Modern American Journal of Engineering, Technology, and Innovation
ISSN(E): 3067-7939
Volume 2, Issue 6, June, 2026
Website: usajournals.org

RENEWABLE ENERGY AND SMART GRID INTEGRATION FOR EFFICIENT URBAN POWER SYSTEMS

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Abstract

This study presents an integrated approach to improving the energy efficiency and reliability of urban power supply systems through the coordinated use of renewable energy sources, battery energy storage systems (BESS), Smart Grid technologies, short-term load forecasting, and multi-objective optimization. The proposed framework combines photovoltaic generation, urban loads, intelligent monitoring, an LSTM-based forecasting module, and an NSGA-II optimization procedure. The forecast is used to schedule storage and balance generation and demand, while the optimization stage searches for technically feasible trade-offs among power losses, voltage quality, reliability, investment cost, and renewable-energy utilization. The reported simulation results show that BESS reduces power losses from 14.2% to 10.8%, voltage deviation from 9% to 4%, and SAIDI from 2.1 h to 1.4 h. In the specific NSGA-II test case, the modeled loss ratio decreases from 14.2% to 7.3%, and the integrated scenario improves network reliability and load balancing. The scientific contribution is the unified assessment of forecasting, storage, intelligent control, and multi-criteria optimization within one urban distribution-network framework.

Keywords: Renewable energy sources, Smart Grid, energy efficiency, photovoltaic systems, battery energy storage systems, LSTM, NSGA-II, urban power supply systems.

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Introduction

The growth of electricity consumption, urbanization, electric-vehicle charging, and environmental requirements is placing increasing pressure on urban distribution networks. Conventional generation and rigid network-control practices are poorly suited to highly variable demand and distributed renewable generation. Photovoltaic and wind systems reduce fuel consumption and emissions, but their output depends on weather and therefore creates power imbalance, voltage fluctuations, reverse power flow, and reserve-management problems [1-2].

These limitations can be reduced when renewable generation is coordinated with BESS and Smart Grid functions. Storage absorbs surplus energy and supplies it during peak demand or voltage disturbances. Smart Grid infrastructure provides real-time measurements, automated control, bidirectional communication, fault detection, and flexible management of distributed resources [3-5]. Together, these technologies transform a passive distribution network into an adaptive system capable of responding to changing load and generation conditions [6, 9-10].

Accurate short-term load forecasting is also essential because storage scheduling and network control depend on expected demand. LSTM neural networks are suitable for nonlinear time-series data and can learn daily, weekly, weather-dependent, and event-driven patterns [13]. However, forecasting alone does not determine the best network configuration or operating policy. Urban power systems require multi-objective optimization because lower losses, higher reliability, acceptable voltage, investment cost, and renewable-energy use are competing goals.

The main part

The purpose of this study is to develop and evaluate a compact integrated framework that combines photovoltaic generation, BESS, LSTM forecasting, Smart Grid control, and NSGA-II optimization. The study focuses on the interaction of these components and on their combined influence on losses, voltage deviation, SAIDI, peak demand, and operating flexibility [10-11].

The proposed urban power supply model consists of five coordinated subsystems: photovoltaic generation, battery storage, urban consumers, a Smart Grid control

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center, and an LSTM-based forecasting module. Field devices and smart meters transmit load, voltage, generation, and battery state-of-charge data to the control center. The controller combines measured and forecast values to determine charging, discharging, switching, and load-management actions. The overall architecture is shown in Figure 1.

