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Artificial Intelligence-Based Incorporation of Energy Storage Systems and Renewable Energy Sources

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Abstract
The broad use of Renewable Energy Sources (RES) is aided by Energy Storage System (ESS), which in turn helps improve new energy consumption capabilities and maintain the reliable and cost-effective functioning of power grids. When RES are incorporated, the ESS is used to equalize electricity production and consumption. Due to its intermittent nature and fluctuating costs, RES necessitated the development of ESS. The current difficulty of energy shortage is significant. It has had an impact on research into alternative energy. To overcome this limitation we introduce Artificial Intelligence (AI). This research aims to fill that gap by presenting an AI approach for use in energy storage systems that make use of renewable energy. ESSs may be integrated into the network; when these ESSs are of sufficient size and strategically placed, they increase the dependability of the entire system. To minimize the yearly cost of the system, which includes energy costs are not specified, and the operational costs of the ESSs, this paper proposes an effective method which is based on the Enhanced Dynamic Grey Wolf Optimizer (ED-GWO) to identify the best size and position of ESSs in a distribution systems. The experimental results show that our technology is more efficient than the other technique.

Keywords: Renewable Energy Sources (RES), Artificial Intelligence (AI), Energy Storage System (ESS), Enhanced Dynamic Grey Wolf Optimizer (ED-GWO)

1. Introduction

Due to growing demands from both energy usage and environmental regulation, the need for energy systems in human civilization has been raising significantly in recent years. The cornerstones to this energy revolution have emerged as cost containment, network replacement, increased flexibility and dependability of power sources, carbon dioxide emission reduction, mitigation of climate change, and dependable power support for distant locations with rising energy needs. Recently, there has been a lot of activity in the development of energy storage systems (ESS), which employ renewable energy to meet requirements for energy efficiency and carbon reduction. Voltage and frequency changes will happen because ESSs (whether employed in grid-connected or island operation) have certain unpredictable and intermittent issues [1]. Due to technology advancements that have steadily decreased their prices and enhanced their efficiency at the same time, renewable energy sources (RESs) have seen a significant expansion in the last ten years. In addition, increasing the amount of power generated by RESs is necessary to minimize reliance on fossil fuels and lower greenhouse gas emissions. This can be done mostly by turning to wind and solar power, however because of the intrinsic nature of these RES; they provide a number of management issues for the electric system [2]. Batteries may be used to solve long-term need mismatches because to their high energy density and low power density, but they are not suited for meeting sudden load needs. Large power densities, in contrast, are seen in Supercapacitors (SCs). They are only suited for accomplishing short-term, low energy needs because to their very low energy density, and they are not ideal for supplying long-term power requirements [3]. Because SCs have a larger power density than BESSs, they may target transient issues that arise briefly. By using both high power and energy densities, the hybridization of BESSs and SCs, or HESS, may therefore be used to meet both urgent and substantial energy needs. The development of a multi-energy storage device is predicted as a preferred option for raising power production and reducing the price of a standalone microgrid since the research community has lately concentrated on standalone renewable energy systems using HESS [4]. The main contribution of this paper is to determine the optimal dimensions and placement of ESSs inside a distribution system. This study intends to bridge that gap by offering an artificial intelligence technique that may be used in energy storage systems that use renewable energy sources.

2. Related works

The study [5] offered a thorough analysis of several issues pertaining to integrated renewable energy system-based power production for smart cities (IRES). It goes into great length into challenges relating to the integration of various energy sources, the usage of smart grids for integration, and ways for scaling IRES utilizing software and artificial intelligence algorithms. The size of IRES in smart cities is the subject of this article's assessment of several AI algorithms.

The research [6] provides a framework on "AI-driven surrogate modeling" and its uses, with a goal on the energy systems and "digital twin paradigm". The role of AI and ML in developing a successful surrogate design is discussed. The development of several surrogate system for various sustainable energy sources is then discussed. Last but not least, the description of "digital twin surrogate models".

