

Forecast-Guided Optimization of Degradation Metrics in Coupled Electrochemical Units

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ABSTRACT

The high efficiency and scalability of the coupled electrochemical units, coupled with their operational flexibility, have made them very popular in modern energy storage and conversion systems. Nevertheless, constant operation with a wide range of load requirements and environmental factors is known to accelerate degradation resulting in lower performance, lowered energy efficiency and reduced service life. The currently available degradation management approaches are largely based on reactive control approaches or the static optimization approach; these approaches cannot effectively use future operating information to make proactive decisions. This paper aims to solve this limitation by suggesting a forecast-directed optimization model to combine predictive forecasting with degradation metric optimizations in coupled electrochemical units. The proposed model forecasts future operating situations based on previous measurements of the system and adds the forecasted data into an optimization plan to ensure less degradation and balanced system operation. The methodology is tested in MATLAB/Simulink simulation environment in different operating conditions with different load profiles. Forecast performance is measured by Mean Absolute Error (MAE), Root means square error (RMSE) and mean absolute percent error (MAPE) in order to prove the correctness of prediction. Additional indicators of degradation such as State of Health (SOH), capacity fade and degradation index are used to evaluate the optimization process. The simulation outcomes confirm that the proposed framework delivers more realistic predicting and greatly enhances degradation handling over traditional methods, which boosts the system reliability, functionality, and durability in the long run. These results show that forecast-guided optimization is one of the useful decision support methodologies to be used in intelligent electrochemical energy systems.

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1. INTRODUCTION

Due to superior power delivery, system flexibility, and system stability, coupled electrochemical units find extensive application in current energy storage and conversion systems. They are typically used in battery energy storage systems, fuel cell, hybrid energy systems, and in renewable energy applications, where several units are used in tandem at varying loads. Non-uniform degradation, however, is frequently occasioned by variations in current, temperature and charging/discharging regimes, resulting in imbalance in capacity, decreased efficiency as well as reduced service life. Thus, to enhance the reliability and life cycle of electrochemical systems good management of degradation is crucial.

Growing interest has been given to degradation-aware operation as a mechanism of reducing the effect of wear and tear in extending the lifespan of a system by readjusting operating conditions to the condition of electrochemical units. The traditional methods largely depend on periodic monitoring or static optimization and cannot predict the future operating conditions. Predictive forecasting is an alternative which is also proactive and based on historical measurements to predict the future behaviour of the system to allow optimization strategies to be used in order to minimize degradation without affecting the system performance.

The field of degradation modelling, forecasting, as well as optimization has undergone extensive

research, but not much has been done in integrating the three in the coupled electrochemical units. The vast majority of the existing methods optimize operation based on only current system information, and hence the decisions can be suboptimal when operating in a dynamic environment. Moreover, the indicators associated with degradation like State of Health (SOH), capacity fade, and degradation index are usually not adequately factored into predictive optimization systems.

The current paper presents a predictive forecast-based optimization framework which incorporates predictive forecasting as well as degradation-conscious optimization of coupled electrochemical units. The given approach forecasts the future working conditions based on the past measurements and introduces them into an optimization strategy to reduce the degradation and balance the working conditions. Performance is determined based on the MAE, RMSE and MAPE and degradation is determined based on SOH, capacity fade and degradation index. Simulation findings show that the proposed framework enhances degradation management, operation efficiency and long-term system reliability as compared to the traditional approaches.

2. RELATED WORK

Stability and long-term performance of proton exchange membrane fuel cells (PEMFCs) are a great area of research since the degradation directly affects the efficiency, performance, and maintenance of such fuel cells. Improvement in durability and performance has been the focus of the design principles of next generation PEMFCs [3]. The main degradation processes in automotive operating conditions are thoroughly studied, and the degradation of catalyst-layers is measured with long-term durability tests [9], [14]. In more recent reviews, the mechanisms, influencing factors, consequences and mitigation strategies of PEMFC stack degradation have been summarised [13]. These studies have greatly enhanced the degradation behaviour understanding but a majority of these are more inclined towards characterising degradation as opposed to operational mitigation by predictive control.

