Recursive Estimation of Solar forecasting at Chulalongkorn University

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Outline

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- Objective
- Method & Result
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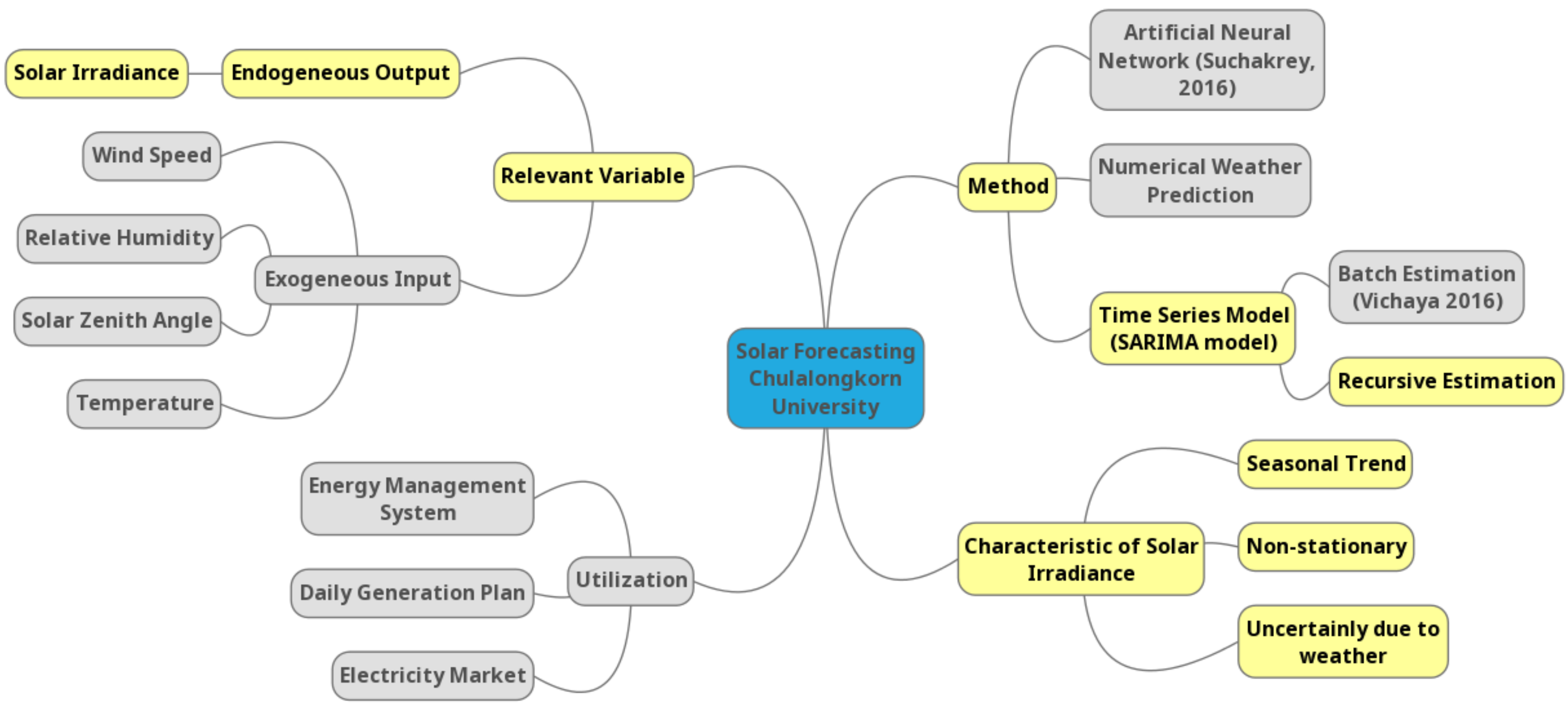
Introduction



Objective

- Apply recursive estimation of parameter on SARIMA model for solar irradiance forecasting at Chulalongkorn University.
- Apply recursive SARIMA model on EE-CU solar power forecasting (SPF) server.

SARIMA model

$$\tilde{A}(L^T)(1-L^T)^D A(L)(1-L)^d I(t) = \tilde{C}(L^T)C(L)e(t)$$

$$\tilde{A}(L^T) = 1 - (\widetilde{A_1}L^T + \widetilde{A_2}L^{2T} + \cdots + \widetilde{A_P}L^{PT})$$
$$A(L) = 1 - (A_1L + A_2L^2 + \cdots + A_pL^p)$$
$$\tilde{C}(L^T) = 1 + (\widetilde{C_1}L^T + \widetilde{C_2}L^{2T} + \cdots + \widetilde{C_Q}L^{QT})$$
$$C(L) = 1 + (C_1L + C_2L^2 + \cdots + C_qL^q)$$

