



Optimization of Internet of Things (IoT) for Smart Grid Energy Management Using Artificial Intelligence (AI) Techniques to Reach SDG7

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Abstract: Every member state of the United Nations has signed on to the Sustainable Development Agenda for 2030, which lays out a plan for a better, more prosperous future. The 17 Sustainable Development Goals (SDGs) call for action from all countries, regardless of their economic status. Sustainable and inexpensive energy for everybody is the focus of this research. Power systems need to be sustainable, secure, and cost-effective while also meeting the increasing need for reliability and quality in distribution networks. The best way to handle large amounts of data stored in an IoT network is via artificial intelligence (AI). The proliferation of smart sensors and the development of lightning-fast internet have contributed to the meteoric rise in popularity of the Internet of Things (IoT). With the help of artificial intelligence and the internet of things, the globe is moving toward using renewable energy sources to power generators. For the purpose of optimizing the Internet of Things (IoT) for renewable energy management control of DC-AC microgrids with PV-Wind systems, this study suggests a new way to simulate an inverter-based microgrid utilizing an ANN and inverter control in order to achieve SDG7. The simulations are conducted using MATLAB/Simulink, and the outcomes demonstrate optimization derived from the system in terms of V_{ph_max} , V_{L-L} , and V_{ph_rms} .

Keywords - Artificial Intelligence (AI), Artificial Neural Network (ANN), Internet of Things (IoT), Smart Grid, Renewable Energy

I. INTRODUCTION

Goal 7 of the United Nations' 2030 Agenda for Sustainable Development (SDG7) was approved on September 23, 2015. Ensuring access to cheap, dependable, sustainable, and contemporary energy for all is their goal statement [1]. For a better and more sustainable future for everybody, we need to follow the Sustainable Development Goals. A number of environmental issues, including pollution of the air, forest loss, depletion of ozone layer, acid rain, emissions of greenhouse gases, water and land usage, species extinction, radioactive emissions, and global warming, are associated with energy consumption and supply concerns [2]. There are a lot of pressing social and economic problems caused by the current energy supply, which impacts both realms [3]. In order to do this and counteract the well-known detrimental impacts of conventional power plants on sustainable development, the focus is now on using these resources within specific limits [4].

It relocated the emphasis to RE sources, which include wind, solar PV, hydropower, geothermal energy tidal, the and biomass [5]. Recent developments in electrical power systems and distributed generation (DG) have inspired ideas for future network technologies such as microgrids. In addition to improving efficiency and stability, DERs (distributed energy resources) and other types of distributed output may be promoted through integration [6]. In addition to reducing or eliminating the production of harmful and exhaust gases like sulfur dioxide and carbon dioxide, using renewable energy sources helps with the creation of environmentally friendly technology, lower electricity costs, job opportunities, improved health, and community development, especially in rural developing nations [7]. Extra intelligence, such as sensing, two-way communication, and enhanced control and administration capabilities, distinguishes a "smart" grid from a traditional one. Therefore, the smart grid can not only detect and respond to changes independently and in real time, but it can also maintain a high degree of efficiency, reliability, and service quality. The Internet of Things (IoT) is considered an essential technology in this regard since it enables the conversion of an ordinary grid into the smart grid [8]. Fig. 1 shows one common usage of IoT with AI: a hub for controlling home gadgets through apps and an internet connection.

automates voltage maintenance, power factor management, and energy output. Products such as concentrated solar power systems, wind turbines, and photovoltaic panels fall under this category [8, 12]. Since the system for smart grids makes use of both non-renewable and renewable energy sources, energy storage is an essential component due to the future usage of stored energy [13]. Smart grids' intended architecture is seen in Fig. 2.

