Energy Load Forecasting & Analysis

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Time Series Model, Analysis and Control
Spring 2020 Course Project

The University of Texas at Austin
Mechanical Engineering
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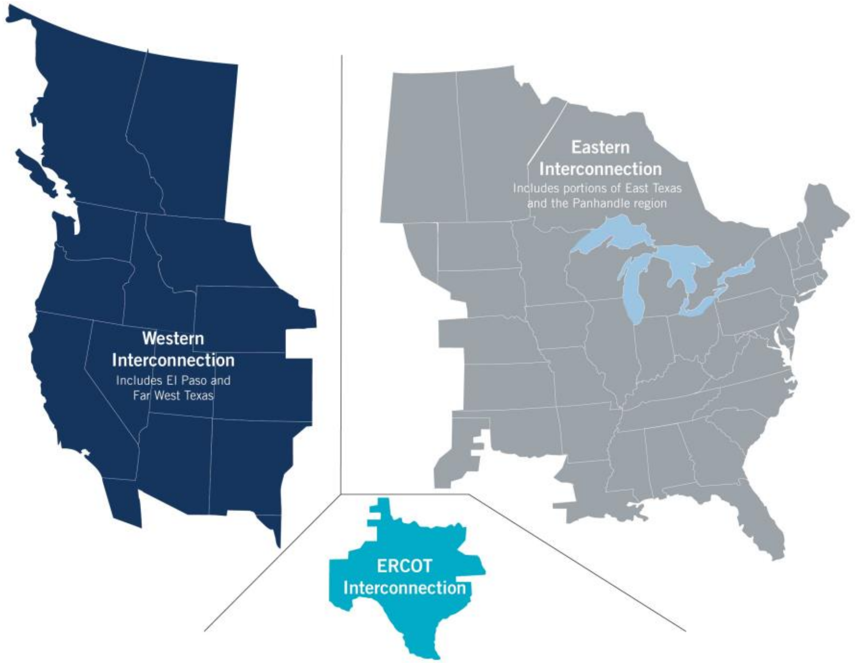
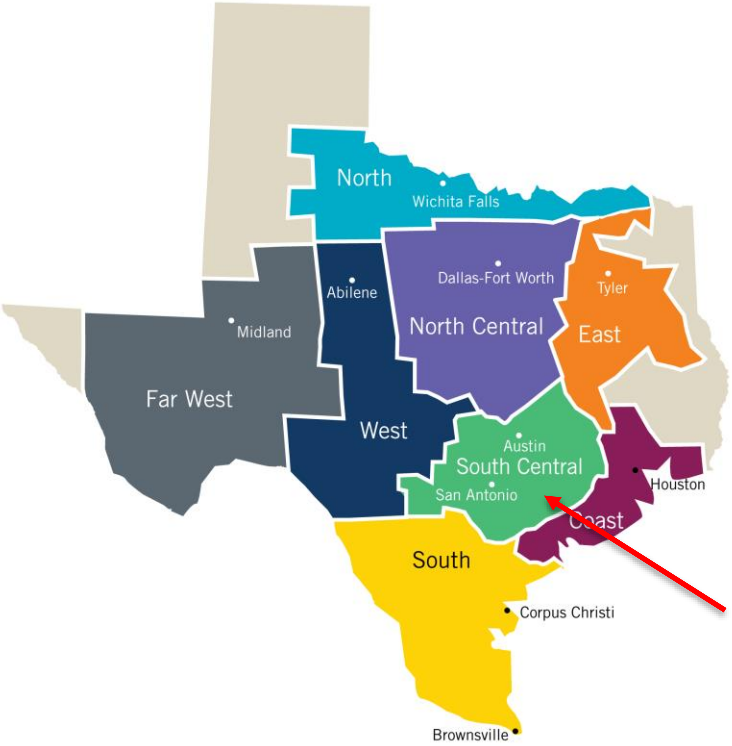
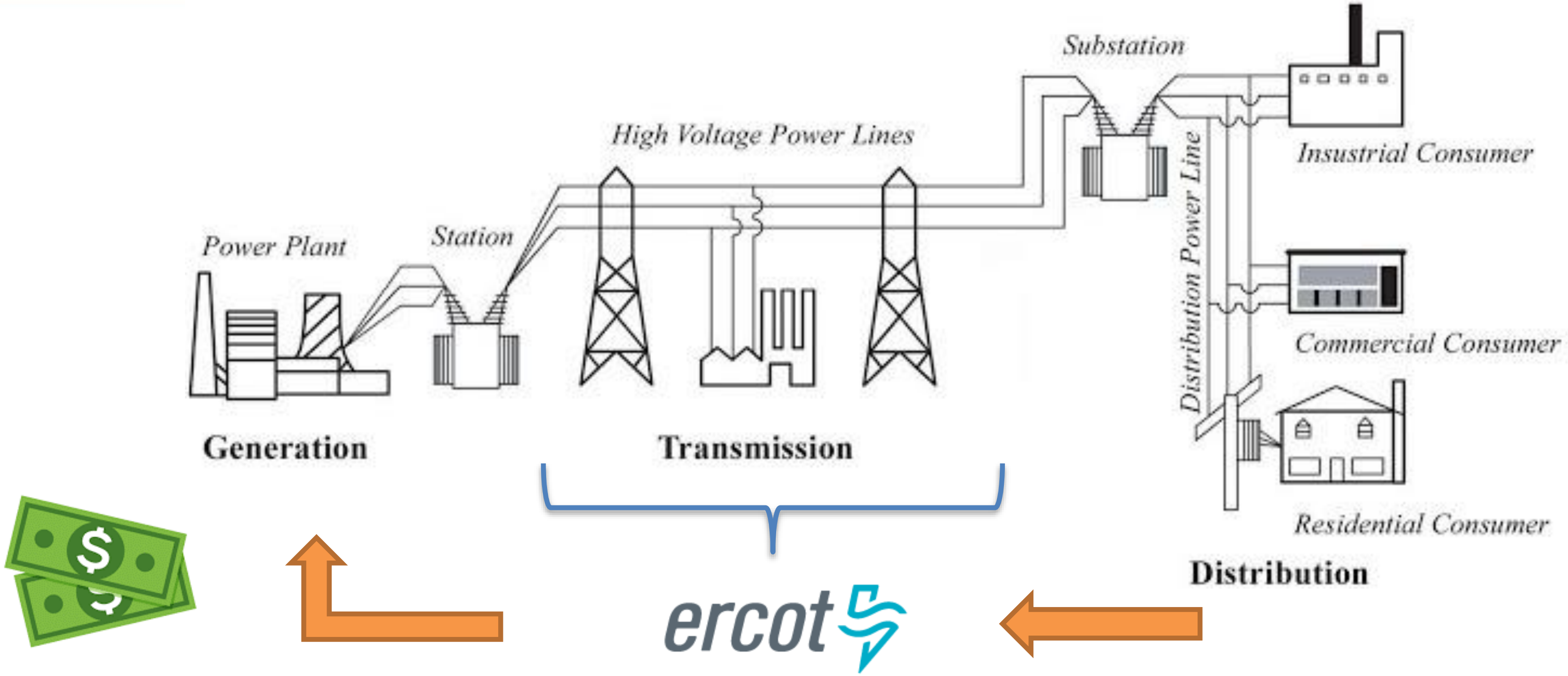
Background

- US national energy grid is comprised of 3 major interconnects
- The Electric Reliability Council of Texas (ERCOT) manages the flow of electric power to 26+ million Texas customers (90% TX electric load)