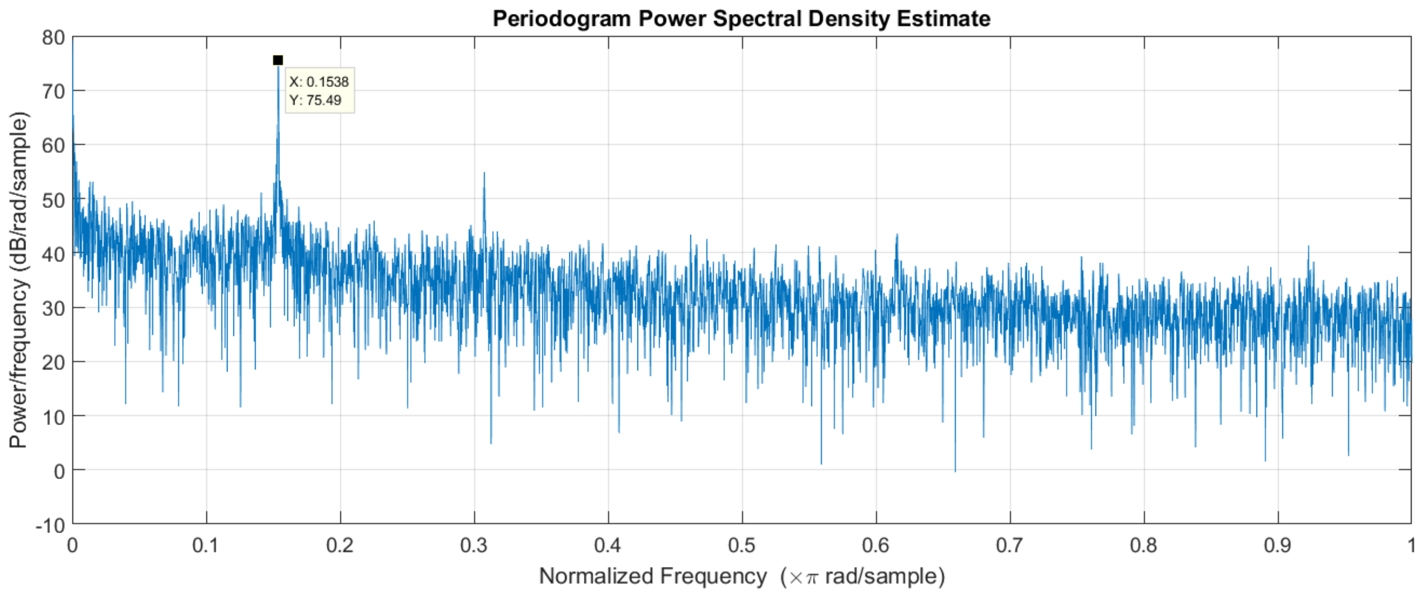
Written as $SARIMA(p,d,q)(P,D,Q)_T$

Method & Result

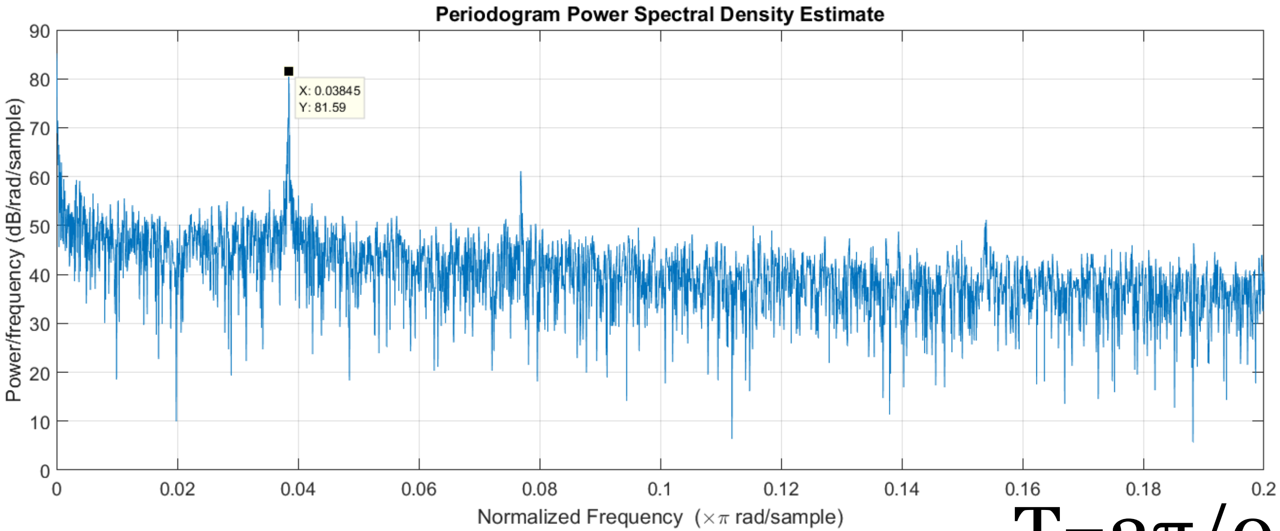
- Find seasonal trend
- Differencing
- ML and Model Validation
- Forecasting

Finding Seasonal Trend

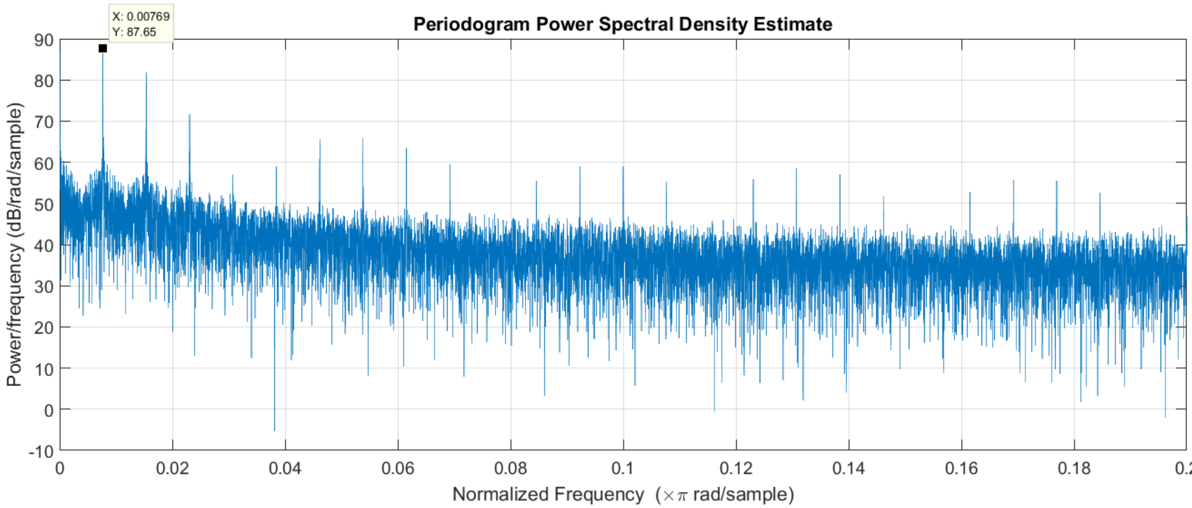
Using Fast Fourier Transform to find the power spectral density(PSD). Only high energy frequency and label them ω_i



