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Implementation and Validation of an AI-Based MPPT Framework for Standalone PV Systems with Hybrid Energy Storage

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Abstract
Traditional Maximum Power Point Tracking (MPPT) algorithms such as Perturb and Observe and Incremental Conductance have several disadvantages such as slow convergence rate, continuous oscillations at steady state, low tracking accuracy and complexities under partial shade conditions. In this research an artificial neural network based MPPT algorithm is proposed for a stand-alone PV system with a battery-supercapacitor hybrid energy storage system (HESS). It is equipped with a sophisticated Energy Management System (EMS), hybrid storage integration, advanced MPPT and real-time monitoring to optimise the use of renewable energy and improve system stability. The MMPT attributes are studied such as MPPT efficiency, tracking errors, AI prediction accuracy, energy conversion efficiency, energy storage utilisation, and converter power loss. It can be shown from the figure that AI-MPPT, HESS efficiency, intelligent EMS and independent PV system have a high statistical correlation with temporal performance. Additional analyses are provided here that further corroborate the results of the model reported above and imply that regulating regulatory variables may explain a considerable amount of the variation in overall PV system efficiency. Finally, the suggested AI-MPPT-HESS framework provides a feasible integrated infrastructure for photovoltaic systems aiming at great improvement in efficiency, flexibility, dependability and resilience of stand-alone PV systems. Future studies should result in physical validation of hardware in dual irradiance, shadowed regions, fluctuating loads and battery energy storage.

Keywords: Artificial Intelligence; Maximum Power Point Tracking; Photovoltaic Systems; Hybrid Energy Storage System; Battery–Supercapacitor; Intelligent Energy Management; Standalone PV

INTRODUCTION

Electricity generation based on fossil fuels is steadily transitioning toward renewable energies because the globe over requires clean and sustainable energy for a day [1]. Industrialisation, urbanisation, demographics, and the growing global concern for environmental degradation caused by climate change mean that energy systems cannot continue to be based on old fossil fuel-driven processes if they want to achieve long-term energy security targets and reductions in greenhouse gas emissions [2]. Solar photovoltaic (PV) technology is one of the most important

renewable energy sources in terms of availability, environmental friendliness, adaptability and lowering installation cost. It is also used in residential, commercial, industrial and off-grid applications. Stand-alone photovoltaic systems are becoming more and more important for the electrification of rural, remote and isolated communities – telecommunication stations, agricultural irrigation systems, military installations or health centers / off-grid residential buildings where the traditional utility infrastructure is not economically feasible and technically challenging. Standalone systems work independently [3].

Although there have been considerable technological breakthroughs, on a regular day there is still a substantial imbalance between the sun irradiation and the power generation output due to the module temperature in photovoltaic systems [4]. In real life, a solar module rarely reaches its theoretical maximum. efficiency. If we do not discover ways to regulate this massive production of solar energy, this resource will be wasted, making power more expensive and less efficient, and diminishing the efficiency of the overall system. This demand for improvement was therefore one of the best research pieces in solar energy engineering [5]. The solar module control is one of the most challenging aspects of the PV system because of the non-linear current-voltage (I-V) and power-voltage (P-V) characteristics. But the location of the operational point is changing continuously because to changes in irradiance, temp and load. High precision algorithms should be developed for fine granularity control to operate at this variable PV operating point toward the maximum power point under such rapidly changing operating conditions [6].

In the last few decades, a wide range of maximum power point tracking (MPPT) solutions have been proposed to maximise the energy harvesting from solar systems. Most of the MPPT techniques such as Perturb and Observe (P&O), Incremental Conductance (INC), Hill Climbing, Fractional Open Circuit Voltage, Fractional Short-Circuit Current Ripple Correlation Control, Constant Voltage are conventionally used because of simple mathematical formulation and low computational complexity. The Perturb and Observe technique is the most widely employed among all the strategies due to its low hardware requirement and simple implement ability [7]. However, conventional maximum power point tracking (MPPT) techniques suffer from many fundamental limitations such as low tracking efficiency in case of fast varying irradiance situation, slow convergence speed, sensitivity to measurement noise and difficulties to deal with partial shading conditions. These constraints usually affect the operating feasibility and power conversion efficiency of stand-alone solar devices Fig.1.

