Solar Irradiance and Load Demand Forecasting based on Single Exponential Smoothing Method

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***Abstract*—Forecasting of the solar irradiance and load demand are essential for system level control and components coordination in the supervisory controller of an off-grid hybrid energy system. This paper presents the analysis of the predictions for solar irradiance and load demand using two different Single Exponential Smoothing forecasting approaches. Both approaches perform prediction based on hourly basis. The first approach uses the current day data while the other uses the previous day data. Comparison between the two approaches is carried out, and the forecast results show that the Single Exponential Smoothing forecast models utilizing the previous day data achieved higher accuracy as compared to the one using the previous hour data.**

***Index Terms*—Prediction model, single exponential smoothing, renewable energy.**

I. Introduction

Forecasting is necessary to provide accurate estimation of the future process. Forecasting applications can be found in stock markets, manufacturing processes, utilities and etc. These organisations rely on forecasting for planning and decision making in daily operations. Recently, the applications of forecasting have been extended to the engineering disciplines. Predictive control of a hybrid energy system (HES) based on the forecasts of the renewable sources and the load demand can be found in [1] and [2].

One of the most commonly used forecasting methods is the Weighted Moving Averages (WMA) technique due to its simplicity which gives more weight on the most recent observation. WMA is also the fundamental of many advanced forecasting methods. The limitation of this method is that the sum of the weight assigned to the observations has to be tantamount to unity [3]. Single Exponential Smoothing (SES) method does not have the limitation as found in WMA. In SES, the core component is the smoothing constant that determines the functionality of a forecast model. It is also referred as the weight assigned to the data and the most recent data have the higher weights as compared to the older data [3]. One example of the application of SES to predict the wind velocity is discussed in [4].

The selection of a forecast technique for a particular application remains an arbitrary subject and highly relies on the characteristics of the time series. Time series is a set of recorded data with equally spaced time intervals for a defined period. These data are used to generate the future unknown data as accurate as possible through a selected forecast technique and the smoothing constant.

This paper presents the analysis of predictions of solar irradiance and load demand using two different SES methods. The first approach uses the current day data to forecast while the other uses the data from the previous day. In the second section of this paper, the generation of a series of testing data using HOMER is presented. Details of the SES approaches are elaborated in section three. The data are analyzed in section four, the comparison between the two models is carried out and the selection criterion for a model is also presented. The appropriate approach will be selected and can be potentially used as a benchmark for the other improved forecast method developed by the author in [5].

II. Solar Irradiance and Load Demand Data Generated Using HOMER

Time series for the solar irradiance and load demand are required to justify the selection for a forecast model. Due to the complete sets of annual data are rarely available especially for an off-grid HES, the hourly data for a year were generated using the Hybrid Optimization Model for Electric Renewables (HOMER) V.2.68 for the solar irradiance and load demand respectively. These data represents the actual or measured data in the forecast model that will be discussed later.

The first time series is the annual hourly solar irradiance for Gaadhoo, Maldives located at 1°49' 12"N, 73°28'11"E. The average monthly weather data of this selected site is obtained from the NASA surface solar irradiance website [6], and the data generation of the synthesised solar irradiance by HOMER as depicted in Fig. 1 is based on the algorithm developed by Graham and Hollands in [7] as stated in the HOMER's manual. The generated solar irradiance as shown in Fig. 2 depicts the common phenomenon of sunshine for five days with varying irradiance that represents the sunny and cloudy days.

The daily load profile in Fig. 3 is estimated based on the load curves according to [8] for outer islands, and the household numbers as given in the electricity assessment sheet for Maldives in [9]. As the activity of the village community is repeating daily, no significant variation in daily load demand pattern is expected. Random variability is taken into account during the generation of synthesized data in HOMER to imitate the realistic load demand profile, which usually consists of random fluctuations in magnitude.

These synthesised time series were exported to MS Excel and were used for two approaches of the SES forecasting methods simulations as discussed in the following sections.