$T = 2\pi / 0.1538\pi \approx 13$



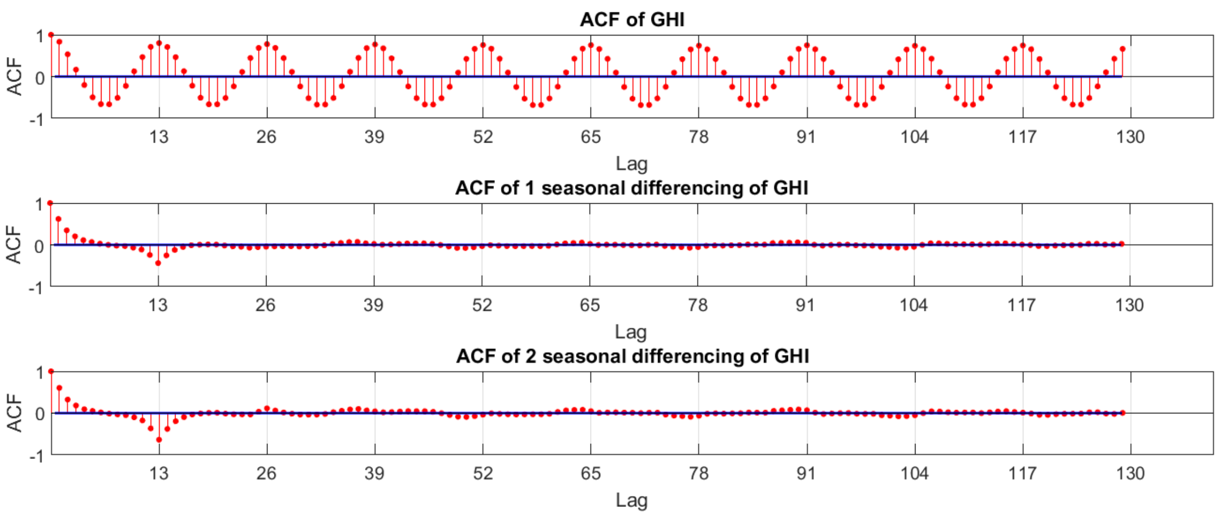
$T = 2\pi / 0.03845\,\pi \approx 52$



$T = 2\pi / 0.00769\,\pi \approx 260$

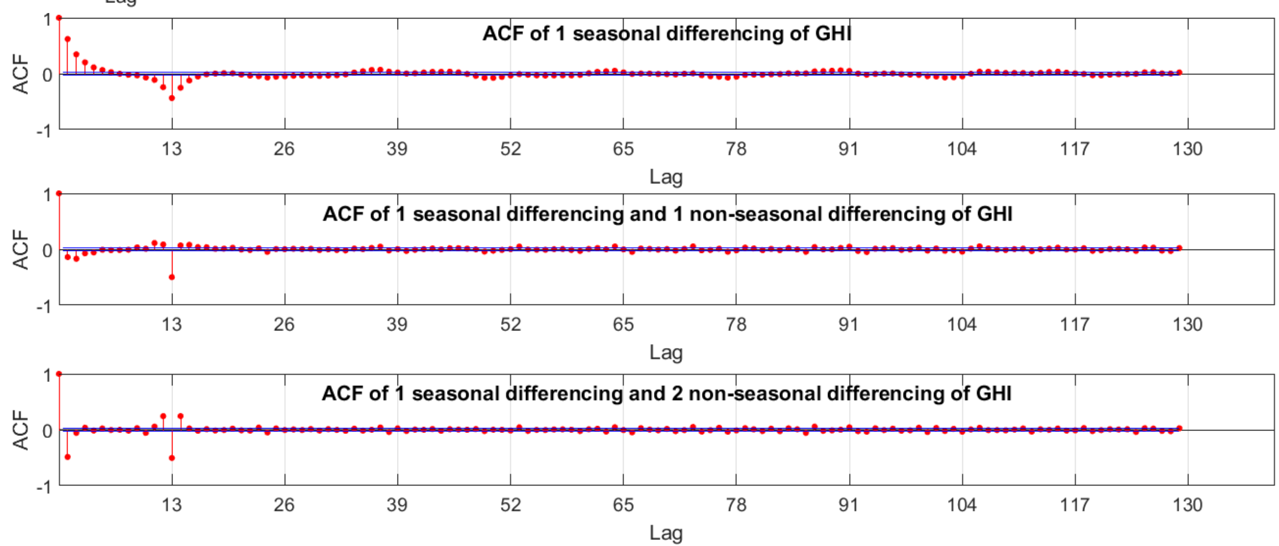
Differencing

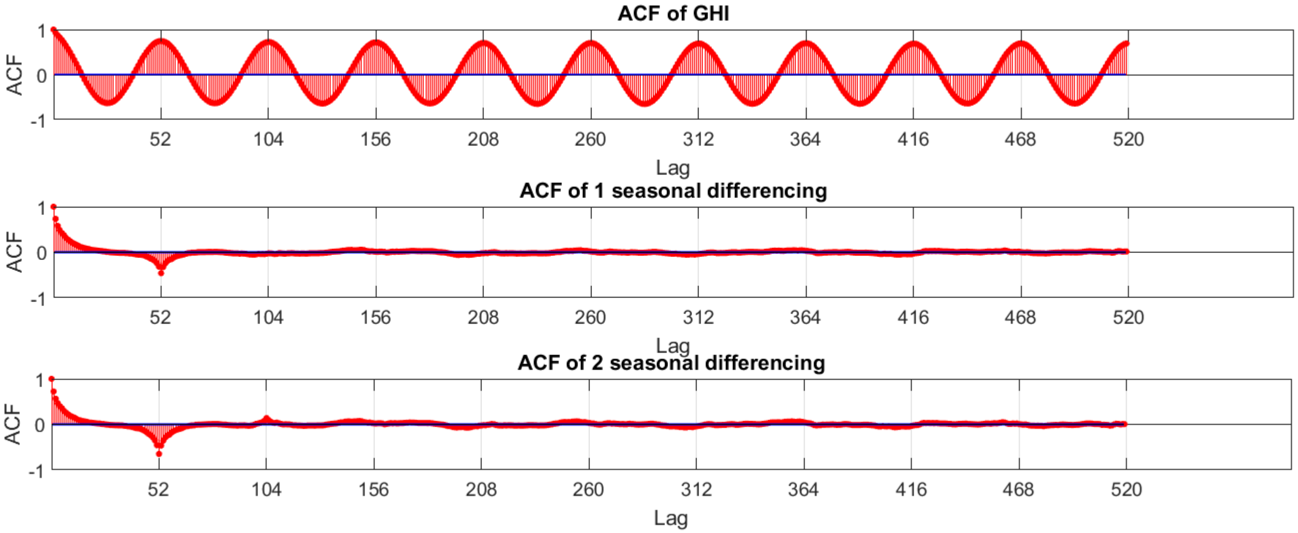
Apply Autocorrelation Function(ACF) and Partial Autocorrelation Function(PACF) finding integrated order d and D



