UNDERGRADUATE RESEARCH OPPORTUNITIES PROGRAMME

(UROP)

PROJECT REPORT

Validation of Demand & Supply Forecasting for Dynamic Resource Planning

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Abstract

In recent years, environmental issues have come to the foreground of political, social and economic discussions. Subsequently, both individuals and producers have been taking a more proactive role in the fight against climate change. From the producer's perspective, energy consumption and efficiency of processes must be optimized to gain cost savings and mitigate redundant energy loss. A possible way to increase efficiency is through the increased use of renewable energy. However, renewable energy poses its own set of obstacles. Uncertainties with both the energy demand and the supply of the energy source (e.g. wind, solar), means despite being a cleaner energy form, there is also huge amounts of energy not being efficiently converted or stored. As a result, accurate forecasting is needed for dynamic resource planning. Time series forecasting in which data analysis and predictions can be made by tracking the changes of a particular commodity over time aids this process. This research seeks to illustrate how said time series analysis can be employed to optimize resource planning.

Preface and Acknowledgements

Undergraduate Research Opportunities Programme (UROP) has been an incredible experience for me. Even though my bachelors did not require me to produce a final thesis of sort, I have been extremely fortunate to be presented an opportunity to have a taste of how research is conducted. It has been a tough and challenging experience, and of course throughout the duration of the programme there were moments of confusion and helplessness. The coronavirus pandemic did not make it any easier, with a lack of physical meetings and resultingly made finding assistance tougher. It was a laborious task – reading documentation on programming packages, learning about time series forecasting and analysis, and the countless hours put into reading scientific papers, producing and fine-tuning the code. But through it all, I have had continuous support and a few individuals to thank, who made this journey that much more enjoyable.

My most sincere thanks and appreciation would go to my supervisor, Dr. Ken Shuan. He has been nothing short of patient, understanding and has been extremely accommodating. I thank him for always being encouraging and always taking the time to check in on my progress and help chart the path forward, and for taking time to look through the drafts and provide constructive feedback.

I would also like to thank Assistant Professor Xiaonan Wang for providing me the opportunity to work with Dr. Ken. As someone from a computer engineering background, it was a challenge for me to do research in a field that was completely out from my knowledge base. Despite this, she made the effort and found a suitable platform for me to contribute during UROP.

I am indebted to many of my friends who have had constantly hear me turn down opportunities to meet because of the work I had to complete for UROP, and who had to deal with me never being there in person for a whole year. I am also indebted to those I constantly had turned to for help and assistance to get the code working to test the models.

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1. Introduction

Since the 1960s, environmental issues have been a global cause of concern (Savasan, 2019). Despite the formation of many international organizations to tackle climate change, more needs to be done as evidence show that climate change is serious and pressing (Stern, 2007). In 2015, countries came together and agreed to cooperate to battle climate change through the Paris Agreement (Blau, 2017). The recent focus on creating a more sustainable future, has path the way for tighter environmental requirements. As a result, various sectors face pressure to further improve product and process performances (Alvandi, Li, Schönemann, Kara, & Herrmann, 2016). Singapore is no different, expressing its support for the United Nations Sustainable Development Goals and having taken several actions to meet its targets including ratifying the Paris Agreement (National Environment Agency, n.d.). Singapore has also been revising its green plan with the latest one being the Singapore Green Plan 2030 – a nationwide movement to advance Singapore's sustainable development by achieving net zero emissions (SG Green Plan, n.d.).

It should be noted that any transition to be more eco-friendly is a long-term and inter-disciplinary process that brings about sustainable modes of production and consumption in various sectors (Ponta, Raberto, Teglio, & Cincotti, 274-300). Rapid developments and production lead to the creation of products through the use of resources viz. machines, inputs such as energy, and materials. However, such mass production has consequently resulted in various harmful emissions such as carbon dioxide, nitrous oxides, or pollutants to the environment (Schonemann, Bockholt, Thiede, Kwade, & Herrmann, 2018). Additionally, the process is not 100% efficient. In other words, while only a fraction of the inputs is being used for the purpose of value-adding, the rest is wasted in terms of energy loss through heat and emission (Herrmann, Bergmann, Thiede, & Zein, 2007).

Energy consumption and efficiency of processes must be optimized, otherwise, not only will potential areas of profit be lost, but the waste of energy, will also severely affect the environment (Herrmann, Bergmann, Thiede, & Zein, 2007). One manner in which this can be addressed is by increasing the use of renewable energy. For example, one of Singapore's key targets was to quadruple solar energy usage (SG Green Plan, n.d.). However, renewable energy does come with its challenges. This leads to a very vital issue as the solar supply is not fixed and is constantly varying in nature. As such, we may witness uncertainties in the supply of renewable energy viz. solar energy, wind energy. Uncertainties with the energy demand in various systems, such as manufacturing systems, residential and commercial buildings (Dannecker, 2015) may also arise; the demand-side takes the form of heating, ventilation and air conditioning systems (HVAC systems) which accounts for more than 50% of the energy consumption (National Climate Change Secretariat, 2020). Similar to solar energy, the HVAC demand is significantly affected by the variations in ambient temperature (Joudi & Al-Amir, 2014) and (Harrington, Aye, & Fuller, 2017).

