INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH
A. S. M. Antony et al., Vol.14, No.1, March, 2024

Energy Storage Systems Using Renewable Energy for Systems With Grid Integration

A. Santhi Mary Antony[1*], Jayarama Pradeep[2], Sri Harsha Arigela[3], Rajesh T[4], P. Elangovan[5], M Ramprasad Reddy[6], Sivasankar G A[7], Dr. A. Rajaram [8]

[1] Electrical and Electronics Eng., Loyola-ICAM College of Eng. and Technology, Chennai, Tamil Nadu 600034, India,
Electrical and Electronics Eng., St. Joseph's College of Eng., Chennai, Tamil Nadu 600119, India.
[3] Mechanical Eng., Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh 522302, India.
[4] Electrical and Electronics Eng., J. B. Institute of Eng. and Technology, Hyderabad, Telangana 500075, India.
[5] Electrical and Electronics Eng., Sreenivasa Ins. of Tech. and Mana. Studies, Chittoor, Andhra Pradesh 517127, India.
[6] Elect. and Electro. Eng., Mohan Babu Uni., Sree Vidyanikethan Eng. College, Tirupati, Andhra Pradesh 517102, India
[7]Dep. of Aeronautical Eng., KIT - Kalaignar Karunanidhi Institute of Technology, Coimbatore, Tamil Nadu 641402, India.
[8] Electronics and Communication Eng., E.G.S Pillay Engineering College, 611 002 Nagapattinam, India

(msanthimary@gmail.com, jayaramapradeep11@gmail.com, sriharsha290@gmail.com, rajesht39@gmail.com, elangovanp67@gmail.com, ramprasadreddy56@gmail.com, sivasankarga20@gmail.com, rajarama20@gmail.com)

*Corresponding Author; A. Santhi Mary Antony, Department of Electrical and Electronics Engineering, Loyola-ICAM College of Engineering and Technology, Chennai, Tamil Nadu 600034, India, msanthimary@gmail.com

Received: 29.05.2023 Accepted:28.10.2023

Abstract - Challenges in remote electricity supply include absent grid infrastructure, geographical barriers hindering conventional power installation, intermittent renewable sources impacting consistency, and limited funding impeding reliable energy solutions.In the light of these challenges, standalone hybrids renewable resources, which include sources of energy that replicate sunlight, wind, and other sources of renewable energy, were proven to be an efficient solution for bringing power to isolated areas which aren't linked to utility systems. The availability of sufficient supplies of energy is constrained by a variety of reasons, involving variations in peak demand, power outages, and other elements. This paper responds to these issues by presenting a comprehensive strategy for effectively harnessing and distributing hybrid renewable energy sources. The key innovation lies in the integration of predictive modeling and advanced optimization techniques. The strategy's core framework leverages the initial utilization of Long Short-Term Memory (LSTM) systems to anticipate weather conditions and load demands, enabling the quantification of uncertainty in energy needs. This predictive capability is pivotal for achieving optimal resource allocation.The goal of doing this is to aid in optimum resources scaling. Central to the proposed approach is the incorporation of the shuffled shepherd optimization algorithm. By merging this algorithm with forecasted data, the paper outlines a methodology for efficiently allocating energy resources. This allocation process, underpinned by real-time predictions, is pivotal for optimizing energy utilization and minimizing inefficiencies.The framework's effectiveness is evaluated using a range of pertinent performance metrics, including fluctuation rates, battery power, Loss of Power Supply Probability (LPSP), prediction accuracy, net current costs, and overall power cost. These metrics facilitate a comprehensive assessment, showcasing the proposed strategy's superiority over existing approaches.

Keywords: Solar PV Systems, Renewable energy systems, energy management, and optimum Sizing.

1. Introduction

There are many applications for RESs, including solar and wind energy. At the moment, attention has been placed on HRES, including solar-wind, PV hydrogen, and many more [1], [2]. An example of an intelligent house would have a television (80W), fans (40W), refrigerator, and LED bulb (20W) (200W). The total amount of electricity required for contemporary architecture is 340W, with individual electrical demands for each element. Presently, various applications of Renewable Energy Sources (RESs), including solar and wind energy, are explored, with a notable emphasis on HRES configurations such as solar-wind and PV hydrogen systems. Off-grid HRES represents a paradigm shift, detaching the hybrid system from electrical grids to achieve self-sufficiency. Off-grids HRES makes it clear that the hybrid system is no longer reliant on the electrical grids and cannot communicate with them. In this case, the full load has to be powered by the HRES's output [3] [4] [5] . HRES size has become the key problem that significantly affects the administration of power. An optimum design is a process of selecting the appropriate state parameters, including the number of winds-turbines, photovoltaic panels, and batteries for the standalone HRES [6], [7]. The challenge of unpredictability is addressed in optimum sizing since dynamic energy production is challenging and essential for immediate power supply. For example, the relevance of loads changes depending on weather conditions and other external variables. In order to reduce the energy costs (COE) as well as the current value costs (NPC), HRES is scaled ideally. The COE and NPC are minimized and the oscillation rates are decreased during this period due to the greatest demand and electricity-generated estimates [8], [9]. Nevertheless, excessive energy use is also a significant issue. The administration of batteries specifically must be optimal; alternatively, upgrades would have to be done more often, thereby increasing the cost. State of Charging (SOC) handling is among the best methods for controlling power. In order to control the SOS levels, the power-limiting mechanism is employed. For a number of purposes, ML and deep learning (DL) techniques are often used in HRESs. Numerous variables, which include systems weight, electrical mileage, and batteries degradation, have to be considered into account in order to maximize the system's efficiency, battery's degradation, and systems weight. When an independent micro-grid is in operation, it may utilize a variety of responsible resources, including biomass, solar energy, hydroelectric power, marine, and so on. PV/WT is used to determine the ideal size of electric hybrid systems. The micro-grids help with higher voltages production of energy along with acting as utility grids in the event of natural catastrophes. The microgrids may examine the consequences of possessing a significant quantity of renewable power linked to this, disperse system frequencies, and apply voltage control strategies. As a result, the microgrid's loads dispatching system is an essential process [10]. For predicting load, a number of methods are used, involving Deep Recurrent Networks, ANN, and SVM. The off-grid hybrids renewable technology used to choose the great supplies for addressing power shortages at peak times. Several agents have been implemented by the off-grid HRES to help with the management of energy. But increasing the number of agents also increases the cost. There are many more methods in the domain of optimum size presented by HRES. Several optimizing strategies, such as the PSO technique, the cuckoo search technique, and more were presented to address issues with optimum scaling. Limiting the possibility that HRES could be linked to the grids is crucial to the achievement of the goals. The enormous amount of historical data is frequently taken into consideration using the optimal size approach. As an outcome, the techniques for optimization are unable to manage the huge volume of entering data. Additionally, PSO, CS, and SA have greater difficulties with convergence than the other methods, which leads to inadequate scaling. The study's synthesis involves a combination of predictive frameworks and optimal sizing, with climate forecasting performed by neural networks and load prediction utilizing ML and DL techniques. These anticipated outcomes are pivotal for establishing effective HRES solutions and addressing energy challenges. In light of these considerations, the study aims to contribute to the advancement of off-grid HRES design, addressing its challenges and optimizing its performance.