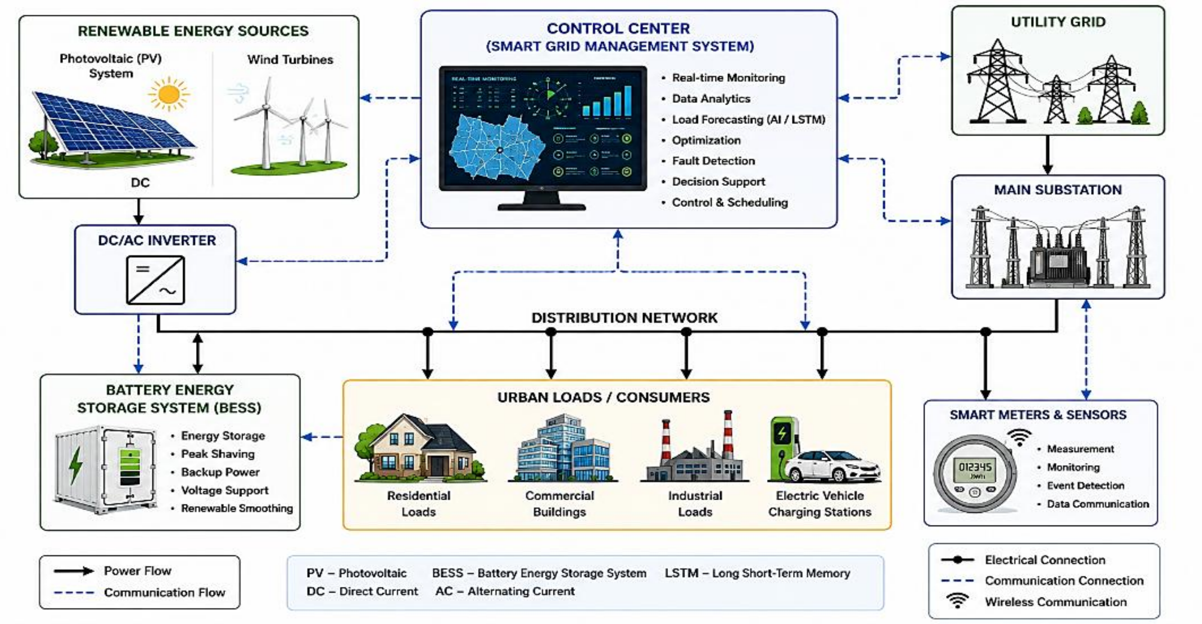

Figure 1. Integrated intelligent urban power supply system

For each time interval t, the active-power balance is represented by:

$$P_{grid}(t) + P_{PV}(t) + P_{BESS}(t) = P_{load}(t) + P_{loss}(t), \quad (1)$$

where P_{grid} is the power exchanged with the utility grid, P_{PV} is photovoltaic output, P_{BESS} is positive during discharge and negative during charging, P_{load} is demand, and P_{loss} represents distribution-network losses. The model evaluates technical constraints and economic indicators simultaneously. The principal operating constraints are acceptable bus voltage, branch-current limits, transformer loading, BESS state-of-charge limits, and power-balance feasibility [2, 11].

The methodology follows four linked stages. First, historical load, weather, renewable-generation, and calendar data are prepared for forecasting. Second, the

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LSTM model predicts short-term demand. Third, the Smart Grid controller uses the forecast to schedule BESS and coordinate distributed resources. Fourth, NSGA-II evaluates candidate operating or design solutions and produces a Pareto set. A final solution is selected according to the preferred compromise among efficiency, reliability, voltage quality, and cost [4, 14].

The LSTM module receives sequences of historical load, meteorological variables, photovoltaic output, hour-of-day, day-of-week, and electric-vehicle charging indicators. Its gated memory structure captures long-term dependencies and reduces the vanishing-gradient problem typical of conventional recurrent networks. The output layer provides the forecast used by the control center for peak-load reduction and generation-demand balancing [5, 9].

