
MACHINE LEARNING ASSISTED ENERGY AUDIT AND POWER CONSUMPTION PREDICTION FOR SOLAR NET-METERING SYSTEMS USING KNN ML ALGORITHM

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Abstract: Energy audit system plays a pivotal role in energy conservation among several industries and household applications. Recent advancements in smart energy management have encouraged the integration of machine learning techniques for forecasting energy consumption and optimizing renewable energy utilization. In this work, initially import and export energy is measured from net metering system for a specific period through a specific IoT enabled system. From the observations, net energy consumption is calculated and used as an input for predictive model. KNN-based predictive model is incorporated to forecast future power consumption using historical import-export energy data collected from the solar net-metering system. The integration of KNN with energy audit systems provides valuable insights into future power demand patterns, enabling industries to optimize energy import-export decisions, improve solar energy utilization, and reduce electricity costs.

Keywords: Energy Audit, Net Metering, IoT, Machine Learning Algorithm, KNN

1. Introduction

Normal energy auditing system has a simple payback period of 9.8 years [1]. The system's cost of energy was estimated as 0.0372 \$/kWh, and the capital cost was \$ 150,887. The solar technologies will altogether abate approximately 91.5 tons of CO₂ and provide a carbon credit gain of \$1,830 annually [2]. Tim Umoe (2022) estimated to be 6.4 years and 4.6 years (when management techniques are applied), which is obviously much shorter than the lifespan of the selected PV module which is 30 years [3]. Net-Metering is sensitive to load profile variation even at constant annual energy load. For this case, different economic parameters were obtained for different two load scenarios [4]. The return of investment of solar PV system implementation for FiT (Feed-in Tariff) and Net metering is 11.5 and 16.1 years respectively [5]. This study provides an insight cost and energy analysis for FiT and Net metering for the university campus which was measured experimentally and predicted using machine learning algorithm. This work reports energy audit-based consumption spectra in residential buildings and reduction in demand by integration of a CO₂ fluid-mediated solar water-heating system to develop ZNE buildings [6]. Improving energy efficiency of similar facilities requires energy conservation practice in terms of operating motors and other HVAC devices off idle-time and non-occupancy period respectively [7]. Previous work has estimated the implementation costs and payback periods for each recommended action can have made [8]. The analysis of the building data has been done with the help of power system analysis software package [9]. The energy audit can provide the non-cost suitable technique for energy savings and profit improvement in the electronic company. Non-benefits for achieving industrial energy efficiency, which should be embodied in the energy auditing framework and considered by plant operations managers during evaluation of energy efficiency investments have been demonstrated [10].

In this specific experimental study, the sample case was done on building electrical setup with comprises of 20 fans, 20 lights, and 2 centralized air conditioning units, each with a capacity of two tons. Additionally, there are various minor electrical fittings in place to facilitate day-to-day operations. Notable feature of this establishment is the presence of solar panels, allowing the generation of solar energy. Importantly, the surplus solar energy is exported back to the Electricity Board (EB), while the shop continues to procure energy from the EB for regular use [11]. Recent advancements in smart energy management have encouraged the integration of machine learning techniques for forecasting energy consumption and optimizing renewable energy utilization. KNN predicts future energy consumption by identifying historical operating conditions similar to the current state and estimating future demand based on neighbouring observations. Several studies have demonstrated the effectiveness of KNN in short-term load forecasting, smart grid energy management, and photovoltaic power prediction [12]. The integration of KNN with energy audit systems provides valuable insights into future power demand patterns, enabling industries to optimize energy import-export decisions, improve solar energy utilization, and reduce electricity costs [13-14]. Among various machine learning approaches, the K-Nearest Neighbours (KNN) algorithm has gained attention due to its simplicity, robustness, and ability to model nonlinear relationships in energy datasets. Several studies have demonstrated the effectiveness of KNN in short-term load forecasting, smart grid energy management, and photovoltaic power prediction. Therefore, in this work, a KNN-based predictive model is incorporated to forecast future power consumption using historical import-export energy data collected from the solar net-metering system based on several previous machine learning techniques used in realistic applications similar to this work [15-18]. KNN predicts future energy consumption by identifying

historical operating conditions similar to the current state and estimating future demand based on neighbouring observations.

