Predicting Electricity Demand and Price

Intro

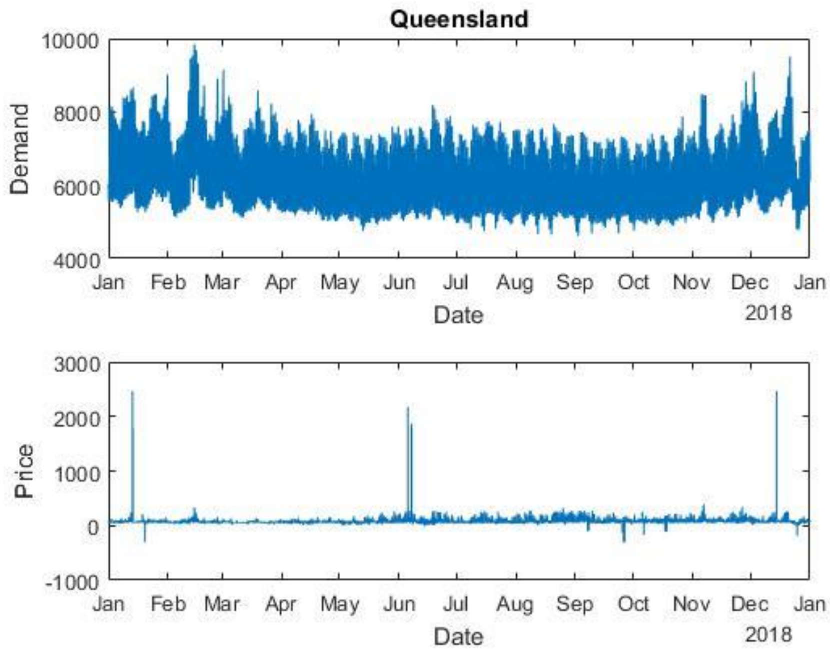
This report was compiled to examine how well a model can predict both the demand and price of electricity in Queensland and South Australia. Data was collected from https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard#aggregated-data. A model that could predict demand could be used to ensure that enough electricity is available, which could be used to limit blackouts. A model that could predict price could be used to ensure something the consumes a lot of power could be ran when price for power is at a low.

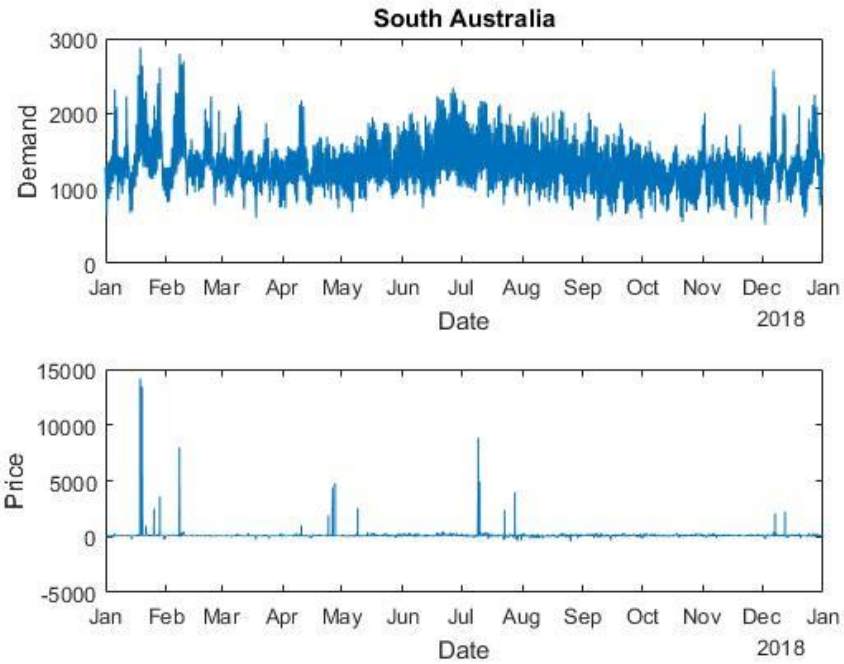
Data

The data collected was price and demand for electricity in Queensland and South Australia. The data found can be downloaded from here https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard#aggregated-data. Each month was downloaded and inserted into a single csv file.