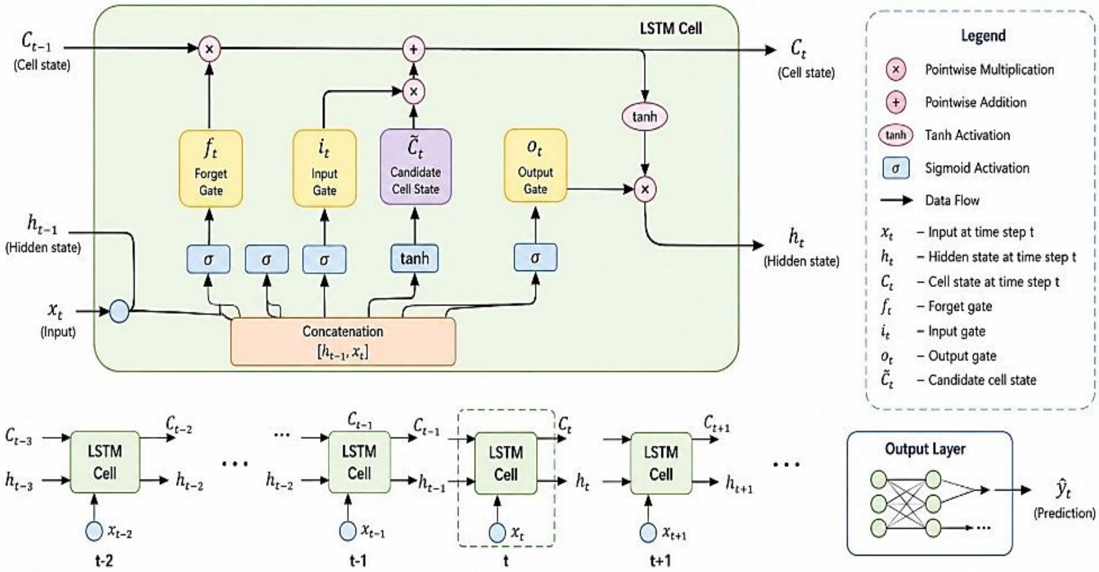

Figure 2. Structure of the LSTM forecasting model

The model is trained on historical urban-distribution data. Forecasting accuracy is evaluated by mean absolute percentage error (MAPE), while training stability is controlled through the number of epochs, batch size, learning rate, optimizer, and activation function. The main settings used in the study are summarized in Table 1.

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Table 1 Main LSTM training parameters

Parameter	Value
Number of epochs	100
Batch size	64
Learning rate	0.001
Optimizer	Adam
Activation function	ReLU

The selected parameters provide a computationally simple baseline for short-term forecasting. The forecast is not treated as an isolated output; it directly supports operational decisions. When demand is expected to rise, the controller preserves sufficient battery energy for peak hours. During periods of low demand and high renewable output, the controller charges the battery while respecting state-of-charge and converter limits [1, 6, 14].

Smart Grid operation is organized around measurement, communication, control, and application layers. Smart meters, sensors, and intelligent electronic devices continuously transmit data to the control center. The controller performs state monitoring, voltage supervision, fault diagnosis, load balancing, and coordinated control of photovoltaic generation and BESS. Compared with a conventional grid, this architecture provides real-time visibility, automated response, faster fault localization, and more flexible renewable-energy integration [3, 5, 7, 15].

BESS is used for peak shaving, voltage support, renewable-energy balancing, emergency supply, and power-quality improvement. During surplus photovoltaic generation, the battery is charged; during peak demand, low voltage, or supply interruption, it discharges. The control logic considers load demand, renewable output, network voltage, and battery state of charge. This prevents indiscriminate cycling and keeps the battery within technically permissible limits.

The comparison in Table 2 isolates the effect of storage in the modeled urban network. The reduction in losses and voltage deviation indicates improved load-flow conditions, while the lower SAIDI value reflects the contribution of backup

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capability and faster restoration. These results describe the storage scenario before the additional NSGA-II optimization stage [15].

Table 2 Network performance with and without BESS

Indicator	Without BESS	With BESS
Power losses	14.2%	10.8%
Voltage deviation	9%	4%
SAIDI	2.1 h	1.4 h
Peak-load level	High	Reduced

Urban distribution-network planning and operation involve conflicting objectives. A solution with minimum losses may require higher investment, while a low-cost solution may reduce voltage margin or reliability. The NSGA-II algorithm is therefore used to generate a set of non-dominated solutions rather than a single result based on an arbitrary weighted sum. The optimization variables may include storage location and rating, operating schedule, feeder configuration, equipment loading, and control settings [12, 14].

The objective vector is expressed as:

$$\min F(x) = [P_{loss}(x), C_{total}(x), SAIDI(x), \Delta U(x), E_{RES}(x)], \quad (2)$$

where x is the decision vector, C_{total} combines investment and operating expenditure, ΔU is the voltage-deviation index, and E_{RES} is renewable-energy utilization. The negative sign converts renewable-energy maximization into a minimization objective. Each candidate must satisfy the power-balance equation, voltage limits, current and transformer-loading limits, BESS energy constraints, and operational feasibility.