2. Related Work

According to [11], in the setting of irregular wind and solar energy resources, the efficacy of integrated renewable battery banks, smart-grids transmission of power innovations, and other alternative sources of power are estimated. The investigation provided the MORSO with a hybrid control algorithms with predictive modeling (MPC) for renewable energy sources and intelligent grid power system electrical voltage regulation solution. The difficulties with tuning variables in the control of frequencies are addressed by achieving online adjustment of the LFC variables using the advised altering regulate approach. The solution under discussion is a closed-loop structure that combines wind, photovoltaic, FC, and batteries can adjust its load while integrating with the power grids. To get the greatest outcomes, all of the controllers configurations in various energy grid units are developed utilizing a tailored optimum approach and the particle swarm optimizations technique rather than a traditional function of objective with fluctuations restrictions. For the purpose of reducing the disparities between consumption and production, MPCs were developed for the forecasting Pv generations, winds-turbines, and battery banks. In this approach, electricity produced is also utilized to reduce the regularity of the controlled loads. The efficiency, reliability, adaptability, and stability of the suggested approach are examined as they relate to the energy systems in the Simulink/Matlab system while evaluating the recommended maintenance technique. The simulated results demonstrate that the suggested control method frequently approaches an ideal operating position, which lowers total users' disutility, restores regular frequencies and planned tie-line reactive and keep up the transmission line's temperature limits. Additionally, the different results demonstrate that convergence continues approach uses the wrong hyper-parameters. Lastly, computerized simulations are employed to show how the suggested technique is resilient, optimum, and effective. In contrast with earlier systems, it is also demonstrated that frequency regulation restores effectively in energy usage. An evaluating approach is additionally employed to determine how effective the recommended approach performs. This work offers forecasts about the performance of integrated battery/FC/Wind/PV maintaining and smart-grids for power in the context of irregular wind and solar power supplies. The research presented an electric controlling system for a grid generation system depending on MOPSO hybrids and MPC hybrid RESs. Utilizing the suggested adaptive control technique, the problems with choosing parameters in the control of load frequencies are addressed by an online change of the load's frequency maintenance features.

The smart grid that combines winds, photovoltaic, FC, and batteries with variable commanding loads is the method under study. To get the best output, all of the regulators' settings for lot of different units including energy grids are built utilizing a tailored optimization issue and an optimized particle-swarming approach, as opposed to employing a typical function of objectives with switching limitations. For the storage batteries, winds turbine, and forecasting Pv generations, MPCs were developed to manage consumption and production in a positive way. This design also included electricity generation to decrease the frequency of the controlled loads. The efficiency, reliability, adaptability, and stability of the suggested technique as it relates to the electrical system are examined in the Simulink/Matlab domain. The findings show that the suggested method can control frequently approaches an ideal operating position that decreases total user circumstances, recovers typical frequencies and established tie-line reactive energy flows, and maintains transposition line temperatures constraints. Additionally, the results from the micro-experiments demonstrate that converging continues even when the controlling mechanism uses the wrong settings. Additionally, computational simulations are employed to establish the suggested strategy's robustness, optimal performance, and effectiveness. As demonstrated, as compared to earlier systems, frequency regulation restores cheaply and effectively in the event of an energy usage disruption.

The sensitivity test additionally serves to access the suggested method[12]. The massive LSS PV tries to bridge the void as Malaysia gets ready to switch power. The management aims to increase the share of renewable power in the generating combination to 20% by 2025. In both the initial and second stages of the LSS system, 958 MW of PV installations are anticipated to be finished by 2020. An overall capability of 500 MW is the goal of the third phase of the LSS scheme. Due to its unpredictable nature, the LSS Photovoltaic array presents the biggest integration difficulty for the worldwide electrical system. The goal of this study is to identify Malaysia's LSS's best possible energy system tactical strategy for managing instability in voltage utilizing an IEEE-bus architecture. Restricted PSS/E and PVSyst perform simulation and administration of the networks type. The goal of this study is to develop an LSS-integrated grid technique that reduces loss in transmission while meeting the requirements of the Malaysian grid codes for energy. Harmony is also addressed while including energy electrical devices for flexible power adaptation. This study is designed to serve as a benchmark for providers of utilities in other countries with similar networks and grids settings [13] [14]. Due to their importance for the types of interconnected renewable sources of energy in the electric power networks, distributed production will become more widespread in a short time. Renewable sources of energy including solar and wind energy are still quite unpredictable since they are powered by wind and rain. These supplies and demands, which may cause erratic variations on both the producing and loading sides, may make even the finest control of energy more challenging. MDP was used to handle the EMS structure, which is described as a Markov management procedure in this research. A new solution to the issue has been proposed in order to shield the administration of capability from excessive grid rates. The battery's energy may now be used more effectively owing to this adaptation. The development of a complete reward system that minimizes the examination of unrealistic acts has increased the efficacy of the data-gathering technique. After that, when considering that future data is unpredictable, the operational expense of the microgrids is reduced by utilizing a Q-learning approach. To determine the efficacy of the recommended EMS, a contrast amongst the trading EMS simulation and the non-trading instance is made utilizing a conventionally constructed loads curve and the photovoltaic profiles with 24-hour horizons.

