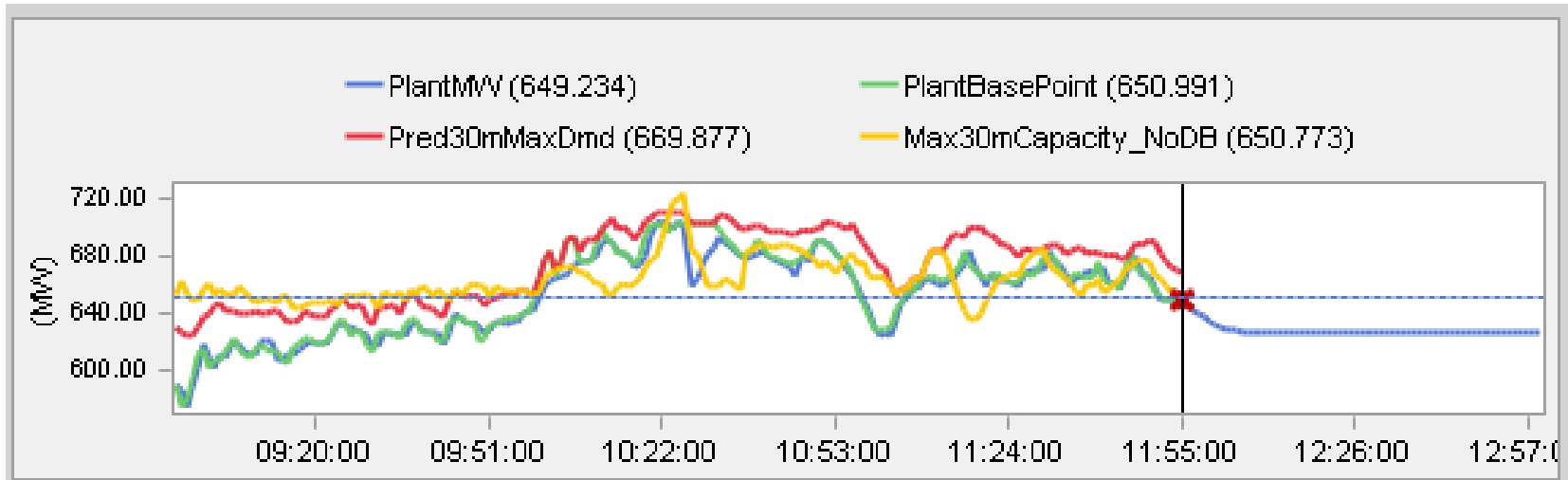


# Closed-Loop Optimizer Manipulated Variables



- Optimizer uses a dynamic model to predict optimal Duct Burner (DB) fuel flow trajectory (GT fuel flow trajectory can also be predicted)
- Then it biases the IGV angle start and stop thresholds in the DCS to inhibit or encourage burner activation
- And biases the DCS fuel flow curve to control DB heat input more precisely, once a DB is running

