



Development of an Intelligent Energy Management System for Smart Grid Applications

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Peer Review Information

Submission: 11 Jan 2021
Revision: 26 Feb 2021
Acceptance: 13 March 2021

Keywords

smart grid, intelligent energy management, demand response, energy storage, load scheduling

Abstract

The increasing penetration of renewable generation, distributed storage, smart meters, controllable loads, and dynamic electricity tariffs has created a need for energy management systems that can make coordinated decisions in real time. This paper presents a methodology for developing an Intelligent Energy Management System (IEMS) for smart grid applications. The proposed architecture combines advanced metering infrastructure, short-term demand and photovoltaic generation information, battery state-of-charge monitoring, user-defined operating constraints, and an intelligent scheduling layer. The control objective is formulated as a multi-objective problem that minimizes electricity cost, peak grid demand, and unnecessary grid import while preserving the required energy service. A simulation-based case study is used to evaluate the method under time-of-use pricing with a photovoltaic source, an 8 kWh battery, and flexible residential loads. Relative to unmanaged operation, the proposed scheduling strategy reduces the daily energy-cost index from 6.61 to 5.06 units, lowers peak grid demand from 4.20 kW to 2.40 kW, and decreases daily grid import from 28.20 kWh to 23.70 kWh. Photovoltaic self-consumption improves from 59.1% to 80.1%. These results indicate that coordinated load shifting and storage dispatch can provide economically and technically useful demand-side flexibility. The methodology is intended as a reproducible framework for subsequent hardware-in-the-loop or field implementation in smart homes, buildings, microgrids, and distribution-level smart grid platforms..

Introduction

Smart grids extend conventional power networks by combining two-way power flow, sensing, communication, automation, and distributed control. The resulting infrastructure enables utilities and consumers to respond to changing demand, distributed generation, electricity prices, and operating constraints rather than relying only on centralized generation control. Communication standards, advanced metering infrastructure, and automated control are therefore fundamental components of smart-grid operation (Güngör et

al., 2011). Broader smart-grid architectures also separate infrastructure, management, and protection functions while emphasizing the use of bidirectional information for efficiency, demand profiling, reliability, and cost reduction (Fang et al., 2012).

Energy management is one of the most important smart-grid functions because consumption patterns can be modified without necessarily reducing the useful energy service delivered to end users. Demand-side management includes efficiency improvement, price-responsive

demand, direct load control, and intelligent operation of flexible resources (Palensky & Dietrich, 2011). Demand response further allows customers to shift or curtail consumption when electricity prices or system stress are high, providing benefits for network planning and peak-load reduction (Siano, 2014). In practical smart environments, the energy management problem becomes more complex when photovoltaic (PV) generation, batteries, electric vehicles, controllable appliances, and user-comfort constraints are considered simultaneously.

Traditional rule-based controllers can operate individual devices, but their decisions are often local and reactive. Intelligent approaches can use historical measurements, forecast information, optimization, and artificial intelligence to coordinate several resources. Recent reviews show that AI techniques are increasingly applied to smart-grid forecasting, energy management, fault diagnosis, stability assessment, and security (Ali & Choi, 2020; Omitaomu & Niu, 2021). Reinforcement learning has also been demonstrated for residential and microgrid energy management where decisions must adapt to changing price and demand conditions (Li et al., 2020; Nakabi & Toivanen, 2021). Against this background, the objective of this paper is to define a compact and implementable methodology for an IEMS that integrates measurement, prediction-ready data processing, multi-objective scheduling, and closed-loop dispatch. The emphasis is on the methodological design and on a transparent simulation case study that can later be extended to field hardware.

Literature Review

Early smart-grid research established the importance of communication networks and standardized data exchange for coordinated control. Güngör et al. (2011) reviewed communication technologies and standards required for monitoring and control, while Fang et al. (2012) organized the smart grid into infrastructure, management, and protection subsystems. On the demand side, Palensky and Dietrich (2011) described demand-side management as a spectrum ranging from efficiency measures to real-time control of distributed resources. Vardakas et al. (2015) later compared demand-response programs, pricing methods, and optimization algorithms,

showing that customer flexibility can be transformed into a controllable grid resource when appropriate incentives and scheduling logic are available.

