Rainfall Runoff Modelling Using Artificial Neural Network

NUS B.ENG.DISSERTATION 2019 Final Presentation

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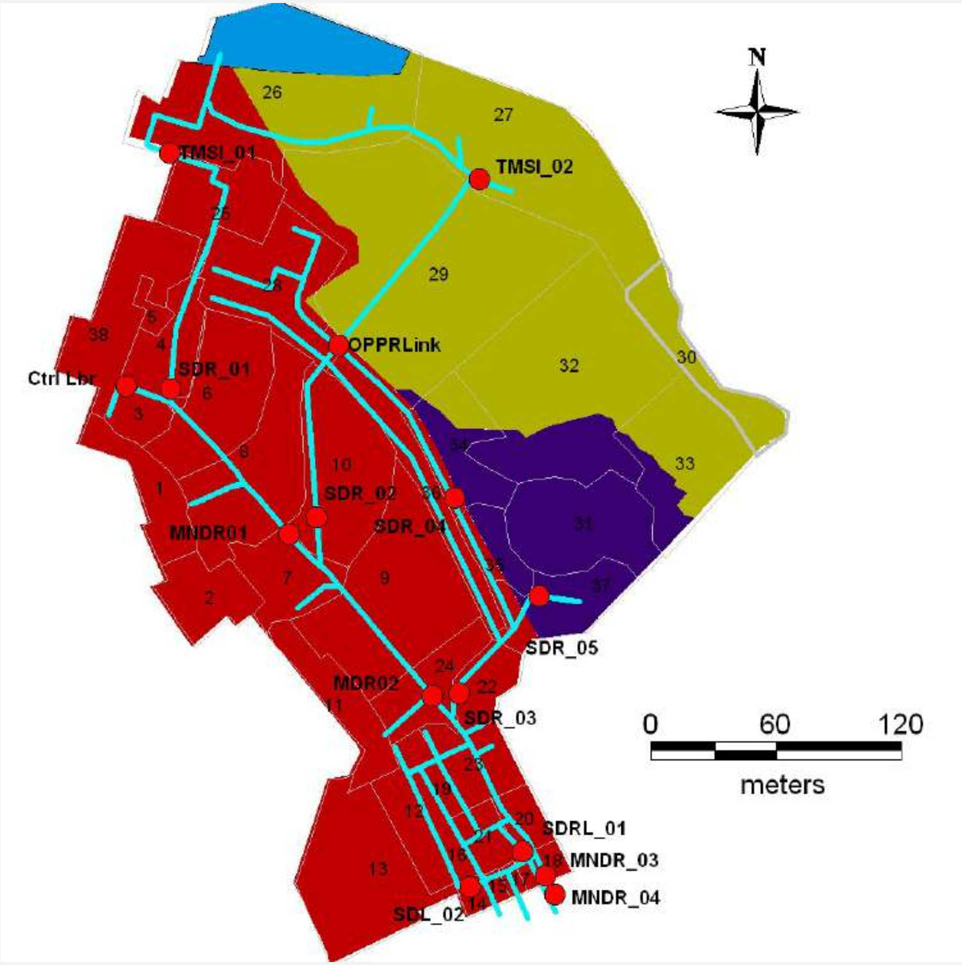
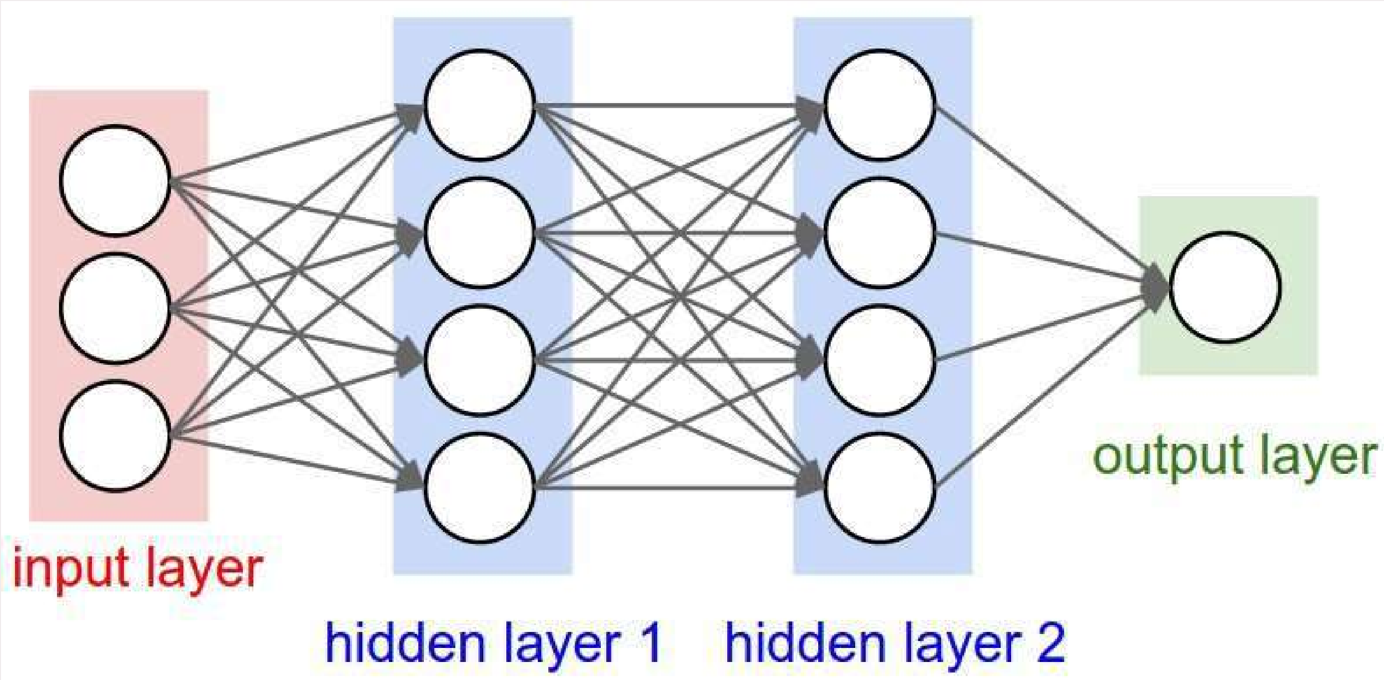
Contents

Project Overview

Aims of the project



- 10, 20- and 60-minute forecast of flow rates at Main Drain_04
- Discuss forecast accuracy as function of lead time



- Universal Approximator
- Pattern recognition and non-linear modelling
- No mathematical model required
- Needs to be carefully trained

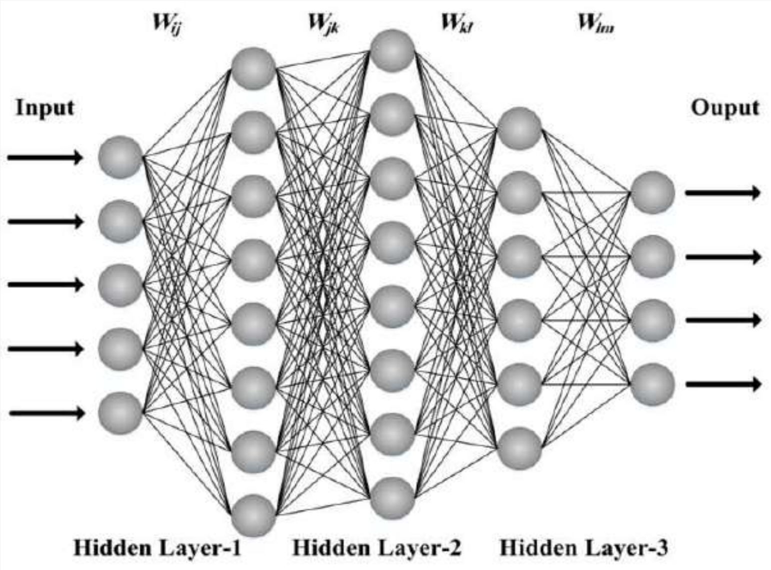
Preparation for training

Selection of relevant parameters

- Selection of Artificial Neural Network structure
- Selection of input and output data sets
- Selection of training, cross-validation and testing data sets

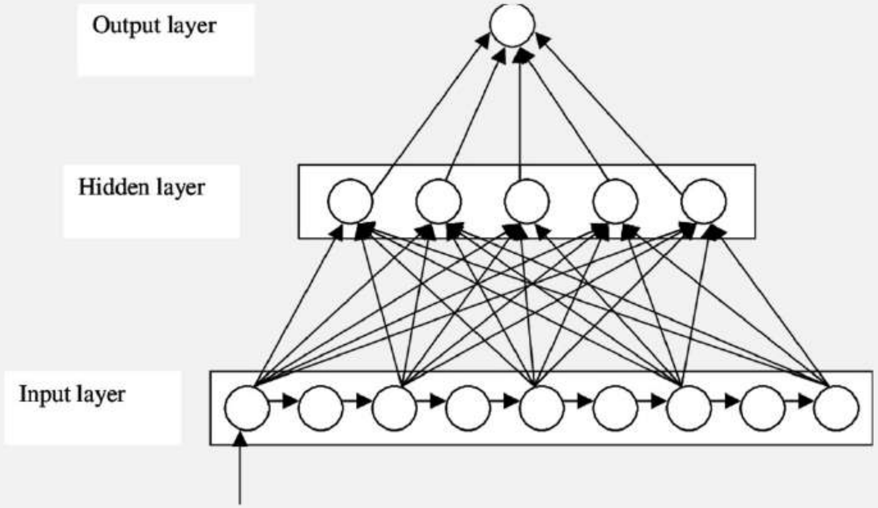
Selection of Neural Network Architecture

Which is the most suitable structure?



Multilayer Perceptron

- Select all inputs at the same time
- Lost the advantage of time-series data



Time-Delayed Neural Network

- Select a window of events for training
- Recognize time difference

Selection of input data

What are my inputs?

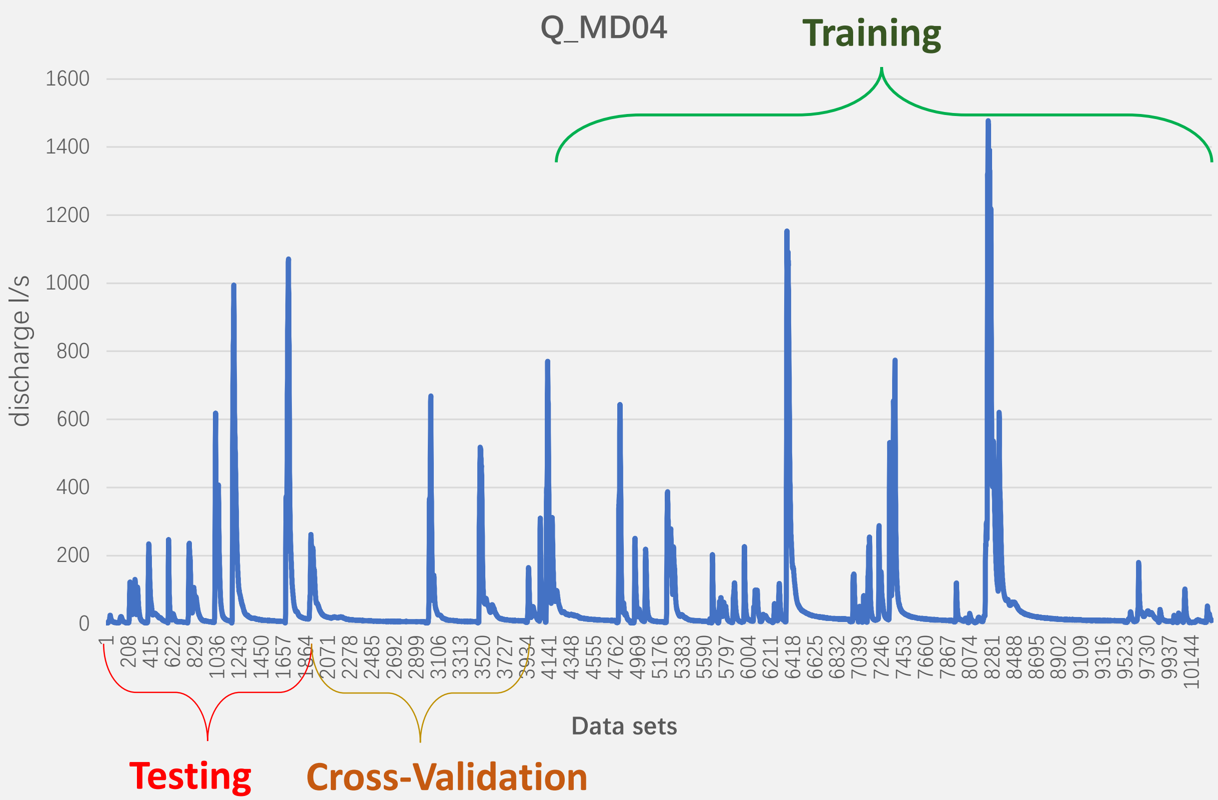
Correlation Factor						
	Q_MD01	Q_MD02	Q_CTRLIB	Q_OPPRL	Raincum	Duration
Rainfall	0.707215	0.795895	0.884045	0.750784	-0.126774	0.216596

