A structured neural network to forecast the Korean electricity load

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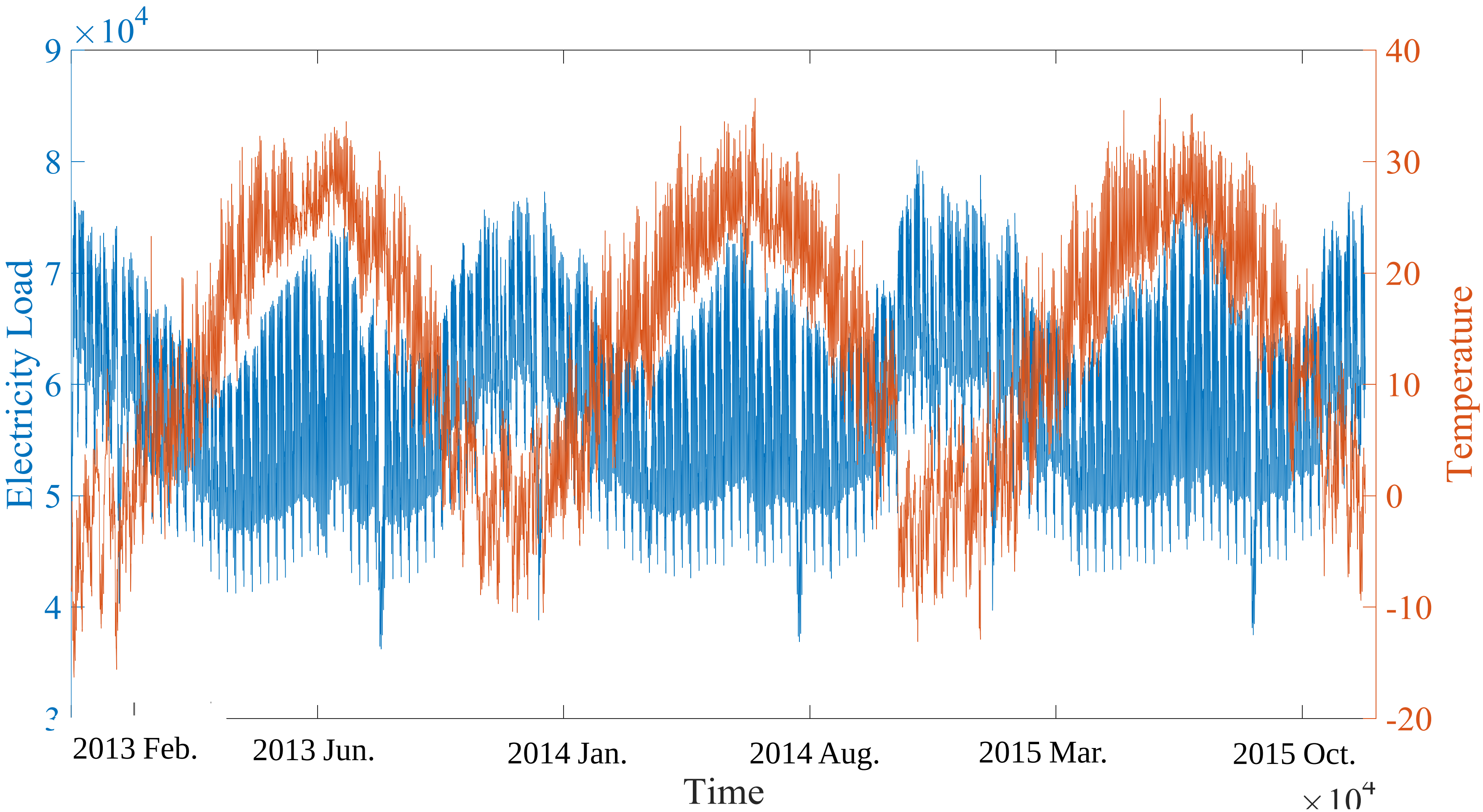
Contents

1. Introduction

- **Electricity load forecasting has been being studied**
  - Accurate load forecasting helps company and country in many aspects
  - Generating company can improve their profits by saving unnecessary operating costs
  - Efficient allocation of resources makes stable electricity supply with reasonable price
- **Especially, a cost-effective generation plan is important for an energy-poor country like Korea**
  - Korea imports about 98% of fossil fuel
- **We forecasted Korean electricity load by reflecting Korean electricity market conditions**
  - Korean electricity market has a cost-based pool rule
  - Korean electricity market operates only a-day ahead market

