Towards Electricity Cost Alleviation by Integrating RERs in a Smart Community: A Case Study

Khursheed Aurangzeb[1], Sheraz Aslam[2], Herodotos Herodotou[2], Musaed Alhussein[1], Syed Irtaza Haider[1]
[1]Computer Engineering Department, College of Computer and Information Sciences,
King Saud University
[2]Department of Electrical Engineering and Computer Engineering and Informatics (EECEI),
Cyprus University of Technology,
Limassol, Cyprus
kaurangzeb@ksu.edu.sa

***Abstract*—The Renewable Energy Resources (RERs) are advantageous in decreasing the carbon emission and energy bill of the users by empowering them to produce their own green energy. However, energy users are not able to sufficiently take paybacks from the RERs without advanced technologies. With the advent of Smart Grids, the potential benefits of RERs and dynamic pricing schemes can be fully exploited. Nonetheless, the big issue is the precise prediction of produced energy by RERs. In current work, we propose an efficient framework which is based on the integration of RERs in a smart community. This framework will be helpful and can be applied for energy management at a community level. We applied the Artificial Neural Network (ANN) model for precise and accurate prediction of produced energy by RERs. Moreover, the considered smart community consists of eighty smart homes and it is also assumed that every consumer has installed RERs including solar panels and wind turbine. Our obtained results show that our proposed framework is suitable for decreasing the energy bill of the smart community. Numerical results indicate that the energy cost of the end customer is reduced by 35 % by installing RERs in smart homes.**

***Index Terms*—Renewable energy integration; Smart home; Energy management; Smart community; Smart grid; Home energy management.**

I. INTRODUCTION

The future Smart Grids (SG) will undoubtedly consist of numerous technologies offering a significant enhancement in the current power systems, which will consequently help in the reduction of the electricity costs and make environment cleaner. The two-way information flow along with interpretability between smart homes has come up with opportunity to optimize power consumption, and concurrently enhance operation of the power system [1]–[3].

The diminishing assets of fossil fuels, the hiking social campaign for green energy, the climate change and the environmental pollution are the main factors for integrating Renewable Energy Resources (RERs) in the power systems. The wind energy, solar energy and the energy from other renewable resources are reliant on the weather conditions which is highly variable both in short term and long term. The high variation in the generated energy through RERs will result in solid fluctuations.

Therefore, accurate and reliable forecasting model are essential for precisely predicting the generated energy through RERs. Such reliable and accurate models will also help in the smooth incorporation of large quantity of renewable energy into the power systems. The growing dissemination of RERs in the energy systems has resulted in the concept of microgrids.

The microgrids are expected to play a significant role in the progression of the SGs [4], [5]. It is expected that the SG will arise as a network of microgrids [6]. The microgrid is a combination of power loads, RERs and energy storage units [7], [8]. From the utility networks point of view, an essential feature of the microgrid is its controllability through the single point of common coupling (PCC). The operation of the microgrid can be switched in two modes i.e. grid-connected or islanded mode by controlling the state of the PCC switch.

In islanded mode, the microgrid is restricted and cannot share the excess generated energy with the external grid. As is clear from the name, in grid-connected mode, the microgrid is linked with external grid and can share the excess generated energy with it [9], [10].

Usually, the RERs including wind turbine and solar panels are among the inspiring resources for resolving the global energy crisis and reducing the impact of carbon emission problems in today's world. By integrating RERs, the end customers have the opportunity to manage their energy demand by generating their own green energy which will help them in reducing their electricity bill.

Due to countless benefits of the RERs, many advanced countries in the world have directives for electricity providing companies to increase the power generation from

Manuscript received 7 January, 2019; accepted 25 April, 2019.
The authors extend their appreciation to the Deanship of Scientific Research at King Saud University for funding this work through research group no (RG-1438-034).

978-1-7281-2209-0/19/$31.00 ©2019 IEEE

wind turbines and solar power plants. For effectively managing the rising energy demands all over the world, the researchers from the industry and academia are concentrating on the challenges of RERs.