The infrastructure decides on an optimum power plan that lowers the costs of energy (also referred to as the costs of power and actually Muhammad, A. N., Bukhori, & Pandunata (2019, October). This is done based on the simulations' findings. Employing the naive Bayes-support vector machines (NBSVM) classifiers, we analyze sentiments of negative as well as positive feedback on YouTube. In each of the cases under consideration, IEEE battery wear was present in the 2019 International Seminar to the Computer Science, IT, and Electrical Engineering (ICOMITEE) (pp. 199–205). However, it was shown that operating expenses for the trading and non-trading EMS systems were reduced by 4.033% in summertime and 2.199% in wintertime [15–21]. Photovoltaic solar panels are gaining popularity at the moment due to their capacity to turn solar energy directly into electrical power. The electricity generated by PV installations is seldom capable to satisfy demand needs fast, though, as there isn't a sufficient supply to swiftly meet customer demands. Grids-connected photovoltaic solar panels have received attention recently due to their usage of stored energy and flexible load management while solving the major quality of power concerns in the networks. This makes solar photovoltaic panels even more effective and useful. Various battery control methods are utilized to increase estimation demands and ensure the optimum inclusion of photovoltaic systems into the energy grids. The extensive deployment of solar photovoltaic panels has been impacted by the growth of electricity policy. The goal of this study is to investigate different modeling and sizing techniques for solar photovoltaic system efficiency. We discuss techniques to optimize photovoltaic systems' energy storage as well as ways to increase their earnings. It has also been examined how inverter/converter innovation, management, and voltages quality concerns relate to the present state of photovoltaic systems innovation in relation to different cellular technologies [22–26].

The mentioned studies are collectively highlight the research gap in the context of irregular wind and solar energy integration. While advancements have been made in integrated renewable battery banks, smart-grid transmission innovations, and alternative power sources, there remains a need to address challenges related to tuning control variables, frequency regulation, and load management in dynamic grid systems. The studies reveal a gap in achieving effective online adjustments for frequency control and load integration, particularly in the presence of fluctuating renewable sources. Furthermore, the investigations emphasize the necessity for tailored optimization approaches and advanced control algorithms to optimize energy generation and consumption while ensuring grid stability. The research also underscores the need for innovative energy management strategies that account for unpredictable renewable supply and demand patterns, while effectively integrating different energy sources like wind, photovoltaic, fuel cells, and batteries. In summary, the research gap pertains to the development of comprehensive and adaptable control strategies that address frequency regulation, load management, and energy optimization in the complex setting of irregular renewable energy resources, ultimately contributing to the stability and reliability of modern power grids [27-31].

3. System Model

Battery lifetime optimization suffers from an absence of demands-side data (critical and non-critical loads), which lowers the efficiency of the system. There is a considerable difference between the efficiency of the system (measured in regards to costs and LSLP) and battery lifespan extensions because the majority of research focuses primarily on the mathematical aspect and actual time battery administration, including battery compensation, hasn't been emphasized. The formulation for cost reduction is as follows:

$$\mathrm{MinC_t}(\mathrm{P_{sa}}(\tau), \mathrm{P_{wt}}(\tau), \mathrm{P_{bt}}(\tau) = \mathrm{Min}\big(\mathrm{C_{sa}}(\tau), \mathrm{C_{wt}}(\tau), \mathrm{C_{bt}}(\tau)\big) \quad (1)$$

Where, the $\mathrm{MinC_t}(\mathrm{P_{sa}}(\tau), \mathrm{P_{wt}}(\tau), \mathrm{P_{bt}}(\tau)$ denotes the minimized cost function representing the total cost of the hybrid renewable energy system (HRES) based on the costs of solar, wind, and battery components. The costs of solar, wind, and batteries are indicated by the letters $C_{sa}(\tau)$, $C_{wt}(\tau)$, , and $C_{bt}(\tau)$, correspondingly, where C_t represents the complete expense of the HRES. The present value of the sum of all expenses, encompassing replacements, investments, operations, and sustaining expenses, is employed to calculate the NPC [32]. These expenses need to be reduced to create a low-cost system. The NPC is established as follows:

$$\mathrm{NPC_{(Hb)}} = \sum_{1}^{\mathrm{LT}} \frac{1}{(1+\mathrm{i_k})^{\mathrm{LT}}} (\mathrm{CHb_c} + \mathrm{Om_c} + \mathrm{R_c} - \mathrm{S_c}) \quad (2)$$

Where Hb refers to the integration of resources for wind and solar power and CHb_c for the overall capital expenditures related to those resources [33]. Om_c indicates operating and maintenance costs and R_c indicates the replacement costs and S_c indicates the salvage costs. The i_k and LT referes the interest rates, and lifetime of projects individually.

The costs of power is a crucial indicator($\mathrm{CoE_{Hb}}$) which quantifies the cost of producing one unit of energy over the lifetime of the HRES. It considers the total costs associated with capital investments, operations, maintenance, and replacements, divided by the total energy output of the system [34]. This also known to be project's financial viability and may be expressed as follows:

$$\mathrm{CoE_{Hb}} = \frac{[\mathrm{Cwt_c} + \mathrm{Om_c} + \mathrm{R_c} + \mathrm{S_c}] \times \frac{\mathrm{i_k}(1+\mathrm{i_k})^{\mathrm{LT}}}{(1+\mathrm{i_k})^{\mathrm{LT}-1}}}{\sum_1^{\mathrm{LT}} \left[\mathrm{E_{sa}} + \mathrm{E_{wt}} + \mathrm{E_d} \times \frac{1}{(1+\mathrm{i_k})^{\mathrm{LT}}}\right]} \quad (3)$$

Where $\mathrm{Cwt_c}$ represents the Capital cost associated with wind turbine resources. E_{sa}, E_{wt} represents the power-produced from the solar, winds power resources and E_d represents the power discharged correspondingly. To demonstrate that a certain project is financially viable, the CoE must be minimized [35].

In order to provide a stable and continuous supply of electrical power, the LPSP—a measurement of the electrical powers produced by the HRES models—should be decreased. The LPSP metric quantifies the proportion of power deficit or loss of supply probability. A lower LPSP value indicates a more reliable HRES model that can consistently meet power demands , the HRES algorithm's LPSP is calculated as,

$$\mathrm{LPSP_{Hb}} = \frac{\sum_{\tau=1}^{k}\big[\mathrm{P_r}(\tau) - [\mathrm{N_{sa}P_{sa}}(\tau) + \mathrm{N_{wt}P_{wt}}(\tau) + \mathrm{P_d}(\tau)]\big]}{\sum_{\tau=1}^{k}[\mathrm{P_r}(\tau)]} \quad (4)$$

Where $P_r(\tau)$ indicates the references energy at time (τ), N_{sa}, N_{wt} represents the numbers of solar photovoltaic arrays and winds-turbines, P_{sa}, P_{wt} represents photovoltaic arrays and winds-turbines and $P_d(\tau)$ indicates the energy discharged at time (τ).

