1. Aftab Ahmad SHAH[1], 2. Zafar A. KHAN[2], 3. Abdullah ALTAMIMI[3]

Department of Electrical Engineering, University of Birmingham, Birmingham, UK (1)
Department of Electrical Engineering, Mirpur University of science and Technology, Mirpur AJK Pakistan (2)
Department of Electrical Engineering, College of Engineering, Majmaah University, Al-Majmaah, 11952, Saudi Arabia (3)
ORCID: 2. 0000-0002-0236-7872, 3. 0000-0003-3149-6865

doi:10.15199/48.2021.12.06

SARIMA and Holt-Winters Method based Microgrids for Load and Generation Forecasting

***Abstract**. The modern power grid faces challenges regarding many complex factors affecting both demand and generation; including growth in demand; incorporating large-scale renewable power penetration; uncertainties in climate change; lack of historical data; and coordination of the large volume of data. These issues have resulted in complications in forecasting load and generation in microgrids. The loads are becoming more erratic and the generation is intermittent. Thus, this paper presents a study of different forecasting approaches for load and generation, by comparing multiple univariate and multivariate methods to analyse their effect. The study also proposes seasonal models: the SARIMA model taking into consideration the historical load, the correlation of weather data and renewable integration to estimate future behaviour of the microgrid by predicting one day ahead using critical load data; whereas the Holt Winters method is used for generation forecasting. A case study is simulated using real-world microgrid data for the selected geographic location in Australia. The results suggest that for the day-ahead load forecast, the SARIMA model performed relatively better compared to MLR, Holt-Winters additive and multiplicative methods; whereas, for generation forecasting, Holt-Winters Additive Method and SARIMA perform well for Autumn and Summer respectively. The results suggest that the proposed approach of using different seasonal models for load and generation forecasting yields higher accuracy as compared to conventional forecasting.*

Streszczenie.** Nowoczesna sieć energetyczna stoi przed wyzwaniami dotyczącymi wielu złożonych czynników wpływających zarówno na popyt, jak i na wytwarzanie; w tym wzrost popytu; włączenie penetracji energii odnawialnej na dużą skalę; niepewność w zmianach klimatu; brak danych historycznych; i koordynacja dużej ilości danych. Problemy te spowodowały komplikacje w prognozowaniu obciążenia i generacji w mikrosieciach. Obciążenia stają się coraz bardziej nieregularne, a generacja jest przerywana. Dlatego w niniejszym artykule przedstawiono badanie różnych podejść do prognozowania obciążenia i generacji, porównując wiele metod jednowymiarowych i wielowymiarowych w celu przeanalizowania ich wpływu. W badaniu zaproponowano również modele sezonowe: model SARIMA uwzględniający obciążenie historyczne, korelację danych pogodowych i integrację odnawialną w celu oszacowania przyszłego zachowania mikrosieci poprzez prognozowanie z jednodniowym wyprzedzeniem przy użyciu danych o obciążeniu krytycznym; natomiast do prognozowania generacji wykorzystywana jest metoda Holta Wintersa. Studium przypadku jest symulowane przy użyciu rzeczywistych danych mikrosieci dla wybranej lokalizacji geograficznej w Australii. Wyniki sugerują, że w przypadku prognozy obciążenia dnia następnego model SARIMA sprawował się relatywnie lepiej w porównaniu z metodami addytywnymi i multiplikatywnymi MLR, Holta-Wintersa; podczas gdy w przypadku prognozowania generacji, metoda Holt-Winters Additive Method i SARIMA dobrze sprawdzają się odpowiednio w okresie jesiennym i letnim. Wyniki sugerują, że zaproponowane podejście polegające na wykorzystaniu różnych modeli sezonowych do prognozowania obciążeń i generacji zapewnia wyższą dokładność w porównaniu z prognozowaniem konwencjonalnym.* (Metoda SARIMA i Holt-Winters do prognozowania obciążenia i generacji w mikrosieciach***)

Keywords: Renewable Energy, SARIMA, Load Forecasting, Microgrid, Holt
Słowa kluczowe: mikrosieci, prognozowanie, SARIMA

Introduction

With technological advancements, the penetration level of renewable energy sources (RES) is increasing rapidly. Concepts of distributed generation at consumer level are becoming commonly used in nearly all countries. Increasing penetration of RES is gradually converting their power systems from being load-led to generation-led. These new factors are gradually making the transition from a centralized electric grid towards a de-centralized grid, as in microgrids. Microgrids can be defined as low-voltage power distribution networks containing different distributed energy generators, energy storage and controllable loads, which can be interconnected with the central grid, or can work in island mode when disconnected from the grid [1]. The microgrid has been a familiar term in off-grid remote electrified systems, particularly in off-grid PV or small hydro power projects; a typical application being off-grid telecommunication projects. In the context of grid connected microgrids, the traditional and uni-directional producer-consumer definition has evolved: where the consumer is also a producer, called a prosumer i.e. producer and consumer [2]. Now with the increase in urbanization and the availability of large-scale distribution, the RES will enable users to produce a huge amount of renewable energy locally for self-consumption and feeding the local community and/or the main grid, in scenarios where surplus energy is generated.