The study [7] designed an "energy management system" to control an MG with batteries and RES. In order to meet energy demand, it was important to reduce costs and maximize profits from the sale of renewable energy. Dynamic programming is employed by the researcher to identify the battery management actions in a non-regulated energy market where power prices change.

The study [8] offered an "attention-based bidirectional long and short-term memory (ABLSTM-ESS) approach for ESS using renewable energy sources, which is an ABLSTM. The presented ABLSTM-ESS approach seeks to decrease power costs while meeting productivity criteria by addressing the optimization issue.

The research [9] highlighted an important challenges and opportunities for in-depth study with an emphasis on completing complete state-of-the-art methodologies leading to efficiency assessment of the provided strategies. The most apparent challenges for employing learning approaches include variances in efficiency, resilience, accuracy values, and generalization capabilities.

The research [10] recommended a novel approach that takes time-varying load restoration capabilities into consideration when assessing the operational dependability of distribution networks. The optimal corrective actions for load restoration are then determined using a sequential network reconfiguration (NR) approach, which takes into consideration feeder reconfigurability and the capability of energy storage systems (ESSs) to provide emergent power.

The research [11-12] created a multi-objective model for the design of a hub, taking into account the changing efficiency of converters, the gradual deterioration of equipment, the yearly increase in load, and the fluctuating cost of energy. The integrated demand response (IDR) program will be used by the users of the planned hub, which will also be outfitted with a power-to-gas (P2G) system.

3. Methods

A. Electric system

The power dynamic of an electrical system may be expressed as where $\mathrm{r-th}$ is the worldwide sample frequency immediate of the day t.

$$\mathcal{P}_0^{(\mathrm{r,t})} + \mathcal{P}_{\mathrm{RES}}^{(\mathrm{r,t})} + \mathcal{L}_0^{(\mathrm{r,t})} = 0 \tag{1}$$

where $\mathcal{L}_0$ represents the load requirement, $\mathcal{P}_{\mathrm{RES}}$ is the energy supplied by non-programmable sources like thermal and hydro, and $\mathcal{P}_0$ is the energy supplied by programmable sources. We suppose $\mathcal{P}_{\mathrm{RES}}$ to be:

$$\mathcal{P}_{\mathrm{RES}}^{(\mathrm{r,t})} = \mathrm{B}_{\mathrm{RES}}^{(\mathrm{r,t})} + \mathrm{G}^{(\mathrm{r,t})} \tag{2}$$

where G is the energy transmitted by the ESS and $\mathcal{P}_{\mathrm{RES}}$ is the energy generated by the RES. $\mathcal{P}_{\mathrm{RES}}$ must therefore be considered upper bounded because of the fundamental, poorly foreseeable character of RESs.

$$\mathcal{P}_{\mathrm{RES}}^{(\mathrm{r,t})} \leq -(1-\sigma).\mathcal{L}_0^{(\mathrm{r,t})} \tag{3}$$

Where σ is the grid stabilisation coefficient, denoting the percentage of load that must be provided by programmed sources to maintain grid stability.

B. Technology for Storing Energy

In this paper, we used AI technology incorporation of energy storage systems and renewable energy sources. The rapid development of AI has enabled the energy sector to automate significant sectors of production and storage. Smart metres, company records, weather predictions, etc. all contribute to the massive amounts of data that grids employ AI to process faster and more efficiently. There are various upsides for manufacturers to use AI. Artificial intelligence (AI) has the potential to enhance plant design for higher productivity, among other uses. Algorithms may improve the efficiency of modern renewable energy sources and wind turbines by predicting when repairs are needed. Artificial intelligence may potentially be used by power systems to anticipate and prevent problems. The energy industry is rich in data that is suitable for use in a variety of AI applications since it is easily available, well-structured, and reliable. To help improve energy storage systems, we incorporate this information into an AI system. With the help of AI, energy companies can process and analyse data more rapidly and with less need for human participation. This allows for a more rapid response to changing circumstances (such as an unexpected power interruption). These innovations reduce costs in production while boosting customer security. As AI becomes more integrated into the world's power systems, it will proactively prevent disruptions. To fulfill the energy needs of the future, smart grids are undergoing a transformation facilitated by artificial intelligence. Electric grid operators will be able to better manage their assets and generate money as energy storage becomes an increasingly important component of the smart grid.