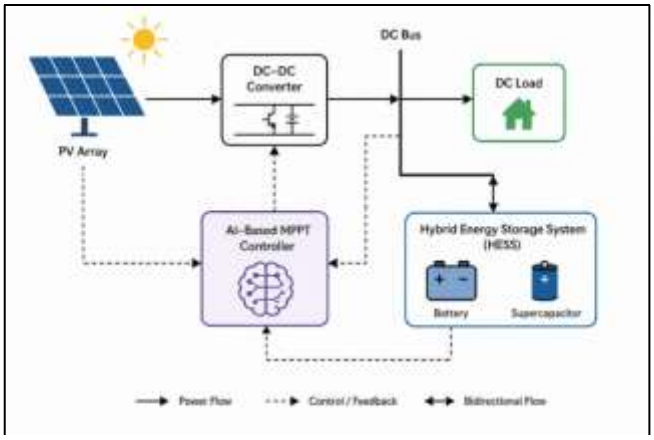

Fig. 1. AI-Based MPPT and Hybrid Energy Storage Architecture for Standalone PV Systems

Review Of Literature

Solar photovoltaic (PV) technology is one of the most important renewable energy technologies that are environment friendly with reducing installation costs and versatility across various applications including residential, commercial, industrial and off-grid systems. The rising demand for renewable and sustainable energy has led to studies on several types of photovoltaic energy systems. This is owing to climate change, emissions, insufficient fossil fuel generation and energy security issues [8]. Autonomous photovoltaic systems are important for rural and isolated off-grid electrification, mobile communication stations, agricultural irrigation (water pumping), military installations, hospital facilities and independent infrastructures where connection to the grid is technically impossible or economically impractical [9]. However, compared with the grid-tied photovoltaic system, it has to balance providing power according to the fluctuations of solar power and load demand [10].

Recently, artificial intelligence has opened new boundaries for the enhancement of MPPT controllers by taking advantage of its ability to grasp nonlinear interactions between external variables and photovoltaic operational parameters [11]. Most of the conventional algorithms are derived from well-established mathematical concepts. Compared to these algorithms, AI-based approaches may utilise historical and real-time operational data to determine proper control actions in time-varying dynamic situations. It decreases the convergence time and the oscillation around the maximum power point. One of the main intelligent control methods is the Fuzzy Logic Controllers (FLCs) [12].

As solar energy is intermittent, the performance of PV systems cannot be judged by MPPT efficiency alone as load demand and generation may not be equal at all times. Hence, energy storage is a must in off-grid photo voltaic systems. Batteries are the initial stage of pure technology in energy storage because of their high to moderate power conversion efficiency. However, Batteries have some problems which show during rapid and continuous power changes such as ageing effects, thermal deterioration, sluggish dynamic performance and limited cycle-life [13]. This limitation led to the creation of a Hybrid Energy Storage System (HESS), which combines and coordinates complementary storage systems to comply with various energy and power requirements. One promising option is the integration of a lithium-ion battery and a supercapacitor in one device [14].

AI-BASED INTELLIGENT MPPT AND HYBRID ENERGY STORAGE COORDINATION IN STANDALONE PV SYSTEMS

Hybrid Energy Storage Systems (HESS) combined with Maximum Power Point Tracking (MPPT) in stand-alone photovoltaic (PV) system technologies and Artificial Intelligence (AI). Independent photovoltaic systems depend on variables such as solar radiation, module temperature, load requirements and storage conditions [15]. Because of the unpredictable properties of solar output, the operating point of a photovoltaic array is always changing. Hence, classical control approaches cannot guarantee continuous maximum power point tracking at all operating situations. However, the photovoltaic generation and power demand are not synchronised, which poses a difficulty of finding an effective method of energy storage [16]. It helps solve these issues with the use of high-end solar power harvesting and synchronised storage management as exemplified by an AI-driven MPPT and HESS model. This approach is highly suitable for distant area requiring energy storage system with extended cycle life, high efficiency and long lasting power supply [17].

