Advanced Building Performance Diagnostics

Detecting Failure and Predicting Performance in Building Systems and Equipment

B2Q Associates, Inc.

Description & Learning Objectives

This workshop will give an overview of Building Analytics, Energy Models, and will discuss how Neural Networks can be used to achieve results not possible with other methods.

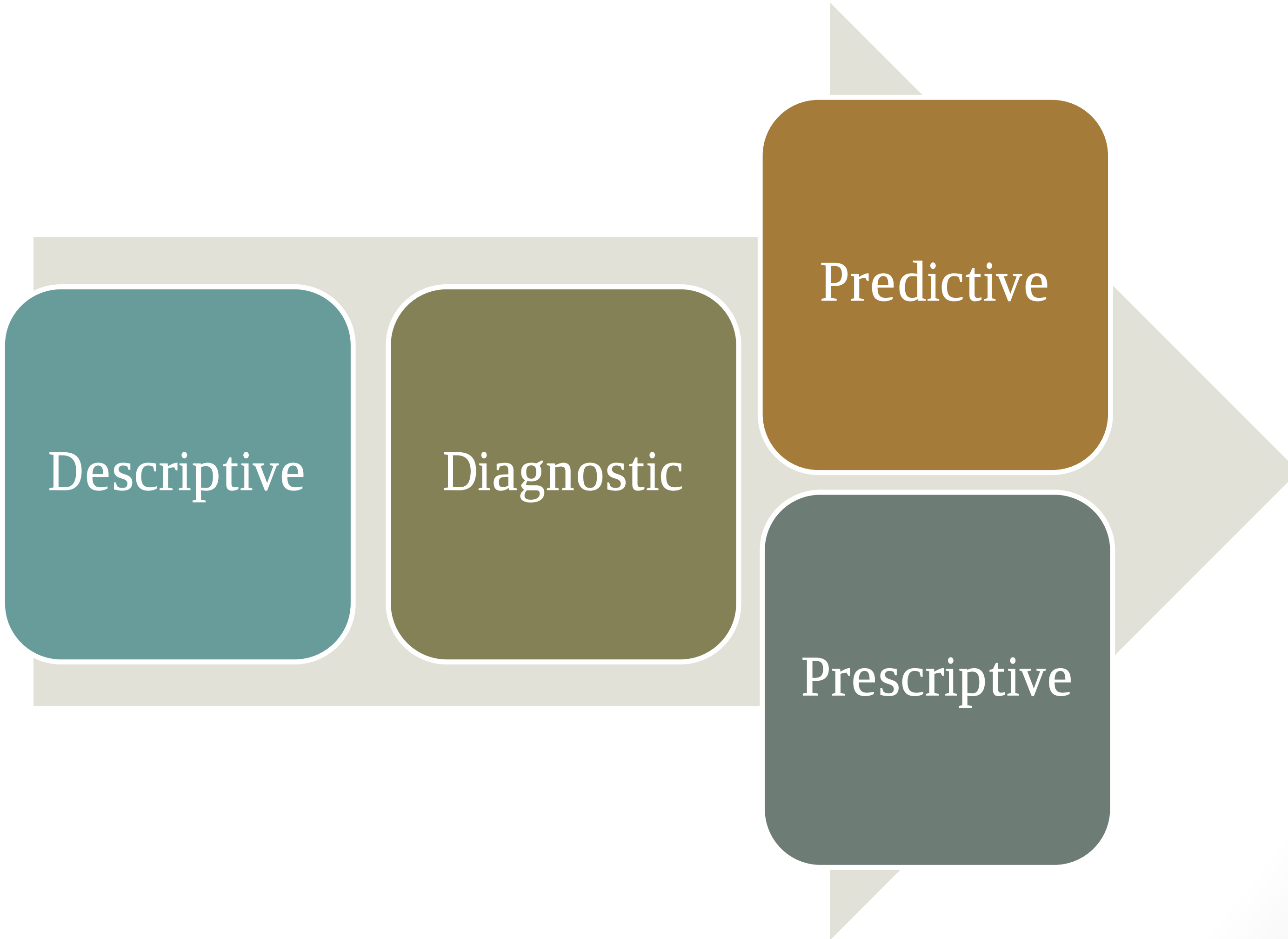
You will learn:

- What analytics are, the different types and methods, and how you can benefit from using them.
- What models are, and how they can be used in analytics for buildings
- How neural networks can be used to gain better insight about equipment and systems

What Are Analytics?

- Analytics = Data Analysis
- Collect and use data to generate insights
- Often use visualization to communicate insight
- Arising from the growing availability of electronic data
- Used to improve the bottom line
  - Cost Reduction
  - Increased Comfort, Quality, Production, etc.
- Wide variety of fields and applications

Types of Analytics



Benefits / Value Proposition

- Gain better understanding of buildings and equipment systems
- Identify issues and opportunities for improvement
- Reduce operating costs and unplanned downtime
- Improve occupant comfort, air quality
- Increase productivity and work/product quality

User Groups

- Engineers / Consultants
- Facility Owners and Managers
- Facilities & Maintenance Staff
- Service Technicians
- Utilities

Methods

Current Fleet Status		
NAME	ALARM	SEVERITY
FAC Air Handler Unit	✓	
FAC Boiler	✓	✓
FAC Chiller	✓	
FAC Cooling Tower	✓	✓
FAC Exhaust Fan	✓	✓
FAC Fan Coil Unit	✓	
FAC Fan Powered Box	✓	
FAC Heating and Ventilation Unit	✓	✓
FAC Primary Chilled Water Loop	✓	✓
FAC Pump	✓	
FAC Roof Top Unit	✓	
FAC Sec Chilled Water Loop	✓	
FAC Shell and Tube HX	✓	✓
FAC VAV Box	✓	

