Determining Real-Time Electricity Price in a Wholesale Electricity Market Integrated with Energy Storage Systems

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Final Year Project Report

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May 2023

Abstract

A Lyapunov control theory based online optimization algorithm is suggested to determine the LMP for CAISO demand data, resulting in a consistent and minimal optimality gap in comparison with offline LP based modeling for LMP determination. The impact of initial energy levels is analyzed with no impact on the cost determination, although the system of charge dynamics of the integrated ESS varies with respect to the initial energy parameters input. A graphic user interface is suggested for the energy dynamic outputs of the ESS system, price outputs, generator outputs and demand, with the option for users to vary their granularity for running the optimization simulation. Overall, the online algorithm can be further improved by implementing variable maximum power parameters for renewable energy and improving the graphical user interface with online data integration of real-time data from ISO providers for LMPs.

Acknowledgement

Sincerest gratitude to my supervisor, Dr Yue Chen, for her patience, unwavering support and intellectual insights into this topic, and her practical and clear lectures on optimization theory and methods.

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1. Nomenclature

$p_b^c(t)$ = Charging power of energy storage.

$p_b^d(t)$ = Discharging power of energy storage.

$E(t)$ = Energy level/state of charge of the storage system at time t.

η = Charging and discharging efficiencies.

$\lambda(t)$ = Dual variable for determining locational marginal price.

$d(t)$ = Demand at time t.

$E_{\max}$ = Maximum energy storage capacity installed on the grid system.

P^{max} = Maximum power capacity of a given generator.

P^{min} = Minimum power capacity of a given generator.

P^u = Maximum power capacity for the energy storage system.

τ = Time value of 5 minutes (1/12th of an hour) for real-time market period.

λ_t = Maximum cost parameter of generators available.

2. Problem Description

2.1 Problem Statement

Many central authorities and utility providers consider decentralization of electricity markets financially and systemically risky due to the current potential for failure of this shift being high. However, as consumers and governing authorities push for more sustainable energy mixes, implementing energy storage systems (ESS) in microgrids for utilizing renewables by storing and dispatching energy when there's demand for it. Such a shift from centrally distributed electricity markets to decentralized markets requires research in restructuring of current algorithms for determining locational marginal prices (LMP) of energy at nodes in the utility grids. Considering the uncertainty of demand and renewable generation parameters, energy storage capacities also remain uncertain throughout the day, hence a method for processing the data required for energy allocation and pricing at microgrids is needed. Currently such uncertainties are handled by using model predictive control (MPC), but the limitations of it are that predictions have a high margin of error resulting in utilities having to secure and deploy ancillary resources in real-time when their predictions fall through. ESS serves as a crucial part of congestion management in decentralized power grids as they can act as microgrid islands at substations, thus integrating ESS parameters in electricity pricing is important for modeling algorithms in optimizing the cost of energy subject to additional security and system constraints. Determining a suitable human-machine interaction between system operators and such algorithms is also necessary for ease of implementation in many of these dynamical systems, hence graphic user interfaces are a useful component for synthesizing and representing the results of these algorithms.

2.2 Significance

Increased energy demands and integration of fluctuating renewable resources are being addressed by projects such as the United States' Autonomous Energy Grids (AEG), calling for more advanced methods for controlling and maintaining grid stability [1]. Electricity prices currently are determined by robust optimization of the energy dynamics of power systems, constrained by transmission security and system constraints. This method relies on data from day-ahead markets, adjusted by hour-ahead and 5-minute interval predictions throughout the day, and for decentralized electricity markets with increased uncertainties, the predictability gap would be too high, hence real-time price determination methods are required [5]. Before expanding current utility systems' transition to ESS integration for decentralized grids, appropriate methods for determining LMP are yet to be explored. Using the Lyapunov stabilization and optimization theory, it is possible to price and manage congestion with respect to system security and constraints whilst addressing uncertain parameters, which is explored in this paper.

2.3 Objectives

The objective of this research focuses on developing an online optimized model to output the price of electricity based on real-time demand, with integrated output of energy storage parameters in the balance market, and analyze the optimality of the results given by this model.

3. Background & Literature Review

3.1 Energy markets

Energy markets consist of day-ahead markets for utilities to secure their energy sources considering predicted demands and future generation scheduling, alongside a real-time market operating at 5 minute intervals for security constrained economic dispatch depending on the current status of the grid and energy consumption [3]. Utilities provide all infrastructure, from generation to transmission, in centralized markets, leveraging them more monopoly and control over the decided uniform clearing price as a consequence of bilateral contracts or pools in the day-ahead or real-time markets [4]. The advantage of this structure is a low potential for market failure, and convenience for regulatory authorities to monitor and enforce noncompliance and obligations of producers, which facilitates commitment and exchange of ancillary services during congestion and grid failure more manageable for independent system operators [4]. In a decentralized energy market, consumers who produce and return electricity grid (also called prosumers), can be expected, shifting the established regulated central market to a wholesale market with varying energy prices at nodes depending on various parameters in real-time [3]. Due to non-mandatory participation, this exposes decentralized markets to higher unreliability risks and potential for ancillary reserves in comparison to centralized markets; however, it also fosters higher competition for energy generation and pricing, beneficial for establishing a flexible market with increased generation capacity over the grid as prosumers are encouraged to participate in the market by generating electricity through renewable systems. Both systems of managing the utility grid and energy markets rely on robust optimization to determine the unit commitment and scheduling of energy generation subject to security and transmission constraints for the system considering either day-ahead scheduling, or resource acquisition [4].

Real-time markets are also referred to as intraday markets with transactions performed at 5 minute intervals, and usually follow a rolling horizon dynamic for a model predictive control (MPC) methodology, with fixed cost and generation output parameters, which works well for a centralized market where demand forecasts can be estimated accurately, but when integrated with ESS dynamics, can yield 40-50 MW errors for storage capacities less than 100 MWh, where the rate of forecast error delines as the capacity increases [14]. Therefore predictive methods are liberal estimates compared to real-time pricing estimates using transmission parameters when ESS are integrated in the grid system [5]. As demand is the main uncertainty factor for electricity pricing in a decentralized market, many robust and stochastic optimization techniques have been tested to manage the dynamical system in electricity markets, resulting in complex computational results not suitable for real-time application because of their time and resource limitations [5]. Therefore, before transitioning centralized grids to decentralized markets, it is required to determine an optimal pricing methodology for decentralized markets to reduce market failure potential and warrant increased generation competition by guaranteeing resource availability and ancillary management systems.

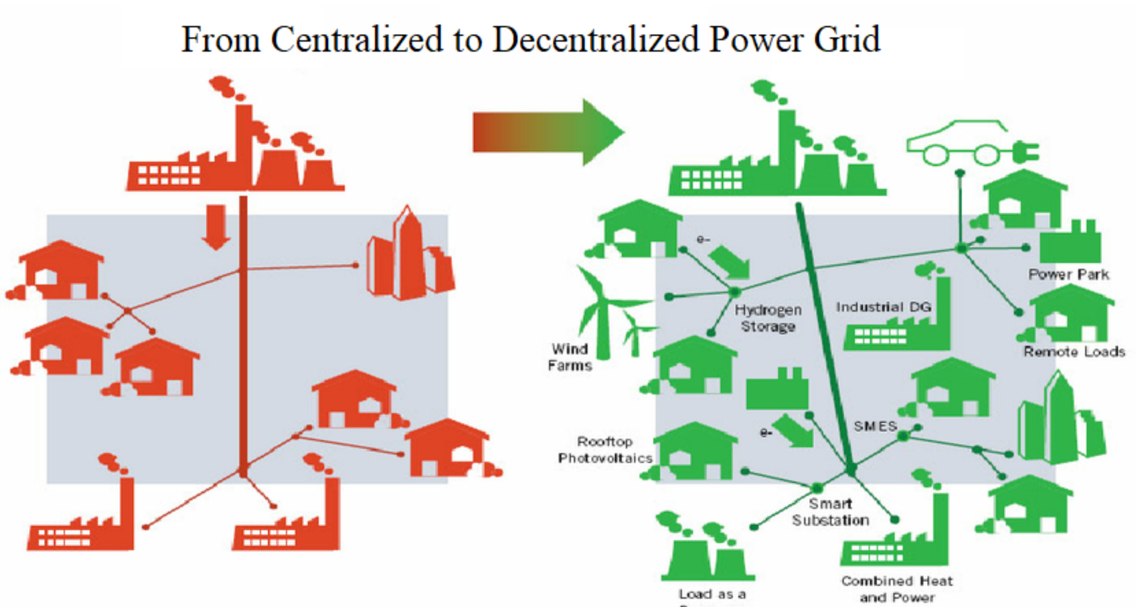

Fig 3 .1: Smart Grids involving distributed energy generation, information networks, system coordination and information networks [15].