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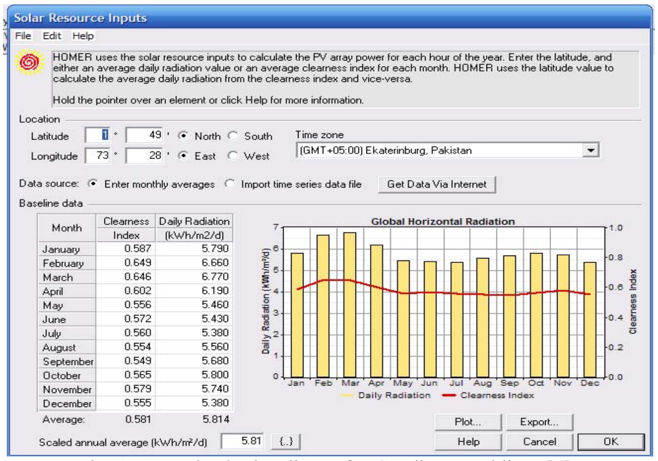

Fig. 1. Annual solar irradiance for Gaadhoo, Maldives.[6]

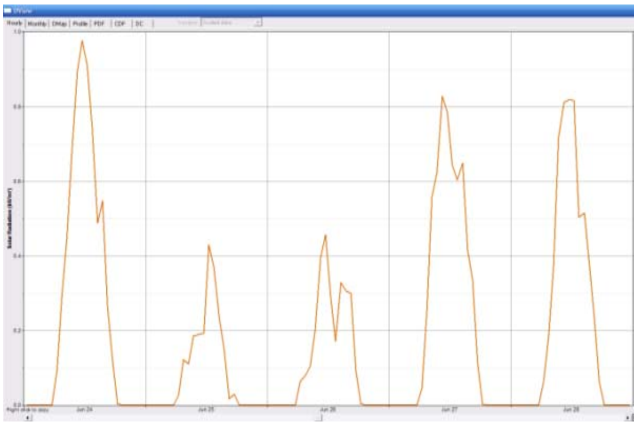
Fig. 2. Simulation of hourly solar irradiation from HOMER

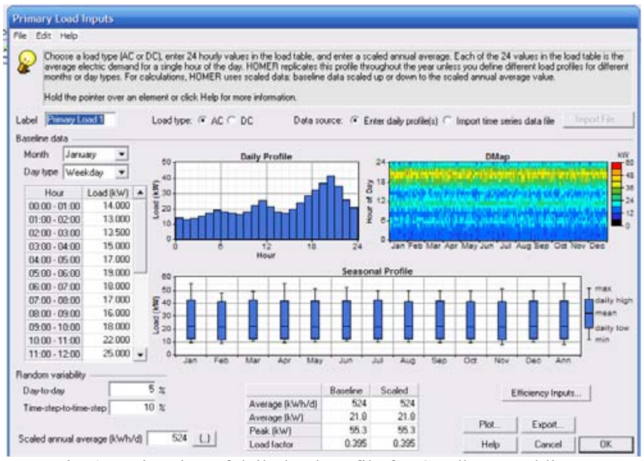

Fig. 3. Estimation of daily load profile for Gaadhoo, Maldives

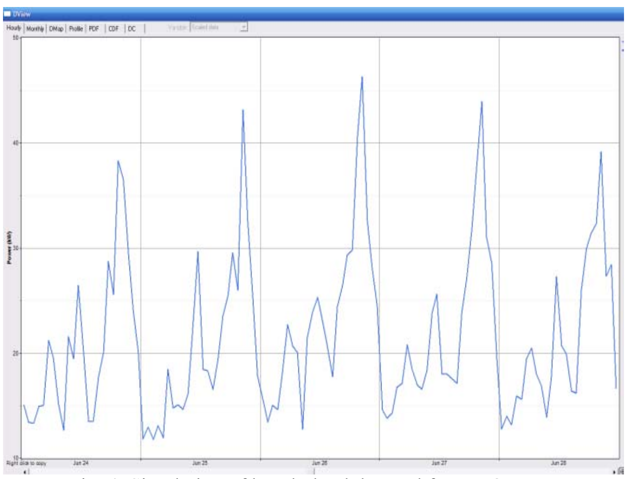
Fig. 4. Simulation of hourly load demand from HOMER