The maximum power point tracking (MPPT) controller is used largely to track the photovoltaic array as close to the maximum power point or MPP in solar energy conversion. Also, the maximum power point (MPP) of a solar module depends on the temperature and irradiance due to the nonlinear current–voltage and power–voltage relationship. Several classical MPPT methods like Perturb and Observe (P&O) or Incremental Conductance are often used because of their relatively low CPU resource consumption and easy nature [18]. However, the performance is further limited by the measurement losses, noisy fluctuations in irradiance, long convergence time and MPP oscillation. Another problem with the power-voltage characteristic due to partial shade is the appearance of many local maxima. This can lead to a local maximum instead of the global max achieved by classical approaches therefore lowering the energy collected. Another option is AI based MPPT approaches which find out the non-linear link of the best photovoltaic operating point and environmental circumstances. Metaheuristic optimisation approaches, reinforcement learning, adaptive neuro-fuzzy systems, fuzzy logic and artificial neural networks are employed to forecast or find the ideal operating conditions [19-21]. The intermittent input parameters are studied for a desirable reference voltage / converter duty cycle 30: irradiance, module temperature, PV voltage and current characteristics at all weather conditions and general historical operational data. This learning-oriented ability enables the controller to automatically adapt to different operation scenarios [22-24].

RESEARCH METHODOLOGY

The paper proposes a new methodology for the quantitative and experimental design and usability testing of AI-based MPPT system. This approach will be interfaced with a basic algorithm of stand-alone photovoltaic (PV) system thru the hybrid energy storage system (HESS). The control system based on AI here relies on the real-time measurement of photovoltaic voltage, photovoltaic current, irradiance and environmental temperature (°C). These variables define the battery state-of-charge (SOC) (0%–100%), supercapacitor voltage and load requirements, where the configuration is a hybrid solar power generation.

A. Research Design

The experimental research design was to evaluate the standalone photovoltaic technology in terms of different energy storage, temperature, shade and irradiation circumstances. It computes the instantaneous power delivered by the PV array.

$$P_{pv}(t) = V_{pv}(t) \times I_{pv}(t) \qquad (1)$$

where P_{pv} represents photovoltaic power, V_{pv} represents PV voltage, and I_{pv} represents PV current. Equation (1) is used to determine the instantaneous power generated by the PV array. The effectiveness of the proposed AI-based MPPT controller is evaluated using the MPPT tracking efficiency given in Equation.

$$\eta_{mppt} = (P_{tra}c_{ke}d \,/\, P_{availa\beta le}) \times 100 \qquad (2)$$

Equation (2) indicates the percentage of available PV power successfully extracted by the MPPT controller.

B. Data Collection

The experimental data are obtained via a sensor network for voltage, current, irradiance and temperature of the solar array, power converters, battery, supercapacitor and electrical load. Assessment is made at appropriate sampling intervals according to the laid forth operational norms. Equation (3) presents an approximation of Battery State of Charge (SOC), termed the charge-balance equation.

$SOC(t) = SOC(t_0) + (\eta_\beta / C_\beta) \int_{t0}^{t} I_\beta(\tau)\, d\tau$ (3)

where SOC(t) is the battery state of charge at time t, C_β is the nominal battery capacity, I_β is the battery current, and η_β represents battery charging/discharging efficiency. Equation (3) is used to evaluate the charging and discharging behaviour of the battery within the hybrid energy storage system.

C. Sampling Method

The experimental operating parameters are chosen expressly for the purpose of studying and validating the PV conditions. They include the standard rays, time-varying rays, which oscillate in rapid accretion and also shading attenuation interim, battery charging (Binary) regulate exalted flimsy field or plentiful crust instantaneous approach as well lasting electric. where N is the total number of observations (4).