Five inputs:

1. Rainfall (unit:mm)
2. Q_Main_Drain_01 (unit: l/s)
3. Q_Main_Drain_02 (unit: l/s)
4. Q_CentralLibrary (unit: l/s)
5. Q_OppResearchLink (unit: l/s)

Desired output:

1. Q_Main_Drain_04 (unit: l/s)



- Most extreme case occurs between No.8037 and No.8611
- Training data should include the most extreme case

PART

02

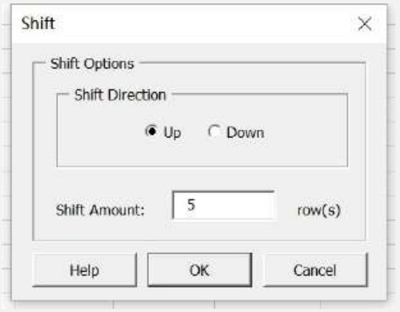
Training Methods

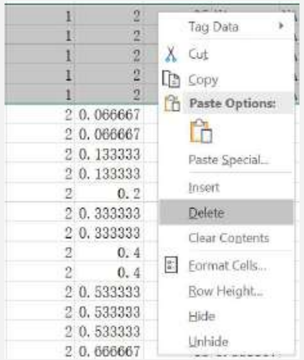
- Naïve forecast
- Predicting difference
- Simple Moving Average
- Box Cox Transformation

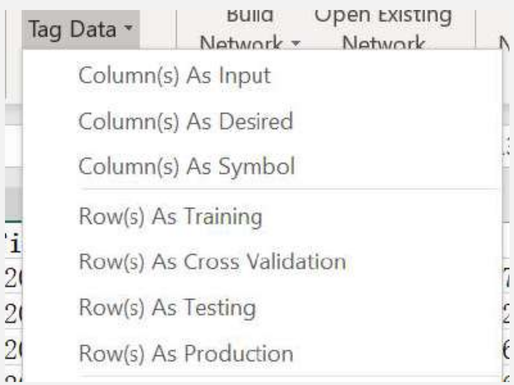
Naive Forecast

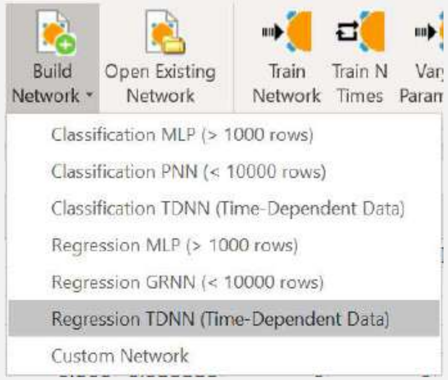
Get familiar with the software

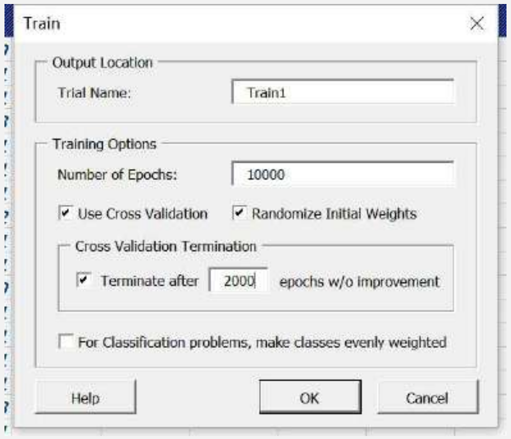
Perform prediction of lead time 5 minutes directly using the raw data