As a result, forecasting is needed for dynamic resource planning. Time series forecasting is a manner in which data analysis and predictions can be made by tracking the changes of a particular commodity over time. This research seeks to illustrate how such forecasting methods can be employed to optimize resource planning.

2. Literature Review

Time series forecasting continues to be the focus area of some of the most intensive researches as even the most marginal of improvements in the accuracy of prediction models can lead to potentially millions saved or gained (Dannecker, 2015). With electricity increasingly becoming the main energy source of the future (Dong, Yang, Reindl, & Walsh, 2013), it is vital that we have accurate load matching predictive analysis in order to not only keep costs low, but to be energy efficient. Forecasting makes use of quantitative models to illustrate trends, changes, developments, or patterns of the variable in question over a period of time (Dannecker, 2015). Some examples of these models would include Autoregressive (AR) (Box, Jenkins, & Reinsel, 2015), Exponential Smoothing (ES) (Taylor, 2010), Autoregressive Integrated Moving Average (ARIMA), among several others. It can be noted that some exponential smoothing models are just special cases of ARIMA models (Abraham & Ledolter, 1983). These models typically capture some form of relationship between the time frame and one or more variables and express them in relation to seasonal changes, trends or external interferences (Dannecker, 2015). There also exist other forms of models by analyzing nonlinear time series such as Artificial Neural Network (ANN) (Dong, Yang, Reindl, & Walsh, 2013).

For the most accurate forecasting models, univariate methods are preferable as they yield more accurate results for short-term forecasting as opposed to multivariate methods (Taylor, 2010). Ideally, after estimating them on a training dataset, one would be able to find the parameters that minimizes the difference between the prediction and the actual value. Almost all forecasting models have some form of error in the predicted output (Khair, Fahmi, Hakim, & Rahim, 2017). Minimizing the difference will ensure a low forecasting error (Dannecker, 2015).

There are various statistical metrics that is used to validate models, by assessing the performances of said models (Chai & Draxler, 2014). While not necessarily used for performance analysis, correlation coefficient (r), or r^2, can be used in signaling a correlation between the variables. In the evaluation of models, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are among the most commonly used (Chai & Draxler, 2014). The two metrics calculate errors in the predicted values slightly differently. While RMSE gives larger weight to larger errors in predicted values, MAE gives all of the errors an equal weight (Chai & Draxler, 2014).

The respective formulas can be found below (Chai & Draxler, 2014):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i|$$

Where e_i is the error margin computed with the following equation,

$$e_i = x_i - \hat{x}_i$$

Where,

x_i = predicted value;

$\hat{x}_i$= actual value

When it comes down to forecasting ambient temperatures, short-term analysis will be essential to plan for excess supply or demand, as well as (and more pertinently) optimal load matching (Reikard, 2008). Such analysis allows for more responsive, and on-the-fly measures, allowing in better handling of changes to either the supply or demand-side of solar energy (Dong, Yang, Reindl, & Walsh, 2013), translating to both greater energy-efficiency and cost effectiveness.

3. Methodology

The overarching aim Using Singapore's hourly temperature data from 2020, training data was split for 1 day, 1week, 1 month and 1 year. The training sets were used to train the model before predicting the values for the following day. For all subsequently mentioned steps, they were done for each set of training data. The overarching aim was to run multiple models, measure the forecasting error and deduce the most accurate model and subsequent predicted values.

A few models – namely, Holt-Winters Exponential Smoothing (HWES), Simple Exponential Smoothing (SES), Seasonal Autoregressive Integrated Moving Average (SARIMA), AR, and ARIMA models were used. Once predictions have been completed by all models, the RMSE, MAE, MAPE, and R-squared values of the model's output were compared as seen in figure 1, and the most accurate model were used as the final predicted value.

