Materials Research Proceedings 43 (2024) 156-163 https://doi.org/10.21741/9781644903216-21

A comprehensive review on computing methods for the prediction of energy cost in Kingdom of Saudi Arabia

Nayeemuddin MOHAMMED[1,a], Andi ASIZ[1,b], Mohammad Ali KHASAWNEH[1,c], Feroz SHAIK[2,d], Hiren MEWADA[3,e], Tasneem SULTANA[4,f*]

[1]Department of Civil Engineering, Prince Mohammad Bin Fahd University, Al Khobar, Kingdom of Saudi Arabia

[2]Department of Mechanical Engineering, Prince Mohammad Bin Fahd University, Al Khobar, Kingdom of Saudi Arabia

[3]Department of Electrical Engineering, Prince Mohammad Bin Fahd University, Al Khobar, Kingdom of Saudi Arabia

[4]Artificial Intelligence and Machine Learning, Godutai Engineering College for Women, Sharnbasva University, Kalaburagi, India

mnayeemuddin@pmu.edu.sa[a], aasiz@pmu.edu.sa[b] mkhasawneh@pmu.edu.sa[c], fshaik@pmu.edu.sa[d], hmewada@pmu.edu.sa[e], tasneemsultana841@gmail.com[f*]

Keywords: Energy, Artificial Neural Network, Prediction Models, Regression, Statistical, Deep Learning

Abstract. Addressing the increasing demand for energy in the Kingdom of Saudi Arabia (KSA) poses challenges and opportunities. This necessitates effective energy planning, diversification of energy sources, and implementation of energy-efficient technologies. This study presents the energy scenario in the KSA. Later, various technical algorithms used for energy prediction from past data, including regression models, statistical models, machine learning and deep learning networks, are presented. The present study revealed that learnable models, specifically neural networks, outperformed statistical and regression networks in predicting energy demands. In addition, statistical models lack predictability and lack adoption with new data.

Introduction

Power is an exceptional resource. There must be an ongoing equilibrium between production and consumption for the power system to be stable, and this equilibrium is economically unstorable. Concurrently, the amount of economic and daily activity during off-peak and peak hours, on weekdays and weekends, etc., and weather-related factors, e.g., temperature, wind speed, precipitation, etc., determine energy demand. The forecasting of electricity is a fundamental need at the government and corporate levels for the decision-making process. Market players hedge against both volume risk and price fluctuations due to the extreme volatility of prices, which can be two orders of magnitude greater than that of any other financial asset or commodity. Thus, forecasting energy costs for a single country is valuable for several reasons. Accurate energy cost predictions enable governments and policymakers to plan for the economic development of a country. Energy costs have a significant impact on various sectors, such as manufacturing, transportation, and agriculture. By forecasting energy costs, governments can assess the competitiveness of industries, attract investments, and develop strategies to ensure an affordable and reliable energy supply. By understanding future energy costs, governments can assess the availability and affordability of energy sources. This knowledge helps in diversifying the energy supply, reducing dependence on volatile or geopolitically unstable sources, and developing strategies to maintain a stable and reliable energy infrastructure.

Materials Research Proceedings 43 (2024) 156-163 https://doi.org/10.21741/9781644903216-21

Predictions of energy costs are essential for developing energy legislation and policy. With the help of these forecasts, governments can create energy-saving policies, incentives, or subsidies that encourage the use of renewable energy sources and sustainable energy practices. Accurate predictions can help policymakers understand the potential impact of policy changes on energy costs for consumers and businesses. By predicting energy costs for a specific country, stakeholders can gain valuable insights for economic planning, energy security, policy formulation, consumer decision-making, and market analysis. These insights contribute to efficient energy management, sustainable development, and the overall well-being of the country and its citizens. There are several methods for predicting the energy cost. A few popular methods are regression analysis, time-series analysis, machine learning approaches, data mining and optimization algorithms. The accuracy and effectiveness of these methods depend on the availability and quality of the data, as well as the specific characteristics of the energy system being analyzed. In practice, a combination of multiple methods or an ensemble approach may be employed to improve the prediction accuracy.