III. Single Exponential Smoothing Method

SES is widely accepted for its nature that requires low computation power. Comprehensive discussion regarding this popular method can be found in [3]. Generally, forecast based on the previous hour actual and predicted values may be suitable for the time series that is continuous. However, this approach may not be suitable for the time series with alternating consecutive numerical and null values such as the cyclic daily solar resource. Two approaches based on the SES method have been studied, these forecast models are written in MATLAB m-file and the simulation results are tabulated in spreadsheet for graph plotting and analysis.

A. Model 1: SES based on the current day most recent forecast and actual values

The first model is the conventional SES, which uses both of the most recent actual and the most recent forecast values in the previous period to perform a new forecast [3]. The new forecast is equal to the previous actual data plus a fraction of the previous forecast value. In (1), the smoothing constant, α represents the weight attached to the most recent actual data. The value of α is between the range of zero to one. The forecast model indicates that the higher the α, the greater the effect of the previous actual data to the prediction, while less impact will be imposed from the previous forecast value. For instance, if α equals to 0.8, the prediction is 80% of the most recent actual data and 20% of the most recent forecast data. The SES forecast model as in (1) is used for the solar irradiance and load demand predictions.

$$X_f(h+1) = \alpha X_m(h) + (1-\alpha) X_f(h) \quad (1)$$

where

$X_f(h+1)$ is the forecast value.

$X_m(h)$ is the actual/measured value prior to the forecast period.

$X_f(h)$ is the old forecast value prior to the forecast period.

The solar irradiance data obtained from HOMER for a selected day is shown in the first column of Fig. 5 and the simulation results of the predicted values employing different smoothing constant ranging from 0.1 to 0.9 are listed in the remaining columns. Fig. 6 shows the testing data and the simulation results for a selected day for the load demand.