# Predicting 30 Minute Max Demand

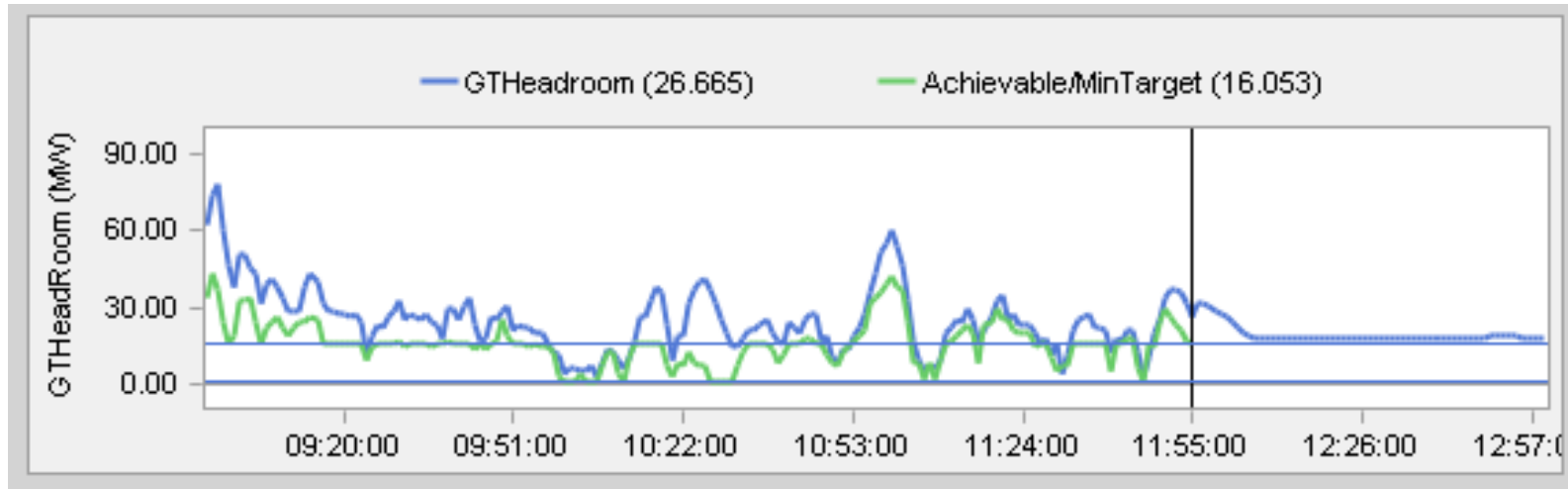


- Neural Net model of future demand and demand variance in 30 minutes
- Inputs: Past demand/demand-variance (series of tap delays), time of day, day of week, ambient temp, humidity, barometric pressure.
- Combined in an ensemble, with a set of rules that leverage the model's prediction error, enforce limits to deal with special cases, and allow for tuning of risk

To create a max limit for likely demand over the next 30 minutes



# Predicting 30 Minute Max Demand



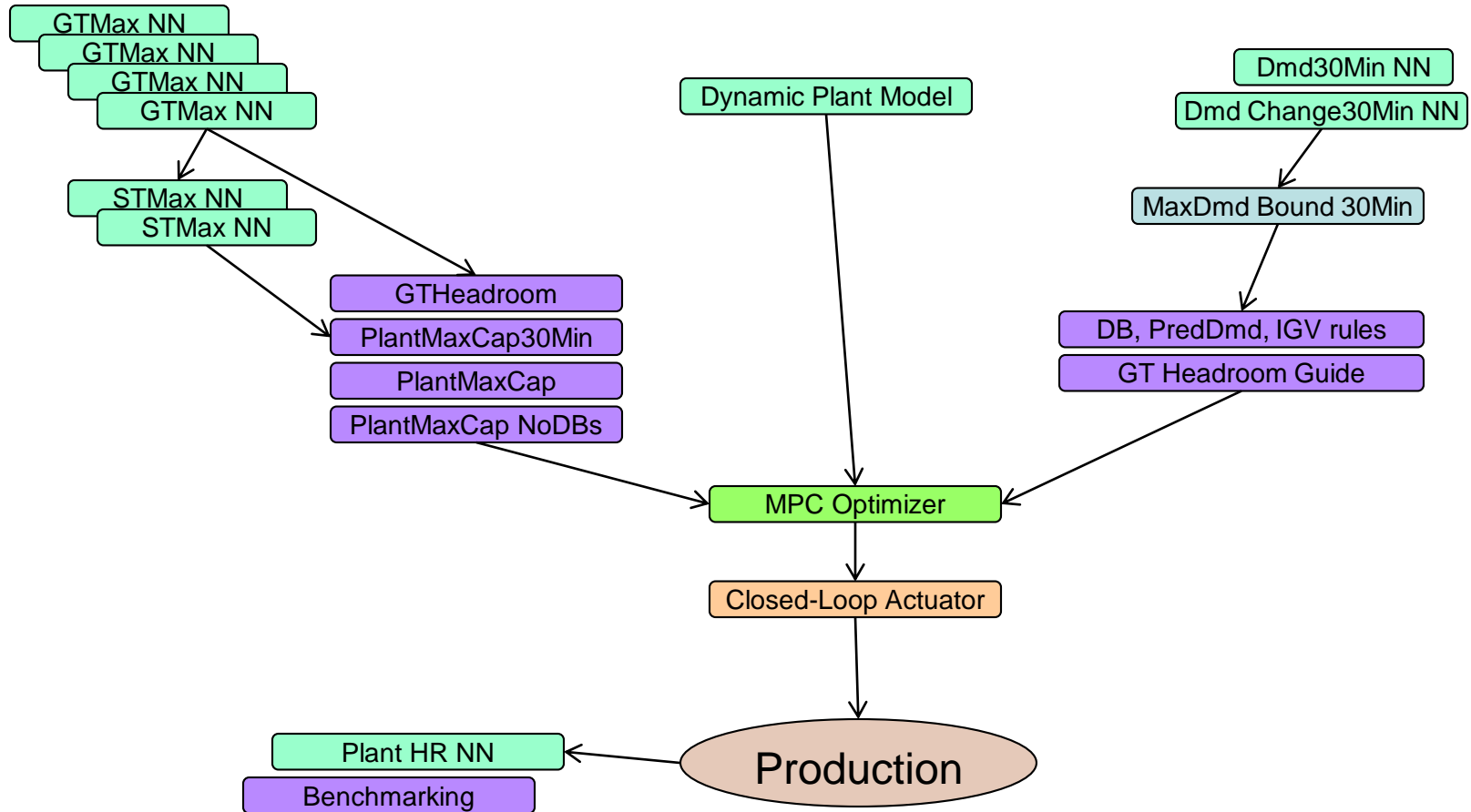
- Prediction of 30-minute max likely demand is compared to 30 minute max plant capability
- Any *potential* shortfall needs to be compensated for by adding duct burner energy and running with more GT capacity in reserve (aka more “GT headroom”)