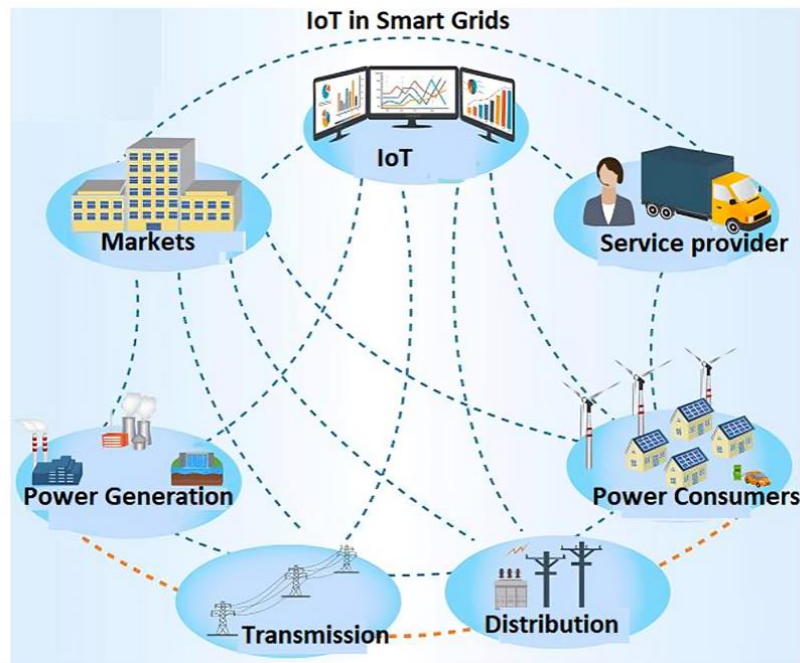


Fig. 2. IoT in Smart Grids

III. MATHEMATICAL AND SIMULATION MODELLING

This is the input to a PI controller, as seen in (1) and whose output is what decides the real reference i^* that is injected. This control is implemented using a proportional-integral controller, and the output of the controller is given by (2).

$$i_d^* = \left(k_{pv} + \frac{k_{iv}}{s} \right) [v_d^* - v_d] \quad (1)$$

$$i_q^* = \left(k_{pv} + \frac{k_{iv}}{s} \right) [v_q^* - v_q]$$

$$u_d = \left(k_{pi} + \frac{k_{ii}}{s} \right) [i_d^* - i_d] + v_d + (\omega L) \times i_q^* \quad (2)$$

$$u_q = \left(k_{pi} + \frac{k_{ii}}{s} \right) [i_q^* - i_q] + v_q - (\omega L) \times i_d^*$$

Here, k_{iv} stands for the integral gain and k_{pv} for the proportional-integral control of the voltage; the latter measures the discrepancy between the inner loop's computed voltage and the reference voltage. However, the inverter's output current is controlled and the outside voltage loop reference current is monitored by the internal current loop. Also, the reference voltages (u_d and u_q) of the direct-quadrature axis for the pulse width modulation (PWM) are created by the current control loop in line alongside the current reference voltages i_d^* and i_q^* that are formed by the power management loop and the voltage control loop in the two systems. The microgrid's operational characteristics are adjusted in real-time to match the present conditions through the simultaneous implementation of simulated impedance and droop controllers. The controller output is shown in (3) when the outer voltages controller is implemented using a PI control technique.

$$i_d^* = \left(k_{pv} + \frac{k_{iv}}{s} \right) [v_d^* - v_d - v_{dpd}] \quad (3)$$

$$i_q^* = \left(k_{pv} + \frac{k_{iv}}{s} \right) [v_q^* - v_q - v_{dpq}]$$

The integral gain of the voltage proportional-integral control is denoted as k_{iv} , and the proportional gain is denoted as k_{pv} (3).

The v_{dp} is the voltage drop caused by the virtual impedance or the grid.

A. Implementation of Inverter Tuning Control Approach

Using off-grid control, functioning as voltage sources, or even partnering with an energy storage system, they directly supply electricity to adjacent loads. Both the reliability and cost-effectiveness of the loads' power supply are improved [14]. One of the main challenges to the reliable functioning of a microgrid is small-signal stability. There exist models with the requisite properties for the numerous frequency ranges (or time spans) of possible concern, and stability analysis in conventional power systems is well-established. We use MATLAB/Simulink for all of our simulations. Figure 3 displays the MATLAB-modeled PWM IGBT Inverter, which controls an LC filter. The goal of this article is to improve power quality by utilizing an inverter control strategy that incorporates AI capabilities.