2. Experimental Methods

Throughout the course of assessment, data have been collected and examined related to the import and export of energy over a specific period. The objective of the analysis is to study about the discernible discrepancy in the energy bill amount, indicating a potential for savings. To address this issue, concrete steps to enhance the efficient utilization of solar energy was considered. Moreover, a set of recommendations has devised to harness solar power more proficiently. These efforts aim to not only minimize energy expenses but also contribute to a sustainable and eco-friendly energy strategy.

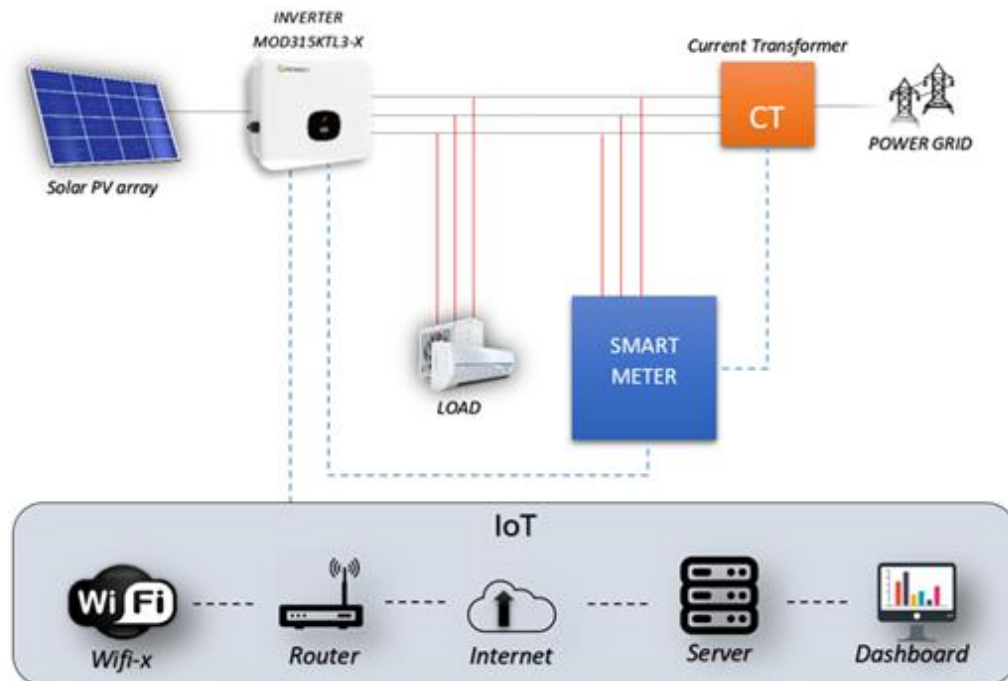


Figure 1 Typical Energy Management System of a Roof Top Facility

Figure 1 shows the flow diagram of energy producing element solar panel to grid export and import integration unit with electricity board which is connected with IOT to improve the operational efficiency. Homeowners and businesses with solar panels or other renewable energy sources can benefit from a billing arrangement called net metering. This arrangement allows them to receive credit for the extra electricity they generate and feed back into the grid. To measure the electricity consumed from and returned to the grid, a bi-directional meter is typically used. The credits from the excess electricity can then be applied to offset future electricity bills. To provide real-time monitoring, control, and optimization of energy generation and consumption, Internet of Things (IoT) technology can be incorporated with net metering. IoT-enabled smart meters which can replace traditional meters to provide real-time data on electricity generation and consumption. These meters can communicate with homeowners and utility providers, enabling remote monitoring and control. Integrating IoT with net metering improves the functionality and efficiency of renewable energy systems, making them more sustainable and accessible. It offers benefits to both energy consumers and utility providers by optimizing energy usage, reducing costs, and enhancing the reliability of the grid.