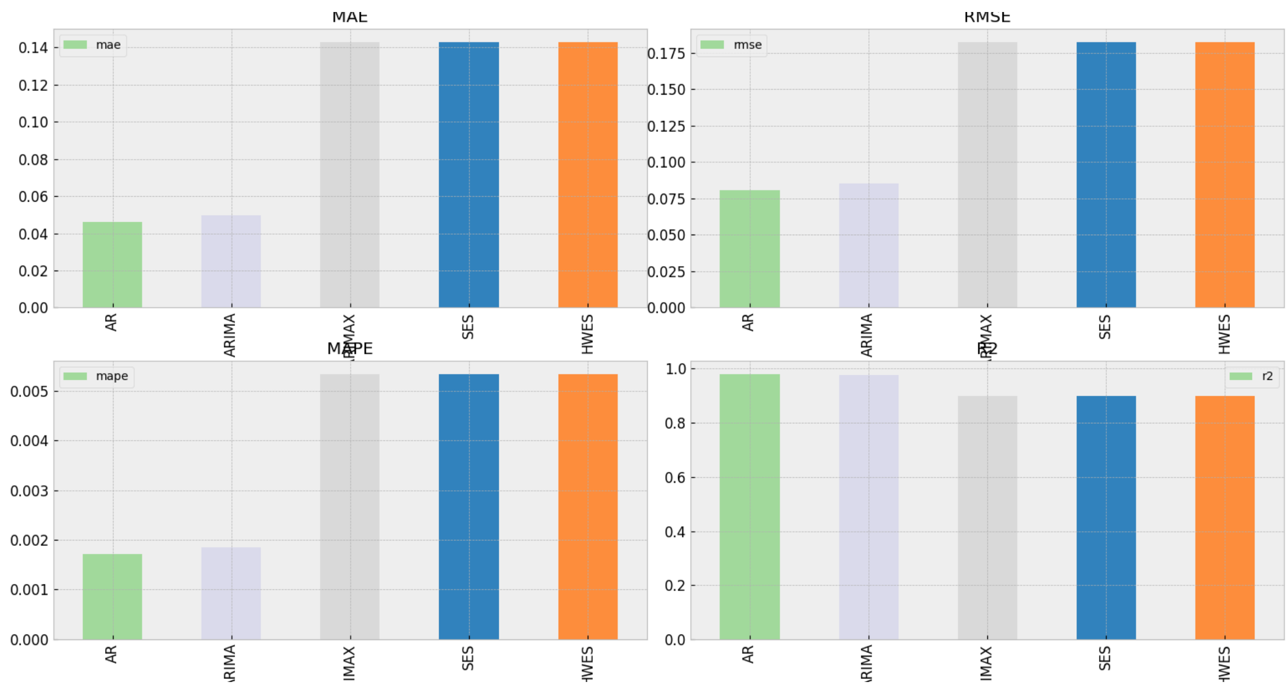

Figure 1: Comparing Forecast Error of Various Models

The data was first processed and then tested for stationarity. For time-series models to be effective, they either run on the assumption that the data is stationary or requires the dataset to be stationary (Chen, Gan, & Chen, 2018). Stationary time series represents data that does not have a variation in the manner in which it is being generated. It does not mean the time series has no variation, but rather the way in which it changes remains the same. Essentially, this allows the data to be represented in the form of a function. There are a few ways in which stationarity can be tested for.

Statistical test such as the Augmented Dickey-Fuller Test, which checks for a unit root in the data by using an ordinary least squares (OLS) estimator (Paparoditis & Politis, 2018) can be used to check for stationarity. Alternatively, graphs can be plotted, identifying for trends or seasonality similar to the plots in figure 2.