Apart from providing clean energy locally, as compared to the grid energy, it will also result in fewer line losses and the option of keeping the loads energized by isolating itself from the grid in case of disturbances; thus, the introduction of the microgrid will lead to a more sustainable energy system [3]. Accurate forecasting of electricity demand is vital for the resilient management of energy systems. For the stability of the grid operation and microgrid operational planning, short-term load forecasting is an essential part of a microgrid energy management system and grid operations. For daily energy management and planning, for both scenarios of improving energy dispatch and overall power system stability, short-term forecasting is of utmost importance.

Load forecasting for microgrids differs from the large power-grid forecasting particularly because of the small number of consumers, resulting in lower load magnitude. This ultimately means that the aggregated effect of the load is less smoothed, resulting in a higher variability of load relative to its mean [4-8]. The lower the magnitude, the higher the variations and uncertainty in loading conditions, increasing the complexity of forecasting process. A small number of consumers and high variations can potentially lead to a significantly incorrect load forecast, and maintaining the accuracy of a forecast in such scenarios is a challenging task. At a higher aggregation level of load, the load curve is smoothed. The intricacy of the load profiles at different levels of load aggregation can be seen in Figure 1 [9], where daily load profiles ranging from a country to a single consumer are shown.

Different load forecasting techniques have been used in the literature to forecast load at an individual level. These are mainly classified into statistical techniques and artificialintelligence-based techniques. The AI-based techniques are complex, require a large amount of data and are black box models. Statistical models are widely used in the energy industry and are considered to be reliable. Many of these techniques include linear regression, multiple linear regression, autoregressive moving average, and seasonal autoregressive integrated moving average. The major advantages of these methods are their simplicity, fast training process, and high degree of interpretability. However, where these are used in grid connected studies, most of the previous work lacks incorporation of the variables which consider RES generation. Therefore, for a microgrid there is an important need for a comprehensive study that considers RES generation as part of the load forecasting.

This paper considers different statistical forecasting techniques to comprehensively forecast the load of a microgrid, and also considers RES generation forecasting separately. Apart from the conventional statistical approaches, the study considers a seasonal auto-regressive integrated moving average (SARIMA) model and the Holt-Winters seasonal method; taking into consideration the historical load, the correlation of weather data and renewable integration, to estimate the future behaviour of the microgrid by predicting one-day-ahead critical data. The study investigates univariate and multivariate methods for forecasting day-ahead electricity load and generation at half-hourly intervals. The univariate methods study past load and generation information, and multivariate methods include the use of both past load, generation information and weather data. Due to the variability of the data, the same houses' data for four seasons is taken separately for modelling and analysis. For the four-seasons, peak demand and generation prediction are also performed and their effectiveness is discussed.

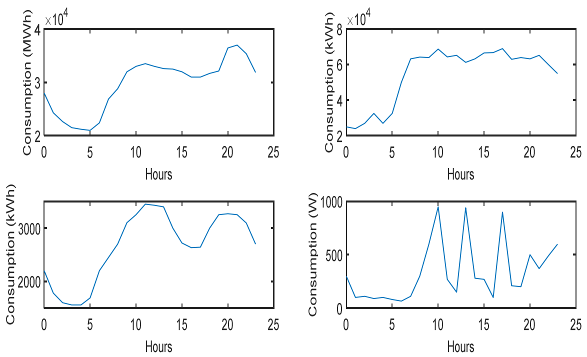

Fig. 1 (a) load profile of country (b) load profile at local substation (c) load profile industrial area (d) residential house load profile

Methodology and Case Study

This study incorporated 300 Australian households' energy data for over three years, with 30 minutes' data resolution [10]. The energy data of the houses, in metropolitan Sydney and surrounding areas, was collected via gross metering and consists of separate metering for PV generation, residential energy usage and controlled load (used for water heating). During the data pre-processing stage, the houses containing the controlled load were deleted to eliminate the impacts of controlled loads on the forecast. Considering the fact that in the case of microgrids, the factors such as temperature and solar irradiation require to be as accurate as possible, only the houses near Newcastle, New South Wales, Australia were selected for short-term forecast purposes. The data of the selected houses was checked for any unusual behaviour in generation or consumption. After necessary data cleansing, the clean generation and consumption data from June 2010 to June 2013 was selected for 26 houses containing only PV generation and residential load. For the analysis of the smart microgrid environment, these 26 households' consumption (peak of 115 kW) and generation data (with collective installed capacity of 61.72 kW) were separately aggregated with 52,560 data points.

For visualization of load with respect to temperature, with the half-hourly energy usage plotted against temperature, no significant change in load with respect to temperature was observed. This is due to the very smaller load size and the daily fluctuations of the load are more severe as compared to the change in load with respect to temperature. So, total daily energy consumption was summed for each day and is plotted against temperature in Figure 2. In the winter and summer, the total daily load has a clear relationship with temperature; while for the spring and autumn seasons it's quadratic.