4	Syn. Solar	alpha=0.1	alpha=0.2	alpha=0.3	alpha=0.4	alpha=0.5	alpha=0.6	alpha=0.7	alpha=0.8	alpha=0.9
197	0	0.2449116	0.135728	0.0568597	0.0193649	0.005389	0.001163	0.000171	1.27E-05	1.77E-07
198	0	0.2204204	0.1085824	0.0398018	0.011619	0.002695	0.000465	5.14E-05	2.54E-06	1.77E-08
199	0	0.1983784	0.0868659	0.0278613	0.0069714	0.001347	0.000186	1.54E-05	5.07E-07	1.77E-09
200	0	0.1785406	0.0694927	0.0195029	0.0041828	0.000674	7.45E-05	4.63E-06	1.01E-07	1.77E-10
201	0	0.1606865	0.0555942	0.013652	0.0025097	0.000337	2.98E-05	1.39E-06	2.03E-08	1.77E-11
202	0	0.1446179	0.0444753	0.0095564	0.0015058	0.000168	1.19E-05	4.16E-07	4.06E-09	1.77E-12
203	0.0531	0.1301561	0.0355803	0.0066895	0.0009035	8.42E-05	4.77E-06	1.25E-07	8.12E-10	1.77E-13
204	0.2196	0.1224505	0.0390842	0.0206126	0.0217821	0.026592	0.031862	0.03717	0.04248	0.04779
205	0.4116	0.1321654	0.0751874	0.0803088	0.1009093	0.123096	0.144505	0.164871	0.184176	0.202419
206	0.6147	0.1601089	0.1424699	0.1796962	0.2251856	0.267348	0.304762	0.337581	0.366115	0.390682
207	0.9452	0.205568	0.2369159	0.3101973	0.3809913	0.441024	0.490725	0.531564	0.564983	0.592298
208	0.9743	0.2795312	0.3785727	0.5006981	0.6066748	0.693112	0.76341	0.821109	0.869157	0.90991
209	1.1176	0.3490081	0.4977182	0.6427787	0.7537249	0.833706	0.889944	0.928343	0.953271	0.967861
210	1.0972	0.4258673	0.6216946	0.7852251	0.8992749	0.975653	1.026538	1.060823	1.084734	1.102626
211	0.8896	0.4930005	0.7167956	0.8788176	0.978445	1.036427	1.068935	1.086287	1.094707	1.097743
212	0.6602	0.5326605	0.7513565	0.8820523	0.942907	0.963013	0.961334	0.948606	0.930621	0.910414
213	0.3947	0.5454144	0.7331252	0.8154966	0.8298242	0.811607	0.780654	0.746722	0.714284	0.685221
214	0.1428	0.530343	0.6654402	0.6892576	0.6557745	0.603153	0.549081	0.500307	0.458617	0.423752
215	0.002	0.4915887	0.5609121	0.5253203	0.4505847	0.372977	0.305313	0.250052	0.205963	0.170895
216	0	0.4426298	0.4491297	0.3683242	0.2711508	0.187488	0.123325	0.076416	0.042793	0.01889
217	0	0.3983668	0.3593038	0.257827	0.1626905	0.093744	0.04933	0.022925	0.008559	0.001889
218	0	0.3585302	0.287443	0.1804789	0.0976143	0.046872	0.019732	0.006877	0.001712	0.000189
219	0	0.3226771	0.2299544	0.1263352	0.0585686	0.023436	0.007893	0.002063	0.000342	1.89E-05
220	0	0.2904094	0.1839635	0.0884346	0.0351411	0.011718	0.003157	0.000619	6.85E-05	1.89E-06

SES / MAE Plot / FEFreqDist / Sheet1

Fig. 5. Partial spreadsheet of the testing data and results of the SES Model 1 for solar irradiance forecast.

4	Syn. Load	alpha=0.1	alpha=0.2	alpha=0.3	alpha=0.4	alpha=0.5	alpha=0.6	alpha=0.7	alpha=0.8	alpha=0.9
197	15.026	26.086679	28.262579	27.966299	26.48395	24.53499	22.5079	20.59952	18.88991	17.38918
198	14.134	24.980611	25.615263	24.084209	21.90077	19.7805	18.01876	16.69805	15.79878	15.26232
199	14.931	23.89595	23.319011	21.099146	18.794062	16.95725	15.6879	14.90322	14.46696	14.24683
200	16.656	22.999455	21.641409	19.248702	17.248837	15.94412	15.23376	14.92266	14.83819	14.86258
201	19.657	22.365109	20.644327	18.470892	17.011702	16.30006	16.0871	16.136	16.29244	16.47666
202	17.585	22.094298	20.446862	18.826724	18.069821	17.97853	18.22904	18.6007	18.98409	19.33897
203	19.998	21.643369	19.874489	18.454207	17.875893	17.78177	17.84262	17.88971	17.86482	17.7604
204	18.722	21.478832	19.899191	18.917345	18.724736	18.88988	19.13585	19.36551	19.57136	19.77424
205	17.321	21.203149	19.663753	18.858741	18.723641	18.80594	18.88754	18.91505	18.89187	18.82722
206	19.845	20.814934	19.195202	18.397419	18.162585	18.06347	17.94762	17.79922	17.63517	17.47162
207	21.528	20.71794	19.325162	18.831693	18.835551	18.95424	19.08605	19.23126	19.40303	19.60766
208	24.974	20.798946	19.76573	19.640585	19.912531	20.24112	20.55122	20.83898	21.10301	21.33597
209	25.08	21.216452	20.807384	21.24061	21.937118	22.60756	23.20489	23.73349	24.1998	24.6102
210	18.397	21.602807	21.661907	22.392427	23.194271	23.84378	24.32995	24.67605	24.90396	25.03302
211	17.156	21.282226	21.008926	21.193799	21.275363	21.12039	20.77018	20.28071	19.69839	19.0606
212	22.978	20.869603	20.23834	19.982459	19.627618	19.13819	18.60167	18.09341	17.66448	17.34646
213	27.417	21.080443	20.786272	20.881121	20.967771	21.0581	21.22747	21.51262	21.9153	22.41485
214	28.333	21.714099	22.112418	22.841885	23.547462	24.23755	24.94119	25.64569	26.31666	26.91678
215	38.376	22.375989	23.356534	24.489219	25.461677	26.28527	26.97628	27.52681	27.92973	28.19138
216	45.096	23.97599	26.360427	28.655254	30.627406	32.33064	33.81611	35.12124	36.28675	37.35754
217	48.919	26.087991	30.107542	33.587478	36.414844	38.71332	40.58404	42.10357	43.33415	44.32215
218	28.561	28.371092	33.869834	38.186934	41.416506	43.81616	45.58502	46.87437	47.80203	48.45932
219	28.505	28.390083	32.808067	35.299154	36.274304	36.18858	35.37061	34.05501	32.40921	30.55083
220	21.49	28.401574	31.947453	33.260908	33.166582	32.34679	31.25124	30.17	29.28584	28.70958