The challenges of RERs include their integration into the power systems, their intermittent nature and the optimal power flow, etc. Various researchers have focused on the intermittent nature of electricity generated through RERs [11], [12]. For effective energy management and planning, one of the most critical problem is the intermittent nature of the RERs. The accurate prediction of the wind energy and solar energy is highly desirable for precisely forecasting the generated energy through these sources.

But the approximation of the generated energy through RERs is heavily dependent on the precision of the weather forecasting model. The precision of the weather forecasting model is dependent on various features such as temperature, pressure, humidity, wind speed and its time-lag. The extremely random variations of the wind speed inclined by: atmospheric circumstances; terrain; weather etc., result in complications for accurate predictions irrespective of whether it is long-term or short-term forecasting [12]. The wind speed and the temperature can be accurately forecasted by applying Deep Neural Network (DNN), Artificial Neural Network (ANN), Long Short-Term Memory Network (LSTM) etc. on long historical collected data [13]–[15].

In this work, we consider the integration of RERs in a residential smart community that consists of eighty smart homes. Each home is equipped with RERs in the form of wind turbine and solar panel. The aim of this work is to evaluate its impact on the electricity cost reduction of the consumer. The main contributions of this work are given below:

- This work efficiently integrates the RERs for greener energy generation in a smart community.
- We formulate the prediction of temperature and weather forecasting problem for approximating the generated energy through RERs.
- Through accurately forecasted wind speed and temperature, the electricity consumption of a smart community has been managed according to power generation.
- Through various simulations, we evaluated the impact of integrating RERs on the electricity cost reduction of the smart community.

The rest of the paper is structured as follows. The related work is presented in the next section. The details of the proposed system model are provided in Section III. The simulation results along with discussions are presented in Section IV. Finally, the contributions of our work are concluded in Section V.

II. RELATED WORK

In the last few years, many researchers have dedicated their efforts to solving the issues of global energy crises. In the current section of our manuscript, some of the relevant research studies are discussed.

The incorporation of RERs in traditional power systems for fulfilling the energy requirement has been explored by the authors in [16]. They proposed to handle the uncertainty of RERs by virtualization and validated their method by performing real time experiments.

In [17], the authors explored a hybrid model for estimating the generated solar energy. Their model is based on a combination of neural network and wavelet transform. The hybrid model was evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The authors validated their proposed model using simulations as well as a real time system of 5 kW. Moreover, they compared their results with other state of the art systems and their suggested model achieved better efficiency.

In our previous work [18], we proposed a Home Energy Management System (HEMS) for achieving targeted aims of reducing electricity cost, decreasing Peak to Average Ratio (PAR) without compromising on the user comfort. For effective energy management of the smart home, we proposed a hybrid algorithm in which we exploited the search space for achieving optimum results. We considered the influence of seasons on the considered performance parameters including PAR, electricity cost and user comfort.

In another work in [19], we designed and evaluated a demand side management (DSM) scheme for efficient energy utilization in a smart home. According to this scheme, the energy consumption patterns of the users is modified for reducing electricity bill, decreasing PAR but without compromising the user comfort. Adaptive cuckoo search (ACS) and elephant herding optimization (EHO) are applied for scheduling the home appliances. Additionally, we developed a new method which we named as hybrid elephant adaptive cuckoo (HEAC). The HEAC uses the features of both ACS and EHO. We achieved better results for HEAC as compared to ACS and EHO.

In our work in [20], we proposed a genetic harmony search algorithm (GHSA) based HEMS for reducing electricity cost and PAR but without compromising user comfort. We considered critical peak pricing (CPP) and real-time electricity pricing (RTEP) tariffs. Through our extensive simulation results, we proved that our proposed HEMS performed better than the existing algorithms in terms of the considered performance parameters including PAR, cost reduction and maximizing customer comfort.