January for South Australia has a different date representation, so Queensland dates will be used instead of South Australia's dates.

Plotting the data





From the plots, Queensland demand peaks in summer and dips in winter. Meanwhile South Australia's summer demand in summer is all over the place and during the winter it peaks compared to the previous and upcoming seasons.

The price plots don't reveal that much.

Table of Means

	Queensland		South Australia	
	Summer	Winter	Summer	Winter
Demand	6670	6054	1370	1391
Price	76	77	120	95

Examining the table, it can be seen that in Queensland the price doesn't change that much, meanwhile in South Australia there is a massive change. Queensland's demand increases by around a tenth in the summer and South Australia's demand change isn't that much.

Queensland also has a much lower price in both seasons compared to South Australia. Queensland considerate higher demand even when multiplying South Australia's by 2.76 to get to compensate for QLD's population.

Modelling the data

When using all the data to create a linear regression model the price and demand the root mean square error for demand in Queensland is 511 and 217 for South Australia. While price error is 18 and 44 for QLD and SA.

When using 50% of the data for training and 50% for testing to create a linear model, the error for predicting the demand and price error it comes to a root mean square error of 512 in demand and 19 for price in QLD. Meanwhile for SA demand error is 217 and 45 for price.

This means when using a model to predict data point it can be somewhat effective.

Uses

I was wondering how well the models could predict the price would be under a threshold and what the true positives, true negatives, false positives and false negatives would be.

When training the model, it used a random 50% of the data points then the model was used to predict the remaining points price.

First, I created a QLD model and tested how well it could predict the price was under a 75 threshold.

True Positive	3477
True Negative	2283
False Positive	911
False Negative	2089

This means a linear model is somewhat good at predicting the price in Queensland.

For South Australia model I wanted prices under 90, which created this table

True Positive	1704
True Negative	2926
False Positive	913
False Negative	3217

A linear regression model is worst when predicting South Australia prices.

Both cases had a lot of false negatives which means it predicts the price wouldn't be under the threshold when it is under the threshold. This means it wouldn't be running as often and would take a more downtime than needed. This is bad.

More models

I'm really interested in this and was wondering how other models could predict when the price is under a threshold and what their true rates and false rates are.

Queensland

Algorithm	True Positive	True Negatives	False Positive	False Negative
Gaussian process regression (Squared exponential kernel)	4499	2392	801	1068
SVM (Linear)	4554	1637	1557	1012
SVM (Gaussian)	5028	2312	881	539
High dimensional linear regression	4513	1691	1503	1053
Tree regression	4087	2515	679	759
Ensemble of regression	4687	2506	688	879

South Australia

Algorithm	True Positive	True Negatives	False Positive	False Negative
Gaussian process regression (Squared	1500	4765	832	1663

exponential kernel)				
SVM (Linear)	796	4941	656	2367
SVM (Gaussian)	1524	5230	367	1639
High dimensional linear regression	798	4931	666	2365
Tree regression	2240	4893	704	923
Ensemble of regression	1877	3950	1647	1286

Useful

Unlikely to get a random number of data points throughout the year and then must predict the rest. I retrieved data from 2017 and 2016 and created a model with all points from them and then used to predict the values for 2018.

Queensland

Algorithm	True Positive	True Negatives	False Positive	False Negative
Linear Regression	4415	4308	2164	6633
Gaussian process regression (Squared exponential kernel)	7599	3935	2537	3449
SVM (Linear)	9482	2008	4464	1566
SVM (Gaussian)	8821	3208	3263	2228
High dimensional linear regression	9459	2210	4362	1589
Tree regression	8437	3344	3128	2611
Ensemble of regression	7538	3674	2798	3510

South Australia

Algorithm	True Positive	True Negatives	False Positive	False Negative
Linear Regression	2331	8481	2689	4019
Gaussian process regression (Squared exponential kernel)	3807	7128	4043	2542
SVM (Linear)	5247	4574	6597	1102
SVM (Gaussian)	4386	5835	5336	1963
High dimensional linear regression	5271	4689	6483	1077
Tree regression	4164	6168	5002	2186
Ensemble of regression	3840	6654	4518	2508