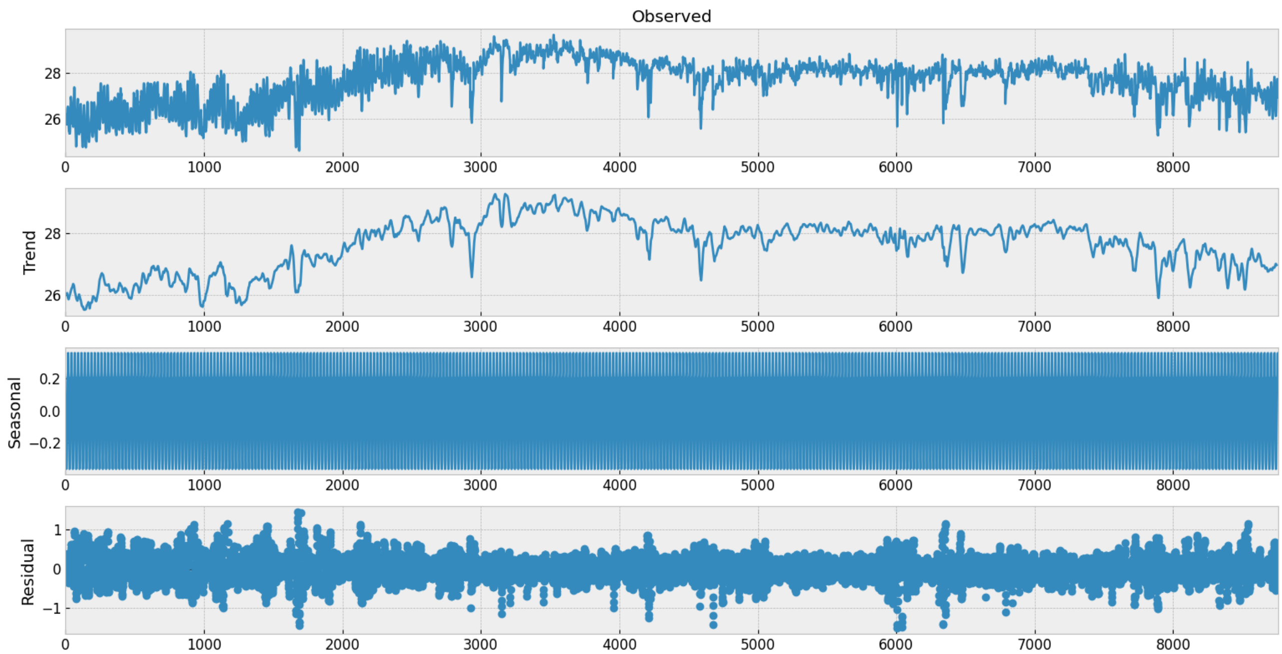

Figure 2: Decomposed Data

For training datasets that were not stationary, either differencing or transformation could have been applied. For this dataset, differencing was done on non-stationary datasets. For both the ARIMA and SARIMAX models, they have to be expressed as an order of (p, d, q) where p is the number of auto-regressive terms, d being the order of difference and q the number of lagged forecast error (Nau, n.d.). p and q-values were selected by plotting and observing an Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) respectively (refer to figures 3 and 4 below). A time series can have components like trend, seasonality, cyclic and residual. An ACF plot considers all these components while illustrating the relationship between the values in the time series, while a PACF is similar to an ACF plot except that it uses its own lagged values (Bielowicz, Chuchro, Jedrusiak, & Wator, 2021). Both p and q can be taken as the lag value after which the PACF and ACF plot initially crosses the upper confidence interval, respectively (Salvi, 2019).

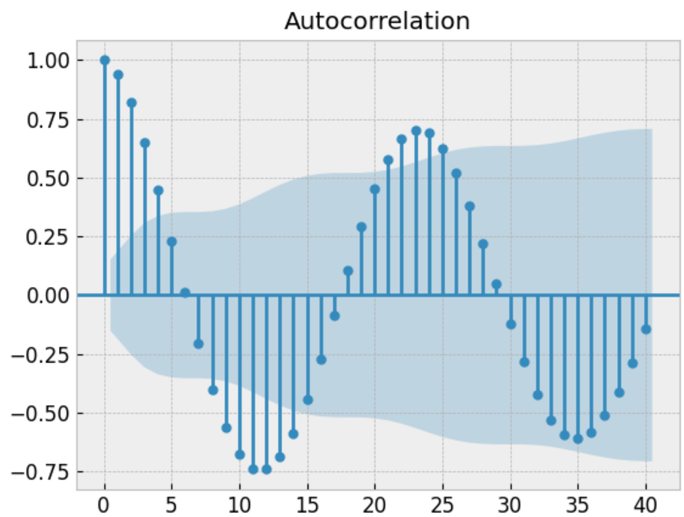

Figure 3: ACF Plot of 1 week worth of hourly temperature

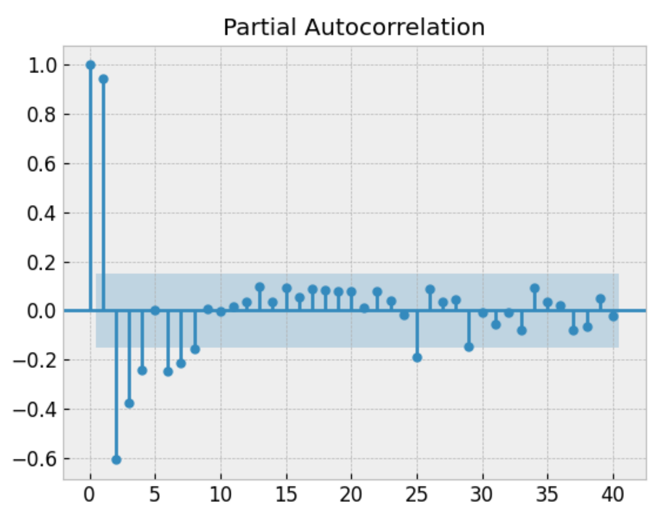

Figure 4: PACF Plot of 1 week worth of hourly temperature

4. Findings

For each of the above-mentioned training sets (1 day, 1 week, 1 month and 1 year), 70% of the hourly data were used as training cases and 30% were used as test case which were used to determine the accuracy of the models. The the autoregressive (AR) model edged all other models tested in all of the 4 cases. This finding seems to confirm that the accuracy is one of the reasons behind AR models popularity in time series analysis (Claeskens, Croux, & Kerckhoven, 2007). Following this, the predicted values based on all of the training data were plotted and compared to determine the most effective time frame for accurate analysis. The predicted temperatures based on the respective models can be seen below in figure 5 and the error margin for each of the models are shown in figure 6.