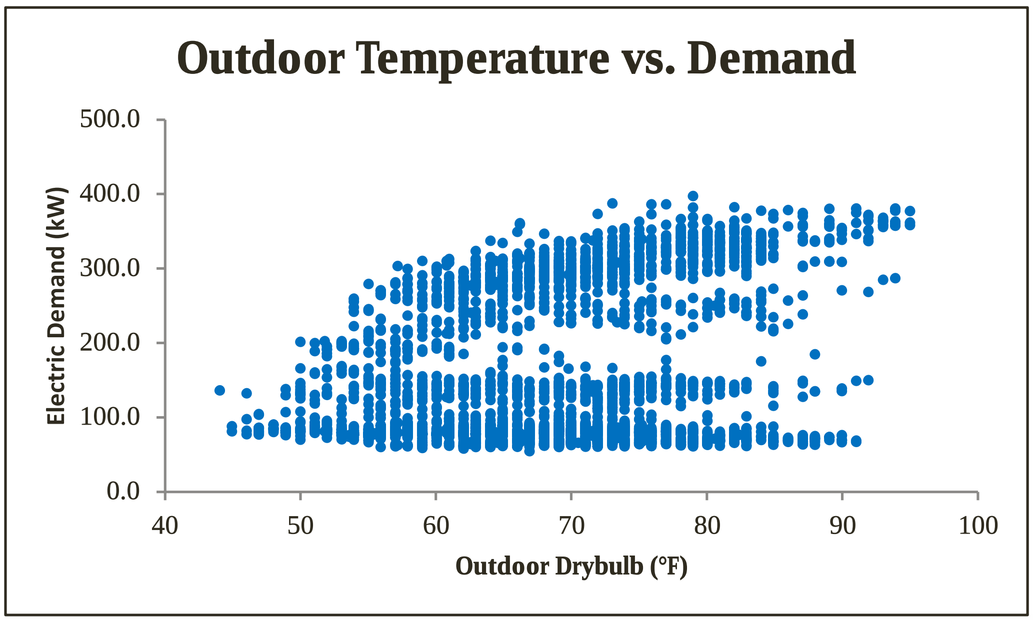
- Alarms
  - Simple Threshold Comparisons
- Fault Detection
  - Rule-based “Checks”
- Analysis Tools
  - Statistics, Data Visualization, Dashboards
- Regression Models
  - Build Relationships Between System Variables

Models: Uses in Building Analytics

- Baselining / Benchmarking
- Advanced Fault Detection
- Extrapolation
- Prediction
- Benefit (Savings) Estimation

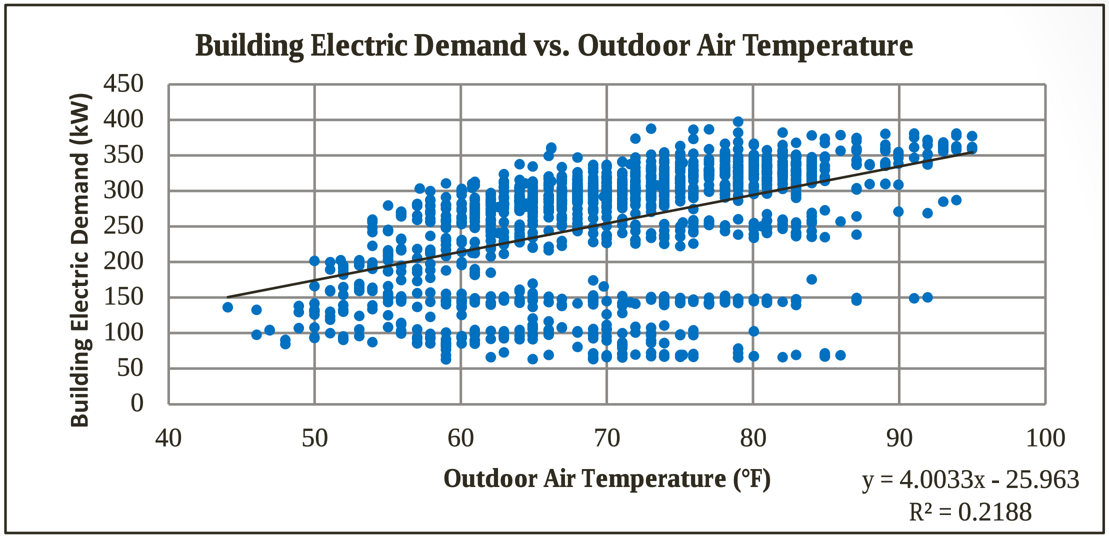
Models: Challenges

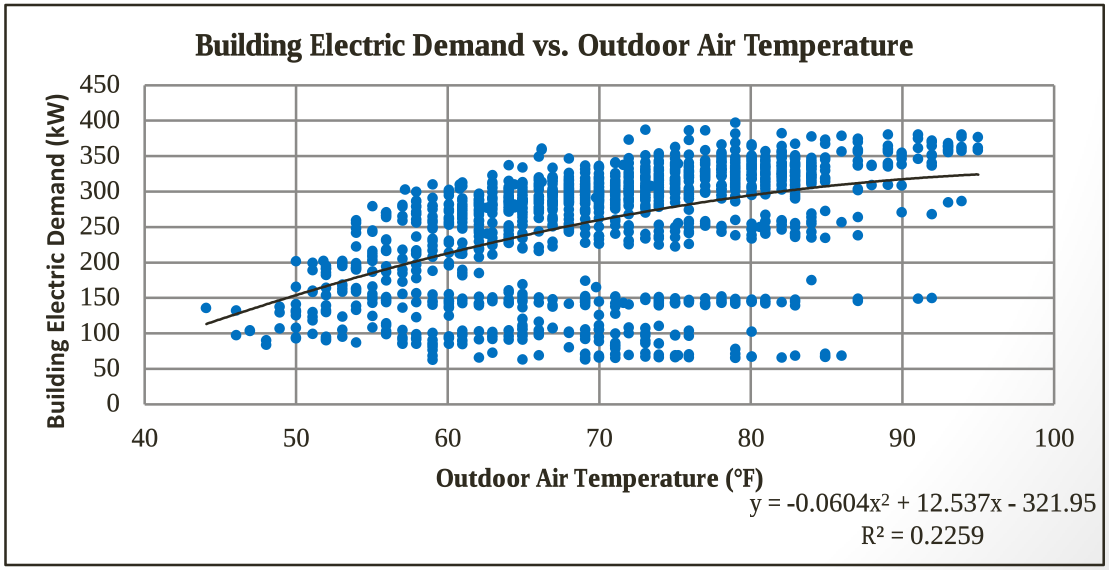
- Matching the level of effort with the level of accuracy desired or needed
- Identifying and accounting for the variables that cause changes in the system
- Understanding how those variables impact the system