C. System for energy storage

The energy that the ESS trades with the grids can be negative or positive based on whether it is acting as a supplemental power supply or a load, still with reference to the general r − th sampling interval of the day t. In view of this, the following parameters can be altered:

$$L_0^{(r,t)} = \frac{1}{2}\left(G^{(r,t)} - \left|G^{(r,t)}\right|\right) \quad (4)$$

$$B_0^{(r,t)} = \frac{1}{2}\left(G^{(r,t)} - \left|G^{(r,t)}\right|\right) \quad (5)$$

Where | · | stand for the “absolute value operator”. As can be seen in Figure 1, where F_g represents the amount of power pulled from the grids by the ESS and B_g represents the amount of power returned to the grid, and whereη_v and η_d represent the discharge and charge energy efficiencies of the ESS, respectively.

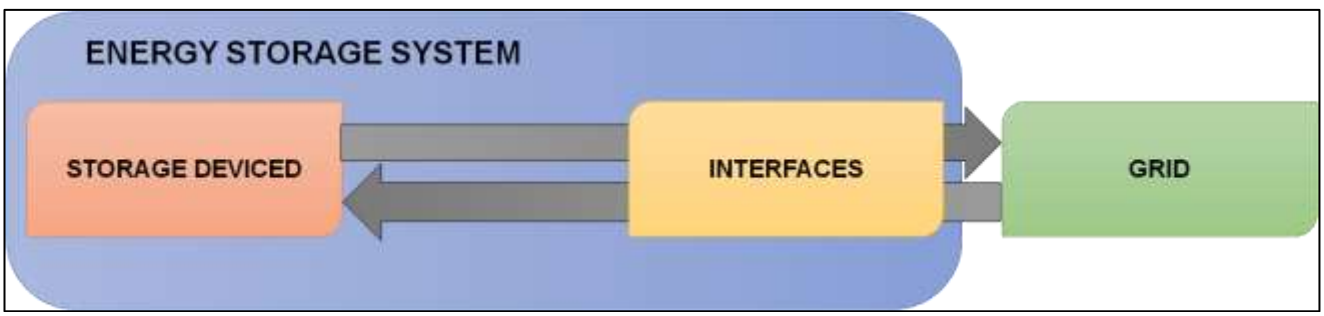

Figure 1: Representation of ESS flow

From figure 1, η_t Represents the proportion of total energy pulled from the grid that is actually retained in the ESS. Similar to this, η_t stands for the proportion of the total energy extracted from the storage devices that is actually sent to the grid by the ESS. Mentioning that F_g and B_g alternately equals zero, the ESS cannot take into and provide energy to the grid at the same time.

In view of (4) and (5), the energy transferred between the ESS and the grid may be stated as follows:

$$G^{(r,t)} = L_g^{(r,t)} + B_g^{(r,t)} \quad (6)$$

The amount of energy stored in an ESS at the $k + 1$ sample time instant may be calculated if the energy exchange with the electric grid during the $r - th$ sampling interval of time of day t has been determined.

$$A^{(r+1,t)} = A^{(r,t)} - \left(\frac{B_g^{(r,t)}}{\eta_t} + \eta_v . L_g^{(r,t)}\right) . D \quad (7)$$

Where D is the duration of time over which the sample was taken. In particular, the greatest amount of energy that may be stored by the ESS, denoted by its rated capacityA_p, is direct proportion to the ESS state-of-charge (SoC). However, F_g andB_g must be constrained in line with in order to meet the ESS operational constraints:

$F^{(r,t)} \leq F_g^{(r,t)} \leq 0$ (8)
$0 \leq B_g^{(r,t)} \leq B^{(r,t)}$ (9)
Where F and B represent the maximum power the ESS may take from and return to the grid, respectively. They are characterised as
$F^{(r,t)} = max\left\{-B_p, \frac{A^{(r,t)}-A_{max}}{\eta_v.D}\right\} \leq 0$ (10)
$B^{(r,t)} = min\left\{-\eta_t.B_p, \eta_t, \frac{A^{(r,t)}-A_{min}}{D}\right\} \geq 0$ (11)

where B_p can be defined as ESS rated power, whereas Emax and Emin are the ESS energy levels based on maximum and minimum respectively, It is directly proportional to the maximum and minimum ESS SoC by the means of A_p. In some particular case, the ESS SoC should not exceed the limits in order to maintain its rated performances and life-time.
where B_p represents the power rating of the ESS, Emax and Emin represent the ESS's maximal and minimal energy levels, and A p relates these values to the ESS's maximal and minimal SoCs. In specifically, the ESS SoC must stay within these limits to maintain its specified performance and longevity.
As a consequence, referring to (10) and (11) $-F$ is equal to the ESS rated power until and unless this does not imply the exceeding A_{max}. Whereas, it can also be computed by imposing, in (7), but the ESS energy level at $r+1$ is equal to A_{max}. In the same way, B is upper bounded based on the accordance as per ESS rated power and A_{min}. At the conclusion, by adding (8) and (9) to each other and substituting the valus of (6), the following (12) is achieved:
$F^{(r,t)} \leq G^{(r,t)} \leq B^{(r,t)}$ (12)

D. Optimization technique
The grey wolf's natural propensity for social probe and predation is the model for ED-GWO. Grey wolves are predatory animals that like to live in packs of five to twelve, with the dominant male being referred to as alpha (α). When it comes to hunting, where to rest, and when to wake up, it's up to this team. Beta (β) wolves are the wolves in the next hierarchy behind theα. The β helps the α on important decisions and provides as a hold for the ideal successor to the α role should that role become vacant. Omega (ω), the lowest rank in the ED-GW hierarchy, is the victim. ω are the last ones who are allowed to eat, and the pack fights to keep from losing ω. Wolf delta (δ) is the fourth categorization that does not fit any of the previous. δ wolves are scouts, sentinels, elders, hunters, and careers. They follow α and β but dominateω. Scouts alert the pack of danger, sentinels guard it, elders give wisdom, and hunters bring food.
In order to define the procedure in ED-GWO, the following equations are used under the assumption that the gradient of the optimal solution isα, thenβ, thenδ, and lastlyω. The updating positions around alpha, beta, gamma and omega are as follows:
$\vec{W}^{l+1} = \vec{W}_o^l - \vec{B}\,.\left|\vec{D}.\vec{W}_o^l - \vec{W}^l\right|$ (13)
Where $\vec{W}_o^l$ represents the location of the prey at iteration and $l\ \vec{W}_o^l l$ represents the position of the grey wolf at iteration k, and $\vec{B}$ *and* $\vec{D}$ represent the "coefficient vectors". Algorithm 1 denotes the process of ED-GWO. After adjusting the placements of each wolf using equation (13), the first three ideal solutions are thought to be alpha, beta and delta the final solution is omega, however, requires further adjustment to improve its position as follows.
$\vec{W}_1 = \left|\vec{W}_\alpha^l - \vec{B}_1.\left|\left(\vec{D}_1.\vec{W}_\alpha^l - \vec{W}^l\right)\right|\right|$ (14)
$\vec{W}_2 = \left|\vec{W}_\beta^l - \vec{B}_2.\left|\left(\vec{D}_2.\vec{W}_\beta^l - \vec{W}^l\right)\right|\right|$ (15)
$\vec{W}_3 = \left|\vec{W}_\delta^l - \vec{B}_3.\left|\left(\vec{D}_3.\vec{W}_\delta^l - \vec{W}^l\right)\right|\right|$ (16)
$\vec{W}^{l+1} = \frac{\vec{W}_1+\vec{W}_2+\vec{W}_3}{3}$ (17)
$\vec{W}_\alpha^l$ is the position of α, $\vec{W}_\beta^l$ is the position of β, and $\vec{W}_\delta^l$ is the position of δ.
Where $\vec{B}_1, \vec{B}_2, \vec{B}_3, \vec{D}_1, \vec{D}_2$ and$\vec{D}_3$are random vectors; and
The current solution position is $\vec{W}$.