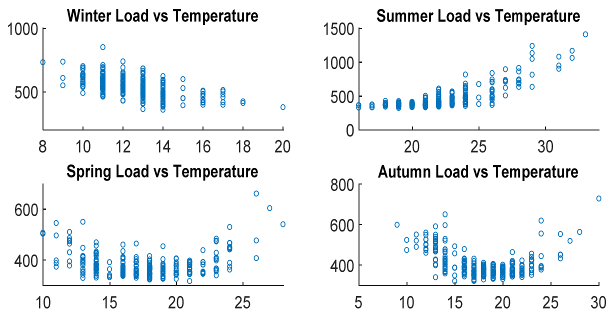

Fig. 2 Temperature (x axis degrees centigrade) vs Sum of Daily Energy Consumption (y axis watt-hour) for all seasons (2010 to 2013)

In Figure 3, the normalized half-hourly load is plotted against the time, showing higher variations in summer as compared to other seasons, which is due to usage of air conditioners in the summer season. Also, the high peak loads are observed in summer as compared to other seasons.

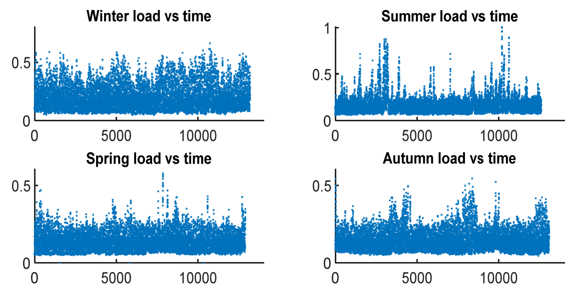

Fig. 3 Normalized load of all seasons vs time (one year- half-hourly energy usage recorded)

Table 1 shows the coefficient of variation (CV) for all the seasons' data over three years. It shows the extent of variability in relation to the mean load and is defined as the ratio of the standard deviation divided by mean. The coefficient of variation is more in winter and summer as compared to the other two seasons.

Figure 4 and Figure 5, present the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the half-hourly loads in the winter season. High autocorrelation of the load time series can be seen at 1- and 48-hours' lags, showing the daily seasonality of data. The ACF and PACF for other seasons also shows a similar trend.

Table 1. Ratio of the standard deviation and mean of the hourly loads for all four seasons

Season	Std/Mean (%)
Winter	55.2138
Summer	52.2523
Autumn	37.2378
Spring	47.1997

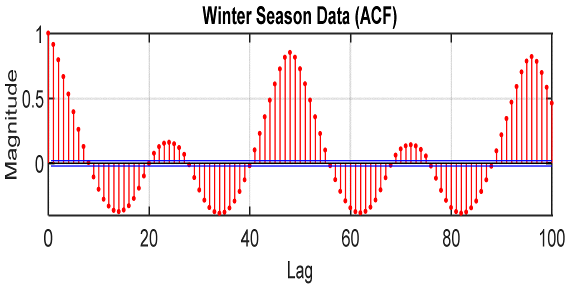

Fig. 4 Auto correlation plot of winter season data

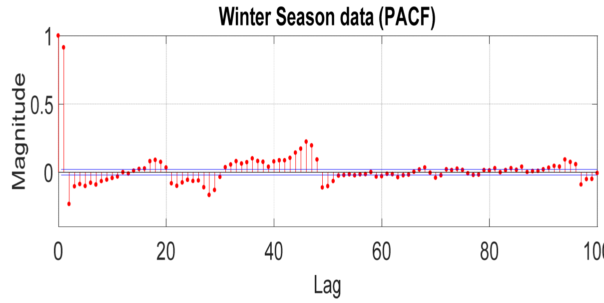

Fig. 5 Partial correlation plot of winter season data

Prediction Models

Three statistical load forecasting methods were used to forecast load data from microgrid consumers. The three methods were: seasonal autoregressive integrated moving average (SARIMA) [11]; multiple liner regression (MLR) [12]; and double exponential smoothing [13]. Except for the MLR, the same models are used for forecasting PV generation also.

The deviations in the model predicted for half-hourly loads for the day from the observations are quantified in terms of mean absolute percentage error (MAPE) of half-hourly loads. For the generation forecast error calculations, the mean absolute deviation (MAD) is used, because of MAPE's inability to address zero values.

Multiple Linear Regression

The purpose of multiple linear regression (MLR) is to model the relationship between different independent variables (e.g. temperature and time of the day) and a dependent variable (electrical load). Generally, the MLR equation can be written as:

(1) $$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + c$$

where Y is the dependent variable; X1 and X2 are the independent variables; and c is the categorical variable. The independent variables are chosen as many weather variables mostly for the large grid data, since for large data, the effect of weather is very profound; such works were done on the Irish electricity supply system [14]. In a similar work for national level data, a regression model was developed for energy consumption in Eastern Saudi Arabia; and the independent variables chosen were weather data, solar radiations population and GDP [15]. However, in the case of the small microgrid, the effect of such variables is very negligible or can't be captured easily because of the high variability of the data.