The reliability of the HRES paradigm is shown by the fluctuating rates, a minimum value of Fr implies greater stability in meeting power demands and minimizing abrupt changes in power output. This stability is crucial for ensuring a reliable and continuous supply of electricity, which is especially important for systems serving critical loads and isolated areas. which may be expressed as follows:

$$\mathrm{F_r(Hb)} = \frac{1}{\mathrm{P_r}(\tau)} \sqrt{\frac{1}{\mathrm{k}} \sum_{\tau=1}^{\mathrm{k}} [\mathrm{N_{sa}P_{sa}}(\tau) + \mathrm{N_{wt}P_{wt}}(\tau) - \mathrm{P_r}(\tau)]^2} \quad (5)$$

Greater reliability is demonstrated in the HRES paradigm when the fluctuating rates are at their lowest point. The anticipated consumption load and weather data are demonstrated in the subsequent for the best size of RESs including winds-turbines, photovoltaic arrays, and banks of batteries [36]. This phase uses two steps of a unique deep and optimized-grap technique to identify variables of state. The suggested method uses previous data to anticipate the demand and weather in the initial phase. The amount of electrical power utilized by the device ρi over a period, which is a representation of the amount of power needed for devices like electric current, lightning, and other appliances, is utilized to evaluate the demands for load. The formulation is as follows:

$$\varepsilon_l = \sum_{i=1}^{n} \rho_i \times t_i \quad (6)$$

This above equation calculates the total electrical energy demand (ε_l) by summing up the products of power demands (ρ_i) and corresponding time durations (t_i) for each device or load. For early forecasting, we propose individualized LSTM networks, a similar deep learning technique. In the initial stage, historic weather conditions and data loads are utilized to compile the predicting data. Estimating the prediction of weather is preferred since forecasts for atmospheric conditions are susceptible to alter as time passes. It is anticipated that this will make precise demand on load and forecasting of the weather feasible. For the purpose of gathering data and predicting the demand for loads, we took into account the following factors. Actual temperatures, relative humidity in proportion, the speeds of the winds in kilometers per hour, climate codes, and classification field that denotes the four distinct weather seasons—0 for springtime, 1 for the summertime, 2 for fall, and 3 for winter—are among these. It also tracks home lifestyle, households economy, weather conditions, and historic power and energy usage of the loads [37].

One neural network framework called LSTM was created expressly for understanding the relationships between both long- and data that get around the problems of expanding and disappearing. The many-in-many-out approach used to run our suggested framework predicts various projections of the present demand using a variety of sources. LSTM offers a robust dependability operation that collects both non-linear and linear time-varying data and improves forecasting demand precision when contrasted with different neural-networks. the 4 gates, including a source gate, a forgot gate, an inside gate, and a result gate, are part of the LSTM specifically. With the cells and gates, the data flow is managed. Fig. 2 demonstrates the suggested method of LSTM. The suggested LSTM algorithm's theoretical formula is described below:

(i) $x(t_i)$ → Input value

(ii) $h(t_{i-1})$ and $h(t_i)$ → Result values across the time t_{i-1} and t_i

(iii) $c(t_{i-1})$ and $c(t_i)$ → Cell-states across the time t_{i-1} and t_i

(iv) $\beta = \{\beta_a, \beta_f, \beta_c, \beta_o\}$ represent the internal state, forget gate, output gate, and input gate biases.

(v) $\overrightarrow{\omega_1} = \{\omega_a, \omega_f, \omega_c, \omega_o\}$ denotes the matrix of weights for output gate, input gate, forget gate, and internal state.

(vi) $\overrightarrow{\omega_2} = \{\omega_{ha}, \omega_{hf}, \omega h_c, \omega_{ho}\}$ denotes the weighted values in the frequent results.

(vii) $\vec{a} = \{a(t_i), f(t_i), c(t_i), o(t_i)\}$ demonstrates correspondingly, the resultant outcomes for the input gates, forget gates, internal gates, and output gates.

An operational LSTM framework is created by taking into account the aforementioned factors is shown in fig.1. The predicted data is then given into the optimization phase, which is the next step. At this point, we recommend the shuffled shepherd optimization($S^0_{m,n}$) technique, it has effectiveness in handling complex optimization problems and can able to quickly converges and well. By incorporating the S2OA into the optimization process, the proposed approach leverages its ability to effectively allocate resources, optimize power generation, and improve the overall efficiency of the HRES. Initially, this formula is applied for initializing both the inputs and S2OA variables.

$$S^0_{m,n} = S_{min} + r * (S_{max} - S_{min}) \tag{7}$$

$$n = 1,2, \ldots i \;\&\; m = 1,2, \ldots . j \tag{8}$$

Here, S_{min} and S_{max} is the minimum and maximum allowable allowable value for the optimization variable. r denotes the randomly selected number between the 1 and 0 correspondingly, i and j denotes in the every group. Each group's member are presented in the primary column, which is described below:

$$M_C = \begin{bmatrix} S_{1,1} & S_{1,2} & S_{1,j} & \cdots & S_{1,n} \\ S_{2,1} & S_{2,2} & S_{2,j} & \cdots & S_{2,n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ S_{i,1} & S_{i,2} & S_{j,2} & \cdots & S_{i,n} \\ S_{j,1} & S_{j,2} & S_{m,j} & \cdots & S_{i,j} \end{bmatrix} \tag{9}$$

The following step is to determine the group member's activity($Step_{n,m}$), which is then classified as either good ($Step^{Best}_{n,m}$)or bad($Step^{Worst}_{n,m}$).

$$Step_{n,m} = Step^{worst}_{n,m} + Step^{Best}_{n,m} \tag{10}$$

Here, n indicates $1,2, \ldots i \;\&\; m = 1,2, \ldots . j$. The following description applies to the end procedure.,

$$\text{new } S_{n,m} = S_{n,m} + Step_{n,m} \tag{11}$$

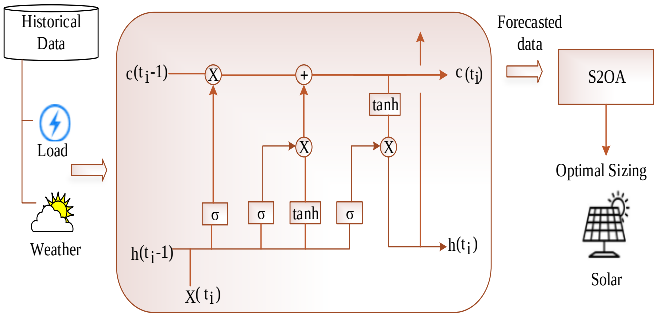

Fig.1 Process of Deep Optimal-Sizing

The S2OA chooses the best size while taking dependability and expense into account. Given the limitations of the anticipated loads and weather conditions, all these variables determine the HRES's optimum scale. Here, we accomplish the following,