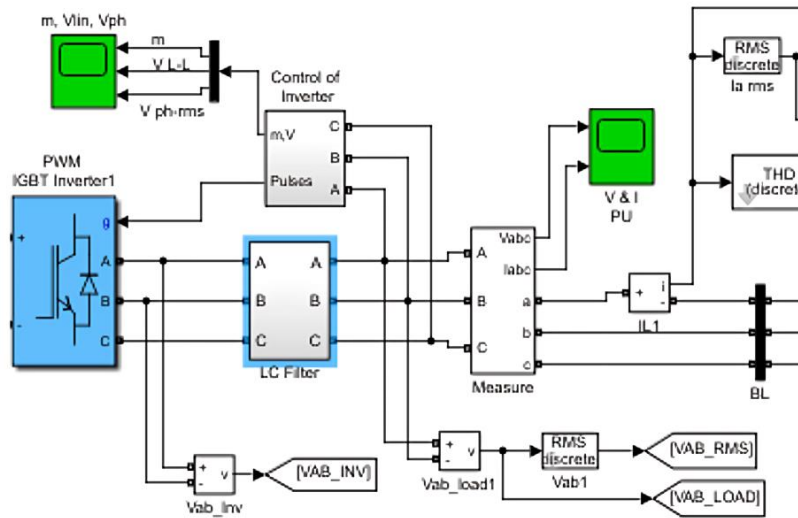


Fig. 3. Inverter in a DC/AC Microgrid

B. Control of the Inverter

The DC microgrid electricity is converted to AC via converters. In order to improve the power quality, the inverter settings are adjusted to provide power that meets the demands. The output measured findings of this research are V_{ph} , V_{L-L} , and V_{ph_rms} , as shown in Fig. 4, which indicates the control of the inverter circuit. At two pulses per planned equation, the V_{ph} is linked to the discrete PWM generator through the V_{abc} inverter.

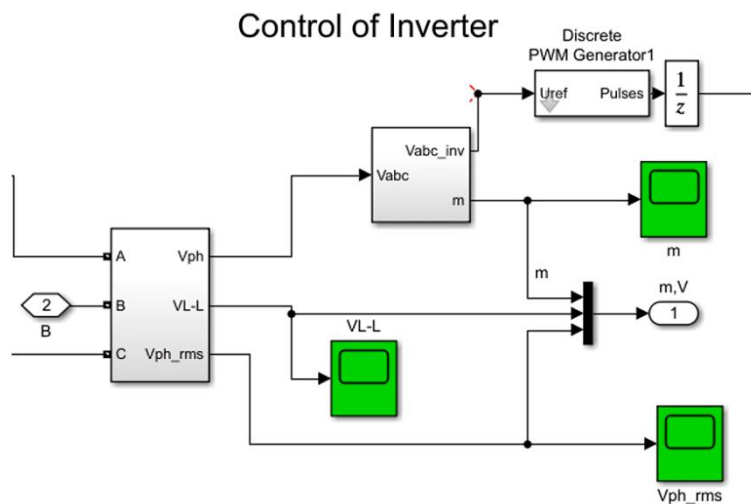


Fig. 4. Control of inverter circuit

C. Applications of Improved Artificial Neural Network Technique for Power Quality Optimization

Artificial neural networks (ANNs) are highly computational models that can be trained to use previous data to learn new input-output mappings. The three layers that comprise an ANN are shown in Fig. 5. These layers are the input layer, the hidden levels (also known as computational layers), and the output layer. The ANN calculation weight and bias are implemented in feed-forward propagation and back-propagation. While feed-forward propagation reliably guesses the results, back-propagation lowers the error between the real and estimated outcomes. The input layer of the neural network processed the dataset that was sent into it. Figure 5 also shows how the data inputted into the artificial neural network (ANN) is shown by (xi). starting point for an ANN's training procedure. The input data is multiplied by weights and added to bias in each hidden layer of the ANN. The more hidden layers an ANN has, the more accurate its predictions will be. The output layer is responsible for generating the desired outcome for the program under consideration by integrating data from the hidden levels. The paper makes use of ANN due to its ability to recover.