2. Data

- **Korean hourly electricity load(MW) and hourly temperature (℃) of Seoul, the capital of Korea from 2013 to 2015**

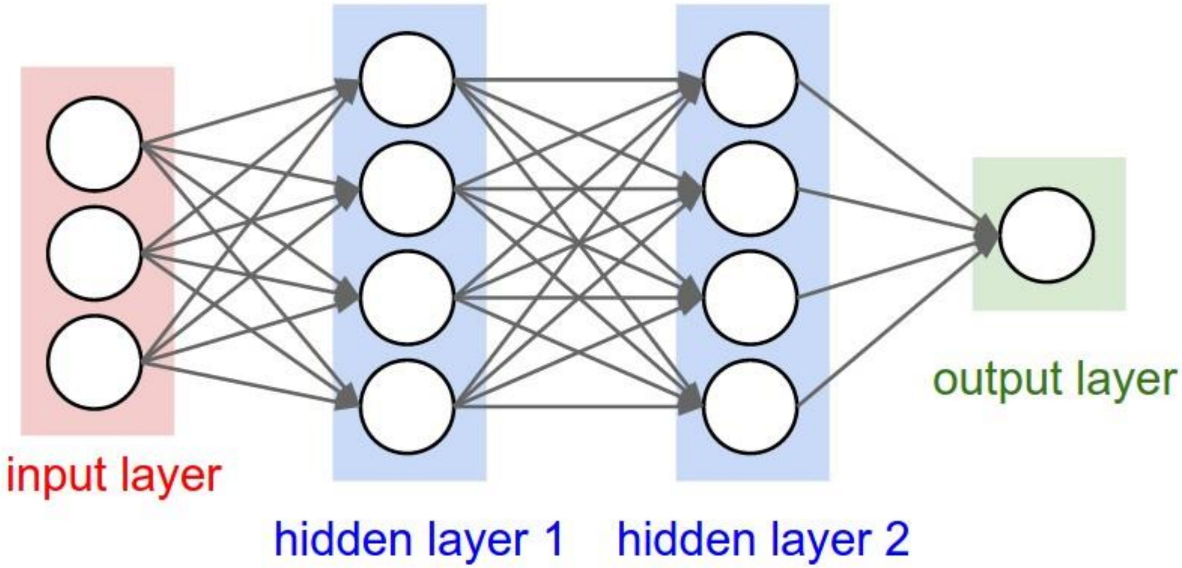


2. Data

- **Korean electricity market operates only a-day ahead market**
  - Power generation plan between 7 p.m. on the present day and 4 a.m. two days ahead is scheduled everyday
  - Power company who wants to participate in the electricity generation have to submit their available generation times, amounts, and prices until 10 a.m. on the present day to the Korean Power Exchange
- **Electricity consumption correlates strongly to temperature fluctuations.**
- **The hourly temperature of Seoul, the capital of Korea could be the representative of Korea's temperature**
  - Residential and commercial electricity consumption are more sensitive to temperature changes than industrial consumption
  - Seoul has the largest population in Korea

3. Method

- **Artificial Neural Network (ANN) is used to forecast future electricity load**
  - ANN is a one of machine learning algorithm which is imitated by human brain
  - Several layers and nodes like neurons of the human brain, transfer functions
  - Normally, information (stimulation) is propagated directly forward from the input layer to the output layer



3. Method

- **ANN has advantage of modelling multi-step ahead target to reflect Korean electricity market's conditions**
  - General forecasting model operates to forecast a step ahead time in iterative way
  - ANN facilitates direct multi step ahead forecasting

$$(x_t, x_{t-1}, x_{t-2.} \dots, x_{t-p}) \mapsto \hat{x}_{t+1}$$

$$(\hat{x}_{t+1}, x_t, x_{t.} \dots, x_{t-p+1}) \mapsto \hat{x}_{t+2}$$

$$(\hat{x}_{t+2}, \hat{x}_{t+1}, x_{t.} \dots, x_{t-p+1}) \mapsto \hat{x}_{t+3}$$

$$\vdots$$

$$(\hat{x}_{t+h-1}, \hat{x}_{t+h-2}, \hat{x}_{t+h-3.} \dots, x_{t-p+h-1}) \mapsto \hat{x}_{t+h}$$

