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Smart Grid Technology and AI Integration for Renewable Energy Management

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ABSTRACT—

The rapid growth of solar and wind power is making electricity networks harder to operate, because renewable output is variable, weather dependent and difficult to predict. Smart grid technology, which adds sensing, two-way communication and automation to the power system, together with artificial intelligence (AI), offers a practical way to manage this variability. This paper reviews the main smart grid technologies and AI techniques used for renewable energy management, and proposes a layered AI-integrated energy management system (EMS) for a solar–battery microgrid. The proposed EMS forecasts solar generation one day ahead and uses the forecast to schedule battery charging and discharging against a time-of-use tariff. A reproducible simulation study with synthetic data (50 kWp solar array, 100 kWh battery, 30 test days) shows that a battery with simple rule-based control reduces electricity cost by 20.2 %, forecast-driven scheduling with a random forest model raises the saving to 22.2 %, and a perfect forecast would give 24.7 %. Challenges such as cyber-security, data quality and cost are discussed, and the paper is written to be accessible to diploma-level engineering students.

***Index Terms*—Smart grid, artificial intelligence, renewable energy, energy management system, solar forecasting, battery storage, microgrid, machine learning.**

I. INTRODUCTION

Electricity systems around the world are changing from a small number of large fossil-fuel power stations to a large number of smaller, cleaner and more distributed sources. Solar photovoltaic (PV) and wind power are growing fastest, and India has announced a target of 500 GW of non-fossil electricity capacity by 2030 [1]. Unlike a coal or hydro plant, a solar array or wind farm cannot be dispatched on demand: its output follows sunshine and wind, can change within minutes when a cloud passes, and is never known exactly in advance. The traditional grid was designed for one-way power flow from large plants to consumers with limited monitoring, so it struggles with voltage rise, reverse power flow, curtailment of surplus energy and the extra reserves needed to cover forecast errors.

The smart grid is the response to these problems. It adds sensors, two-way communication, automation and data analytics to the physical power system, so that generation, storage and consumption can be observed and coordinated in near real time [2], [3]. A modern distribution network produces large amounts of data from smart meters, inverters, protection devices and weather stations. This volume is beyond manual analysis, and artificial intelligence (AI), especially machine learning (ML), can convert such data into forecasts, schedules and alarms.

This paper is written for diploma-level engineering students and has five objectives: (i) to explain the key technologies of a smart grid; (ii) to review AI techniques for forecasting, optimisation and fault detection in renewable energy systems; (iii) to propose a layered AI-integrated energy management system (EMS) for a solar–battery microgrid; (iv) to evaluate the proposal by a reproducible simulation of forecasting accuracy and cost saving; and (v) to discuss the practical challenges of deployment.

The main contributions are a clear architecture and workflow for AI-based energy management, a complete simulation that can be repeated with free software, and an honest comparison of rule-based, forecast-driven and perfect-forecast battery scheduling. Section II describes smart grid technologies, Section III the challenges of renewable integration, Section IV the AI techniques, Section V the proposed system, Section VI the simulation study and results, Section VII the practical implementation and applications, Section VIII the benefits and challenges, and Sections IX and X the future scope and conclusions.

II. SMART GRID TECHNOLOGIES

A. Architecture and Key Elements

A smart grid overlays a communication and information layer on the physical power system of generation, transmission, distribution and consumers [2], [3]. Its defining features are two-way flow of both energy and information, real-time measurement, automated control and active participation of consumers. Table I lists the principal technologies and their roles.

TABLE I

KEY SMART GRID TECHNOLOGIES AND THEIR ROLES

Technology	Function in the smart grid	Typical link
Smart meter (AMI)	Records interval energy data; supports two-way billing and control	RF mesh, cellular
SCADA / PMU	Real-time monitoring and phasor measurement of grid state	Fibre, IEC 61850
Inverter / DER controller	Converts PV and battery power; follows set-points	Modbus, IEC 61850
Energy storage system	Shifts energy in time; smooths PV and wind output	CAN, Modbus
Distribution automation	Locates and isolates faults; restores supply	Fibre, LTE / 5G
AI-based EMS	Forecasts, schedules and optimises resources	MQTT, IP

B. Communication and Standards

Devices from many manufacturers must exchange data reliably, so standards are central. The IEEE 2030 guide describes a reference model for smart grid interoperability [4], and the IEC 61850 series defines data models and services for substation automation and distributed energy resources (DER) [5]. Legacy protocols such as Modbus and DNP3 remain common at the device level. Wired media such as optical fibre and power-line carrier offer high reliability, while wireless links such as RF mesh, Wi-Fi, LTE and 5G are used where cabling is costly. For lightweight telemetry from field devices to analytics platforms, publish/subscribe protocols such as MQTT are widely used. Latency needs differ greatly: protection signals need milliseconds, supervisory control needs seconds, and meter reading needs minutes to hours.

