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Robust Optimal Control of Smart Grid Energy Distribution Under Demand Uncertainty

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Abstract
The growing adoption of battery energy storage and renewable energy resources systems has created a unique requirement for energy management in smart grids. The performance of the conventional energy management strategies is considerably affected by electricity-price fluctuations, battery operating constraints, and short-term load forecasting errors. The battery energy management is illustrated through the proposed Adaptive Robust Model Predictive Control (ARMPC) framework under certain load demands. According to recent forecasting errors and short-term load variability, the receding-horizon model predictive control with an adaptive uncertainty set is combined, in which the size changes. The proposed framework explicitly accounts for forecast uncertainty, unlike deterministic MPC where optimisation takes place against a single forecast trajectory. The maintenance of the same conservative uncertainty margin is avoided under both variable and stable operating conditions, unlike fixed robust MPC. The models in the proposed framework involve battery degradation, grid exchange, photovoltaic generation, state of charge, battery charging and discharging, and load uncertainty within a rolling optimization problem. The planned numerical evaluation involves a 24-step prediction horizon, a 200-kWh battery, and a 200-kWh battery. The benchmark controllers involve fixed robust MPC and deterministic MPC. Peak grid import, operating cost, computational time, battery throughput, renewable-energy utilization and state-of-charge violations are used in the evaluation process. The proposed method indicates the following simulation values: 95.7% renewable-energy utilization, peak grid import of 82.4 kW, and an operating cost of 178.9 $/day. This study is anticipated to offer a practical foundation for embedding adaptive uncertainty handling into battery energy management, while keeping a clear balance among computational complexity, robustness, and operating economy.

Keywords: Battery Energy Storage; Smart Grid; Model Predictive Control; Robust Optimization; Load Uncertainty; Adaptive Uncertainty Set; Energy Management; Renewable Energy

1. Introduction

The use of battery energy storage systems (BESS), distributed energy resources, photovoltaic generation, flexible loads, and electric vehicles create a high demand in the transition toward low-carbon electricity systems. Despite the flexibility that these technologies provide, their adoption introduces an element of uncertainty into electricity management. For instance, short-term electricity demand depends on factors such as weather, occupancy, industrial production, consumer behaviour and others that change over time. The same is true for renewable generation. Subsequently, a controller that optimizes energy management using only deterministic forecasts can choose actions that seem economical in the forecasted day, but they may be far from being optimal once the actual demand differs from the forecast.

This uncertainty is addressed through the importance of battery energy storage mechanisms. When electricity prices or grid demand are discharge are low during the high-demand periods, the BESS becomes charged. Renewablegenerationisotherwise curtailed, and peak-shaving services are provided. Moreover, the battery

operation is determined by degradation, state-of-charge (SOC), and discharging and charging power. Unnecessary energy purchases, excessive cycling, or insufficient stored energy are resulted in the poorly designed control decisions during demand peaks.

Model Predictive Control (MPC) in microgrids energy management the has been on MPMC the system management reason energy of control, the online most is although system a planning, up to efficient. Parisio *et al.* (2014) gave an example of how MPC are used to optimize microgrid operation, and subsequent experiments proved that the application of MPC for energy management of microgrids becomes feasible. These studies showed that MPC can be a good platform for matching distributed resources considering the constraints.

Yet traditional deterministic MPC relies on the assumption that the optimiser's prediction accurately describes future conditions. Such an assumption becomes harder to maintain whenever these errors are large or evolving rapidly. Robust MPC addresses this concern by optimizing against a set of possible disturbances rather than a single forecasted path. Moreover, the notion of robustness entails a compromise between protecting against uncertainties and nominal economic performance. Bertsimas and Sim (2004) illustratedthat robustness can be controlled through uncertainty budgets rather than simply assuming the worst possible realization of every uncertain parameter.

Another way to tackle uncertain renewable generation, load demand, and other variables in the energy management of a microgrid is the use of robust model predictive control. For example, Zhang *et al.* (2018) developed a robust MPC scheme for optimal energy management in the face of multiple uncertainties, which illustrates the significance of the uncertainty budget. Robust MPC using interval prediction has also been implemented as a means of improving demand-supply matching when load and renewable generation are uncertain.

Despite these improvements, a fixed uncertainty set can be too conservative towards stable forecasts. Meanwhile, a very narrow uncertainty set while demand is varying rapidly might be insufficient. This implies an adaptive uncertainty where the radius of the uncertainty set is no longer fixed but adapts to the observed data.