- Optimal size reduces the costs
- Enhanced dependability such as continuous electricity supply
- Predicting further reduces the uncertainty

The following formula can be used to express the overall power produced by the suggested method:

$$\rho_{total}(t) = \sum_{pv=1}^{Q_n} \rho_{pv}(t) + \sum_{pv=1}^{Q_m} \rho_{wT}(t) + \sum_{pv=1}^{Q_o} \rho_{bb}(t) \tag{12}$$

Here Q_n, Q_m and Q_o are the total number of winds-turbines, solar cells, and banks of batteries, correspondingly. Equation (12) represents the HRES's total power generation, encompassing contributions from solar, wind, and battery components. It underscores the integral role of accurate power estimation and resource optimization in achieving the overarching objectives of stable, cost-effective, and reliable energy supply in the proposed hybrid renewable energy system [38].

In conclusion, incorporating optimization based on predictions enhances the system's ability to make proactive and well-informed decisions. By leveraging the LSTM model's predictive capabilities, the framework can identify system configurations that maximize efficiency, reduce costs, and extend the overall lifetime of the hybrid renewable energy system. This synergy between predictive modeling and optimization is a key strength of the proposed approach, ensuring that real-time and future conditions are considered when making critical energy management decisions.

4. Results & Discussion

The proposed battery lifetime optimization framework relies on historical data collected from the hybrid renewable energy system. Load demand data, weather conditions, energy generation from solar and wind sources, and battery behavior patterns are crucial inputs. These data are collected over a specific time period and undergo preprocessing steps to ensure accuracy and consistency. Validation of the data involves cross-referencing with reliable sources, and data quality checks are performed to identify and rectify any outliers or inconsistencies. Several input parameters are considered in the optimization process. These parameters encompass weather-related variables such as temperature, wind speed, and humidity, which impact energy generation. Load demand data, classified by type (critical and non-critical), is another key input. Battery characteristics, including capacity, efficiency, and degradation rates, are also incorporated. Economic factors like capital costs, operating and maintenance expenses, and interest rates play a role in the cost calculations. To develop and validate the battery lifetime optimization model, the dataset is divided into three subsets: training, testing, and validation data. The training data constitute a significant portion of the historical records and are used to train the LSTM network. Testing data are separate from the training set and are employed to fine-tune the model and assess its performance. Validation data, representing an independent set of historical records, are used to evaluate the model's predictive capabilities and ensure its generalizability to new data [39] [40].

Utilizing MATLAB R2020b's simulation method, the proposed framework is evaluated. The setup options required for the simulated technique are listed in Table 3 below. The energy production mechanism in the simulation is composed of grids turbines and solar panels. Table 4 contains the list of variables utilized in the simulated investigation. The Simulink architecture for the suggested solution has also been created.

Initially, the battery power of current methods is contrasted with that of our recommended approach. This comparison also takes into consideration the total number of repetitions and accounts for both solar and grid-connected power. In comparison to past approaches, the suggested solution improved the bank of batteries power, increasing the lifespan of the battery. It accomplished this by incorporating battery control methods such as modes choice, compensation, and the correct size. Fig.2 compares the bank of batteries power of our proposed technique, which takes into consideration both solar and grid-connected power and alternative current techniques.

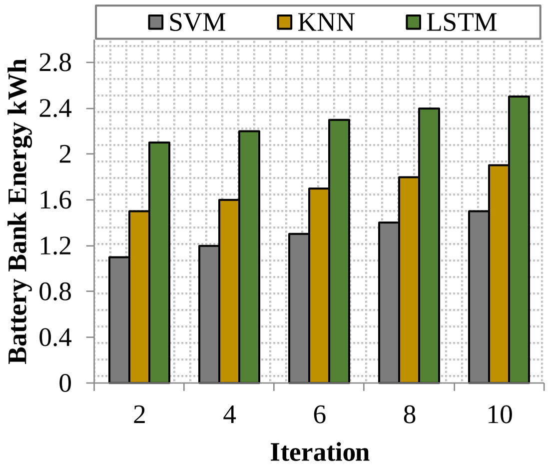

Fig.2. Battery bank energy (both solar and grid battery)

The suggested approach has increased the bank of battery power to around 2.3kWh once solar and grid-connected power were combined, and this is preferable to merely taking into consideration solar power or grids power. The present methodologies have an optimal energy consumption of about 1.6kWh, however, the suggested strategy possesses a larger power capability. The finding that our recommended design efficiently improves the power output of the battery banks.

The recommended strategy's net present cost, that incorporates hybrid sources of energy, is depicted in Fig.3. Our suggested algorithm's net present expense, which accounts for the grids and solar power resources equally, is compared to that of earlier methods with regard to the total number of repetitions.

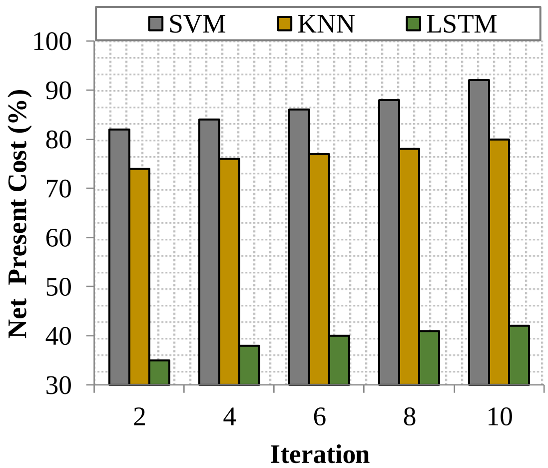

Fig.3. Net present costs (both solar and grids battery)

In comparison with utilizing grid (58.2%) or the solar energy (56%), the hybrid system's net present cost for the scheduled tasks is 39.2%. The hybrid power system's cost comparison with only one source of energy demonstrates that it is more expensive and less efficient. Additionally, 86.4% of the net current costs demonstrate how cost-effective the prior procedures performed. Overall, the hybrid approach demonstrates economic viability and long-term cost savings.