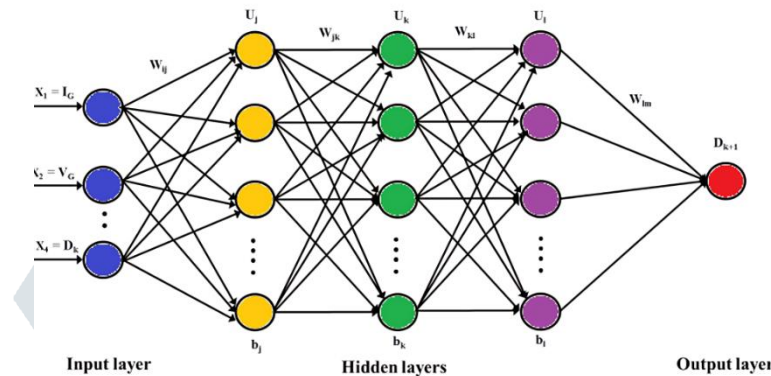


Fig. 5. Basic arrangement of ANN

D. Mathematical Modelling for ANN in Hybrid system

Dropping from a height. When optimizing for a cost function, gradient descent is the method of choice to identify a local minimum of a differentiable function. Gradients are used to measure the fluctuation in the output and to modify the weights when that inputs are altered slightly. With the help of (4), which outlines the cost function that is employed to minimize the difference between the ideal and anticipated outcome,

$$f(w, b) = \frac{1}{N} \sum_{i=1}^n (y_i - (wx_i + b))^2 \tag{4}$$

So, to determine the cost function's gradient in (5), we apply (4).

$$f'(w, b) = \left(\begin{matrix} \frac{df}{dw} \\ \frac{df}{db} \end{matrix} \right) = \left(\begin{matrix} \frac{1}{N} \sum -2x_i (y_i - (wx_i + b)) \\ \frac{1}{N} \sum -2 (y_i - (wx_i + b)) \end{matrix} \right) \tag{5}$$

By repeating the process over the input datasets, the hidden layer's fresh weights 'w' and biases 'b' are found. The next step is to find the partial derivatives in order to solve the gradient function. This new gradient displays the slope of our cost function at our present position (the current parameter values) and also indicates the direction in which we may shift our parameters to minimize the cost function. The learning rate is a hyperparameter that may be used to reduce the cost function. We regulate the size of our update ($\alpha=0.001$) with this learning rate, which functions as a hyperparameter during ANN training. It takes 100 training epochs to get the desired output from the model. It is the Sigmoid function's derivative. The goal of the ANN controller is to trigger the GTI (0/1) switches using a PWM signal. As an activation function, the sigmoid function is used to limit the output values delivered to GTI switches. The function's probability range is 0 to 1, as shown in (6). For an input of 0, the sigmoid function returns 0.5. When given a large positive integer, it produces a result very near to 1. When given a negative integer, the sigmoid function delivers a result extremely close to zero. As a result, it finds use in models that need to project the result as an output.

$$f(x) = \frac{1}{1+e^{-x}} \tag{6}$$

IV. RESULTS DISCUSSION

Cooperative and distributed control systems of smart grid applications are the subject of this research, which combines artificial intelligence (ANN) along with the inverter controls (IC) technique in the Internet of Things (IoT). As a convenience, we shall use the umbrella term "distributed control" going forward in this paper. When it comes to inverter control and ICANNs, asymptotic consensus protocols form the foundation. They provide the groundwork for future talks about ways to improve the stability and speed of convergence. At the intermediate level of a pipeline scenario, an artificial neural network multiplies weights and adds bias; the network's main function transfers any input to the desired target value. Using the current dataset to train an artificial neural network finds the hidden layer parameters (weights) that minimize the expense of the function and decrease the discrepancy among the predicted value as well as the model output. Here we may observe the ICANN approach in action. Fig. 6 shows the results of modeling and simulating an AC load-connected PV/wind system including energy storage using MATLAB/Simulink.