Conceptual process of iterative forecasting

$$(x_t, x_{t-1}, x_{t-2.} \dots, x_{t-p}) \mapsto \hat{x}_{t+1}$$

$$(x_t, x_{t-1}, x_{t-2.} \dots, x_{t-p}) \mapsto \hat{x}_{t+2}$$

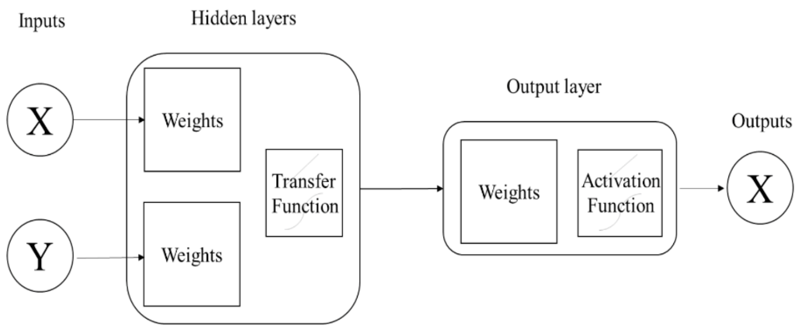
$$(x_t, x_{t-1}, x_{t-2.} \dots, x_{t-p}) \mapsto \hat{x}_{t+3}$$

$$\vdots$$

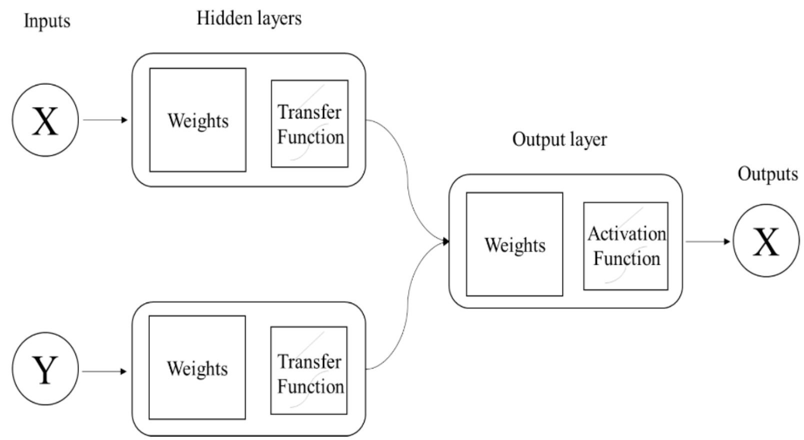
$$(x_t, x_{t-1}, x_{t-2.} \dots, x_{t-p}) \mapsto \hat{x}_{t+h}$$

Conceptual process of direct forecasting

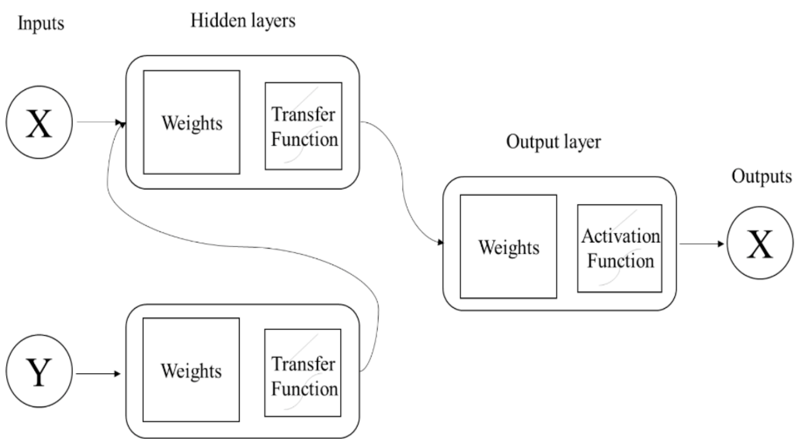
3. Method



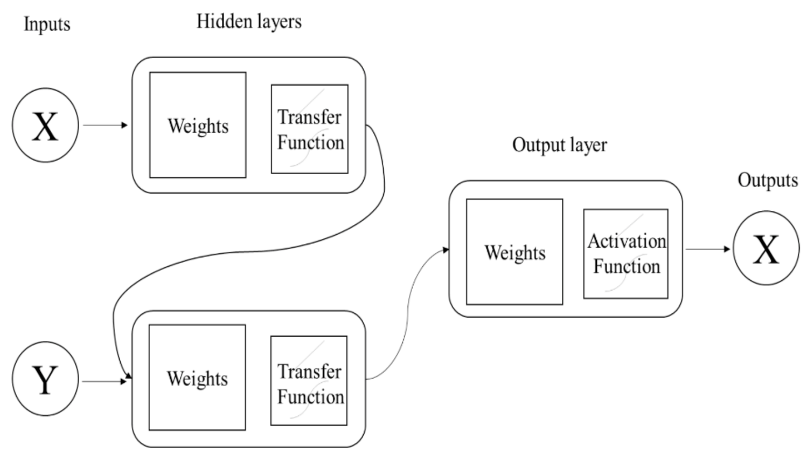
X and Y are included in a single layer



X and Y are independent



Y causes X



X causes Y

4. Results

- **Before make the structure of ANN we checked the granger causality between electricity load and temperature**
  - We conducted unit-root test first