Models: Traditional Methods

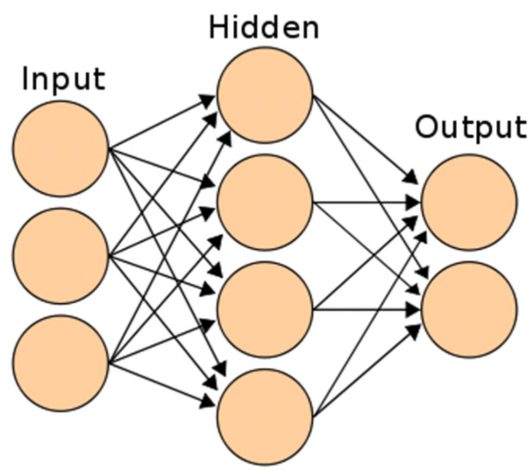
- Regressions
  - Linear
  - Polynomial
  - Logarithmic
  - Multivariate





Neural Network Models

- Based on mathematical models of the brain
  - Automatically "learns" how variables affect system through "training"
- Allow complex nonlinear relationships to be developed
- Limitations
  - Cannot identify relationships that do not exist
  - Training data (independent variables) must be available

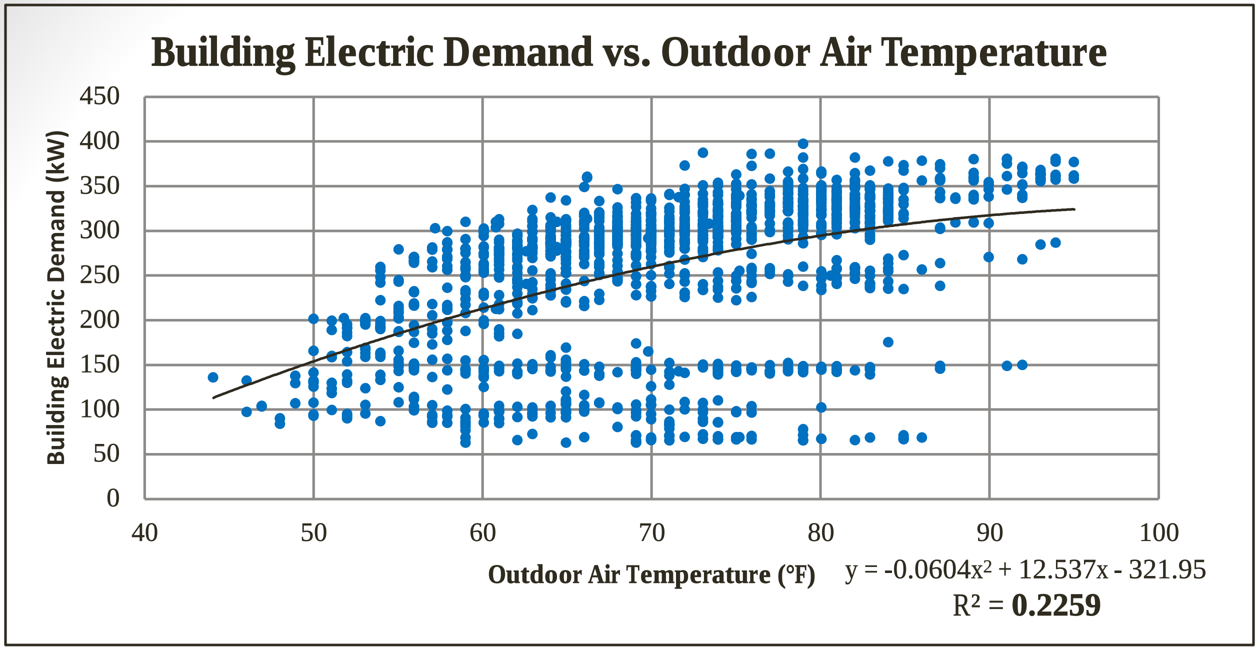


Example:
Modeling & Predicting Building Electric Demand

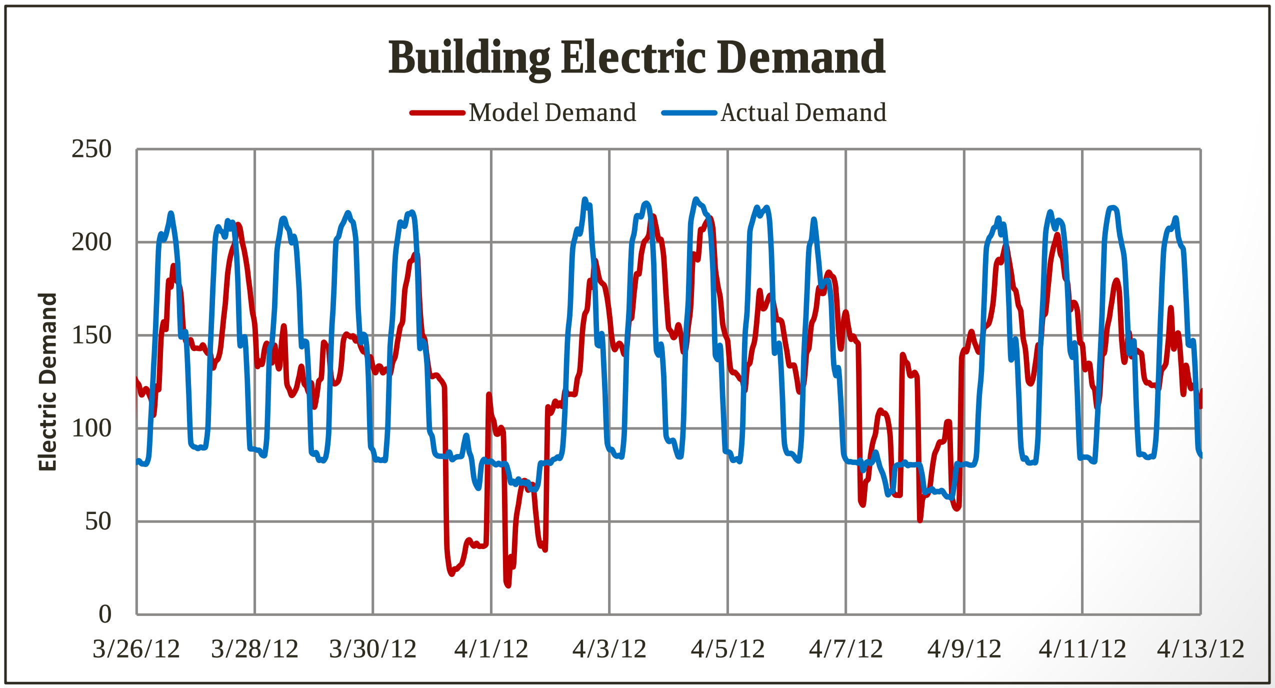
- Motivation
  - Whole-building electric demand is difficult to model & predict accurately
  - There is value in being able to predict demand and forecast consumption
  - Benchmarking and tracking energy consumption or savings is made difficult by changes in ambient conditions, occupancy, etc.
    - Standard weather normalization techniques can fall short