3.2 Energy storage on grid

Central control and energy allocation are some of the leading challenges in decentralized energy markets due to increased prosumer participation, resulting in unreliable renewable generation and demand parameters [1]. ESS are a widely adopted solution to hedge these uncertainties on a nodal level, available in many forms such as pumped hydropower, supercapacitors, flywheels, batteries, superconducting magnets, and compressed air, which can have varying response times ranging from milliseconds to 12 minutes [2]. ESS coupled with bidirectional converters, changing their role from rectifiers to inverters during discharging and vice versa during charging, are an efficient and economic solution in microgrids for congestion management [2]. Battery Energy Storage Systems (BESS) have a response time of a few seconds with an efficiency ranging between 60-80%, and are already being implemented in California's Hecate Grid, one of the world's largest decentralized electricity markets, with a capacity of 1200 MWh [6]. Utilizing ESS dispatch on a utility grid requires optimization of the capacity sizing, which can be determined by objectives minimizing microgrid costs subject to emissions, load, scheduling, fuel consumption and availability of main-grid power constraints, ESS investment and maintenance, and grid operation costs as variables in the constraints of the problem [9]. A significant portion of these factors are financial in nature for ESS installation, indicating its economic significance for nodal price management, in which ESS operation and scheduling is robustly optimized similar to other power generation and electricity supply resources in the main grid [8]. A real-time output of electricity prices is beneficial for ESS operators to determine their system's installation capacity and performance in comparison to the main grid, allowing for more optimal scheduling in the future without relying on the MPC approach with uncertain main grid parameters like demand.

3.3 Locational Marginal Price (LMP) Optimization

General principles of economics determining prices of resources using a supply-demand curve equilibrium are not applicable to the unpredictable energy markets due to fluctuating demands, thus prices have to be determined in relation to market clearing conditions such as supply-demand balance for each of the nodes with respect to transmission and congestion constraints. Interior point algorithms for AC OPF dispatch have been considered yielding complex computational models, hence the more popular approach for LMP estimation by system operators is dependent on the linear programming approximation of DC OPF's dual result, constrained by security and economic dispatch given the simplicity and efficiency of the models [4]. LMP is given from the duality of the Lagrangian multiplier of the non-convex KKT market balance conditions (eq.2), with the objective of minimizing cost of power subject to power generation capacity limits (eq.1), physical losses and generation shift factors, which have to be computed with LP at each of the grid's nodes, with dimensions of numbers of transmission constraints and number of generators [7]. LMP is composed of congestion, energy and marginal loss components, and in ideal systems with no physical losses considered, the general output of the dual variable is considered as the LMP; however, many operators incorporate marginal losses into their pricing due to slack bus parameters and the chance of LMP exceeding the highest cost parameters of generators [7]. Due to the mandatory participation and regulation enforced on system operators, marginal losses cannot be rebuked on consumers of centralized electricity markets, leading to formation of a loss revenue fund for hedging losses in LMP for central utilities [10]. As decentralized markets don't have similar mandatory participation structures, hedging losses requires arbitrage policies and energy sharing mechanisms via algorithms between prosumers of a system to optimize the total social welfare with game theory applications, where either intermediary agents (such as the grid provider) can manage these opportunities (this might reduce the total social welfare), or integrated with contract sharing on the grid for energy blockchain methods [11,12].

3.4 Real-time Optimization of Dynamic Energy Systems

Dynamic energy systems in networks are popularly optimized using control theory methods, and one popular mechanism is the Lyapunov control and optimization theory. Dynamical energy systems require stochastic optimization approaches, amongst which the Lyapunov control theory reformulates the original objective by considering queueing and future scheduling energy dynamics to reduce energy consumption and cost parameters, and has been successfully modeled in various network strategies for smart grid distribution [23]. This optimization method, due to its stochastic nature, provides variable outputs due to non-deterministic evaluation algorithms focusing on generating a drift-plus-penalty problem in which the system is optimized to balance the queue and drift bound, where the queues are formulated to be mean rate stable [24].

4. Proposed Solution Methods

4.1 Offline model

The LMP is obtained from the dual of market clearing conditions (eq.2), where the sum of the powers (generated, charged and discharged at a node) is equivalent to the demand. The objective function represents the minimization of cost of power generation (eq.1), where respective cost parameters and power generation for each generator are multiplied and summed for each period.

$$\min_{p(t),\, \forall t} \sum_{t} c(t)p(t) \qquad \text{(eq.1)}$$

Subject to the following constraints:

$$p(t) - p_b^c(t) + p_b^d(t) = d(t) \ : \ \lambda(t),\ \forall t \qquad \text{(eq.2)}$$

$$P^{min} \leq p(t) \leq P^{max},\ \forall t \qquad \text{(eq.3)}$$

$$E(t+1) = E(t) + p_b^c(t)\eta - p_b^d(t)/\eta,\ \forall t \qquad \text{(eq.4)}$$

$$0 \leq E(t) \leq E_{\max},\ \forall t \qquad \text{(eq.5)}$$

$$0 \leq p_b^c(t), p_b^d(t) \leq P^u, \quad \forall t \qquad \text{(eq.6)}$$

Eq.3 represents the power constraint of generators between their maximum and minimum generation potential, whilst eq.4 represents the energy dynamic of ESS constrained by the power charging and discharging requirements in eq.6, considering the maximum power capacity of the ESS. The total capacity of ESS is constrained by eq.5. This model assumes perfect economic competition in respect to energy allocation and pricing. It also assumes that the ESS doesn't charge from the main grid as it's meant to supply energy instead of acting as an additional load on the modeled grid system. For feasibility, this further implies that the system must have enough supply from generators to meet the demand, and the ESS is there to offset the LMP in order to prevent deployment of high cost parameter generators. Physical losses resulting in marginal loss cost for LMP are not considered in the dual variable result, as physical losses and implementation of slackbus are not constrained in this problem as it would increase the complexity of the problem formulation. Ramp rate dynamics are also not factored in the problem formulation, hence energy transmission from the source to the grid is considered instantaneous in this model.

4.2 Online model

The offline model is converted to an online model using the Lyapunov control theory. To cope with the uncertainty of the demand, a stochastic optimization approach is taken, hence the expected values of the cost of energy generation are implemented to model the objective, whilst introducing the time period value with the parameter of τ, variable depending on the granularity at intervals of 5, 15, 30 and 60 minutes. To convert from offline to online, a time-average model of the node's energy dynamic is modeled (eq.8), changing the cost minimization of the offline LP (eq.7) to a stochastic minimization of long-term time-average cost of power generation, eq.9 [5].

$$max \sum_{t=0}^{T-1} \lambda_t(\tau(c(t)p(t)))$$

(eq.7, s.t eq.2-eq.6)

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\tau(c(t)p(t))] = 0$$

(eq.8)

$$min \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\lambda_t \cdot \tau(c(t)p(t))]$$

(eq.9, s.t.eq.2,3,6,8)

λ_t represents the cost of electricity at a certain node for period t, with T representing the total number of generator parameters. Eq.8 limits the problem given that as the time of a period progresses (i.e.

assuming a long-term horizon approach), the expected value of the sum of the power generation and cost of generation approaches zero as close as possible, hence allowing minimization of power generation depending on their cost parameters at the node. Eq. 9 becomes the objective of this model, subject to eq.8. As eq.8 is the minimal cost of electricity generation for the period, eq.4 and eq.5 are not required for the objective's constraints since eq.8 represents the energy dynamics in eq.5 and energy level in real-time in eq.4 instead of the deterministic approach required in the original offline LMP model. The time-average constraint of eq.9 over the long-term brings the system towards mean rate stability from the Lyapunov control optimal theory, requiring an online energy dynamic algorithm for a dynamic convex optimization problem to determine the LMP at the node [5,16]. The virtual queue dynamics are defined with Q_t as the backlog of the queue (eq.10), where η is defined by eq.11 (as the lower level of the energy dynamic of our ESS is defined as 0, we can remove the term E^{low}):

$$Q_t = E_t - \eta,\ \forall t \qquad \text{(eq.10)}$$

$$\eta = E^{low} + \tau P^{u} + V\lambda_{\max} = \tau P^{u} + V\lambda_{\max} \qquad \text{(eq.11)}$$

$\lambda_{\max}$ is the maximum electricity price, determined from the highest cost parameter of all the available power generators, with V representing the weight coefficient [5]. The Lyapunov function is a non-negative scalar for representing the multiple dynamical states of the energy system, and by formulating the Lyapunov drift-plus-penalty algorithm, joint network stability can be maintained by choosing the optimal state by minimizing the penalty [18]. It is not necessary to formulate all the drift-plus penalty formulations of all the nodes for every independent period as it would render eq.9 unsolvable, hence we assume the upper-bound of the drift-plus penalty with $\lambda_{\max}$ value in eq.11 [5, 18]. The weight coefficient, V, varies stochastically between $[0, V_{\max}]$, hence the value of $V_{\max}$ is estimated in eq.12 to respect the energy dynamics and power generation constraints in eq.5 [5]:

$$V_{\max} = \frac{E_{\max} - 2\tau P^{u}}{\lambda_{\max}} \qquad \text{(eq.12)}$$

The queue is updated every time interval by eq.13 to calculate the backlog to substitute the energy dynamic in eq.5 whilst stochastically satisfying the expected value for backlog in eq.14 [5].

$$Q_{t+1} = Q_t - \tau\left(p_b^{c}(t)\eta - p_b^{d}(t)/\eta\right) \qquad \text{(eq.13)}$$

$$\mathbb{E}[Q_t] = Q_0 + \sum_{t=0}^{T-1} \mathbb{E}\left[\tau\left\{p_b^{c}(t)\eta - p_b^{d}(t)/\eta\right\}\right] \qquad \text{(eq.14)}$$