Recently in [21], we proposed a support vector quantile regression based short-term load probability density prediction method. We performed a comparison between three kernel functions including Gaussian kernel, the linear kernel and polynomial kernel. We evaluated the predicted precision of the power load using data-sets from Singapore. The performance of the proposed method was compared with Support Vector Regression and Firefly Algorithm and we achieved better results. The energy management of single home and smart building has been explored in [22], **Error! Reference source not found.**.

The SG will offer substantial improvement by applying numerous latest technologies in the current power systems. It will help in achieving potential benefits of RERs and dynamic pricing schemes by employing the latest Information and Communication Technologies (ICT). But, energy management in SG is thought-provoking due to the fact that RERs generate energy in an indeterministic way. It is explained in [24] that excess-generation from RERs in off-peak hours results in the well-known “duck curve” problem.

The “duck curve” problem results in “under-loaded” generator unit. The under-loading of the generator unit influences the individual components of the power system as well as its overall performance because of imbalance between generation and demand.

The efficiency of the SG can be guaranteed by maintaining ample energy balancing between demand and generation side. The efficiency of the SG is usually compromised because of the intermittent nature of RERs. The growing dissemination of RERs and their variable power generation results in “Duck curve” problem [24].

The integration of Energy Storage System (ESS) in the power system is an effective tool for improving the elasticity of the demand side for the alleviation of disproportion in demand-generation. Recently, in [24], we considered the radial structure of the distribution grid along with usually used configuration topology of building integration with ESS and RERs. We considered a multilevel Multi Agent System (MAS) optimization framework based on Particle Swarm Optimization (PSO).

In [24], our aim has been on optimal co-scheduling of electricity demand and supply resources and we considered ToU pricing tariff. The MAS structure allows Plug and Play (PnP) functionality and it controls the RERs adaptively for accomplishing load balancing. The PnP algorithm deactivates/activates the ESS to balance energy mismatch during the off-peak and peak hours. The excess energy generated by RERs is stored in ESS and this stored energy is retrieved/used in suitable time for meeting local demand. Through heavy simulation, we proved that the proposed MAS helped to maintain load balancing without compromising the user comfort.

In the current work, we considered the same topology configuration of integration of RERs in the power systems. The aim is to determine the impact of integration of RERs on the cost reduction of electricity of a smart residential community.

III. THE PROPOSED SYSTEM MODEL

In current work, a SG model for a smart community having almost similar energy needs is assumed. Every customer has installed smart meter for real time pricing and load demand exchange purposes. Additionally, the bidirectional communication between the utility company and customers is also assumed.

At all times, it is intentional to reduce the bill of the energy-users without compromising on the comfort level. Integrating RERs in the smart homes, assists in decreasing the energy cost. It also helps in balancing the demand-generation mismatch. Incorporating RER in smart homes also assists in sustaining satisfactory user comfort and satisfying the energy needs of the users.

Occasionally, during off-peak hours, the energy produced by RERs is higher than the energy demand of the user. The consequences of this are an imbalance in demand and generation. The concern of the mismatch between the production and demand is the main cause for the “duck curve” issue [24].

The framework of the considered SG is presented in Fig. 1. As can be seen in Fig. 1 that both the RER and ESS are incorporated in the SG framework. The ESS is added for mitigating the effect of the “duck curve” issue. Recently in [24], we have proposed and evaluated load balancing methods and techniques for user comfort management.

We assumed the Time of Use (ToU) energy tariff for calculating the cost of the electricity consumed [1]. The ToU pricing tariff is presented in Fig. 2. The twenty-four-hour time period is assumed.

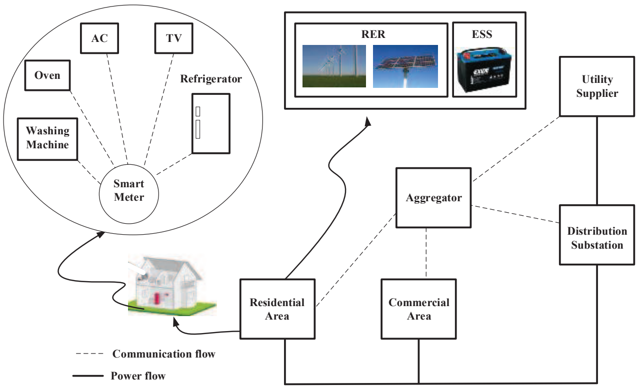

Fig. 1. The Proposed Smart Grid Framework.