Correct prediction of degradation and useful life has emerged as a significant research focus of smart electrochemical systems. Recent reports have surveyed deep-learning methods to predict remaining

useful life of hydrogen fuel cell, and found recurrent neural networks to be effective in nonlinear degradation modelling [1]. The lifetime prediction has also been enhanced to also incorporate the recovery phenomenon of reversible voltage loss [6]. Semi-empirical models based on electrochemical knowledge and measured operating variables have also been incorporated into models of semi-empirical degradation prediction and electrochemical impedance spectroscopy-based health-management models have been designed to monitor PEMFC [7], [16]. Even though these predictive techniques are highly accurate in prediction, they tend to be used in conditions assessment and prognostics and not in real time operational optimization.

Energy management based on optimization has also been noted to have been given a lot of attention towards enhancing the efficiency and longevity of electrochemical energy systems. Combined thermal management and fuel-cell operation have been suggested as a method of reducing the degradation of fuel-cells by using health-conscious energy-management strategies [2]. They have also used hierarchical model predictive schemes that have optimized eco-driving and energy control and explicitly taken fuel-cell degradation into account [5]. Thorough survey has also noted the increased significance of health-conscious energy-management methods in fuel-cell hybrid electric cars [10]. Moreover, the design of electrochemical catalysts and materials used to create membranes have also helped to improve durability and electrochemical performance by improving the material stability and degradation resistance [4], [8], [15]. However, most of the existing optimization procedures are mainly based on the prevailing operating conditions and rarely use predictive forecasting to pre-emptively compute the future operating strategies.

Although significant progress has been made in degradation modelling, forecasting and optimization, there are various research gaps. Current research typically examines prediction of degradation [1], [6], [7], health-conscious energy management [2], [5], or prediction mechanisms of degradation [9], [13], [14] as distinct research challenges, but little of the research has been integrated between these areas. Moreover, there have been comparatively limited studies on the development of such unified frameworks which integrate short-term forecasting with degradation-based optimization of coupled

electrochemical units. Consequently, predictive information is not fully used to enhance load allocation, minimize capacity degeneration, and overall long-term operation effectiveness. To overcome these shortcomings, this paper suggests a Forecast-Guided Optimization (FGO) model which combines LSTM-based operating-condition forecasting with degradation-conscious optimization to enhance State of Health, minimize degradation, increase energy-utilization efficiency, and enable reliable long-term operation of coupled electrochemical systems.

3. FORECAST-GUIDED OPTIMIZATION FRAMEWORK

3.1 Coupled Electrochemical System Model

The suggested forecast-guided optimization system is designed to operate within a coupled electrochemical system comprising of a series of electrochemical units

that work in synergy to meet dynamic load conditions. The operating measurements, in terms of voltage, current, temperature and power, are constantly available to a centralized monitoring module by each unit. The measurements are employed to describe the current operating conditions of the system and can be used as inputs in forecasting and degradation prediction. The scheme combines four consecutive modules, the coupled electrochemical system model, the forecasting model, the estimation of the degradation, and the optimization strategy. This combined architecture allows proactive operational decision making using future operational prediction with degradation-conscious optimization to enhance system reliability and longevity. The general structure of the suggested methodology is presented in Fig. 1.