Example: Modeling & Predicting Building Electric Demand

- 145,000 ft^2 four-story office building in Rhode Island
- Typically occupied Monday - Friday
- Date Range: 5/11/2012 – 2/1/2013
- Trend Data Available:
  - Outdoor Air Dry-bulb Temperature (°F)
  - Outdoor Air Dew-point Temperature (°F)
- Other Dependent Variables:
  - Hour of Day
  - Day of Week
- Neural Network modeling used to forecast whole-building electric demand 18 hours ahead
- Other Uses: Benchmark and track energy use over time



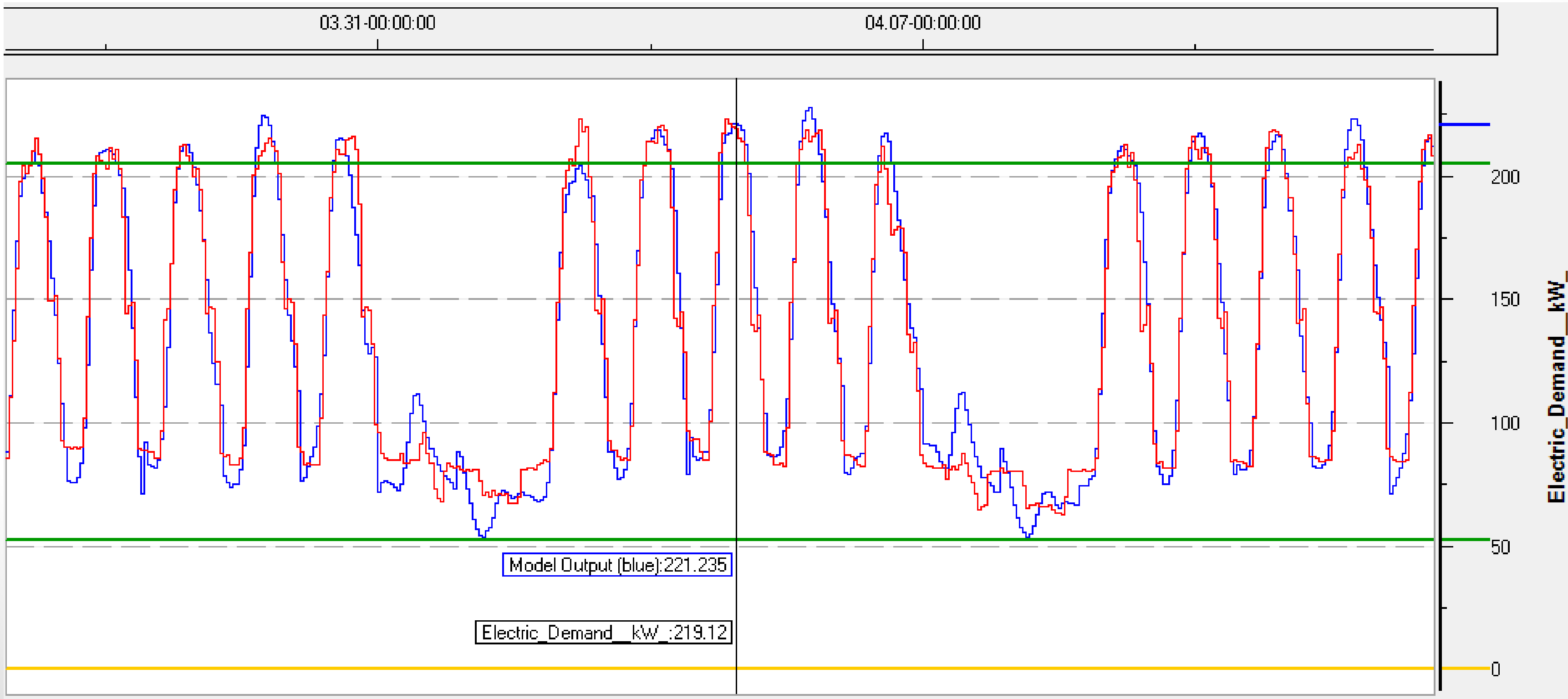
Regression Statistics	
Multiple R	0.485756
R Square	**0.235959**
Adjusted R Square	0.235705
Standard Error	75.96178
Observations	9023