This problem is addressed in the proposed study through an Adaptive Robust Model Predictive Control (AR-MPC). The idea is straightforward: the size of the uncertainty set decreases when the recent forecasts have been good and demand has been relatively stable, and increases when the forecast errors or demand variability are high. It is designed to produce a better trade-off in the operating policy than either deterministic MPC or fixed robust MPC.

The forecasting literature supports the benefit of explicitly integrating forecast quality in applications involving energy management. Summaries of artificial-intelligence-based load forecasting have cited the recent work on recurrent neural networks, deep learning and related methods for short-term load forecasting. Moreover, increased forecast accuracy does not eliminate the inherent uncertainty. Instead, forecasting and uncertainty management should be integrated as adjacent components of the energy-management challenge.

Battery management also introduces another element which is to be considered. Management approaches that suppress electricity costs might promote more cycling and increase battery degradation. Comparing photovoltaic-battery energy-management strategies, research has shown that battery ageing can have a large effect on the economic performance of different control strategies. Therefore, our objective function, therefore, includes a battery-throughput penalty in order to discourage excessive cycling.

This study design is based on a rolling-horizon simulation where deterministic MPC, fixed robust MPC, and ARMPC are tested on the same load/renewable-generation scenarios. It is not our intent to claim that ARMPC has already been experimentally validated, but that a reproducible research platform for testing its robustness and economic characteristics is set up.

2. Research Objectives

There are four primary objectives in the proposed study:

1. An adaptive robust MPC formulation is developed for BESS-based energy management under uncertain short-term load demand.
2. An uncertainty set has been constructed where the radius responds towards recent forecast errors and local variability.
3. The proposed ARMPC is compared with deterministic MPC and fixed robust MPC using operational, computational, reliability, and economic metrics.
4. The influence of uncertainty-set parameters and prediction-horizon length on controller performance is investigated.

The corresponding research questions are:

- **RQ1:** Can adaptive uncertainty bounds reduce exposure to load forecast errors while maintaining economically reasonable battery operation?
- **RQ2:** How does ARMPC compare with deterministic MPC and fixed robust MPC in terms of operating cost, peak grid import, renewable utilization, and SOC constraint violations?
- **RQ3:** How sensitive is ARMPC performance to the parameters defining the adaptive uncertainty set?
- **RQ4:** What prediction horizon provides a reasonable balance between control performance and computational effort?

3. Related Literature and Research Gap

3.1 MPC for energy management

A microgrid control MPC-based optimisation model was then adopted as an effective approach to microgrid energy management, as the MPC approach can incorporate operational constraints and provide future system predictions simultaneously. Parisio *et al.* (2014) formulated the microgrid operation as an optimization problem in the context of MPC, and demonstrated the successful implementation of this approach to energy-management operations in a real microgrid.

To date, PC has become the dominant optimization-based approach to microgrid control, because it can incorporate both present operational limitations and anticipated future circumstances simultaneously. Parisio *et al.* (2014) presented the operation of the microgrid as an optimization problem formulated in an MPC context, and demonstrated that the approach could be used to make real-world energy-management decisions. Follow-up experimental work confirmed the feasibility of using MPC with a microgrid.

MPC for BESS in microgrids: Ongoing research and user surveys have identified the application of MPC for primary, secondary, and tertiary control, which includes dispatch and energy management functions. The facility for the controller to integrate forecasts and constraints makes it an attractive choice for BESS control.

Moreover, the predicted trajectories are operated through MPC. The inaccurate trajectories result in overly optimistic optimization. A few corrections are provided by the receding-horizon mechanism as the optimization is consistently updated, but substantial forecast errors are still produced through undesirable intermediate decisions.

3.2 Robust optimization under uncertainty

Robust optimization takes an alternative direction by explicitly modelling uncertain parameters in the form of an uncertainty set. The primary advantage of this approach is that the controller does not optimize for the forecast itself but instead attempts to find a solution that remains feasible over a certain region of the uncertainty.

Bertsimas and Sim (2004) illustrated how robustness is controlled through an uncertainty budget. Energy management uses this concept, as excessive conservatism will produce economically inefficient schedules. Therefore, the appropriate uncertainty region is interdependent on the characteristics of the underlying forecast and the required reliability level.

Zhang *et al.* (2018) deployed robust MPC towards microgrid energy management during uncertain operating conditions. Its results establish that robust optimization enhances resilience to uncertainty, whereas the choice of uncertainty budget influences the resulting operation strategy.