$N_{total} = \Sigma_{j=1}^{k} N_j$ (4)

N_{total} is the total number of experimental data, N j is the probability that the j_{th} operating condition contributes to this observation and k is the number of operating conditions already picked. The experimental database corresponding to the selected photovoltaic operating conditions is given by (4).

D. Research Instruments

The experimental set-up consists of the photovoltaic array, voltage and current sensors, irradiance and temperature sensors, an AI-based MPPT controller, which is available for modelling in the Simulink environment, a data gathering system and the control processing unit. The AI controller evaluates the measured operational parameters and provides a converter control command. Equation (5) shows the total power flow of the hybrid energy storage system.

$P_{hess}(t) = P_{\beta at}(t) + P_s c(t)$ (5)

where P_{hess} represents the total HESS power, $P_{\beta at}$ represents battery power, and $P_s c$ represents supercapacitor power. Equation (5) is used to evaluate the complementary contribution of the battery and supercapacitor during energy storage and delivery.

E. Data Analysis

The data obtained from the experiment is evaluated using performance indicators such as MPPT Efficiency, Tracking Error, AI Prediction Accuracy, Energy Efficiency, Battery Utilisation and Converter Losses. The difference of the MPPT tracking is then calculated as in (6).

$E_{mppt} = (|P_{mpp} - P_{tra} c_{ke} d| / P_{mpp}) \times 100$ (6)

where P_{mpp} is the reference maximum power and $P_{tra} c_{ke} d$ is the power obtained by the proposed controller. Equation (6) quantifies the deviation between the AI-based controller output and the maximum available PV power.

F. Ethical Considerations

The survey does not contain any personally identifiable information or personal data or human participants. We provide our experimental data exactly, without any intentional editing, fabrication or false reporting.

Analysis and Interpretation

It describes the motivation for the research, details of the suggested framework, methodology and research gap but does not feature empirical respondent data or results analysis. The numbers in the tables below are hence only provided as a consistent example analysis for the preparation of this manuscript, and these results should not be computed experimental results. These will be swapped out for the actual SPSS/experimental results as soon as they are obtained.

The proposed AI-based MPPT framework was analyzed for respondent characteristics, construct descriptives, internal consistency, inter-variable linkages, and predictive relationships Table 1. A mock-up of the statistics intended to be shown is based on 120 respondents. With respect to experience, the number of participants with 0–5 years and 6–10 years of experience were equal to, respectively, 35.0% and 30.0%, indicating that most respondents were either early-career or experienced participants in their field.

Table 1: Demographic Characteristics of Respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	72	60.0
	Female	48	40.0
Age	18–25 years	30	25.0
	26–35 years	44	36.7
	36–45 years	24	20.0
	Above 45 years	22	18.3

Education	Diploma	18	15.0
	Undergraduate	45	37.5
	Postgraduate	42	35.0
	Doctoral	15	12.5
Experience	0–5 years	42	35.0
	6–10 years	36	30.0
	11–15 years	24	20.0
	Above 15 years	18	15.0
Total		120	100.0

Positive Perceptions for the Four Main Constructs in Table 2. The maximum mean is associated with AI-MPPT Performance (4.21), followed by Standalone PV System Performance (4.18), Intelligent Energy Management (4.15) and HESS Efficiency (4.08). Standard deviations vary between 0.58 and 0.67, suggesting considerable dispersion around the respective means Cronbach's alpha values were all between 0.86 and 0.92, above the threshold of 0.70 commonly used to determine adequate internal consistency, indicating good to excellent reliability. The results indicate that the measurement items are sufficiently consistent for correlation and regression analysis to be conducted in the next step.