So, the independent variables of temperature and its square (for capturing the non-linear relation of the loads to temperatures) were selected and each hour of the day was taken as the categorical variable (by giving each hour of the day a binary value in the model calculation).

For the modelling of the load forecast, different models of MLR were tested with the past data, and the final model was selected based on the least value of variance or mean squared error (MSE). In the final model Pi, the load consumption at each half hour i, can be expressed as

(2) $$P_i = a + b_1 t_2 + b_2 t_2^2 + c_i$$

where *a* is the y intercept (constant computed); *b* is the coefficient; and *ci* is the categorical variable calculated for each half hour of the day.

For the consumption forecast, we got different values when the model was tested, forecasting for an hour ahead in different seasons of the year. However, in the case of the generation, the results were not satisfactory. The relation between temperature and the PV output was negligible, especially considering the combined capacity for the PV panels; so MLR forecast results for generation are not discussed in this study.

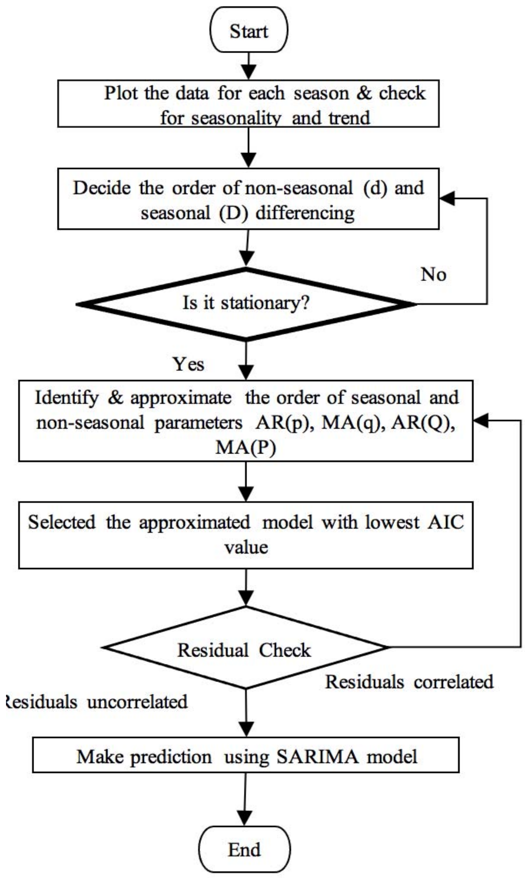

Fig. 6 SARIMA model flow chart

ARIMA and SARIMA Models

By applying regression methods to a set of past load data, models are generated defining how load changes over time. Forecasting for the future is carried out using these models. Two of the basic forms of time-series models are, the autoregressive model (AR) and the moving average (MA). The AR model is used in time-series data when it is linearly dependent on the historical values; while the MA is used when the time series is a function of the mean value from current and previous white noise error terms. The order of the AR(p) and MA(q) are generally represented by p and q, which also represents the degree of the model dependency on past values at corresponding time step lags, p and q [16].

The ARIMA forecasting model is applicable on time series if the time series is stationary (whose characteristics like its mean, variance, autocorrelation, etc. are all constant over time) and have a decreasing auto-covariance function [17]. A general ARMA(p,q) model can be represented as follows:

(3) $$\phi_p(B)X_t = \theta_q(B)\ \varepsilon_t$$

(4) $$\phi_p(B) = (1\text{-}B\phi_1 - B2\phi_2 - \ldots\ldots\ldots\ldots +Bp\,\phi_p$$

(5) $$\theta_p(B) = (1+B\theta_1+B\theta_1+\ldots\ldots\ldots\ldots +Bq\,\theta_q)$$

where $\phi(B)$ represents the autoregressive (AR) portion of the model; $\theta(B)$ represents the moving average (MA) of the model; and B is the backshift operator Bjxt = xt-j; Xt is the time series defined; and ε_t are the power usage and noise at time t respectively [17].

Also, when the series is not stationary, differencing is applied to make it stationary and decrease autocovariance; the method is the autoregressive integrated moving average (ARIMA) model. An ARIMA (p,d,q) model for the time series Xt is expressed as

(6) $$\phi_p(B)(1\text{-B})^{d}X_t=\theta_q(B)\ \varepsilon_t$$

Where d is the order of differencing for making the series stationary; an ARIMA model without differencing is the ARMA (p,q) model.

Thus, SARIMA stands for seasonal (AR) auto regressive integrated (MA) moving average. Seasonality in a time series is a regular pattern that repeats itself after an equal amount of time. Figure 6 shows the flow chart for the SARIMA model.

A SARIMA (p, d, q, P, D, Q) model can be represented using the following equation:

(7) $$\phi_P(B^s)\phi_p(\text{B})^{d}Y_t=\theta_Q(B^s)\theta_q(B)\ \varepsilon_t$$

Where,

(8) Yt = $(1\text{-}B)^{d}(1\text{-}B^{s})^{D}X_t$

Where D is the seasonal order of differencing; P is the seasonal autoregressive factor; and Q is the seasonal moving average factor. The model of goodness of fit is evaluated using the Akaike information criteria (AIC). The AIC is used to compare models with a varying number of explanatory variables.

