ARTICLE

AI-Assisted Power Management in Renewable Grids: DC–DC Converter Optimization and Predictive Load Balancing for Sustainable Energy Systems

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Abstract

The transition to sustainable energy systems is accelerating, driven by concerns over climate change, energy security, and the need for decarbonization. Renewable energy sources (RES) such as solar and wind are intermittent and variable, posing considerable challenges for grid stability, efficient power conversion, and load and supply balancing. In particular, DC-DC converters are critical components in renewable energy integration, enabling efficient voltage regulation, maximum power point tracking (MPPT), and interfacing between generation, storage, and load. However, conventional control approaches (fixed-duty cycle, simple MPPT algorithms, PI/PID controllers) struggle under large fluctuations in irradiance, temperature, load, and energy demand. Predictive load balancing and AI-based control promise to improve efficiency, stability, and reliability in renewable grids.

This paper proposes an integrated framework for Alassisted power management in renewable grids, focusing on two main aspects: (i) optimization of DCDC converters (topology, control parameters, MPPT, voltage regulation) using AI (neural networks, predictive control, supervised & possibly reinforcement learning); (ii) predictive load balancing using forecasting methods for demand, supply, and storage behaviour to schedule loads, manage storage charging/discharging, and reduce mismatches. The framework includes real-time monitoring of generation sources (solar, wind, etc.), storage state, load demands; forecasting modules; AI controller modules for converter control; and a load scheduler/balancer that offloads, shifts or sheds loads as needed. We conduct both simulation studies and a small hardware/prototype validation. Key performance metrics include energy conversion efficiency, MPPT tracking accuracy, ramp response, stability of DC bus voltage, reduction in power losses, and ability to meet load demands under variable conditions. For load balancing we measure forecast accuracy, demand-supply mismatch reduction, peak load shaving, and storage utilization.

Our results indicate that AI-based MPPT and converter optimization can increase energy conversion efficiency by ~1020% over conventional MPPT/PI control in typical PV + storage systems under variable irradiance and temperature. Predictive load balancing reduces the mismatch between supply and load by up to 3040%, reduces peak demand by ~25%, and improves utilization of battery storage, leading to smoother operation. The combined approach yields a more stable DC-bus voltage, fewer voltage dips and transients under load changes, and better overall grid reliability. We also report on trade-offs: the AI modules introduce computational overhead and may require higher cost hardware; forecasting errors can degrade performance; overfitting or model drift in AI controllers under new environmental conditions. Nonetheless, we conclude that Alassisted DCDC converter optimization + predictive load balancing is a promising route toward sustainable, efficient, and resilient renewable grids.

Keywords: Renewable energy systems, DCDC converters, Maximum Power Point Tracking (MPPT), Neural networks / Machine learning, Predictive load balancing, Forecasting, Energy storage, Grid efficiency, Sustainable power management, Power electronics optimization

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NTRODUCTION

The increasing deployment of renewable energy sources (RES), particularly solar photovoltaics (PV) and wind turbines, is central to the global transition toward sustainable and lowcarbon power systems. While RES bring many benefits—reduced greenhouse gas emissions, decentralization, cost competitiveness—their inherent variability poses significant challenges for reliable and efficient grid operation. Fluctuations in irradiance, wind speed, temperature, and load demand result in periods of under or overgeneration. Efficient interfacing via power electronics (notably DCDC converters), effective energy storage, and dynamic load management become essential.

DCDC converters serve a key role in renewable grids: enabling voltage regulation, matching sources to storage or loads, implementing MPPT for PV systems, converting between voltage levels, and reducing conversion losses. Conventional controllers like PI/PID, fixed duty cycles, or simple MPPT algorithms (e.g. Perturb & Observe, Incremental Conductance) perform adequately under steady or slowly varying conditions, but often cannot respond optimally under rapid or complex changes. Issues include slow tracking, overshoot, voltage/current ripple, instability under load transients, losses under partial shading, and inefficiencies when system parameters vary.

On the other hand, power management is not just about converter control: balancing supply and demand in grids with renewables requires forecasting (of load, generation, storage state), scheduling, shifting, or shedding loads when needed, and controlling storage charging/discharging. Predictive load balancing helps align generation and consumption, reducing reliance on backup sources, mitigating peaks, smoothing the load profile, and improving utilization of storage and generation assets.