Source: EROCT



- ERCOT manages & operates a wholesale electricity market balancing demand & generation
- Excessive generation can lead to damage to grid systems (thermo.) while proper capacity is required to prevent black out
- Difference generation sources have “ramp up times” & inherit energy transmission limitations
- ERCOT currently aims for 12.5% margin on required load

Source: Warren Lasher – “Senior Director of System Planning” at ERCOT

Motivation

- Sophisticated models used to predict energy load but margins are decreasing to competitive prices
- Power dispatch requirements outputs need to be scheduled based on “short term” 1 hr and daily forecasts & mid term 7 day forecasts
- Robust modeling reduces risk of overloading energy grid and damaging subsystems
- Improved forecasting improves competitive energy pricing & cost to customers
- Able to anticipate energy load reducing dependency on thermal fleet & better utilization of renewable sources

Objective

Attempt to improve energy load predictions using ARMA modeling techniques

ERCOT South Central Zone Energy Load

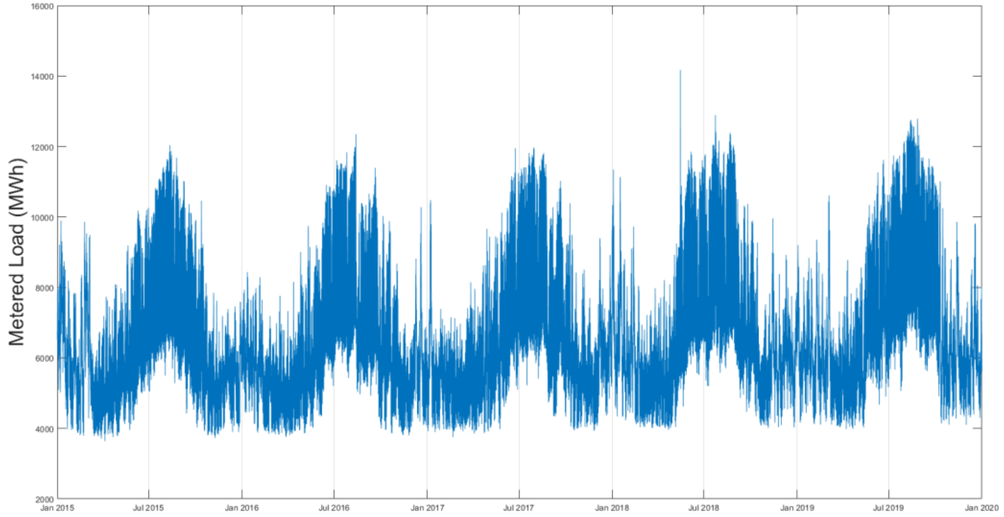
Description

- Training Data: [01/01/2015 – 12/31/2019]
- Forecasting Test: [01/01/2020 – 01/07/2020]
- Sampling Interval: hourly

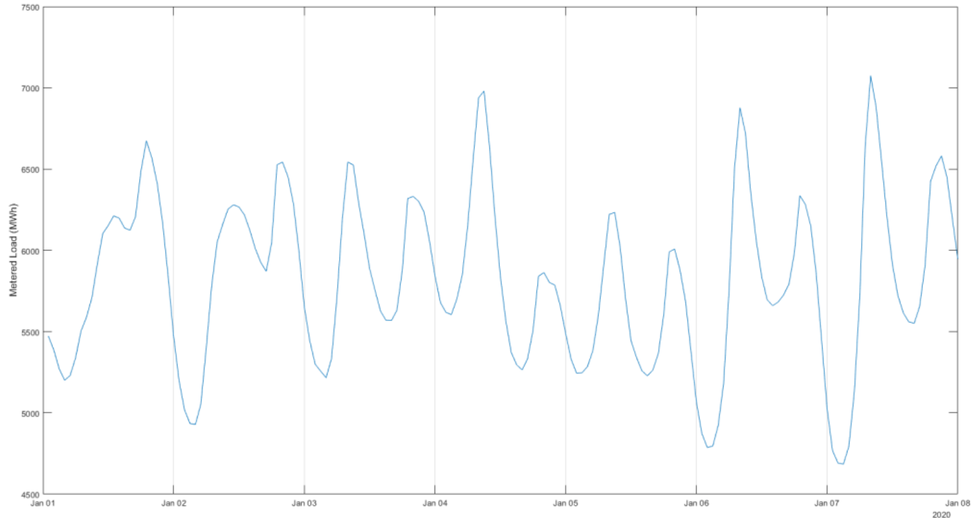
Trends & Seasonality

- Upward linear trend with time – pop. growth
- Yearly – seasonal weather dependent
  - Period = ~8774
- Daily – daily temperatures & habits
  - Period = 24

Training Data



Test Data



Data Processing

Heteroscedasticity

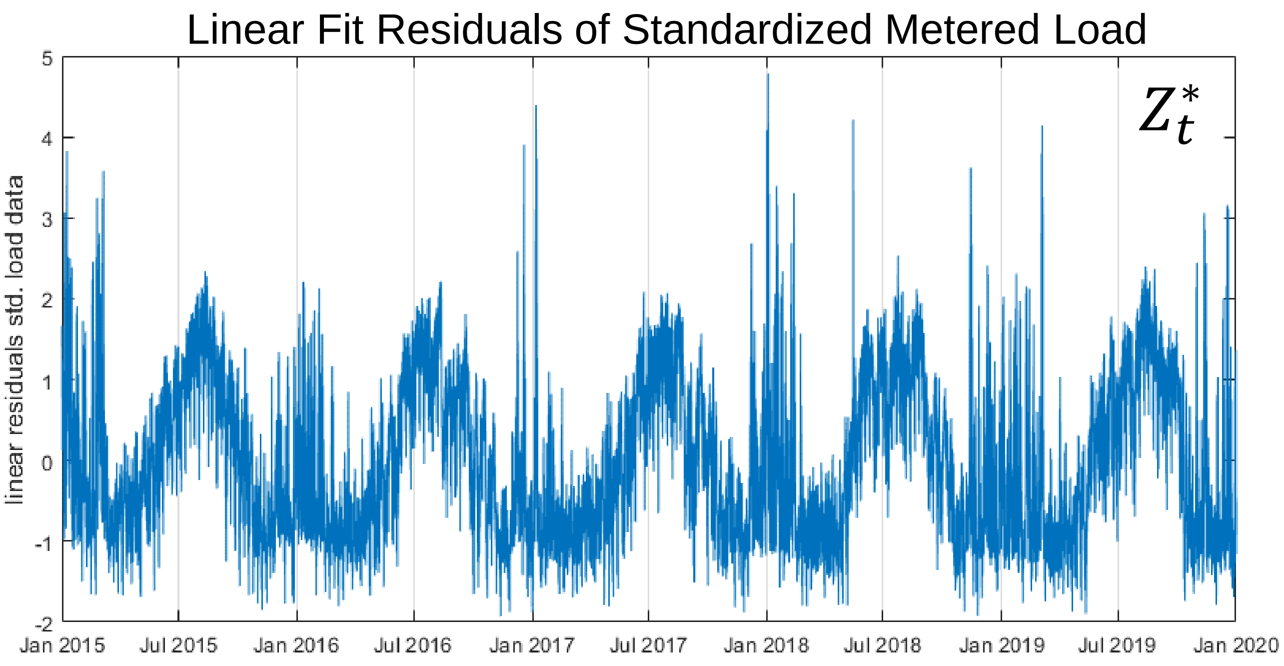
- Varying mean and variance of load data (L_t) with time
- Addressed via following standardization:

$$\left.\begin{aligned} Z_t &= Z_{h+24k} = \frac{L_{h+24k} - \mu_h}{\sigma_h} \\ \sigma_h &= \sqrt{\sum_{k=0}^{d} \frac{(L_{h+24k} - \mu_h)^2}{d-1}} \\ \mu_h &= \frac{1}{d} \sum_{k=0}^{d} L_{h+24k} \end{aligned}\right\} \begin{aligned} h &= 1,2,\ldots,24 \\ k &= 0,1,2,\ldots,d \end{aligned}$$