In regard to global power consumption, the Kingdom of Saudi Arabia (KSA) ranks fourteenth. There has recently been remarkable growth in every sector of the Saudi Arabian economy, but the generation and consumption of electrical power have been particularly impressive. The government is currently working on strategies to improve this industry in the future. This is because it is crucial to sustainable development goals and because Vision 2030 requires the use of renewable energy to power the nation. Saudi Arabia generated an estimated 374 tera watt hours (TWh) of electricity in 2022, up 2% from 367 TWh in 2021 [1].

This paper presents recent algorithms used for energy prediction. Initially, an energy scenario in the KSA and various developed countries was presented. This paper focuses on various algorithms presented in the literature for accurate energy forecasting. Finally, limitations were presented.

Energy scenario in KSA

Resources for renewable and sustainable energy (RnSE) have gained prominence recently as being essential to the stability of economies throughout the world. Recent research has identified renewable and sustainable energy (RnSE) resources as a critical component of a healthy global economy, especially in industrialized nations like the Kingdom of Saudi Arabia (KSA) [2]. Saudi Arabia, as the biggest economy in the GCC, is heavily dependent on non-renewable resources for its economic growth. As such, it is imperative that the country look into alternate energy sources. In the region, using solar applications especially photovoltaics is seen to be the most cost-effective way to supply basic energy services [3]. Residential structures have received the majority of attention, although commercial and educational building construction is rapidly increasing [4]. The levelized cost of energy and the net present cost are used to compare the photovoltaic (PV) energy outputs of the Kingdom of Saudi Arabia with those of potential PV energy customers, such as European countries, China, India, and Pakistan [5]. Compared to the Mass Burn with recycling scenario, the Mass Burn scenario may yield twelve times as much. To compare the two situations in terms of economic, social, technological, and environmental factors need required another studies [6].

Future substantial expansion in the country's energy consumption is predicted due to a number of variables, including cheap energy prices, high economic growth, and a growing population [7]. After the construction and industrial sectors in Saudi Arabia, the electricity industry as a whole had the second-highest carbon emissions in 2018 [8].

Energy Cost Prediction Models

The Gaussian process creates a prediction function for the energy consumption with confidence bounds by modelling the intricate interactions between the input machining parameters and the

Materials Research Proceedings 43 (2024) 156-163 https://doi.org/10.21741/9781644903216-21

output energy consumption. Prediction models that consider various operations and process characteristics may be created using sophisticated data collecting and processing techniques to estimate a machine tool's energy usage [9]. Predicting energy usage in office buildings in cold climates was done using neural network prediction models based on evolutionary algorithms and back propagation. The highest RMSE value of the enhanced GA-BP neural network was 0.36, and the maximum MAPE value was 0.29%; both evaluation indicators were less than those of the BP prediction technique [10].

The prediction algorithm was built using two available datasets of residential and commercial structures. Accurate assessment of the energy consumption in buildings is essential for both energy policy and building energy management. The main difference between this model and the shallow machine learning (ML) model is the quantity of linear or non-linear transformations applied to the input data. The deep neural network model often makes numerous modifications to the input data before generating an output. The planned design model for the ANN-Levenberg Marquardt tool, which is employed in ANN. 3 hidden layers, with 3 inputs employed to design the model for regression and optimization using artificial neural network Levenberg Marquardt tool in MATLAB application. Each layer has different neurons such as 35, 20 and 10 were suggested to get more accuracy of prediction as shown in Figure 1 [11]. Cao et al., created and evaluated an integrated learning method that uses data permutation to gauge the significance of features in order to reduce the instability issue with building management systems [12], [13].