C. Microgrids and Energy Storage

A microgrid is a group of loads and DER with defined boundaries that can operate connected to the main grid or islanded from it [6]. Control is usually hierarchical: primary control keeps voltage and frequency stable within milliseconds, secondary control restores them and shares power among units, and tertiary control, where the EMS sits, decides economic dispatch over hours or days [6]. A battery energy storage system (BESS) supports all three levels. It can smooth rapid PV fluctuations, store midday surplus for the evening peak, and reduce purchases when grid tariffs are high.

D. Smart Meters and Data

Smart meters record consumption at intervals of 15 to 60 minutes and send it to the utility. The resulting data supports load forecasting, theft detection, consumer segmentation and demand response programmes [7]. The same communication network can also carry price signals and control commands back to the consumer, closing the loop between the utility and the load.

III. CHALLENGES OF RENEWABLE INTEGRATION

Variability and uncertainty. Solar output rises and falls with the sun and with clouds, and wind output follows gusts and weather fronts. Forecast errors force the operator to hold extra reserve capacity, which raises cost and emissions.

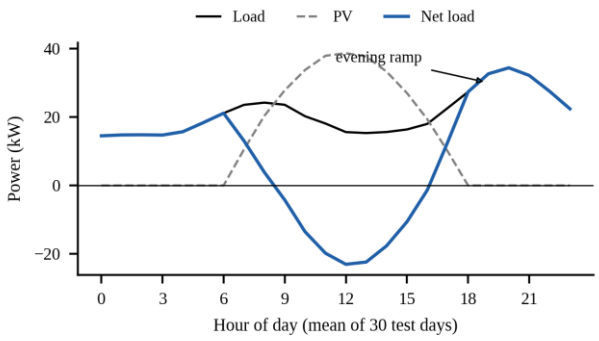
Net-load ramps. When PV output falls in the evening, just as household demand rises, conventional plants must ramp up quickly. This pattern, often called the duck curve, becomes steeper as PV capacity grows.

Distribution-level effects. Rooftop PV can push power back into feeders designed for one-way flow, causing voltage rise, overloaded transformers and protection mis-operation. Inverter-based sources also contribute less inertia than synchronous machines, which makes frequency control more demanding.

Economics. Surplus PV energy at midday may be curtailed or exported at a low price, while the same consumer buys expensive energy during the evening peak. Storage and intelligent scheduling are needed to shift energy from the first period to the second.

Fig. 1 illustrates the net-load problem with the simulated microgrid of Section VI. On average, PV output exceeds the load from 09:00 to 16:59 and the net load (load minus PV) falls to about −23 kW at noon, meaning surplus power. By 20:00 the net load has risen to about 34 kW, a swing of about 36 kW in only four hours after 16:00, which the grid or a battery must supply.

Fig. 1. Mean daily load, PV output and net load of the simulated microgrid.



IV. AI TECHNIQUES FOR RENEWABLE ENERGY MANAGEMENT

AI covers machine learning, deep learning, fuzzy logic, evolutionary algorithms and reinforcement learning. Table II summarises the techniques most relevant to renewable energy management and the data they use.

TABLE II

AI TECHNIQUES AND TYPICAL APPLICATIONS

AI technique	Typical use	Typical inputs
Linear regression	Baseline PV and load forecast	Time, lagged values
Random forest	Day-ahead PV and load forecast	Weather, history, time
LSTM network	Sequence forecast of PV and wind	Long time series
Fuzzy logic / ANN	MPPT and inverter control	Voltage, current
PSO / genetic algorithm	Sizing and scheduling	Cost, constraints
Reinforcement learning	Adaptive battery and demand control	Prices, SOC, forecasts
Clustering, anomaly detection	Fault and theft detection, consumer grouping	Smart-meter data

A. Forecasting

Accurate forecasts of PV, wind and load are the foundation of an AI-based EMS. Reviews of PV forecasting describe methods ranging from persistence and statistical models to ML and hybrid physical models [8], and deep learning has become popular for renewable forecasting because it can learn complex non-linear patterns [9]. Long short-term memory (LSTM) networks are suited to sequences because they keep information over many time steps [10]. Random forests combine many decision trees and are robust, fast to train and easy to use on small data sets [11]. Typical inputs are irradiance or cloud-cover forecasts, temperature, recent measurements and time-of-day features.