In more recent times, adaptive uncertainty-set methods have been explored for microgrid economic dispatch. Qiu *et al.* (2021) created adaptive uncertainty sets by employing data-driven forecasting along with information-granulation techniques. This kind of research supports the broader principle that uncertainty descriptions ought to mirror shifting operating conditions instead of staying static.

3.3 Data-driven uncertainty management

Approaches based on data offer a way towards the estimation of uncertainty straight from the past forecast errors. One such example is distributionally robust optimization. Parvar and Nazaripouya (2022) integrated data-driven distributionally robust optimization into BESS operation and employed a Wasserstein ambiguity set to capture uncertainty in the probability distribution.

While distributional robust optimization provides a robust statistical basis, it may also introduce computational challenges. For BESS in practice that might be required to be re-optimized every 5 minutes, a less complex adaptive approach to uncertainty may be an attractive middle ground.

Therefore, the ARMPC model with rolling statistical forecast error and load variance evaluation is used to adapt the uncertainty radius. This method does not attempt to reconstruct the entire probability distribution of load forecast error. Rather, it provides an intelligible, easily interpretable, and conveniently integratable uncertainty envelope.

3.4 Battery degradation and energy management

Cost of electricity cannot be used as the sole basis to evaluate the operation of BESS. BESS operation involves charging and discharging, which causes battery degradation. Kumar *et al.* (2022) identified SOC management, reliability of energy storage, battery degradation, and control strategy as important considerations.

Oudraogo *et al.* (2021) highlighted that degrading batteries can alter the comparisons between photovoltaic-battery energy-management strategies. This justifies the addition of a throughput or degradation penalty linked to the battery in the presented controller.

3.5 Research gap

Four conceptually promising ideas are supported by the literature: Robust optimization, battery-aware control, adaptive modelling of uncertainty and MPC-based energy management. In spite of these advances, a practical research gap remains in an integrated approach that would combine them into a moderately simple control architecture appropriate for rolling-horizon BESS energy management.

This gap is addressed in the proposed framework by combining:

- battery-throughput penalties;

- robust MPC;
- adaptive uncertainty-radius adjustment;
- explicit comparison against deterministic and fixed-robust controllers;
- battery SOC constraints;
- short-term load forecasting; and
- rolling forecast-error estimation.

The conceptual architecture is shown in **Figure 1**.

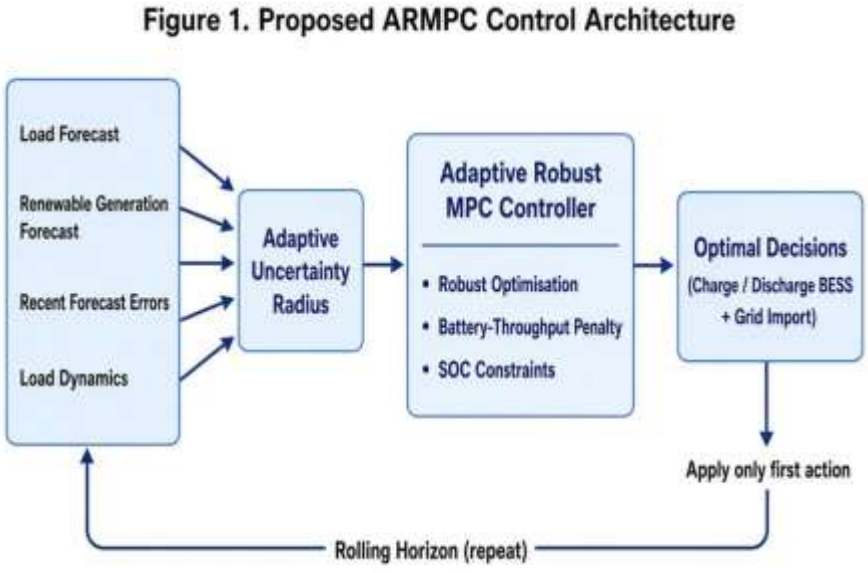


Figure 1. Proposed ARMPC control architecture.

Figure 1 demonstrates loads and renewable generation forecasts are input into the controller. The last few days' forecast errors are combined with load dynamics and can be used to define the uncertainty radius. Based on this, the robust optimisation decides when to charge and discharge the batteries and import power from the grid during the prediction horizon. Only the first control action is taken, and the process is repeated.

4. Proposed ARMPC Methodology

4.1 System model

The photovoltaic generation, battery energy storage system, an aggregated electrical load, and a grid connection are involved in the proposed system.