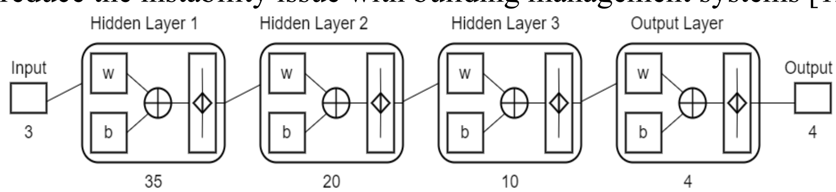

Fig 1. Design modeling for ANN-LM tool in ANN [13]

Kim et al., investigated and used the response surface approach in conjunction with the statistical method to create a prediction model for residential building energy consumption. In Seoul and Busan apartment buildings, higher window and wall thermal transmittances and infiltration rates led to higher heating energy consumption; conversely, higher SHGC was linked to reduced cooling energy consumption [14]. The suggested deep learning technique was used to forecast the energy usage of a particular building for which data on energy use over a 12-month period was gathered. The results of the experiment and comparison show that the deep learning approach performs better than a number of well-liked conventional machine learning techniques [15], [16].

Limitations in Energy Cost Prediction Models

When comparing the ANN to the BP neural network, the ELM significantly enhanced it. In contrast to typical feedforward neural networks, the ELM randomizes the network weight of a single hidden layer. The inverse matrix of Moore-Penrose is used to determine the outputs. As a result, the output calculation speed and generalization precision are rather high, and it is difficult to reach a local maximum [17]. Support vector machines (SVM), artificial neural networks (ANN), decision trees, and other statistical methods are examples of learning algorithms [18],[19]. Building and region scales are examples of spatial scales. Both short-term and long-term temporal granularities are available. There are several types of energy consumption forecast, such as total, heating, cooling, and lighting. Real and simulated datasets are two examples of dataset types [20].

Energy Cost Prediction Models Applied to KSA Scenario

The Kingdom of Saudi Arabia, an expanding nation, is seeing remarkable developments in a range of fields, such as the medical, educational, engineering, and urban sectors, particularly in the economic and industrial realms. Planning for capacity, transmission, and price all depend on the ability to forecast energy use. The aspects of power consumption forecasting vary depending on the prediction perspective. Almuhaini's research forecasted annual TEC using statistical and machine learning techniques, namely ARIMAX, BOA–SVR, and BOA–NARX models [21]. ANFIS combines fuzzy logic and neural networks, it usually consists of five layers: fuzzification, fuzzy rule evaluation, normalization, defuzzification, and output. Each layer performs a specific function in the inference process [22]. Training includes the ANFIS model using a hybrid learning algorithm that combines gradient descent and least squares estimation. Figure 2 shows the design modelling steps involved in ANFIS method of prediction [23], [24]. These tactics function even in the absence of prior understanding of the previously outlined systems. By correctly analyzing a dataset that includes obtained output and input parameters, they try to understand the link between outputs and inputs [25], [26] .

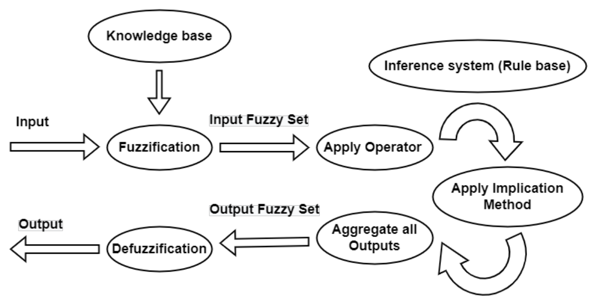

Fig 2. Design modeling for ANFIS tool in ANN [26]

A government agent may utilize the generated energy prediction model to help them plan corrective steps for future school building, design with minimal energy consumption, and make the most use of their limited finances [27]. Model accuracy and computing capacity are increased by new technological advancements including parametric modelling, simulation, and artificial neural networks (ANNs). Elbeltagi et al., used ANN application to forecast the energy demand for residential structures. Artificial neural networks (ANNs), simulation, and parametric modelling are examples of recent technology developments that improve model accuracy and processing power [28], [24]. Table 1 shows the renewable energy cost aspects and prediction of models applied in Kingdom of Saudi. Table 2 shows the study of various ANN and machine learning network used successfully in forecasting the energy consumption within different zone of Saudi Arabia. Table 2 shows deep network [29] performed best in compared to machine learning with least error in the prediction over large-scale dataset.