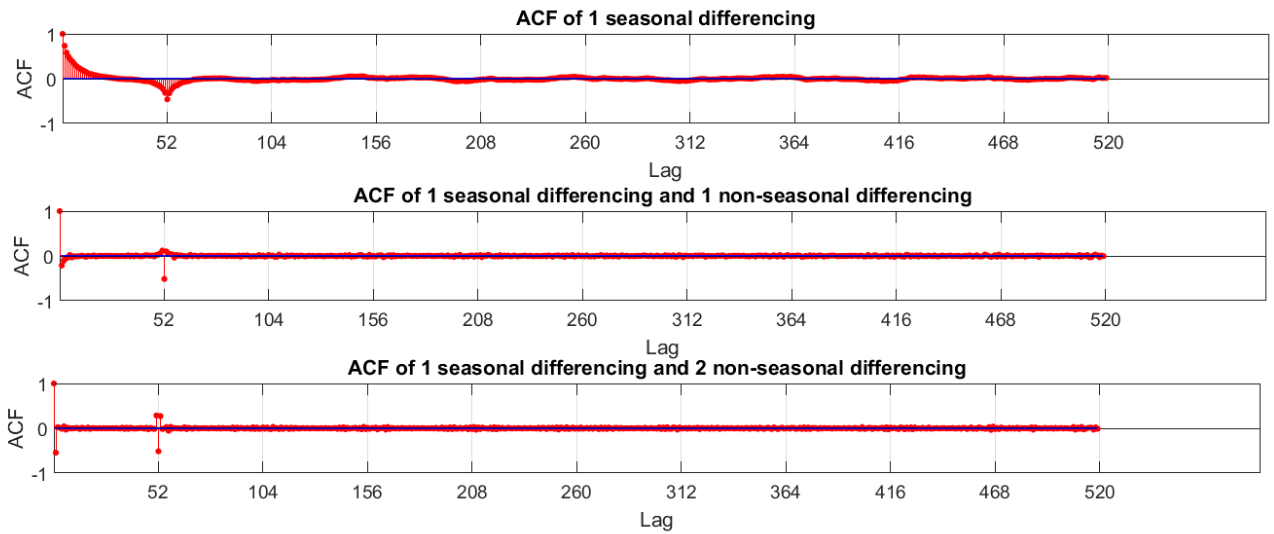
Choose D=1

Choose d=1

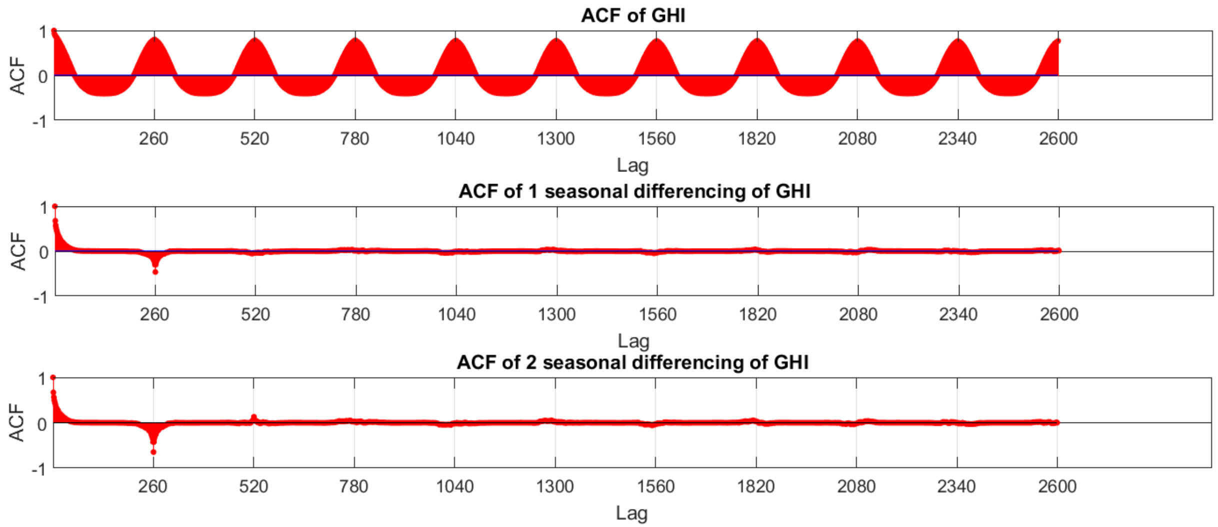




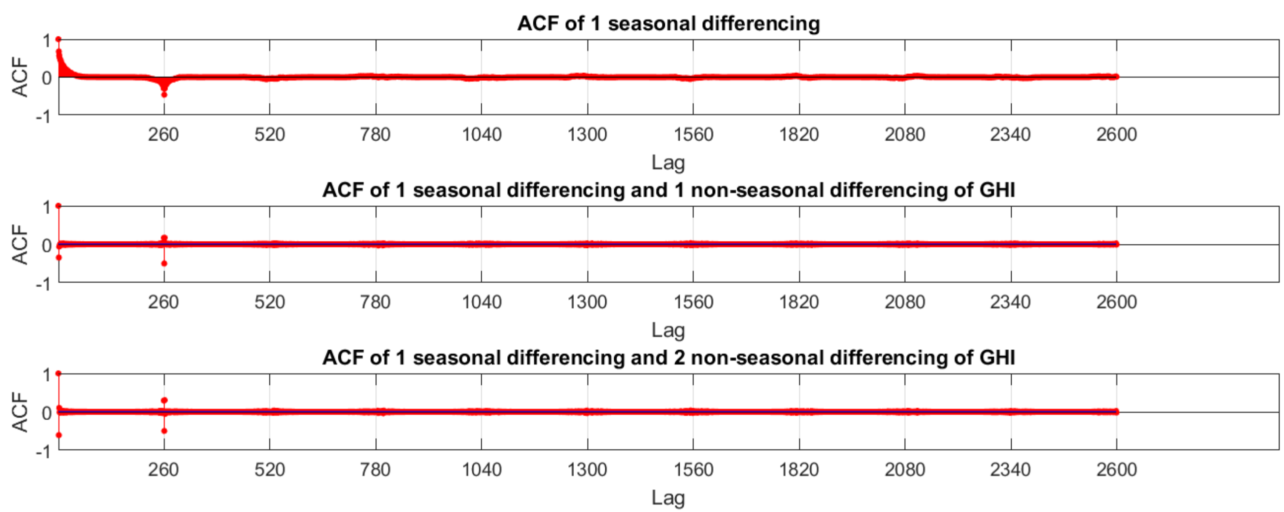
Choose
D=1



Choose
d=1



Choose D=1



Choose d=1

Range of order to choose model

	60 minutes	15 minutes	3 minutes
AR(p)	0-8	0-8	0-5
MA(q)	0-4	0-4	0-4
SAR(P)	0-4	0-6	0-2
SMA(Q)	0-1	0-1	0-1

Maximum Likelihood Estimation

$$\hat{\theta}_{ML} = \max_{\theta} -\frac{N-p}{2}\ln(2\pi) - \frac{N-p}{2}\ln(\sigma^2) - \sum_{t=p+1}^{N} \frac{v(t)^2}{2\sigma^2}$$

where,

$$\theta = \begin{bmatrix} A_1 & A_2 & \dots & A_p & C_1 & C_2 & \dots & C_q \end{bmatrix}$$

$$\begin{bmatrix} v(p+1) \\ v(p+2) \\ \vdots \\ v(N) \end{bmatrix}$$

$$= \begin{bmatrix} y(p+1) \\ y(p+2) \\ \vdots \\ y(N) \end{bmatrix} - \begin{bmatrix} y(p) & y(p-1) & \cdots & y(1) & v(p) & v(p-1) & \cdots & v(p-q+1) \\ y(p+1) & y(p) & \cdots & y(2) & v(p+1) & v(p) & \cdots & v(p-q+2) \\ \vdots & & & \vdots & \vdots & & & \vdots \\ y(N-1) & y(N-2) & \cdots & y(N-p) & v(N-1) & v(N-2) & \cdots & v(N-q) \end{bmatrix} \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_p \\ C_1 \\ C_2 \\ \vdots \\ C_q \end{bmatrix}$$