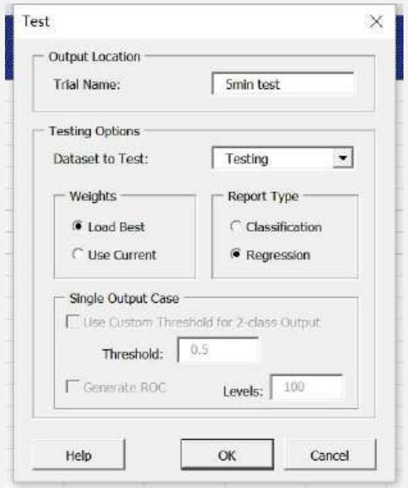




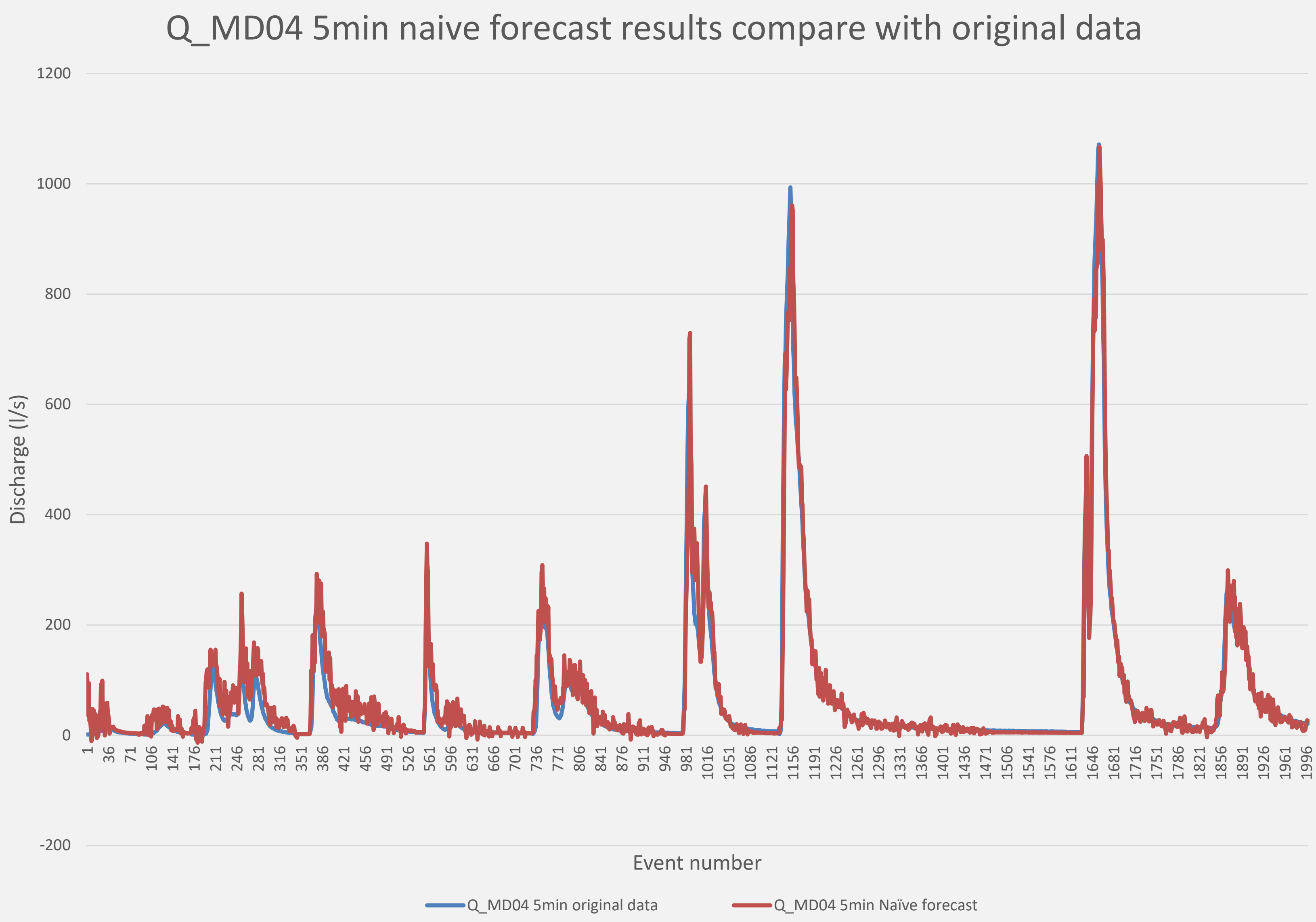




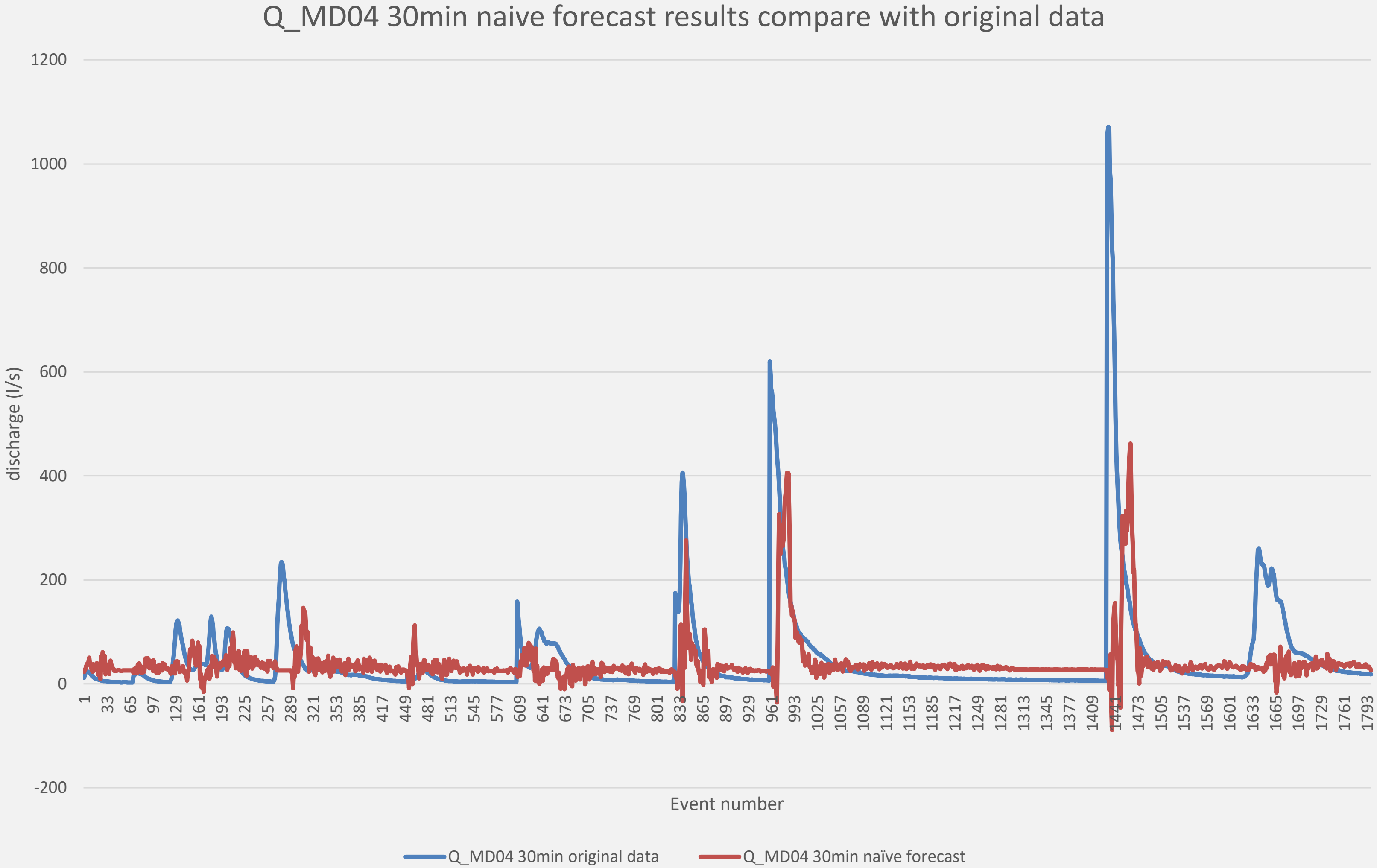




Performance	Q_MD04 5min
RMSE	32.11084633
NRMSE	0.021767896
MAE	16.96863799
NMAE	0.011503015
Min Abs Error	0.00483469
Max Abs Error	252.2893476
r	0.974397408
Score	96.6448296



Naive Forecast (30min) – How to improve?

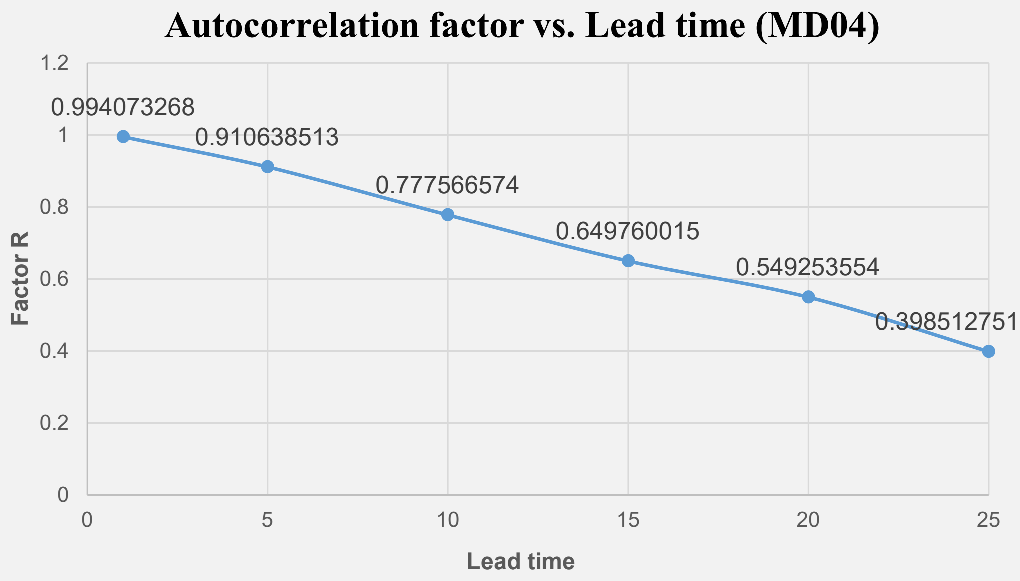


Correlation factor

r = 0.24

Taking the difference

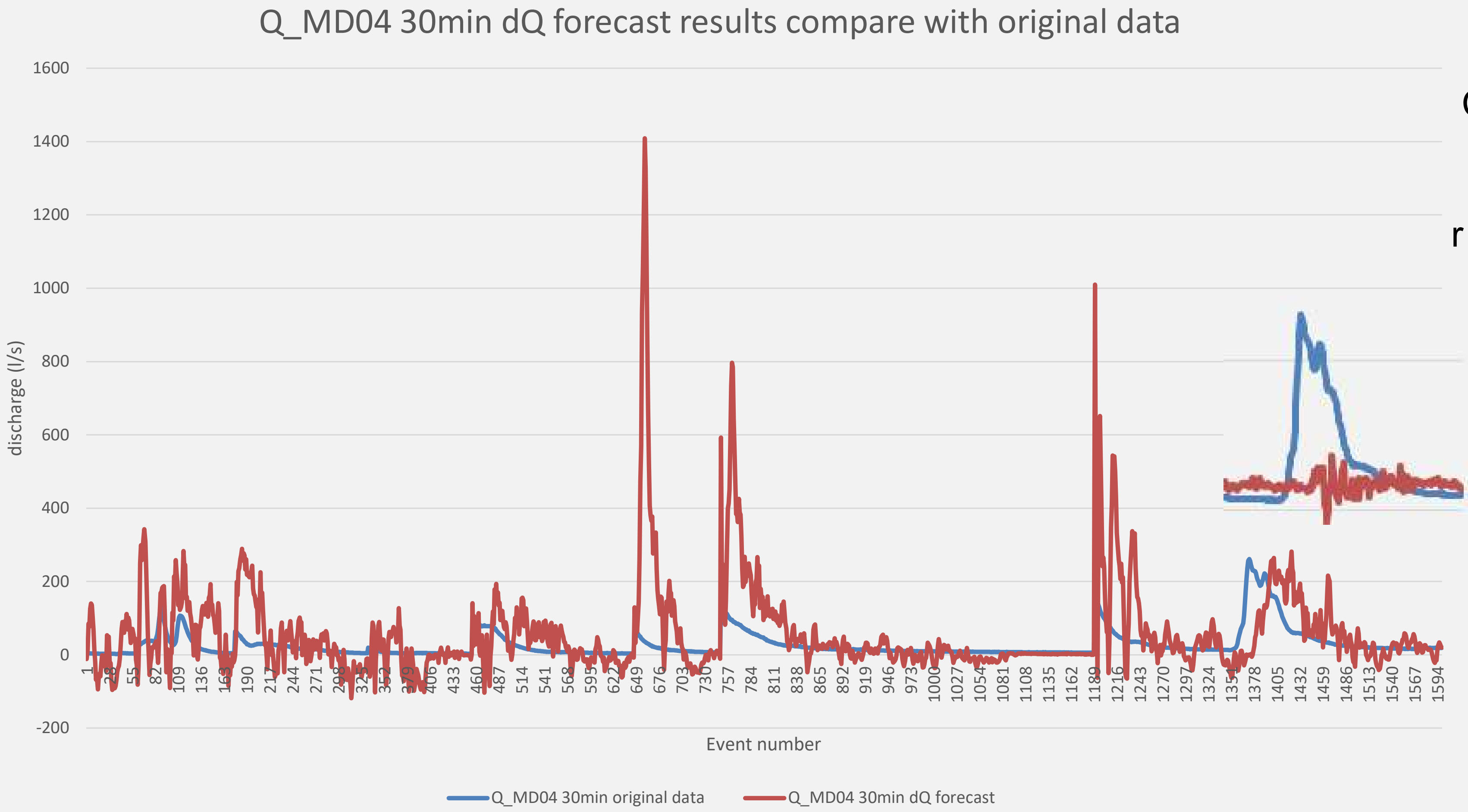
Will it help to improve the prediction accuracy?



- The TDNN will be trained to response to dQ with given data sets.

$$Q(t+n) = Qt + \widehat{dQ}$$

dQ Forecast (30min)

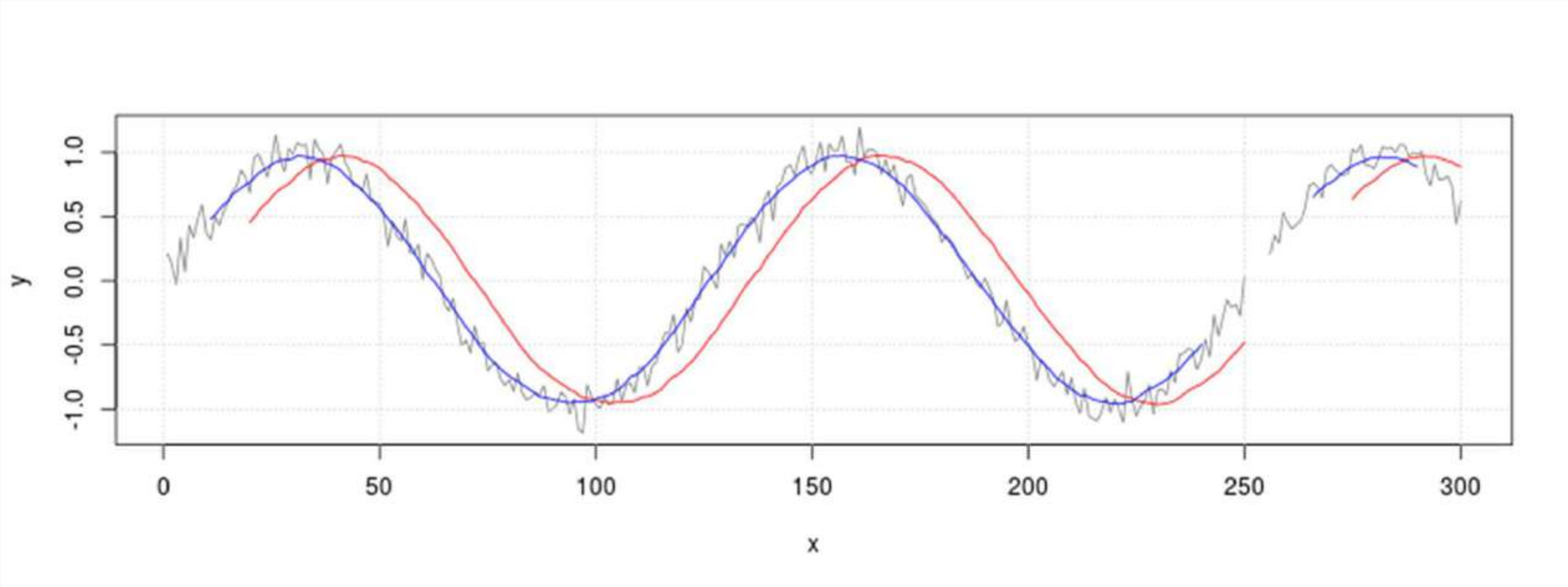


Correlation factor

r = 0.38

Introducing Moving Average

Help to get a better trend



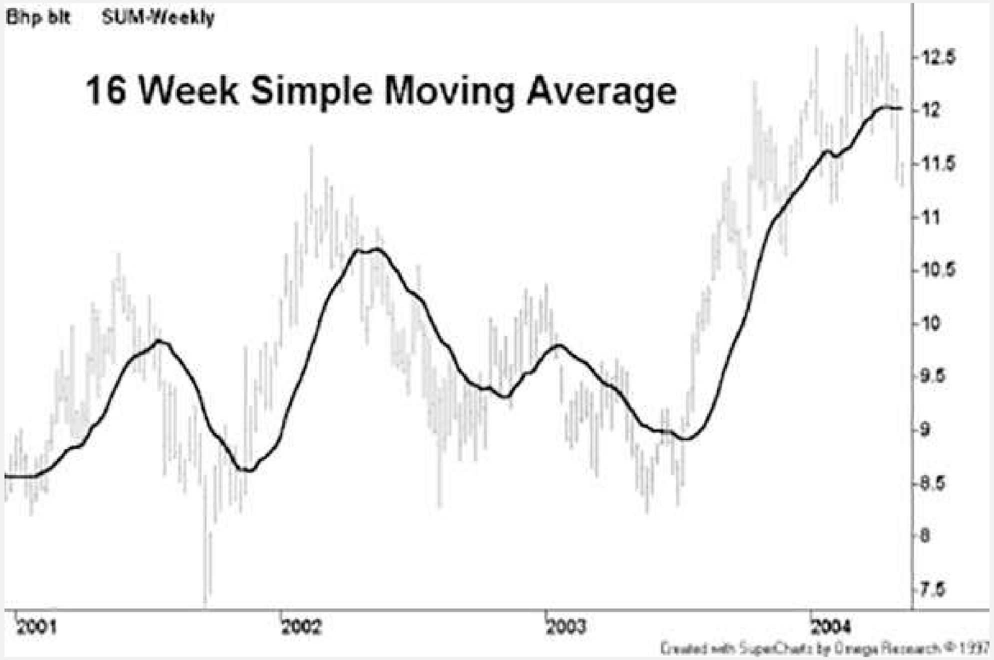
- No information about abnormal data
- Define a better trend of flow
- Filter out potential “noise”