Non-stationarity – Det. Trend

- Linear trend with time

$$Z_t = \beta_0 + \beta_1 t + Z_t^*$$



Scalar ARMA Model

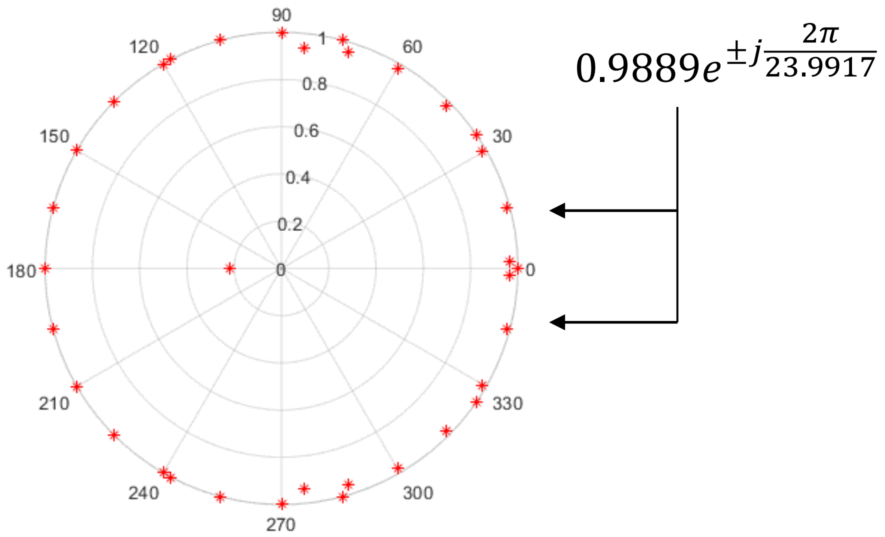
ARMA(2n, 2n-1) F-Test Procedure

- ARMA(36,35) found to be adequate
- RSS_o = 262.34

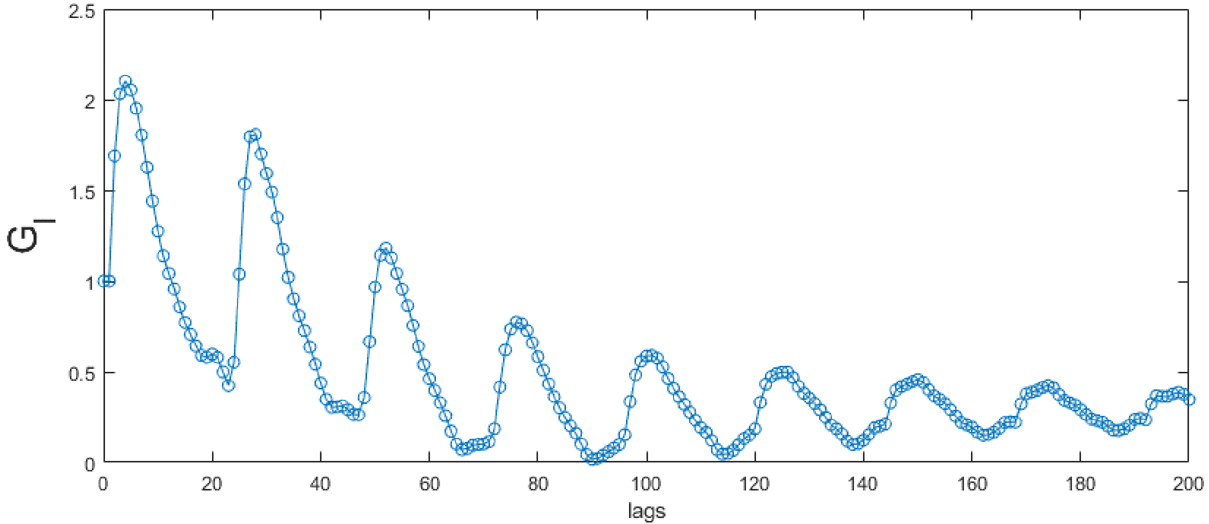
Probable Stoch. Seasonality

- 12 pairs of equally spaced roots close to unit circle (period ~24 hours)

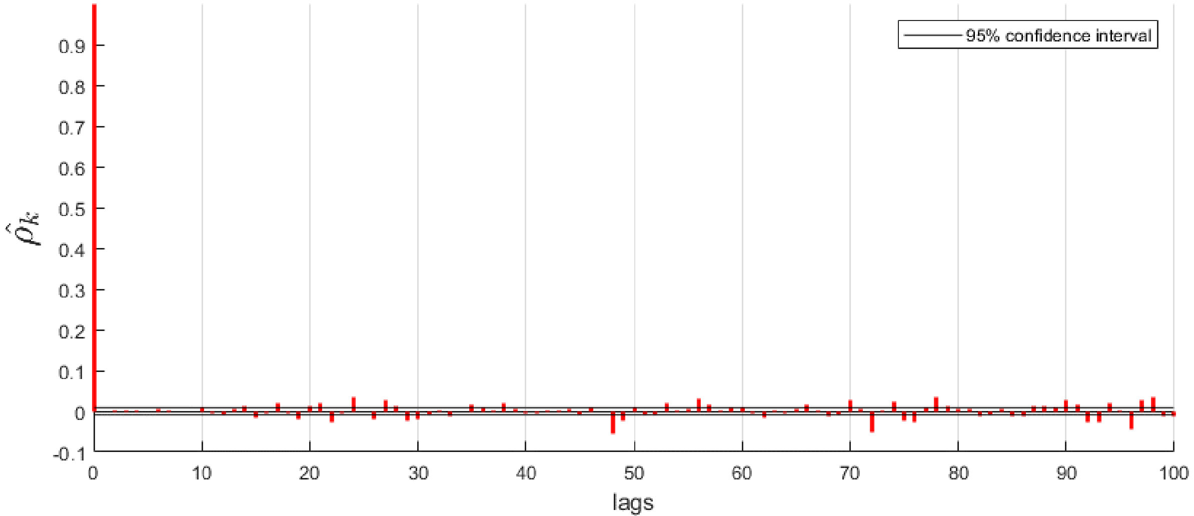
AR Roots of ARMA(36,35) model



Green's Function Coefficients



Autocorrelations of Residuals



Parsimonious Model Test

Creation of Parsimonious Time Series

- Since all 24 roots close to the unit circle are equally space 15 deg. apart, they can be represented via:

$$\lambda_k = e^{j\frac{2\pi}{24}k}, k = 0,1,2, \dots, 23$$

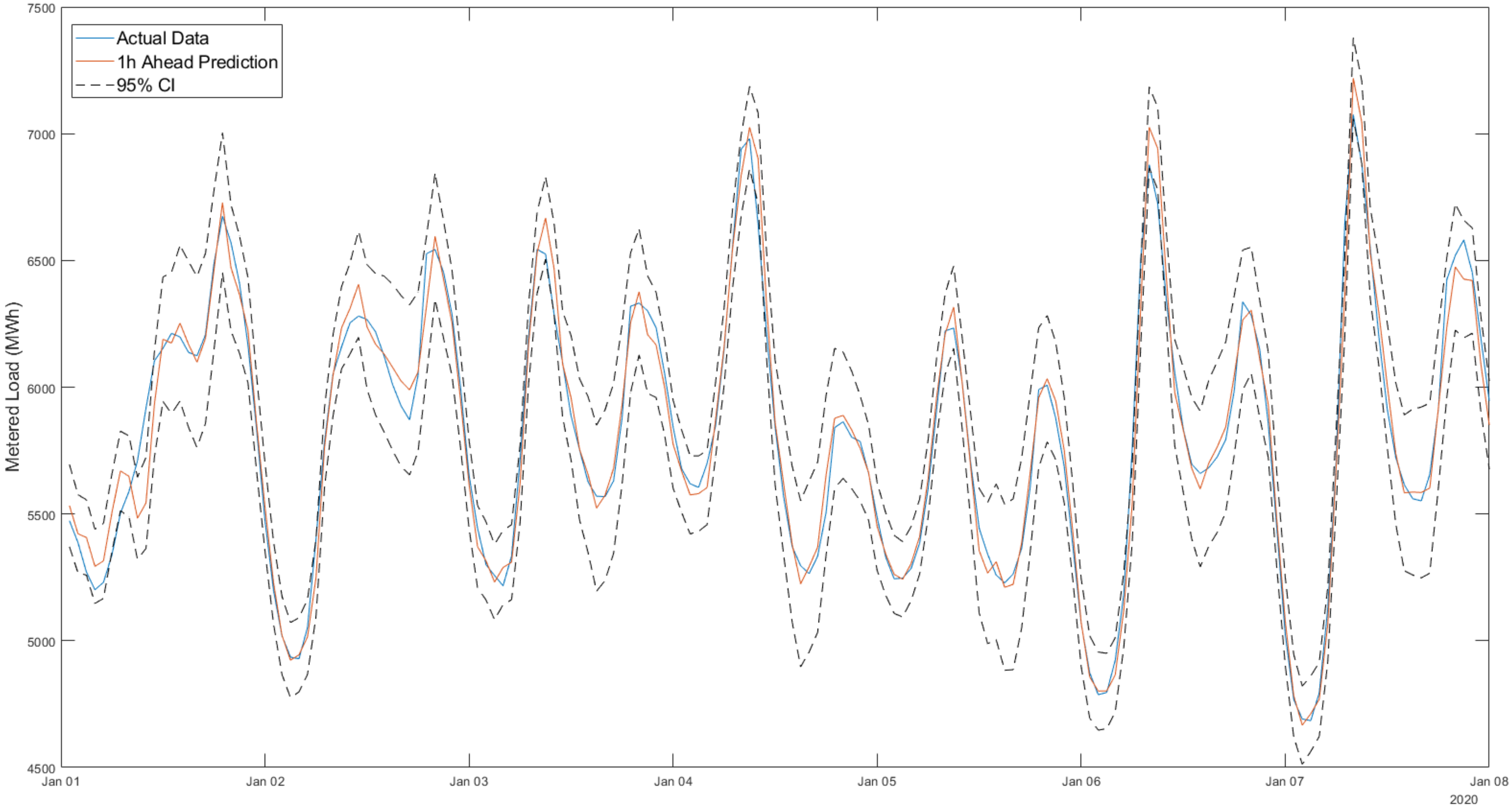
- Definition of the parsimonious time series

$$P_t = (1 - B^{24})Z_t^*$$

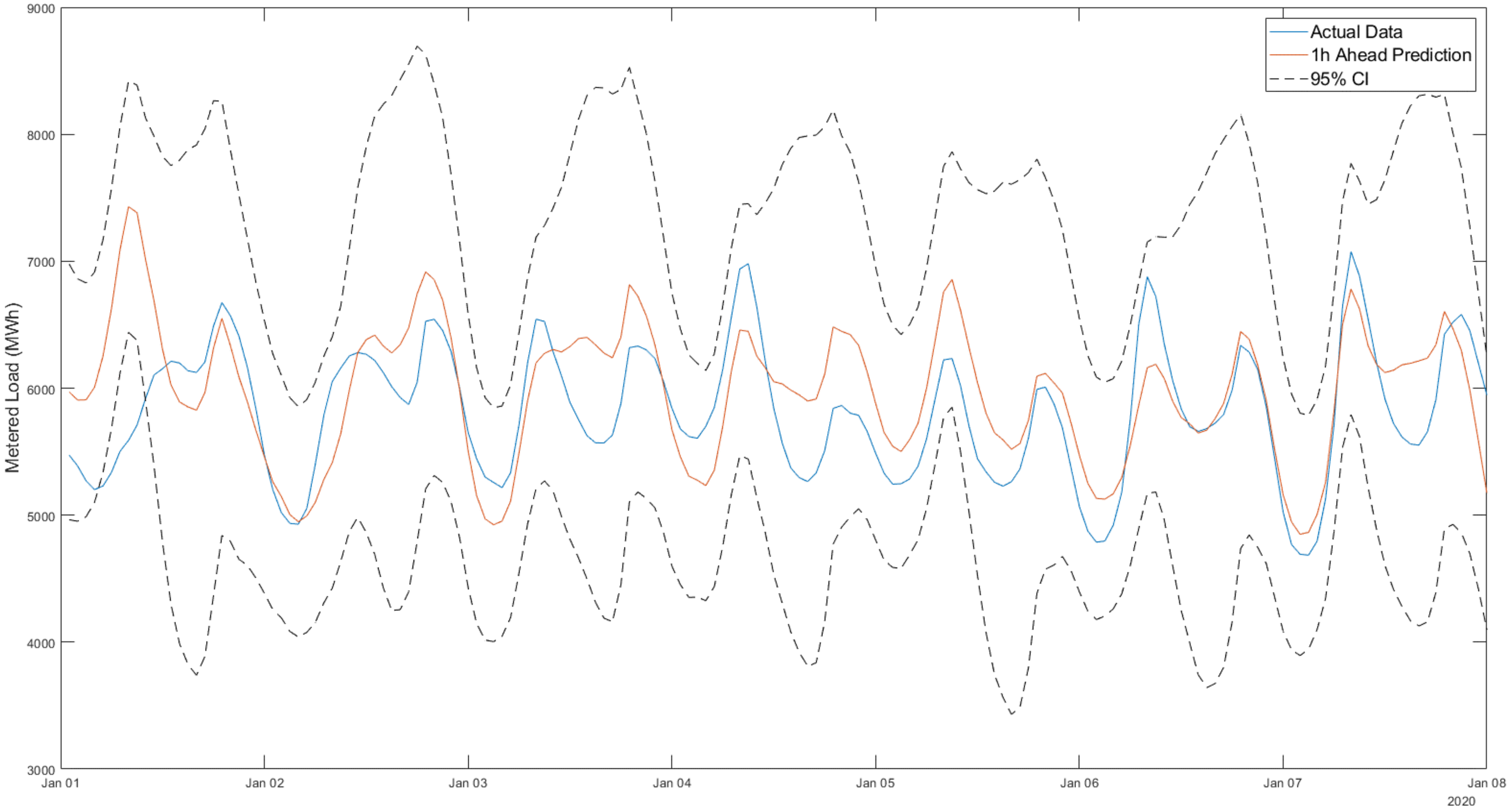
Testing Parsimonious Model

- ARMA(12,35) fit to parsimonious time series
- RSS_1 = 276.21 (RSS_o = 262.34)
- $F = 96.39 > F_{0.95}(24, \infty)$
- Parsimonious model is therefore **NOT ADEQUATE**