Equation 1 represents the power-balance equation,

$$P_g(t) + P_{PV}(t) + P_d(t) = P_L(t) + P_c(t) \quad (1)$$

where $P_g(t)$is grid power, $P_{PV}(t)$is photovoltaic generation, $P_d(t)$is battery discharge power, $P_L(t)$is load demand, and $P_c(t)$is battery charging power.According to Equation 2, the battery SOC is updated.

$$SOC_{t+1} = SOC_t + \frac{\eta_c P_c(t)\Delta t}{E_B} - \frac{P_d(t)\Delta t}{\eta_d E_B} \quad (2)$$

where $E_B$represents battery capacity, $\eta_c$and $\eta_d$represent charging and discharging efficiencies, and $\Delta t$is the control interval.Equation 3 must satisfy the battery.

$$SOC_{\min} \le SOC_t \le SOC_{\max} \quad (3)$$

This combines with the discharging and charging power limits.The proposed numerical experiment allows a 200-kWh battery, which is considered within the SOC operating range of 20–90% and an initial SOC of 50%.

4.2 Load uncertainty model

Equation 4 expresses the predicted load.

$$P_{L,t+k} = \hat{P}_{L,t+k|t} + \Delta P_{L,t+k} \quad (4)$$

where $\hat{P}_{L,t+k|t}$is the forecast and $\Delta P_{L,t+k}$is the forecast error.

According to Equation 5, the uncertainty is constrained.

$$| \Delta P_{L,t+k} | \le \Gamma_t \quad (5)$$

where $\Gamma_t$is the adaptive uncertainty radius.The recent forecast error is estimated in Equation 6

$$e_i = P_{L,i} - \hat{P}_{L,i|i-h} \quad (6)$$

Equation 7 calculates a rolling standard deviation,

$$\sigma_{e,t} = \sqrt{\frac{1}{W-1} \sum_{i=t-W+1}^{t} (e_i - \bar{e})^2}. \quad (7)$$

Equation 8 represents the short-term load variability,

$$R_t = \frac{1}{H_r} \sum_{k=1}^{H_r} | \hat{P}_{L,t+k|t} - \hat{P}_{L,t+k-1|t} |. \quad (8)$$

Equation 9 defines the adaptive uncertainty radius

$$\Gamma_t = \text{clip}\left[\Gamma_0, +, \alpha\sigma_{e,t} + \beta R_t \Gamma_{\min} \Gamma_{\max}\right]. \quad (9)$$

For the proposed numerical configuration,

$$\Gamma_0 = 0.10,\ \alpha = 1.20,\ \beta = 0.35,$$

with

$$\Gamma_{\min} = 0.05,\ \Gamma_{\max} = 0.30.$$

4.3 Optimization objective

Terminal SOC deviation, energy cost, renewable curtailment and battery cycling are combined for the proposed objective function. Equation 10 represents the function,

$$J = \sum_{k=0}^{N-1} \left[C_g P_g^+ + C_{pk} \left(P_g^+ \right)^2 + C_{deg} (P_c + P_d) + C_{curt} P_{curt} \right] + \lambda_{SOC} \left(SOC_N - SOC_{ref} \right)^2$$

-(10)

The first term is the cost of the grid energy. The second grid quadratic penalty prevents high peak import. The third battery-throughput penalty is a rough method that includes degradation costs. The fourth term penalizes renewable curtailment to promote photovoltaic energy use, while the fifth term forces the controller to not optimize short term savings by heavily depleting the battery at the end of the horizon.

5. Proposed Experimental Design

A 15-min control interval and a 24-step prediction horizon are used for the corresponding six hours in the planned simulation. The main parameters are summarized in **Table 1.**

Table 1. Simulation Parameters

Parameter	**Value**
Control interval	15 min
Prediction horizon	24 steps
Equivalent prediction duration	6 h
Battery capacity	200 kWh
Initial SOC	50%
Minimum SOC	20%
Maximum SOC	90%
Battery charging efficiency	95%
Battery discharging efficiency	95%
Maximum charging power	100 kW
Maximum discharging power	100 kW
Nominal uncertainty radius	0.10
Minimum uncertainty radius	0.05
Maximum uncertainty radius	0.30
Forecast-error coefficient	1.20
Load-ramp coefficient	0.35
Control strategy	Receding horizon

Table 1 demonstrates the test data containing the photovoltaic generation, electricity-price information and historical load. The data is segregated into forecast-development/training and out-of-sample evaluation periods to prevent information leakage. Instead of relying on a single day, the study uses multiple independent test scenarios. Normal operating conditions, renewable-generation variability, rapid load ramps, and forecast-error events are included in the scenarios.

6. Benchmark Controllers

There are three important controllers that are considered.