At the building and household level, intelligent energy scheduling became a key research direction. Pipattanasomporn et al. (2012) developed an intelligent home energy management algorithm that manages high-power appliances according to priority and maintains consumption under specified limits. Beaudin and Zareipour (2015) reviewed home energy management modelling and highlighted the trade-off among model complexity, uncertainty, occupant preferences, and optimality. Zhou et al. (2016) examined smart-home energy management architecture, distributed renewable resources, communication infrastructure, and scheduling strategies. Tuballa and Abundo (2016) placed these developments within the wider evolution of smart-grid technologies and emphasized distributed generation, sensing, communication, automation, and storage as enabling technologies.

Later studies increasingly connected energy management with intelligent computation. Shareef et al. (2018) reviewed demand-response-enabled home energy management, smart technologies, and intelligent controllers, noting the role of smart meters and scheduling in reducing energy use and reshaping load profiles. Ali and Choi (2020) surveyed AI for distributed smart grids, including energy management, demand response, renewable integration, and storage. Li et al. (2020) formulated residential energy management as a sequential decision problem and used deep reinforcement learning to learn scheduling policies under uncertain electricity prices and resident activity. Nakabi and Toivanen (2021) compared deep reinforcement learning algorithms for microgrid energy management with flexible demand, while Omitaomu and Niu (2021) summarized AI applications across smart-grid operation and emphasized both the opportunity and the need for reliable, scalable deployment. These studies motivate an IEMS architecture that is modular: sensing and forecasting can evolve independently, while the scheduling layer receives standardized state variables and produces constrained device-level actions.

Table 1. Representative literature supporting the proposed IEMS methodology.

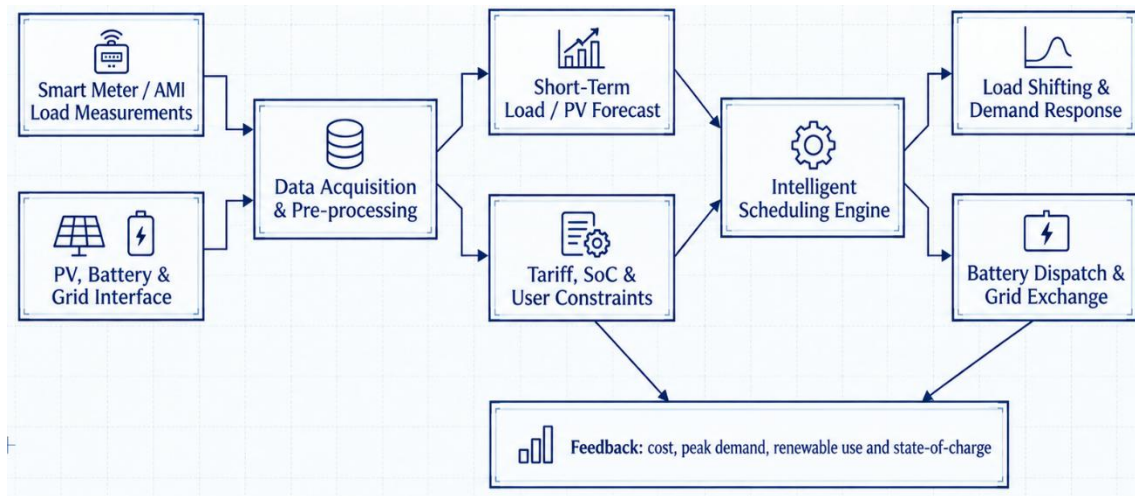
Study	Primary focus	Methodological relevance
Pipattanasomporn et al. (2012)	Intelligent HEM and DR	Priority-based appliance control under power limits
Beaudin & Zareipour (2015)	HEMS modelling review	Objectives, uncertainty, comfort and complexity
Zhou et al. (2016)	Smart HEMS architecture	DER, storage and appliance scheduling integration
Shareef et al. (2018)	HEMS and intelligent control	DR-enabled smart-meter-based scheduling
Ali & Choi (2020)	AI in distributed smart grids	AI for EMS, DR, DER and storage
Nakabi & Toivanen (2021)	DRL microgrid EMS	Adaptive control of flexible loads and storage