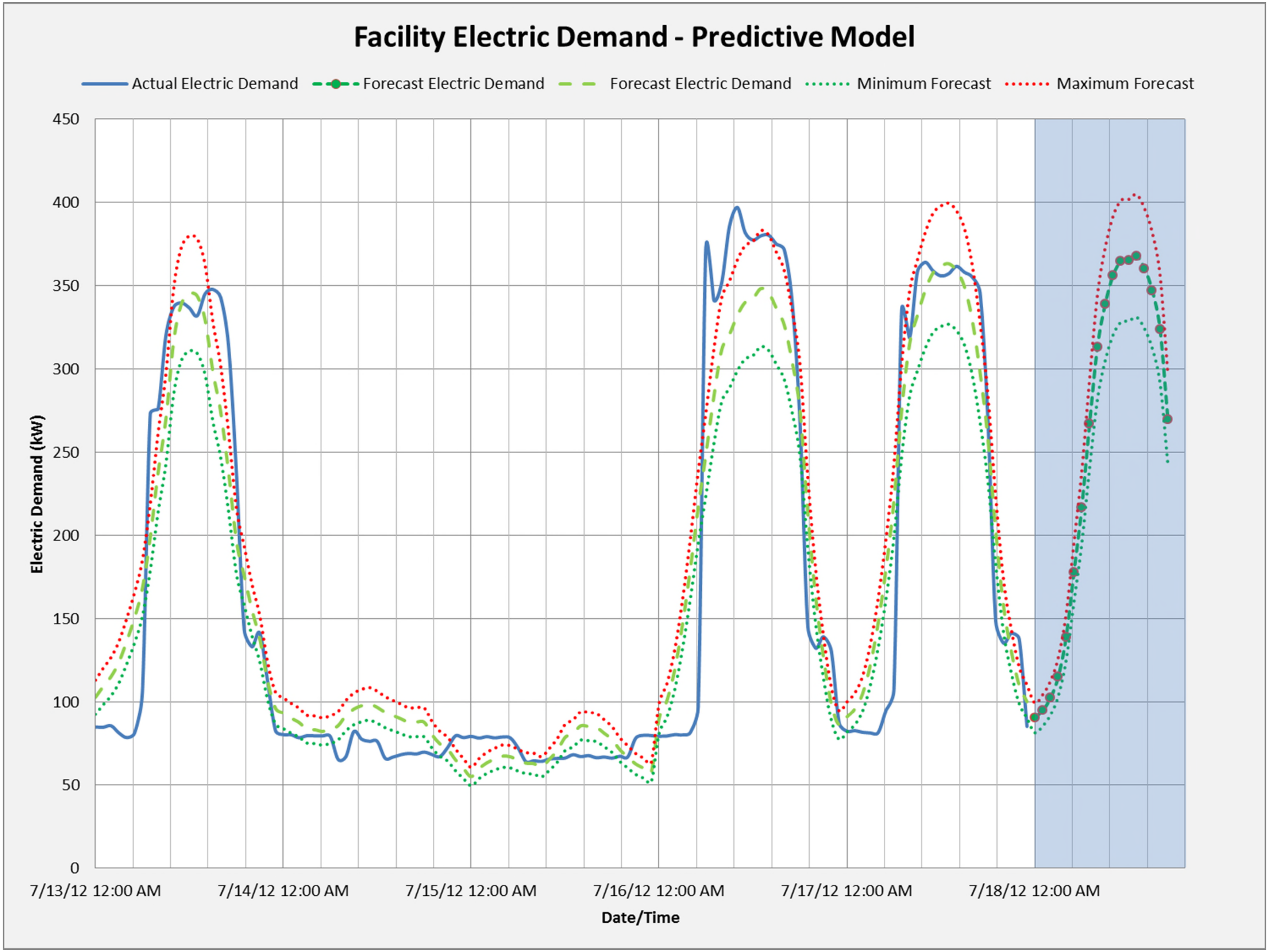


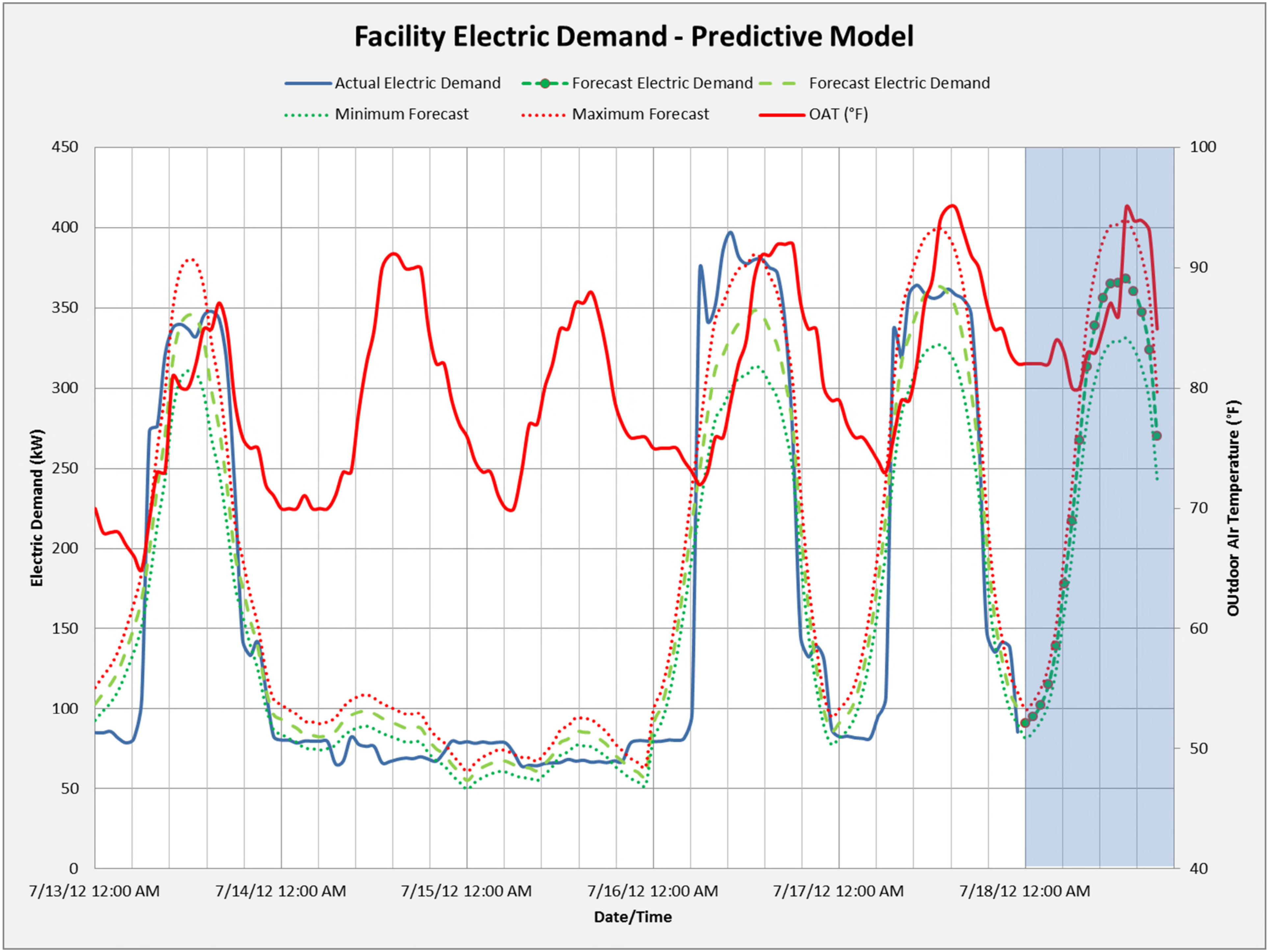
Neural Network Model Results: GE Proficy. Continuous Troubleshooter