Table 1 Displays the detailed renewable energy cost aspects and prediction

	Aspects	Description	Ref.
Energy Scenario	Energy Production	Significant investments in renewable energy, particularly solar energy	[30]
	Renewable Energy	Ambitious plans to develop renewable energy sector, with a focus on solar and wind energy	[31]
Energy Cost Prediction models	Artificial Neural Networks (ANN)	Machine learning models that can capture complex relationships in energy cost data	[32]
	Support Vector Machines (SVM)	Machine learning models that can analyze and forecast energy costs based on historical data	[33]

Limitations in energy cost prediction models	Data Availability	Limited availability of high-quality historical data, especially for newer technologies and renewable sources	[34]
Prediction models applied in K. S. A	Hybrid Models	Combine multiple approaches (e.g., regression, machine learning) for more accurate energy cost predictions	[36]

Table 2 Analysis of various prediction algorithm adopted for electricity cost analysis in KSA

Ref	Goal	Analysis
[39]	Energy const prediction using ANN/BIM model for residential building in KSA	Design Builder was used to create a 3D model, and the energy usage was determined. The dataset covers building area, type of air conditioning, glazing system, and envelope system.
[40]	Energy consumption in school building in Riyadh, KSA	To find the best network model, several neural network (NN) design topologies were tested. The developed model had an accuracy of roughly 87.5%.
[41]	Photovoltaic power output prediction in Jubail Industrial City, KSA.	Optimal database finding suitable merit indicator can enhance the performance.
[29]	Forecasting annual electricity consumption in Saudi Arabi	A Bayesian optimized non-linear autoregressive network was developed for forecasting energy consumption.

Conclusion

Advancements in infrastructure and laying down new large projects and increasing populations in the KSA led to increased energy demands. Vision 2030 is nominated with a large number of new projects; therefore, it is necessary to forecast future energy demands. We presented a scenario in which energy requirements are met in the KSA. Later, the various algorithms presented in the literature for energy forecasting were presented. The algorithms were categorized into statistical models, i.e., ARIMAX and BOA; machine learning algorithms, including regression networks; KNN and SVM; and ANN networks, which include deep CNNs, BPNs, ANNs, and long short-term memory (LSTM). The study revealed that deep CNN performance is better than that of statistical models, which lack accuracy and adaptivity.

References

[1] "U.S. Energy Information Administration," International Energy Statistics. Accessed: Feb. 20, 2024. [Online]. Available: Energy Institute, Statistical Review of World Energy, 2023

[2] Y. H. A. Amran, Y. H. M. Amran, R. Alyousef, and H. Alabduljabbar, "Renewable and sustainable energy production in Saudi Arabia according to Saudi Vision 2030; Current status and future prospects," *Journal of Cleaner Production*, vol. 247, p. 119602, Feb. 2020. https://doi.org/10.1016/j.jclepro.2019.119602

[3] M. A. Salam and S. A. Khan, "Transition towards sustainable energy production – A review of the progress for solar energy in Saudi Arabia," *Energy Exploration & Exploitation*, vol. 36, no. 1, pp. 3–27, Jan. 2018. https://doi.org/10.1177/0144598717737442

[4] M. Abdul Mujeebu and O. S. Alshamrani, "Prospects of energy conservation and management in buildings – The Saudi Arabian scenario versus global trends," *Renewable and*

Sustainable Energy Reviews, vol. 58, pp. 1647–1663, May 2016. https://doi.org/10.1016/j.rser.2015.12.327

[5] M. Zubair, A. B. Awan, R. P. Praveen, and M. Abdulbaseer, "Solar energy export prospects of the Kingdom of Saudi Arabia," *Journal of Renewable and Sustainable Energy*, vol. 11, no. 4, p. 045902, Jul. 2019. https://doi.org/10.1063/1.5098016