Methodology

1. System Architecture and Data Flow

The proposed IEMS is organized as a closed-loop decision system. Measurements from smart meters and distributed devices are collected through advanced metering infrastructure. The minimum state vector contains time-indexed active power demand, available PV generation, battery state of charge (SoC), electricity price, and the operating state of flexible loads. Measurements are time-aligned, missing samples are flagged, and physically invalid values

are filtered before the scheduling cycle. The architecture follows the general smart-grid requirement for two-way sensing and control identified in communication and smart-grid surveys (Güngör et al., 2011; Fang et al., 2012). A forecast interface is included so that short-term load and PV predictions can be supplied by statistical, machine-learning, or deep-learning models. AI-based forecasting and control are consistent with the techniques reviewed by Ali and Choi (2020) and Omitaomu and Niu (2021).

**Figure 1.** Proposed architecture of the Intelligent Energy Management System.

2. Optimization Model and Control Logic

At each scheduling interval, the controller determines the timing of flexible loads and the charge/discharge power of the battery. The objective is represented by a weighted cost function $J = w_1 C_{\text{energy}} + w_2 P_{\text{peak}} + w_3 E_{\text{grid}} + w_4 D_{\text{comfort}}$, where C_{energy} is the electricity-purchase cost, P_{peak} is the maximum grid demand during the horizon, E_{grid} is imported grid energy, and D_{comfort} is a penalty applied

when a controllable task is moved outside its user-defined preferred window. The weights allow a utility, building manager, or consumer to place greater emphasis on cost, peak reduction, renewable utilization, or comfort. This formulation reflects the multi-objective character of energy-management problems discussed in HEMS literature (Beaudin & Zareipour, 2015; Zhou et al., 2016).

Power balance is enforced at every interval as $P_{\text{grid}}(t) + PPV(t) + P_{\text{dis}}(t) = P_{\text{load}}(t) + P_{\text{ch}}(t)$,

where P_{ch} and P_{dis} denote battery charging and discharging power. The battery update is $SoC(t+1) = SoC(t) + \eta_c P_{ch}(t) \Delta t - [P_{dis}(t) \Delta t / \eta_d]$, subject to $SoC_{min} \leq SoC(t) \leq SoC_{max}$ and converter power limits. Charging and discharging are mutually exclusive. Flexible appliances are represented by an energy requirement, earliest start time, latest finish time, and maximum deferral. The scheduler first allocates flexible energy to low-price or PV-rich intervals and then dispatches the battery to absorb otherwise exported PV energy and to reduce high-tariff peaks. This logic is deliberately modular: a particle-swarm, mixed-integer, model-predictive, or reinforcement-learning optimizer can replace the scheduling engine without changing the sensing or actuation interfaces. Demand-response surveys support this separation between pricing signals, optimization logic, and controllable loads (Siano, 2014; Vardakas et al., 2015).

3. Simulation Design

A 24-hour simulation with one-hour intervals was constructed to demonstrate the methodology. The unmanaged reference profile consumes 40.5 kWh/day and has an evening peak of 4.2 kW. Rooftop PV contributes 20.8 kWh/day. A battery with 8 kWh nominal capacity is constrained to 20–90% SoC, with a 2.5 kW power limit and 95% charging/discharging efficiency. A three-level time-of-use tariff is used, with the highest tariff applied during the evening peak. Two kilowatt-hours of flexible appliance demand can be shifted from the 18:00–21:00 period into the midday PV window. These settings represent a small smart-building or residential prosumer and are consistent with the resource combinations commonly discussed in HEMS and smart-grid studies (Zhou et al., 2016; Shareef et al., 2018).

Table 2. Main simulation parameters used for methodology evaluation

Parameter	Value used in simulation
Scheduling horizon / step	24 h / 1 h
Daily electrical demand	40.5 kWh
Daily PV production	20.8 kWh
Battery capacity	8.0 kWh; 20–90% SoC
Battery power / efficiency	2.5 kW / 95% charge and discharge
Flexible load	2.0 kWh shiftable within allowed windows
Tariff levels	0.10, 0.15–0.18 and 0.30 cost units/kWh

4. Evaluation Procedure

The evaluation is performed in four sequential steps. First, the baseline is calculated by supplying the original load from PV whenever available and importing any deficit from the grid; excess PV is exported because no coordinated storage policy is applied. Second, flexible demand is moved from high-price evening intervals to daytime intervals with available PV. Third, the battery charges from PV surplus, maintains reserve for the evening period, and discharges to limit peak grid demand. Fourth, performance is calculated using daily energy-cost index, peak grid demand, total grid import, PV self-consumption, and preservation of total served load. The reported values are simulation outputs from this parameterized case study and should be interpreted as proof-of-method rather than field-validated performance.