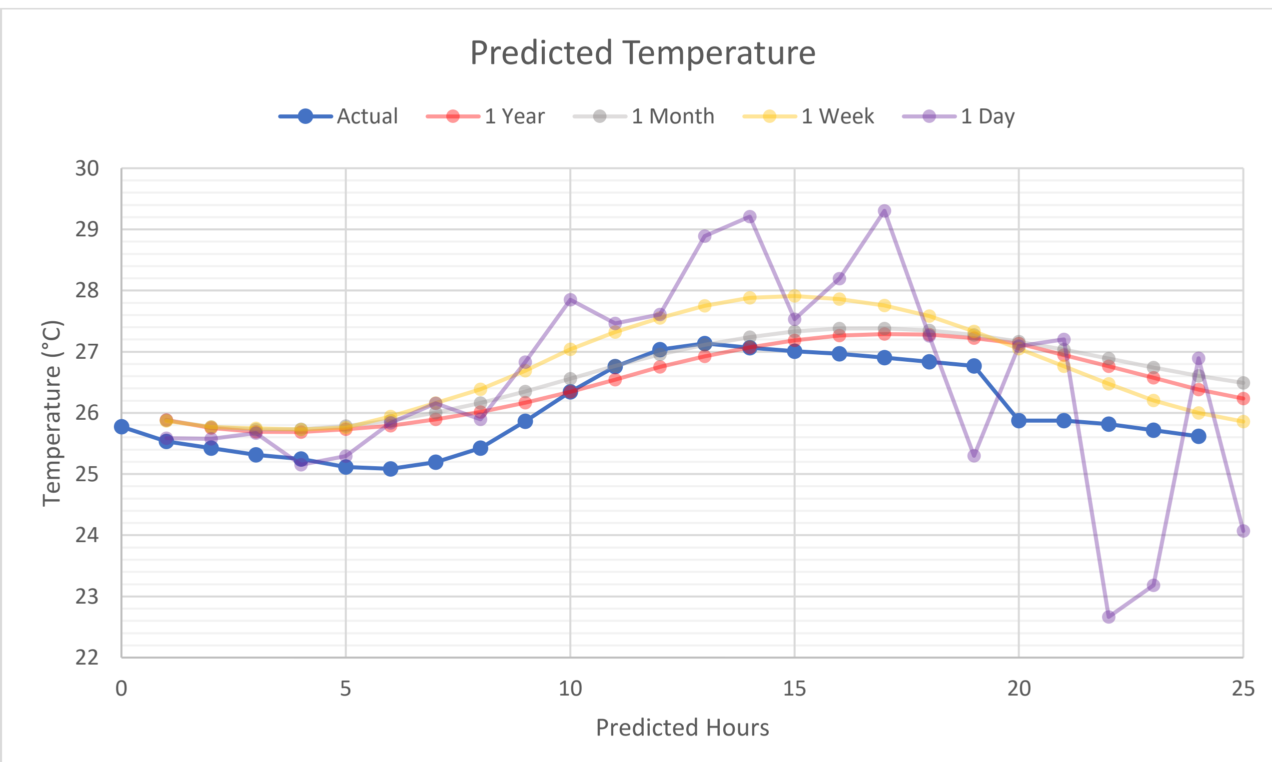

Figure 5: Predicted Hourly Temperature Plot

As seen in the figure, the predictions based on the temperatures from a day in advance, resulted in the most fluctuating, and inaccurate results.

The MAE values for each of the models were calculated and summarized in table 1 below.

Table 1: MAE Values for AR Models

	Model			
	1 year	*1 month*	*1 week*	*1 day*
MAE Value	*0.447266*	*0.553391*	*0.666735*	*1.142401*

Additionally, the RMSE values were calculated and table 2 below summarizes the RMSE values for each model.

Table 2: RMSE Values for AR Models

	Model			
	1 year	*1 month*	*1 week*	*1 day*
RMSE Value	*0.531748*	*0.639433*	*0.741504*	*1.419335*

Confirming the observations, the model that was fed 1-year data was the most accurate of the four. The mean and standard deviation of the actual temperatures were 26.06856 and 0.52754 respectively. The mean and standard deviation of the most accurate model (1-year), were 26.50174 and 0.58533, respectively. A chart with the hourly error percentage is plotted below, and a table of the exact error margin can be found in table 3.