Examining the LPSP of the recommended paradigm while accounting for solar and grid sources of energy. Fig.4 contrasts the suggested approach to the existing ones while accounting for hybrid renewable energies and taking into consideration the total amount of repetitions. The LPSP of our prototype is quite small due to the effective battery management of energy. As a consequence, the energy supply is sufficient and there aren't any shortages of electricity, leading to improved stability and consistency in delivering electrical energy to consumers. This increased reliability is particularly advantageous for remote or off-grid areas where consistent power availability is crucial for various applications, including critical services and everyday activities. Existing approaches for managing batteries poorly cause an increase in LPSP.

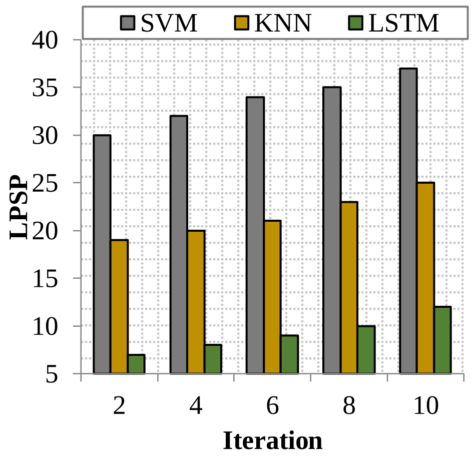

Fig.4. LPSP (both solar and grid battery)

This highlights how well the recommended approach combines and handles data from various sources of energy. The LPSP is one of the current approaches, and its uptake of 33.6%, which is over three-times the rate of alternative methods, leads to an assumption that the framework is effective. The extent assessment was carried out to fluctuations for the framework, and the proposed approach incorporates the energy resources.

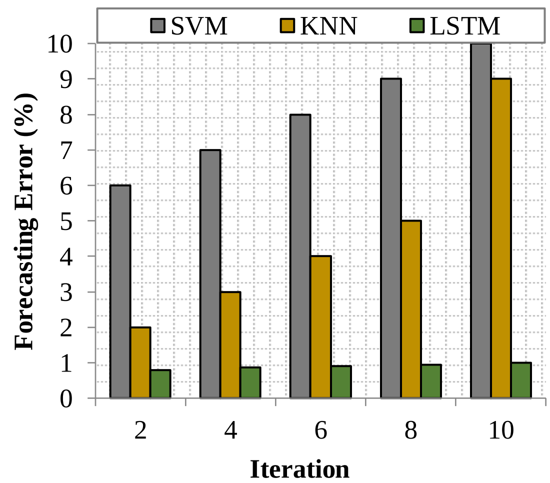

Fig.5. Forecasting error (both solar and grid battery)

Fig. 5 compares the recommended system's and current approaches' predictions of correctness for the total amount of repetitions. The minimal prediction inaccuracy of our suggested approach is due to a combined estimation of demand for loads and weather that considers hybrids sources of energy. Users that keep large volumes of historical data permit precise weather conditions and load predictions with little inaccuracy. The present approaches cannot manage the large training dataset, leading to predicting errors. By providing accurate weather and load demand estimates, the model minimizes inefficiencies and ensures optimal resource allocation, resulting in proposed approach improvements in energy management and system reliability.

The cost of energy for this suggested strategy, which uses grid and solar energy sources. Fig.6 contrasts the CoE of the approaches now in use with those of our proposed framework, which incorporates hybrid energies. Since it utilizes the greatest use of the available resources to provide an appropriate electrical supply with minimal shortages, the suggested approach results in decreased CoE. As a result, battery capacity gradually increases and the CoE decreases. The ineffective power administration of the current techniques led to wasted energy. This reduction in CoE translates to enhanced economic efficiency, benefiting end-users by potentially lowering energy costs and increasing the overall affordability of the hybrid energy system. The focus on minimizing CoE aligns with the broader goal of establishing sustainable and cost-effective energy solutions for various applications and regions.

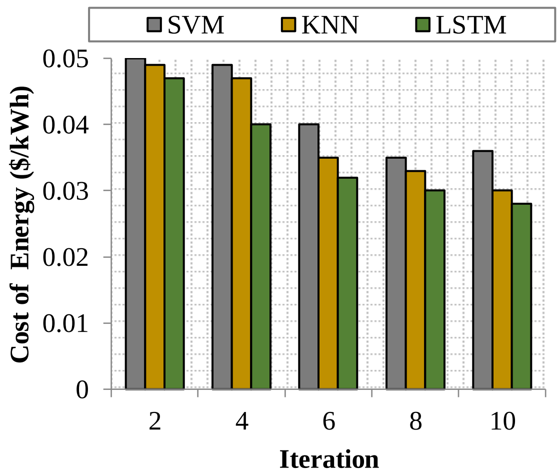

Fig.6. cost of energy (both solar and grid battery)

Consequently, the variation rate of our suggested models, which account for both solar power and power grid sources are investigated.

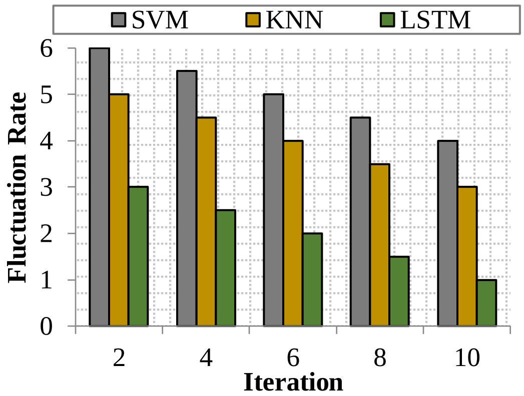

Fig.7. fluctuation rate (both solar and grid battery)

In Fig.7, the solution to our recommended algorithm's cost-effectiveness is load prediction that lead to changes in the energy supply. The lack of consideration for uncertainty in the present methodologies leads to a higher fluctuating rates. In the suggested model, hybrid sources of power are considered; their rate of fluctuation is roughly 2.1%, which is less than that of renewable irradiation (3.5%) or electrical grids (4%). This explains about how the suggested system efficiently handles the unpredictability of the loads. As demonstrated by the existing approaches' fluctuation rate of around 5.4%, our suggested method offers a dependable supply of power.