3. Energy Audit Methodology

The first step involves the collection of data of all sorts such as the solar panel reading, two tons AC units, minor electrical fittings and the different type of loads connected, the usage hours which involves surveys, observations and measurements [15]. The data that has been gathered is examined to determine the rate of energy consumption, understand the patterns of energy usage, and extract other pertinent information. The findings from this analysis are then translated into visual representations, such as graphs and charts, to facilitate a more accessible and intuitive comprehension of the data. Increasing the number of solar panels in the current setup is not a favourable solution. It is recommended to set the air conditioning temperature within the range of 20-23°C from 11 am to 5 pm, and then adjust it to 25-26°C. Alternatively, one air conditioner could be used after 6 pm, along with the use of BLDC fans strategically placed in various locations. This measure can result in a savings of 8 units of electricity per day, which translates to a total saving of Rs. 4500 over a span of 2 months. The total electricity consumption from the grid (EB power import) has exceeded 2000 units. A significant portion of the

energy needs has been met by solar power generation, with 1400 units generated. Out of this, 700 units were consumed, and the remaining 700 units were exported. When considering the combined electricity usage from both the grid and solar sources, the total consumption stands at approximately 2700 units. On average, this equates to around 52 units per working day. With an assumption of a 12-hour working day and all air conditioning units operating continuously, the average electricity consumption is approximately 4.3 units per hour. Industries generate electricity using solar panels and send the excess power back to the electricity board. However, the electricity board charges them a high fee for this power. This results in significant financial losses for the industries. Therefore, the government should implement new regulations that allow industries to use the power they generate directly. If these regulations are not adopted, it will continue to be a financial burden for the industries. Table 1 consolidates the import, export and net energy metering data for the considered three days in kWh.

Table 1. Three days' energy metering data (KWh)

Day	Time	Import	Export	Net
1	09:48 PM	34473.22	17472.65	17000.60
1	12:02 PM	34479.62	17476.88	17002.75
1	04:30 PM	34486.12	17482.45	17003.69
1	06:08 PM	34493.50	17482.56	17010.98
1	07:02 PM	34498.48	17482.56	17015.96
2	02:45 PM	34516.65	17494.28	17022.40
2	03:46 PM	34520.18	17494.53	17025.67
2	04:54 PM	34524.48	17494.57	17029.95
2	05:50 PM	34527.64	17494.57	17033.09
2	06:43 PM	34531.15	17494.57	17036.62
3	08:22 AM	34540.71	17495.85	17044.89
3	10:22 AM	34545.22	17498.00	17047.21
3	12:40 PM	34547.35	17503.20	17044.13
3	02:30 PM	34549.44	17506.80	17042.63
3	06:39 PM	34562.08	17509.42	17052.68

4. Solar Energy Generation Comparison between 2019 to 2024 total performance report

Figures 2 (a &b) indicates the solar energy comparison between 2019 to 2023 and also indicates that solar energy generation significantly increased in the year 2021, whereas solar energy production was relatively low in the initial years (2019 and 2020). This highlights the growing importance of solar energy in the energy generation landscape over a specific period. All these data are monitored through centralised energy monitoring server for future prediction and estimation. Figure 2c indicates the day-wise energy generation comparison for a month and also illustrates a consistent upward trend in solar energy production on a day-to-day basis within a given month. This gradual increase in solar energy generation underscores the progressive nature of solar power throughout the month.

