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Abstract. As the world seeks sustainable energy solutions, Internet of Things (IoT) applications demand consistent and efficient power sources. This paper presents an innovative hybrid renewable energy system, seamlessly integrating solar photovoltaic panels, wind turbines, and hydrogen fuel cells, tailored for IoT applications. Through machine learning algorithms, our proposed system not only optimizes energy generation in real-time but also ensures uninterrupted energy supply to IoT devices and consumers, even in fluctuating environmental conditions. This universal approach markedly diminishes the dependence on non-renewable energy sources, promoting a greener and more resilient energy infrastructure. The incorporation of hydrogen fuel cells uniquely positions our system as a reservoir for excess energy, ensuring consistent power even when solar or wind outputs diminish. Moreover, by synchronizing IoT devices with our energy system, we have procured real-time data on energy dynamics, facilitating unparalleled optimization and reduced wastage. The presented system shows the way for a sustainable future through the efficient green energy generation with the ever-evolving landscape of IoT applications and machine learning techniques.

Keywords: Hybrid Renewable Energy, IoT Applications, Machine Learning, Hydrogen Fuel Cells.

1 Introduction

The rapid advancement in the Internet of Things (IoT) and Machine Learning (ML) technologies has revolutionized numerous sectors, prominently including the energy domain. IoT devices, when integrated with ML algorithms, can facilitate efficient energy generation, storage, and consumption by ensuring real-time monitoring and predictive analytics. Hybrid renewable energy systems, combining solar, wind, and hydrogen fuel cells, stand as a demonstration to this convergence. These hybrid systems offer a sustainable solution for green energy generation, mitigating the intermittencies associated with individual renewable sources. Influencing IoT for data acquisition from diverse sensors and ML for data analysis, these systems can optimize energy production based on environmental factors and consumption patterns, indicating a new era of eco-friendly and efficient energy management. The Internet of Things (IoT) is driving the Fourth Industrial Revolution, bringing with it vast networks of interconnected devices that transform our daily lives [1]. Recent projections suggest that by 2025, there will be over 75 billion IoT devices worldwide [2]. While the
adoption rate and technological advancements are commendable, they also pose challenges in terms of energy consumption and supply [3].

IoT devices, spanning various sectors like smart homes, smart cities, and industrial systems, need energy solutions that are consistent, sustainable, and green [4]. Traditional energy sources, largely based on fossil fuels, are rapidly depleting and contribute significantly to global carbon emissions [5]. This necessitates a transition to more renewable and cleaner energy sources [6].

Hybrid renewable energy systems, which synergistically combine multiple energy sources such as solar, wind, and tidal, promise increased efficiency and reliability [7]. The introduction of hydrogen fuel cells in these systems offers the potential for high-density energy storage, ensuring uninterrupted energy supply during periods of low renewable energy harvest [8].

Solar energy, being the most abundant energy source, has been widely used in IoT applications, but its intermittent nature remains a challenge [9]. Wind energy, on the other hand, offers another vast resource but its efficiency can be variable based on geographic location and seasonal factors [10]. The promise of hydrogen as a clean fuel source has gathered significant attention in the last decade, and its integration into hybrid energy systems is seen as a pivotal advancement for future energy infrastructures [11].

Machine learning algorithms, with their capacity to analyze large datasets and make predictive decisions, are being integrated into energy management systems [12]. By doing so, these algorithms optimize energy generation, storage, and distribution dynamically, tailoring energy provision to actual demand and environmental conditions [13]. Such innovations are pivotal, especially considering the dynamic nature of energy demand in IoT ecosystems [14].

Furthermore, as IoT devices are inherently data-centric, their synergy with a smart energy system can create a feedback loop where energy usage data further refines and improves energy supply dynamics [15]. This holistic and integrated approach can lead to significant reductions in energy wastage, increase overall system efficiency, and greatly diminish the environmental footprint of IoT systems [16].

As the digital age progresses, the interdependence of IoT and energy will only deepen. Therefore, crafting sustainable, smart, and adaptive energy solutions is not just beneficial, but imperative for a greener and more efficient future [17]. This paper investigates into the intricacies of a hybrid renewable energy system tailored for IoT, exploring its design, advantages, and potential implications for future energy and digital landscapes with the explore of IoT and renewable energy sources. [18].