MZ2

$$\text{SMA} = \frac{A_1 + A_2 + A_3 + \cdots + A_n}{n}$$

A_n = the data at time n

n = the number of total data points



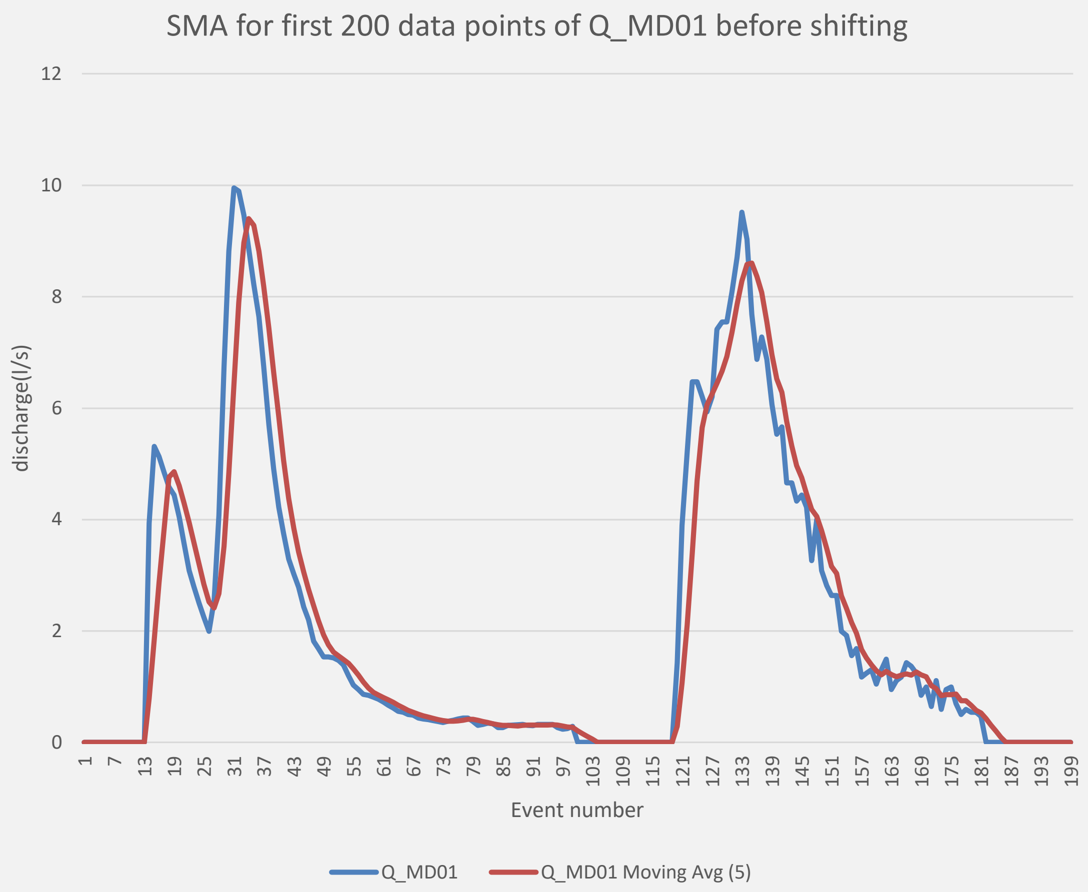
Lag of Simple Moving Average

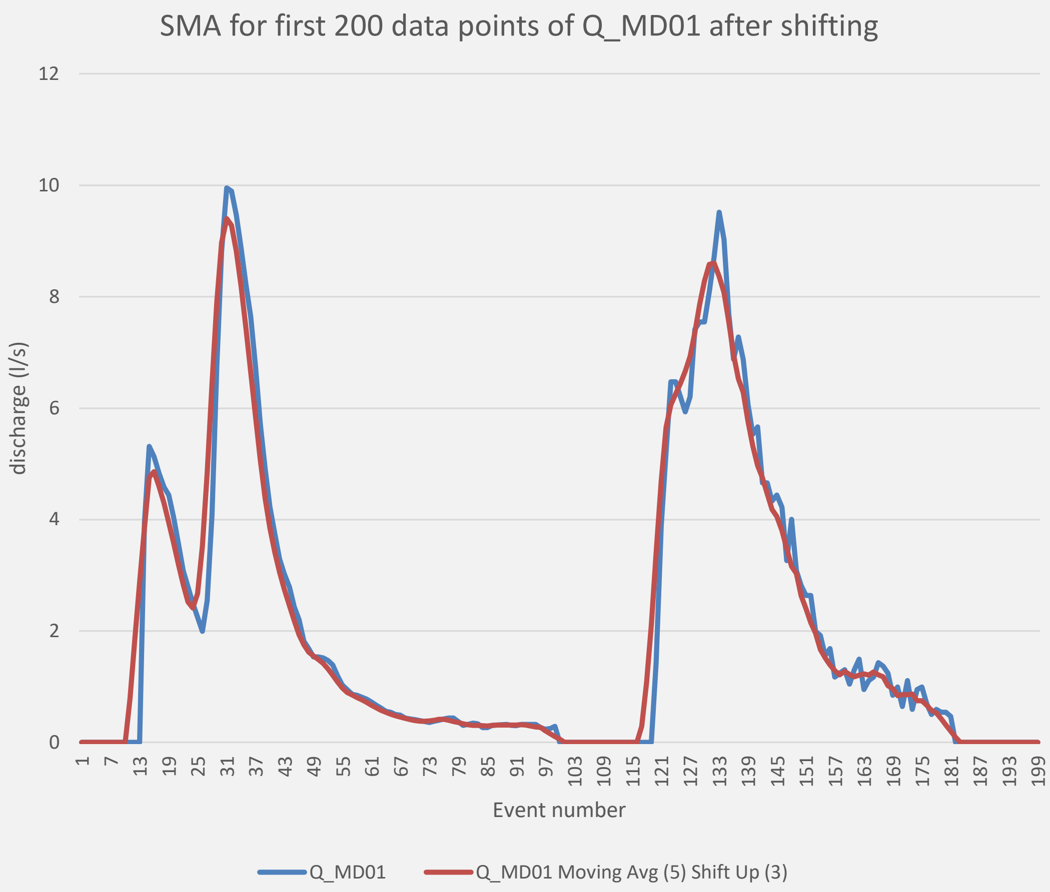
Slide 16

MZ2 MoranZ Zhu, 1/5/2019

Reduce the lag

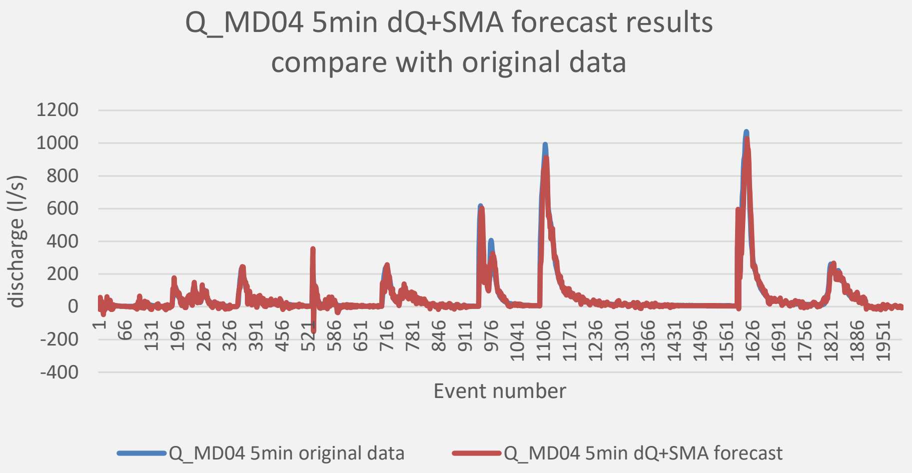
Notice the peak values

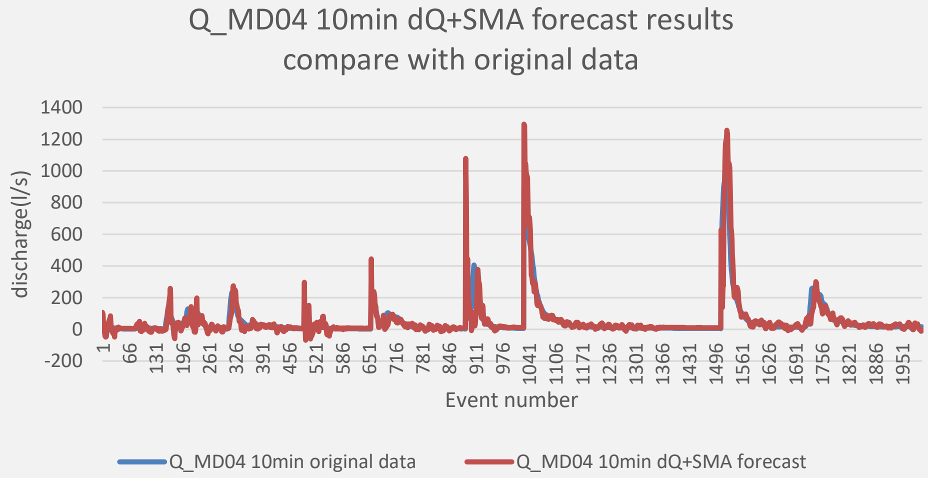


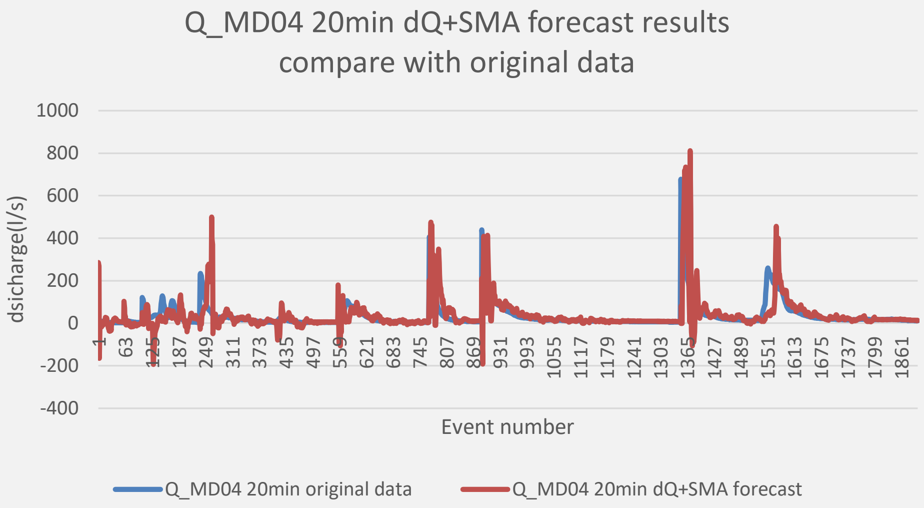


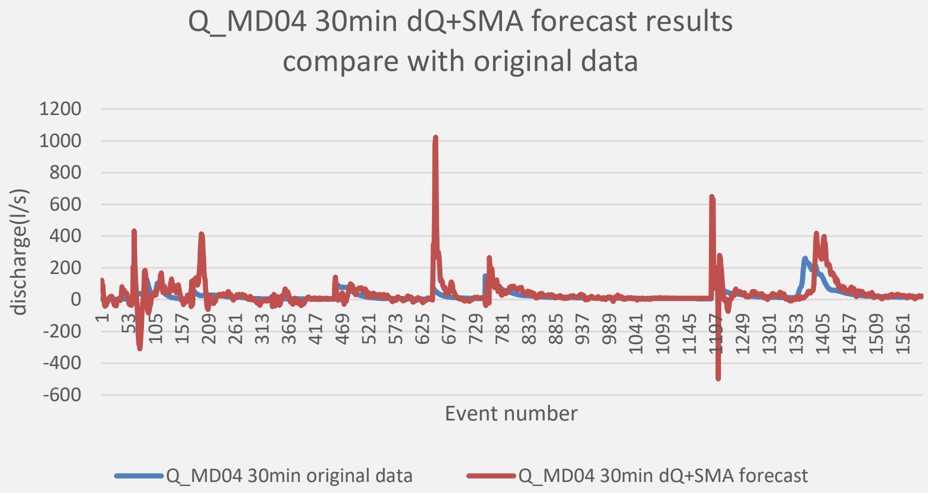
Improvement based on dQ method

SMA+dQ method





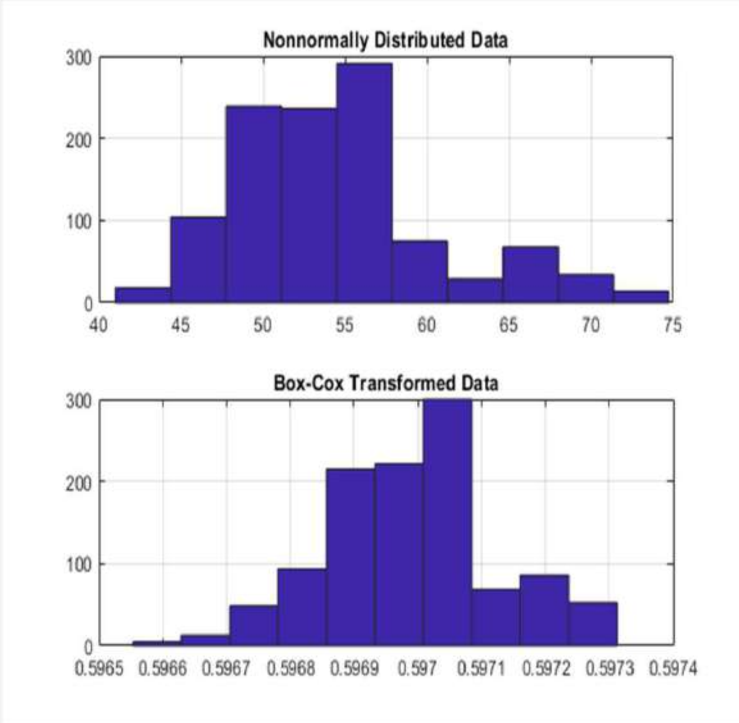




Box Cox Transformation

Normalize the data

- ANN responses well against normalized data (data at a comparable range)
- Improve quality of forecast
- Z-score, T-score, Rescaling…
- Widely used: Box Cox Transformation
- Named after *George Box* and *Sir David Roxbee Cox* in 1964.



Box Cox Transformation

Relevant formulas

- Parameter (λ)
- Optimum value of λ depends on results (difficult to obtain)

$$y(\lambda) = \begin{cases} \dfrac{y^{\lambda} - 1}{\lambda}, if\ \lambda \neq 0 \\ log\, y\, , if\ \lambda = 0 \end{cases}$$

➢ Only for positive (+) y values