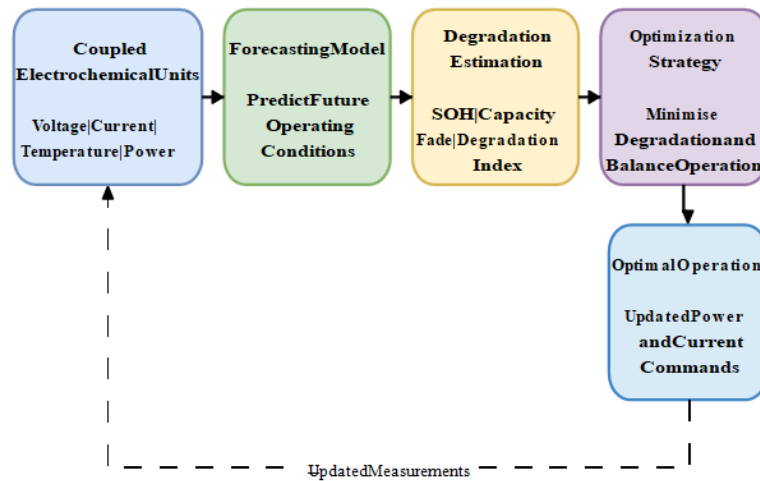


Fig. 1. Proposed Forecast-Guided Optimization Framework

3.2 Forecasting Model

The forecasting model is based on the idea of predicting the future operating conditions, on the basis of past operating measurements that are taken between the two electrochemical units coupled together. The input feature is a voltage, current, temperature, power demand and past operating conditions over a defined observation period. These measurements are then used to predict the future operating variables based on the prediction interval to enable the optimization module to make proactive operational decisions. The forecast model can be written as.

$$\hat{X}_{t+h} = f(X_t, X_{t-1}, \dots, X_{t-n+1}) \quad (1)$$

where $\hat{X}_{t+h}$ denotes the forecasted operating variable at prediction horizon h , X_t represents the current operating measurement, n is the historical observation window, and $f(\cdot)$ denotes the forecasting function. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used to determine the accuracy of the predictions. Fig. 2 shows us the forecasting process and flow of information.

3.3 Degradation Estimation

The degradation estimation module appraises the health of every electrochemical unit based on both the measured and predicted operating conditions. The main degradation measure is the State of Health

(SOH) that indicates the remaining capacity of the electrochemical unit in comparison with the rated capacity. SOH is given by:

$$SOH(\%) = \frac{C_{current}}{C_{rated}} \times 100 \quad (2)$$

where $C_{current}$ is the current available capacity and C_{rated} is the rated capacity. In addition to SOH, the framework monitors capacity fade and degradation index to quantify the ageing behaviour of individual units. These metrics of degradation give valuable data needed in the identification of units that are ageing faster and are later on during optimization module to refine the operational decisions.

3.4 Optimization Strategy

The optimization approach makes use of the predicted operating conditions along with the forecasted degradation measures to yield the

optimum operating configuration of the coupled electrochemical units. It is aimed at minimizing the degradation with balanced distribution of power and safe operation of the system with realistic operating conditions. The optimization problem is set as follows:

$$\min J = w_1 D + w_2 E + w_3 P \quad (3)$$

where D denotes the degradation cost, E represents the forecasting error, P corresponds to the power imbalance, and w_1, w_2 and w_3 are weighting coefficients satisfying $w_1 + w_2 + w_3 = 1$. The optimization algorithm keeps revising operating choices as per projections of system behaviour to minimize degradation whilst keeping up safe operating limits and balanced operation in the entire electrochemical units. The entire forecast guided optimization process that is embraced in this work is represented in Fig. 2.