The integration of IoT and Machine Learning with hybrid renewable energy systems presents an outstanding opportunity to redefine our energy paradigms. The integration of solar, wind, and hydrogen fuel cells, strengthened by the predictive power of artificial intelligence, guides in a future where energy is not only green but is also efficiently managed and distributed. The challenges posed by the energy demands of various customers and especially number of IoT devices can be effectively met with this synergistic approach. As the world increasingly inclines towards a digitally connected landscape, it becomes imperative to adopt energy systems that are sustainable, adaptive, and intelligent. The exploration and adoption of these advanced hybrid systems are not just an academic exercise but a significant step towards a sustainable and interconnected future.

2 Related Literature

The integration of the Internet of Things (IoT) into various sectors, including smart homes, cities, and industrial settings, has prompted significant academic interest in the energy requirements of these evolving ecosystems [19]. This literature review aims to provide a
comprehensive overview of the current research landscape, with a focus on renewable energy solutions tailored for IoT applications.

2.1 IoT and Energy Demand

The explosion in the number of IoT devices has presented a pressing challenge in terms of energy consumption [20]. The dynamic energy demands of modern IoT ecosystems, emphasizing the need for sustainable and consistent power sources [21].

2.2 Renewable Energy in IoT

The role of renewable energy in IoT applications has gained prominence over the last decade. The potential of solar energy in powering IoT devices, noting the challenge of intermittency. Meanwhile, the research into wind energy provided insights into its seasonal and geographic variations and implications for IoT applications [22].

2.3 Hybrid Renewable Energy Systems

Hybrid systems, which combine multiple renewable energy sources, have been proposed as a solution to the variability of individual sources by integrating solar, wind, and tidal energy, a more consistent energy output could be achieved [23].

2.4 Hydrogen Fuel Cells and Energy Storage

Hydrogen's potential as an energy medium in hybrid systems has gained traction. The hydrogen fuel cells, with their high-density energy storage, can buffer periods of low energy harvest, ensuring a steady supply. The hydrogen was proposed as a bridge between renewable energy and IoT applications [24].

2.5 Machine Learning and Energy Optimization

The recent integration of machine learning with energy systems offers avenues for dynamic energy management. The machine learning algorithms could optimize energy distribution, adjusting to changing environmental and demand conditions [25]. The potential for machine learning to refine energy supply dynamics based on real-time data from IoT devices [26].

2.6 Gap in the Literature

While significant strides have been made in exploring renewable energy for IoT, there remains a dearth of research focusing on the integration of these technologies into a cohesive system. Moreover, the role of machine learning in harmonizing energy generation from solar, wind, and hydrogen sources for IoT applications remains an underexplored domain [27, 28].

3 Methodology and Proposed System Design

The methodology to implement the IoT and Machine Learning based Green Energy Generation using Hybrid Renewable Energy Sources of Solar, Wind and Hydrogen Fuel Cells was structured into distinct phases to ensure a comprehensive investigation into the hybrid renewable energy generation system tailored for IoT applications.
3.1 Proposed System Design

3.1.1 Hybrid Energy System

We conceptualized a proposed hybrid renewable energy system as shown in Fig. 1 by combining photovoltaic solar panels, wind turbines, and hydrogen fuel cells. The choice for these particular sources was predicated upon their relative abundance and compatibility within our intended Machine Learning and IoT applications.

![Proposed Hybrid Renewable Energy System](image)

**Fig. 1.** Proposed Hybrid Renewable Energy System

3.1.2 IoT Integration

The designed energy system was integrated with standard IoT devices, consisting of environmental sensors (temperature, humidity, light intensity) and actuators.

3.2 Data Collection

3.2.1 Energy Generation Data

We employed high-precision data loggers connected to each energy source to record hourly generation rates over a period of six months.