Results

The IEMS changes the timing and source of energy without reducing the total daily electrical service. The baseline daily cost index is 6.61 units, whereas coordinated scheduling reduces it to 5.06 units, a 23.45% improvement. Peak grid demand decreases from 4.20 kW to 2.40 kW, corresponding to a 42.86% reduction. Grid import falls from 28.20 kWh to 23.70 kWh because more PV energy is consumed locally and stored for later use. PV self-consumption increases from 59.1% to 80.1%, while the total served load remains 40.5 kWh in both cases. The reduction therefore results primarily from temporal coordination and storage dispatch rather than energy curtailment.

Table 3. Comparative results for unmanaged and intelligent energy management.

Performance indicator	Baseline	Proposed IEMS	Change
Daily energy-cost index	6.61 units	5.06 units	–23.45%
Peak grid demand	4.20 kW	2.40 kW	–42.86%

Daily grid import	28.20 kWh	23.70 kWh	-15.96%
PV self-consumption	59.1%	80.1%	+21.0 percentage points
Total load served	40.5 kWh	40.5 kWh	No reduction

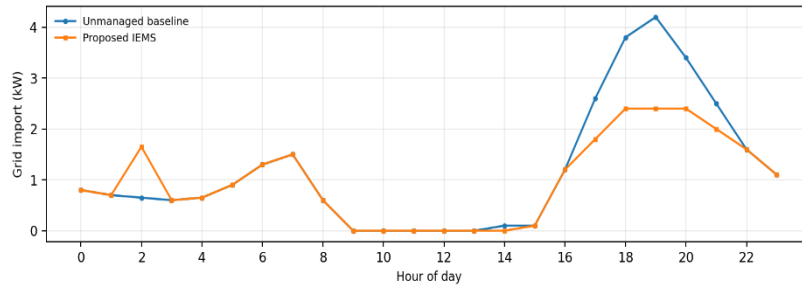


Figure 2. Hourly grid-import profile showing peak reduction under the proposed IEMS.

The largest technical benefit is peak reduction, because the controller reserves stored energy for the evening period instead of discharging as soon as a deficit occurs. This behavior illustrates why coordinated scheduling can outperform independent device-level rules. Higher PV self-consumption also decreases dependence on the external grid and reduces export of locally generated energy. These trends agree with prior literature showing that intelligent demand response, scheduling, and adaptive control can reshape consumption and improve energy utilization (Pipattanasomporn et al., 2012; Shareef et al., 2018). Deep reinforcement-learning studies further suggest that the scheduling layer can be made adaptive when stochastic prices, occupant behavior, and renewable uncertainty become dominant (Li et al., 2020; Nakabi & Toivanen, 2021).

The results are sensitive to storage size, flexibility windows, tariff spread, forecast error, and user constraints. A system with limited shiftable demand or a flat tariff will naturally achieve smaller financial savings, while higher PV surplus and stronger peak pricing increase the value of storage coordination. Consequently, the numerical percentages should not be generalized to all smart grids; the principal contribution is the workflow by which an IEMS transforms measured states and policy constraints into traceable actions and comparable performance indicators.

Conclusion and Discussion

This paper developed a methodology for an Intelligent Energy Management System intended for smart-grid applications. The proposed design combines smart-meter measurements, distributed generation and battery states, tariff and user constraints, a forecast-ready data layer, and a multi-objective scheduling engine. The architecture is compatible with conventional

optimization as well as advanced AI controllers, which is important because smart-grid research has progressively moved from fixed demand-response rules toward data-driven and adaptive energy management (Ali & Choi, 2020; Omitaomu & Niu, 2021). The simulation case study demonstrates how load shifting and battery coordination can reduce cost, peak demand, and grid import while increasing local use of photovoltaic generation. Several limitations define the next stage of development. The current evaluation uses deterministic profiles and does not model forecast uncertainty, communication delay, battery degradation cost, voltage constraints, cyber-security threats, or user override behavior. A practical implementation should use 15-minute or sub-hourly measurements, rolling forecasts, explicit battery-aging penalties, and a fallback safety controller. Hardware-in-the-loop testing should then be conducted using a smart meter, controllable relay or smart plug, battery inverter interface, and an edge controller before deployment on an active distribution feeder. Future work should also compare mixed-integer optimization, model-predictive control, and reinforcement-learning policies under identical data and constraints. Such validation would determine whether the added computational complexity of intelligent methods yields sufficient operational benefit for real smart homes, buildings, and microgrids.