SES / MAE Plot / FEFreqDist / Sheet1

Fig. 6. Partial spreadsheet of the testing data and results of the SES Model 1 for load demand forecast

As observed from Fig. 5 and Fig. 6, since the load demand is continuous all the time, there is no limitation of employing this forecasting technique for this instance. However, this technique results continuous data during the absence of solar resource particularly between evening and dawn. This appears to be undesirable as it leads to high overall forecast errors.

B. Model 2: SES based on the previous day forecast and actual values

In order to overcome the limitation of the first approach especially when applied to forecast the solar irradiance, the second approach uses the previous day data for prediction. The smoothing constant performs the same function as in the first approach where higher α results higher impact of the actual data of the same period in the previous day and lower effect of the forecast value of the same period in the previous day or vice versa.

$$X_f(d,h+1) = \alpha X_m(d-1,h+1) + (1-\alpha)X_f(d-1,h+1) \quad (2)$$

where

$X_f(d,h+1)$ is the forecast value.

$X_m(d-1,h+1)$ is the actual or measured value of the previous day of the same hour as the forecast period.

$X_f(d-1,h+1)$ is the forecast value in the previous day of the same hour as the forecast period.

Fig. 7 and Fig. 8 show the partial testing data and forecasting results using the second approach of SES. It is worth noting the prediction of the solar irradiance forecast using this approach provides preferable results where the problem of the first approach is eliminated. As shown in the spreadsheet, the model is able to predict properly regardless of the intermittence of the solar irradiance. While this is an appropriate model for the solar irradiance forecast, it is valid for the load demand forecasting as well. Since the daily energy demand for a remote area community usually has the similar daily pattern, it is very likely to increase the accuracy of the prediction for each forecast period compared to the previous method.