The function of eq.14 is similar to eq.8, thus eq.15 is formulated by considering similar limits to that of eq.14, proving that the virtual queuing system is also mean rate stable as its limit approaches the minimal possible value of 0 [5,18]. This an additional constraint for the objective of eq.9 to maximize grid stability whilst optimizing the real-time LMP and energy cost considering the ESS dynamic.

$$\lim_{T\to\infty} \frac{1}{T}\mathbb{E}\Big[Q_t\Big] = 0 \qquad \text{(eq.15)}$$

The final objective function for the online algorithm is similar to eq.9, subject to constraints in eq.2,3,6,8,10,14. The Lyapunov function of the problem provides system operators with the decision to offload the utility system or offload the system backlog, giving a trading off proposition for every time period τ [5, 19]. The Lyapunov function formulation is given by eq.16, which converts to the drift-plus-penalty based on time variations, represented by eq.17 [5,18].

$$L_t=(1/2)(Q_t)^2 \qquad \text{(eq.16)}$$

$$\Delta t=L_{t+1}-L_t=(1/2)[(Q_{t+1})^2 - (Q_t)^2] \qquad \text{(eq .17)}$$

$$\text{Revenue} = V\lambda_t\tau(c(t)p(t)) \qquad \text{(eq.18)}$$

Minimizing the gap between the trade-offs is the optimal solution for each period, given by the difference between the period and time adapted cost function of the node and the Lyapunov drift given in eq.18 (i.e. Δt-Revenue). The cost function is calculated by the weight coefficient for the trade-off potential between the drift and cost, with more weight given to the cost parameter reduction depending on eq.12. The queue parameters in eq.13 are substituted in eq.17 resulting in eq.19 to determine the upper bound of the Lyapunov drift-plus-penalty problem, given as follows [5].

$$\Delta t(\text{up\_bound}) =(1/2)[(\tau(p_b^c(t)\eta - p_b^d(t)/\eta))^2 + \tau Q_t(p_b^c(t)\eta - p_b^d(t)/\eta)]$$

$$\leq (\tau P^u)^2/2 + \tau Q_t(p_b^c(t)\eta - p_b^d(t)/\eta) \qquad \text{(eq.19)}$$

Thus the online optimization problem becomes to minimize the upper bound of the queue-stability and upper bound of the energy cost trade-off, subject to the original constraints in eq.2,3,6:

$$\min \tau Q_t(p_b^c(t)\eta - p_b^d(t)/\eta)+V\lambda_t\tau(c(t)p(t)) \quad \text{(eq.20, eq.2,3,6)}$$

This method doesn’t allow retrieval of LMP as a simple dual due to the objective’s quadratic non-convexity resulting from the two different time dependent functions for cost of energy and queue, thus λ_t determines the LMP for period t given by the highest cost parameter of the active generators operating at period t, giving the marginal electricity cost for the node. The full program and algorithm is programmed in Appendix A, represented by the following steps:

Lyapunov Online Algorithm

I. Set the period and steps for data depending on granularity
II. Declare the initial energy level (E_0, Q_0, Vmax)

III. For each period, retrieve Q_t, E_t, and demand at period t.

IV. Solve the optimization problem of eq.20.

V. Retrieve the maximum cost parameter of the active generators to determine the LMP for the time period.

VI. Update Q_{t+1}, E_{t+1} given by eq.13. (eq.4 for E(t+1) converts to eq.13 as well when time factor is considered).

VII. Repeat solving the optimization problem for the next period (i.e. update t=t+1), going back to step III.

5. Results & Discussion

5.1 Online Model Results

The data for this simulation is taken from CAISO's demand generation and cost parameters available in Appendix B for the date of 17th February, 2023 [25]. The following data is output from the system with the granularity of 5 minutes:

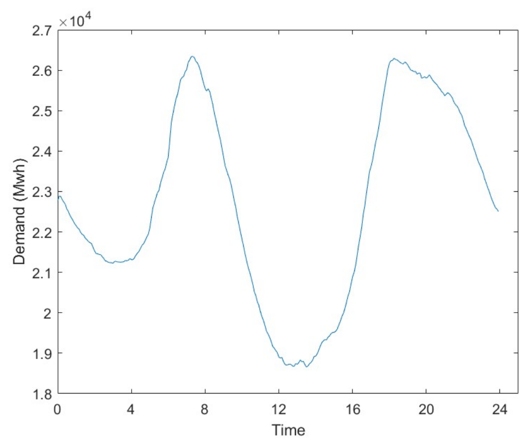

Figure 5.1.1 - Demand variation over time.

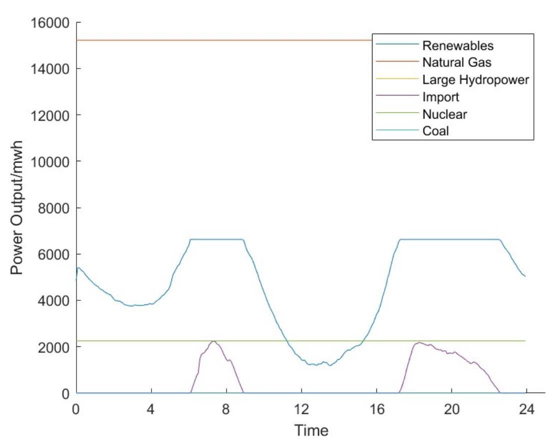

Figure 5.1.2 - Generator power output of optimization algorithm.

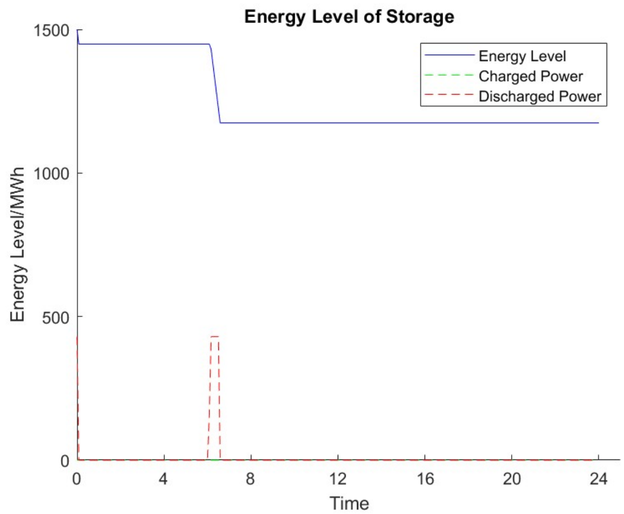

Figure 5.1.3 - ESS level output from optimization algorithm for charging and discharging, given initial energy level of 1500 MWh.

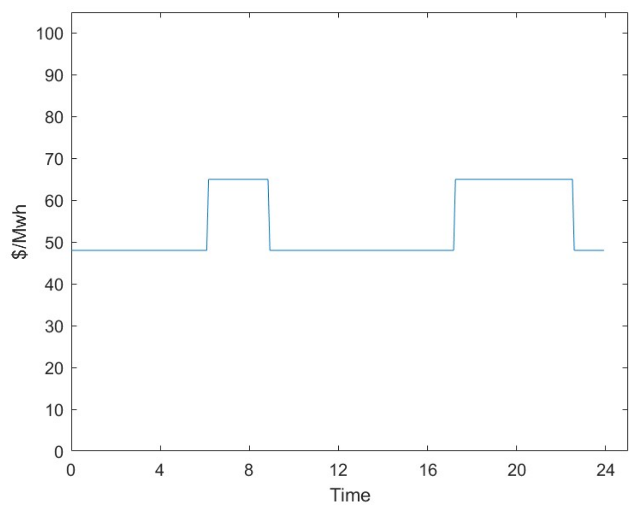

Figure 5.1.4 - LMP output for each period, taken from the output of maximum cost parameter of active generators indicated in Figure 5.1.2.

The formulation is indicated to be functional as the optimization doesn't deploy the maximum cost parameter of the generators (large hydropower), and only deploys the maximum LMP cost parameter from imported energy during peak demand hours (between hour 6-9 and 18-22). This correlation between LMP and demand is consistent with the performance of general robust optimization of dynamical power systems in grid networks, represented by the offline linear program model (next section).

5.2 Offline Model Results

The offline model optimizes the output power and electricity cost, and the consequent deployment of the ESS to reduce electricity cost per unit, by considering the demand over the entire day. For the same demand data set and and initial storage as the online model, the following are the results output by the offline model:

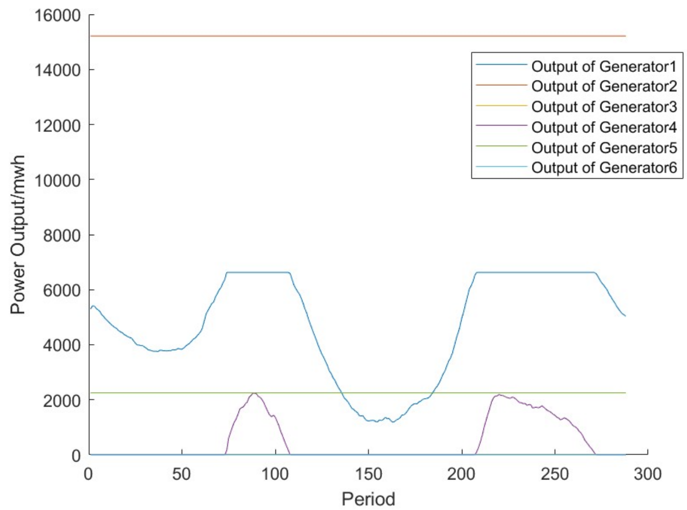

Figure 5.2.1 - Output of different generators under offline model optimization (with generator 1,2,3,4,5 and 6 representing renewables, natural gas, large hydropower, import, nuclear and coal respectively).