Algorithm 1: Process of ED-GWO

Initialize Wolves' population randomly,

Calculate the corresponding objective function (E°),
Save the first three best Wolves as α, β, and δ,
While (l < max_iteration)
For each agent
Update the position of the current agent via eqn.(3.d)
End
Update the vectors B and D
Calculate the objective function of all agents
Update α, β, and δ, positions
L = l + 1
End
Print the best position ($\overrightarrow{W}_{\alpha}$)

4. Result and discussion

Here, the existing methods are Internet of Things (IoT [13]), Blockchain [14], Machine learning (ML [15]) and our proposed technique is artificial intelligent-enhanced dynamic gray wolf optimization method (AI+ED-GWO).

Energy consumption is the total amount of energy required to carry out an activity, produce an item, or even just occupy a structure. It is critical to have a solid understanding that the use of energy does not always originate from a single source of energy. In point of fact, it is a widespread fallacy to believe that in order to conserve energy, one must save electricity. In reality, it may be an entirely other kind of energy source that has the biggest influence on a certain activity. When compared to other traditional methods, our proposed method AI+ED-GWO provides low level of energy consumption. Figure 2 represented energy consumption with existing and proposed method.

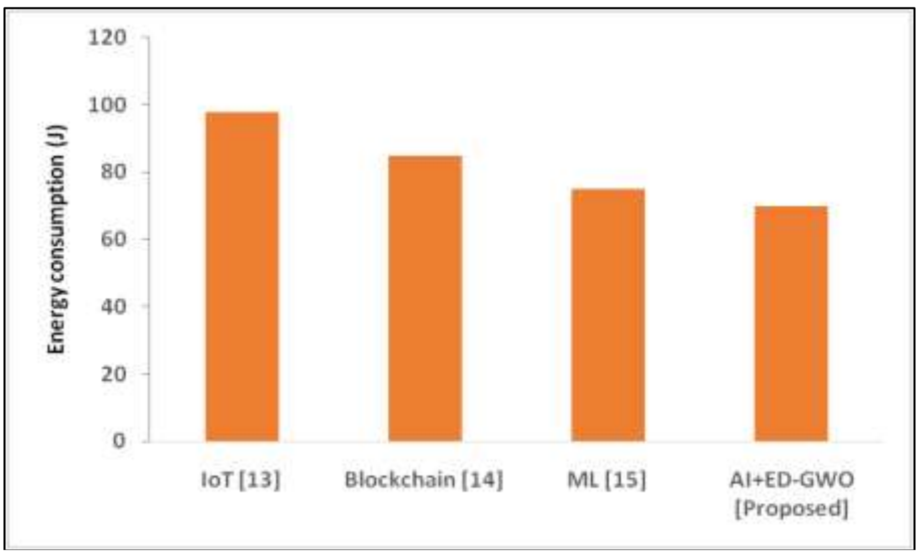

Figure 2: Comparison of energy consumption with traditional and suggested technique

Table 1: Performance of energy consumption with traditional and suggested technique

	Energy consumption (J)
IoT [13]	98
Blockchain [14]	85
ML [15]	75
AI+ED-GWO [Proposed]	70

Table 1 represented a performance of energy consumption with traditional and suggested technique. Efficiency is frequently defined as a percentage of the outcome that could ideally be expected. For instance, if there were no energy loss due to friction or other causes, then hundred percent of the fuel or other input would be used to produce the desired result. This would be an efficient use of resources. When compared to other traditional methods, our suggested technique AI+ED-GWO provides high level of efficiency. Figure 3 denotes the comparison of efficiency with traditional and suggested methods.