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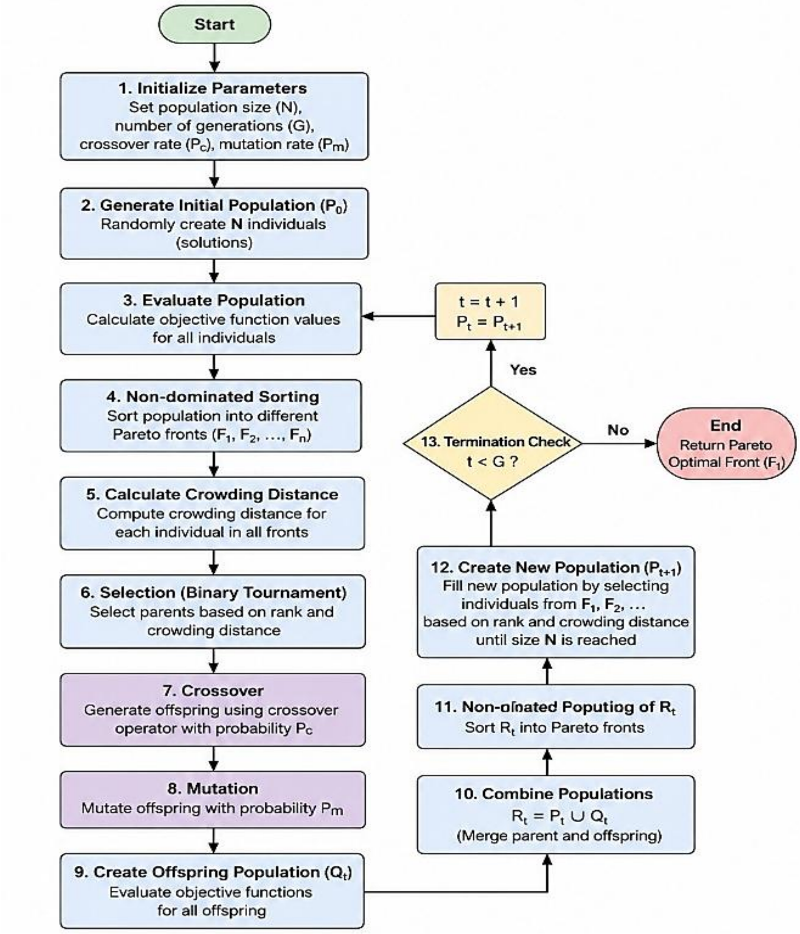

Figure 3. NSGA-II optimization procedure

The algorithm begins by generating an initial population of feasible candidate solutions. Each candidate is evaluated using the technical and economic models. Non-dominated sorting assigns Pareto ranks, and crowding distance preserves diversity. Binary selection, crossover, and mutation generate offspring, after which parent and offspring populations are combined. The best-ranked and most diverse solutions are retained until the termination condition is reached. This process yields a Pareto front that exposes the trade-offs among losses, cost, reliability, voltage quality, and renewable-energy use [4, 8].

A feasible-first rule is applied: candidates violating voltage, current, transformer-loading, or battery constraints cannot dominate feasible solutions. This is important because an apparently inexpensive or low-loss configuration is useless

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if it creates unacceptable voltage or equipment overload. The final choice is made from the Pareto set according to the decision maker's priorities or by the minimum normalized distance to an ideal point [14].

Results and Discussion

The simulations show that coordinated renewable generation, BESS, Smart Grid control, forecasting, and multi-objective optimization improve the main technical indicators of the urban network. In the BESS-only comparison, power losses decrease from 14.2% to 10.8%, voltage deviation decreases from 9% to 4%, and SAIDI improves from 2.1 h to 1.4 h. These changes indicate lower feeder loading, better voltage support, and improved continuity of supply.

The NSGA-II test case produces a stronger improvement in the selected network configuration. As shown in Figure 4(a), the modeled loss ratio falls from 14.2% before optimization to 7.3% after optimization. Figure 4(b) shows that the optimized voltage profile remains higher along the feeder and avoids the severe end-of-line voltage drop observed in the baseline case. Across the broader integrated scenario, the study reports an annual loss reduction of approximately 18% and a SAIDI improvement of about 22%. These figures should be interpreted according to their respective baseline scenarios rather than as one identical comparison [7].