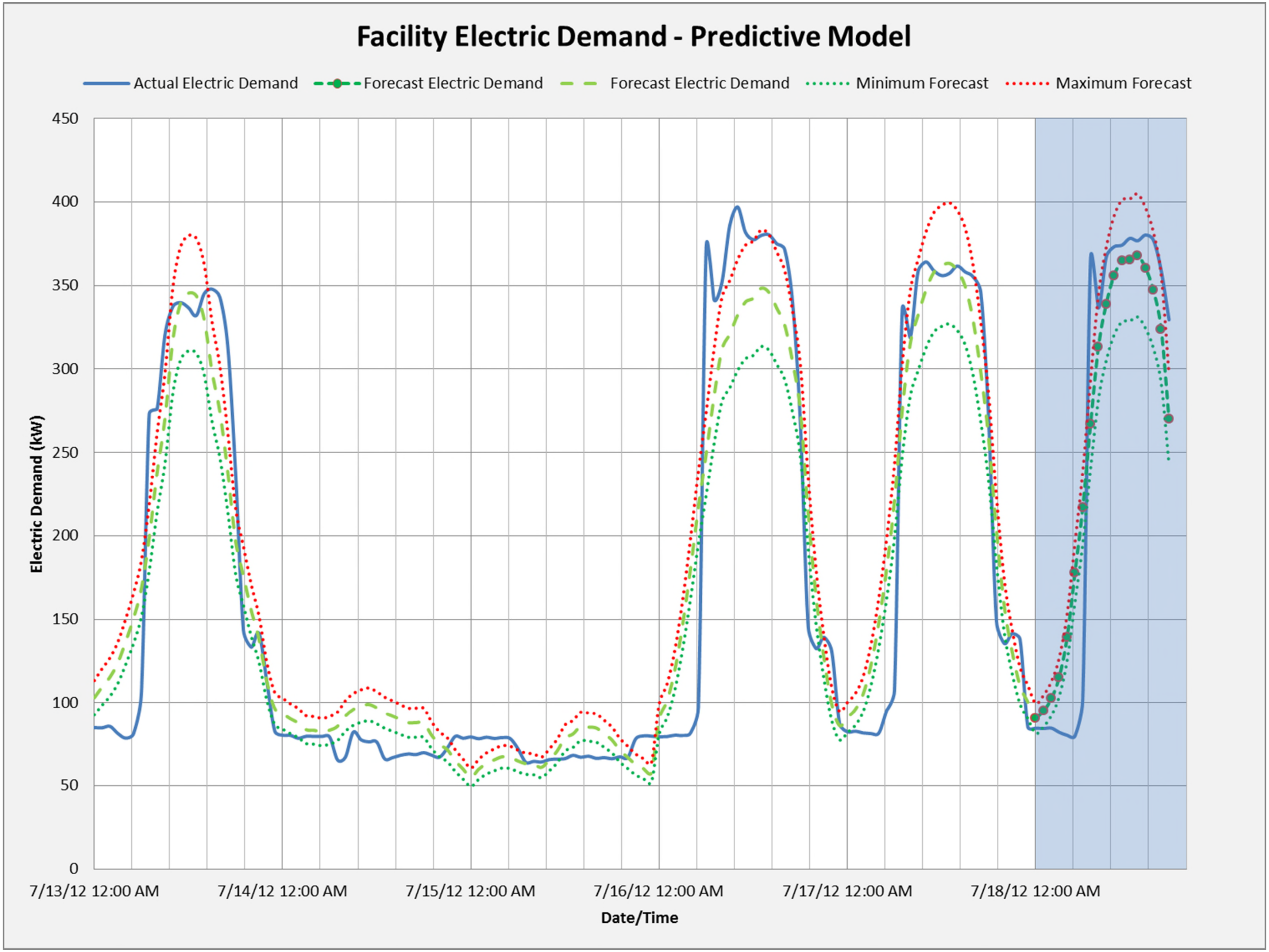
Model statistics:

Statistic	Value
Number of construction cases	311
Number of validation cases	133
Number of patterns not used for training	25807
Model fit on construction cases	96%
Model fit on validation cases	93%




Facility Electric Demand - Predictive Model
Actual Electric Demand
Forecast Electric Demand
Forecast Electric Demand
Minimum Forecast
Maximum Forecast
Electric Demand (kW)
0
50
100
150
200
250
300
350
400
450
7/13/12 12:00 AM
7/14/12 12:00 AM
7/15/12 12:00 AM
7/16/12 12:00 AM
7/17/12 12:00 AM
7/18/12 12:00 AM
Date/Time


Facility Electric Demand - Predictive Model
Actual Electric Demand
Forecast Electric Demand
Forecast Electric Demand
Minimum Forecast
Maximum Forecast
OAT (°F)
Electric Demand (kW)
0
50
100
150
200
250
300
350
400
450
OUtdoor Air Temperature (°F)
40
50
60
70
80
90
100
7/13/12 12:00 AM
7/14/12 12:00 AM
7/15/12 12:00 AM
7/16/12 12:00 AM
7/17/12 12:00 AM
7/18/12 12:00 AM
Date/Time