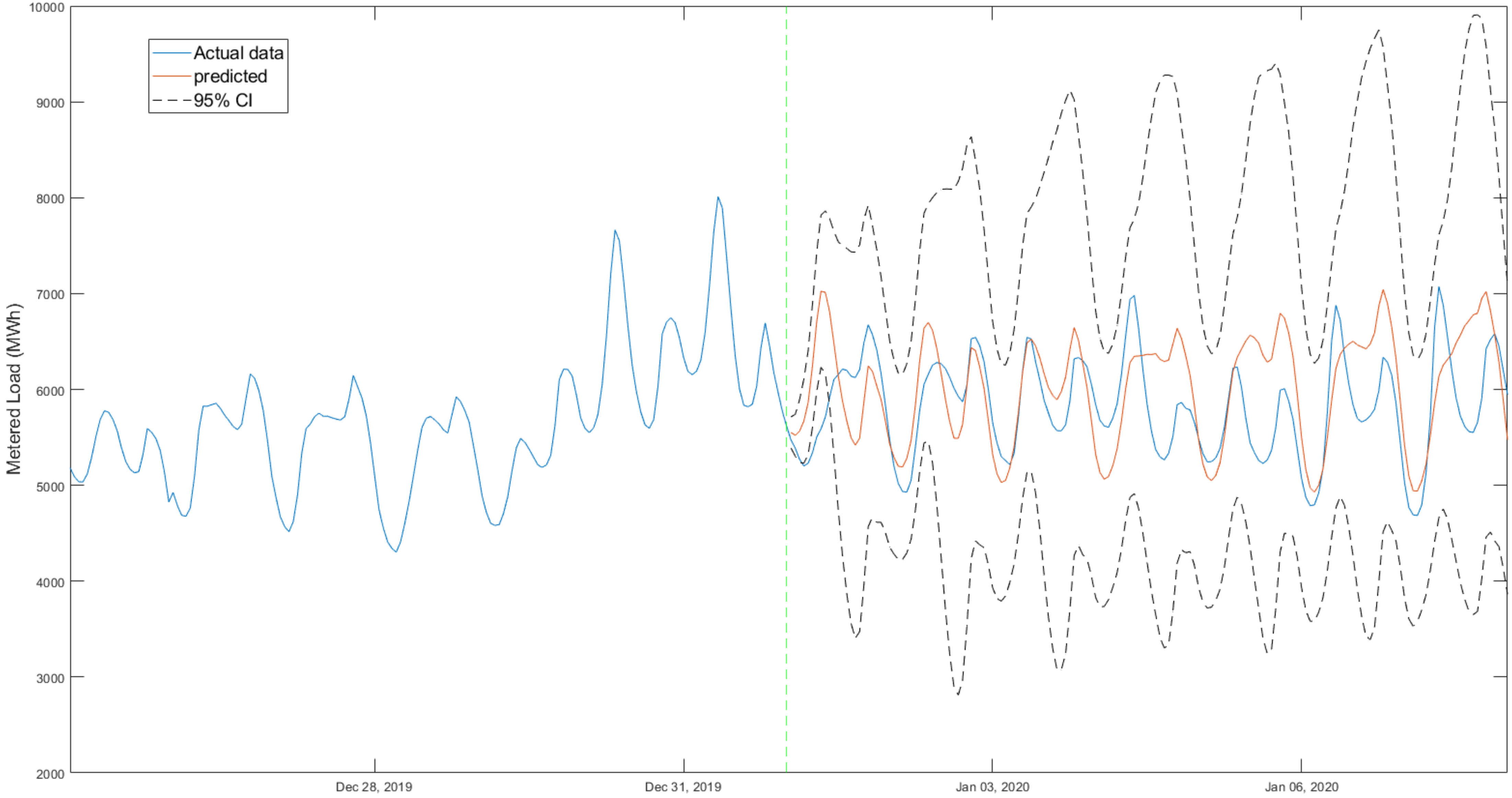
ARMA 1 Hour Ahead Predictions



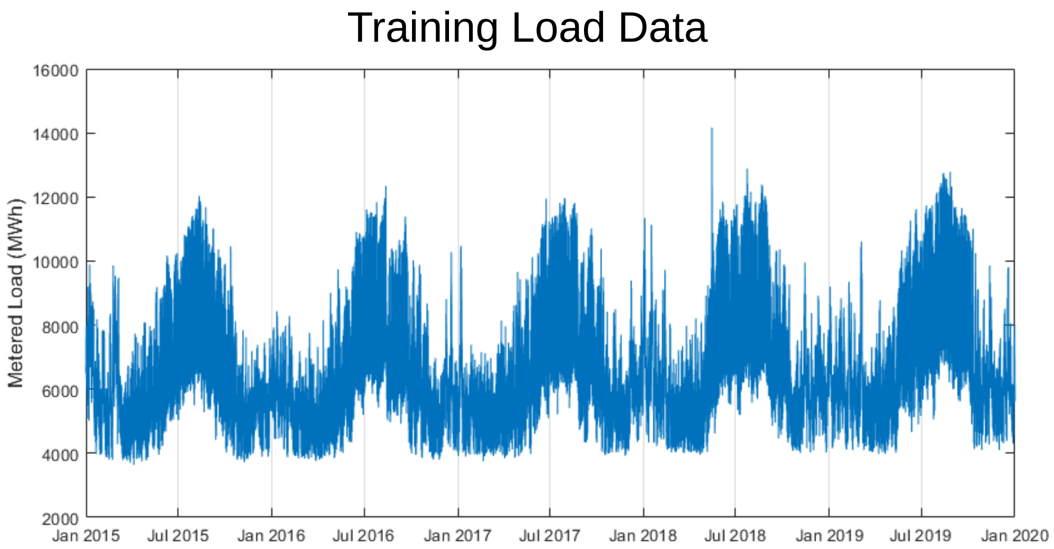
ARMA 24 Hour Ahead Prediction



ARMA 1 Week Forecast

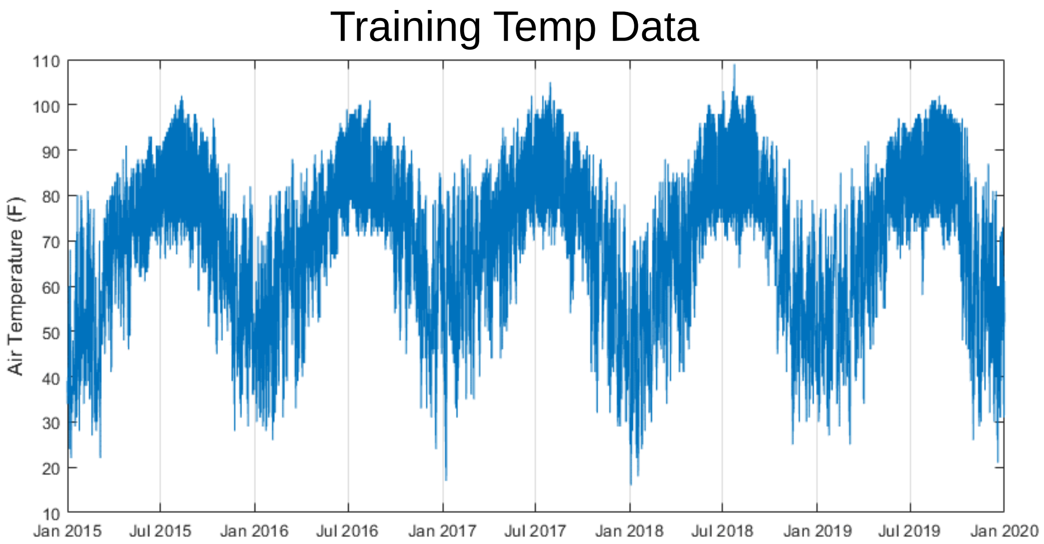


ARMAV Model Using Air Temperature Input



AUS Hourly Air Temperature Data (T_t)