B. Optimisation and Control

Dispatch is an optimisation problem: choose battery, grid and flexible-load actions that minimise cost subject to the power balance and equipment limits. It can be solved by linear or mixed-integer programming, by metaheuristics such as particle swarm optimisation (PSO) and genetic algorithms, or by reinforcement learning (RL), in which an agent learns a control policy by interacting with a simulated or real environment and receiving rewards for low cost [12]. RL needs no explicit model of the system but needs much data and careful safety constraints.

C. Fault Detection and Demand Response

Anomaly detection on inverter and meter data can reveal failing equipment, shading, soiling of panels or electricity theft earlier than manual inspection. Clustering groups consumers with similar load shapes so that demand response offers can be targeted, for example by shifting water heating or electric-vehicle charging to hours of surplus solar energy.

D. Edge and Cloud Deployment

Light models such as linear regression or random forests can run on a low-cost edge gateway in the plant, which keeps working when the internet link fails. Heavier models such as deep networks are usually trained in the cloud and, if necessary, compressed before being sent to the edge. For a diploma project, an inexpensive single-board computer with free Python libraries is sufficient.

V. PROPOSED AI-INTEGRATED EMS

A. System Architecture

The proposed system has three layers, as shown in Fig. 2. The physical layer contains solar PV, a wind turbine, battery storage, the utility connection and smart loads such as electric vehicles, each with a smart meter or intelligent electronic device (IED). The communication layer, based on AMI, SCADA, IEC 61850 and MQTT, carries measurements upward and set-points downward. The top layer is the AI-based EMS, containing forecasting, optimisation and anomaly-detection modules.

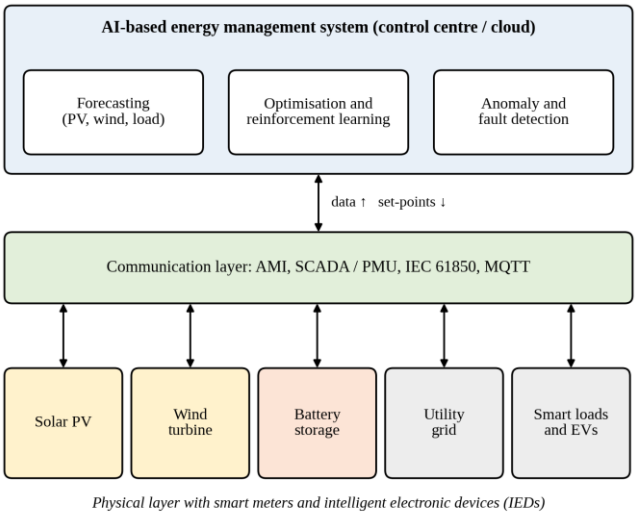


Fig. 2. Layered architecture of the proposed AI-integrated energy management system.

B. Operating Workflow

Fig. 3 shows the cycle executed by the EMS. Data from meters, weather services and SCADA are cleaned and converted into features, and the forecasting module predicts generation and load. The optimiser uses the forecasts, tariffs and battery state to compute set-points, which are sent to the inverters, battery and controllable loads. Measured results are then compared with forecasts, alarms are raised on large deviations, and the models are periodically retrained. Hard safety limits, such as the battery current, voltage and temperature limits and anti-islanding protection, remain in the local controller so that an AI fault can never override them.

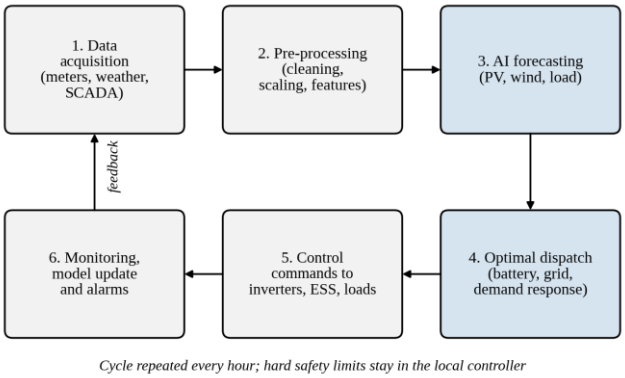


Fig. 3. Operating workflow of the AI-based EMS.