With the ACF plot of the three years of data in Figure 4, we can see strong seasonality after 48 intervals, but no apparent trend. Since a seasonality after the 48th interval is clear, we will take the 48th difference of the time series and check if the differenced series has any trend or seasonality apparent in the ACF. From the ACF and PACF plots of seasonally differenced series below, we can see the series is stationary.

From the ACF and PACF of the seasonally differenced time series, the exact SARIMA model is not clear, as seen from Figure 7, so 66 potential SARIMA models are checked with multiple sets of past data, to find the one with the least AIC value. The final parameters p, d, q, P, D and Q are chosen comparing different model AIC values [18], and that is calculated by:

(9) $$AIC = -ln(L)+2m$$

Where, L is the maximined likelihood function of the model; and m is the number of parameters given by (p+q+1).

Using most of the past data, the AIC values were calculated for all the 66 possible combinations of SARIMA models; and the AIC value of the 66 models was compared to find the one with the lowest AIC value. Based on the methodology, SARIMA (1,0,2) (3,1,2) 48 was selected.

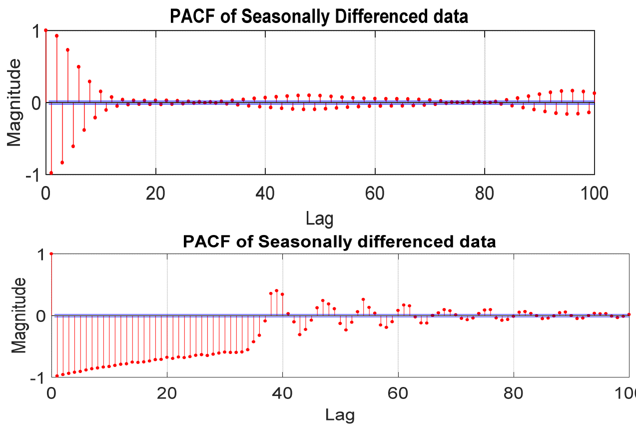

Fig. 6 ACF and PACF of seasonally differenced time series

On checking for the residuals of the model with the lowest AIC value, by plotting the ACF and PACF of the residuals, we can see in Figure 7 that the residual is white noise as there are no significant spikes or there is no correlation. Figure 8 shows the residuals with autocorrelation. With that value of the SARIMA model, the forecasting for a day ahead is carried out. The calculated value of the MAPE turned out to be 11.028% and a comparison of observed and forecasted load is given in Figure 9.

The same methodology is adopted for the remaining three seasons. For the PV generation forecast, day time from 7 am to 7 pm is considered. Since there were 24 half-hourly observations during the day time, the seasonality of a value of 24 is used.

Holt-Winters Seasonal Method

The Holt-Winters method uses exponential smoothing. It assigns more weight to recent data values and assigns less weight to the older data. The Holt-Winters method uses an improved method of exponential smoothing where three different smoothing formulae are applied to the series. The method considers the level, trend and seasonality of the time series using three equations, one for each and a final one for the forecast equation. For the level, trend and seasonal component, it has smoothing parameters for each.

Depending on the nature of the seasonal component, there are two elements First is the additive model, where the seasonal variations are roughly constant; and the second is the multiplicative method, where the seasonal variations are changing proportional to the level of the series [19].

In our case, due to changing behaviour of the data, both additive and multiplicative models are considered.

The additive model from [20] is given as:

$$a_t = \alpha(Y_t - s_{t-p}) + (1-\alpha)(a_{t-1} + b_{t-1}) \quad (10)$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \quad (11)$$

$$s_t = \gamma(Y_t - a_t) + (1-\gamma)s_{t-p} \quad (12)$$

where:

$$\hat{y}_{T+\tau} = a_T + \tau\, b_T + s_T \quad (13)$$

α, β and γ are the smoothing parameters; *at* is the smoothed level at time *t; bt* is the change in the trend at time *t, st* is the seasonal smooth at time *t, p i*s the number period of seasonality, in this case of consumption forecast is 48 and for the generation forecast it is 25 for 24 hours.