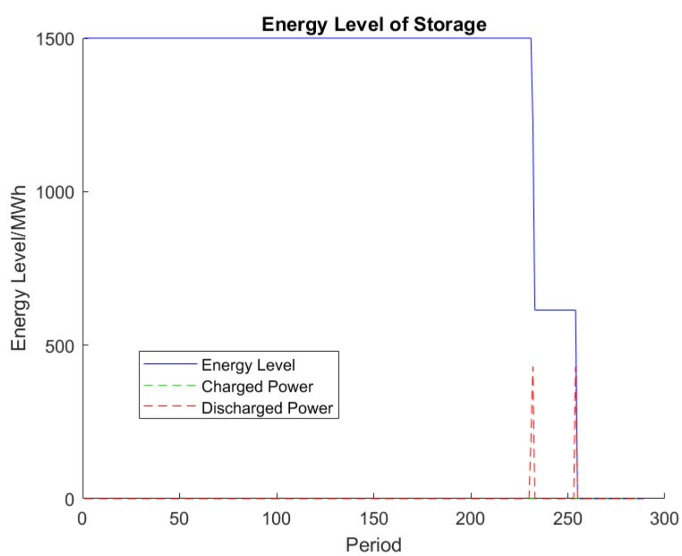

Figure 5.2.2 - ESS level for offline optimization algorithm with same initial energy level as online model.

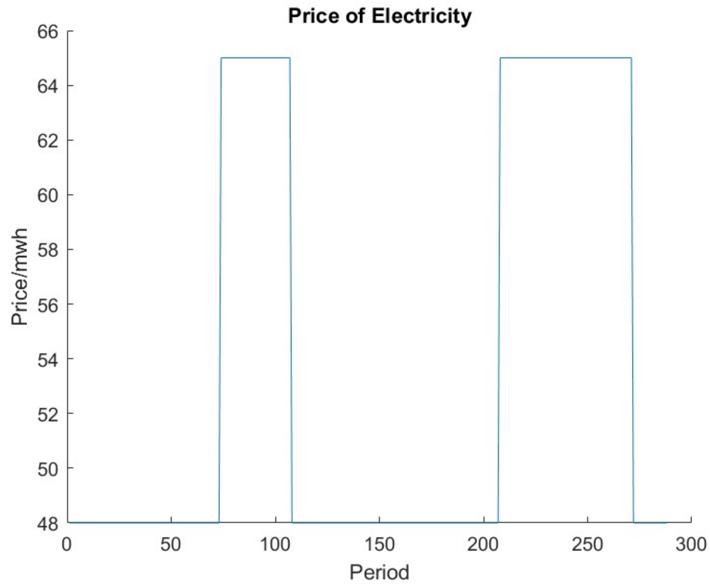

Figure 5.2.3 - Offline model price output by considering dual constraint of eq.2.

As seen from the above figures, the price and generator output of the offline model is very similar to the online model's results, despite a more delayed response in discharging the ESS. However, the total cost estimate output by the online model and offline models are approximately 3.565×10^8 USD and 3.560×10^8 USD respectively for this data sample, representing that the cost estimate of the offline model is generally lower due to forecasting of future demands being available.

5.3 Impact of Weight Parameter

The weight parameter places prioritization on the cost-revenue function of power generation in relation to the penalty of the queue backlog. By varying the maximum weight, Vmax, through the variable β as follows: V=βVmax, where β changes from 0.5-1.2 at intervals of 0.1, the following result can be obtained for the total cost of energy output with relation to beta (with a granularity of 5 minutes):

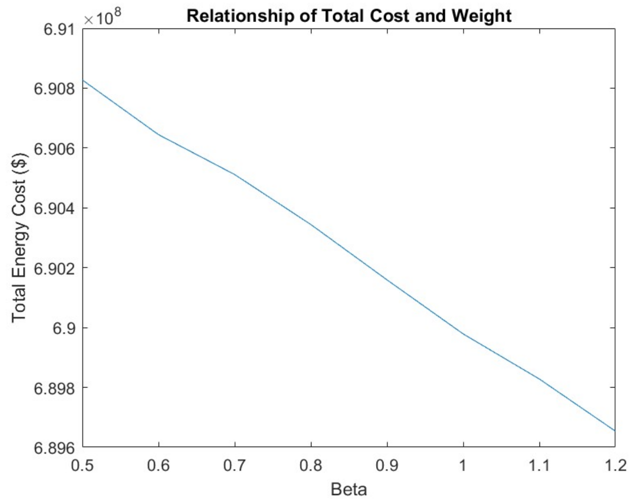

Figure 5.3.1 - Total cost relationship with weight parameter variation.

As seen from the aforementioned figure, as the value of the maximum weight parameter is increased, the total cost is reduced. However, when the value of β exceeds 1, the maximum energy level will be exceeded for the ESS system, thus it is not feasible to implement a weight parameter greater than Vmax, which would happen if the operator would try to reduce the total cost parameter even more after it's already been reduced by the system. Overall, the difference between the maximum and minimum cost in Figure 5.3.1 is only 0.17%, thus the weight parameter doesn't seem to significantly impact the cost revenue function in the Lyapunov dynamic of the system.

5.4 Impact of Granularity

The computing time is significantly reduced as granularity is increased as the number of periods to be solved is reduced, although the cost is seen to increase as granularity increases. As the granularity is used to calculate the Vmax for the objective function in eq.12, it can be seen that with increase of granularity in Table 5.4.1, the Vmax decreases, which is expected as the granularity is the difference between the maximum storage parameter, double the granularity of the maximum power capacity of the storage, taken as a ratio of the maximum cost parameter of all possible generators. Thus as granularity increases, there is less emphasis placed on the cost output function, seen by the declining values of total cost output as the granularity increases. Thus to receive better results, higher resolution for the data (thus lower time granularity) is recommended, although this would require more computing time as more periods are generated for the same 24 hour interval for the data provided. Thus the optimal performance for this optimization algorithm is expected with higher granularity, and lower granularity is useful for users not seeking high resolution outputs or constrained by computing resources for their data time frame.

Time (minutes / granularity)	*Vmax*	*Total Cost Output (USD)*
5 (1/12)	19.7937	356513718
15 (1/4)	18.4286	356009510
30 (1/2)	16.381	355194528
60 (1)	12.2857	350113368

Table 5.4.1 - Effect of granularity on weight and total cost output for energy parameters.

5.5 Impact of Initial Storage Level

The input for the initial storage data affects the optimization algorithm's prioritization for discharging it to balance LMP when demand is high, or charging it when demand is low. The output result for the system of charge dynamics for the ESS level for varying levels of initial energy levels ranging from 0 to the maximum storage capacity is displayed through Figures 5.5.1-5.5.6, all with maximum storage capacity of 2150 MWh:

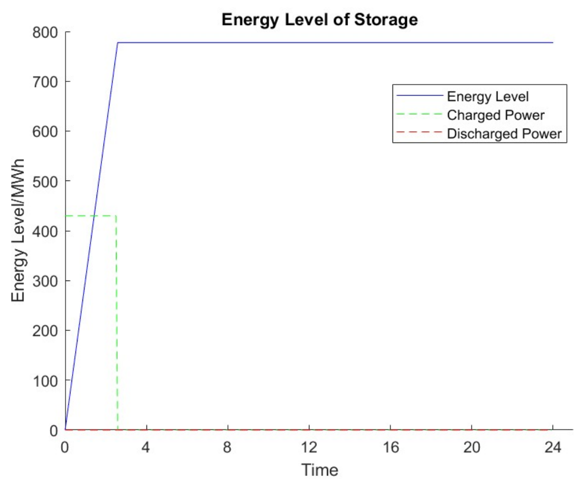

Figure 5.5.1 ESS Dynamic for initial energy level of 0 MWh.

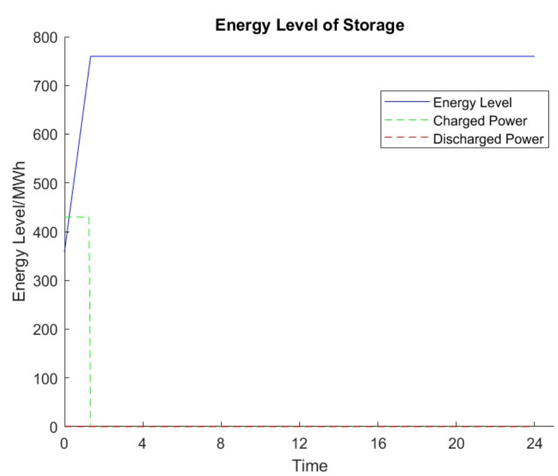

Figure 5.5.2 ESS Dynamic for initial energy level of 358 MWh.