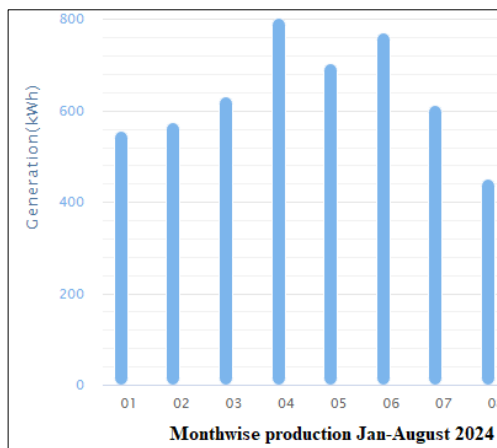


Figure 2a Month wise Energy production data

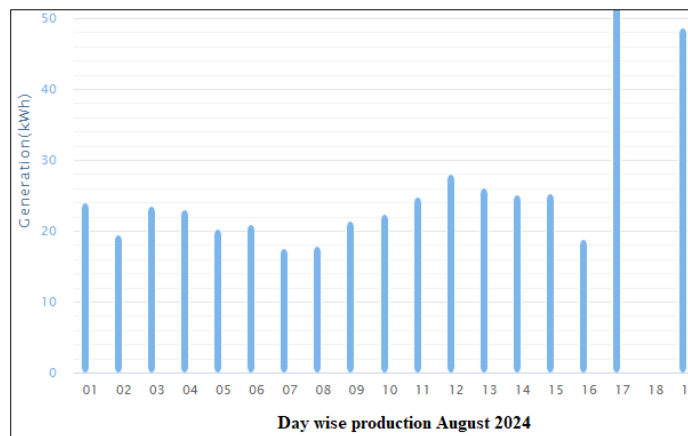


Figure 2b Day-wise Energy Generation Comparison for a month

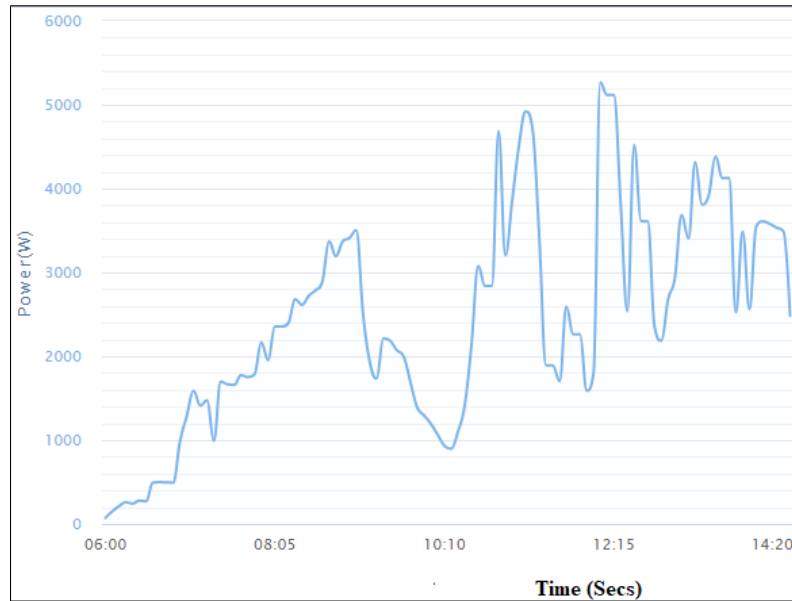


Figure 2c Energy Generation Comparison for a Particular Day

5. KNN-Based Power Consumption Prediction

To predict future power consumption, a K-Nearest Neighbours (KNN) regression model was developed using the historical energy import and export readings collected from the net-metering system. The input features consisted of energy import values, energy export values, and time indices, while the target variable was the net energy consumption [19-21]. Among various machine learning approaches, the K-Nearest Neighbours (KNN) algorithm has gained attention due to its simplicity, robustness, and ability to model nonlinear relationships in energy datasets [22-23]. Prior to training, the dataset was normalized to eliminate scale variations among parameters. The KNN algorithm determines the K closest observations based on Euclidean distance and estimates future energy consumption as the average of neighbouring samples. In this study, K=3 was selected after evaluating prediction stability. The trained model was then used to forecast future power consumption trends for subsequent operational periods. Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. The comparison between actual and predicted values demonstrates a strong correlation as given in Table 2, with only minor deviations observed at certain operating points. The prediction accuracy indicates that KNN can effectively identify similar historical operating conditions and utilize them for forecasting future energy demand.

Table 2. KNN results actual vs Predicted Energy Consumption

Sample	Actual Net Energy (kWh)	Predicted Net Energy (kWh)
1	17000.60	17001.20
2	17002.75	17003.10
3	17003.69	17004.05
4	17010.98	17009.80
5	17015.96	17014.75
6	17022.40	17021.65
7	17025.67	17024.90
8	17029.95	17029.10
9	17033.09	17032.30
10	17036.62	17035.75
11	17044.89	17043.95
12	17047.21	17046.10
13	17044.13	17044.80
14	17042.63	17043.20
15	17052.68	17051.35

The forecast results shown in Figure 3 reveals an increasing trend in net energy consumption during peak operational hours, primarily due to continuous air-conditioning usage and increasing building load demand. Such predictive information enables facility managers to schedule energy-intensive operations during periods of higher solar energy generation and thereby reduce dependency on imported grid power. The integration of machine learning with the energy audit framework provides an intelligent decision-support mechanism for optimizing

energy utilization. Furthermore, accurate prediction of future consumption can assist in demand-side management, battery storage scheduling, and efficient planning of solar energy export to the grid. The proposed KNN model therefore enhances the practical value of the energy audit by transforming historical measurements into actionable future energy forecasts.