5. Conclusion & Future Work

This work offers a useful approach for controlling and growing hybridization sources of renewable energy sources through data-driven approaches. The LSTM system is employed for predicting load uncertainties after using historical information to forecast weather conditions and load needs. It is done to help with appropriate resources sizing. The resources are also sized using the shuffled shepherd optimization technique to make the greatest use of the anticipated data.This approach successfully overcomes the limitations of existing methods, optimizing resource allocation and achieving lower Loss of Power Supply Probability (LPSP) and forecasting errors. The proposed model also significantly reduces the Cost of Energy (CoE), showcasing its economic efficiency and potential benefits for end-users. The conducted simulations, carried out using MATLAB R2020a, have rigorously validated our approach. By meticulously comparing our model against alternative strategies across diverse metrics such as fluctuating rates, battery power, current value expenses, and costs of energy, we have demonstrated the robustness and effectiveness of our approach. Looking ahead, we acknowledge the potential for further refinement and enhancement. Future iterations of this research will leverage cutting-edge techniques to elevate the precision and performance of our proposed model, thereby paving the way for its broader implementation and making a lasting impact on remote area energy accessibility.

Declaration:

Ethics Approval and Consent to Participate:

No participation of humans takes place in this implementation process

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

Funding:

No funding is involved in this work.

Data availability statement:

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study

Conflict of Interest:

Conflict of Interest is not applicable in this work.

Authorship contributions:

All authors are contributed equally to this work

Acknowledgement:

There is no acknowledgement involved in this work.

References

[1] R.Dhiman, and D.G. Sharma, 2022, Developing Solar Photovoltaic Systems - Investigating Modeling and Sizing Techniques and Power and Technical Challenges.

[2] R.K.Patnaik,P.S.Bharathi,S.K.Mathiyalagan, R.Thumma, G.Saravanan, M.S.Alanazi, , V.Sivaraman, A. Elfasakhany, and A. Belay, 2022, "The Potential Role of PV Solar Power System to Improve the Integration of Electric Energy Storage System", International Journal of Photoenergy.

[3] P. Ashok Babu, JL. Mazher Iqbal,S.Siva Priyanka, M. Jithender Reddy, G. Sunil Kumar, R.Ayyasamy, "Power control and optimization for power loss reduction using deep learning in microgrid systems," Electric Power Components and Systems.;52(2):219-32, January 2024.

[4] K.Amjad, M.R.Javeed, M.Umar, M.S.Khalid, H.E.Gelani, and F. Dastgeer, 2020, "ANN based optimization of price-based demand response management for solar powered nanogrids", 2020 IEEE 23rd International Multitopic Conference *(INMIC)*, 1-5.

[5] A.K.Mishra, and B.Singh. 2021. Grid-Integrated SRM-Driven Solar Water Pump With Power Flow Management, IEEE Journal of Emerging and Selected Topics in Power Electronics, *9*, 2723-2734.

[6] Y.Allahvirdizadeh,M.Mohamadian,M.Haghifam, and A.Hamidi, 2017, "Optimization of a Fuzzy Based Energy Management Strategy for a PV/WT/FC Hybrid", International Journal of Renewable Energy Research.

[7] R.Rajasekaran, and P.U. Rani, 2020, "Bidirectional DC-DC converter for microgrid in energy management system", International Journal of Electronics, 108, 322 - 343.

[8] Y.Z. Zhang, 2018, Control and power management of photovoltaic systems with plug-in hybrid electric vehicles as energy storage.

[9] N.Kim, M.Biglarbegian, and B. Parkhideh, 2018, “Flexible high efficiency battery-ready PV inverter for rooftop systems”, 2018 IEEE Applied Power Electronics Conference and Exposition (APEC), 3244-3249.

[10] F.Harmouch, A.F.Ebrahim, M.M.Esfahani, N.Krami, N.Hmina, and O.A. Mohammed, 2019, “An Optimal Energy Management System for Real-Time Operation of Multiagent-Based Microgrids Using a T-Cell Algorithm”, Energies.

[11] A.Elgammal, and T.Ramlal, 2021, Optimal Frequency Control Management of Grid Integration PV/Wind/FC/Storage Battery Based Smart Grid Using Multi Objective Particle Swarm Optimization MOPSO and Model Predictive Control (MPC), European Journal of Engineering and Technology Research.

[12] A.Elgammal, and T. Ramlal, 2021, “Optimal Model Predictive Frequency Control Management of Grid Integration PV/Wind/FC/Storage Battery Based Smart Grid Using Multi Objective Particle Swarm Optimization MOPSO”, WSEAS TRANSACTIONS ON ELECTRONICS.

[13]P. Ashok Babu, JL. Mazher Iqbal,S.Siva Priyanka, M. Jithender Reddy, G. Sunil Kumar, R.Ayyasamy, “Power control and optimization for power loss reduction using deep learning in microgrid systems,” Electric Power Components and Systems.;52(2):219-32, January 2024.

[14]Mohanan, M, and Y.I. Go, 2020, “Optimized Power System Management Scheme for LSS PV Grid Integration in Malaysia Using Reactive Power Compensation Technique”, Global Challenges, 4.

[15]G.M.Muriithi, and S.Chowdhury, 2021, “Optimal Energy Management of a Grid-Tied Solar PV-Battery Microgrid”, A Reinforcement Learning Approach, Energies.

[16]D. N. V. S. L. S. Indira, Rajendra Kumar Ganiya, P. Ashok Babu, A. Jasmine Xavier, L. Kavisankar, S. Hemalatha, V. Senthilkumar, T. Kavitha, A. Rajaram, Karthik Annam, and Alazar Yeshitla, “Improved Artificial Neural Network with State Order Dataset Estimation for Brain Cancer Cell Diagnosis”, BioMed Research International, vol. 2022, 10 pages, 2022.

[17]P. Ganesh, G. B. S. R. Naidu, Korla Swaroopa, R. Rahul, Ahmad Almadhor, C. Senthilkumar, Durgaprasad Gangodkar, A. Rajaram, and Alazar Yeshitla, Implementation of Hidden Node Detection Scheme for Self-Organization of Data Packet, “Wireless Communications and Mobile Computing”, vol. 2022, 9 pages, 2022, https://doi.org/10.1155/2022/1332373.

[18]Rajaram, and K. Sathiyaraj, “An improved optimization technique for energy harvesting system with grid connected power for green house management”, Journal of Electrical Engineering & Technology, vol. 2022, pp. 1-13, 2022.

[19]M. Dinesh, C Arvind, S.S Sreeja Mole, C.S. Subash Kumar, P. Chandra Sekar, K. Somasundaram, K. Srihari, S. Chandragandhi, and Venkatesa Prabhu Sundramurthy, “An Energy Efficient Architecture for Furnace Monitor and Control in Foundry Based on Industry 4.0 Using IoT”, Scientific Programming, vol. 2022, Article ID 1128717, 8 pages, 2022. https://doi.org/10.1155/2022/1128717.