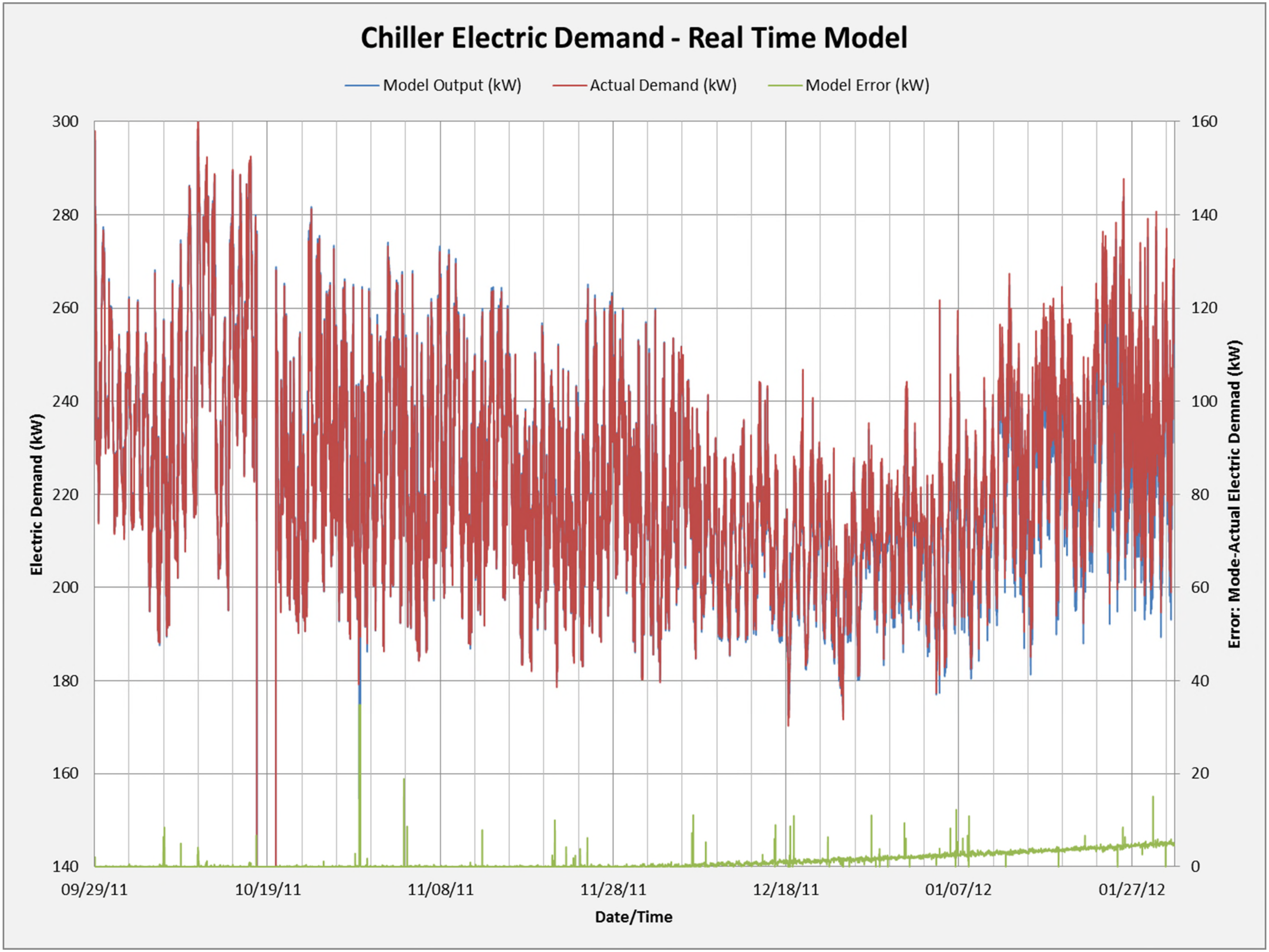

Facility Electric Demand - Predictive Model
Actual Electric Demand
Forecast Electric Demand
Forecast Electric Demand
Minimum Forecast
Maximum Forecast
450
400
350
300
250
200
150
100
50
0
Electric Demand (kW)
7/13/12 12:00 AM
7/14/12 12:00 AM
7/15/12 12:00 AM
7/16/12 12:00 AM
7/17/12 12:00 AM
7/18/12 12:00 AM
Date/Time

Example:
Chiller Efficiency Model

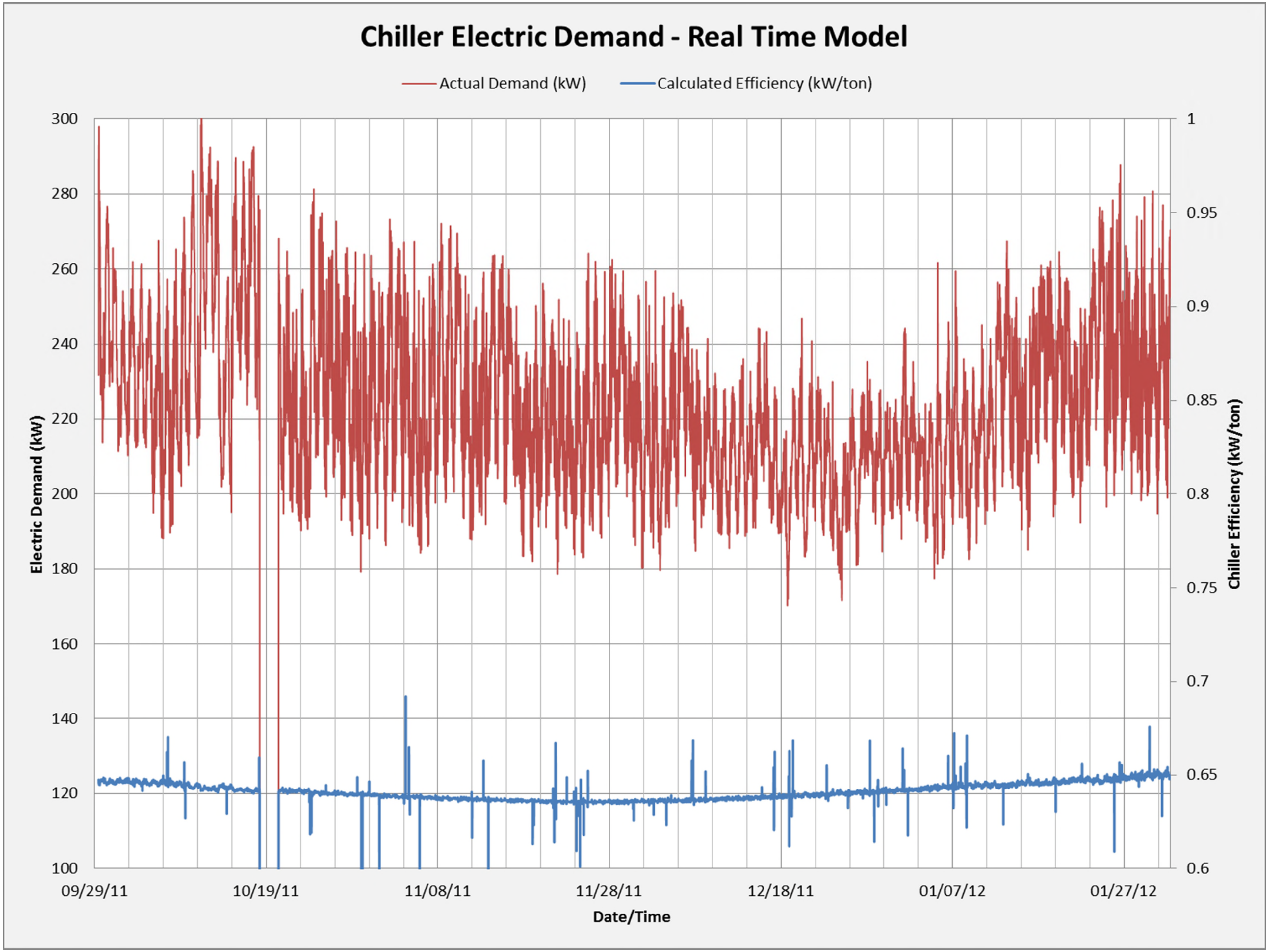
- Motivation
  - Small losses in chiller efficiency can result in large impacts to plant energy consumption and cost
  - Reduced chiller efficiency can indicate maintenance issues that could lead to unplanned downtime
  - Several variables contribute to chiller efficiency, making it difficult to use simple rule-based fault detection to identify issues