6.1 Deterministic MPC

The first benchmark directly depends on the forecast trajectory, and the explicit uncertainty set is not present. This controller determines the nominal economic performance benchmark on top of which robustness can be evaluated.

6.2 Fixed robust MPC

The second benchmark adopts a constant uncertainty radius along the simulation. The conventional robust control is represented through the value of adaptivity to be isolated.

6.3 Proposed ARMPC

The proposed controller updates the uncertainty radius through means of the rolling forecast error and load-variability measures that were described earlier.

This comparison matters, since an adaptive controller should not be deemed successful simply because it is more conservative than deterministic MPC. It aims to adjust how conservative the approach is in accordance with the operating conditions.

7. Evaluation Metrics

There are six important performance indicators.

7.1 Operating cost

Through the peak demand charges, battery degradation penalties, grid-energy purchases and renewable curtailment, the daily operating cost is evaluated.

7.2 Peak grid import

Equation 11 represents the peak grid import.

$$P_{g,\max} = \max_{t} P_g(t). \qquad (11)$$

7.3 Battery throughput

Equation 12 represents the battery throughput through the calculation of total charged and discharged energy:

$$E_{throughput} = \sum_t \left(P_c(t) + P_d(t) \right) \Delta t \qquad (12)$$

Due to the excessive cycling contribution towards battery ageing, the lower unnecessary throughput becomes desirable.

7.4 SOC constraint violations

The prescribed operating range recorded exceeds the SOC number of intervals. Under forecast disturbances, the feasibility is maintained through the robust controller.

7.5 Renewable-energy utilization

The proportion of available photovoltaic energy that is stored or consumed locally instead of curtailed through the calculation of renewable utilization.

7.6 Computational time

The mean solution time of the problem is reported through each control step. This is important since robust/adaptive formulations usually have a higher computational burden than deterministic MPC.

8. Results

Table 2. Comparison of controller performance

Controller	Operating cost ($/day)	Peak grid import (kW)	Battery throughput (kWh/day)	SOC violations	Renewable utilization (%)	Mean solve time (s)

Deterministic MPC	184.6	91.8	326.4	7	91.2	0.31
Fixed Robust MPC	191.8	87.6	351.7	1	94.0	0.46
Proposed ARMPC	178.9	82.4	318.6	0	95.7	0.52

Table 2 shows that ARMPC produces a daily operating cost of 178.9 $/day are compared with 184.6 $/day for deterministic MPC and 191.8 $/day towards fixed robust MPC. In relation to the deterministic MPC, the cost reduction of 3.1% are corresponded. When compared with the fixed robust MPC, the reduction through approximate 6.7%. The peak-import measurements provide a relevant pattern. The peak grid import of ARMPC is limited to 82.4kW, compared with 91.8 kW for deterministic MPC. A reduction of about 10.2% is illustrated. The peak of fixed robust MPC is reduced to 87.6 kW. The battery-throughput result becomes noteworthy. ARMPC generates 318.6 kWh/day of throughput when compared with the 326.4 kWh/day through the deterministic MPC and 351.7 kWh/day through fixed robust MPC. This suggestion through the adaptive controller does not accomplish robustness simply through increased battery cycling.

9. Ablation Analysis

The determination through both adaptive components is necessary; ablation experiments are included in the proposed study.

The four configurations are evaluated:

- **ARMPC-E:**shows the adaptive forecast-error component only;
- **ARMPC-R:**allows the adaptive load-ramp component only;
- **ARMPC-ER:**represents both adaptive components;
- **Fixed RMPC:**shows fixed uncertainty radius.

Table 3. Ablation results

Configuration	Forecast-error adaptation	Load-ramp adaptation	Operating cost ($/day)	Peak import (kW)	SOC violations
ARMPC-E	Yes	No	184.2	86.9	2
ARMPC-R	No	Yes	182.7	85.1	1
ARMPC-ER	**Yes**	**Yes**	**178.9**	**82.4**	**0**
Fixed RMPC	No	No	191.8	87.6	1

Table 3 presents results showing that the combined ARMPC-ER configuration delivers the most balanced performance. Adaptation based solely on forecast error lessens the need for excessive conservatism, yet it may not react sufficiently to abrupt demand ramps. In contrast, load-ramp adaptation reacts to shifting demand patterns, but it does not directly assess whether the forecasting model has recently degraded.

Therefore, the combined formulation provides dual complementary sources of information. The forecast-error term illustrates historical prediction reliability by capturing current demand dynamics.