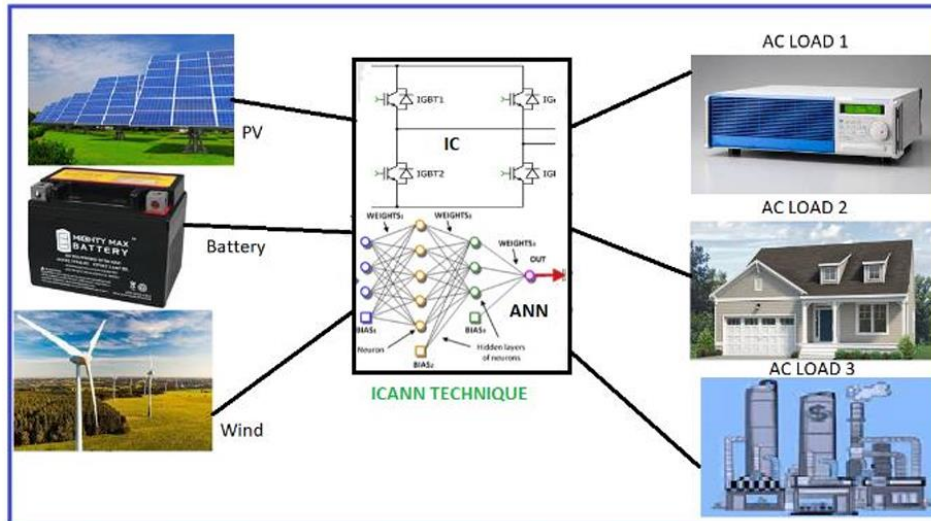


Fig. 6. Main ICANN technique application control block

During the inverter simulation, the V_{ph_max} is displayed in Fig. 7. Here, all three answers fall inside the 5% zone, and at $t=0.05$ and $t=0.22$ seconds, one demux is much lower than 0.98 pu. The output follows the same pattern with frequent spikes in between; it hits a maximum of 1.02 pu and then drops until $t=0.025$ seconds. Active power, current, voltage, & frequency dynamic responses corroborate the simulation's thorough model. Microgrids powered by solar PV and wind may use this modeling method for low-voltage ride-through, and big grid-connected batteries that store electricity can use it for interface control.

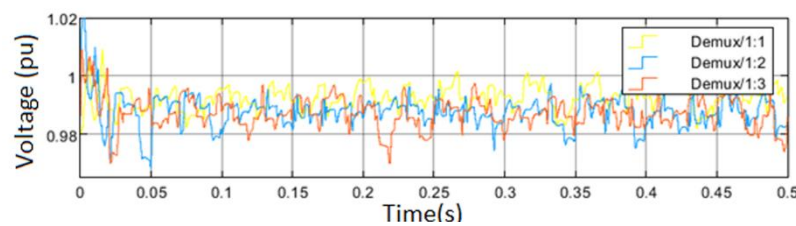


Fig. 7. V_{ph_max} during inverter simulation

As the load demand increases, the microgrid output varies, as seen in Figure 8. The output of the inverter-controlled VL-L simulation. The three demux/2 remain in a state of equilibrium for the whole reaction. After the inverter control, the output is spread equally. A continuous voltage of no more than 500 V is provided. These pulses accurately activate the IGBT-based switch's switching function and change the operational mode in the switching control system. The proposed method of balanced voltage sag is tested by creating a 50% voltage sag using the main grid error, triple-phase to ground.

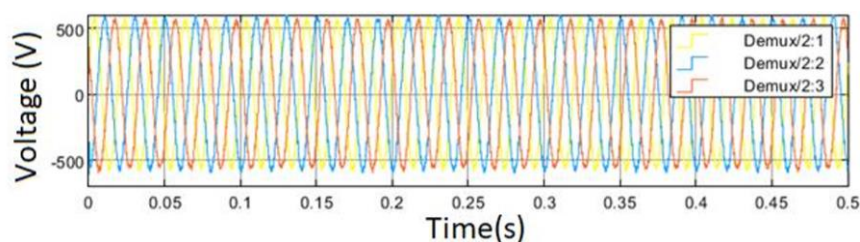


Fig. 8. VL-L inverter simulation

But droop control and sudden power imbalance are different in island mode. In Figure 9, we can see the inverter output controller's optimization process, V_{ph_rms} . The PI controllers that regulate the system's current and voltage are identical. Before $t=0.05$, there is a 230 V increase in the phase voltages, which is significantly higher than the average. Following that, the system is constantly stabilized, ensuring that it never drops below 230 V. There is a spike at demux/3:3 at $t=0.23$ seconds, but the system is able to keep its composition and remain on the correct scale. Figure 16 displays the magnitude that causes the current amplitude to grow proportionally. The system's secondary control mechanism incorporates the secondary power reference.