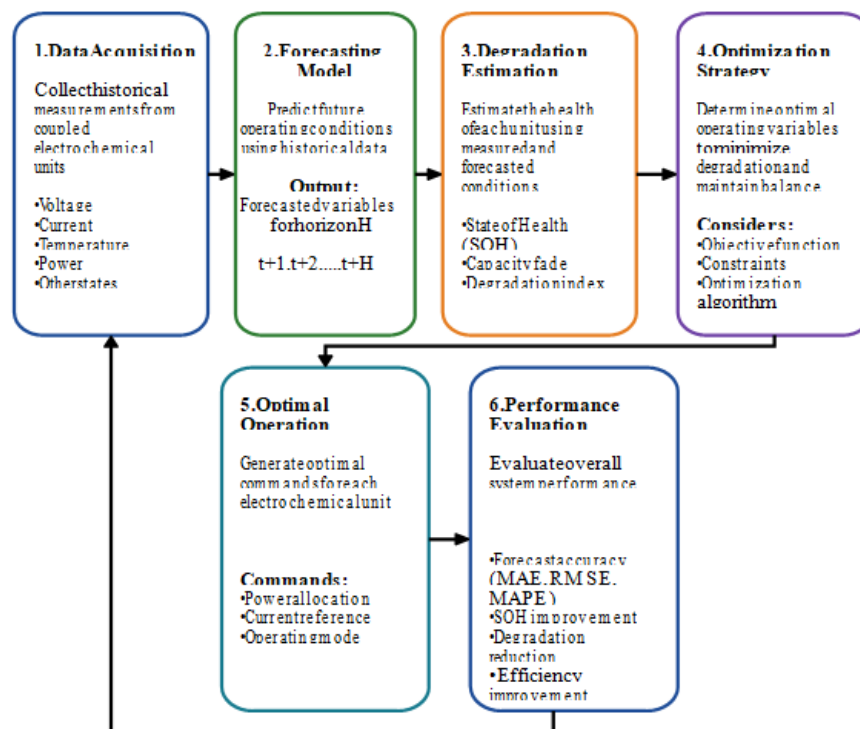


Fig. 2. Forecast-Guided Optimization Workflow

4. EXPERIMENTAL SETUP

4.1 Simulation Platform

The suggested forecast-based optimization model was transferred to MATLAB/Simulink to assess the coupled units of electrochemical operation when under dynamic operating conditions. The simulation system was a network of four identical electrochemical units

that were coupled with a centralized energy-management controller. Voltage, current, temperature, and power demand measurements and operating-state measurements were taken and inputted into the forecasting model during every simulation step. The simulation was done during a 24 h operating period with a sampling interval of 1 min to include both the operating short-term variations and long-term degradation behaviour.

4.2 System Parameters

The simulation parameters which were stated in Table 1 offered a realistic operating environment which would be used to evaluate the proposed framework. The system comprised of four electrochemical units with ratings of 48 V and 100 Ah with starting SOH at 100%. The range of 2 -8 kW and 24 h simulation period with 1 min sampling interval allowed testing under different operating conditions. A 6-step forecast horizon was employed enabling proactive power allocation that managed to enable better degradation management and energy use during the simulation.

Table 1. Simulation Parameters

Parameter	Value
Number of electrochemical units	4
Nominal voltage	48 V
Rated capacity	100 Ah
Initial State of Health (SOH)	100%
Load-demand range	2-8 kW
Sampling interval	1 min

Simulation duration	24 h
Forecast horizon	6-time steps

4.3 Forecasting Dataset

Table 2 forecasting configuration allowed the LSTM model to discover short-term temporal interactions between voltage, current, temperature, power demand and past operating states. The future conditions were predicted using a 12 time-steps or 12 min horizon (depending on the chosen sampling interval) to predict future conditions. The network used 64 hidden units, and learning rate of 0.001 with a maximum of 100 training epochs which was enough to give the model enough capacity without being so complex to compute. The data was separated into 70 percent training, 15 percent validation, and 15 percent testing that is equal to about 1,008, 216, and 216 samples of the 1,440-point daily profile, respectively. The loss function was the Mean Squared Error which helped to discourage large forecasting errors and enhance the stability of predictions.

Table 2. Forecasting Model Configuration

Configuration	Value
Forecasting model	LSTM
Input features	Voltage, Current, Temperature, Power, Previous states
Observation window	12-time steps
Hidden units	64
Learning rate	0.001
Maximum epochs	100
Training / Validation / Testing	70% / 15% / 15%
Loss function	Mean Squared Error (MSE)

4.4 Baseline Methods

Comparison of the proposed method with three baseline strategies was made; equal power allocation, degradation-aware allocation with only current SOH, and forecast-based allocation with no degradation optimization. The baseline methods were tested under the same operating conditions, load profiles and simulation settings in order to have a fair performance comparison.