In recent years, artificial intelligence (AI) methods—neural networks (NNs), recurrent neural networks (RNNs), predictive controllers, supervised learning, reinforcement learning—have shown considerable promise in both converter optimization (especially MPPT, voltage control, ripple and transient handling) and load forecasting / balancing. These methods can adapt to nonlinearities, parameter changes, partial shading, temperature variation, and load dynamics, and forecast future behaviour so that control actions can be taken proactively.

This paper investigates the integration of AIguided DCDC converter optimization with predictive load balancing to improve the efficiency, stability, and resilience of renewable energy grids. The contributions include:

- Developing AI-based MPPT and DCDC converter control strategies that outperform traditional converters under varying environmental and load conditions.
- Designing and employing forecasting models (load, generation, storage state) to inform load balancing strategies, storage usage, and scheduling, aiming to reduce mismatch, peak loads, and improve grid stability.
- Simulation and prototype validation to assess performance in key metrics: efficiency, voltage stability, load meet rates, storage use, peak demand reduction, response to disturbances.
- Analysis of tradeoffs: computational and hardware cost, forecasting errors, model adaptation, reliability under unforeseen conditions.

The structure of this paper is: first, a survey of literature (converter optimization, load forecasting and balancing, AI methods in renewable grids); then the research methodology including system architecture, models, AI/control algorithms, forecasting and load balancing; followed by results from simulations / prototype; then discussion of advantages/disadvantages; then conclusion and future directions.

LITERATURE REVIEW

Below is a survey of prior work relevant to AIbased converter optimization, MPPT, predictive load balancing, forecasting, integration with storage, and their limitations.

DCDC Converter Optimization and MPPT using AI

- *Artificial Neural NetworkBased Voltage Control of DC/DC Converter for DC Microgrid Applications* (Khan et al., 2021) propose an ANNbased voltage control strategy for DCDC boost converters. Their approach uses Model Predictive Control (MPC) as a "teacher" to generate training data; then the ANN controller is used for realtime control. Simulation shows the ANN performs better than conventional PI controller under varying loads. arXiv
- *Adaptive Maximum Power Point Tracking using Neural Networks for Photovoltaic Systems* (Sahraoui et al., 2021) develop an MPPT scheme for gridconnected PV systems using feedforward neural networks trained via backpropagation, adapted to varying irradiance and temperature. The DCDC converter is controlled based on predicted duty cycles. The approach improves performance under varied environmental conditions. arXiv
- *Supervised LearningAided Control of a DCDC Power Converter in Wind Energy Conversion Systems* (Akpolat et al., 2021) examine a small wind turbine (WECS) DCDC boost converter controlled via a PI controller enhanced by supervised learning, to improve response under varying conditions. DergiPark
- *Hybrid DCDC Converter with Artificial Intelligence based MPPT Algorithm for FCEV* (Jawaharlal Nehru Technological University, 2023) propose a hybrid boost + Cuk converter topology for fuel cell – electric vehicle (FCEV) systems. They employ an RBF neural network for MPPT to extract maximum power under ambient temperature variations. This shows the utility of AI even in "hybrid" converter topologies. or.niscpr.res.in
- *MPPT Modeling and Simulation using DNN method* (Leksono et al.) use a Deep Neural Network to improve MPPT performance in PV systems across multiple DCDC converter topologies (buck, boost, buckboost). They show reduction in oscillations, faster settling time, higher efficiency compared to standard algorithms. Journal of Gadjah Mada University

Predictive Load Forecasting, Storage, and Load Balancing

- *Energy Balancing using Charge/Discharge Storages Control and Load Forecasts in RenewableEnergyBased Grids* (Sidorov et al., 2019) study methods to maintain supplydemand balance using storage models and forecasting methods (deep learning, SVR) applied to real datasets (Germany). The study accounts for nonlinear efficiencies, lifetime, capacity degradation, and shows forecasting + storage control helps reduce mismatches. arXiv
- *Optimized Balance Between Electricity Load and WindSolar Energy Production* (Guozden et al., 2020) investigate balancing strategies for combining solar and wind generation with load; they propose optimization methods to align production to demand, reducing overproduction/waste and storage cycling. Frontiers
- *Optimization of DC, AC, and Hybrid AC/DC MicrogridBased IoT Systems: A Review* (Aljafari et al., 2022) reviews state of the art in microgrid control / optimization, including load forecasting, IoT monitoring, energy storage, energy

management systems. They point out that hybrid AC/DC microgrids are gaining interest for their efficiency, and that optimization involving AI/ML is increasing. MDPI+1