# Closed-Loop Optimizer Objectives

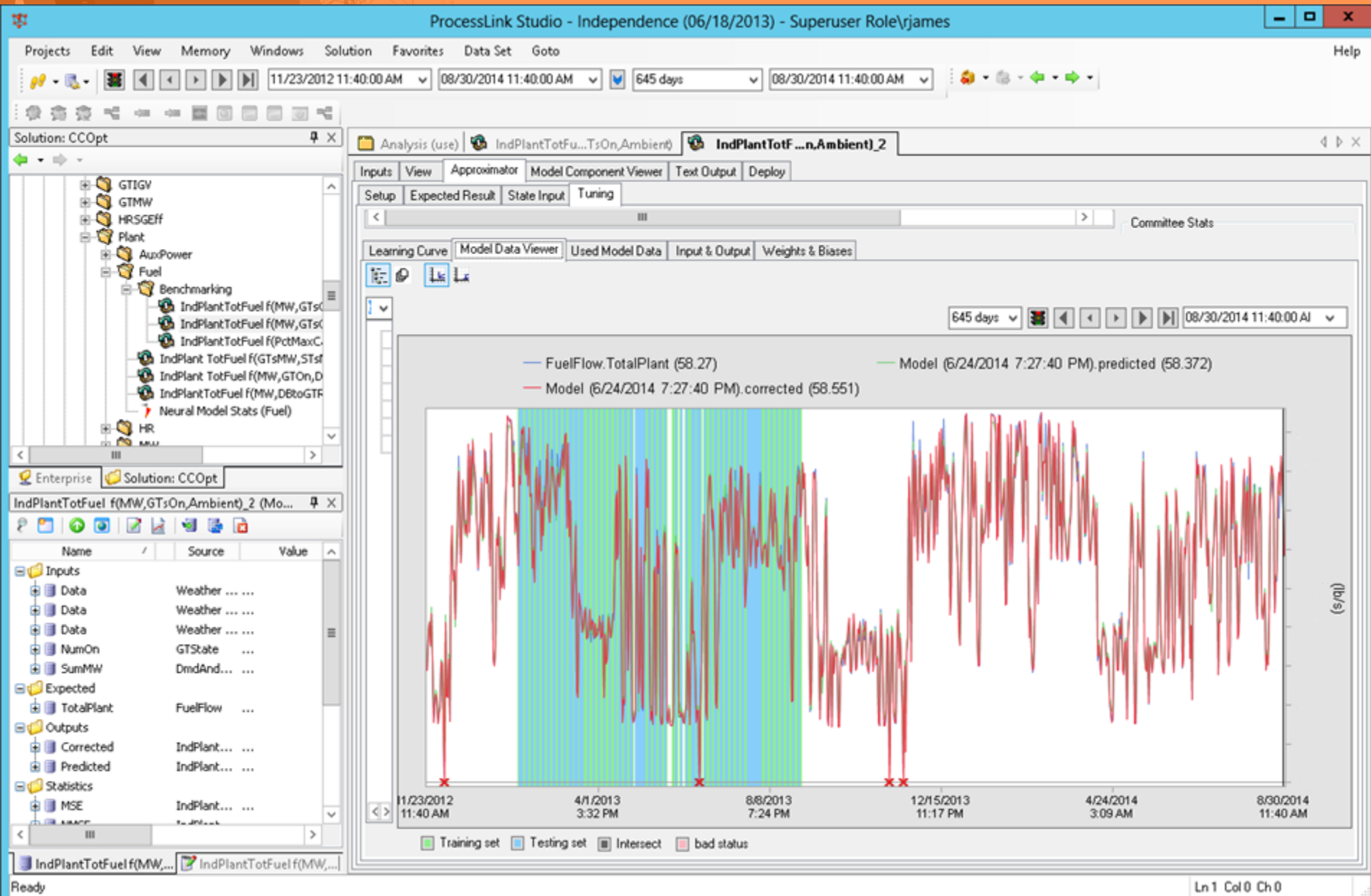
- Dampen ST swings
- Maintain sufficient spare GT capacity to meet possible future demand ramps
- Minimize DB fuel