4.5 Evaluation Metrics

Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used as measures of forecasting performance. The coupled electrochemical unit's behaviour in degradation was evaluated by State of Health (SOH), capacity fade and degradation index. Besides this,

the system performance overall was also considered with regard to the efficiency of energy-utilisation, operating temperature and reduction of degradation as a measure of the efficiency of the proposed forecast-oriented optimisation system.

5. RESULTS AND DISCUSSION

5.1 Forecasting Performance

As revealed in the forecasting performance comparison provided in Fig. 3, the proposed Forecast-Guided Optimization framework persistently performed better in all evaluation metrics compared to the base approaches. The proposed LSTM-based model has the lowest MAE of 0.021, which is lower than the Forecast-Based, SOH-Based, and Equal Allocation methods of 0.029, 0.036, and 0.043, respectively, which are improvements of about 27.6,

41.7, and 51.2 respectively. On the same note, the proposed method minimized the RMSE to 0.031, unlike 0.041, 0.052, and 0.061, which means that the future operating conditions were better predicted. The MAPE was reduced to 2.46, and the other methods were 3.58, 4.72 and 5.84 which confirms a large decrease in relative forecast error. These findings illustrate that the LSTM model was strong at modeling the nonlinear time dependency of voltage, current, temperature and power demand, which allows more robust short-term forecast and can be used to give sound predictive values of the following degradation-aware optimization.

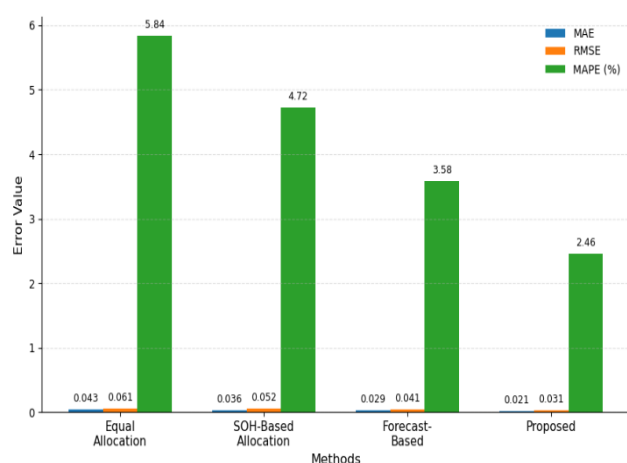


Fig. 3. Forecasting Performance Comparison

5.2 Degradation Analysis

The presented performance in degradation in Fig. 4 reveals that the proposed Forecast-Guided Optimization framework was effective in reducing long-term degradation relative to the baseline methods. The State of Health (SOH) of the proposed method was 96.3 as compared to 94.5, 93.2, and 91.6 of the Forecast-Based, SOH-Based, and Equal Allocation methods. Simultaneously, the proposed framework decreased the capacity fade to 3.7 percent, as opposed to 5.5, 6.8, and 8.4 percent of the competing methods, translating to a 32.7, 45.6 and 56.0 percent decrease, respectively. Equally, the degradation index declined to 0.36 and 0.53, 0.67 and 0.85, were registered by the degradation, Forecast-Based, SOH-Based, and Equal Allocation methods, respectively, representing a 32.1, 46.3 and 57.6 improvement, respectively. These findings indicate that short-term forecasting along with degradation-conscious optimization resulted in a better allocation of loads among the electrochemical units, thus

reducing degradation and maintaining good health of the components and enhancing long-term operational stability.