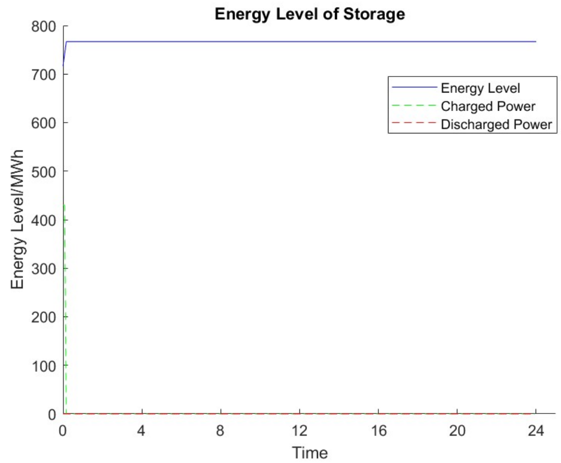

Figure 5.5.3 ESS Dynamic for initial energy level of 716 MWh.

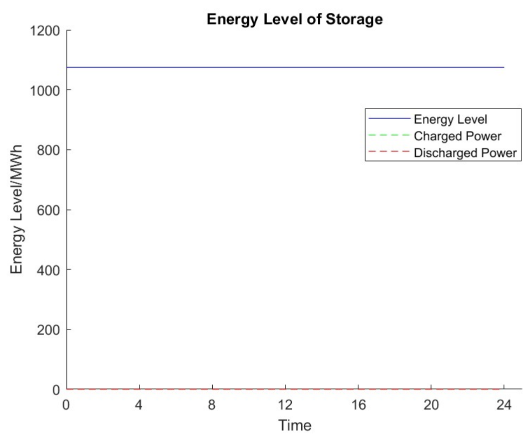

Figure 5.5.4 ESS Dynamic for initial energy level of 1075 MWh.

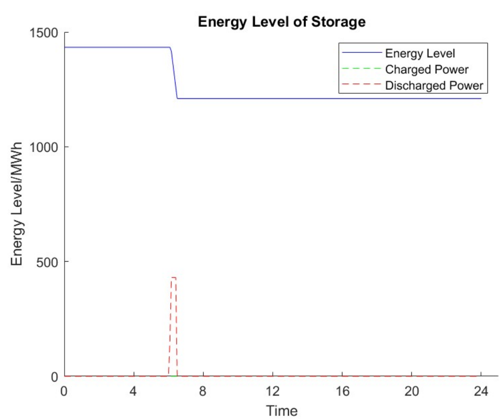

Figure 5.5.5 ESS Dynamic for initial energy level of 1433 MWh.

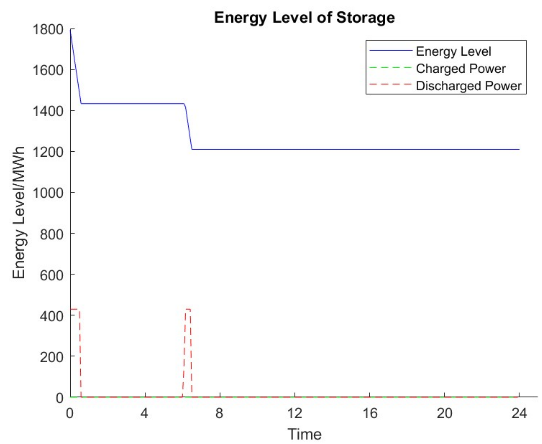

Figure 5.5.6 ESS Dynamic for initial energy level of 1792 MWh.

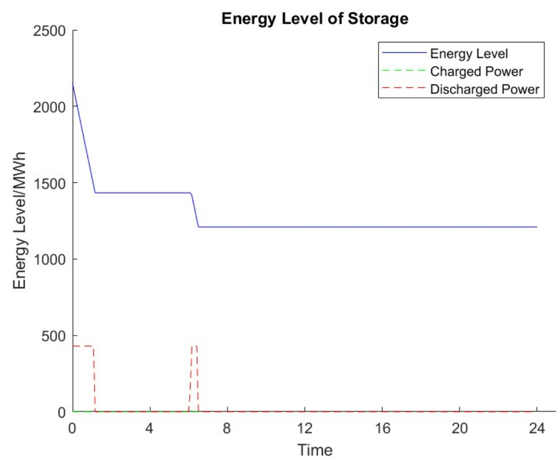

Figure 5.5.7 ESS Dynamic for initial energy level of 2150 MWh.

As seen from these figures, it seems that if the initial energy level is below or equal to 1075 MWh, the ESS state of charge charges or doesn't change (i.e. doesn't discharge), whilst if it's greater than 1075 MWh, the system has a tendency to level off at 1210 MWh after discharging. 1075 MWh is equivalent to the expression of Emax/2, and shows that the optimality function has a tendency to bring the system towards stability by not exceeding the Emax/2. This can possibly be explained by the queue conditions in which the gap between each period's energy level and queue is given by eq.10, hence the system tries to ensure the queue is minimal by bringing the energy dynamic to at least half its value. However, the initial energy level doesn't have any effect on the optimal price, which is consistent with the data provided in Figure 5.1.4. Hence the cost function is not affected much by the ESS dynamics, although it ensures to maintain the minimum cost parameter for active generators in use by discharging into the grid to maintain a consistent LMP regardless of its initial stage.

5.6 Combined Impact of Granularity and Initial Storage Level

As the granularity changes as well, the relation of initial storage seems to vary as well due to the gap between demands between periods increasing when granularity is decreased. Figures 5.5.1-5.5.7 display the results of various initial energy inputs with a granularity of 5 minutes, whilst with the granularity of 60 minutes, the total energy system level varies according to Figure 5.6.1, whilst the power charged and discharged is displayed in Figure 5.6.2 and Figure 5.6.3 respectively. Based on Figure 5.6.1, the energy level is not able to congregate at a stable point for different initial energies like it does towards 1075 MWh for a granularity of 5 minutes, thus the charged and discharged power dynamic is also more variable as the time granularity is increased.

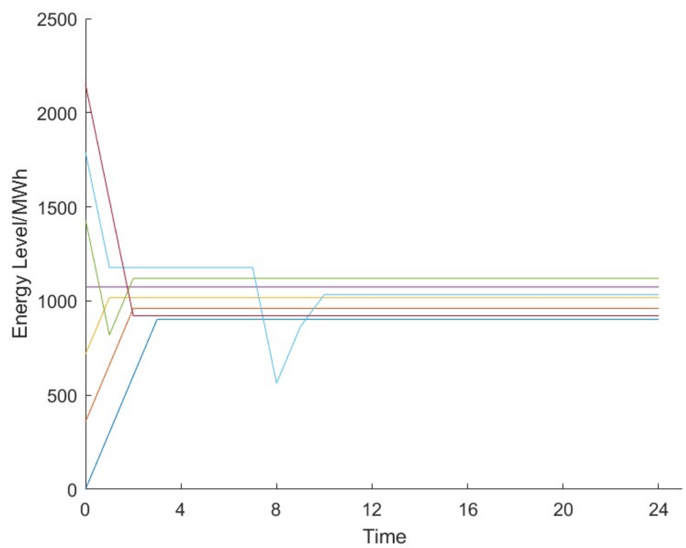

Figure 5.6.1 - Initial energy level (given by y-intercept) and performance of ESS over 60 minute granularity.

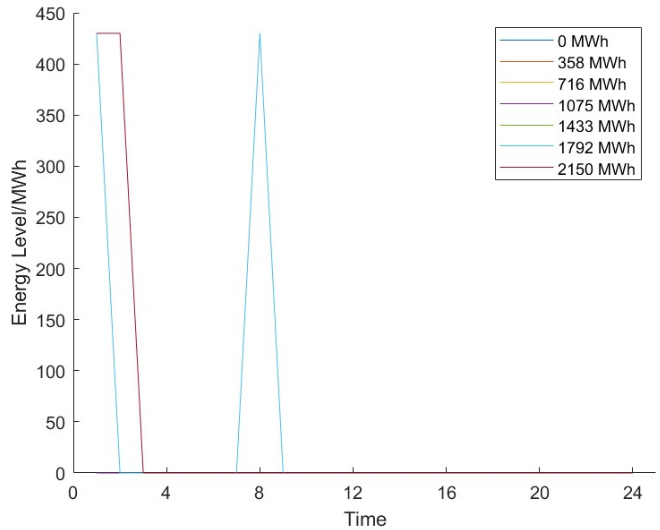

Figure 5.6.2 - Discharged power for varying initial energy levels.

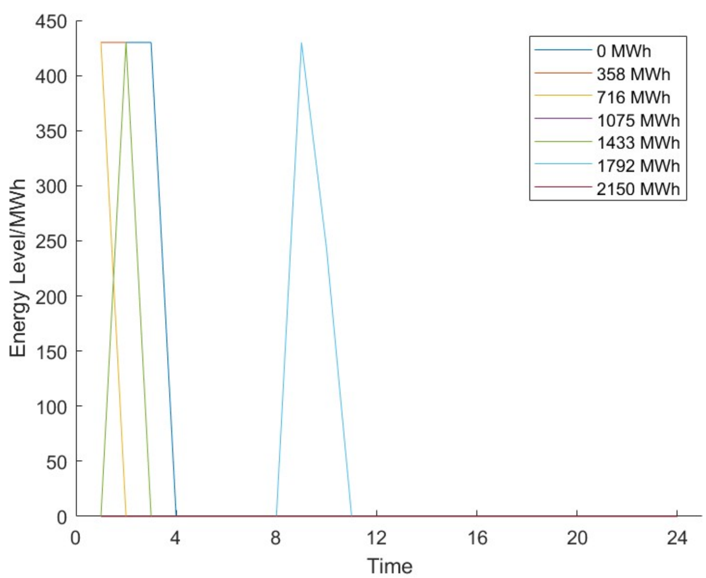

Figure 5.6.3 - Charged power for varying initial energy levels.