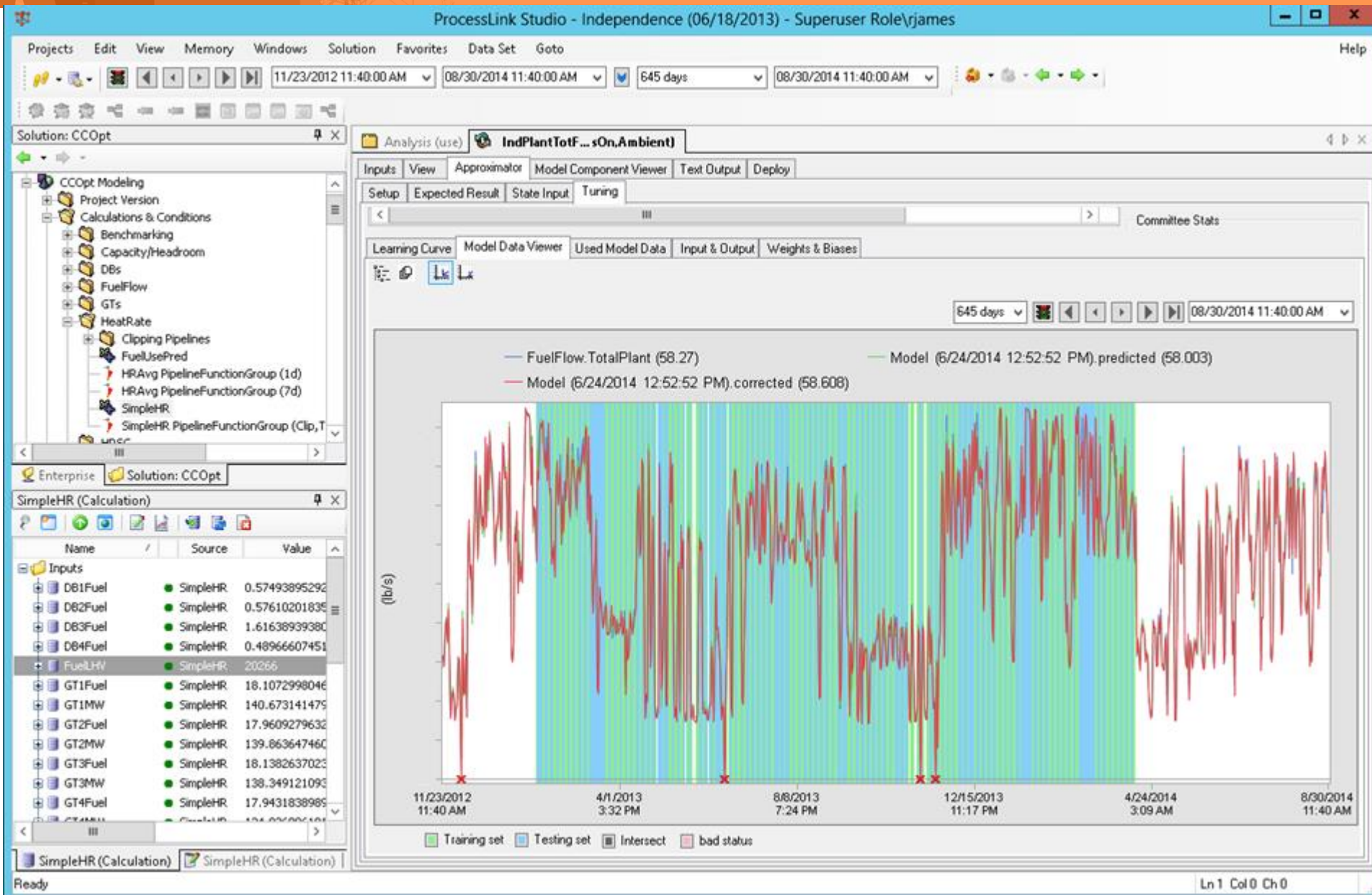
# Evolution



# Real-Time Analytics: Benchmarking



# Real-time Analytics: Benefits Benchmarking



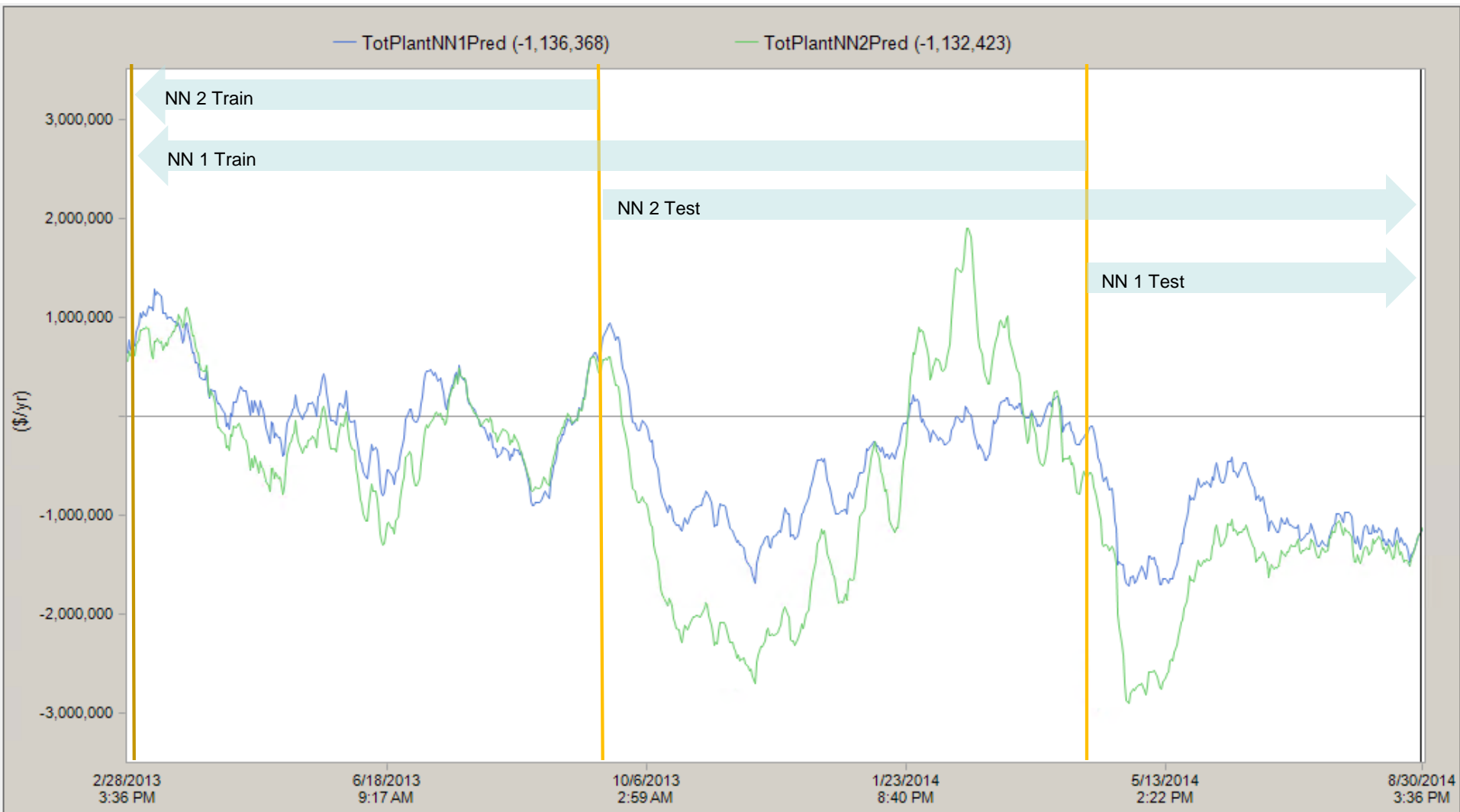
# Benefits Benchmarking

## Project Timeline:

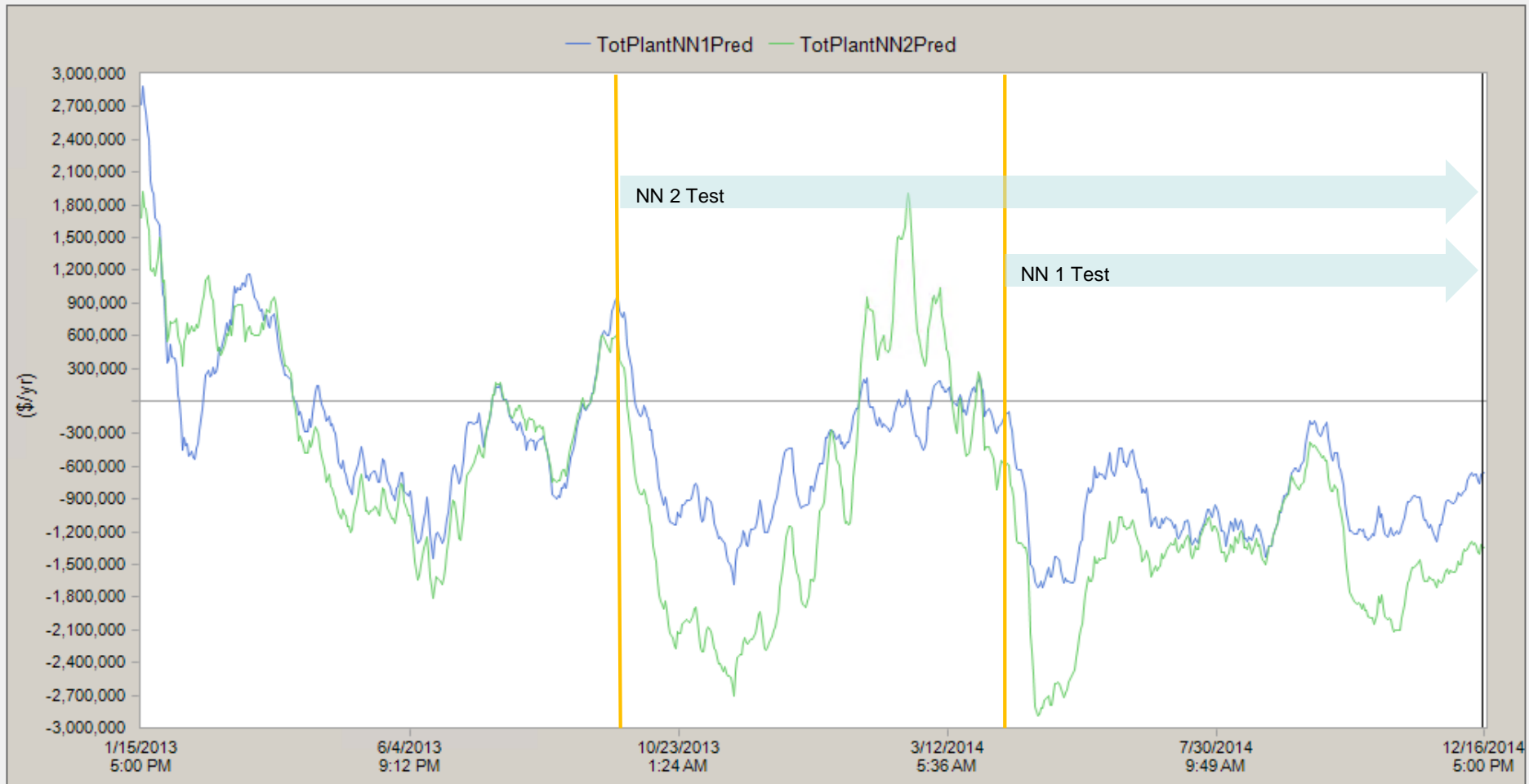
- March 2013 Project kickoff
- September 2013 Initial closed-loop optimizer was tested.
- April 2014 New version of the optimizer was deployed using Model Predictive Control (MPC) and a neural-first principles hybrid model to predict max plant capability

		Test Set : #2 (9/1/13-6/24/14)			Test Set: #1 (4/11/14-6/24/14)	
		Training Bias	Estimated Change	Estimated Change minus Training Bias	Estimated Change	Estimated Change minus Training Bias
NNModel 1	Trained on all available data prior to 4/11/14	\$ (43,250)			\$ (915,402)	\$ (872,152)
NNModel 2	Trained on all available data prior to 9/1/13	\$ (396,753)	\$ (808,459)	\$ (411,706)	\$ (1,615,300)	\$ (1,218,546)

# Benefits Benchmarking (8/30/14)



# Benefits Update (12/16/2014)





# Benefits Update (12/22/2014)