VI. SIMULATION STUDY AND RESULTS

A. Test System and Data

To demonstrate the value of AI-based scheduling, a grid-connected microgrid with a 50 kWp PV array and a 100 kWh battery was simulated in Python using NumPy and scikit-learn [13]. No field measurements were used: hourly data for 90 days were generated synthetically with a fixed random seed so that every result can be reproduced. PV power is modelled as the clear-sky output multiplied by a clearness index,

$$P_{PV}(t) = P_{cs}(t) \cdot k(t) \qquad (1)$$

where k depends on a day-level weather state and an hourly cloud process, both with memory, so that cloudy days tend to follow cloudy days. The load has morning and evening peaks with random daily scaling. Table III lists the parameters. The tariff and export price are assumed illustrative values, not actual utility rates.

TABLE III

SIMULATION PARAMETERS

Parameter	Value
PV array	50 kWp; mean daylight output 22.8 kW
Load	Mean 503 kWh/day; evening peak about 35 kW
Battery	100 kWh, 10 kWh minimum, 40 kW, 95 % each way
Tariff (assumed)	₹5 (23:00–05:59), ₹10 (18:00–22:59), ₹7 otherwise
Export price (assumed)	₹3 per kWh
Data	90 days hourly; 60 days training, 30 days test

B. Forecasting Models

A day-ahead forecast of the hourly clearness index was made for each daylight hour of the next day. Inputs were the hour, the clear-sky power, the clearness index at the same hour on the previous two days, and the mean daylight clearness of the previous day and of the previous three days. Three models were compared: persistence, which repeats yesterday's value; linear regression; and a random forest with 200 trees [11], trained on the first 60 days and tested on the last 30. Accuracy is measured by the mean absolute error (MAE) and the root-mean-square error (RMSE) over daylight hours,

$$\mathrm{MAE} = (1/N)\,\Sigma\,|F_i - A_i| \qquad (2)$$

$$\mathrm{RMSE} = \sqrt{[(1/N)\,\Sigma\,(F_i - A_i)^2]} \qquad (3)$$

where F_i and A_i are the forecast and actual PV power in kW. Table IV and Fig. 4 show the results. The random forest has the lowest MAE, and linear regression the lowest RMSE, but all three models are close, because the synthetic weather has a strong random component that no model can predict a day ahead. Persistence is already a strong baseline when weather has memory.

TABLE IV

DAY-AHEAD PV FORECAST ACCURACY (30 TEST DAYS)

Model	MAE (kW)	RMSE (kW)	nMAE (%)
Persistence	4.87	7.93	21.4
Linear regression	4.83	6.95	21.2
Random forest	4.73	7.32	20.8

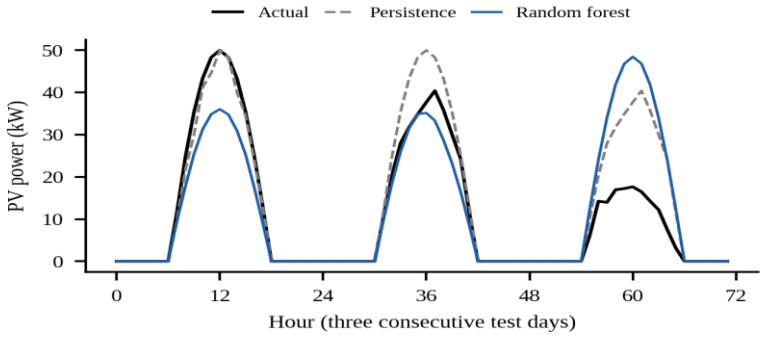


Fig. 4. Actual and forecast PV power for three consecutive test days.