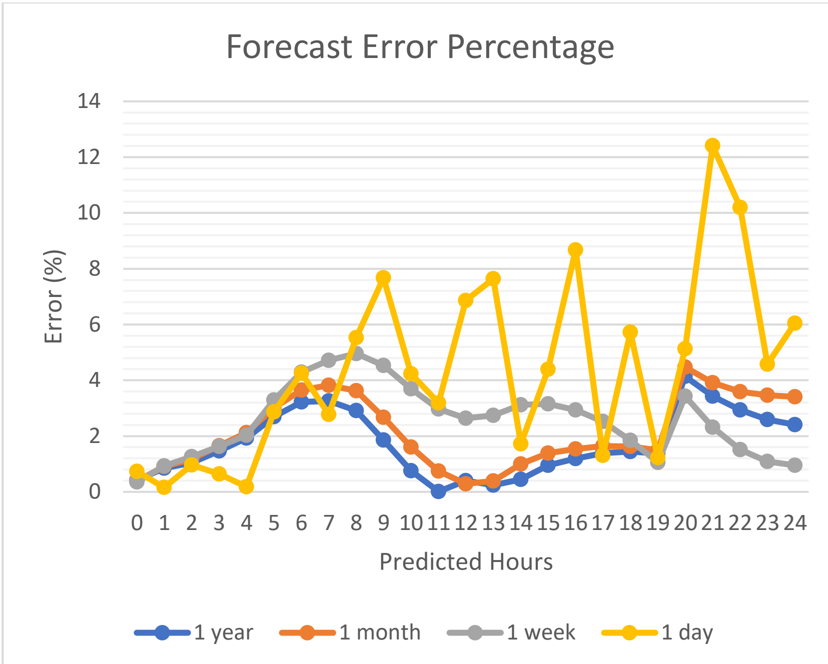

Figure 6: Hourly Forecast Error Margin

Table 3: Error Margins

	Error %			
Actual Temp	1-year	1-month	1-week	1-day
25.77616	0.416086	0.392586	0.351991	0.734357
25.53616	0.853556	0.907253	0.922919	0.155401
25.42616	1.043037	1.185746	1.26633	0.965827
25.31616	1.468529	1.654506	1.631921	0.642931
25.24616	1.928962	2.125511	2.025571	0.186543
25.11616	2.694415	3.013854	3.287097	2.863862
25.08616	3.217679	3.653149	4.284821	4.26017
25.19616	3.260559	3.824386	4.715907	2.778174
25.42616	2.909165	3.624591	4.960718	5.524798
25.86616	1.858544	2.674148	4.531114	7.671178
26.34616	0.75692	1.603388	3.696288	4.232501
26.75616	0.010627	0.742965	2.967266	3.187254
27.03616	0.405131	0.288501	2.638486	6.861639
27.13616	0.234597	0.38646	2.744066	7.635849
27.06616	0.443045	0.993849	3.12065	1.725211

27.00616	0.950032	1.386257	3.159226	4.396016
26.96616	1.196349	1.541229	2.93472	8.669708
26.90616	1.390873	1.637654	2.519642	1.310824
26.83616	1.449286	1.626296	1.845421	5.726516
26.76616	1.379319	1.487736	1.059111	1.225245
25.87616	4.136756	4.46823	3.432855	5.124135
25.87616	3.435011	3.909959	2.312796	12.41122
25.81616	2.933741	3.587065	1.509185	10.20066
25.71616	2.589747	3.460141	1.094151	4.572971
25.61616	2.408748	3.406011	0.952731	6.039971

For all of the predicted values using the 1-year data, the error margin is within 5% with most within 3% of the actual values. As such we can make use of the year-long data model to optimize manufacturing processes where the efficiency is dependent on the ambient temperature. The graph below shows the actual temperature and the best predicted temperature (greyed out).

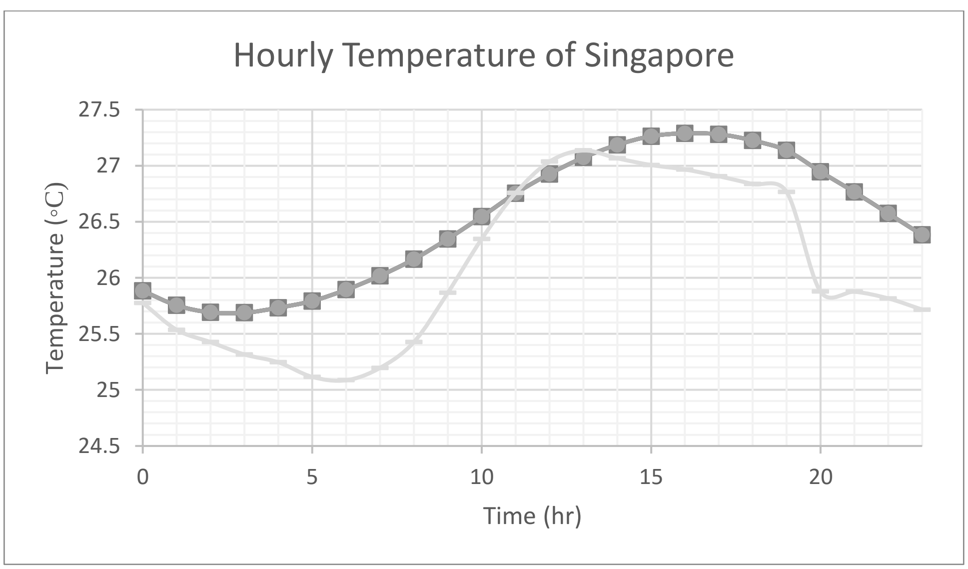

Figure 7: Actual and Predicted Hourly Temperature

5. Discussion & Future Works

According to reports, Air Conditioning and Mechanical Ventilation (ACMV) systems account for more than 50% of the total energy consumption of the building (National Climate Change Secretariat, 2020). Evidence from energy consumption breakdowns conducted on said ACMV systems alludes to the fact that the fans can consume up to 35% of the energy consumption; with the chillers consuming up to a whopping 55% (National Climate Change Secretariat, 2020). The ambient temperature affects an air-cooled chiller's ability to dissipate heat as the ambient air and refrigerant temperature gradient is used in the condensation process by inducing a heat transfer. Using the forecasted ambient temperature, the power consumption of vapour compression refrigeration systems can then be forecasted. The total heat transfer reduces as a result of the increase in ambient temperature as the rise causes a decrease in the temperature differential (Allain, 2017). This is similar to water chillers; the water temperature within the facilities can increases due to a rise in ambient air temperatures. Consequently, this reduces the water chiller condenser's capability to transfer process heat from the refrigerant to facility water. This means that the resulting higher condensing pressures and temperatures can lead to a reduction in system performance (Boyd Corporation, n.d.). As such, forecasting ambient temperature to optimize power consumption would result in both cost and energy-savings. The compressor power can be calculated with the following equation:

$$P_{ref} = \frac{f \oint P_{com}\, dV}{\eta_{com,mec}}$$

Where,

P_{com} is the pressure of the compressor,

V_{com} is the compressor capacity in m^3,

$\eta_{com,mec}$ is the mechanical efficiency of compressor

In the above model, it is assumed that there is (i) constant cooling load; (ii) constant compressor and motor speed and efficiency; (iii) constant temperature difference between the condenser and ambient temperature; (iv) perfect sealing; and (v) adiabatic compression. The graph below illustrates the results of the simulated refrigeration power based on the ambient temperature data, with the operating conditions shown in the subsequent table.