5.7 Comparison with Offline Model

As seen from Table 5.7.1, the consistency of the optimality gap remains to be the same, at around ~0.1%, with very few variances as the period increases, as shown in Figure 5.7.1. This could possibly be due to the similarity of the input data sets for each period, where the similarities between the demand inputs can explain the similar optimality gap, and differences between peak demands and trends for the data sets used. This optimality gap also shows that the Lyapunov function succeeds in reducing the energy cost, a consistent factor against the offline LP model, which is optimal for system operators over utility grids as the trendline of the optimality gap is decreasing as the total number of periods increases.

Time Horizon		*Total Cost (10^9 USD)*		*Optimality Gap (%)*
Hours	*Periods*	*Lyapunov Online*	*Offline LP*	
24	288	0.437350159	0.4333	0.926067801
48	576	0.874700318	0.8667	0.914635314
72	864	1.251715382	1.240409853	0.903202827
96	1152	1.583851228	1.569455302	0.9089190705
120	1440	1.892129051	1.874714812	0.9203515575
144	1728	2.163433491	2.143769631	0.9089190705
168	2016	2.452367344	2.429796943	0.9203515575

Table 5.7.1 - Optimality gap between online and offline algorithm.

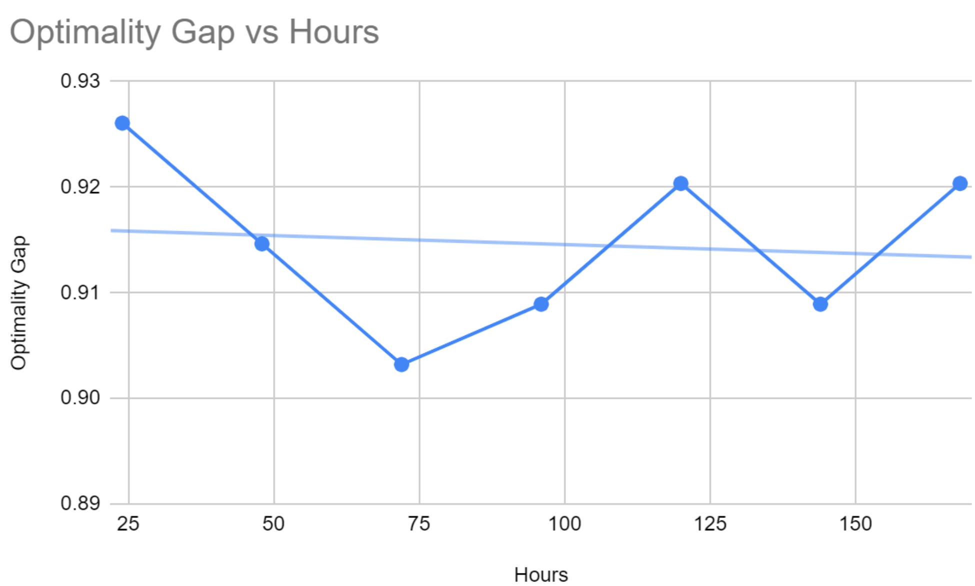

Figure 5.7.1 - Plotting of optimality gap with respect to periods, with a visibly decreasing trend line.

5.8 Comparison with CAISO LMP Data

The data for 2213 CAISO LMP nodes was averaged for each period of 1 hour over 24 hours, and the result of the average LMP is given in Figure 5.8.1 in comparison to the online algorithm with a granularity of 60 minutes (for 24 hour resolution). The output suggests the online algorithm developed follows the trends of price inflation during high demand and vice versa, although the smoothness of the curve is not as variable, perhaps due to the limited amounts of generator parameters input in the algorithm. As the generator parameters for the 2213 nodes is a lot more detailed than the 6 generation parameters input for our test data, it can be assumed that further addition of parameters for each node, in addition to calculating the LMP output for various nodes, can yield better estimates for LMP in comparison to the current real world data. The CAISO LMP additionally considers parameters of congestion, marginal loss, energy cost, and carbon emissions, and our input data for cost parameters correlates with estimates shown in Appendix B, thus the difference in the input of cost parameters can be an additional reason for the discrepancy between the model and actual energy costs. As marginal loss was also not considered in the online algorithm, it can be explained the consistent increase of the actual LMP values in comparison to the minimal cost parameters of the online algorithm.

Additionally, the CAISO power data also relies on variable cost parameters as the maximum power available from renewable generation varies throughout the day according to Figure 5.8.2. Therefore in the objective constraint for eq.3, the maximum power for renewable generators is also variable throughout the day, hence a deterministic approach as used by this online algorithm is vastly different from the real-life behavior of the power system dynamic in this ISO. Utilizing this variable constraint of maximum power for renewable generation for determining LMP is a possible method of improving the online optimization algorithm to get more consistent data with that of the real CAISO average LMPs.

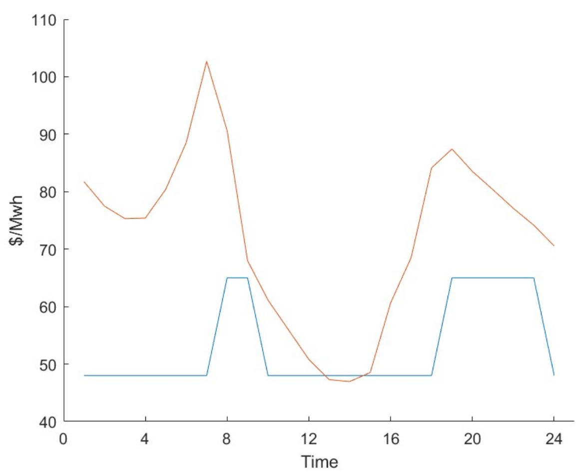

Figure 5.8.1 - Average CAISO LMP (orange) for 17th February, in comparison with the LMP output of the online algorithm for a period of 24 hours.

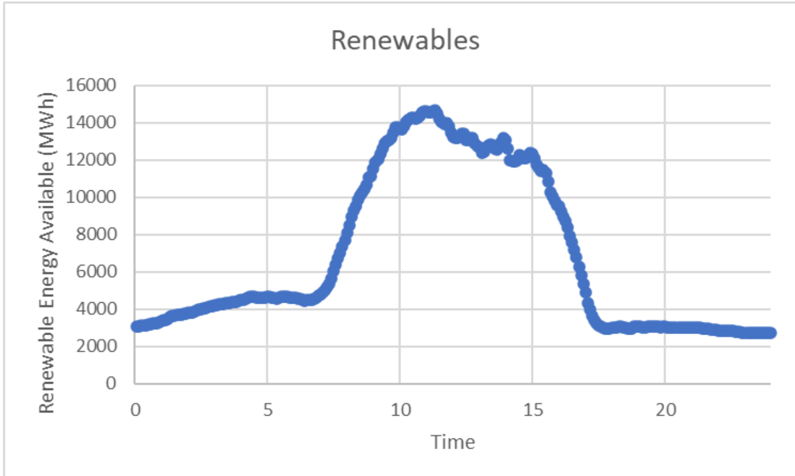

Figure 5.8.2 - Renewable energy supply availability for the day of 17th February in CAISO.

5.9 Suggested Graphic User Interface

As suggested, the impact of a GUI facilitates ease of deployment of complex algorithms for online dispatch, hence this is a proposed app system for running the simulation for the data available for a specific node, with input requirements of demand, maximum and minimum generation parameters, cost parameters of each generator, initial energy storage, maximum energy storage capacity and energy power capacity required as inputs from the user:

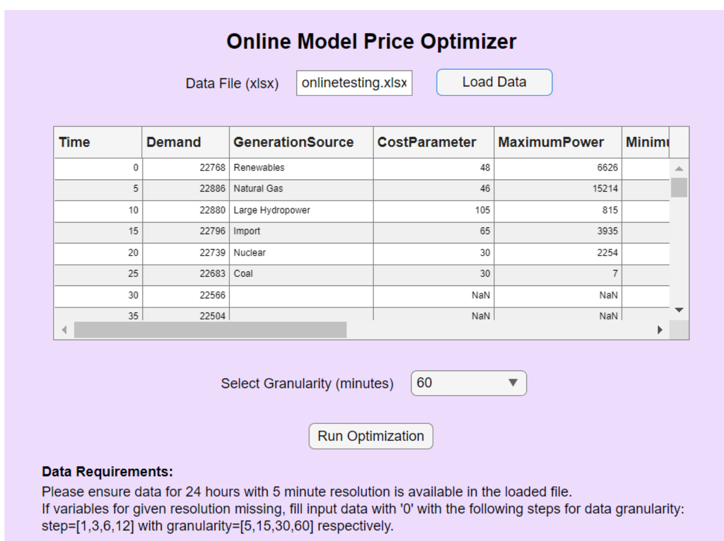

Image 5.9.1 - Sample GUI input window for user to load data, select granularity, and run optimization algorithm.