3.2.2 IoT Consumption Data

Using a suite of IoT devices deployed across a controlled environment, we collected data on energy consumption patterns, device uptime, and downtime.
3.3 Machine Learning (ML) Model Development

3.3.1 ML Based Methods

Artificial Neural Networks (ANNs) stand out as a cutting-edge approach in the application of Machine Learning techniques. ANNs are designed to process information on a grand scale in parallel, and once adequately trained with the right data, they can carry out nonlinear calculations quickly. Some renowned techniques employed within ANNs to match the functionality of various systems include Radial Basis Function Neural Networks (RBFNN), Back Propagation Neural Networks (BPNN) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) [29]. In this paper, we are primarily using RBFNN features for training of solar, wind and hydrogen fuel energy data, based on that our self-adaptive system can train itself periodically based on local weather conditions and predict the availability of local solar, wind energy and Hydrogen fuel energy.

The structure of an RBFNN is depicted in Fig. 2, and it integrates an input layer, a hidden layer, and an output layer. The radial basis function (RBF), as described in Equation 1, serves as the activation mechanism for the hidden neurons in the RBFNN.

\[ 
\phi_i = \exp\left(-\frac{\sum_{j=1}^{m}(x_i - w_{ij})^2}{2\sigma^2}\right) \tag{1} 
\]

where, \( \phi_i \) is the hidden neuron’s activation function, \( x_i \) is the input vector, \( w_{ij} \) is the connection weight between \( i^{th} \) neuron and \( j^{th} \) neuron and \( \sigma \) is the spread of RBFNN.

Once the target objective is met, the trained RBFNN is assessed using data similar to the training set but with fresh entries. If the outcomes derived from the trained RBFNN are precise, it confirms the local availability solar, wind and hydrogen fuel energy via proposed RBFNN.

3.3.2 Model Selection

Given the time-series nature of our data, we chose Long Short-Term Memory (LSTM) networks as our machine learning model for prediction and optimization tasks.

3.3.3 Training and Validation

Using 70% of our collected data for training and 30% for validation, we trained our LSTM model with our Machine Learning algorithms of Radial Basis Function Neural Network
(RBFNN), Back Propagation Neural Network (BPNN) and Adaptive Neuro Fuzzy Inference System.

3.4 Optimization and Analysis

3.4.1 Dynamic Energy Switching
With the trained LSTM model, we implemented an algorithm that dynamically switches between energy sources based on predicted consumption patterns, ensuring efficient energy usage.

3.4.2 Performance Metrics
The success of the hybrid system was gauged using metrics like Mean Absolute Error (MAE) for prediction accuracy and System Efficiency Ratio (SER) for overall system performance.

3.5 Validation and Testing

3.5.1 Real-world Deployment
The proposed system was then deployed in a real-world smart home environment, housing IoT devices, for a period of 3 months. The performance was observed under different conditions to validate the findings from controlled environments.

3.5.2 Feedback Loop Integration
Continuous data from real-world testing was reintroduced into the model, allowing for a feedback loop that further refined our machine learning predictions and energy optimization. The methodologies employed ensure a rigorous and iterative approach to understand and optimize a hybrid renewable energy system for IoT applications. The aim is to offer insights that are both theoretically sound and practically implementable.

4 Test System and Results

4.1 Proposed Test System
The data obtained from our hybrid renewable energy system tailored for IoT applications over the observation period yielded several significant findings through the proposed system design as shown in Fig.1 and its corresponding implementation block diagram as shown in Fig. 3.
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4.2 Results

4.2.1 Case-1: Energy Generation Patterns

**Solar Energy**

Over the six-month period, our photovoltaic solar panels produced an average of 15 kWh/day. Peaks in energy production were observed between 11:00 AM and 3:00 PM, coinciding with maximum sun exposure.

**Wind Energy**

Wind turbines generated an average of 10 kWh/day. Notably, peak wind energy production occurred during the early morning and late evening, complementing the solar generation dips.

**Hydrogen Fuel Cells**

These cells consistently provided an average energy output of 5 kWh/day, serving as a reliable backup during periods of reduced solar and wind generation.

The obtained results from the proposed test system of case-1 are presented in Table 1.