[6] O. K. M. Ouda, H. M. Cekirge, and S. A. R. Raza, "An assessment of the potential contribution from waste-to-energy facilities to electricity demand in Saudi Arabia," *Energy Conversion and Management*, vol. 75, pp. 402–406, Nov. 2013. https://doi.org/10.1016/j.enconman.2013.06.056

[7] F. Alrashed and M. Asif, "Prospects of Renewable Energy to Promote Zero-Energy Residential Buildings in the KSA," *Energy Procedia*, vol. 18, pp. 1096–1105, Jan. 2012. https://doi.org/10.1016/j.egypro.2012.05.124

[8] S. Alsulamy, A. S. Bahaj, P. James, and N. Alghamdi, "Solar PV Penetration Scenarios for a University Campus in KSA," *Energies*, vol. 15, no. 9, Art. no. 9, Jan. 2022. https://doi.org/10.3390/en15093150

[9] R. Bhinge, J. Park, K. H. Law, D. A. Dornfeld, M. Helu, and S. Rachuri, "Toward a Generalized Energy Prediction Model for Machine Tools," *Journal of Manufacturing Science and Engineering*, vol. 139, no. 041013, Nov. 2016. https://doi.org/10.1115/1.4034933

[10] J. Huang, H. Lv, T. Gao, W. Feng, Y. Chen, and T. Zhou, "Thermal properties optimization of envelope in energy-saving renovation of existing public buildings," *Energy and Buildings*, vol. 75, pp. 504–510, Jun. 2014. https://doi.org/10.1016/j.enbuild.2014.02.040

[11] N. Mohammed, P. Palaniandy, and F. Shaik, "Solar photocatalytic biodegradability of saline water: Optimization using RSM and ANN," presented at the AIP Conference Proceedings, AIP Publishing, 2022.

[12] W. Cao *et al.*, "Short-term energy consumption prediction method for educational buildings based on model integration," *Energy*, vol. 283, p. 128580, Nov. 2023. https://doi.org/10.1016/j.energy.2023.128580

[13] N. Mohammed, P. Palaniandy, and F. Shaik, "Optimization of solar photocatalytic biodegradability of seawater using statistical modelling," *Journal of the Indian Chemical Society*, vol. 98, no. 12, p. 100240, Dec. 2021. https://doi.org/10.1016/j.jics.2021.100240

[14] D. D. Kim and H. S. Suh, "Heating and cooling energy consumption prediction model for high-rise apartment buildings considering design parameters," *Energy for Sustainable Development*, vol. 61, pp. 1–14, Apr. 2021. https://doi.org/10.1016/j.esd.2021.01.001

[15] C. Li, Z. Ding, D. Zhao, J. Yi, and G. Zhang, "Building Energy Consumption Prediction: An Extreme Deep Learning Approach," *Energies*, vol. 10, no. 10, Art. no. 10, Oct. 2017. https://doi.org/10.3390/en10101525

[16] N. Mohammed, P. Palaniandy, F. Shaik, B. Deepanraj, and H. Mewada, "Statistical analysis by using soft computing methods for seawater biodegradability using ZnO photocatalyst," *Environmental Research*, vol. 227, p. 115696, Jun. 2023. https://doi.org/10.1016/j.envres.2023.115696

[17] Z. Geng, Y. Zhang, C. Li, Y. Han, Y. Cui, and B. Yu, "Energy optimization and prediction modeling of petrochemical industries: An improved convolutional neural network based on cross-feature," *Energy*, vol. 194, p. 116851, Mar. 2020. https://doi.org/10.1016/j.energy.2019.116851

[18] N. Mohammed, "Characterization of sustainable concrete made from wastewater bottle caps using a machine learning and RSM-CCD: towards performance and optimization," presented at

the AToMech1-2023 Supplement, Nov. 2023, pp. 38–46. https://doi.org/ 10.21741/9781644902790-4