The user can choose the granularity to optimize their data with, and the following is output once the optimization is run:

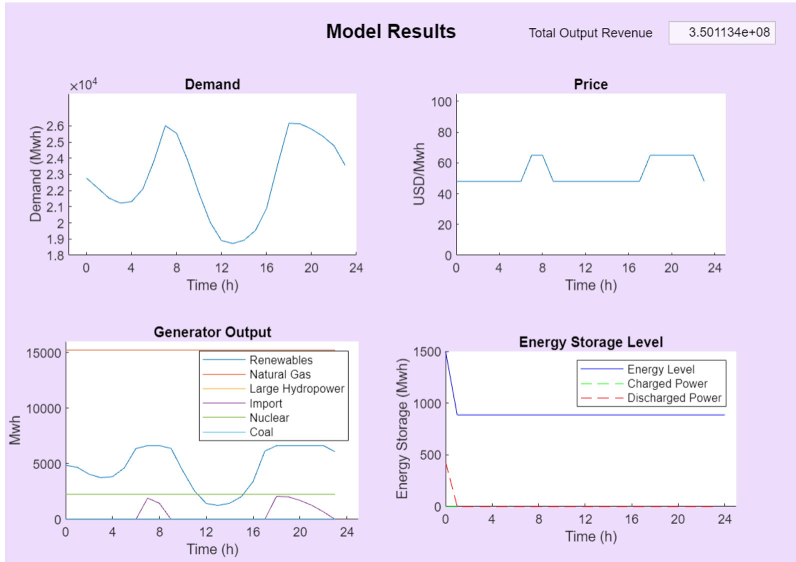

Image 5.9.2 - Sample output of the GUI displaying results of the online optimization.

This output window is useful for allowing users to display their simulation results for online optimization over large periods of time. To implement this design further, it may be integrated with online databases from ISOs to obtain the demand and generation parameters in real-time, after which it can be plotted with a real-time moving display for the data points and be optimized and deployed in real-time as well. However, as no such back-end or online database provisions are accessible to us for now, we can consider this as a further area of exploration, as the real-time output of the functions will be more valuable for system operators to monitor the energy dynamics of the grid.

6. Conclusion

The proposed online optimization algorithm determines the LMP price based on the input of demand uncertainties, although integrating the renewable generation uncertainties can further optimize it to fit real-life models. This system also has a reliable optimality gap in comparison with the offline LP model, and reduces the costs by approximately ~0.1%, which is not a significant difference although it can be pronounced when considering the magnitude of revenue potential lost from the gap. Implementing the renewable variation of maximum renewable energy available throughout the day can further improve the online algorithm to meet the standards of the present LMP determining systems used by CAISO. Integrating operational and real-time data transfer between the grid and the GUI can further increase the implementability of the model for system operators considering ESS dispatch to reduce LMP during peak demand timeframes.

Although currently the infrastructure of centralized grid systems may not permit real-time ESS dispatch and price optimization in all locations, with greater implementation of renewable energy storage on grids in the future, the uncertainty of demand-supply relationships will become more prominent. In such cases, such stochastic robust algorithms can be a potential alternative to the deterministic model-predictive control algorithms currently used by utility providers. Additionally, the cost of ESS energy itself is not modeled in this algorithm, which would require factors such as ramping rates of different ESS types, energy degradation over time due to frequent switching, and ESS cost of installation and operations [26]. As such, integrating modeling of variable renewable generation and the ESS dynamics in greater detail can increase the effectiveness and implementability of this algorithm for real-life utility grids and ESS dispatch.

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Appendix A - Online Optimization Algorithm

All code and data can be found on the following github repository link:
[*https://github.com/eshaneeb/FYP_Code.git*](https://github.com/eshaneeb/FYP_Code.git)

```
%inputs=[demand,cost_para,max_pow,min_pow,max_stor,max_pow_cap,num_gen,eff,tau
,period]
%outputs=[total_rev,pow,pow_char,pow_discharge,ener_lev,pi]
function
[total_rev,pow,pow_char,pow_discharge,ener_lev,pi,v,granularity]=periodonlineo
ptimize(time_input,demand,cost_para,max_pow,min_pow,max_stor,max_pow_cap,eff,i
nitial_ener,v)
num_gen=numel(cost_para);
if time_input==double(5)
   granularity=double(1/12);
   period=1440./5;
   step=1;
elseif time_input==double(15)
   granularity=double(1/4);
   period=1440./15;
   step=3;
elseif time_input==double(30)
   granularity=double(1/2);
   period=1440./30;
   step=6;
elseif time_input==double(60)
   granularity=double(1);
   period=1440./60;
   step=12;
else
   error('Please enter a granularity of 5, 15, 30 or 60 minutes for data with
5 minute resolution.')
end
k=numel(demand)-1;
%variables
pow=sdpvar(num_gen,k);
ener_lev=sdpvar(1,k+1);
pow_char=sdpvar(1,k);
pow_discharge=sdpvar(1,k);
%non-decision variables
queue=zeros(1,k+1);
pi=zeros(1,k); %prices
```

```
if ~exist('v','var')
   v=(max_stor-2*granularity*max_pow_cap)/(max(cost_para));
end
ener_lev(1)=initial_ener; %initialization of Eo,Qo, V;
queue(1)=ener_lev(1)-(granularity*max_pow_cap+v* max(cost_para));
for i=1:step:k %solve optimization for all periods, update of period (t=t+1);
step
   %for period i observe Qt, Et, and demand(i)
   %objective for period i
   objective=0;

objective=objective+v*granularity*cost_para*pow(:,i)+granularity*queue(i)*(pow
_char(i)*eff-pow_discharge(i)/eff)%need to change
   constraints=[ener_lev(end)==0];
   for j = 1:num_gen
       constraints= [constraints,
(sum(pow(:,i))-pow_char(i)+pow_discharge(i)==demand(i))];
       constraints= [constraints, min_pow<=pow(:,i)<=max_pow];
       constraints= [constraints, 0<=pow_char(i)<=max_pow_cap];
       constraints= [constraints, 0<=pow_discharge(i)<=max_pow_cap];
   end

options=sdpsettings('solver','gurobi+','gurobi.dualreductions',0,'gurobi.nonco
nvex',2,'gurobi.infunbdinfo',1)
   optimize(constraints,objective,options) %solve the problem
   if isnan(double(pow(:,i)'))~=1
       p=double(pow(:,i)); %get power and costpara for period
       cp_=cost_para';
       field=[];
       values=[];
       for j =1:num_gen %organize power output and cost for period if !=0
              if p(j)~=0
                field(end+1)=p(j);
                    values(end+1)=cp_(j);
              end
       end
       pi(i)=max(values); %get the LMP for period, max cost of active
generators

ener_lev(i+step)=ener_lev(i)+granularity*(pow_char(i)*eff-pow_discharge(i)/eff
);

queue(i+step)=queue(i)+granularity*(pow_char(i)*eff-pow_discharge(i)/eff);
   end
end
pow=pow(:,1:step:end);
ener_lev=ener_lev(:,1:step:end);
pow_char=pow_char(:,1:step:end);
pow_discharge=pow_discharge(:,1:step:end);
```

```
pi=pi(:,1:step:end);
total_rev=0;
for i=1:numel(pi)
   total_rev=total_rev+step*sum(pi(i)*pow(:,i));
end
ener_lev=double(ener_lev);
pow_char=double(pow_char);
pow_discharge=double(pow_discharge);
pow=double(pow);
pi=double(pi);
end
```

Appendix B - Reference Data for 17th February

Cost parameters estimated from:

- Renewables https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2022/Jul/IRENA_Power_Generation_Costs_2021_Summary.pdf
- Natural Gas https://www.globalpetrolprices.com/natural_gas_prices/
- Large Hydropower https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2012/RE_Technologies_Cost_Analysis-HYDROPOWER.pdf
- Imports https://www.iea.org/reports/projected-costs-of-generating-electricity-2020
- Nuclear https://www.statista.com/statistics/184754/cost-of-nuclear-electricity-production-in-the-us-since-2000/

Appendix C - Data Retrieval Function from Reference Data and Output Figure Function

```
function
[demand,cost_para,max_pow,min_pow,max_stor,max_pow_cap,num_gen,eff,initial_ener,text]=getdata(Data)
demand=rmmissing(Data.Demand);
cost_para=rmmissing(Data.CostParameter)';
max_pow =rmmissing(Data.MaximumPower);
min_pow =rmmissing(Data.MinimumPower);
max_stor=rmmissing(Data.MaximumStorageCapacity);
max_pow_cap=rmmissing(Data.StoragePowerCapacity);
num_gen=numel(cost_para);
eff=rmmissing(Data.Efficiency);
initial_ener=rmmissing(Data.InitialStorage);
text=rmmissing(Data.GenerationSource);
end
```

```
function
[figure1,figure2,figure3,figure4]=outputfigures(demand,granularity,ener_lev,po
w_char,pow_discharge,pow,max_stor,price,cost_para,text)
num_gen=numel(cost_para);
ener_lev=double(ener_lev);
pow_char=double(pow_char);
pow_discharge=double(pow_discharge);
pow=double(pow);
max_stor=double(max_stor);
price=double(price);
if granularity==double(1/12)
   period=1440./5;
   step=1;
elseif granularity==double(1/4)
   period=1440./15;
   step=3;
elseif granularity==double(1/2)
   period=1440./30;
   step=6;
elseif granularity==double(1)
   period=1440./60;
   step=12;
end
demand=demand(1:step:end);
%Figure outputs
figure1=figure('Name','Demand');
plot(0:granularity:(24-granularity),demand);
set(gca,'xtick',0:4:24);
xlabel('Time');
ylabel('Demand (Mwh)');
max_cost_para=max(cost_para);
figure2=figure('Name','Electricity Price');
plot(0:granularity:(24-granularity),price);
set(gca,'xtick',0:4:24);
ylim([0,max_cost_para]);
xlabel('Time');
ylabel('$/Mwh');
figure3=figure('Name','Generator Output')
for i=1:num_gen
   hold on
   plot(0:granularity:(24-granularity),pow(i,:));
end
xlabel('Time')
set(gca,'xtick',0:4:24);
ylabel('Power Output/mwh')
legend (text)
figure4=figure('Name','Energy Level Over Time')
hold on
plot(0:granularity:24, ener_lev, 'b');
```

```
plot(0:granularity:(24-granularity), pow_char,'--g');
plot(0:granularity:(24-granularity), pow_discharge,'--r');
title('Energy Level of Storage')
xlabel('Time')
ylabel('Energy Level/MWh')
set(gca,'xtick',0:4:24);
legend('Energy Level','Charged Power','Discharged Power')
end
```