Firstly, the initial values are defined,

$$a_p = \frac{1}{p}(Y_1 + Y_2 + \ldots + Y_p) \quad (14)$$

$$b_p = \frac{1}{p}\left[\frac{Y_{p+1} - Y_1}{p} + \frac{Y_{p+2} - Y_2}{p} + \ldots + \frac{Y_{p+p} - Y_p}{p}\right] \quad (15)$$

$$s_1 = Y_1 - a_p,\quad s_2 = Y_2 - a_p,\quad \ldots,\quad s_p = Y_p - a_p \quad (16)$$

For all the four seasons' data, the smoothing values are first estimated by forecasting for an earlier equations, from all the possible combinations of the smoothing

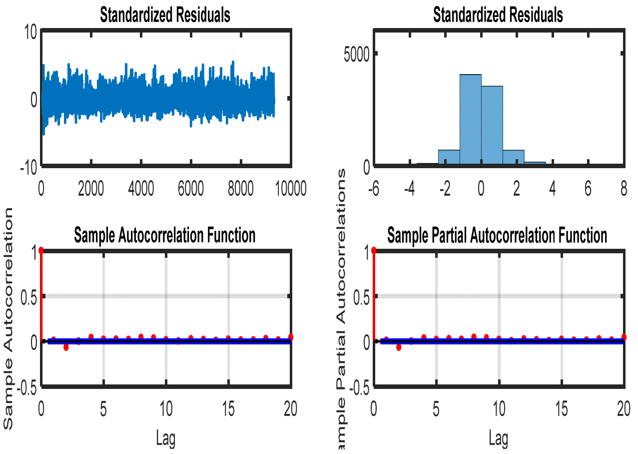

Fig. 7 Residuals of the SARIMA model, show the error has not correlation and same as white noise

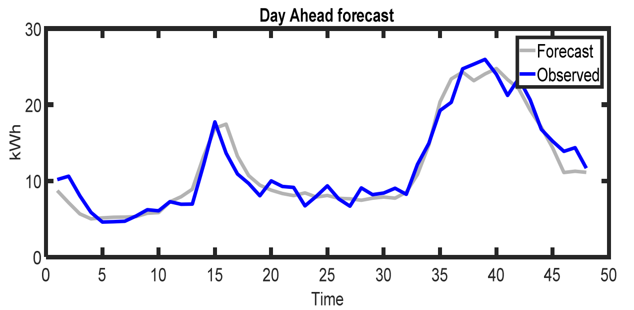

Fig. 8 Day-ahead forecast plotted against the observed data, using the SARIMA model

Parameters. The final values are selected by comparing the MSE of the earlier day forecast versus observation values for all possible combinations of the smoothing parameters [20].

For the Holt-Winters multiplicative model as in [20]:

$$a_t = \alpha\frac{Y_t}{s_{t-p}} + (1-\alpha)(a_{t-1} + b_{t-1}) \quad (17)$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \quad (18)$$

The initializing values are the same as in the additive method, while:

$$s_1 = \frac{Y_1}{a_p},\quad s_2 = \frac{Y_2}{a_p},\quad \ldots,\quad s_p = \frac{Y_p}{a_p} \quad (20)$$

With the same procedure used for calculating the smoothing parameters, the final prediction for period $T+\tau$:

$$\hat{y}_{T+\tau} = (a_T + \tau\, b_T)s_T \quad (21)$$

Results

This section delineates on the results of forecasting using the four models. For all the four seasons, data for the 26 households' prediction errors are compared using MAPE for half-hourly load predictions; then MAPE for daily peak load predictions (peak load hours of the residential houses were taken from 5 pm to 11 pm); and finally, then MAD for half-hourly energy generation. For comparison of generation and load forecast errors, the load forecast errors are also calculated in terms of MAD.

An overall comparison of load forecast shows that the SARIMA model performed relatively better than the rest of the models. The highest forecast accuracy was achieved in summer; whereas autumn proved to be the worst forecast season, as can be seen from Figure 10 and the peak of errors follows the same trend, as shown in Figure 11. However, for the generation forecast, the Holt-Winters additive method performed significantly better than the others. Contrary to the load forecast MAPE, the generation forecast was least accurate during the summer, and during the other seasons the accuracy level of the forecast using the Holt-Winters additive method remains almost the same. A comparison of Figures 12 and 13 shows that if we consider MAD, the highest forecast accuracy can be achieved during the summer; but for the load forecast, the SARIMA model gives the best predictions.

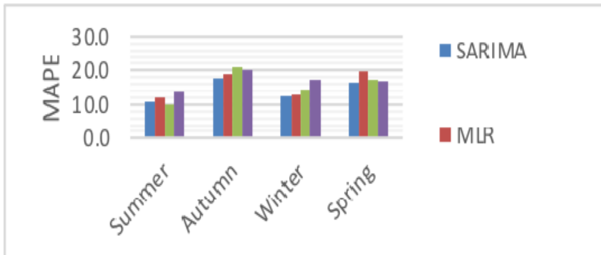

Fig. 9 Consumption forecast MAPE for all models

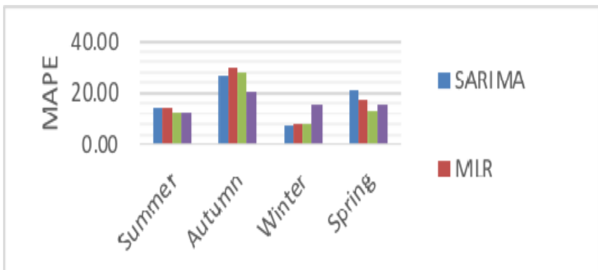

Figure 10 Comparison of MAPE errors of day-ahead peak load predictions across all model and seasons data