[19] N. Mohammed, P. Palaniandya, F. Shaik, and H. Mewada, "EXPERIMENTAL AND COMPUTATIONAL ANALYSIS FOR OPTIMIZATION OF SEAWATER BIODEGRADABILITY USING PHOTO CATALYSIS," *IIUM Engineering Journal*, vol. 24, no. 2, pp. 11–33, Jul. 2023. https://doi.org/10.31436/iiumej.v24i2.2650

[20] K. Amasyali and N. El-Gohary, "Machine learning for occupant-behavior-sensitive cooling energy consumption prediction in office buildings," *Renewable and Sustainable Energy Reviews*, vol. 142, p. 110714, May 2021. https://doi.org/10.1016/j.rser.2021.110714

[21] S. H. Almuhaini and N. Sultana, "Forecasting Long-Term Electricity Consumption in Saudi Arabia Based on Statistical and Machine Learning Algorithms to Enhance Electric Power Supply Management," *Energies*, vol. 16, no. 4, Art. no. 4, Jan. 2023. https://doi.org/10.3390/en16042035

[22] N. Mohammed, P. Palaniandy, and F. Shaik, "Pollutants removal from saline water by solar photocatalysis: a review of experimental and theoretical approaches," *International Journal of Environmental Analytical Chemistry*, vol. 103, no. 16, pp. 4155–4175, Dec. 2023. https://doi.org/10.1080/03067319.2021.1924160

[23] A. Abubakar Mas'ud, "Comparison of three machine learning models for the prediction of hourly PV output power in Saudi Arabia," *Ain Shams Engineering Journal*, vol. 13, no. 4, p. 101648, Jun. 2022. https://doi.org/10.1016/j.asej.2021.11.017

[24] N. Mohammed, A. Asiz, M. A. Khasawneh, H. Mewada, and T. Sultana, "Machine learning and RSM-CCD analysis of green concrete made from waste water plastic bottle caps: Towards performance and optimization," *Mechanics of Advanced Materials and Structures*, pp. 1–9, Aug. 2023. https://doi.org/10.1080/15376494.2023.2238220

[25] N. Mohammed, P. Palaniandy, and F. Shaik, "Optimization of solar photocatalytic biodegradability of seawater using statistical modelling," *Journal of the Indian Chemical Society*, vol. 98, no. 12, p. 100240, Dec. 2021. https://doi.org/10.1016/j.jics.2021.100240

[26] N. Mohammed, P. Palaniandy, F. Shaik, H. Mewada, and D. Balakrishnan, "Comparative studies of RSM Box-Behnken and ANN-Anfis fuzzy statistical analysis for seawater biodegradability using TiO2 photocatalyst," *Chemosphere*, vol. 314, p. 137665, Feb. 2023. https://doi.org/10.1016/j.chemosphere.2022.137665

[27] A. Alshibani, "Prediction of the Energy Consumption of School Buildings," *Applied Sciences*, vol. 10, no. 17, p. 5885, Aug. 2020. https://doi.org/10.3390/app10175885

[28] E. Elbeltagi and H. Wefki, "Predicting energy consumption for residential buildings using ANN through parametric modeling," *Energy Reports*, vol. 7, pp. 2534–2545, Nov. 2021. https://doi.org/10.1016/j.egyr.2021.04.053

[29] S. H. Almuhaini and N. Sultana, "Forecasting Long-Term Electricity Consumption in Saudi Arabia Based on Statistical and Machine Learning Algorithms to Enhance Electric Power Supply Management," *Energies*, vol. 16, no. 4, Art. no. 4, Jan. 2023. https://doi.org/10.3390/en16042035

[30] J. B. Smith and J. Ming, "Renewable energy research leases: Prospects and opportunities on the Hawaiian Outer Continental Shelf (OCS)," in *OCEANS'11 MTS/IEEE KONA*, Sep. 2011, pp. 1–5. https://doi.org/ 10.23919/OCEANS.2011.6107285