The ANN model is applied for forecasting wind speed and the temperature. The forecasted temperature and wind speed are used for approximating the harvested solar and wind energy, respectively. The Fig. 3 shows the implemented ANN based prediction model that is used in this work.

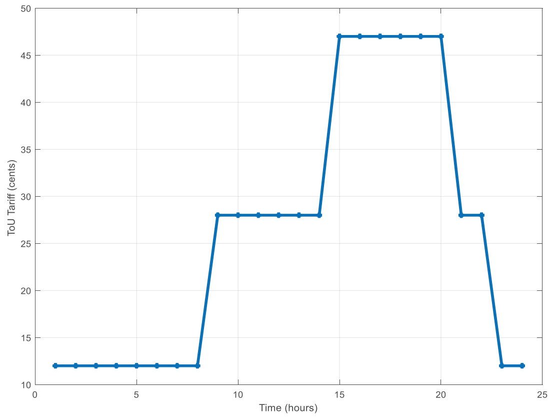

Fig. 2. The applied Time of Use (ToU) pricing tariff.

Figure 4 discloses the relationship between the energy produced and the temperature of the solar cell. It is evident from Fig. 3 that the electricity produced by the solar panel is increased with the increase in temperature of the solar cells. The reason behind this is that the power produced by solar cells is reliant on the temperature. We have retrieved the data from [25] and used it for approximating the produced power using (1). The equation (1) is borrowed from our recent work **Error! Reference source not found.**

$$P_t^{pv} = \eta^{pv} \cdot A^{pv} \cdot Irr \cdot (1 - \frac{1}{200}(T_t - 25)). \qquad (1)$$

The hourly produced power from the solar cell is represented by P_t^{pv}. The area and efficiency of the solar cells are denoted by A^{pv} and η^{pv} respectively. The solar irradiance is denoted by Irr and hourly temperature is denoted by Tt.

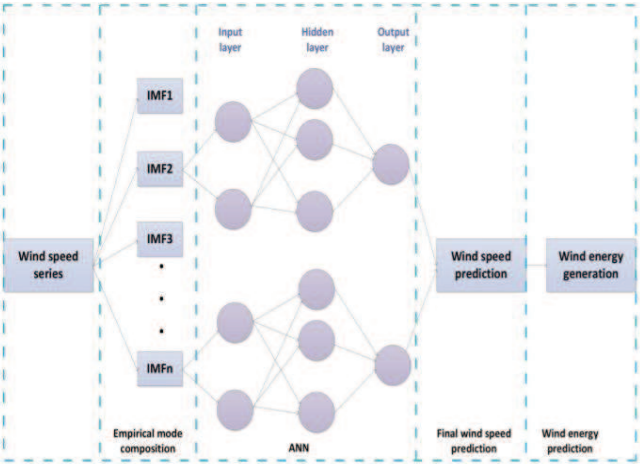

Fig. 3. The Implemented ANN model for weather prediction.

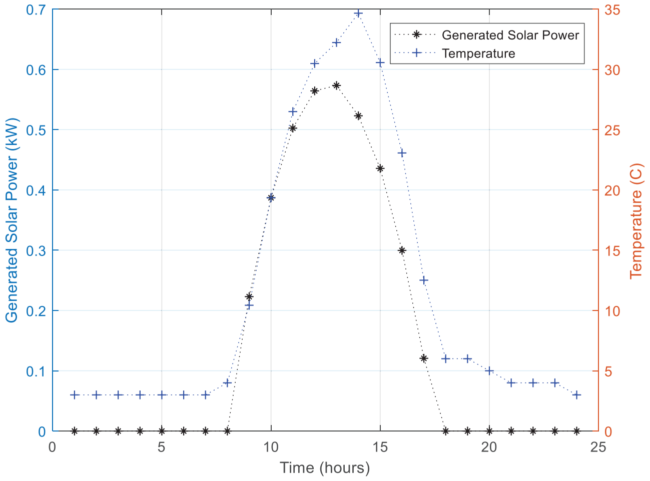

Fig. 4. The relationship between solar irradiance and generated power.