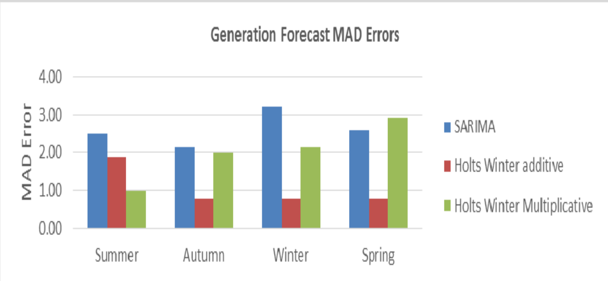

Fig. 11 Generation forecast error in mean absolute deviation (MAD)

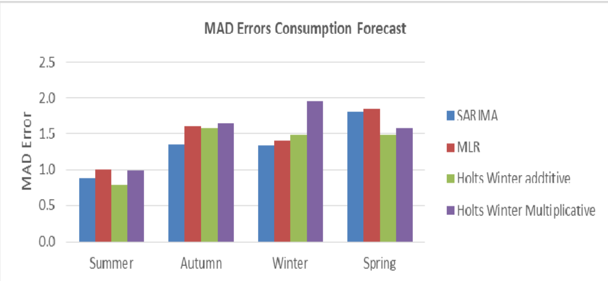

Fig. 12 MAD error for consumption forecast

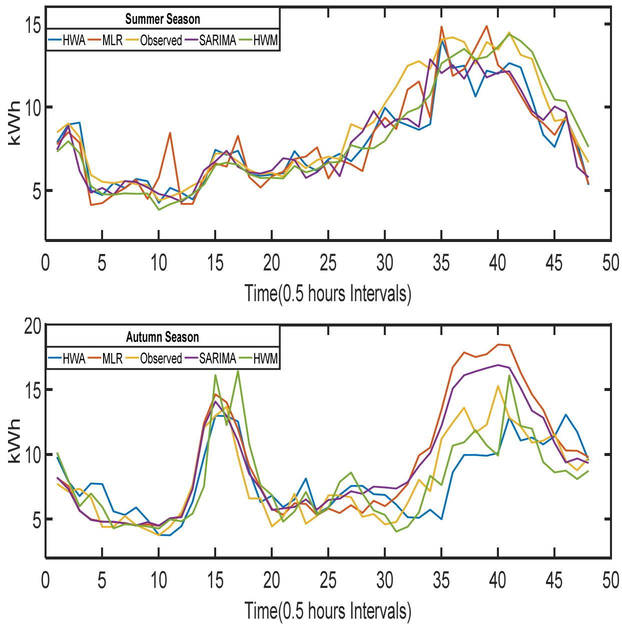

Fig. 13 the consumption forecast for summer and autumn seasons plotted

Figures 14 and 15 show a comparison of observed/real load during a typical working day of the autumn and summer seasons, with all models for load and generation forecasts respectively. It can be clearly seen that the generation forecast is better achieved using the Holt-Winters additive method during the autumn season. Whereas, the prediction made by SARIMA follows the observed value more closely as compared to the HWA.

The results suggest that a single approach to forecast both load and RES generation is not as efficient as a combination of different approaches. The future of microgrids greatly depends on accurate forecasts and more research, which should consider a variety of upcoming technologies, such as electric vehicles. They need to be addressed as separate variables in the future studies.

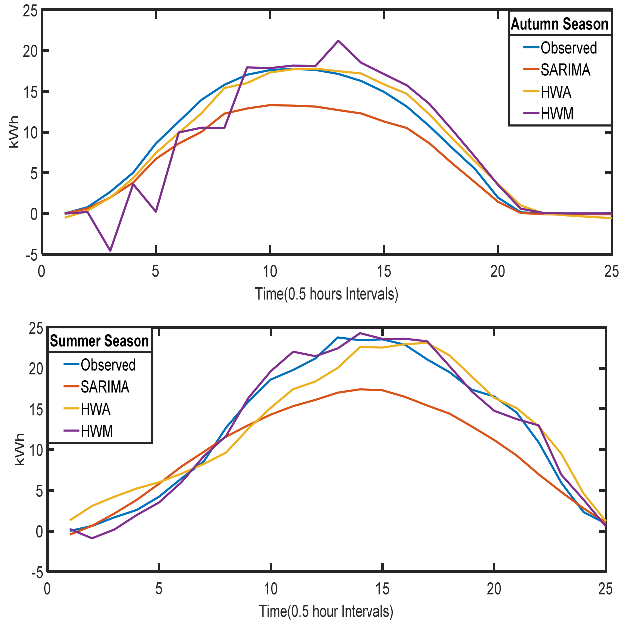

Fig. 14 Generation forecast for autumn and summer seasons

Conclusion

Forecast errors in microgrids are typically high as compared to centralised grids due to the uncertainties in the load behaviour and intermittency of the renewable generation. This paper investigated the accuracy of different statistical forecasting models for load and generation forecasts in a microgrid, and proposes a combination of different seasonal models to improve the forecast accuracy for the microgrid. Smart meter data from a real-world microgrid was used, having half-hourly data resolution, and a generation forecast of the PV generation was also performed.