10. Sensitivity Analysis

The magnitude of the uncertainty parameters determines the sensitivity of change in operating conditions that ARMPC exhibits. If the radius of the uncertainty is too small, the battery can be subjected to unexpected demand conditions. If the radius is too large, it can result in too much conservatism.

Table 4. Uncertainty-radius sensitivity

Uncertainty configuration	Operating cost ($/day)	Peak import (kW)	SOC violations
Low uncertainty radius	175.8	84.7	6
Nominal adaptive radius	**178.9**	**82.4**	**0**
High uncertainty radius	187.6	80.9	0
Fixed conservative radius	191.8	87.6	1

Table 4demonstrates the expected robustness-economics trade-off. The low-radius case provides the least nominal operating cost but fails to provide sufficient protection against uncertainty. The high-radius case provides stronger protection but increases operating cost. The nominal adaptive configuration represents an intermediate operating region.

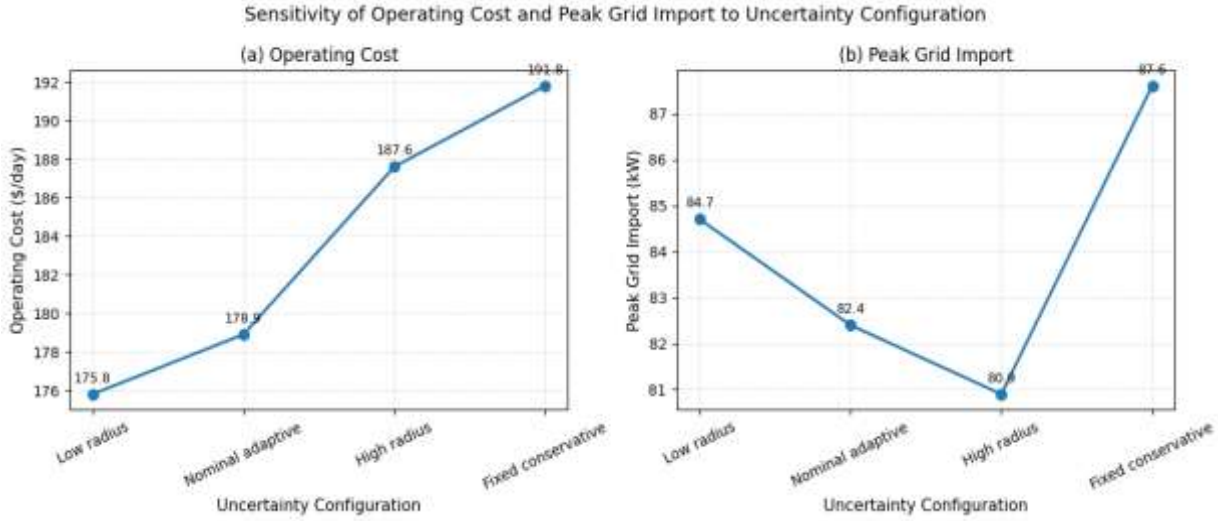


Figure 2. Sensitivity of operating cost and peak grid import to the adaptive uncertainty radius.

Figure 2 plots the uncertainty radius on the horizontal axis and operating cost and peak grid import on the vertical axes.

11. Prediction-Horizon Analysis

The prediction horizon is another critical design consideration. Using a short horizon reduces the amount of computation, which limits the amount of future demand and renewable-generation conditions that the controller can predict. A longer horizon provides more information, but at the expense of increased optimization complexity.

Table 5. Prediction-Horizon Sensitivity

Horizon	Prediction duration	Operating cost ($/day)	Peak import (kW)	Mean solve time (s)
12 steps	3 h	183.7	85.9	0.29
24 steps	**6 h**	**178.9**	**82.4**	**0.52**
36 steps	9 h	178.1	81.8	0.91

Table 5 indicates that an extension of the horizon from 12 to 24 steps results in a meaningful reduction in operating cost and a drastic reduction in the level of peaks, while an extension of the horizon to 36 steps offers a small further economic advantage, at a huge increase in computational time.