4	Syn. Solar	alpha=0.1	alpha=0.2	alpha=0.3	alpha=0.4	alpha=0.5	alpha=0.6	alpha=0.7	alpha=0.8	alpha=0.9
197	0	0	0	0	0	0	0	0	0	0
198	0	0	0	0	0	0	0	0	0	0
199	0	0	0	0	0	0	0	0	0	0
200	0	0	0	0	0	0	0	0	0	0
201	0	0	0	0	0	0	0	0	0	0
202	0	0	0	0	0	0	0	0	0	0
203	0.0531	0.0403912	0.0493832	0.0546814	0.0578977	0.059956	0.061337	0.062264	0.06284	0.063147
204	0.2196	0.1624756	0.2038453	0.2317207	0.252217	0.268634	0.282598	0.294905	0.306085	0.316727
205	0.4116	0.2830903	0.3634931	0.4127219	0.4443723	0.466072	0.48189	0.49409	0.504312	0.514262
206	0.6147	0.4217134	0.5179325	0.5724232	0.6028878	0.618848	0.62511	0.624244	0.618238	0.60945
207	0.9452	0.409094	0.6073143	0.7161992	0.7770797	0.811448	0.829316	0.83506	0.831158	0.820219
208	0.9743	0.3983058	0.5968843	0.7036149	0.7642308	0.801356	0.824666	0.83788	0.843117	0.843107
209	1.1176	0.5437172	0.7220085	0.8238634	0.8867035	0.928785	0.957709	0.976271	0.986083	0.989401
210	1.0972	0.505244	0.6825768	0.7867126	0.8534271	0.900158	0.934027	0.957469	0.971838	0.979389
211	0.8896	0.3925962	0.5725428	0.6780358	0.7445419	0.789498	0.820352	0.840067	0.850509	0.854134
212	0.6602	0.2904523	0.4322811	0.5138737	0.5623088	0.591667	0.608631	0.616353	0.616878	0.612392
213	0.3947	0.200376	0.2739589	0.319887	0.3483101	0.365041	0.373343	0.37522	0.372262	0.366109
214	0.1428	0.0728031	0.0960765	0.1107548	0.1204344	0.126946	0.131143	0.133441	0.134159	0.133681
215	0.002	0.0010361	0.0013288	0.0015292	0.001672	0.00178	0.001866	0.001939	0.002001	0.002055
216	0	0	0	0	0	0	0	0	0	0
217	0	0	0	0	0	0	0	0	0	0
218	0	0	0	0	0	0	0	0	0	0
219	0	0	0	0	0	0	0	0	0	0
220	0	0	0	0	0	0	0	0	0	0

SES / MAE Plot / FEFreqDist / Sheet1 / Sheet2

Fig. 7. Partial spreadsheet of the testing data and results of the SES Model 2 for solar irradiance forecast

4	Syn. Load	alpha=0.1	alpha=0.2	alpha=0.3	alpha=0.4	alpha=0.5	alpha=0.6	alpha=0.7	alpha=0.8	alpha=0.9
197	15.026	13.426088	13.502239	13.47342	13.41928	13.37759	13.36258	13.37803	13.42579	13.51062
198	14.134	12.547149	12.870517	13.052095	13.167902	13.26662	13.37619	13.50958	13.66973	13.85397
199	14.931	14.199406	13.847095	13.740555	13.713593	13.6913	13.64787	13.57922	13.4877	13.37563
200	16.656	16.924607	15.67262	14.915062	14.473528	14.23555	14.13256	14.12335	14.18208	14.28973
201	19.657	19.222371	18.151677	17.733744	17.627837	17.6504	17.71617	17.79723	17.89642	18.03172
202	17.585	21.360919	20.058515	19.228349	18.644273	18.19007	17.81402	17.49829	17.23999	17.0408
203	19.998	18.134204	17.780988	17.620015	17.571561	17.60204	17.70187	17.87189	18.11643	18.44135
204	18.722	16.084133	15.399374	15.10709	15.036965	15.08563	15.19484	15.33545	15.49604	15.67558
205	17.321	15.626118	15.212404	15.042326	15.023473	15.09988	15.23788	15.41643	15.62097	15.83981
206	19.845	18.334778	17.475375	17.097163	16.998117	17.05806	17.20868	17.41249	17.64888	17.90548
207	21.528	22.316176	22.689389	23.025988	23.325487	23.60278	23.87194	24.13862	24.3991	24.64405
208	24.974	26.423133	25.335947	24.953888	25.017895	25.36923	25.90879	26.5713	27.31111	28.0959
209	25.08	20.583498	18.873562	17.947963	17.523406	17.41817	17.51926	17.75854	18.09633	18.51101
210	18.397	18.777405	18.400804	18.205322	18.145207	18.19447	18.34007	18.5765	18.90171	19.31398
211	17.156	16.881353	16.540223	16.395931	16.404499	16.52741	16.7325	16.99431	17.294	17.6192
212	22.978	17.849299	18.696451	19.007218	19.05167	18.99878	18.94898	18.9586	19.05713	19.25833
213	27.417	23.752094	23.419374	23.497065	23.793281	24.17835	24.56949	24.91896	25.20499	25.42451
214	28.333	27.573783	27.790974	27.749691	27.677085	27.67891	27.78878	28.00436	28.31204	28.70125
215	38.376	30.96504	29.834232	29.301213	29.166852	29.31907	29.69048	30.23299	30.90563	31.67162
216	45.096	36.994075	36.370929	36.417462	36.801961	37.3496	37.98039	38.66553	39.39931	40.18343
217	48.919	42.370832	40.876324	40.392926	40.506595	40.96277	41.61071	42.36411	43.17469	44.01567
218	28.561	34.643203	32.085063	30.831433	30.38844	30.46851	30.90863	31.61623	32.53701	33.63912
219	28.505	25.765193	26.155375	26.365862	26.515222	26.68002	26.90237	27.19969	27.57526	28.02784
220	21.49	19.958023	19.220492	18.513002	17.887296	17.3645	16.94594	16.62168	16.37692	16.19641