$$y(\lambda) = \begin{cases} \dfrac{(y + \lambda_2)^{\lambda_1} - 1}{\lambda_1}, if\ \lambda_1 \neq 0 \\ log\ (y + \lambda_2)\, , if\ \lambda_1 = 0 \end{cases}$$

➢ For 0 or negative (-) y values

Mathematical calculations

λ = 2,

$$y'(2) = \frac{y^2-1}{2}$$

λ = 1,

$$y'(1) = y - 1$$

λ = 0.5,

$$y'(0.5) = \frac{\sqrt{y}-1}{0.5} = 2\sqrt{y} - 2$$

λ = -0.5

$$y'(-0.5) = \frac{\frac{1}{\sqrt{y}}-1}{-0.5} = 2 - \frac{2}{\sqrt{y}}$$

λ = -1

$$y'(-1) = \frac{\frac{1}{y}-1}{-1} = 1 - \frac{1}{y}$$

Box Cox Transformation

Application

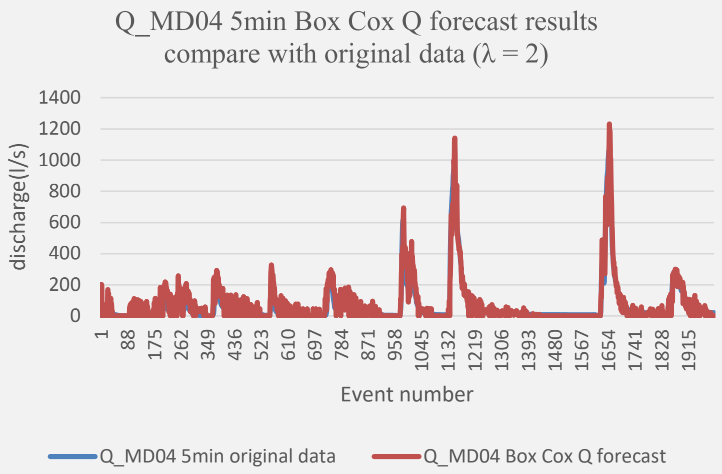
- Apply for original data and difference (dQ) data
- With different lambda (λ) values
- For various lead time

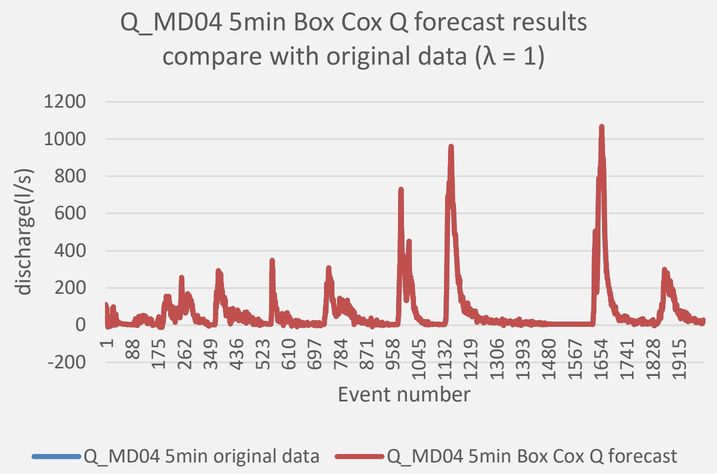
- E.g. For lead time 5 minutes

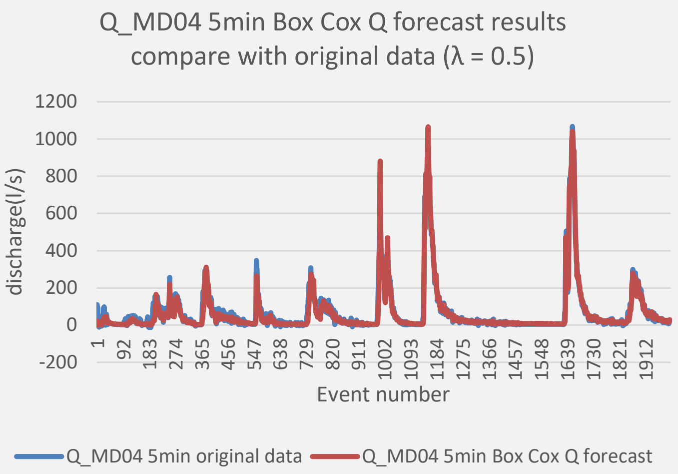
  λ = 2, 1, 0.5, -1, -0.5

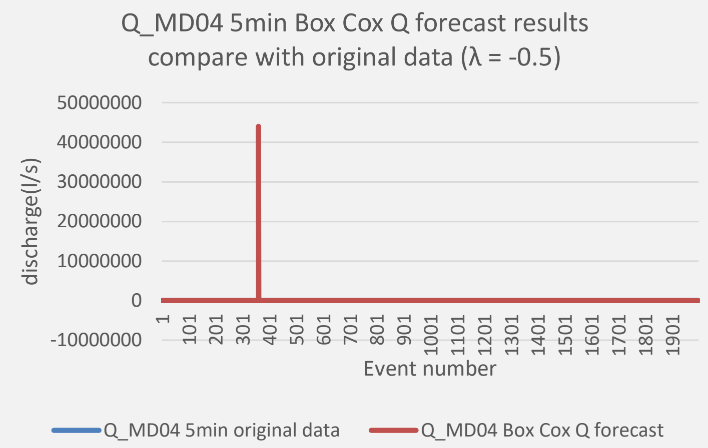
Box Cox Transformation

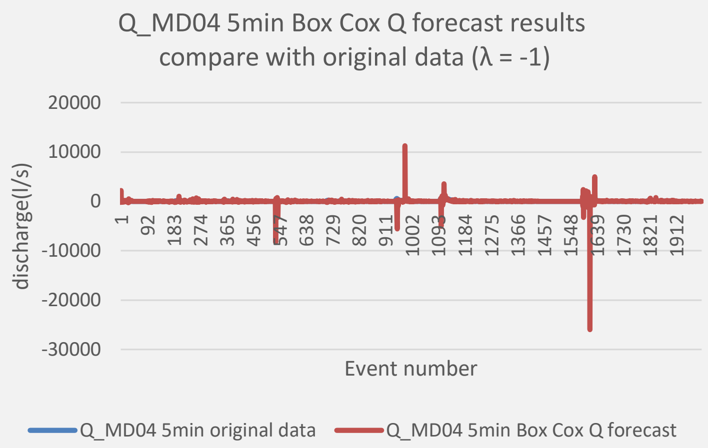
5 minutes with original data











Box Cox Transformation

Making some adjustments

- When λ value is negative, forecast results are inaccurate+
- Conclude that negative λ is not close to the optimum λ value
- Compute Box Cox Transformations for λ = 2, 1, 0.5
- Avoid wasting of time