Figure 5 discloses the relationship between the power produced and the wind speed of the wind turbine.

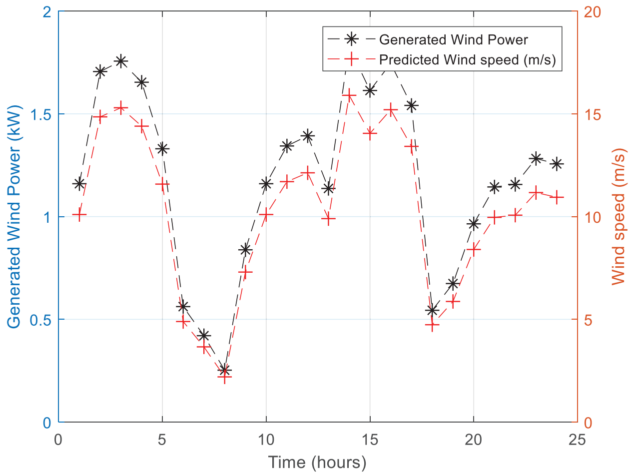

Fig. 5. The electricity generated by the wind turbine.

It is evident from Fig. 4 that the electricity produced by the wind turbine is increasing with the increase in the rotor's wind speed. The reason is that electricity production from the wind turbine is deeply reliant on the wind speed. The electricity production from the wind turbine is calculated by implementing (2) from our recent work **Error! Reference source not found.**

$$P_t^{wt} = \frac{1}{2} C_p \cdot \lambda \cdot \rho \cdot A \cdot (V_t^{wt})^3. \tag{2}$$

In (2), the produced electricity from the wind turbine is denoted by P_t^{wt} and the C_p is the power coefficient. The produced electricity from the wind turbine is also dependent on-air density ρ, the area swept by rooter blades A and wind speed V_t^{wt}.

IV. RESULTS AND DISCUSSIONS

In this section, the results are presented and are discussed in detail. A smart residential community consisting of eighty homes as the consumer of the electricity is considered. It is assumed that every smart home has installed its own RER i.e., wind turbine and solar energy. Moreover, for simulations, we have used Windows-based Computer System Intel Core i5, having 8 GB of RAM.

Every user consumes its own generated energy from RER and the deficit energy is purchased from the commercial grid. If in any hour, there is excess energy generated by RERs, then it will be stored in the ESS for later use. The combined electricity demand of the considered smart community consisting of eighty homes is presented in Fig. 6. There are three peak periods i.e. early morning, lunch and evening time.

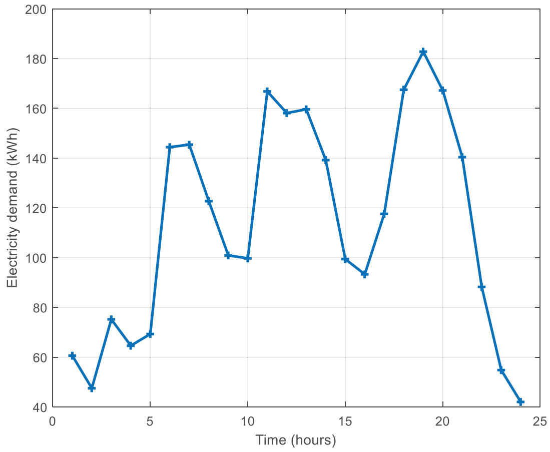

Fig. 6. The electricity demand of the smart community.

Figure 7 displays the electricity demand, the produced electricity using RERs and the purchased electricity. During off-peak hours, it can be perceived that the electricity need can be satisfied by the power produced from RERs. It means that the user will not need to purchase electricity from the utility company in the off-peak hours. But in the peak hours, the unmet power need of the user will be purchased from the electricity company. During off-peak hours, we can see that electricity produced by RERs is more than the demand. The excess energy can be saved in the ESS and can be used in the later hours.