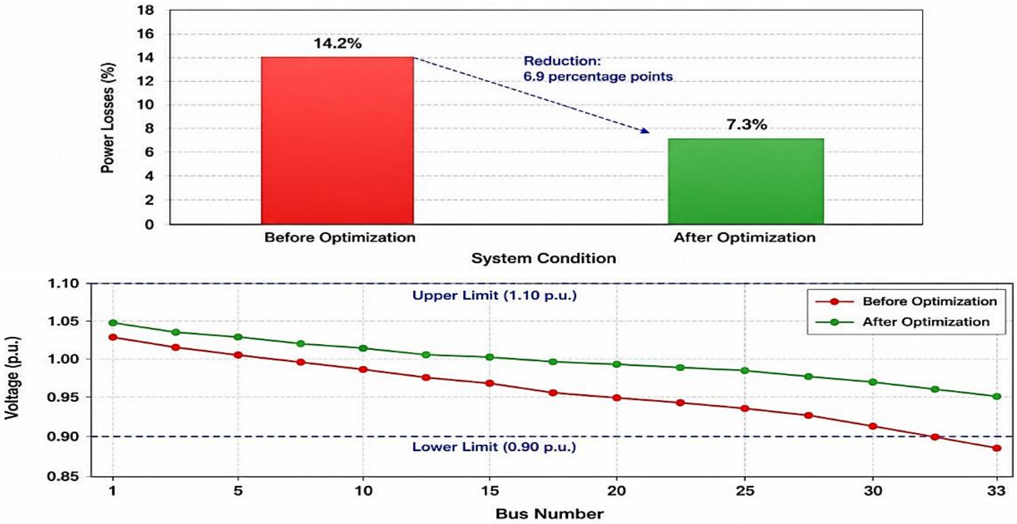

Figure 4. Power-loss reduction and voltage-profile improvement after optimization

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The results are explained by three coordinated mechanisms. First, forecasting allows the controller to anticipate demand instead of reacting after a peak has already occurred. Second, BESS shifts energy from low-demand or high-generation periods to peak periods, reducing current and voltage drop. Third, NSGA-II identifies operating and design combinations that balance loss reduction with cost and reliability rather than improving one indicator at the expense of the others.

The Smart Grid layer also increases operational flexibility. Real-time data exchange allows faster fault detection, remote switching, and adaptive resource scheduling. This capability is especially important in urban networks with distributed photovoltaic systems and electric-vehicle charging, where load and generation patterns change rapidly. The integrated framework therefore provides greater value than isolated implementation of storage, forecasting, or optimization [8].

Nevertheless, the results depend on the quality of input data and model assumptions. Battery degradation, communication delay, forecast error, converter efficiency, tariff structure, and component failure rates can materially affect the selected solution. The numerical results should therefore be validated using site-specific load profiles, weather data, network parameters, and multi-year reliability records before practical deployment.

The proposed approach has several practical limitations. BESS requires high initial investment and its lifetime depends on cycling depth, temperature, and operating strategy. Smart Grid deployment introduces communication and cybersecurity risks, while LSTM performance depends on the quantity and representativeness of historical data. NSGA-II can also become computationally expensive when the network model contains many buses, operating scenarios, and discrete design variables [3].

For practical implementation, the framework should include battery degradation cost, communication failure scenarios, forecast uncertainty, cyber-protection requirements, and sensitivity analysis for economic parameters. The control center must also retain safe fallback rules so that loss of communication or forecasting error does not cause unacceptable voltage, overload, or battery operation.

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Conclusion

This study reformulates the improvement of urban power supply efficiency as an integrated forecasting, control, storage, and optimization problem. The proposed architecture combines photovoltaic generation, BESS, Smart Grid monitoring, LSTM-based demand forecasting, and NSGA-II multi-objective optimization. BESS reduces the modeled loss ratio from 14.2% to 10.8%, voltage deviation from 9% to 4%, and SAIDI from 2.1 h to 1.4 h. In the specific optimization case, losses decrease from 14.2% to 7.3%, while the feeder voltage profile becomes more stable. The integrated scenario also reports an approximately 18% reduction in annual losses and a 22% improvement in SAIDI.

The main value of the method is not any single component, but the coordinated use of forecasting, storage scheduling, real-time control, and Pareto-based decision making. This coordination improves energy efficiency, reliability, voltage quality, renewable-energy utilization, and operational flexibility. Future work should validate the framework on measured urban-network data and include uncertainty, battery aging, communication constraints, and cybersecurity in the optimization model.

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