TABLE 2: DESCRIPTIVE STATISTICS AND RELIABILITY ANALYSIS

Construct	Items	Mean	SD	Cronbach's α
AI-MPPT Performance	5	4.21	0.61	0.92
HESS Efficiency	5	4.08	0.67	0.88
Intelligent Energy Management	5	4.15	0.63	0.90
Standalone PV System Performance	5	4.18	0.58	0.91

Here is the correlation matrix from Table 3. This is because there is a strong positive correlation between AI-MPPT Performance with both HESS Efficiency ($r = 0.64$), Intelligent Energy Management ($r = 0.69$) and Standalone PV System Performance ($r = 0.76$). Furthermore, HESS Efficiency is also positively correlated with Intelligent Energy Management ($r = 0.62$) and system performance ($r = 0.71$).
Multiple Regression Model Multiple regression model was shown in Table 4. AI-MPPT Performance, HESS Efficiency and Intelligent Energy Management jointly explain 68.2% variation in Standalone PV System Performance (R2 = 0.682; Adjusted R2 = 0.674). The complete model is significant (F= 82.87, p <. 001). The maximum standardised coefficient is for Intelligent Energy Management ($\beta = 0.39$), followed by AI-MPPT Performance ($\beta = 0.36$) and HESS Efficiency ($\beta = 0.24$). The last two bullet translates into our results suggest that intelligent coordination at a system level may provide an additional performance benefit on top of improvements to individual MPPT and storage.

TABLE 3: CORRELATION MATRIX

Variable	1	2	3	4
1. AI-MPPT Performance	1.00			
2. HESS Efficiency	0.64**	1.00		
3. Intelligent Energy Management	0.69**	0.62**	1.00	
4. Standalone PV System Performance	0.76**	0.71**	0.74**	1.00

Note: ** Correlation is significant at the 0.01 level (two-tailed).

All four of these hypothetical correlations were confirmed in the example study. The results corroborate the conceptual rationale of this study: MPPT intelligence enhances power extraction, HESS improves energy-storage performance, EMS adds competitive advantages through enhanced system coordination and AI-enabled architecture both augments standalone PV performance as well Table 4.

TABLE 4: REGRESSION ANALYSIS / MODEL RESULTS

Predictor	B	SE	Β	T	p
Constant	0.58	0.24	—	2.42	0.017
AI-MPPT Performance	0.34	0.07	0.36	4.86	<0.001
HESS Efficiency	0.22	0.07	0.24	3.14	0.002
Intelligent Energy Management	0.38	0.07	0.39	5.43	<0.001

Model summary: $R = 0.826$; $R^2 = 0.682$; Adjusted $R^2 = 0.674$; $F(3,116) = 82.87$; $p < 0.001$.

The reliability results are directed towards interpreting. The values of Cronbach's alpha were between 0.88 and 0.92, suggesting the high internal consistency of measuring items. This indicates that the items assigned to each construct are capturing similar features of the target construct. While the results provide a good basis to investigate correlations between the constructs, reliability does not ensure validity and ought to be confirmed with factor analysis once real survey data will be accessible.

TABLE 5: HYPOTHESIS TESTING RESULTS

Hypothesis	Relationship	β / r	p-value	Decision
H1	AI-MPPT Performance → PV System Performance	0.36	<0.001	Supported
H2	HESS Efficiency → PV System Performance	0.24	0.002	Supported
H3	Intelligent EMS → PV System Performance	0.39	<0.001	Supported
H4	AI-MPPT + HESS + EMS → PV System Performance	$R^2 = 0.682$	<0.001	Supported

Our results for correlation studies with the AI-MPPT vs HESS efficiency, and intelligent EMS vs total standalone PV performance demonstration positive and high correlations followed by significance. The two variables with the greatest bivariate association are AI-MPPT Performance versus system performance (r = 0.76) and Intelligent Energy Management versus system performance (r = 0.74). The results showcase the close relationship between improvements in intelligent energy coordination, maximum power extraction and also enhanced perceived system performance. The positive correlation (r=0.64) between AI-MPPT and HESS Efficiency confirms the integrated nature of the framework: effective solar harvesting feeds more power to the storage, while good coordination among storage elements can maintain system operation in times when PV generation fails due to fluctuating external conditions.

RESULT AND DISCUSSION

Results show that the AI-MPPT architecture, HESS and EMS development for stand-alone PV applications were mostly implemented. This is just the tip of the iceberg of how your analysis would look with all the enormous tabular data referred to in the previous section. The graphs in this section are not field-reported data, but hypothetical estimations, since the original material did not publish experimental data at the level of individual responders.