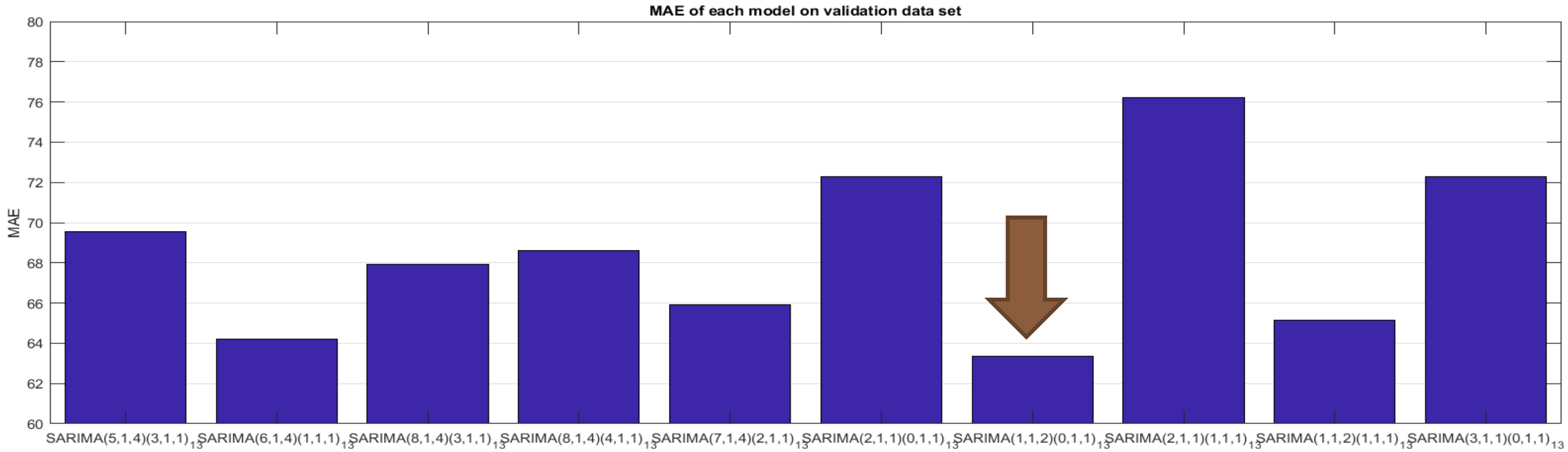
Model Validation

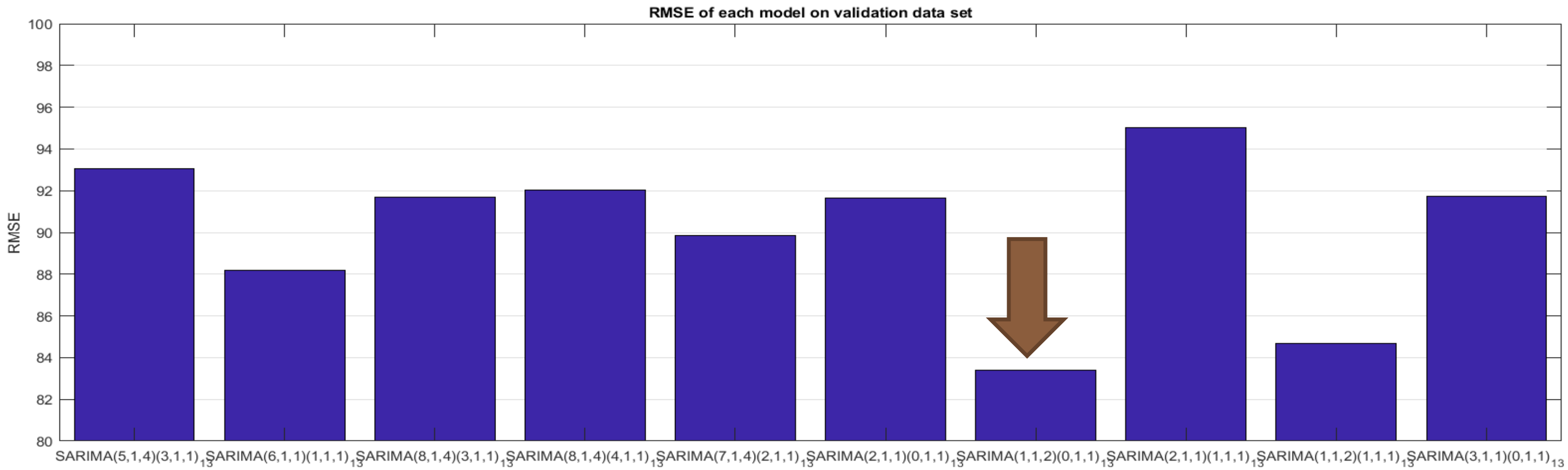
$$\text{AIC} = -2logL + 2d$$

$$\text{BIC} = -2logL + dlogN$$

where,
logL is log-likelihood function
d is number of parameters
N is number of data

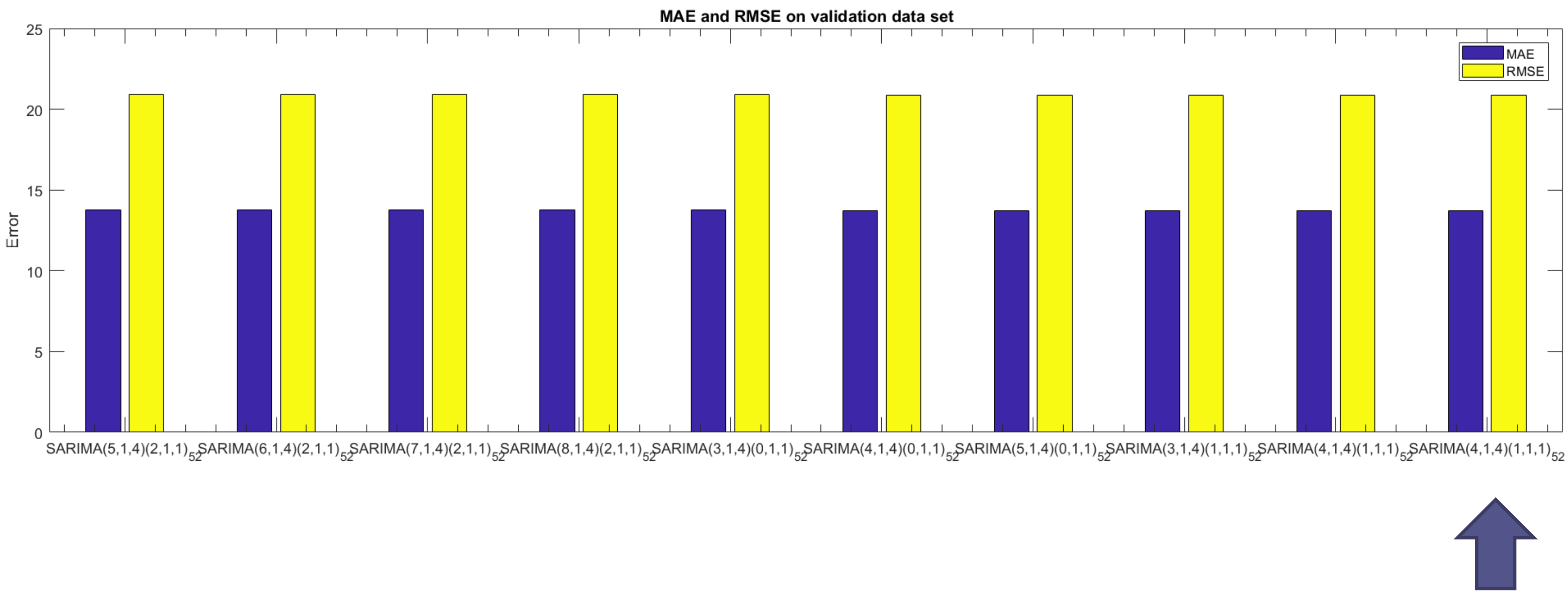
Error on validation data set of 60 minutes data set