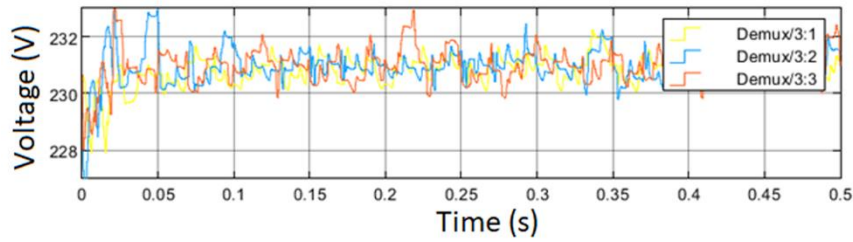


Fig. 9. V_{ph_rms} Inverter

The simulation accounts for variations in bus rms voltage and system frequency. In Figure 10, we can see the low-pass filter's Subsystem 1/2 V_{lin} . At $t=0.05$ seconds, the system frequency and bus voltage reach a maximum of 600 V, which is well within the typical range while operating in off-grid connected mode. Thus, the strategy schemes mode operation may be initiated by simultaneously switching the IGBT diode switching reactor in series with all phases in balanced transient conditions as well as with the affected phase in unbalanced scenarios.

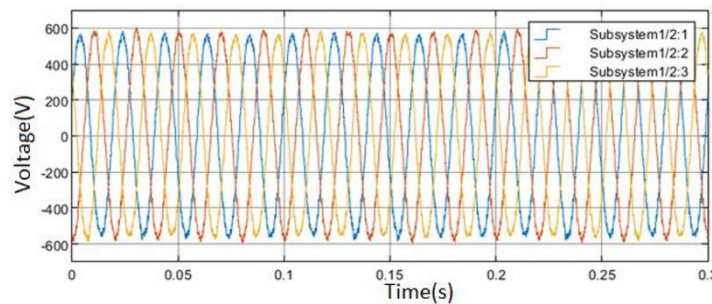


Fig. 10. V_{lin} LC filter for subsystem 1

The inverter's control filter circuit voltage V_{ph_rms} is shown to be unstable by the system. Smothering and raising the output voltage are crucial roles played by the RMS discrete v_{ab1} , 2, and 5. A V_{ph_rms} Inverter from the control circuit is shown in Figure 11. When all parameters are set at $t=0.025$ seconds, the V_{ph_rms} inverter spikes & hits 233 V. At $t=0.05$ seconds, only the demux/3:2 is enabled. The highest value of demux/3:3 is 233 V at $t=0.225$ seconds. Across the board, the outcomes are inconsistent. The microgrid voltage is rectified for efficient functioning of the microgrid through the deployment on the recommended strategy schemes for hybrid microgrid, even under main grid transient situations. The voltage of the microgrid has gone raised. Figure 11 therefore depicts a smooth transition between the system and disorder states. So, as shown, the LC filter for DERs has a properly restricted output current.