[31] W. Strielkowski, L. Civín, E. Tarkhanova, M. Tvaronavičienė, and Y. Petrenko, "Renewable Energy in the Sustainable Development of Electrical Power Sector: A Review," *Energies*, vol. 14, no. 24, Art. no. 24, Jan. 2021. https://doi.org/10.3390/en14248240

[32] B. Bush, N. Brunhart-Lupo, B. Bugbee, V. Krishnan, K. Potter, and K. Gruchalla, "Coupling visualization, simulation, and deep learning for ensemble steering of complex energy models," in *2017 IEEE Workshop on Data Systems for Interactive Analysis (DSIA)*, Oct. 2017, pp. 1–5. https://doi.org/ 10.1109/DSIA.2017.8339087

[33] J. Zhang, Q. Liu, Q. Wang, R. Tang, Y. He, and N. Tai, "Data-Driven Intelligent Fault Diagnosis Technology for Transmission Lines of Wind Power Renewable Energy System," in *2023 3rd International Conference on Energy, Power and Electrical Engineering (EPEE)*, Sep. 2023, pp. 246–251. https://doi.org/ 10.1109/EPEE59859.2023.10351976

[34] X. Yang *et al.*, "Optimal Distribution Network Planning with CVaR Model Considering Renewable Energy Integration," in *2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2)*, Oct. 2018, pp. 1–6. https://doi.org/ 10.1109/EI2.2018.8582256

[35] K. Kampouropoulos, F. Andrade, E. Sala, A. G. Espinosa, and L. Romeral, "Multiobjective Optimization of Multi-Carrier Energy System Using a Combination of ANFIS and Genetic Algorithms," *IEEE Transactions on Smart Grid*, vol. 9, no. 3, pp. 2276–2283, May 2018. https://doi.org/10.1109/TSG.2016.2609740

[36] M. M. Samy, H. H. Sarhan, S. Barakat, and S. A. Al-Ghamdi, "A Hybrid PV-Biomass Generation Based Micro-Grid for the Irrigation System of a Major Land Reclamation Project in Kingdom of Saudi Arabia (KSA) - Case Study of Albaha Area," in *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, Jun. 2018, pp. 1–8. https://doi.org/ 10.1109/EEEIC.2018.8494543

[37] Y. Bhandari, S. Chalise, J. Sternhagen, and R. Tonkoski, "Reducing fuel consumption in microgrids using PV, batteries, and generator cycling," in *IEEE International Conference on Electro-Information Technology , EIT 2013*, May 2013, pp. 1–4. https://doi.org/ 10.1109/EIT.2013.6632692

[38] M. Patterson, N. F. Macia, and A. M. Kannan, "Hybrid Microgrid Model Based on Solar Photovoltaic Battery Fuel Cell System for Intermittent Load Applications," *IEEE Transactions on Energy Conversion*, vol. 30, no. 1, pp. 359–366, Mar. 2015. https://doi.org/10.1109/TEC.2014.2352554

[39] A. Alshibani and O. S. Alshamrani, "ANN/BIM-based model for predicting the energy cost of residential buildings in Saudi Arabia," *Journal of Taibah University for Science*, vol. 11, no. 6, pp. 1317–1329, Nov. 2017. https://doi.org/10.1016/j.jtusci.2017.06.003

[40] A. Alshibani, "Prediction of the Energy Consumption of School Buildings," *Applied Sciences*, vol. 10, no. 17, Art. no. 17, Jan. 2020. https://doi.org/10.3390/app10175885

[41] A. Abubakar Mas'ud, "Comparison of three machine learning models for the prediction of hourly PV output power in Saudi Arabia," *Ain Shams Engineering Journal*, vol. 13, no. 4, p. 101648, Jun. 2022. https://doi.org/10.1016/j.asej.2021.11.017

[42] T. Alquthami and A. Alaraishy, "Comprehensive Energy and Cost evaluation through detailed Auditing and Modeling for Mosque in Saudi Arabia," vol. 16, no. 9, 2021.