References

Güngör, V. C., Sahin, D., Kocak, T., Ergüt, S., Buccella, C., Cecati, C., & Hancke, G. P. (2011). Smart grid technologies: Communication technologies and standards. *IEEE Transactions on Industrial Informatics*, 7(4), 529–539. <https://doi.org/10.1109/TII.2011.2166794>

- Palensky, P., & Dietrich, D. (2011). Demand side management: Demand response, intelligent energy systems, and smart loads. *IEEE Transactions on Industrial Informatics*, 7(3), 381–388.
<https://doi.org/10.1109/TII.2011.2158841>
- Fang, X., Misra, S., Xue, G., & Yang, D. (2012). Smart Grid—The new and improved power grid: A survey. *IEEE Communications Surveys & Tutorials*, 14(4), 944–980.
<https://doi.org/10.1109/SURV.2011.101911.00087>
- Pipattanasomporn, M., Kuzlu, M., & Rahman, S. (2012). An algorithm for intelligent home energy management and demand response analysis. *IEEE Transactions on Smart Grid*, 3(4), 2166–2173.
<https://doi.org/10.1109/TSG.2012.2201182>
- Siano, P. (2014). Demand response and smart grids—A survey. *Renewable and Sustainable Energy Reviews*, 30, 461–478.
<https://doi.org/10.1016/j.rser.2013.10.022>
- Vardakas, J. S., Zorba, N., & Verikoukis, C. V. (2015). A survey on demand response programs in smart grids: Pricing methods and optimization algorithms. *IEEE Communications Surveys & Tutorials*, 17(1), 152–178.
<https://doi.org/10.1109/COMST.2014.2341586>
- Beaudin, M., & Zareipour, H. (2015). Home energy management systems: A review of modelling and complexity. *Renewable and Sustainable Energy Reviews*, 45, 318–335.
<https://doi.org/10.1016/j.rser.2015.01.046>
- Zhou, B., Li, W., Chan, K. W., Cao, Y., Kuang, Y., Liu, X., & Wang, X. (2016). Smart home energy management systems: Concept, configurations, and scheduling strategies. *Renewable and Sustainable Energy Reviews*, 61, 30–40.
<https://doi.org/10.1016/j.rser.2016.03.047>
- Tuballa, M. L., & Abundo, M. L. (2016). A review of the development of Smart Grid technologies. *Renewable and Sustainable Energy Reviews*, 59, 710–725.
<https://doi.org/10.1016/j.rser.2016.01.011>
- Shareef, H., Ahmed, M. S., Mohamed, A., & Al Hassan, E. (2018). Review on home energy management system considering demand responses, smart technologies, and intelligent controllers. *IEEE Access*, 6, 24498–24509.
<https://doi.org/10.1109/ACCESS.2018.2831917>
- Ali, S. S., & Choi, B. J. (2020). State-of-the-art artificial intelligence techniques for distributed smart grids: A review. *Electronics*, 9(6), 1030.
<https://doi.org/10.3390/electronics9061030>
- Li, H., Wan, Z., & He, H. (2020). A deep reinforcement learning based approach for home energy management system. 2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT).
<https://doi.org/10.1109/ISGT45199.2020.9087647>
- Nakabi, T. A., & Toivanen, P. (2021). Deep reinforcement learning for energy management in a microgrid with flexible demand. *Sustainable Energy, Grids and Networks*, 25, 100413.
<https://doi.org/10.1016/j.segan.2020.100413>
- Omitaomu, O. A., & Niu, H. (2021). Artificial intelligence techniques in smart grid: A survey. *Smart Cities*, 4(2), 548–568.
<https://doi.org/10.3390/smartcities4020029>