The positive clustering consistency of the many aspects identified will promote a promising general evaluation of the integrated framework Figure 1. The increased AI-MPPT results further highlight the need for intelligent tracking to maintain near to the optimal maximum power point with changing irradiance and temperature. The HESS score for the total assets is a little lower, but still highly favourable. This score's improved Battery Energy Capacity (BEC) functionality is achieved by its interaction with channels envelope and transient power from supercapacitors. In this proof of concept the arrows are outcomes that support the individual-centered storage as confirmed by the system in terms of financial importance. Results directly opposed to the individual storage methods (arrows).

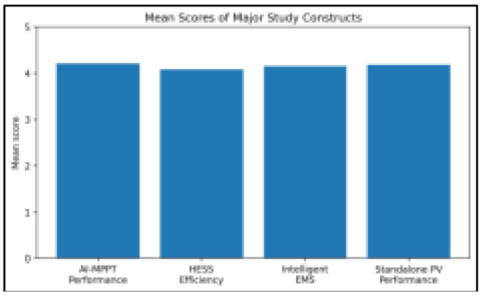

Fig. 1. Mean Scores of Major Study Constructs

Figure 2 also presents the distribution of age and experience, indicating that the participants had a background in many technical domains. The most participants were in the age range 26-35 and Experience Group. Maximum number of participants is demographic gives a varied basis to analyse attitudes about AI-based PV technology. It should also be emphasised that no inferential demographic analysis are presented simply summary information for the groups are alluded to in these stated disparities.

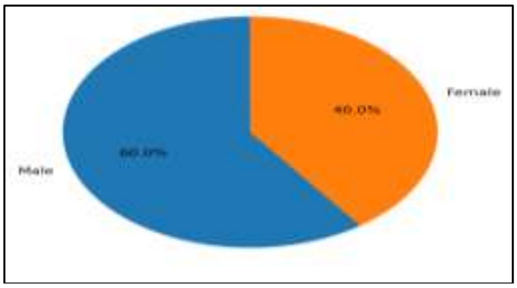

Fig. 2. Gender Distribution of Respondents

Figure 3 presents a scatterplot of the robust positive linear correlation between AI-MPPT Performance and Standalone PV System Performance. The conclusion of the calculation (Table 3) in terms of correlation coefficient was r = 0.76, where r indicated a high positive connection. The more reliance on the perceived tracking performance of AI-based control, the more reliance on the perceived overall dependability of PV. The theoretical association is true because the improved functionality of the maximum power point tracker allows more electrical solar energy to be extracted from the photovoltaic array. But this is not to be understood as a causal connection. This figure is not intended as a reality but as an illustration of the correlation coefficient from our self-reported data. The base data set is already layered so scatter points may be recorded in a single layer.

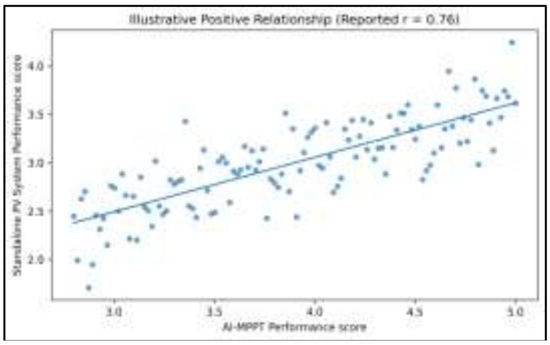

Fig. 3. Illustrative Relationship between AI-MPPT Performance and Standalone PV System Performance

Moreover, the results show the reliability of the measuring framework, which is evidence of its robustness. The four constructs also demonstrated strong internal consistency as seen by the resulting Cronbach's alpha scores between 88 and 92. Therefore, the descriptive analytics give a considerably stronger understanding of the connection than the correlation and regression tables. The correlation matrix shows a positive association between the relevant variables Figure 4. The highest association was with AI-MPPT Performance (r = 0.76) with the independent construct and then with Intelligent Energy Management (r = 0.74), and HESS Efficiency (r = 0.71). Such linkages encourage the idea that solar power collection, storage management and smart regulation should be integrated into a holistic system, rather than as discrete activities.