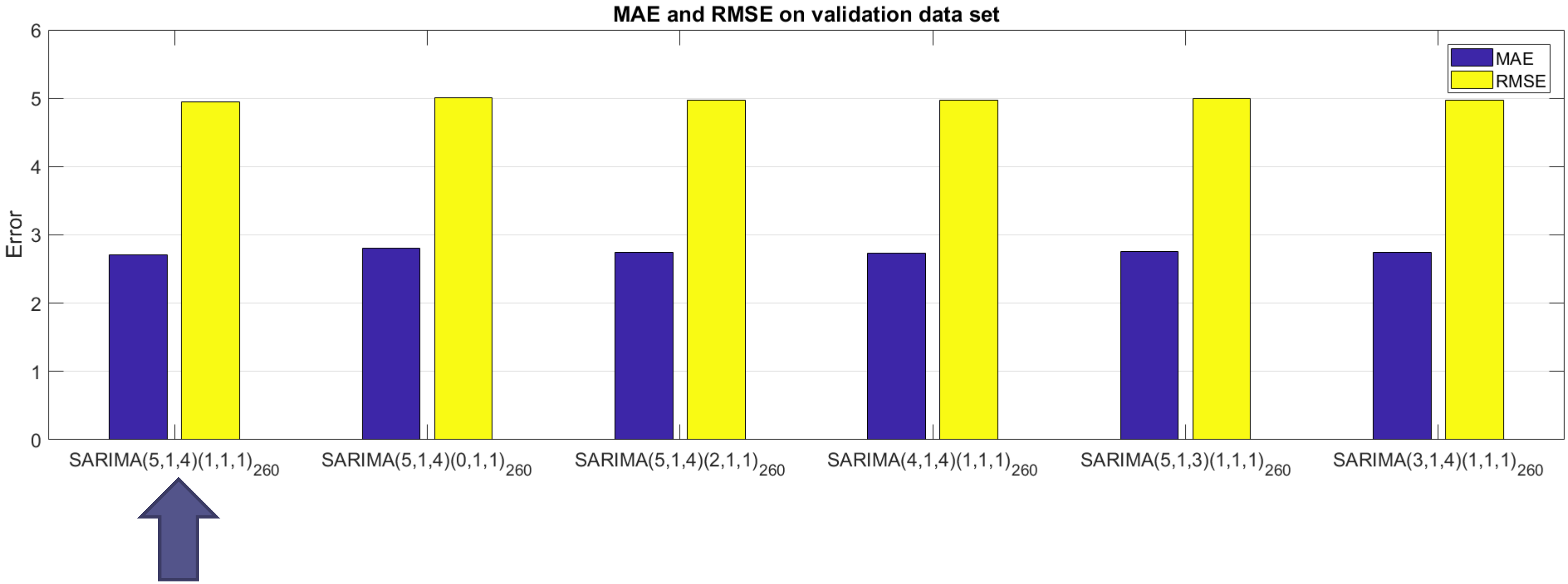
Thus, this data use $SARIMA(1,1,2)(0,1,1)_{13}$

Error on validation data set of 15 minutes data set



Thus, this data use $SARIMA(4,1,4)(1,1,1)_{52}$

Error on validation data set of 3 minutes data set



Thus, this data use $SARIMA(5,1,4)(1,1,1)_{260}$

$SARIMA(1,1,2)(0,1,1)_{13}$ defined as

$$(1-L^{13})(1-0.588L)(1-L)I(t)=(1-0.878L-0.113L^{2})(1-0.933L^{13})e(t)$$

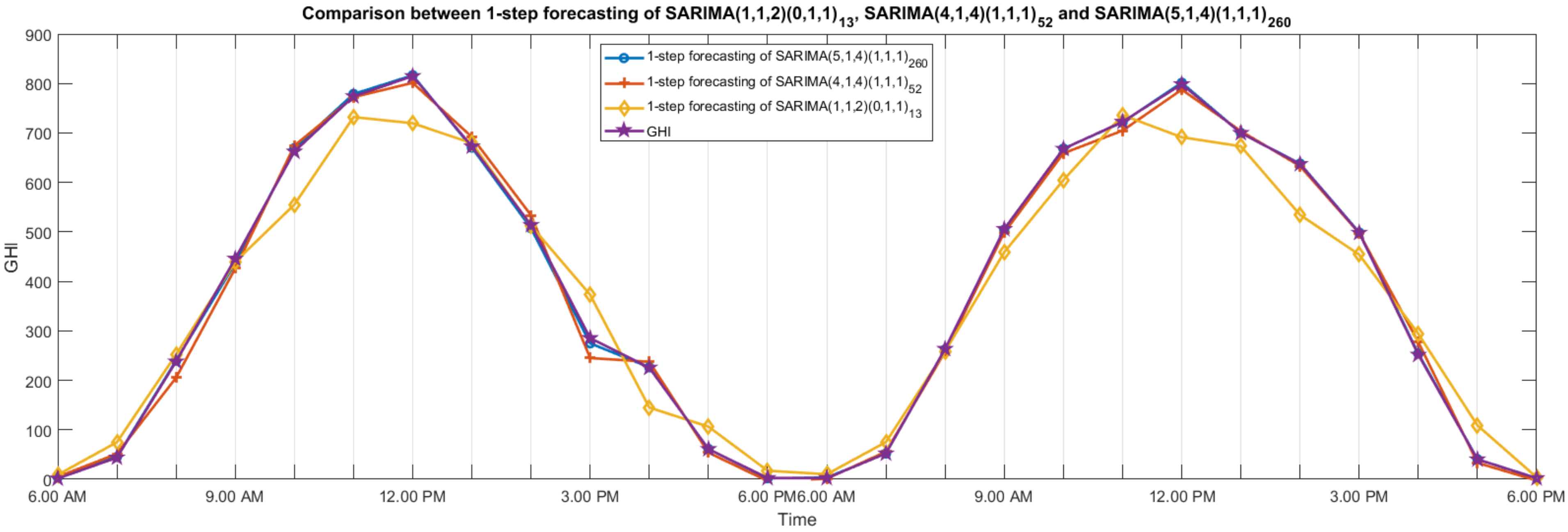
$SARIMA(4,1,4)(1,1,1)_{52}$ defined as

$$(1-0.011L^{52})(1-L^{52})(1-0.880L+0.179L^{2}-0.106L^{3}-0.033L^{4})(1-L)I(t)$$
$$=(1-0.338L+0.111L^{2}-0.089L^{3}-0.673L^{4})(1-0.947L^{52})e(t)$$