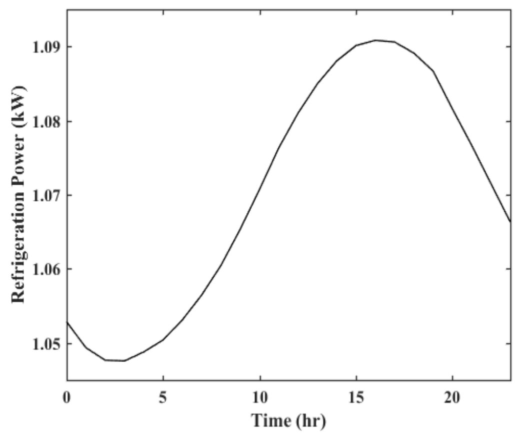

Figure 8: Simulated Hourly Refrigeration Power

Table 4: Operating Conditions of Refrigeration System

Operating Conditions of Refrigeration System	
Working Fluid	R134a
Degree of superheat, T_{sph}	27.8˚C
Saturated temperature of evaporator, T_{eva}	7.2˚C
Compressor speed, f	50 Hz / 3000 rpm
Cooling load, Q_{load}	5.2 kW
Compressor size, V_{com}	43 cc
Mechanical efficiency of compressor, $\eta_{com,mec}$	385%

Additionally, in the case of solar irradiation, a similar forecast was done. This time, the most accurate plot was seen to be using the equivalent month data. In other words, if you are planning to predict January 2021 solar irradiation, then making use of January 2020 data is seen to provide the best results. However, it is to be noted that the solar irradiation is largely affected by cloud cover and weather changes. As is, weather prediction models do have its limitations and can even be inaccurate the further a forecast goes (Moran, et al., 2016). As such the predictions made for solar irradiations are more inaccurate than those of temperature. Despite these inaccuracies, it is still wise to make such forecasting as studies have shown significant energy-savings even with inaccurate data (Barzin, Chen, Young, & Farid, 2016). The table below shows the actual solar irradiance compared with the best predicted solar irradiance values.

Table 5: Hourly Solar Irradiation Forecast

Actual	Predicted	Error Margin
0	0	0
0	0	0
0	0	0
0	0	0
0	0	0
0	0	0
0	0	0
0	0	0
44.5	45.51324	2.276934
166.43	168.8645	1.46275
308.83	338.0195	9.451654
538.45	594.9381	10.49087
339.98	363.1021	6.801012
251.87	530.44	110.6007
463.69	451.2127	2.690873
234.96	324.9694	38.3084
121.04	390.5437	222.6567
75.65	157.0964	107.6621
44.5	152.3246	242.3024
17.8	121.7611	584.0513
0	0	0
0	0	0
0	0	0
0	0	0
0	0	0

The hourly solar irradiance of the predicted values (greyed out) is plotted below along with the actual values.