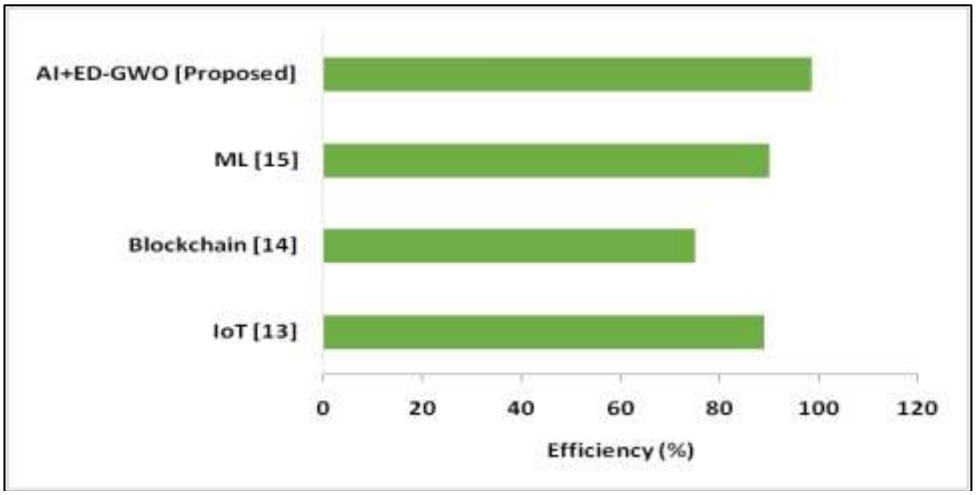

Figure 3: Result of efficiency with existing and proposed method

Table 2: Performance of efficiency with traditional and suggested method

	Efficiency (%)
IoT [13]	89
Blockchain [14]	75
ML [15]	90
AI+ED-GWO [Proposed]	98.5

Table 2 denotes a performance of efficiency with traditional and suggested technique. The approach will have a direct impact on the intervention that comes later, perhaps influencing its effectiveness, use, or quality. When compared to other existing methods, our proposed method AI+ED-GWO provides low level of implementation cost. Figure 4 denotes the outcome of implementation cost with traditional and suggested technique.

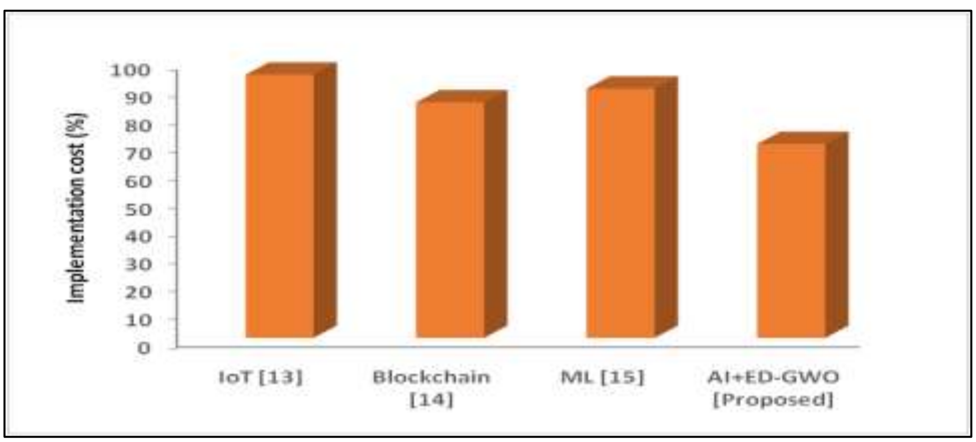

Figure 4: Result of implementation cost with traditional and suggested technique

Table 3: Performance of implementation cost with traditional and suggested method