SES / MAE Plot / FEFreqDist / Sheet1

Fig. 8. Partial spreadsheet of the testing data and results of the SES Model 2 for load demand forecast

IV. Data Analysis and Evaluation

Basically, the selection of a forecasting model depends on the characteristics of the time series and also the applications. Forecast model with different values of smoothing constant, α, results in different degree of accuracy. The choice of α might not be critical in certain applications, where α can be selected randomly in between the commonly acceptable range from 0.1 to 0.5 [3]. However, when accuracy is an important aspect to be considered, the optimum α should be chosen based on certain statistic relative measure of forecast accuracy such as the forecast error in (3) and the mean absolute error (MAE) in (4) and (5) [3]. The MAE calculated based on the simulation results for one year is used to facilitate the model comparisons which consequently determine the best choice of α for the forecast model.

$$FE_X(h_s) = X_m(h_s) - X_f(h_s) \quad (3)$$

$$MAE_X = \frac{1}{n_s-(h_s-1)}\sum_{h}^{n}|FE(h)| = \frac{1}{n_s-(h_s-1)}\sum_{h_s}^{n_s}|X_m(h) - X_f(h)| \quad (4)$$

where

X_m is the measured or the actual variable.

X_f is the forecast variable.

MAE is the mean absolute error.

n_s is the total number of errors.

h_s is the first hour for MAE calculation.

The performances of the SES Model 1 and SES Model 2 are summarised in Table I and II. Apparently, predictions for both of the solar irradiance and the load demand using the SES Model 1 are less accurate as compared to the SES Model 2. Minimal errors are observed for the forecast model SES Model 1 using the highest α, which indicates the forecast is highly relative to the actual data in the previous period and the relativity on the previous forecast value is low. This is due to the variation that is likely to occur hourly between the previous and the current data. On the other hand, SES Model 2 gives overall lower prediction errors than the former method. Although this approach relies on the past day data, it appears to be an advantage for the prediction especially for the time series that has similar daily pattern, where today prediction is based on the data of the same period in previous day.