<table>
<thead>
<tr>
<th>Month</th>
<th>Solar Panels</th>
<th>Wind Turbines</th>
<th>Hydrogen Fuel Cells</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>14.2</td>
<td>10.5</td>
<td>5</td>
</tr>
<tr>
<td>February</td>
<td>15.1</td>
<td>9.8</td>
<td>5</td>
</tr>
<tr>
<td>March</td>
<td>16.5</td>
<td>11.2</td>
<td>5</td>
</tr>
<tr>
<td>April</td>
<td>17.8</td>
<td>10.4</td>
<td>5</td>
</tr>
<tr>
<td>May</td>
<td>16.9</td>
<td>9.5</td>
<td>5</td>
</tr>
<tr>
<td>June</td>
<td>14.7</td>
<td>10.7</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 1. Daily Energy Production Rates (kWh/day) of Case-1
4.2.2 Case-2: IoT Energy Consumption Patterns

Average energy consumption of the IoT devices in our controlled environment was 25 kWh/day. Peak consumption was observed during early mornings (6:00 AM to 8:00 AM) and evenings (6:00 PM to 9:00 PM). The corresponding results of this case-2 are shown in Fig. 4.

4.2.3 Case-3: Machine Learning Model Performance

The LSTM model exhibited a Mean Absolute Error (MAE) of 0.5 kWh in predicting daily energy consumption patterns of IoT devices, suggesting a high degree of accuracy in forecasting energy needs. The corresponding results of this case-2 are shown in Fig. 5.

4.2.4 Case-4: Dynamic Energy Source Switching

Over the observation period, the algorithm effectively sourced 60% of required energy from solar panels, 30% from wind turbines, and 10% from hydrogen fuel cells. This dynamic switching ensured a consistent energy supply to IoT devices, even during periods of reduced generation from individual sources.

4.2.5 Case-5: Real-world Validation

In this study, the efficacy of combining solar, wind, and hydrogen fuel cells to power IoT applications was substantiated by consistent energy production rates over a span of six months. The variable energy demands of IoT devices throughout the day, as visualized in Fig. 4, were aptly met by the hybrid system. Crucially, the LSTM model's accuracy in forecasting these demands, evident in Fig. 5, underscores the potential of integrating machine learning with renewable energy sources. This approach not only aligns with global
sustainability goals but also offers promising implications for diverse IoT domains, championing a shift towards more sustainable and efficient energy solutions.

![Hourly Energy Consumption vs. LSTM Model’s Predictions](image)

**Fig. 5.** LSTM model’s prediction accuracy visualized against actual energy consumption patterns.

![Solar energy prediction using RBNN](image)

**Fig. 6.** Solar energy prediction using RBNN

In the real-world smart home environment, the proposed hybrid system effectively predicts the local solar energy using RBFNN machine learning method and its corresponding result shown in Fig. 6. It indicates that the proposed system prediction accuracy is realistic when compared with actual solar energy.
5 Conclusion

The integration of hybrid renewable energy sources with machine learning, as presented in this paper, signifies a profound evolution in the quest for sustainable energy solutions tailored for the Internet of Things (IoT). Our findings indicate that solar, wind, and hydrogen fuel cells, when optimally harnessed, can not only consistently power IoT applications but also counteract the typical intermittency associated with individual renewable sources. By leveraging a Long Short-Term Memory (LSTM) model, the energy consumption patterns of IoT devices were accurately predicted, which is paramount for the proactive management of energy resources. Furthermore, when juxtaposed with existing solutions in the field, our approach not only promotes green energy but also addresses the unique, fluctuating demands of IoT infrastructures, from smart homes to expansive smart cities. Such adaptability, underscored by real-time adjustments and predictions, exemplifies a notable advancement in energy-efficient technologies.

This paper also bears implications for future studies and applications. While the current system has demonstrated significant potential, there remains an opportunity to incorporate additional renewable sources and optimize the system for diverse climatic and geographical regions. Similarly, the machine learning model can be further refined, considering other predictive algorithms or neural network architectures to enhance accuracy. Beyond the technical realms, this study reaffirms the broader goal of environmental sustainability in technological advancements. As global connectivity burgeons, there exists a concurrent responsibility to minimize the ecological footprint. Our work serves as a testament to this objective, offering a blueprint that marries innovation with conservation. Future endeavours in this domain would benefit from building upon this foundation, further pushing the boundaries of what's achievable at the nexus of IoT and green energy.

References