- Similar underlying dynamics
- Peaks in load data match with extreme temperatures
- Standardized to address heteroscedasticity



ARMAV Model Structure

$$\begin{bmatrix} Z_t^* \\ T_t \end{bmatrix} = \begin{bmatrix} AR_{11}(B) & AR_{12}(B) \\ 0 & AR_{22}(B) \end{bmatrix} \begin{bmatrix} Z_t^* \\ T_t \end{bmatrix} + \begin{bmatrix} MR_{11}(B) & 0 \\ 0 & MR_{22}(B) \end{bmatrix} \begin{bmatrix} a_{Z_t^*} \\ a_{T_t} \end{bmatrix}$$

ARMAV Model

ARMAV Model Structure

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Fitted ARMAV Model

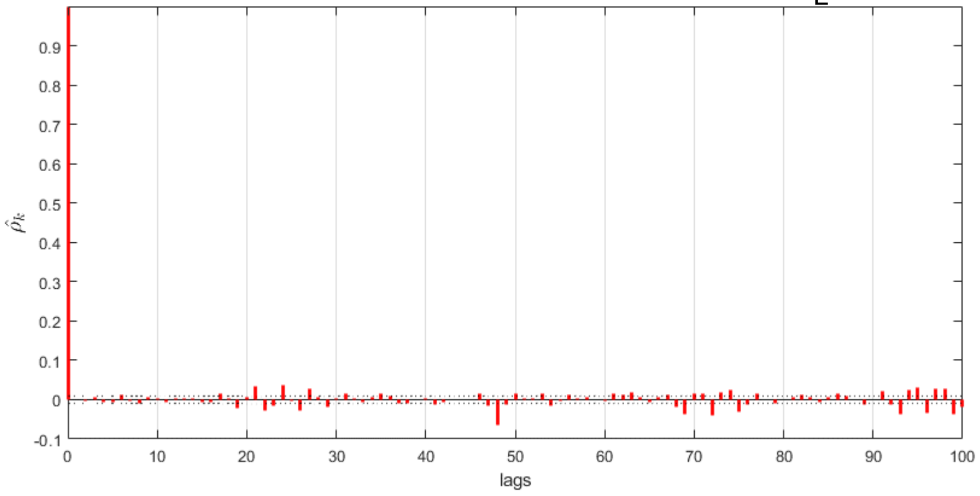
- ARMAV(30,30,29) fitted to Z_L^* using min AIC value
  - RSS_V = 269.079 > RSS_o = 262.34 (scaler ARMA)
- Forced fitted ARMA(30,29) for T_L (better residuals)

Characterizing Prediction Uncertainty

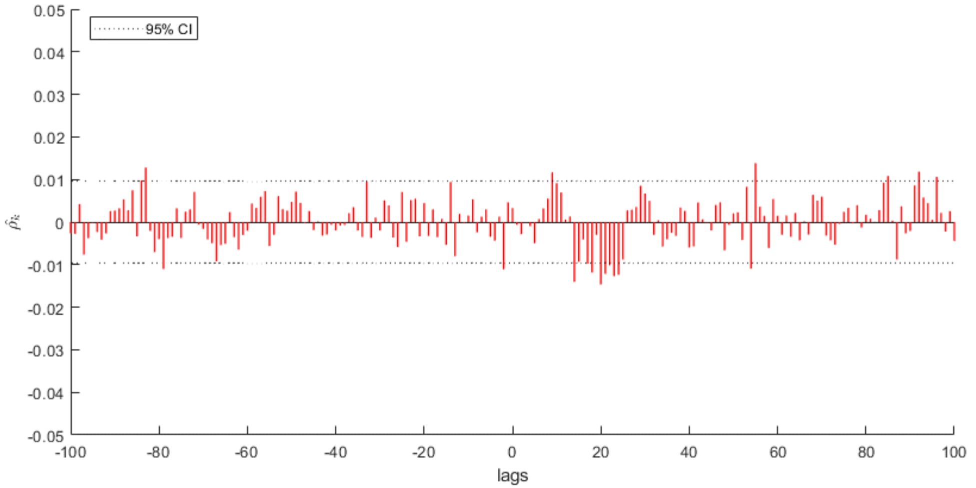
$$Z_L^* = \frac{MA_{11}(B)}{1-AR_{11}(B)} a_{Z_L^*} + \frac{AR_{12}(B)MA_{22}(B)}{(1-AR_{11}(B))(1-AR_{22}(B))} a_{T_t}$$

$$Var\left[\widehat{e_{Z_L^*}}(l)\right] = \left(\sum_{i=0}^{l-1} G^2_{(Z_t^*)_i}\right)\sigma^2_{Z_L^*} + \left(\sum_{i=0}^{l-1} G^2_{(T_t)_i}\right)\sigma^2_{T_t}$$