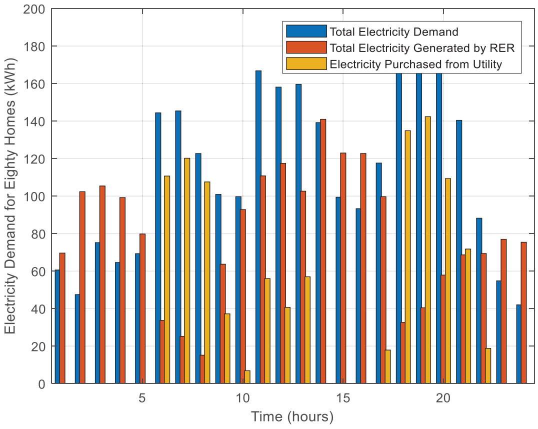

Fig. 7. The electricity generated by RERs and its demand.

Figure 8 displays the per hour cost of different components including the total cost, the total saving delivered by the RERs and the total cost of the energy purchased from the electricity company. During off-peak hours, we can observe that the power demand is satisfied by the RERs and hence the user will not pay any cost. But during peak hours, the unmet demand of the power is purchased from the utility company, which the user needs to pay.

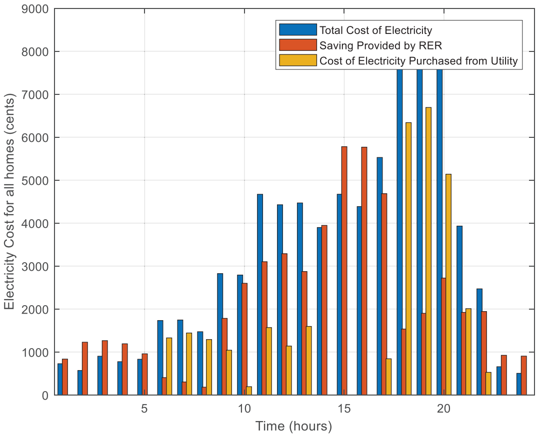

Fig. 8. The hourly cost of the various components of the electricity.

Figure 9 displays the various components of the electricity i.e. the total cost without RER, the saving delivered by RERs and the cost of the electricity purchased from the electricity providing company.

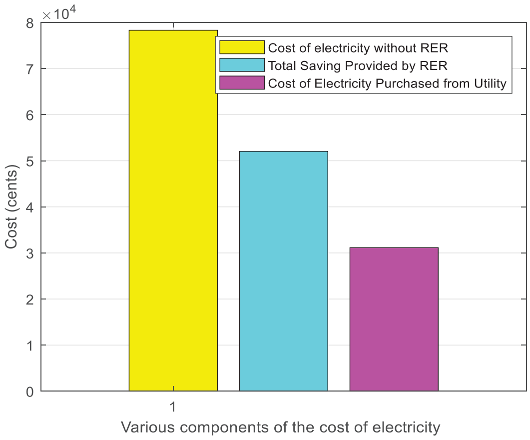

Fig. 9. The cost of the various components of the electricity.

We can see that reasonable saving can be achieved by installing RERs. This will result in a significant reduction in the cost of the electricity purchased from the utility company. Figure 8 shows that the electricity cost of the end customer is reduced by 35 % by installing RERs in smart homes.

V. CONCLUSIONS

In current work, we proposed and assessed an efficient framework based on the incorporation of RERs for energy management in a smart residential community. Occasionally, the energy produced by RERs is extra than the energy needed by the user and the consequence of this is the mismatch in demand and production. This mismatch results in the well-known problem of “duck curve”. We assumed a residential smart community comprising of 80 smart homes. Furthermore, every smart home is assumed to have installed RERs in the form of solar panels and wind turbine. Simulation results show that the proposed framework is appropriate for both predicting the energy produced through RERs as well as for reducing the electricity cost of the end customers. Moreover, when RERs are integrated in a smart community, definitely load burden on commercial grid is also reduced. Our obtained results indicate that the electricity cost of the end user is reduced by 35 % by installing RERs in the smart homes.