Box Cox Transformation

Applying for dQ method

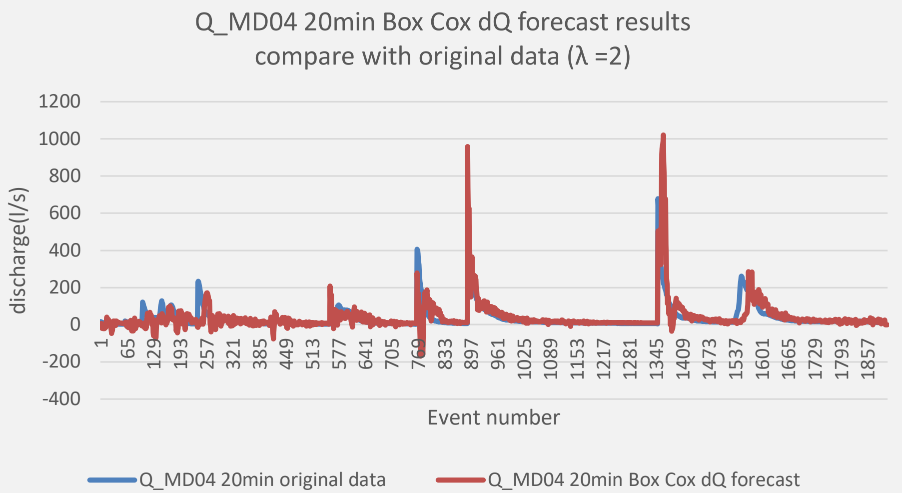
- Box Cox transformed dQ
- Negative values exist in dQ
- Use the second equation provided by Box and Cox

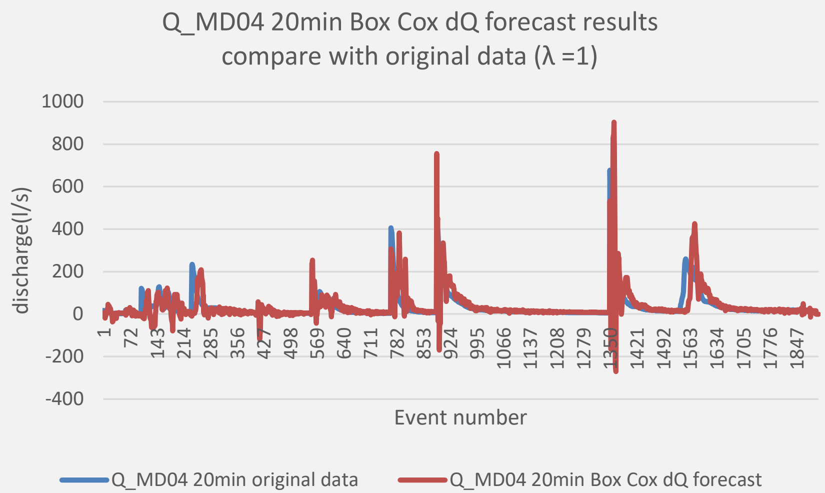
$$y(\lambda) = \begin{cases} \dfrac{(y+\lambda_2)^{\lambda_1} - 1}{\lambda_1}, if\ \lambda_1 \neq 0 \\ log\ (y+\lambda_2)\,, if\ \lambda_1 = 0 \end{cases}$$

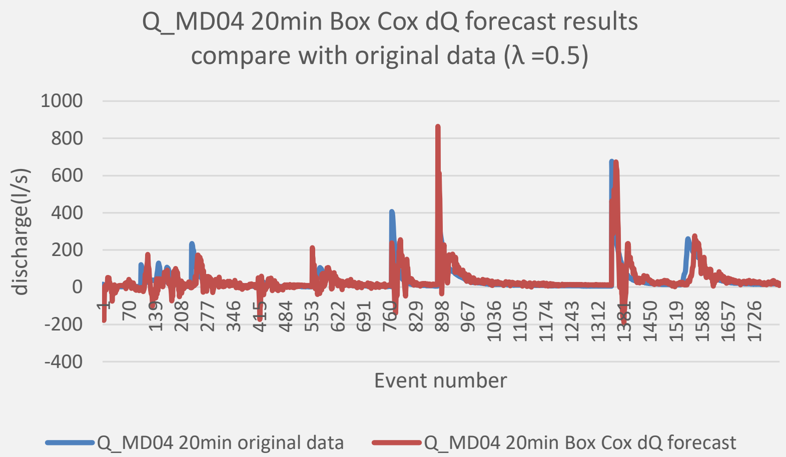
- Add a numerical value to all data points
- Obtain positive data points
- Minus this numerical value in the last step

Box Cox Transformation

Some results of Box Cox transformed dQ method







- Different λ values give different forecast results

PART

03

Training results

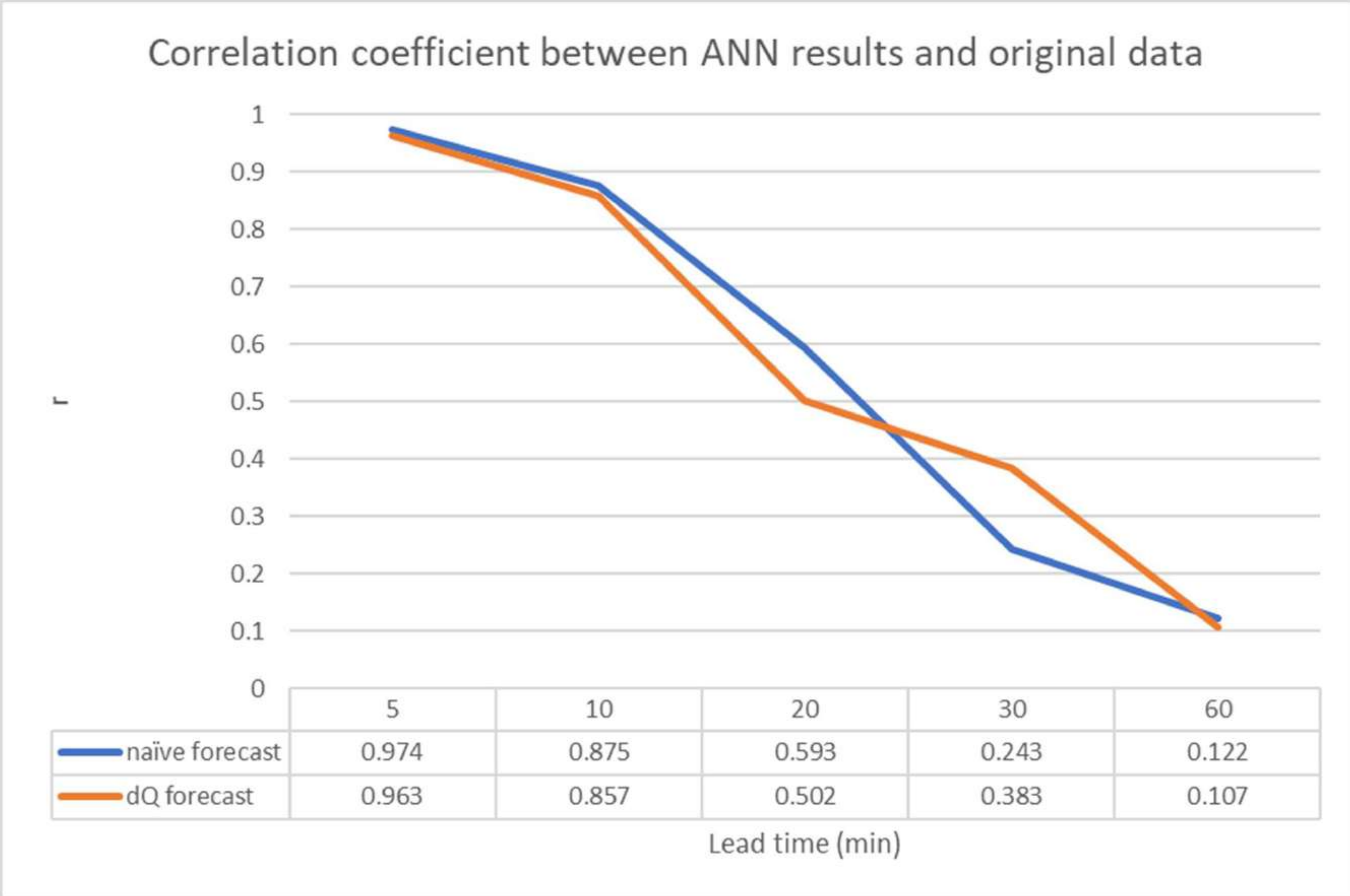
- Comparing results of different methods

Comparing naïve forecast with dQ forecast

Using correlation coefficient

Correlation coefficient between ANN results and original data

naïve forecast		dQ forecast	
Lead time	r	Lead time	r
5	0.974	5	0.963
10	0.875	10	0.857
20	0.593	20	0.502
30	0.243	30	0.383
60	0.122	60	0.107

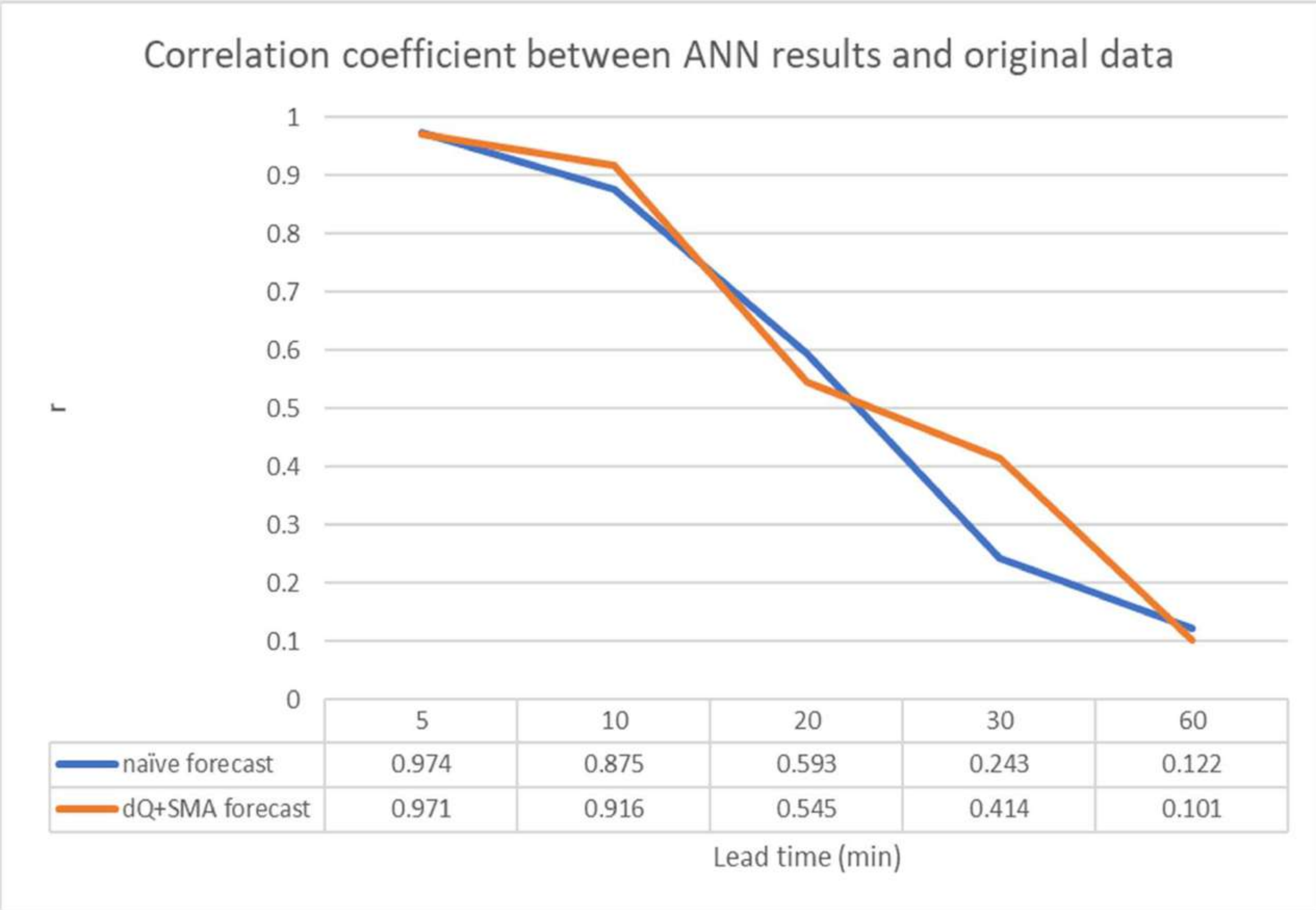

Correlation coefficient between ANN results and original data
r
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
5 10 20 30 60
naïve forecast 0.974 0.875 0.593 0.243 0.122
dQ forecast 0.963 0.857 0.502 0.383 0.107
Lead time (min)