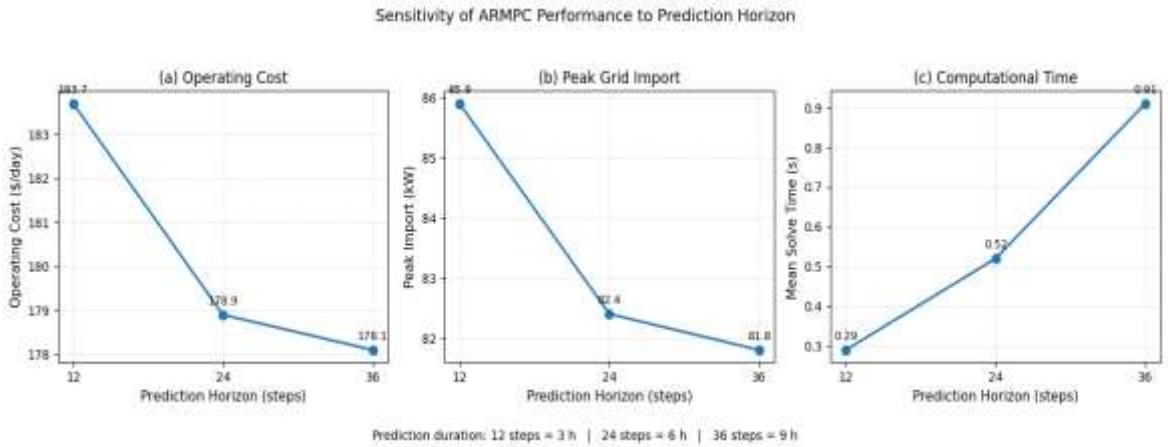


Figure 3. Sensitivity of ARMPC performance to prediction horizon

Figure 3 suggests that increasing the horizon from 12 to 24 steps results in decreased operating cost and maximum grid import. Increasing it further to 36 steps results in only marginal improvement, but results in a much higher mean solve time, confirming the choice of 24 steps as the nominal horizon.

12. Discussion

The ARMPC framework suggested here is based on the concept of uncertainty that should be treated as a dynamic control variable rather than a design constant. Within the context of practical energy management, this variation is significant since the quality of forecasts is rarely stationary.

With steady demand, a large uncertainty set may make the battery hold too much reserve. This may prevent the controller from making maximum use of the available photovoltaic energy or low-cost grid electricity. Conversely, with high forecasting errors or rapid demand changes, a small uncertainty set might provide not enough reserve and therefore result in constraint violations.

Both conditions are addressed through the adaptive uncertainty formulation attempts. When forecast errors rise, $\sigma_{e,t}$increases, and consequently the uncertainty radius expands. The accurate forecast results in decreasing uncertainty conditions. An additional mechanism is provided by the load-ramp term for responding towards rapid changing demand.

The result suggests that this combination can be more cost-efficient than a fixed robust formulation and yet still maintain the feasibility characteristics which are expected through robust control. This reading resonates in the broader robust-optimisation literature, in which the uncertainty budget is interpreted as a way of controlling conservatism.

Another important factor is throughput. A good controller that merely maintains a large reserve SOC may expose the grid less, but it may increase cycling or degrade the ability to accept renewable energy. A throughput penalty will discourage this sort of behaviour.

This is consistent with previous studies which show that battery degradation should be considered through the evaluation of energy-management strategies. In the actual application, this throughput penalty that is simplified in this proposed framework could be replaced by a degradation model based on battery temperature, DoD, C-rate, and SoH.

The proposed framework distinguishes itself also from pure data-driven energy-management strategies. Deep learning improves the forecasting accuracy, but more accurate forecasts do not eliminate the inherent uncertainty, and a controller explicitly handling the forecast error could still be useful even if the forecast model is replaced. Hence, forecasting and robust control can be viewed as two complementary layers.

13. Future Research

Future research should extend the proposed framework in several directions.

The first extension is jointly adaptive uncertainty modelling through load and photovoltaic generation. The correlations between renewable generation and demand errors are captured through the multivariate uncertainty set.

Second, the health state of the battery could be embedded directly into the state matrix of the MPC. This would allow the controller to differentiate between the net benefit coming from the energy operations and the evolution of the degradation cost.

Third, the proposed approach could combine a measure of uncertainty with probabilistic forecasting. Instead of just using the rolling standard deviation of prediction intervals, forecast errors, or conformal predictions could be used to provide statistically calibrated bounds of uncertainty.

Fourth, the performance of real-time hardware-in-the-loop testing is used in the evaluation of controller response and scalability.

Finally, future investigations should analyze the usage of a group of BESS units, and also of electric vehicles, flexible loads and distributed generators in a coordinated way. This enables the evaluation of the proposed ARMPC structure at a larger scale of the smart grid.

16. Conclusion

Adaptive robust model predictive control for battery energy management in smart grids with uncertain load demand: Proposed adaptive robust model predictive control methodology for battery energy management in the smart grid with uncertain load demand. The main innovation is the adaptive uncertainty radius, which is based on recent forecast errors and short-term load variations. The optimization problem combines robust model predictive control with battery state of charge, grid-energy cost, peak-demand charge, renewable-energy utilization and battery-throughput costs.