In the future, we will implement multi-headed convolutional neural network model for accurate energy prediction in a smart community.

REFERENCES

[1] S. Aslam, Z. Iqbal, N. Javaid, Z. Khan, K. Aurangzeb, S. Haider, “Towards efficient energy management of smart buildings exploiting heuristic optimization with real time and critical peak pricing schemes”, *Energies*, vol. 10, no. 12, p. 2065, 2017. DOI: 10.3390/en10122065.

[2] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, A. Leon-Garcia, “Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid”, *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, 2010. DOI: 10.1109/TSG.2010.2089069.

[3] D. Niyato, Lu Xiao, Ping Wang, “Machine-to-machine communications for home energy management system in smart grid”, *IEEE Communications Magazine*, vol. 49, no. 4, pp. 53–59, 2011. DOI: 10.1109/MCOM.2011.5741146.

[4] N. W. A. Lidula, A. D. Rajapakse, “Microgrids research: A review of experimental microgrids and test systems”, *Renewable and Sustainable Energy Reviews*, vol. 15, no. 1, pp. 186–202, 2011. DOI: 10.1016/j.rser.2010.09.041.

[5] A. Mehrizi-Sani, R. Iravani, “Potential-function based control of a microgrid in islanded and grid-connected modes”, *IEEE Trans. Power Systems*, vol. 25, no. 4, pp. 1883–1891, 2010. DOI: 10.1109/TPWRS.2010.2045773.

[6] H. Farhangi, “The path of the smart grid”, *IEEE Power and Energy Magazine*, vol. 8, no. 1, pp. 18–28, 2010. DOI: 10.1109/MPE.2009.934876.

[7] J. H. Eto, R. Lasseter, D. Klapp, A. Khalsa, B. Schenkman, “The CERTS Microgrid Concept, as Demonstrated at the CERTS/AEP Microgrid Test Bed”, 2018. [Online]. Available: https://certs.lbl.gov/publications/certs-microgrid-concept-demonstrated

[8] R. H. Lasseter, P. Paigi, “Microgrid: a conceptual solution”, in *IEEE 35th Annual Power Electronics Specialists Conf.*, Aachen, Germany, Germany, 2004, pp. 4285–4290. DOI: 10.1109/PESC.2004.1354758.

[9] W. K. A. Najy, H. H. Zeineldin, W. L. Woon, “Optimal protection coordination for microgrids with grid-connected and islanded capability”, *IEEE Trans. Industrial Electronics*, vol. 60, no. 4, pp. 1668–1677, 2013. DOI: 10.1109/TIE.2012.2192893.

[10] A. Mehrizi-Sani, R. Iravani, “Potential-function based control of a

microgrid in islanded and grid-connected modes", *IEEE Trans. Power Systems*, vol. 25, no. 4, pp. 1883–1891, 2010. DOI: 10.1109/TPWRS.2010.2045773.

[11] A. Maffei *et al.*, "A semantic-middleware-supported receding horizon optimal power flow in energy grids", *IEEE Trans. Industrial Informatics*, vol. 14, no. 1, pp. 35–46, 2018. DOI: 10.1109/TII.2017.2655047.

[12] A. A. Kadhem, N. Wahab, I. Aris, J. Jasni, A. Abdalla, "Advanced wind speed prediction model based on a combination of weibull distribution and an artificial neural network", *Energies*, vol. 10, no. 11, p. 1744, 2017. DOI: 10.3390/en10111744.

[13] S. Pusat, "Effect of time horizon on wind speed prediction with ANN", *Journal of Thermal Engineering*, pp. 1770–1779, 2017. DOI: 10.18186/journal-of-thermal-engineering.372218.