Comparing naïve forecast with dQ+SMA forecast

Using correlation coefficient

Correlation coefficient between ANN results and original data

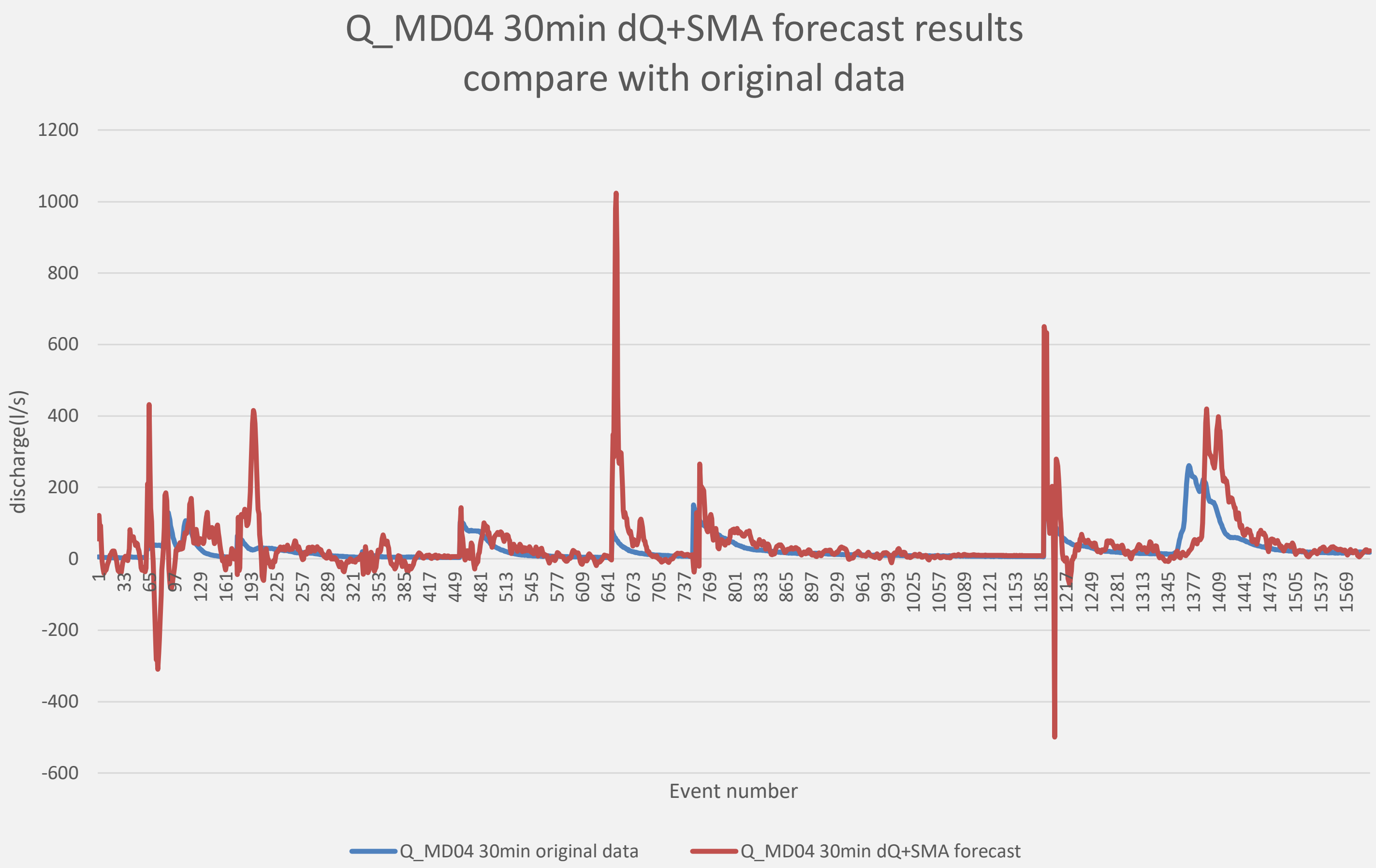
naïve forecast		dQ+SMA forecast	
Lead time	r	Lead time	r
5	0.974	5	0.971
10	0.875	10	0.916
20	0.593	20	0.545
30	0.243	30	0.414
60	0.122	60	0.101



	5	10	20	30	60
naïve forecast	0.974	0.875	0.593	0.243	0.122
dQ+SMA forecast	0.971	0.916	0.545	0.414	0.101

Good at capturing trend

dQ+SMA forecast advantages



Limitations of naïve forecast

Some problems

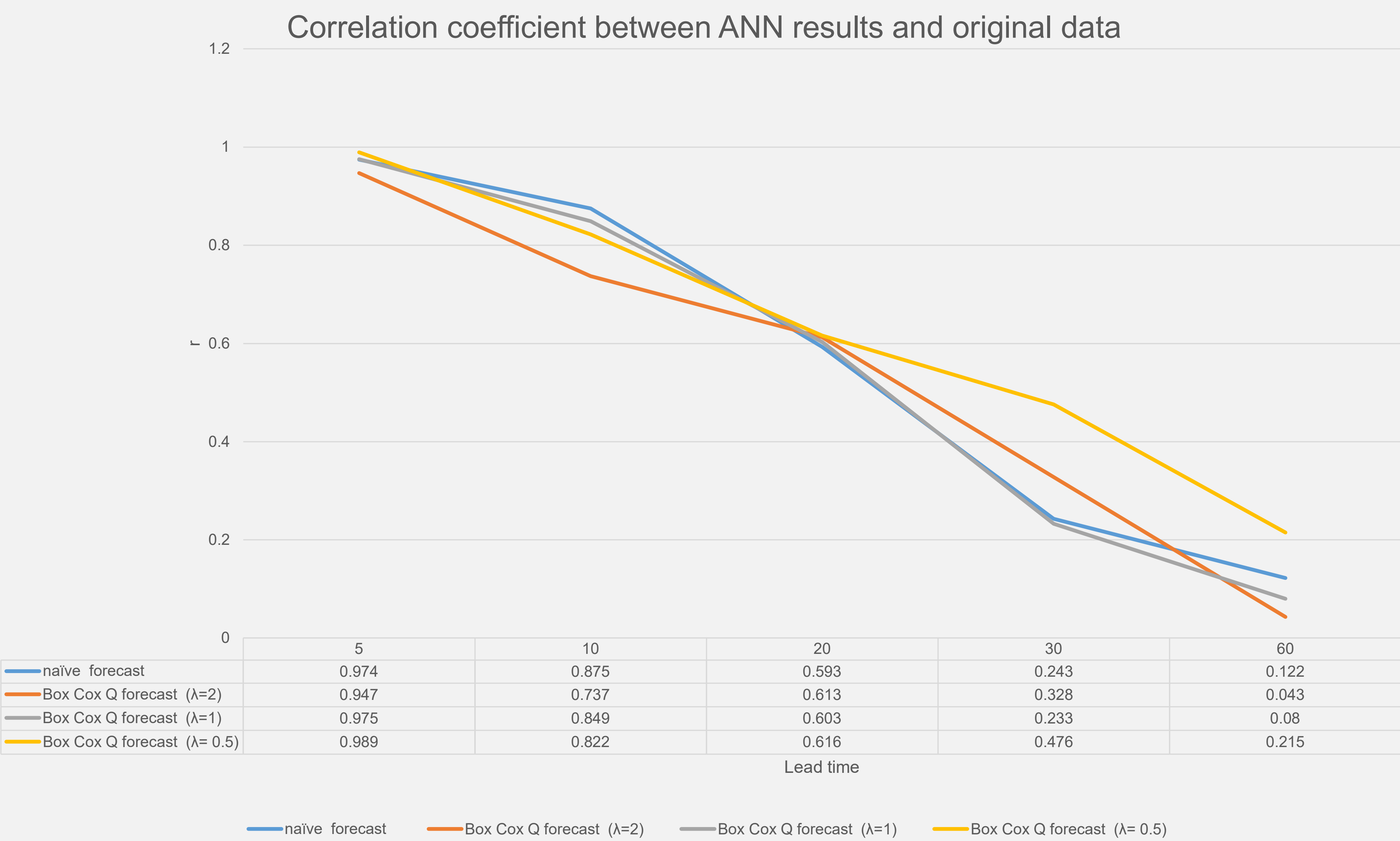
- Naïve forecast could sometimes produce relatively good results
- Does not have real forecast ability
- Relies on numerical values of historical data
- Unable to find the underlying pattern unless a strong pattern exists
- Usually does not respond to any random variations
- In practice, used as a reference in comparing with more complex methods

Comparing naïve forecast with Box Cox Q forecast

Using correlation coefficient

Correlation coefficient between ANN results and original data

naïve forecast		Box Cox Q forecast (λ=2)		Box Cox Q forecast (λ=1)		Box Cox Q forecast (λ= 0.5)	
Lead time	r	Lead time	r	Lead time	r	Lead time	r
5	0.974	5	0.947	5	0.975	5	0.989
10	0.875	10	0.737	10	0.849	10	0.822
20	0.593	20	0.613	20	0.603	20	0.616
30	0.243	30	0.328	30	0.233	30	0.476
60	0.122	60	0.043	60	0.08	60	0.215