It was determined that the accuracy of prediction is highly sensitive to the variable selection and availability of historic data. The forecast results suggest that for load forecasting, the SARIMA model performs the best. Whereas, for generation forecasting, the Holt-Winters additive method achieved the highest accuracy for autumn, and for summer, SARIMA performed better. Future works could include the consideration of electric vehicles as separate variables, which again can be used as load as well as virtual power plants.

Acknowledgments
The corresponding author would like to thank Majmaah University for their support.

Corresponding Author
Abdullah Altamimi
Assistant professor of electrical power system
Email: a.altmimi@mu.edu.sa
Department of Electrical Engineering, Majmaah University, Al-Majmaah, 11952, Saudi Arabia

REFERENCES

[1] D. T. Ton and M. A. Smith, "The U.S. Department of Energy's Microgrid Initiative," *The Electricity Journal,* vol. 25, pp. 84-94, 2012/10/01/ 2012.
[2] S. Grijalva and M. U. Tariq, "Prosumer-based smart grid architecture enables a flat, sustainable electricity industry," in *ISGT 2011*, 2011, pp. 1-6.
[3] R. H. Lasseter and P. Paigi, "Microgrid: a conceptual solution," in *2004 IEEE 35th Annual Power Electronics Specialists Conference (IEEE Cat. No.04CH37551)*, 2004, pp. 4285-4290 Vol.6.
[4] S. Subbayya, J. G. Jetcheva, and W. P. Chen, "Model selection criteria for short-term microgrid-scale electricity load forecasts,"

in *2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*, 2013, pp. 1-6.
[5] Aslam, S., Herodotou, H., Mohsin, S.M., Javaid, N., Ashraf, N. and Aslam, S., "A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids," in *Renewable and Sustainable Energy Reviews*, 144, p.110992, 2021.
[6] Zhou, B., Meng, Y., Huang, W., Wang, H., Deng, L., Huang, S. and Wei, J., "Multi-energy net load forecasting for integrated local energy systems with heterogeneous prosumers," in *International Journal of Electrical Power & Energy Systems*, 126, p.106542, 2021.
[7] Z. Khan, D. Jayaweera, and H. Gunduz, "Smart meter data taxonomy for demand side management in smart grids," in *Probabilistic Methods Applied to Power Systems (PMAPS), 2016 International Conference on*, 2016, pp. 1-8.
[8] Zeng, P., Jin, M. and Elahe, M.F., "Short-Term Power Load Forecasting Based on Cross Multi-Model and Second Decision Mechanism," in *IEEE Access*, 8, pp.184061-184072, 2020.
[9] L. Hernandez, C. Baladrón, M. J. Aguiar, B. Carro, J. A. Sanchez-Esguevillas, and J. Lloret, "Short-Term Load Forecasting for Microgrids Based on Artificial Neural Networks," *Energies,* vol. 6, 2013.
[10] (2017, August 2017). http://www.ausgrid.com.au/Common/About-us/Corporate-information/Data-to-share/Solar-home-electricity-data.aspx#.WZqeEiiGO00.
[11] G. E. P. B. G. M. J. a. G. C. Reinsel, *Time series analysis: Forecasting and control* EngleWood Cliffs New Jersey: Prentice Hall 1994.
[12] W. N. V. a. B. D. Ripley, *Modern Applied Statistics with SPLUS*. New York Springer-Verlag, 1999. .
[13] J. W. T. L. M. d. M. a. P. E. McShary, "A Comparison of univariate methods for forecasting electricity demand up to a day ahead," *International Journal of Forecasting,* vol. 22, pp. 1-16, 2006. .
[14] O. Hyde and P. F. Hodnett, "An adaptable automated procedure for short-term electricity load forecasting," *IEEE Transactions on Power Systems,* vol. 12, pp. 84-94, 1997.
[15] A. Z. Al-Garni, Y. N. Al-Nassar, S. M. Zubair, and A. Al-Shehri, "Model for Electric Energy Consumption in Eastern Saudi Arabia," *Energy Sources,* vol. 19, pp. 325-334, 1997/05/01 1997.
[16] G. E. P. B. G. M, *Time series analysis: forecasting and control revised ed[M]* Holden-Day, 1976.
[17] T. A. Reddy, *Applied Data Analysis and Modeling for Energy Engineers and Scientists*. London: Springer, 2010.
[18] G. M. J. George E. P. Box, Gregory C. Reinsel, Greta M. Ljung, *Time Series Analysis: Forecasting and Control*, 5 ed. EagleWood Cliffs, New Jersey: Prentice Hall, 2015.
[19] G. A. Rob J Hyndman *Forecasting: principles and practice*: OTexts, 2014.
[20] M. Yar and C. Chatfield, "Prediction intervals for the Holt-Winters forecasting procedure," *International Journal of Forecasting,* vol. 6, pp. 127-137, 1990/01/01/ 1990.