Variable	ADF test	ADF GLS test	PP test	KPSS test
Electricity load	-29.6863*	-29.1401*	-42.2477*	0.2927*
	(-3.9584)	(-3.4800)	(-3.9584)	(0.2160)
Temperature	-5.5865*	-3.9115*	-6.8128*	0.6334*
	(-3.9584)	(-3.4800)	(-3.9584)	(0.2160)

Notes: * means that the null hypothesis is rejected at the 1% significance level.
The values in parentheses are critical values at the 1% significance level.

- Unit-root test shows that there is no unit-root in accordance with majority rule
- From the results, we can decide the model to identify the direction of causality

4. Results

- **Granger causality test conducted by Wald test shows that there is bidirectional causality relationship**

	Electricity load causes *temperature*	*Temperature* causes *electricity load*
F-statistic	57.8551 (0.0000)	50.5476 (0.0000)
Chi-square	1388.5230 (0.0000)	1213.142 (0.0000)

- Although, the test results show bidirectional relationship we doubted the results
- It is natural that electricity demand to be affected by temperature, but the opposite is not the case
- We confirmed that how this result is expressed in the forecasting results

4. Results

- **The tables show the forecasting results for the last twenty Fridays at 1 am, 6am in 2015**

Model	Single layer with one variable	Single layer with two variables	Independent two layers	Temperature causes load	Load causes temperature
MAPE	0.60%	0.56%	0.50%	0.48%	0.54%
T/V ratio	70/30	70/30	80/20	80/20	80/20
Hidden nodes	28	9	19,3	32,8	11,3

Note: T/V ratio refers to the training/validation ratio of the input data.

Model	Single layer with one variable	Single layer with two variables	Independent two layers	Temperature causes load	Load causes temperature
MAPE	0.56%	0.89%	0.53%	0.51%	0.56%
T/V ratio	70/30	80/20	80/20	75/25	80/20
Hidden nodes	39	10	40,2	35,5	36,3

Note: T/V ratio refers to the training/validation ratio of the input data.

4. Results

- **The tables show the forecasting results for the last twenty Fridays at 12 pm, 6pm in 2015**

Model	Single layer with one variable	Single layer with two variables	Independent two layers	Temperature causes load	Load causes temperature
MAPE	3.32%	3.43%	3.17%	2.93%	3.28%
T/V ratio	70/30	70/30	80/20	75/25	80/20
Hidden nodes	21	37	33,4	29,3	30,2

Note: T/V ratio refers to the training/validation ratio of the input data.

Model	Single layer with one variable	Single layer with two variables	Independent two layers	Temperature causes load	Load causes temperature
MAPE	3.57%	4.82%	3.40%	3.21%	3.23%
T/V ratio	70/30	70/30	80/20	85/15	80/20
Hidden nodes	31	9	33,3	40,3	14,5

Note: T/V ratio refers to the training/validation ratio of the input data.

4. Results

- **The tables show the forecasting results for the last twenty Fridays at 12am in 2015**

Model	Single layer with one variable	Single layer with two variables	Independent two layers	Temperature causes load	Load causes temperature
MAPE	1.61%	2.11%	1.52%	1.44%	1.52%
T/V ratio	70/30	70/30	80/20	80/20	80/20
Hidden nodes	14	8	35,2	9,2	24,3

Note: T/V ratio refers to the training/validation ratio of the input data.

5. Conclusions

- **Every cases show that fourth model is the best forecasting model**
  - Fourth model made by accordance with granger causal results
  - Fifth model was also made by granger causal result but it did not show good forecasting performance
  - We concluded that fifth model's relationship is a spurious relationship and therefore, this relationship couldn't improve the forecasting performance
- **Real causal relationship of time series data could improve the performance of ANN**
- **This finding may be valid to only Korean electricity load case, so that we are planning to extend our findings to other country's electricity load and another energy commodities like oil and natural gas**

Thank you

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