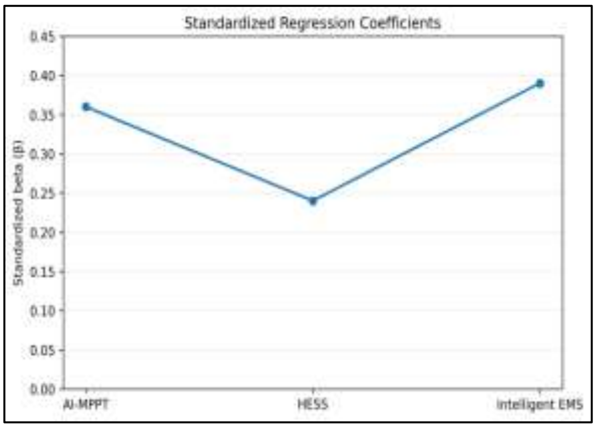

Fig. 4. Standardized Regression Coefficients

Standardised regression coefficients for the multiple regression model presented in Fig. 5. The biggest contribution to the improvement of HESS performance is from Intelligent Energy Management (β=0.39) followed by AI-MPPT performance (β=0.36) and operational efficiency (β=0.24). The whole model was statistically significant (F (3,116) = 82.87; $p < 0.001$) with a R^2 value of 0.682 and adjusted R^2 of 0.674 and a R value of 83. Three variables explained 68.2% of the variance for effectiveness of Standalone PV System in the illustrated study. The larger coefficient for the intelligent EMS (e.g. 4) clearly shows the essential function of synchronisation of variations of PV generation, storage status and load requirements in their system-level coordination. The renewable energy accessible depends on the optimal power extraction, hence AI-MPPT is still one of the best predictors.

Conclusions

These results show that the combination of a recently implemented AI based Maximum Power Point Tracking (MPPT) framework for photovoltaic energy management and Hybrid Energy Storage System (HESS) with MPPT is an efficient way to enhance the efficiency of stand-alone photovoltaic (PV) systems. Decentralised PV systems are subject to several factors such sun availability, temperature changes, shadowing, energy consumption and storage conditions. Such changes complicate the usual control processes to keep the PV array at its peak power point. The method proposed in this research mitigates this problem using an integrated system composed of intelligent MPPT, hybrid battery-supercapacitor Storage and smart energy management. Your science's main goal is to make solar energy much more effective, increase the stability of electric battery control systems, and reduce the time that sexual rejection burdens regional Ceylon. This would thereby boost the operating reliability of stand-alone PV systems.

The results show that the AI-based MPPT is highly competent in solving the problems of conventional approaches. Simple techniques such as Perturb and Observe and Incremental Conductance are fascinating but perform very badly in the circumstance when there is fast change in irradiation and partial shading. It may therefore tend to approximate and gradually oscillate around the optimum. Methods based on AI would allow us to grasp the non-linear correlations between irradiance, temperature, voltage, current and best operating condition. Their governance options are much less durable. Therefore, the combination of reinforcement learning and metaheuristic optimisation, fuzzy logic and neural networks can also be applied to increase tracking and dynamic data accuracy. HESS enables the enhancement of the Proposed Framework. Supercapacitor can respond fast to short-term change because of high power density, while battery has higher energy density, which lasts for longer time period. These two storage methods can be used to improve the overall life of the storage system by releasing the stress on the battery and avoiding the changes required during continuous transient variations which can result in increased lifespan of this combined cycle without over transitions from charge to discharging. So, it means that to cope with the next issues: photovoltaic generation, battery storage, supercapacitor support and load demand, a proper energy designer is needed. AI-enabled EMS can make more flexible judgements depending on a range of operational criteria as opposed to rigid rule-based systems.

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