[14] J. N. K. Liu, Y. Hu, Y. He, P. W. Chan, L. Lai, "Deep neural network modeling for big data weather forecasting", *Studies in Big Data*, vol. 8, pp. 389–408, 2015. DOI: 10.1007/978-3-319-08254-7_19.

[15] A. Gensler, J. Henze, B. Sick, N. Raabe, "Deep Learning for solar power forecasting — An approach using AutoEncoder and LSTM Neural Networks", in *IEEE Int. Conf. Systems, Man, and Cybernetics (SMC 2016)*, Budapest, Hungary, 2016, pp. 002858–002865. DOI: 10.1109/SMC.2016.7844673.

[16] M. S. Hasan, Y. Kouki, T. Ledoux, J.-L. Pazat, "Exploiting renewable sources: when green sla becomes a possible reality in cloud computing", *IEEE Trans. Cloud Computing*, vol. 5, no. 2, pp. 249–262, 2017. DOI: 10.1109/TCC.2015.2459710.

[17] P. Chaudhary, M. Rizwan, "Energy management supporting high penetration of solar photovoltaic generation for smart grid using solar forecasts and pumped hydro storage system", *Renewable Energy*, vol. 118, pp. 928–946, 2018. DOI: 10.1016/j.renene.2017.10.113.

[18] M. H. Rahim, A. Khalid, N. Javaid, M. Alhussein, K. Aurangzeb, Z. A. Khan, "Energy efficient smart buildings using coordination among appliances generating large data", *IEEE Access*, vol. 6, pp. 34670–34690, 2018. DOI: 10.1109/ACCESS.2018.2805849.

[19] M. Rahim, A. Khalid, N. Javaid, M. Ashraf, K. Aurangzeb, A. Altamrah, "Exploiting game theoretic based coordination among appliances in smart homes for efficient energy utilization", *Energies*, vol. 11, no. 6, p. 1426, 2018. DOI: 10.3390/en11061426.

[20] H. Hussain, N. Javaid, S. Iqbal, Q. Hasan, K. Aurangzeb, M. Alhussein, "An efficient demand side management system with a new optimized home energy management controller in smart grid", *Energies*, vol. 11, no. 1, p. 190, 2018. DOI: 10.3390/en11010190.

[21] M. Khan, N. Javaid, S. Javaid, K. Aurangzeb, "Kernel based support vector quantile regression for real-time data analysis", in *Int'l Conf. On Innovation And Intelligence For Informatics, Computing, And Technologies*, 2018. Accepted for publication.

[22] M. Awais, N. Javaid, K. Aurangzeb, S. Haider, Z. Khan, D. Mahmood, "Towards effective and efficient energy management of single home and a smart community exploiting heuristic optimization algorithms with critical peak and real-time pricing tariffs in smart grids", *Energies*, vol. 11, no. 11, p. 3125, 2018. DOI: 10.3390/en11113125.

[23] M. H. Rahim, A. Khalid, N. Javaid, M. Alhussein, K. Aurangzeb, Z. A. Khan, "Energy efficient smart buildings using coordination among appliances generating large data", *IEEE Access*, vol. 6, pp. 34670–34690, 2018. DOI: 10.1109/ACCESS.2018.2805849.

[24] O. ur Rehman, S. A. Khan, M. Malik, N. Javaid, S. Javaid, K. Aurangzeb, "Optimal scheduling of distributed energy resources for load balancing and user comfort management in smart grid", in *Int'l Conf. On Innovation And Intelligence For Informatics, Computing, And Technologies*, 2018. Accepted for publication

[1] Time of use tariff of California. [Online]. Available: https://www.sce.com/residential/rates/Time-Of-Use-Residential-Rate-Plans

[25] Solar resource data. [Online]. Available: https://pvwatts.nrel.gov/pvwatts.php

[26] A. Khalid, S. Aslam, K. Aurangzeb, S. Haider, M. Ashraf, N. Javaid, "An efficient energy management approach using fog-as-a-service for sharing economy in a smart grid", *Energies*, vol. 11, no. 12, p. 3500, 2018. DOI: 10.3390/en11123500.