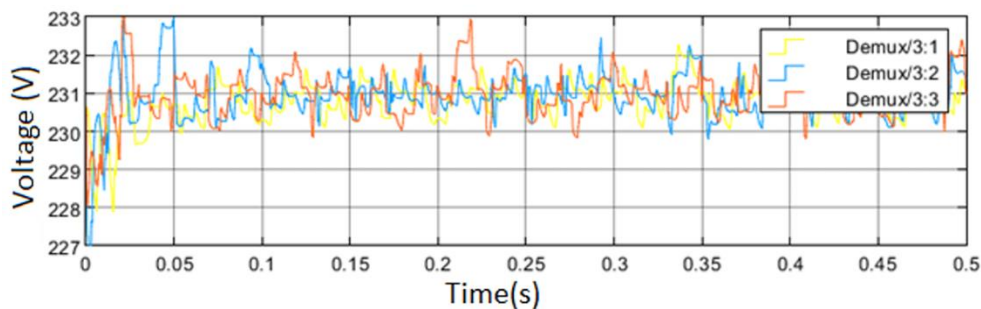


Fig. 11. V_{ph_rms} Inverter

Only in this way can the right people join the discussion about AI & its role in modern life. Having said that, the degree of difficulty is higher than that. Accurate information on the aim and its value must be supplied to decision-makers. They need to get this done before they can deal with the problem and its consequences properly. Academics need to cut to the chase and eliminate unnecessary language if they want to teach the general public about AI. All SDGs' output elasticity ratios are shown in Fig. 12. Since SGD7 is so far behind the top-ranked SDG 14, it is clear that it needs a lot of work.

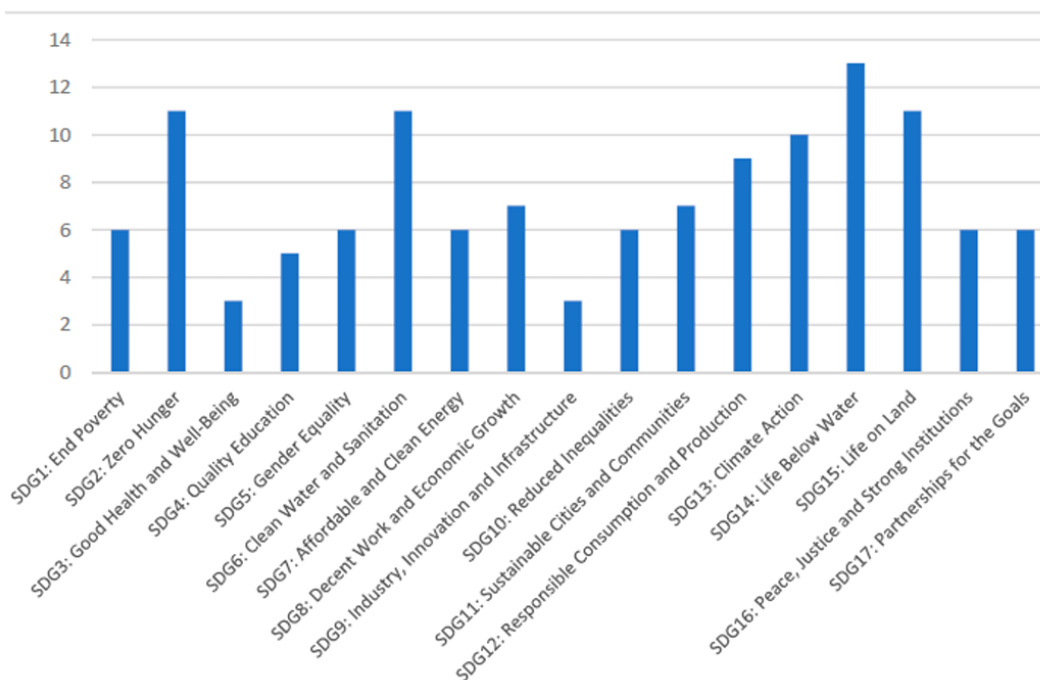


Fig. 12. Performance difference across the SDGs 17

V. CONCUCLUSION

Renewable energy-based smart grid investment is on the rise, and this study focuses on artificial intelligence applications in the internet of things. Smart grids' Internet of Things (IoT) may benefit greatly from AI-based technologies. It is difficult for a microgrid to function independently since the interface inverters are designed to regulate the voltage and frequency of the isolated system. A hybrid voltage source controller is built by merging the standard grid-forming control of interfaces power electronic inverters with droop and virtual impedance controls. The results show that the proposed ICANN method improves power control in all cases, independent of the load. Because normal electrical loads are so demanding, it is essential to dynamically modify control settings in order to keep up with the constantly changing microgrid load status. Crucial components are the inverter and LC filters. This control improves power regulation, as shown in the simulations, regardless of the load changes. Applying AI will enhance performance, making it significant as a solution and for the future, and the smart grid simulation findings are gratifying.

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