C. Dispatch Strategies

Five strategies were compared. The first is no storage, where the battery is absent. The second is rule-based, where the battery charges from any PV surplus and discharges to cover any deficit at once. The third to fifth are predictive: the battery charges from surplus PV, discharges only in the peak-tariff hours, and in the cheap night hours is charged from the grid up to a target level computed from the forecast. The target is the battery capacity minus the PV surplus forecast for the next morning and afternoon, so that grid energy is bought only when the sun is not expected to fill the battery. The three predictive versions use the persistence forecast, the random forest forecast and a perfect forecast, the last being an upper bound. At every hour the power balance and the battery state of charge must satisfy

$$P_{PV} + P_{dis} + P_{imp} = P_{load} + P_{ch} + P_{exp} \qquad (4)$$

$$E(t+1) = E(t) + \eta\,P_{ch}\,\Delta t - P_{dis}\,\Delta t / \eta \qquad (5)$$

where E is the stored energy, $\eta = 0.95$ is the one-way efficiency, and the subscripts denote import from the grid, export to the grid, charging and discharging. The cost over the test period and the saving relative to the no-storage case are

$$C = \Sigma\, [c(t)\, P_{imp}(t) - c_x\, P_{exp}(t)]\, \Delta t \qquad (6)$$

$$S = (C_0 - C) / C_0 \times 100\ \% \qquad (7)$$

where $c(t)$ is the time-of-use tariff, c_x the export price and C_0 the cost without storage.

D. Dispatch Results

Table V gives the results for the 30 test days. Adding a battery with simple rules already reduces cost by 20.2 % and raises the share of PV energy used on site from 60.9 % to 87.5 %. Predictive scheduling with the random forest forecast raises the saving to 22.2 %, close to the 24.7 % possible with a perfect forecast, so the gain from AI is about two percentage points over the rule-based case and about half a point over the persistence forecast. The reason is visible in Fig. 5: the rule-based battery often empties before the evening peak, whereas the predictive controller keeps energy for the peak and tops it up from cheap night power when a poor solar day is expected. Fig. 6 compares the costs.

TABLE V

COST AND ENERGY RESULTS OVER 30 TEST DAYS

Strategy	Cost (₹)	Import (kWh)	Peak import (kWh)	PV used (%)	Saving (%)
No storage	64,377	9,693	4,621	60.9	0.0
Rule-based	51,370	7,561	2,897	87.5	20.2
Predictive, persistence	50,392	7,941	2,379	83.3	21.7
Predictive, random forest	50,088	7,626	2,449	86.8	22.2
Predictive, perfect forecast	48,483	7,622	2,107	87.3	24.7

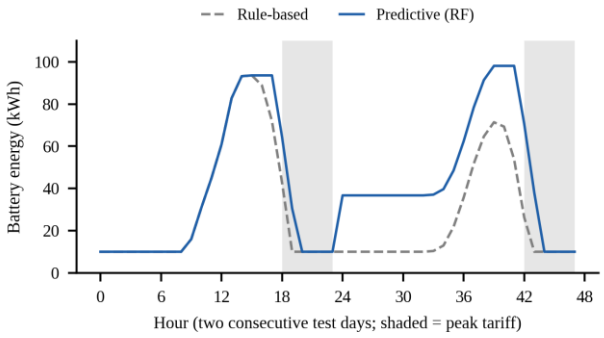


Fig. 5. Battery energy under rule-based and predictive control on two test days.

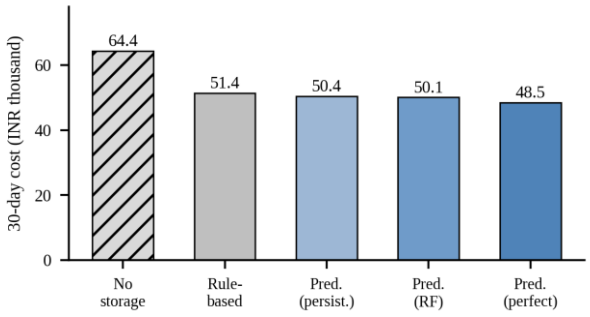


Fig. 6. Electricity cost over the 30 test days for the five strategies.

E. Effect of Battery Size

The simulation was repeated for battery sizes from 50 to 200 kWh with the power rating unchanged. Table VI shows that every strategy saves more with a larger battery, but the extra benefit of forecasting grows much faster: the advantage of the random forest scheduler over the rule-based one rises from 1.9 percentage points at 50 kWh to 7.8 points at 200 kWh. A small battery is emptied every evening whatever the strategy, whereas a large one must be planned, because filling it from the grid when the sun will do the job wastes money, and leaving it half empty before a cloudy day wastes the peak-tariff opportunity. The gap between the random forest and the perfect forecast also widens with size, which shows the value of better forecasts for larger systems.