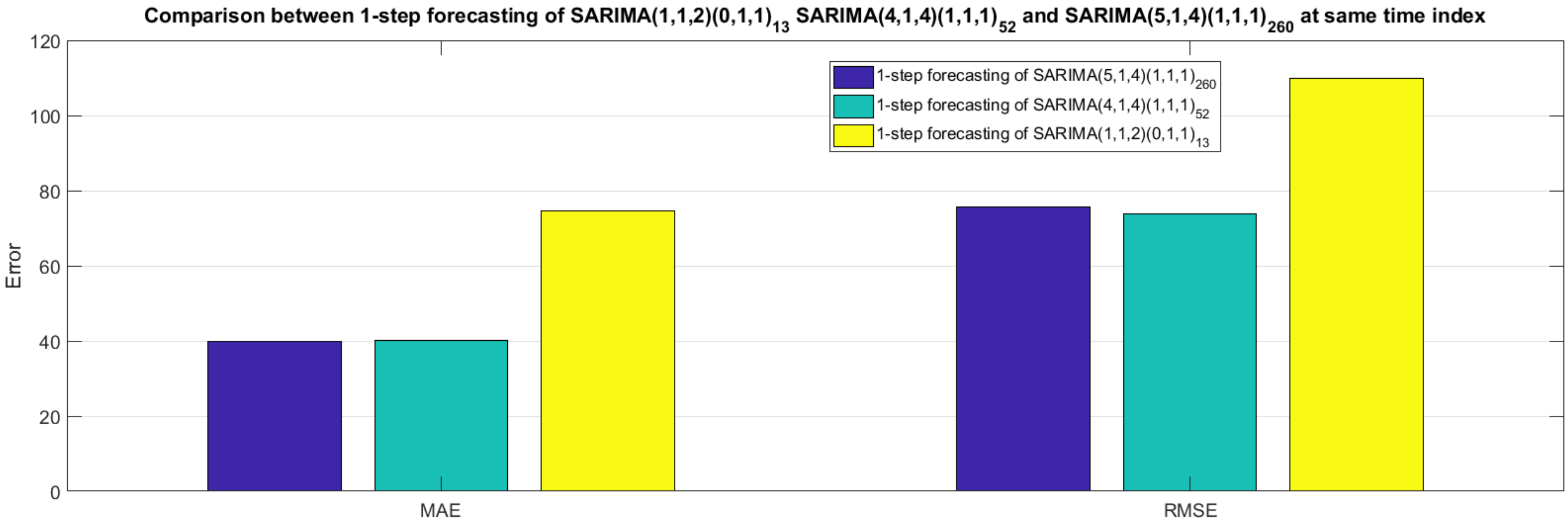
$SARIMA(5,1,4)(1,1,1)_{260}$ defined as

$$(1-0.034L^{260})(1-L^{260})(1-2L+0.829L^{2}+0.530L^{3}-0.298L^{4}-0.034L^{4})(1-L)I(t)$$
$$=(1-1.609L+0.285L^{2}+0.565L^{3}-0.138L^{4})(1-0.949L^{260})e(t)$$

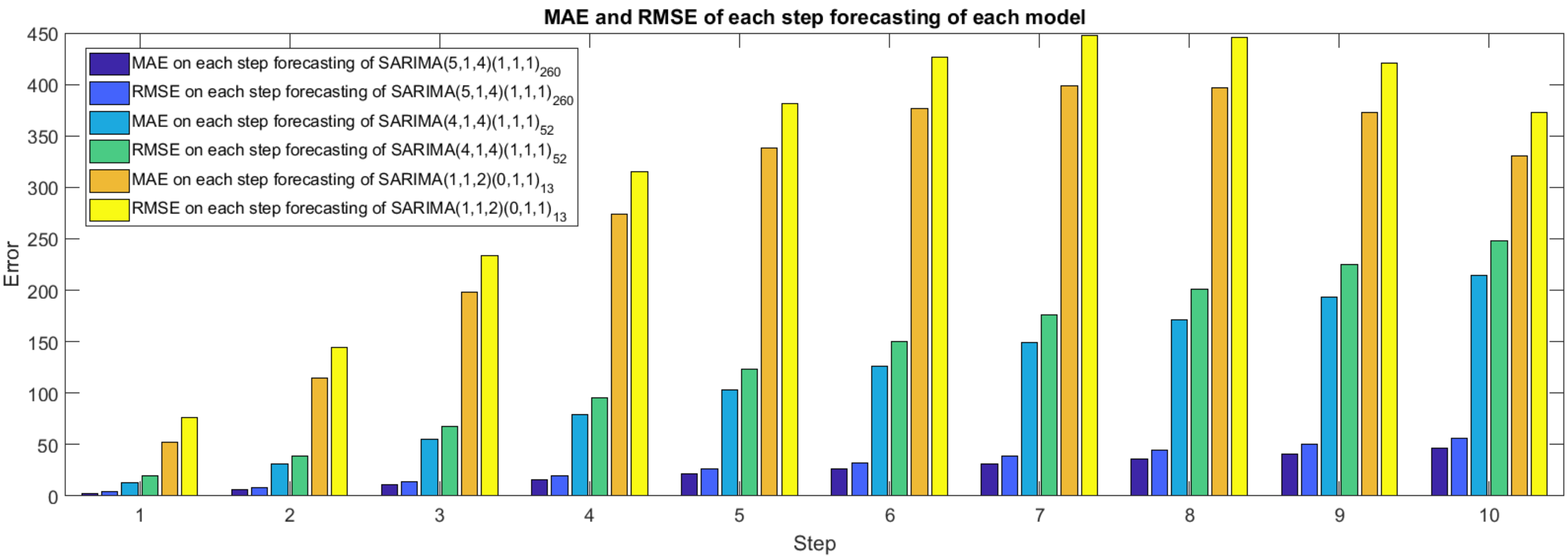
Forecasting Result



Error on 1-step forecasting of each model



Forecasting Error



Conclusion

Q & A