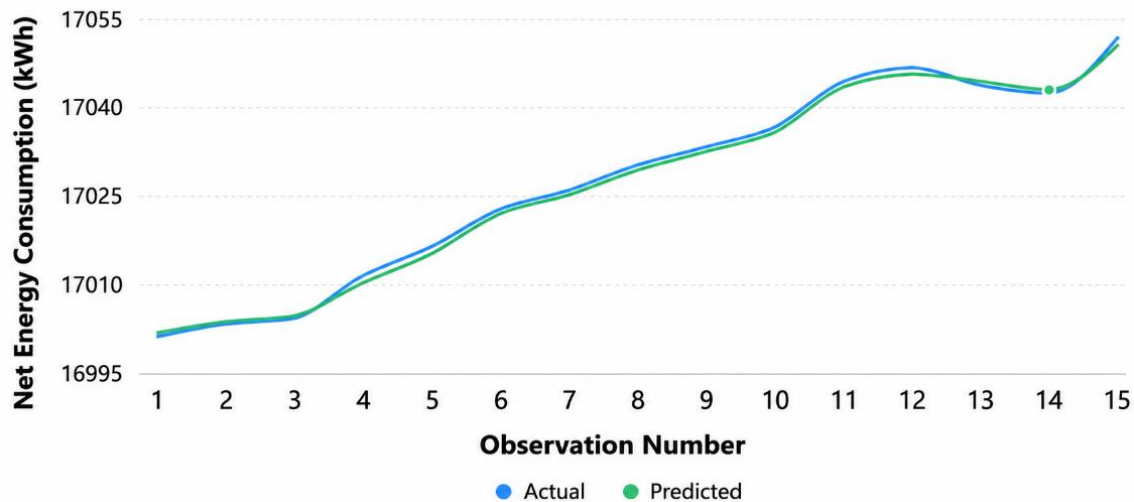


Figure 3. KNN accuracy result Actual Vs Predicted output

6. Conclusion

The combination of energy auditing, solar net-metering analysis, and machine learning-based forecasting provides a comprehensive framework for intelligent energy management. The proposed approach offers industries a practical pathway toward reducing energy costs, improving renewable energy utilization, and achieving long-term sustainability goals. Future work may focus on developing advanced forecasting models using larger datasets and comparing the performance of KNN with other machine learning algorithms such as Random Forest, Support Vector Regression, and Artificial Neural Networks to further improve prediction accuracy and energy management efficiency.

References

- [1] S. W. Chisale and P. Mangani, "Energy audit and feasibility of solar PV energy system: Case of a commercial building," *Journal of Energy*, vol. 2021, pp. 1–9, 2021.
- [2] I. Bosu, H. Mahmoud, and H. Hassan, "Energy audit, techno-economic and environmental assessment of integrating solar technologies for energy management in a university residential building: A case study," *Applied Energy*, vol. 341, p. 121141, 2023.
- [3] A. T. Umoette, U. J. Paul, and E. A. Ubom, "Energy audit and standalone solar-power generation design for Akwa Ibom State University Main Campus," *Energy*, vol. 8, no. 6, 2023.
- [4] M. A. Omar and M. M. Mahmoud, "An economic evaluation of residential grid-connected PV systems based on net-metering and feed-in-tariff schemes in Palestine," *International Journal of Renewable Energy Research*, vol. 8, no. 4, pp. 16–27, 2018.
- [5] R. H. Tan and T. L. Chow, "A comparative study of feed-in tariff and net metering for UCSI University North Wing Campus with 100 kW solar photovoltaic system," *Energy Procedia*, vol. 100, pp. 86–91, 2016.
- [6] A. R. Kalair, M. Seyedmahmoudian, N. Abas, M. S. Saleem, A. Stojcevski, S. Mekhilef, and K. Koh, "Energy audit in buildings for sustainable economic development," in *Proc. International Conference on Applied Economics*, Cham, Switzerland: Springer, 2022, pp. 587–612.
- [7] O. E. Atiba, U. K. Efemwenkiele, R. O. Olatunji, O. S. Ohunakin, D. S. Adelekan, and O. A. Oyeleke, "Walk-through energy audit of an institutional building," in *Journal of Physics: Conference Series*, vol. 1378, no. 3, Art. no. 032051, 2019.
- [8] S. Soni, I. Kaur, and D. Kumar, "Optimization of electricity bill on study of energy audit by using grid integration of renewable energy sources," in *Cognitive Informatics and Soft Computing: Proceedings of CISC 2017*, Singapore: Springer, 2019, pp. 669–676.
- [9] A. R. Yusoff, M. M. Foudzi, M. Y. Taib, and A. A. Shah, "Monitoring energy audit for energy savings using non-cost technique at electronics company," *Journal of Modern Manufacturing Systems and Technology*, vol. 5, no. 1, pp. 71–79, 2021.
- [10] A. Kluczek and P. Olszewski, "Energy audits in industrial processes," *Journal of Cleaner Production*, vol. 142, pp. 3437–3453, 2017.