Appendix D - Comparison Functions for Evaluating Algorithm

```
%comparison with offline LMP
%offline LP for multiple periods
offline_rev=0;
p=0;
granularity=double(1/12);
filenames=["onlinetesting.xlsx","data1.xlsx", "data2.xlsx", "data3.xlsx",
"data4.xlsx", "data5.xlsx", "data6.xlsx", "data7.xlsx"]; %add filenames to
test, each file with 288 periods
offline_revenues=zeros(1,numel(filenames));
periods=zeros(1,numel(filenames));
for i=1:numel(filenames)
   clearAllMemoizedCaches;
   filename=char(filenames(1));
   opts = detectImportOptions(filename,'NumHeaderLines',0);
   data = readtable(filename,opts);

[data_demand,data_cost_para,data_max_pow,data_min_pow,data_max_stor,data_max_p
ow_cap,data_num_gen,data_eff,~,text]=getdata(data);

[total_rev,pow,pow_char,pow_discharge,ener_lev,prices]=offline(granularity,dat
a_demand,data_cost_para,data_max_pow,data_min_pow,data_max_stor,data_max_pow_c
ap,data_eff);
   offline_rev=offline_rev+total_rev;
   offline_revenues(i)=offline_rev;
   p=p+288;
   periods(i)=p;
end
%online revenue for multiple periods
online_revenues=zeros(1,numel(filenames));
periods=zeros(1,numel(filenames));
online_rev=0;
p=0;
for i=1:numel(filenames)
   clearAllMemoizedCaches;
   filename=char(filenames(1));
   opts = detectImportOptions(filename,'NumHeaderLines',0);
   data = readtable(filename,opts);
```

```
[data_demand,data_cost_para,data_max_pow,data_min_pow,data_max_stor,data_max_p
ow_cap,data_num_gen,data_eff,initial_ener,text]=getdata(data);

[total_rev,pow,pow_char,pow_discharge,ener_lev,pi,v]=periodonlineoptimize(gran
ularity,data_demand,data_cost_para,data_max_pow,data_min_pow,data_max_stor,dat
a_max_pow_cap,data_num_gen,data_max_pow_cap,data_eff);
   online_rev=online_rev+total_rev;
   online_revenues(i)=online_rev;
   p=p+288;
   periods(i)=p;
end

%comparison with CAISO supply data
clearAllMemoizedCaches;
filename='caisolmpdata.xlsx';
opts = detectImportOptions(filename,'NumHeaderLines',0);
data = readtable(filename,opts);
%average LMP for all CAISO Nodes over 24h period, 2213 nodes for 24h=53112
%total data elements
avg_lmp=zeros(1,24);
y=1;
for t=1:24
       o=double(t);
       x=t*2213;
       sumlmp=0;
       count=0;
       for i=y:x
           if data.Hour(i)==o & data.LMP(i)~=0
               sumlmp=sumlmp+data.LMP(i);
               count=count+1;
           end
       end
       y=y+2213;
       avg_lmp(t)=sumlmp/count;
end

clearAllMemoizedCaches;
filename='onlinetesting.xlsx';
opts = detectImportOptions(filename,'NumHeaderLines',0);
data = readtable(filename,opts);
%run model for 24 hour data and output figures
[data_demand,data_cost_para,data_max_pow,data_min_pow,data_max_stor,data_max_p
ow_cap,data_num_gen,data_eff,initial_energy,text]=getdata(data);
num_gen=numel(data_cost_para);
max_cost_para=max(cost_para);
[total_rev,pow,pow_char,pow_discharge,ener_lev,pi,v,granularity]=periodonlineo
ptimize(time_input,data_demand,data_cost_para,data_max_pow,data_min_pow,data_m
ax_stor,data_max_pow_cap,data_eff,initial_energy)
```

```
[a,b,c,d]=outputfigures(data_demand,granularity,ener_lev,pow_char,pow_discharg
e,pow,data_max_stor,pi,data_cost_para,text)
%combined effect of granularity and Eo
time_input= [5,15,30,60];
%model analysis
% effect of granularity on energy storage charge and discharge?
[test_granular,reve_,vmax]=impact_granular(data_demand,data_cost_para,data_max
_pow,data_min_pow,data_max_stor,data_max_pow_cap,data_num_gen,data_eff,initial
_energy)
[sensi,rev]=impact_weight(data_demand,data_cost_para,data_max_pow,data_min_pow
,data_max_stor,data_max_pow_cap,data_num_gen,data_eff,initial_energy)
[pow_char,pow_discharge,ener,pri]=effect_Eo(time_input,
data_demand,data_cost_para,data_max_pow,data_min_pow,data_max_stor,data_max_po
w_cap,data_eff)
%functions for model analysis
%analyse impact of granularity
function
[g,revenues,weight]=impact_granular(data_demand,data_cost_para,data_max_pow,da
ta_min_pow,data_max_stor,data_max_pow_cap,data_num_gen,data_eff,initial_energy
)
g=[double(5),double(15),double(30),double(60)];
revenues=zeros(1,numel(g));
weight=zeros(1,numel(g));
for j=1:numel(g)
   granularity=g(j);

[total_revenue,~,~,~,~,~,v]=periodonlineoptimize(granularity,data_demand,data_
cost_para,data_max_pow,data_min_pow,data_max_stor,data_max_pow_cap,data_num_ge
n,data_eff,initial_energy);
   revenues(j)=total_revenue;
   weight(j)=v;
end
end
%analyse impact of Vmax
function
[beta,revenues]=impact_weight(data_demand,data_cost_para,data_max_pow,data_min
_pow,data_max_stor,data_max_pow_cap,data_eff,initial_ener)
beta=0.5:0.1:1.2;
granularity=double(5);
vmax=(data_max_stor-2*granularity*data_max_pow_cap)/(max(data_cost_para));
revenues=zeros(1,numel(beta));
v_values=zeros(1,numel(beta));
for k=1:numel(beta)
   v=0;
   v=v+beta(k)*vmax;
   v_values(k)=v;

[total_revenue]=periodonlineoptimize(granularity,data_demand,data_cost_para,da
```

```
ta_max_pow,data_min_pow,data_max_stor,data_max_pow_cap,data_eff,initial_ener,v
);
   revenues(k)=total_revenue;
end
end
%impact of initial energy level --> granularity must be set to 5 minutes
%for the function to work
function
[pow_char,pow_discharge,ener,pri]=effect_Eo(time_input,data_demand,data_cost_p
ara,data_max_pow,data_min_pow,data_max_stor,data_max_pow_cap,data_eff)
i=double(data_max_stor./6);
%time_input,data_demand,data_cost_para,data_max_pow,data_min_pow,data_max_stor
,data_max_pow_cap,data_eff
v=0:i:data_max_stor;
k=numel(data_demand)-1;
if time_input==double(5)
   step=1;
elseif time_input==double(15)
   step=3;
elseif time_input==double(30)
   step=6;
elseif time_input==double(60)
   step=12;
end
x=(1:step:k);
y=numel(x);
p=numel(data_cost_para);
ener=cell(p,y+1);
pri=cell(p,y);
pow_char=cell(p,y);
pow_discharge=cell(p,y);
%time_input,demand,cost_para,max_pow,min_pow,max_stor,max_pow_cap,eff,initial_
ener,v
for l=1:numel(v)
   ener_o=v(l);

[~,~,z,x,s,t,~]=periodonlineoptimize(time_input,data_demand,data_cost_para,dat
a_max_pow,data_min_pow,data_max_stor,data_max_pow_cap,data_eff,ener_o);
   ener(l,:)=num2cell(double(s));
   pri(l,:)=num2cell(double(t));
   pow_char(l,:)=num2cell(double(z));
   pow_discharge(l,:)=num2cell(double(x));
end
end
%impact of cost parameter proximity (run after optimization has been run)
function
[ma,mi,avg_para,stdev]=cost_prox(data_cost_para,total_revenue,ener_level)
ma=max(data_cost_para);
mi=min(data_cost_para);
```

```
avg_para=mean(cost_para);
stdev=std(cost_para);
x=plot(data_cost_para,total_revenue);
y=plot(data_cost_para,ener_level);
end
```