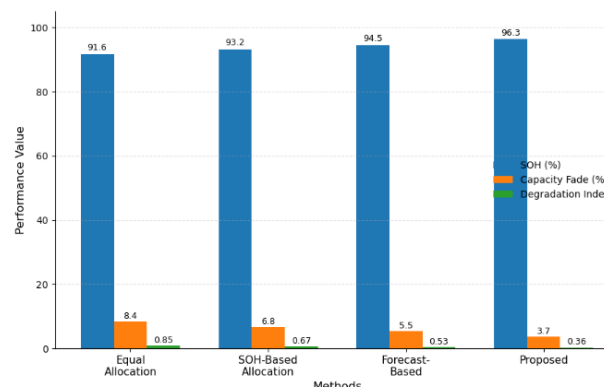


Fig. 4. Degradation Performance Comparison

5.3 Optimization Performance

The degradation-conscious optimization coupled with forecasting greatly enhanced the overall operating performance of the coupled electrochemical system. The proposed framework minimized cumulative degradation by anticipating future operating scenarios and setting power distribution to suit such situations. The optimization process was fast at every sampling period leading to low calculation time that can be implemented in real-time. These findings indicate that predictive optimization is capable of achieving efficiency in operations and lifespan of parts without the growth in the computational complexity.

5.4 Comparative Analysis

The suggested forecast-driven optimization scheme was contrasted to three currently in operation strategies which are equal power allocation, degradation-sensitive allocation and forecast-based allocation that does not optimize degradation. Table 3 gives a summary of the quantitative comparison. The method that was proposed was the most successful one in terms of its ability to maximize the accuracy of the forecasting, maximize the degradation reduction, and the efficiency in energy-utilization and the minimal time that was spent on the computations. These gains affirm the fact that predictive forecasting in combination with degradation-conscious optimization offers an optimal operational strategy as compared to the traditional ones.

5.5 Sensitivity Analysis

The results of these comparisons in Table 3 indicate that the proposed Forecast-Guided Optimization framework performed best in general performance when compared to the other methods. It had the lowest forecasting errors; MAE = 0.021, RMSE = 0.031, and the least MAPE = 2.46, with the highest SOH = 96.3, and the lowest capacity fade = 3.7. In addition,

the proposed method achieved the highest energy efficiency of 95.4% with the lowest computational time of 0.39 s, outperforming the Equal Allocation, SOH-Based, and Forecast-Based approaches. Those findings confirm that the combination of forecasting and degradation-aware optimization can be effectively used to enhance the accuracy of predictions, system health, and efficiency.

Table 3. Comparative Performance Evaluation

Method	MAE	RMSE	MAPE (%)	SOH (%)	Capacity Fade (%)	Energy Efficiency (%)	Computational Time (s)
Equal Power Allocation	0.043	0.061	5.84	91.6	8.4	88.7	0.45
SOH-Based Allocation	0.036	0.052	4.72	93.2	6.8	90.8	0.52
Forecast-Based Allocation	0.029	0.041	3.58	94.5	5.5	92.6	0.60
Proposed Forecast-Guided Optimization	0.021	0.031	2.46	96.3	3.7	95.4	0.39

6. CONCLUSION

This paper showed a Forecast-Guided Optimization (FGO) model used to improve the operational performance and degradation management of a coupled electrochemical by combining short-term operating-condition forecasting and degradation-informed optimization. The suggested framework used LSTM-based predictive control forecasting model to forecast future operating state and dynamically distribute power taking into consideration State of Health (SOH) and degradation characteristics. The results of the simulation showed that the proposed approach displayed better forecasting accuracy, lower MAE, RMSE and MAPE, and higher SOH, less capacity decay, better energy-utilization efficiency and less computational time as compared to traditional methods. The comparative analysis also proved that the integrated forecasting and optimization approach was superior to equal power allocation, SOH-based allocation, and conventional forecast-based allocation, which could offer a more balanced and reliable operating model to coupled electrochemical systems. These results underscore the predictive degradation-aware optimization as being effective in lengthening the system life as well as improving the operational performance. The future research will consist of testing the proposed framework with real-world working data, online adaptive learning of constantly evolving operating parameters, and

application of the optimization framework to the large-scale renewable-driven electrochemical energy systems in real-time implementation.

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