	Implementation cost (%)
IoT [13]	95

Blockchain [14]	85
ML [15]	90
AI+ED-GWO [Proposed]	70

Table 3 denotes the performance of implementation cost with traditional and suggested methods. Memory consumption refers to the amount of memory that is used by certain software while it is being run. It should not be necessary to explain the meaning of this word since every programme makes use of the system memory to store instances of variables. The greater the number of variables, the greater the amount of memory that will be required. As a result, it is a well accepted principle that increasingly complex programs call for an increased amount of memory. When compared to other traditional methods, our proposed method AI+ED-GWO provides low level of memory consumption. Figure 5 denotes the outcome of memory consumption with traditional and suggested technique. Table 4 denotes the performance measures of memory consumption.

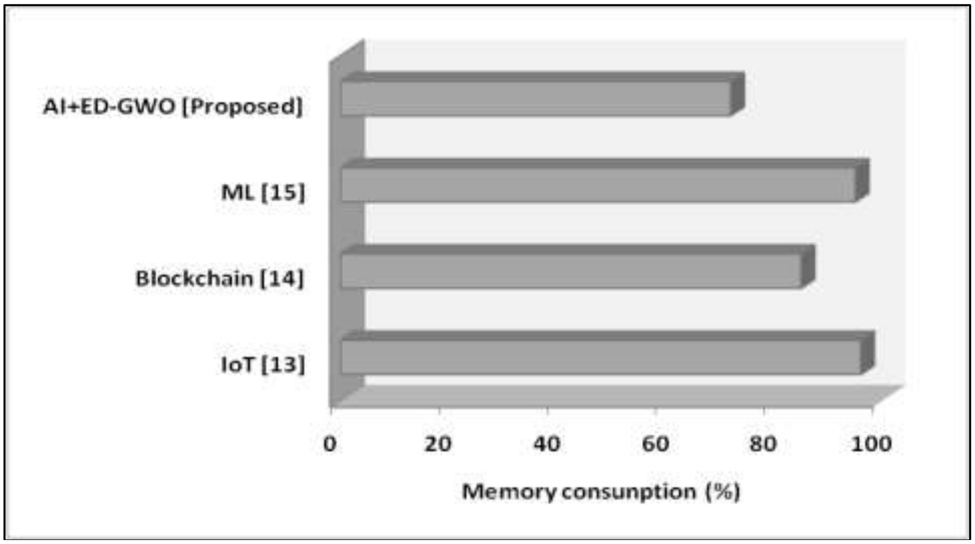

Figure 5: Result of memory consumption with traditional and proposed method

Table 4: Performance of memory consumption with traditional and suggested method

	Memory consumption (%)
IoT [13]	96
Blockchain [14]	85
ML [15]	95
AI+ED-GWO [Proposed]	72

5. Conclusion

The RESs assist to relieve the energy cost of end-users by providing them with the ability to create green energy, which in turn helps to alleviate the cost. The intermittent nature of their power production, on the other hand, presents challenges for energy management and planning. Within the scope of this investigation, we designed and evaluated an efficient framework of AI+ED-GWO management for energy storage system. Our proposed method AI+ED-GWO provides better performance than other existing methods to provide high efficiency and with low cost of implementation, memory consumption and energy consumption. In the future, we are going to put our suggested concept into practice by implementing it in real-time case findings. Our study is going in a number of different directions, one of which is to create a framework for energy management and forecasting in other energy-consuming sectors, such as the industrial sector.

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