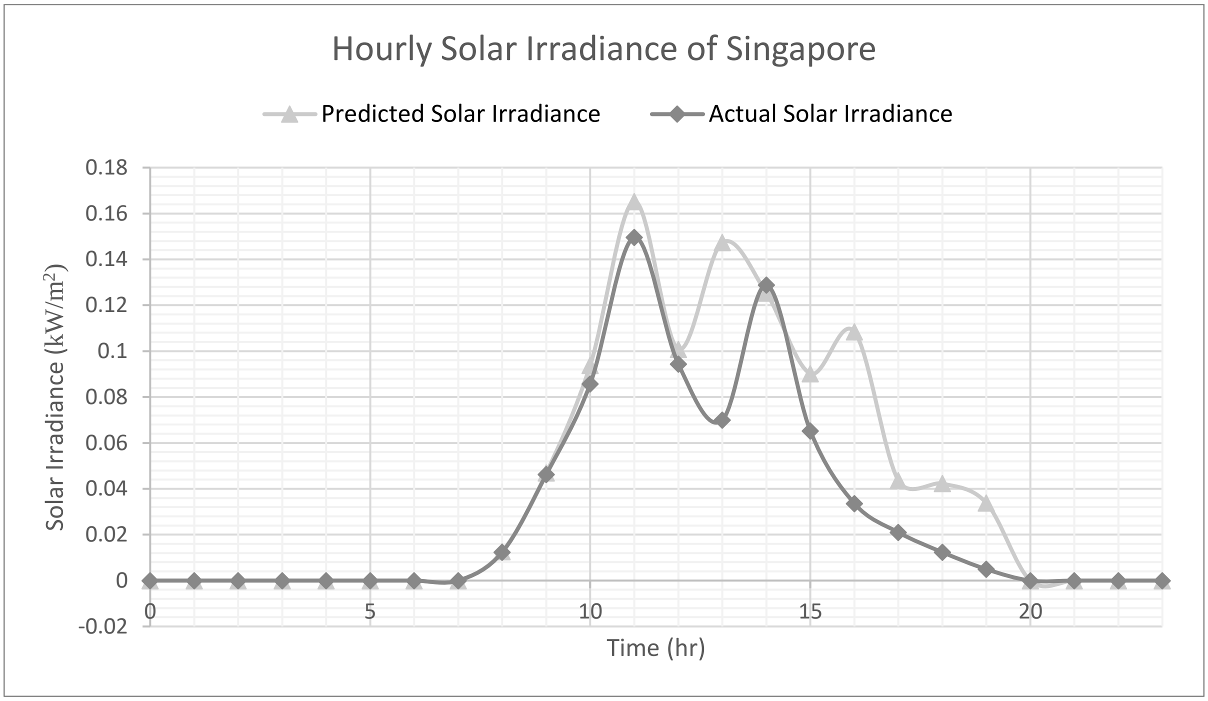

Figure 9: Actual and Predicted Hourly Solar Irradiance

Irradiance can also be converted to solar power and can be obtained with the following equation (United States Environmental Protection Agency, n.d.):

$$P_{PV} = A \times \eta_{PV} \times I \times PR$$

Where,

A: total solar panel area (m^2)

η_{PV}: solar panel efficiency

I: instantaneous solar irradiance (W/m^2)

PR: performance ratio, or coefficient of losses which ranges between 0.5 – 0.9

This allows for users and producers of solar energy, to predict the optimal times in which to utilize or store solar power, leading to improved efficiency and greater cost savings. In this case, $A = 56, \eta_{PV} = 0.2, and\ PR = 0.8$. The solar power generation for both the predicted and actual values are shown in figures 9 and 10 below.

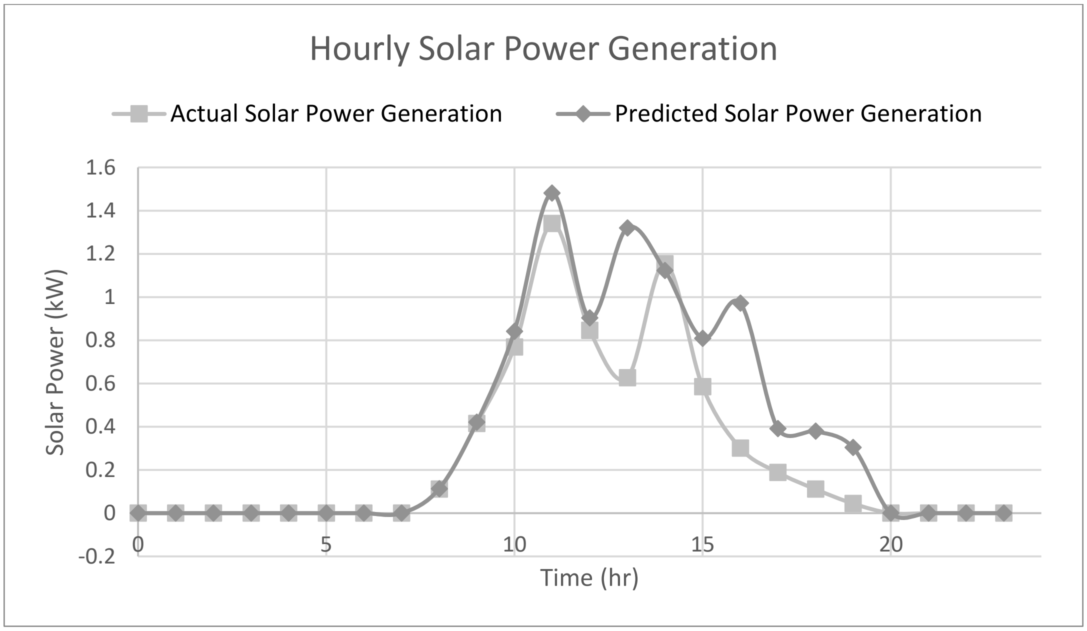

Figure 10: Actual and Predicted Hourly Solar Power Generation

There are a few things to note from this study. (1) No model was tested with data beyond 1-year; and (2) No model optimization were conducted, and the forecasting models were tested using existing python packages. For (1), it is noted that from the data, models got progressively better with an increase in the number of data for hourly temperature. In other words, the model with 1-year worth of data fared better than the one with 1-month worth of data, which fared better than the model fed with 1-week data. However, and more importantly, the threshold was not verified in this study. It would be useful to find an upper bound, beyond which the model does not improve significantly. This will allow for not only more accurate results, but also be more efficient as it saves on both the time and space complexity.

As for point (2), no further optimizations were performed on all of the models. As noted in numerous papers, optimization of time series models will result in more accurate responses (Ouyang, 2017). As such, fine-tuning parameters and creating a more tailored model to the use case will result in improved accuracy of the models. However, for the purpose of validating models as is, no optimizations were conducted. In order to obtain more accurate results for real world optimization to models are highly recommended. Clearly there is value in forecasting the supply and demand of solar irradiation and temperature in order to experience cost and energy savings. Ideally, we would need to work towards a much more accurate forecasting methods for a longer time period which would allow us to prepare beforehand and better allocate resources well in advance.

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