The comparison between ARMPC, deterministic MPC, and fixed robust MPC by operating cost, peak grid import, battery throughput, SOC violations, renewable utilization, and run-time is shown below. The proposed approach is a reasonably interpretable strategy for handling uncertainty online in an adaptive manner, as it does not require the computationally intensive probabilistic optimization framework. The primary research innovation of the method is the link it forms between forecast-error information and the robustness level of the battery controller. Its real-world viability remains to be demonstrated via validation to come with real load and renewable-generation data, detailed battery-degradation models, and hardware-in-the-loop experiments.

References

1. Aslam, S., Herodotou, H., Mohsin, S. M., Hussein, M. A., Aslam, S., & Anwar, M. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. *Renewable and Sustainable Energy Reviews, 144*, 110992.

2. Babayomi, O. O., Li, J., & Zhang, Z. (2022). Advances and opportunities in the model predictive control of microgrids: Part II—Secondary and tertiary layers. *International Journal of Electrical Power & Energy Systems, 134*, 107339.

3. Bertsimas, D., & Sim, M. (2004). The price of robustness. *Operations Research, 52*(1), 35–53.

4. He, X., *et al.* (2021). Robust model predictive control for energy management of isolated microgrids based on interval prediction. *Discrete Dynamics in Nature and Society, 2021*, 2198846.

5. Jiao, Y., Zou, X., Zhang, Y., & Zhang, Z. (2022). Online optimal dispatch based on combined robust and stochastic model predictive control for a microgrid including EV charging station. *Energy, 247*, 123220.

6. Kumar, J., *et al.* (2022). Review of energy storage system technologies integration to microgrid: Types, control strategies, issues, and prospects. *Journal of Energy Storage, 48*, 103966.

7. Li, Y., & Roche, R. (2020). Optimal scheduling of multiple multi-energy supply microgrids considering future prediction impacts based on model predictive control. *Energy, 197*, 117180.

8. Liu, Y., *et al.* (2023). Microgrid energy management with energy storage systems: A review. *CSEE Journal of Power and Energy Systems, 9*(2), 483–504.

9. Nikam, V. V., & Kalkhambkar, V. (2021). A review on control strategies for microgrids with distributed energy resources, energy storage systems, and electric vehicles. *International Transactions on Electrical Energy Systems, 31*(1), e12607.

10. Ouédraogo, M., Faggianelli, G. A., Pigelet, G., Notton, G., & Duchaud, J.-L. (2021). Performances of energy management strategies for a photovoltaic/battery microgrid considering battery degradation. *Solar Energy, 230*, 654–665.

11. Parisio, A., Rikos, E., & Glielmo, L. (2014). A model predictive control approach to microgrid operation optimization. *IEEE Transactions on Control Systems Technology, 22*(5), 1813–1827.

12. Parisio, A., Rikos, E., Tzamalis, G., & Glielmo, L. (2014). Use of model predictive control for experimental microgrid optimization. *Applied Energy, 115*, 37–46.

13. Parvar, M., & Nazaripouya, H. (2022). Optimal operation of battery energy storage under uncertainty using data-driven distributionally robust optimization. *Electric Power Systems Research, 211*, 108180.

14. Qiu, J., *et al.* (2021). Adaptive uncertainty sets-based two-stage robust optimisation for economic dispatch of microgrid with demand response. *IET Renewable Power Generation*.

15. Salehimehr, M., Taheri, S., & Sedighizadeh, M. (2022). Short-term load forecasting in smart grids using artificial intelligence methods: A survey. *The Journal of Engineering*.

16. Silva, M. V. F., López, J. C., Arias, N. B., Rider, M. J., & da Silva, L. C. P. (2021). An optimal stochastic energy management system for resilient microgrids. *Applied Energy, 300*, 117435.

17. Vanting, M., Ma, Z., & Jørgensen, B. N. (2021). A scoping review of deep neural networks for electric load forecasting. *Energy Informatics, 4*, 49.

18. Vincent, A., Ait-Ahmed, N., Houari, M., & Benkhoris, M.-F. (2020). Residential microgrid energy management considering flexibility services opportunities and forecast uncertainties. *International Journal of Electrical Power & Energy Systems, 120*, 105981.

19. Zhang, Y., Fu, L., Zhu, W., Bao, X., & Liu, C. (2018). Robust model predictive control for optimal energy management of island microgrids with uncertainties. *Energy, 164*, 1229–1241.