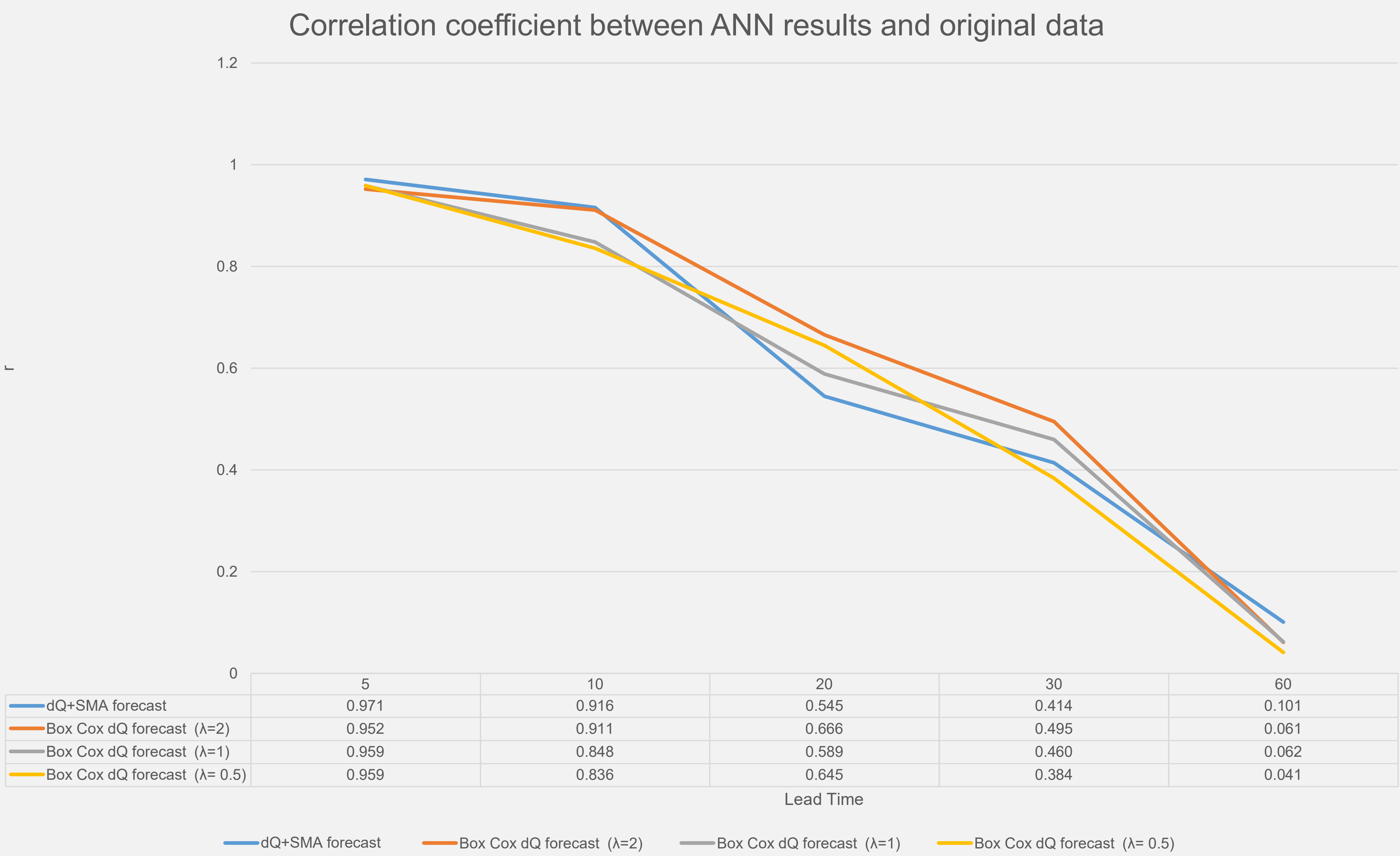
	5	10	20	30	60
naïve forecast	0.974	0.875	0.593	0.243	0.122
Box Cox Q forecast (λ=2)	0.947	0.737	0.613	0.328	0.043
Box Cox Q forecast (λ=1)	0.975	0.849	0.603	0.233	0.08
Box Cox Q forecast (λ= 0.5)	0.989	0.822	0.616	0.476	0.215

Comparing dQ+SMA forecast with Box Cox dQ forecast

Using correlation coefficient

Correlation coefficient between ANN results and original data

dQ+SMA forecast		Box Cox dQ forecast (λ=2)		Box Cox dQ forecast (λ=1)		Box Cox dQ forecast (λ= 0.5)	
Lead time	r	Lead time	r	Lead time	r	Lead time	R
5	0.971	5	0.982	5	0.959	5	0.959
10	0.916	10	0.851	10	0.848	10	0.836
20	0.545	20	0.666	20	0.589	20	0.645
30	0.414	30	0.495	30	0.460	30	0.384
60	0.101	60	0.061	60	0.062	60	0.041



	5	10	20	30	60
dQ+SMA forecast	0.971	0.916	0.545	0.414	0.101
Box Cox dQ forecast (λ=2)	0.952	0.911	0.666	0.495	0.061
Box Cox dQ forecast (λ=1)	0.959	0.848	0.589	0.460	0.062
Box Cox dQ forecast (λ= 0.5)	0.959	0.836	0.645	0.384	0.041

PART

04

Discussion

- Some deeper thoughts

Respective advantages and limitations

For different methods

- Two complex methods
  - **dQ+SMA**
  - Box Cox dQ

- dQ+SMA
  - Trend is captured at high accuracy
  - Peak values my not be very accurate
  - Could be used to forecast baseflow/subsurface flow

- Limitations
  - Determining the window period
  - Too short → lose general trend
  - Too long → undesirable lag
  - More training and testing attempts could be made using different window periods

Respective advantages and limitations

For different methods

- Two complex methods
  - dQ+SMA
  - **Box Cox dQ**

- Box Cox dQ
  - Peak value is captured at high accuracy
  - Forecast of low magnitude values my not be very accurate
  - Could be used to forecast flooding cases

- Limitations
  - Determining the lambda (λ) values
  - Different λ values for different series of data
  - Requires time and effort
  - More training and testing attempts with different λ values

About lead time of 60 minutes

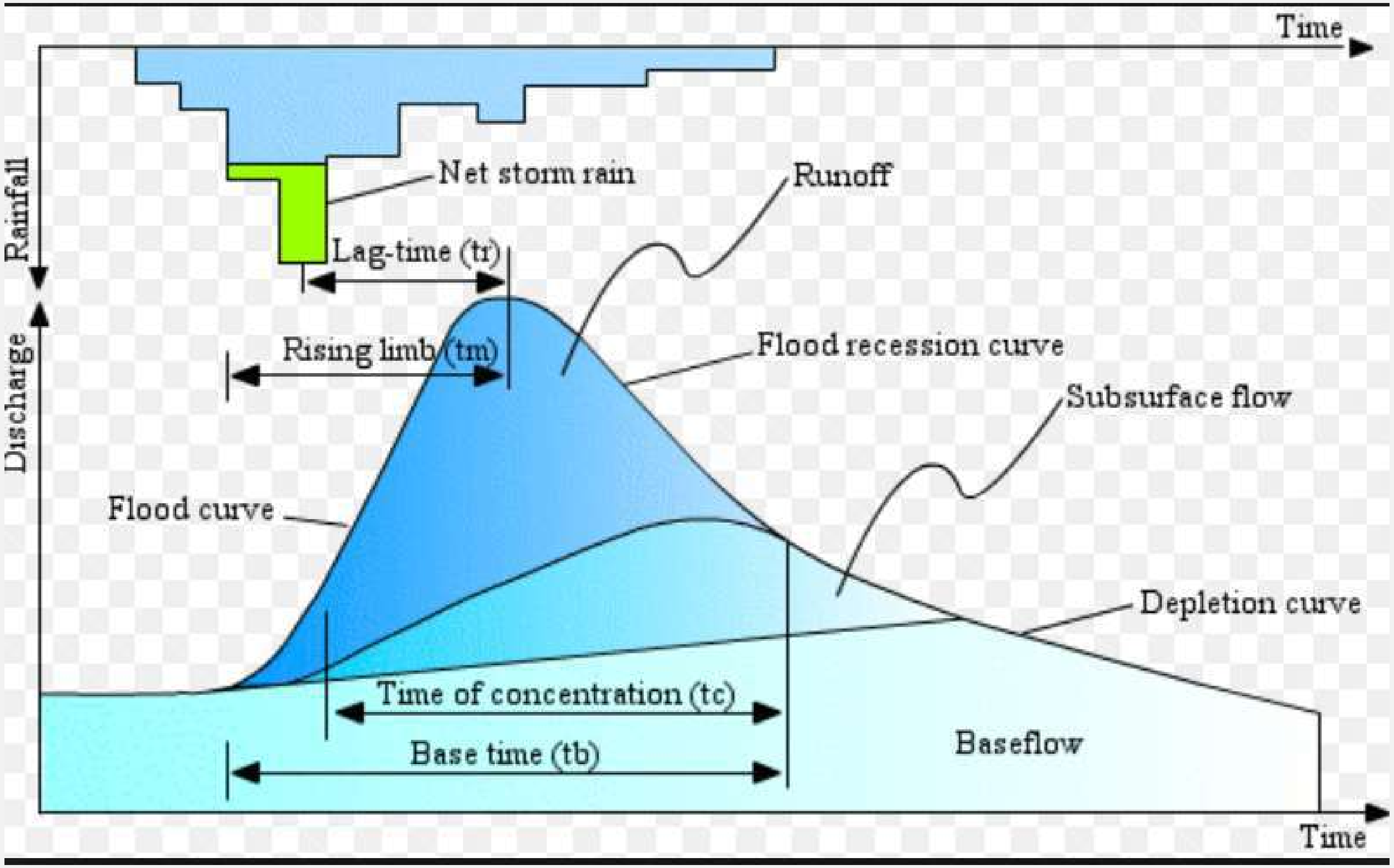
Why is it not accurate?

- Lead time exceeds the capacity of prediction for this catchment area
- Limitation of forecast depends on catchment concentration time (Tc)
- 60 minutes is larger than catchment concentration time for Kent Ridge Catchment
- Data from large public main drains could be used to forecast lead time of 60 minutes

Some take-away points

Lessons learnt during FYP

- Research attitude
  - ➢ Logic
  - ➢ Looking for solutions/alternatives
  - ➢ Patience
  - ➢ Carefulness
- Report writing skills
- Microsoft Excel skills
- Data analytic skills (methods and techniques)
- Knowledge about Artificial Neural Network


Time
Rainfall
Net storm rain
Runoff
Lag-time (tr)
Discharge
Rising limb (tm)
Flood recession curve
Subsurface flow
Flood curve
Depletion curve
Time of concentration (tc)
Base time (tb)
Baseflow
Time

Thank You

References

Algorithms for Designing Feedforward Networks. (2015). Feedforward Neural Network Methodology Information Science and Statistics, 129-202. doi:10.1007/0-387-22649-4_5

Babovic, V., & Keijzer, M. (2002). Rainfall Runoff Modelling Based on Genetic Programming. Hydrology Research, 33(5), 331-346. doi:10.2166/nh.2002.0012

Chadalawada, J. & Havlicek, V. & Babovic, V. (2017). A Genetic Programming Approach to System Identification of Rainfall-Runoff Models. Water Resources Management. 10.1007/s11269-017-1719-1.

Cheng, R. (2017). Box-Cox Transformations. Oxford Scholarship Online. doi:10.1093/oso/9780198505044.003.0010

Govindaraju, R. S., & Rao, A. R. (2000). Artificial neural networks in hydrology. Dordrecht: Kluwer Academic.

Hall, S. (2016). Modeling Rainfall Runoff. Eos. doi:10.1029/2016eo062109

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. International Journal of Forecasting, 22(4), 679-688. doi:10.1016/j.ijforecast.2006.03.001

Liu, J., Savenije, H. H., & Xu, J. (2003). Forecast of water demand in Weinan City in China using WDF-ANN model. Physics and Chemistry of the Earth, Parts A/B/C, 28(4-5), 219-224. doi:10.1016/s1474-7065(03)00026-3

Moving Average. (2005). Dictionary of Statistics & Methodology. doi:10.4135/9781412983907.n1213

Pattie, D. C., & Snyder, J. (1996). Using a neural network to forecast visitor behavior. Annals of Tourism Research, 23(1), 151-164. doi:10.1016/0160-7383(95)00052-6

Rainfall Runoff Modelling. (2012). Flood Risk Assessment and Management, 80-86. doi:10.2174/978160805047511101010080

Reeves, C. R. (1995). Training Set Selection in Neural Network Applications. Artificial Neural Nets and Genetic Algorithms, 476-478. doi:10.1007/978-3-7091-7535-4_123

Sakia, R. M. (1992). The Box-Cox Transformation Technique: A Review. The Statistician, 41(2), 169. doi:10.2307/2348250

Sun, Y. & Babovic, V. & Soon C, E. (2012). Artificial neural networks as routine for error correction with an application in Singapore regional model. Ocean Dynamics. 62. 10.1007/s10236-012-0524-x.

Selection of Initial Conditions During Neural Network Adjustment — Typical Neural Network Input Signals. (2007). Neural Networks Theory, 207-222. doi:10.1007/978-3-540-48125-6_12

Zhang, T., & Yang, B. (2017). Box–Cox Transformation in Big Data. Technometrics, 59(2), 189-201. doi:10.1080/00401706.2016.1156025