TABLE I: MEAN ABSOLUTE ERROR FOR THE SOLAR IRRADIANCE FORECAST MODEL WITH VARIOUS SMOOTHING CONSTANTS

α	Methods	
	SES (Model 1)	*SES (Model 2)*
0.1	0.3077	0.1401
0.2	0.2900	0.1407
0.3	0.2651	0.1417
0.4	0.2397	0.1429
0.5	0.2173	0.1446
0.6	0.1983	0.1468
0.7	0.1823	0.1501
0.8	0.1690	0.1543
0.9	0.1582	0.1594

TABLE II: MEAN ABSOLUTE ERROR FOR THE LOAD DEMAND FORECAST MODEL WITH VARIOUS SMOOTHING CONSTANTS

α	Methods	
	SES (Model 1)	*SES (Model 2)*
0.1	6.1992	1.9783
0.2	5.8379	2.0297
0.3	5.4382	2.0911
0.4	5.1054	2.1582
0.5	4.8172	2.2322
0.6	4.5536	2.3143
0.7	4.3205	2.4047
0.8	4.1273	2.5065
0.9	3.9739	2.6199

Fig. 9 and Fig. 11 graphically illustrate the prediction for both parameters using the SES Model 1 with α equals to 0.9 for a selected day. Most of the time, deviations are found between the predicted and the testing data. The entire prediction curve shows a lagging pattern to the synthesized data. In consequence, these accumulating inaccuracies have caused the high forecast errors. In contrast, only minor discrepancies are observed for the predictions of the solar irradiance and the load demand using the SES Model 2 as depicted in Fig. 10 and Fig. 12. As the principle of this method is to manipulate the previous day data of the same period as the forecast, the curves of the predicted data are not far apart from the synthesised data's curves.

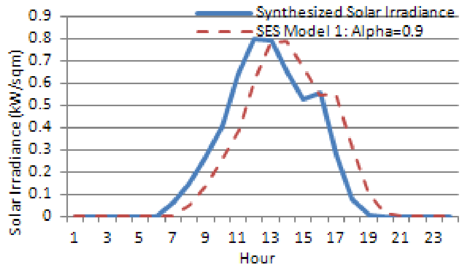

Fig. 9. Prediction accuracy of solar irradiance for a selected day using SES Model 1

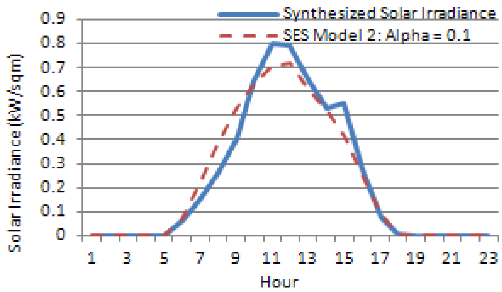

Fig. 10. Prediction accuracy of solar irradiance for a selected day using SES Model 2

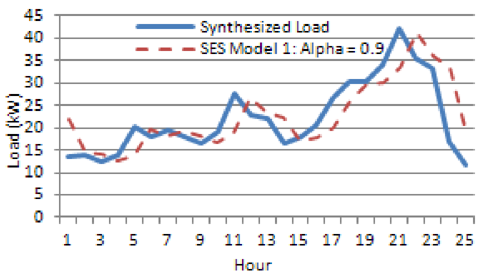

Fig. 11. Prediction accuracy of load demand for a selected day using SES Model 1

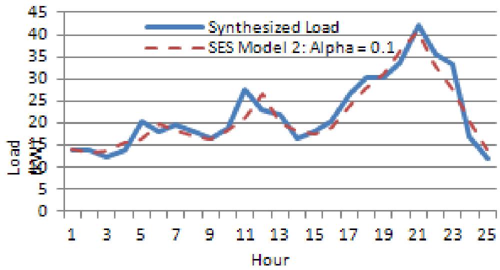

Fig. 12. Prediction accuracy of load demand for a selected day using SES Model 2

V. CONCLUSIONS

The synthesized load demand and the synthesized daily solar irradiance time series that consists of numerical and null values are used to justify the function of two different SES approaches. Based on the analysis, the SES Model 2 has demonstrated better capability and prediction performance for the given sets of testing data. It has also been verified that, the SES Model 2 outperforms the SES Model 1 for prediction of time series with intermittence. Although the prediction based on the SES Model 2 is not completely accurate, it produces marginally low errors. Thus, the SES Model 2 can potentially be a benchmark for other advanced forecasting methods developed based on the foundation of SES.

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