TABLE VI

COST SAVING VERSUS BATTERY SIZE (30 TEST DAYS)

Battery (kWh)	Rule-based (%)	Predictive, RF (%)	Perfect forecast (%)
50	9.4	11.3	11.6
100	20.2	22.2	24.7
150	27.1	30.6	36.7
200	29.5	37.3	41.9

F. Discussion and Limitations

Storage provides most of the benefit, and AI adds a smaller but real improvement whose size depends on how predictable the weather is, on the tariff spread and on battery size. Because the data are synthetic, the numbers show the method rather than the performance of an actual plant. The model also ignores battery ageing, inverter losses, demand charges and export limits. A pilot with measured data from a campus or housing society is the natural next step, and the same code can be re-run with real files.

VII. IMPLEMENTATION ROADMAP AND APPLICATIONS

A. Roadmap for a Student Project

A small working prototype can be built in six steps. (1) *Measure:* use energy meters with a Modbus or serial interface for the PV array, battery and load, and an irradiance or temperature sensor. (2) *Transport:* read the meters with a microcontroller or single-board computer and publish the values over MQTT to a Mosquitto broker. (3) *Store and display:* keep the readings in a database and show them on a Node-RED or Grafana dashboard. (4) *Learn:* train the forecasting model with scikit-learn on the stored history and retrain it every week. (5) *Decide:* run the scheduling rules of Section VI-C as a Python script that first only recommends set-points. (6) *Act safely:* after the recommendations have been checked against reality, send set-points to the inverter or battery management system through the gateway, keeping protection limits in the device itself. Testing first on a 12 V PV and battery bench avoids risk to mains equipment.

B. Applications

The same architecture applies at several scales. Table VII lists typical applications, the AI function in each and the main benefit.

TABLE VII

APPLICATIONS OF AI-INTEGRATED SMART GRIDS

Application	AI function	Main benefit
Rooftop PV in a housing society	Day-ahead PV and load forecast; battery schedule	Lower peak-hour purchase
College or industrial campus	Demand forecast; HVAC load shifting	Lower demand charges
Village or farm feeder	Pump scheduling to match solar hours	Better use of solar energy
EV charging hub	Smart charging using PV forecast	Flatter evening peak
Wind–solar hybrid plant	Ramp forecast; curtailment reduction	Fewer grid-code violations

VIII. BENEFITS AND CHALLENGES

Benefits. AI-integrated smart grids allow a higher share of renewable energy without loss of reliability, reduce electricity cost and peak demand, cut emissions, detect faults earlier and give consumers more control over their consumption.

Cyber-security and privacy. Networked inverters, meters and controllers enlarge the attack surface of critical infrastructure [14]. Strong authentication, encryption, network segmentation and regular updates are essential, and fine-grained meter data can reveal household habits, so it must be protected and anonymised where possible.

Data, cost and skills. Models need clean, sufficient data, and missing or wrong readings degrade forecasts. Sensors, communication and storage require investment, and utilities need staff who understand both power systems and data science. ML models can also drift as weather patterns and equipment change, so performance must be monitored and models retrained.

Trust and interoperability. Operators hesitate to hand control to models they cannot explain, so simple, interpretable models and safe fall-back rules are valuable. Multi-vendor equipment must follow open standards if systems are to work together.

IX. FUTURE SCOPE

Promising directions include: (1) federated learning, which trains shared models without moving private meter data; (2) transformer and hybrid physics–ML forecasting models that use satellite and sky-camera images; (3) deep RL for real-time control of batteries, electric vehicles and flexible

loads; (4) peer-to-peer energy trading on secure ledgers; (5) digital twins of microgrids for safe testing of controllers; (6) vehicle-to-grid services; and (7) integration of green hydrogen and long-duration storage for seasonal balancing.

X. CONCLUSION

This paper reviewed smart grid technologies and AI techniques for managing renewable energy and proposed a layered AI-integrated EMS that forecasts solar generation and schedules battery storage against a time-of-use tariff. A reproducible simulation of a 50 kWp, 100 kWh microgrid showed that a battery with simple rules cut electricity cost by 20.2 %, forecast-driven scheduling with a random forest raised this to 22.2 %, and a perfect forecast would give 24.7 %. Storage therefore delivers most of the benefit, and AI adds a measurable further gain that grows with forecast accuracy and tariff spread. With open standards, free software and low-cost hardware, such systems are within reach of diploma-level projects, and the next step is validation with measured data from a real installation.

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