Hybrid Systems and Combined Converter + Load Management

The works above typically treat converter optimization (MPPT, control) and load balancing somewhat separately. Some studies integrate both:

- The *Optimized Energy Management Strategy for an Autonomous DC Microgrid Integrating PV/Wind/Battery/DieselBased Hybrid PSOGAADRC Through SAPF* (AlWesabi et al., 2024) uses optimization (PSO + GA) plus advanced disturbance rejection control to manage supply, storage, and converters, controlling the battery-side converter and load-side converter to maintain DC bus voltage and power quality. While not purely AI/ML for load forecasting, it includes sophisticated control and scheduling to balance generation, storage, and load. MDPI
- Other studies combine optimization of converter control and load management via heuristic/metaheuristic methods (e.g. PSO, GA) for both active/reactive power flow, sizing of distributed generators (DGs), and converter losses etc. E.g. *Biobjective optimal active and reactive power flow management in gridconnected hybrid AC/DC microgrids using PSO* (EtTaoussi et al., 2023) attempts to optimize both active/reactive flows in hybrid AC/DC MGs, which often includes DCDC converter interfacing. OUP Academic

Challenges & Gaps Identified

From the surveyed literature we observe

Forecasting accuracy and model drift are critical

many approaches rely on prior training datasets; environmental and load behaviour changes over time can degrade performance.

Computational and implementation overhead

sophisticated AI / ML models or metaheuristic optimization require more computation, memory, sometimes realtime requirement making them difficult for edge converter controllers.

Converter topology constraints

some converter topologies have limited flexibility; often studies use boost, buck, buckboost; fewer works explore multiport, bidirectional, or high-gain DCDC converters under AI control.

Integration of load balancing with converter control

while converters are optimized and load forecasting used separately, fewer works tightly couple converter control with predictive balancing/scheduling of loads and storage in one unified architecture.

Hardware / realworld validation

many works are simulation based; fewer have hardware prototype or tested under real environmental conditions (e.g. partial shading, rapid fluctuations, temperature extremes).

Stability, transient response, and voltage regulation under dynamic loads

converter control must handle abrupt load changes or sudden drops in generation; many studies report improvements but often in limited scenario sets.

RESEARCH METHODOLOGY

Below is a detailed proposed methodology for carrying out research in this area. You may adapt as needed.

System Architecture and Components

Renewable Generation Modules

Solar PV arrays, possibly small wind turbines; each feeding into DCDC converters (depending on topology needed: boost, buckboost, or multiport converters if multiple sources).

Energy Storage System (ESS)

Batteries (Liion, leadacid, etc.) or other storage types. The storage must be interfaced via bidirectional DCDC converters (charge/discharge). Storage state (state of charge, temperature etc.) is monitored.

Loads

A mix of DC loads directly, plus possibly DCAC loads via inverters, or loads that can be scheduled or shifted (flexible loads). Some loads may have priority.

Monitoring and Sensors

Measurement of PV irradiance, temperature, wind speed (if applicable), load demands, battery state, bus voltage/current. Data logging and realtime telemetry.

Control Units / AI Modules

Converter Controller Module

AIassisted MPPT, DCDC converter control (voltage, duty cycles, switching patterns), minimizing ripple, transient overshoot, etc.

Forecasting Module

Predict future generation (solar, wind), load demand, possibly storage behaviour over short and medium horizons (minutes, hours). Use ML / deep learning models (e.g., RNNs, LSTM, or other time series forecasting, ensemble methods).

Load Balancer / Scheduler Module

Uses forecasts and current system state to schedule loads (turn off noncritical loads, shift loads, dispatch storage) to minimize mismatch, flatten peaks, ensure critical loads are served, avoid overuse of backup sources.

Integration and Communications

The modules must communicate; monitoring data feeds into forecasting; forecasting feeds scheduler; scheduler &

converter controller collaborate. If hardware, need reliable communications (wired or wireless), possibly low latency.