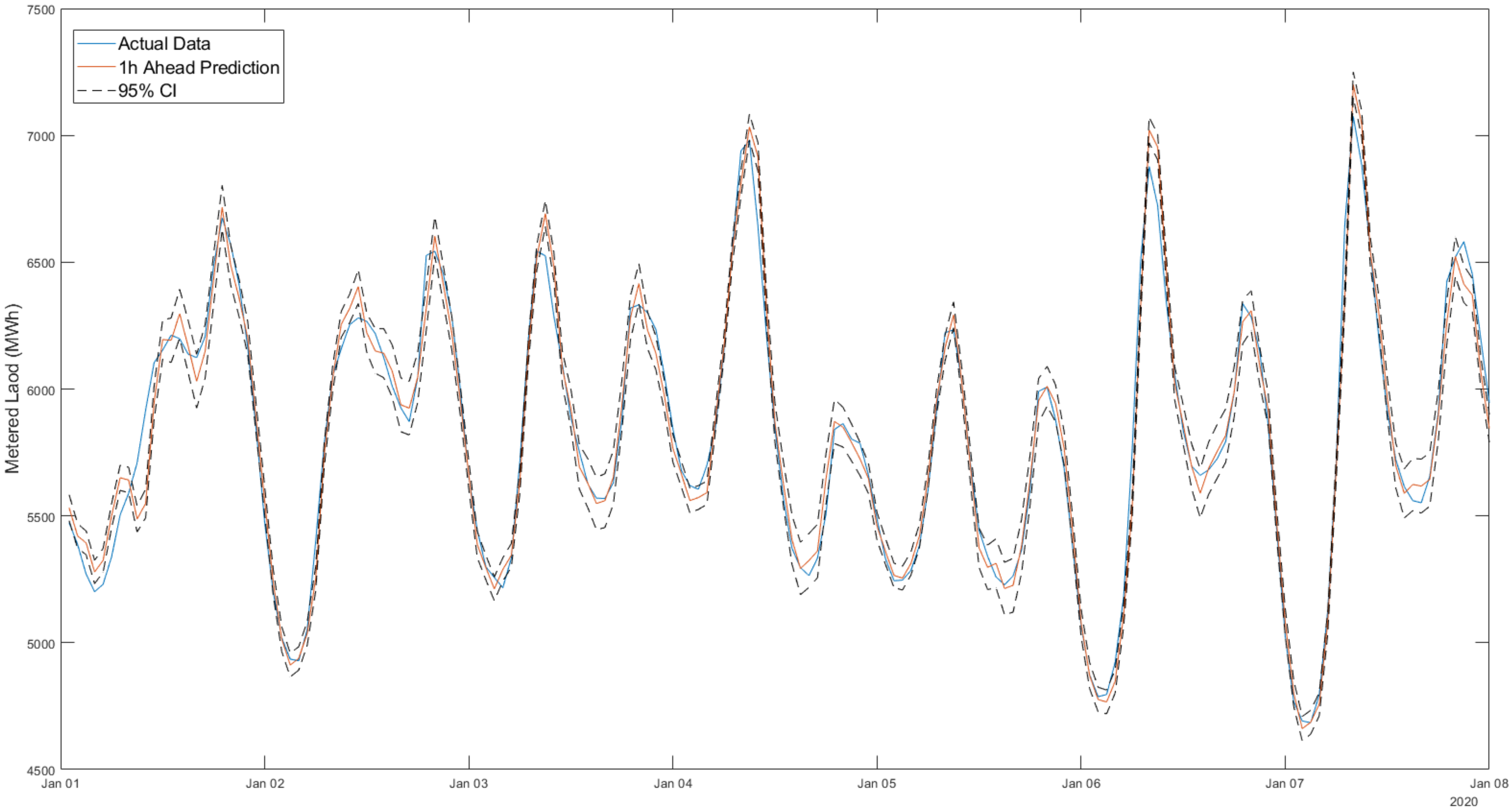
Autocorrelations of residuals of Z_L^*



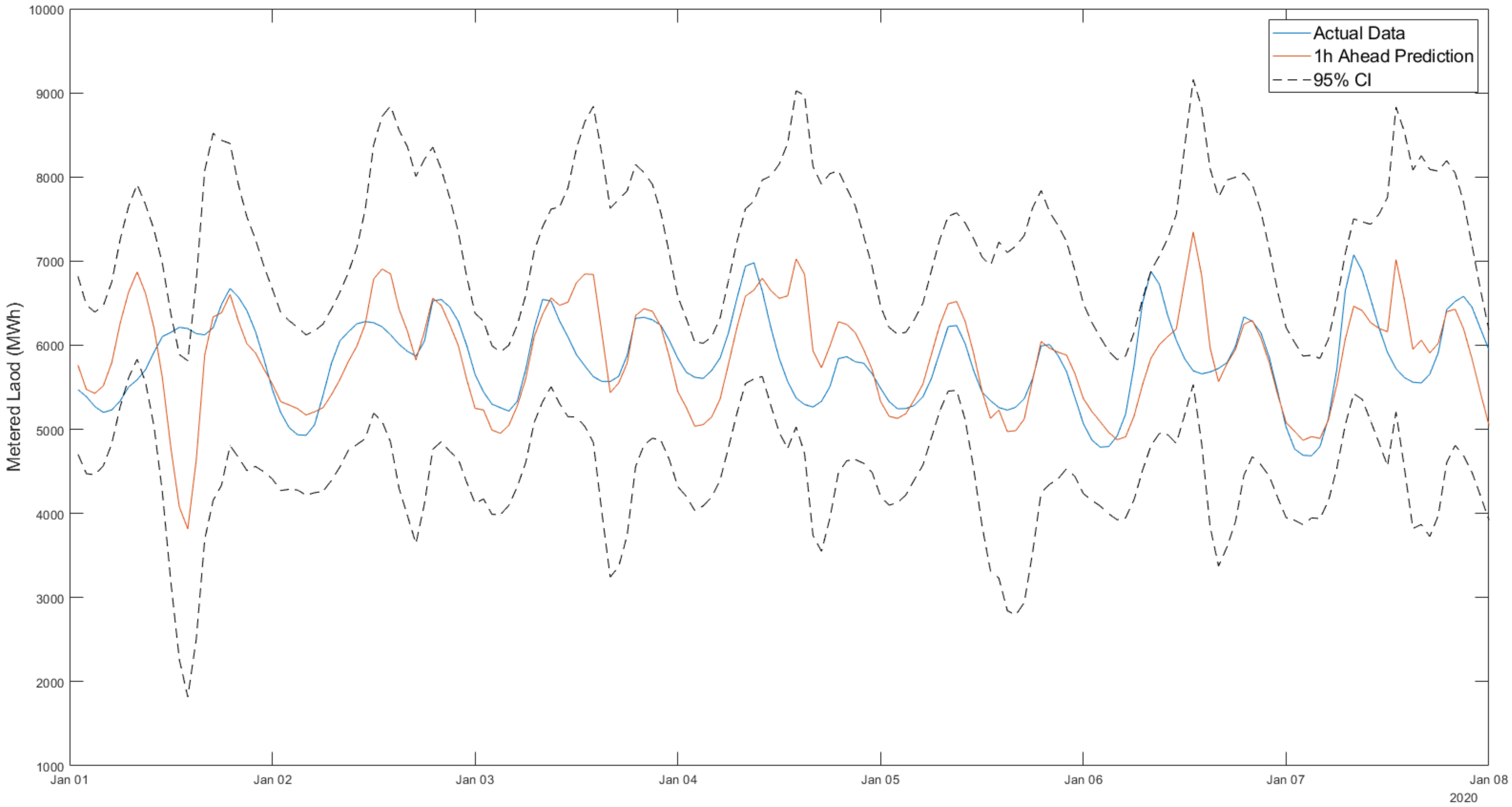
Cross correlation of residuals



ARMAV 1 Hour Ahead Load Predictions



ARMAV 6 Hour Ahead Load Predictions

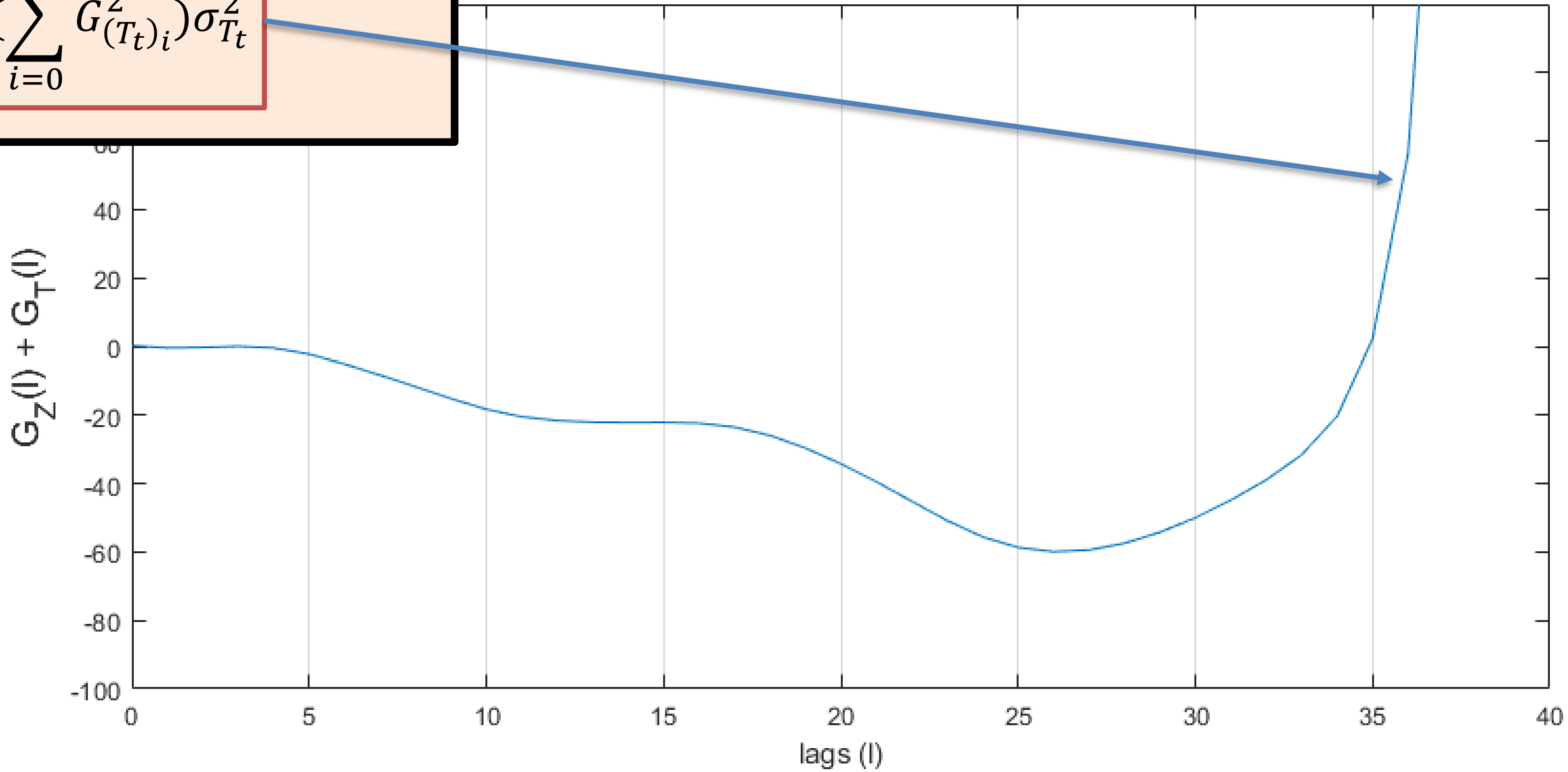


ARMAV Instability

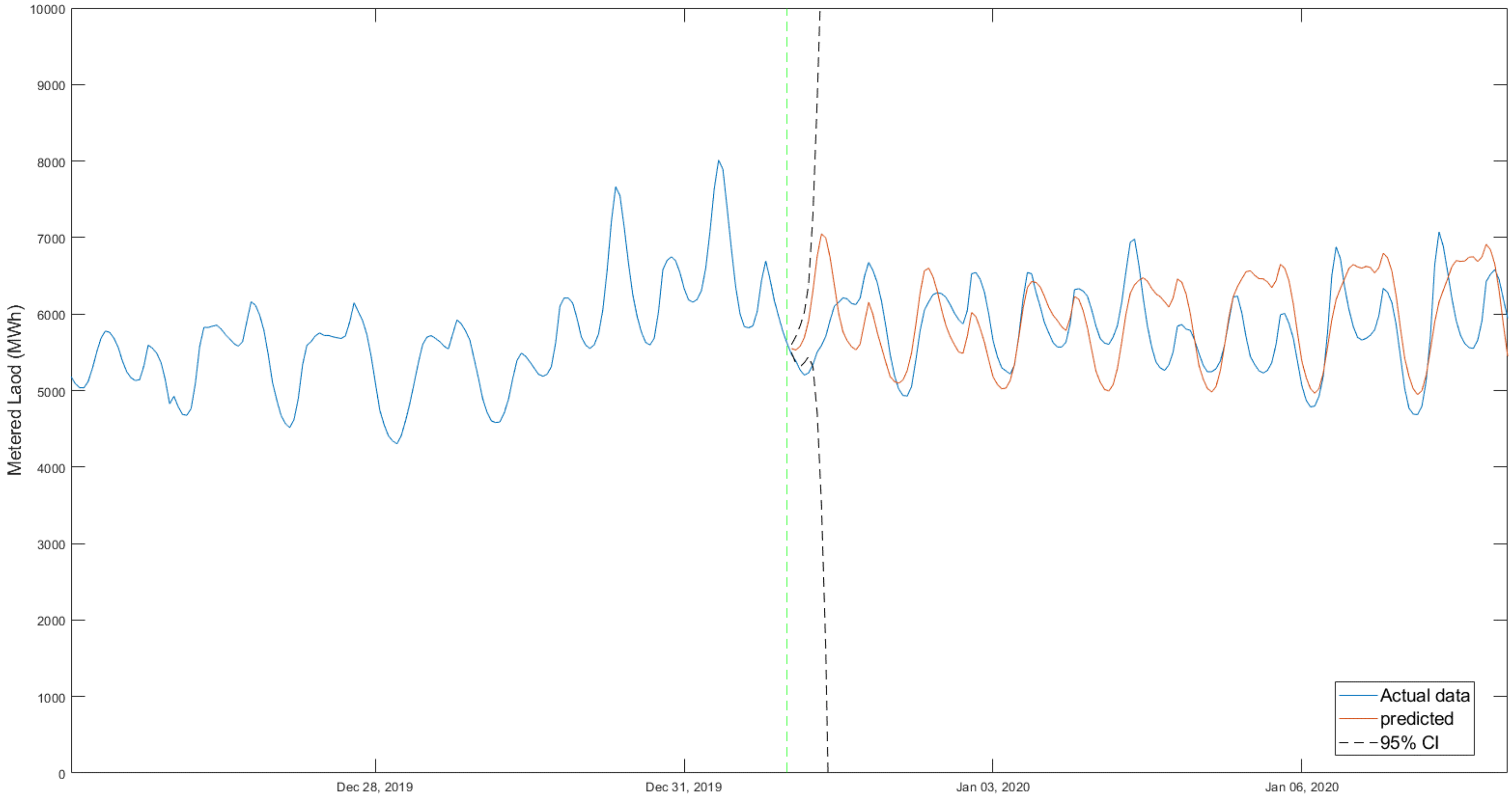
Characterizing Prediction Uncertainty

$$Z_L^* = \frac{MA_{11}(B)}{1-AR_{11}(B)} a_{Z_L^*} + \frac{AR_{12}(B)MA_{22}(B)}{(1-AR_{11}(B))(1-AR_{22}(B))} a_{T_t}$$

$$Var[\widehat{e_{Z_L^*}}(l)] = (\sum_{i=0}^{l-1} G^2_{(Z_t^*)_i})\sigma^2_{Z_L^*} + \boxed{(\sum_{i=0}^{l-1} G^2_{(T_t)_i})\sigma^2_{T_t}}$$



ARMAV 1 Week Forecast



Conclusions

Hourly metered load data was processed and ARMA models were fit to linear residuals

ARMA model predictions were converted back to real values and performance was assessed

Scalar ARMA model fitted to linear residuals of standardized load data is best at overall prediction

Vectoral ARMA model able to very accurately predict metered load values out to ~6 hours ahead but model instability results in infinite confidence bounds further out

Vectoral ARMA might benefit from additional inputs or temperature data may need to have deterministic seasonality's removed before fitting model