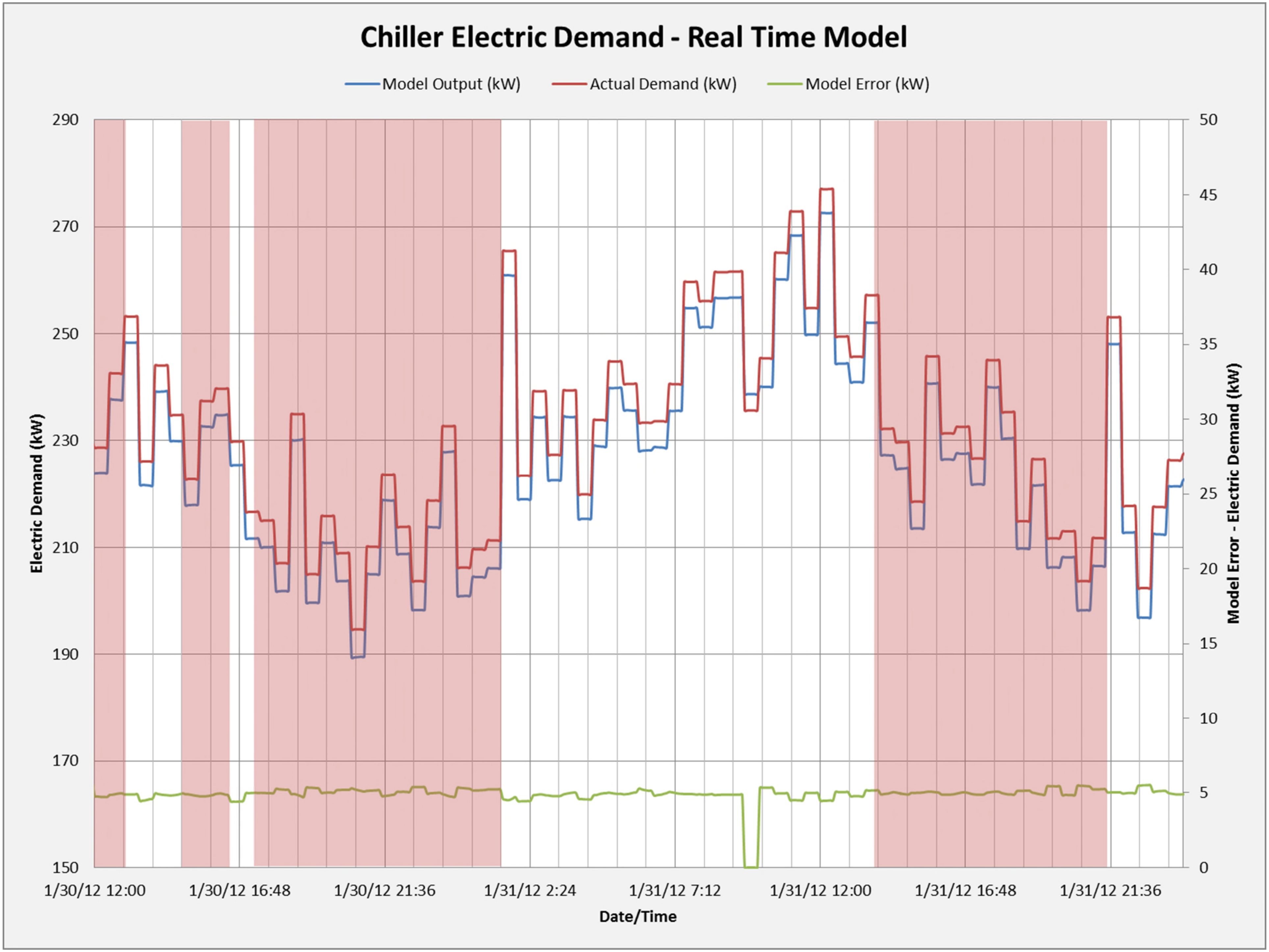
Example: Chiller Efficiency Model

- 600 ton VFD chiller
- Training data set included 2 months of trends (Sept – Oct)
  - Data Points Used:
    - Chiller Water Load (tons)
    - Leaving CHW Supply Temperature (°F)
    - Entering CW Supply Temperature (°F)
    - Dependent Variable – Chiller Input Power (kW)
- Deployed in real-time using FCX to identify when chiller power exceeds model prediction
- Detected degradation in efficiency
  - Caused by poor condenser water chemical treatment (scaling on condenser tubes)



Chiller Electric Demand - Real Time Model
Model Output (kW)
Actual Demand (kW)
Model Error (kW)
Electric Demand (kW)
300
280
260
240
220
200
180
160
140
Error: Mode-Actual Electric Demnad (kW)
160
140
120
100
80
60
40
20
0
09/29/11
10/19/11
11/08/11
11/28/11
12/18/11
01/07/12
01/27/12
Date/Time


Chiller Electric Demand - Real Time Model
Actual Demand (kW)
Calculated Efficiency (kW/ton)
Electric Demand (kW)
300
280
260
240
220
200
180
160
140
120
100
Chiller Efficiency (kW/ton)
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
09/29/11
10/19/11
11/08/11
11/28/11
12/18/11
01/07/12
01/27/12
Date/Time


Chiller Electric Demand - Real Time Model
Model Output (kW)
Actual Demand (kW)
Model Error (kW)
Electric Demand (kW)
Model Error - Electric Demand (kW)
290
270
250
230
210
190
170
150
50
45
40
35
30
25
20
15
10
5
0
1/30/12 12:00
1/30/12 16:48
1/30/12 21:36
1/31/12 2:24
1/31/12 7:12
1/31/12 12:00
1/31/12 16:48
1/31/12 21:36
Date/Time

Live Demonstration

- Model deployed as an analytic using FacilityConneX
  - Monitoring-based commissioning software platform
  - Employs fault-detection diagnostics and predictive neural-network models to identify efficiency opportunities
    - Air- and water-side HVAC systems
    - Compressed air systems
    - Energy meters
  - Built on the GE Proficy Suite of Industrial Automation Software

Questions