[20]RP Prem Anand, and A Rajaram, “Effective timer count scheduling with spectator routing using stifle restriction algorithm in manet”, IOP Conference Series: Materials Science and Engineering, vol. 994, no. 1, pp. 012031, 2022.

[21]C. R.Rathish, and A.Rajaram, “Efficient path reassessment based on node probability in wireless sensor network”, International Journal of Control Theory and Applications, 34.2016 (2016): 817-832.

[22]K. Kumar, Vinoth, and A. Rajaram, “Energy efficient and node mobility based data replication algorithm for MANET”, 2019.

[23]K. Mahalakshmi, K. Kousalya, Himanshu Shekhar, Aby K. Thomas, L. Bhagyalakshmi, Sanjay Kumar Suman, S. Chandragandhi, Prashant Bachanna, K. Srihari, and Venkatesa Prabhu Sundramurthy, “Public Auditing Scheme for Integrity Verification in Distributed Cloud Storage System”, Scientific Programming, vol. 2021, Article ID 8533995, 5 pages, 2021. https://doi.org/10.1155/2021/8533995.

[24]J. Divakaran, Somashekhar Malipatil, Tareeq Zaid, M. Pushpalatha, Vilaskumar Patil, C. Arvind, T. Joby Titus, K. Srihari, M. Ragul Vignesh, Baswaraj Gadgay, and Venkatesa Prabhu Sundramurthy, “Technical Study on 5G Using Soft Computing Methods”, Scientific Programming, vol. 2022, Article ID 1570604, 7 pages, 2022. https://doi.org/10.1155/2022/1570604.

[25]S. Shitharth, Pratiksha Meshram, Pravin R. Kshirsagar, Hariprasath Manoharan, Vineet Tirth, and Venkatesa Prabhu Sundramurthy, “Impact of Big Data Analysis on Nanosensors for Applied Sciences Using Neural Networks”, Journal of Nanomaterials, vol. 2021, Article ID 4927607, 9 pages,2021,https://doi.org/10.1155/2021/4927607

[26]Rajaram, and K.Sathiyaraj, An improved optimization technique for energy harvesting system with grid connected power for green house management. Journal of Electrical Engineering & Technology, 2022 Sep;17(5):2937-49.

[27]Xiaorui Shao, and Chang Soo Kim, "Multi-step short-term power consumption forecasting using multi-channel LSTM with time location considering customer behavior", *IEEE Access*, vol. 8, pp. 125263-125273, 2020.

[28]E. Bekiroglu, and M. D. Yazar, "MPPT Control of Grid Connected DFIG at Variable Wind Speed", *Energies*, vol. 15, no. 9, pp. 3146, Apr. 2022.

[29]H. Jinqiao, C. Leng, B. Liu, Z. Chen, and L. Zhenlin, “Analysis of flame characteristics of low calorific value

gas diffusion combustion under the action of thermal dynamics", Combustion Theory and Modelling Volume 24, 2020 - Issue 5, (book),https://doi.org/10.1080/13647830.2020.1793001

[30]M.L. Ramadhan, J. Carrascal, A. Osorio, and J.P. Hidalgo, "The effect of moisture content and thermal behaviour on the ignition of Eucalyptus saligna leaves", International Journal of Wildland Fire 30(9): 680-690, 21 June 2021, https://doi.org/10.1071/WF20069

[31]B. Sarsembayev, D. Zholtayev, and T. D. Do, "Maximum Power Tracking of Variable-Speed Wind Energy Conversion Systems based on a Near-Optimal Servomechanism Control System", *Optim. Control Appl. Methods*, vol. 43, no. 3, pp. 904-924, 2022.

[32]H. Shekhar , C. Bhushan Mahato , SK. Suman ,S. Singh , L. Bhagyalakshmi ,M. Prasad Sharma , B. Laxmi Kantha, SK. Agraharam , A. Rajaram, "Demand side control for energy saving in renewable energy resources using deep learning optimization," *Electric Power Components and Systems*. 26;51(19):2397-413, November 2023.

[33]R. Kalpana, V S, R. Lokanadham, K. Amudha, GN, Beena Bethel,AK Shukla, PR, Kshirsagar, A. Rajaram, "Internet of Things (IOT) Based Machine Learning Techniques for Wind Energy Harvesting," Electric Power Components and Systems, 14:1-7, December 2023.

[34]C, V. K., A. Chaturvedi , A. T., Srinivas, P. V. V. S., P.S Ranjit, R. Rastogi, Arun, M. R., & A. Rajaram, "AI-IOT-Based Adaptive Control Techniques for Electric Vehicles," Electric Power Components and Systems, 1–19, January 2024.

[35]A. Sahbani, K. Cherif ,KB. Saad, "Multiphase Interleaved Bidirectional DC-DC Converter for Electric Vehicles and Smart Grid Applications," International Journal of Smart Grid-ijSmartGrid, 28;4(2):80-7, June 2020.

[36]K. Lentswe, A.Mawire, "Charging Energetic and Exergetic Evaluation of A Combined Solar Cooking and Thermal Energy Storage System," In2022 11th International Conference on Renewable Energy Research and Application (ICRERA), (pp. 71-76), IEEE, September 2022.

[37]H. Abouelgheit, "Impact of on-Load Tap Changers and Smart Controllers on the Distributed Renewable Energy Hosting Capacity," International Journal of Smart Grid-ijSmartGrid, 29;6(4):132-5, December 2022.

[38]B. Azibek, N. Zhakiyev,A. Ibraimova, Y.Akhmetbekov, "Increasing total hosting capacity using energy storages during renewable energy expansion," In2022 11th International Conference on Renewable Energy Research and Application (ICRERA), (pp. 414-417), IEEE, September 2022.

[39]A. AlKassem , M. Al Ahmadi, A. Draou, "Modeling and simulation analysis of a hybrid PV-wind renewable energy sources for a micro-grid application" In2021 9th International Conference on Smart Grid (icSmartGrid,) (pp. 103-106), IEEE, June 2019.

[40]SS.Charqaouy, D.Saifaoui, O.Benzohra, A. Lebsir, "Integration of Decentralized Generations into the Distribution Network-Smart Grid Downstream of the Meter," International Journal of Smart Grid, 4(1), March 2021.