- [11] Y. Wang, Q. Chen, T. Hong, and C. Kang, "Review of smart meter data analytics: Applications, methodologies, and challenges," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 3125–3148, 2019.
- [12] L. Hernández, C. Baladrón, J. M. Aguiar, L. Calavia, B. Carro, A. Sánchez-Esguevillas, *et al.*, "Short-term load forecasting for microgrids based on artificial neural networks and K-nearest neighbours algorithms," *Energies*, vol. 7, no. 3, pp. 1576–1598, 2014.
- [13] T. Ahmad and H. Chen, "Short and medium-term forecasting of cooling and heating load demand in building environment with data-mining based approaches," *Energy and Buildings*, vol. 166, pp. 460–476, 2019.
- [14] Y. Wang, J. Wang, and G. Zhao, "Application of K-nearest neighbour algorithm in short-term electric load forecasting," *Energy Procedia*, vol. 152, pp. 284–289, 2018.
- [15] A. Ahmad, N. Javaid, A. Mateen, M. Awais, and Z. A. Khan, "Short-term load forecasting in smart grids: An intelligent modular approach," *Energies*, vol. 12, no. 1, Art. no. 164, 2019.
- [16] D. Wang, Y. Luo, and X. Grunder, "Solar irradiance prediction for photovoltaic systems using machine learning methods," *Renewable Energy*, vol. 145, pp. 2187–2199, 2020.
- [17] S. Fan, L. Chen, W. Lee, and J. Zhang, "Building energy consumption prediction using K-nearest neighbor algorithm and feature selection," *Energy Reports*, vol. 7, pp. 920–930, 2021.
- [18] S. Shankar, G. Abbas, M. M. Chander Prakash, and V. E. Sathishkumar, "Predictive Modelling of PM2.5 Impact on Pulmonary Function Among Indian Textile Workers Diagnosed with Chronic Obstructive Pulmonary Disease: A Machine Learning-Based Study," *PMRP Journal of Research—Part A: Computational Engineering*, vol. 1, no. 1, pp. 1–13, 2025.
- [19] S. M. Moghimi, T. A. Gulliver, and I. T. Chelvan, "Energy Management in Modern Buildings Based on Demand Prediction and Machine Learning—A Review," *Energies*, vol. 17, no. 3, Art. no. 555, 2024.
- [20] N. Ahmed, Y. Ding, G. Canti, and N. Anglani, "Sustainable Building's Energy Management with Artificial Intelligence and Machine Learning: A Decadal Scoping Review (2014–2024)," *Energy Reports*, vol. 12, pp. 109082, 2026.
- [21] R. Kowalik, M. Nowak, and P. Zieliński, "Artificial Intelligence in Photovoltaic-Integrated Buildings: Forecasting, Optimization and Energy Management," *Energies*, vol. 19, no. 11, Art. no. 2534, 2026.
- [22] Vaisali S, Maheswari C, Shankar S, Naveenkumar R. Predicting the performance of assistive device for elderly people using weighted KNN machine learning algorithm. *Journal of Back and Musculoskeletal Rehabilitation*, Vol.38, no.4, pp.852-864. 2025.
- [23] Priyanka E. Bhaskaran, C. Maheswari, S. Thangavel, M. Ponnibala, T. Kalavathidevi, N.S. Sivakumar, IoT Based monitoring and control of fluid transportation using machine learning, *Computers & Electrical Engineering*, Vol. 89, p.106899, 2021.