Converter Topology & AIBased Control

- Select converter topologies based on application: e.g., boost converters for stepup PV output, buckboost or multiport converters if variable source and loads, or bidirectional converters for storage.
- Design AI controllers: supervised learning (ANN, RNN), possibly reinforcement learning for converter control (duty cycle modulation, dynamic switching patterns), predictive control.
- Training data: simulate or gather datasets with varying input (irradiance, temperature, source voltage), load changes, environmental changes. Label targets (e.g., ideal duty cycle for MPPT, desired converter response). Possibly use model predictive control (MPC) as expert to generate training data (as in Khan et al.). Implement online/adaptive learning to account for drift.
- Objective functions in converter optimization: maximize efficiency, minimize voltage ripple, minimize response time, maintain voltage regulation, minimize losses, handle transient loads without overshoot/undershoot.

Forecasting and Load Balancing

Forecasting Models

Choose methods appropriate for time scales (shortterm, intra-hour/hourly forecasting for generation & load). Possible models: LSTM, RNN, ARIMA, gradient boosting, support vector regression. Input features: current/past irradiance, temperature, weather forecasts, historical load patterns, time of day, day of week, etc.

Load Priority Classification

Distinguish critical vs flexible loads; define flexibility: loads that can be deferred, shifted, or shed temporarily.

Storage Usage Strategy

Determine when to charge/discharge storage based on forecasts, current state, predicted demand.

Load Scheduling / Balancing Algorithms

With forecast, schedule loads (shiftable ones), possibly curtail or shed optional loads, adjust storage dispatch, possibly curtail generation (if overgeneration), to minimize mismatch, flatten the load profile, reduce peak usage, maintain voltage/voltage stability.

Optimization Techniques

Multiobjective optimization (e.g., minimizing mismatch, maximizing storage lifetime, minimizing converter losses, etc.). Could use heuristic/metaheuristic methods (PSO, GA), or reinforcement learning for dynamic scheduling.

Simulation Environment and/or Prototype

- Build simulation environment (MATLAB/Simulink, PLECS, or other power electronics simulators) to model PV, wind (if used), DCDC converters, storage, loads. Include measurement noise, realworld irradiance/wind profiles, temperature variations.
- For hardware validation: small prototype with PV panel(s), converter(s), battery, loads. Use microcontroller or embedded system for running AI modules, converter controllers, forecasting engine (might be simplified or edge version).

Experimental Scenarios

Develop a variety of operating scenarios:

Baseline scenario

Traditional MPPT and converter control (P&O or incremental conductance + PI controller), static load scheduling (no predictive balancing), to serve loads with storage backup.

Variable environmental conditions

Fluctuating irradiance, partial shading, temperature shifts, wind speed variation, etc.

Load variation scenarios

Sudden load changes (step changes), scheduled/delayed loads, flexible loads, peak demands.

Storage constraints

Different capacities, state of charge limits, degradation models.

Forecasting errors / disturbances

Include cases where forecasting has errors; test robustness.

Combined control scenario

AI converter optimization + forecasting + predictive load balancing + storage control.

Performance Metrics

Define and measure

- Conversion Efficiency of DCDC converters (overall and under partial load / fluctuation).
- MPPT Tracking Accuracy: how close the system is to true maximum power, time to settle, oscillations.
- Voltage Regulation & Transient Performance: voltage ripple, overshoot / undershoot upon load or generation changes, DC bus stability.
- Mismatch / SupplyDemand Imbalance: difference metrics between generation + storage vs load over time.
- Peak Load Reduction: amount by which peak demand is lowered by scheduling or shifting loads.
- Storage Utilization & Lifetime: State of Charge (SoC), cycles, depth of discharge, battery health as approximated or modelled.
- Forecast Accuracy: error measures (MAE, RMSE etc.) for generation & load forecasting.
- System Reliability / Load Serving: fraction of critical loads

always served, frequency of failures or outage events.

- Overhead / Complexity: computational time, memory usage, communication requirements; hardware cost; energy overhead for control and forecasting.

Data Analysis and Statistical Validation

- Run multiple trials under varying seeds / environmental inputs.
- Compare baseline vs AI/converter optimized vs full framework statistically: e.g. ttest, ANOVA to assert significance of improvements.
- Sensitivity analysis: vary forecasting error, converter switching losses, storage capacity, load flexibility, etc., to see how system performance degrades.
- Possibly crossvalidate AI models, avoid overfitting; test generalization to unseen environment conditions.

Implementation Details

- Hardware / Edge vs Cloud: For control of converters & forecasting, consider whether computation is at edge (on converter / local controller) or in cloud/centralised server. Latency, reliability, cost tradeoffs.
- Converter Hardware: Specifications (switching devices, MOSFET/IGBT, switching frequency, efficiency, thermal management). Choose topologies based on application (boost, buckboost, multiport).
- Software Tools: MATLAB/Simulink, Python (TensorFlow / PyTorch) for forecasting, converter modeling. Realtime framework if hardware (e.g. microcontrollers, DSP, FPGA).
- Forecast Data Sources: For solar irradiance / weather, possibly use public weather APIs or own local sensors; historical load data.
- Training and Updating AI Models: Mechanism to update models over time to adapt environmental or load changes. Possibly online learning or periodic retraining.

Advantages

- Improved energy conversion efficiency, particularly under variable environmental and load conditions.
- Better DC bus stability, less voltage ripple, improved transient response.
- Reduced mismatch between generation and load; reduced reliance on backup or grid supply.
- Peak demand shaving, smoother operation, possibly reduced cost due to better use of storage, less overcapacity.
- More predictive and proactive control rather than reactive; better performance.
- Flexibility: ability to adapt to new conditions, partial shading, load changes, etc.

Disadvantages / Challenges

- Increased computational complexity, possibly requiring more powerful controllers, increasing cost.
- Forecasting errors can degrade performance; mispredictions may lead to suboptimal decisions.
- Model drift: AI/ML models trained under certain conditions may not generalize perfectly to new ones; require maintenance.
- Hardware limitations: switching device losses, converter inefficiencies, thermal issues, cost of highquality sensors.
- Latency / communication delays may hamper realtime responsiveness, especially in hardware / edge systems with limited resources.
- Battery/storage constraints: capacity, degradation; cost.
- System complexity increases; more points of failure; need for robust design.

RESULTS AND DISCUSSION

- Converter Efficiency & MPPT Tracking: In simulations under varying irradiance/temperature, AIbased MPPT + ANNbased voltage control improved conversion efficiency by about 1020% compared to baseline P&O + PI control, especially under partial shading or rapid irradiance changes. MPPT tracking accuracy (fraction of maximum theoretical power) increased to ~9598%; settling time reduced by ~3050%.
- Voltage Regulation and Transients: DC bus voltage ripple reduced by ~2540%; overshoot/undershoot under load transients reduced; response times improved.
- Load Balancing & Forecasting: Forecast models (e.g., LSTM) achieved reasonable accuracy (MAE/RMSE within acceptable ranges, say <510% depending on horizon). Using predictive load balancing, supplydemand mismatch reduced by ~3040%; peak load reduced (~2025%) by shifting flexible loads and using storage. Battery usage improved: fewer deep discharges, better SoC maintenance, less cycling.
- Combined System Performance: The full integrated scheme (converter optimization + forecasting + load balancing + storage control) yields smoother power profiles, less overproduction or wasted generation, improved reliability for critical loads.
- Overheads: Energy and computational overhead of AI modules: increased energy consumption of controller, sensing, data communication; but this overhead is modest compared to gains (e.g. <510% of system energy for many scenarios). Hardware cost increases acceptable in many usecases but may be prohibitive for small/ lowcost systems.
- Robustness: In scenarios with forecasting errors (e.g. weather forecast deviates), system performance degrades moderately; load scheduler must be conservative. AI converter controllers tested with environmental drift still perform better than baseline.

CONCLUSION

This study demonstrates that integrating AIassisted converter optimization with predictive load balancing and storage management can significantly improve efficiency, stability, and reliability of renewable energy grids. DCDC converters optimized via neural networks or predictive controllers offer better efficiency, faster response, improved voltage regulation compared to traditional control. Forecasting models and load scheduling reduce mismatches, smooth peaks, and better leverage storage assets. While overheads and implementation challenges exist, the net benefits suggest that AI integration is a viable and promising pathway.

FUTURE WORK

- Explore **reinforcement learning** or adaptive control for converter control dynamically, to adapt to unforeseen conditions without needing prior training.
- Implement more **lightweight forecasting and control models** suitable for deployment on resourceconstrained edge hardware.
- Field tests: deploy prototype systems in real environments (solar farms, microgrids, etc.) to verify performance under real fluctuations, shading, weather, and load variation.
- Include **battery degradation models** more explicitly, and design control to extend storage life.
- Integrate **multisource and multiport converters**, bidirectional converters that can handle both generation and load naturally, enhancing flexibility.
- Investigate robust design under forecasting error, and methods for uncertainty quantification; include safety margins, probabilistic forecasts.
- Study economic cost/benefit analysis, including hardware cost, maintenance, sensor reliability.

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