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Impacts of Temporal Resolution and System Efficiency on PV Battery System Optimisation

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Abstract

Power scheduling optimisation is crucial to the economic profitability of a battery integrated solar system. Despite the growing number of PV battery scheduling optimisation studies, most literature uses relatively low temporal resolution in their optimisation cost functions which is different from the real-time scenario where realised costs are derived instantaneously. It is unclear how accurate these estimations are and how they can impact the conclusions of an optimisation model. Furthermore, most studies use quite rough estimations of battery system efficiency which could potentially lead to inaccurate estimations of state-of-charge and optimised costs. In this work, we assess the impacts of applying various temporal resolutions and efficiency settings on optimised costs and savings in a rule-based and a linear programming PV battery optimisation model. It is shown that using input data with hourly temporal resolution and a rule-based model could respectively lead to 2.9% and 12.6% underestimations of optimised costs and savings to a battery owner with flat tariff. A temporal resolution equal to or finer than 5-minute is proven to minimise the errors related to lower temporal precisions. Significant cost and saving errors are found with constant efficiency settings by comparing the results derived by using real-time data from Australian residential battery consumers with our simulation results.

1. Introduction

As of April 2017, more than 1.66 million PV systems have been installed in Australia, with a total capacity of over 5.92 GW (APVI, 2017). Most of the installed systems are residential, and as the generous solar feed-in tariffs have expired for most Australian residential customers, energy storage is being considered as an option to increase the economic profitability of PV systems through functionalities including maximising self-consumption, peak shaving and price arbitrage. As a result, 6750 battery systems were installed in 2016, a significant uptake compared to 500 in 2015 (Sunwiz, 2017).

Optimising the charging/discharging activities of batteries is crucial to realise the full potential benefit of a PV-battery system. Many studies have sought to solve this sequential stochastic optimisation problem using various optimisation techniques such as linear programming, quadratic programming, dynamic programming and model predictive control.

Moreover, due to the intrinsic intermittency of solar energy and large variations in demand profiles, forecasts of solar generation and electricity consumption are often integrated in these optimisation frameworks to facilitate predictive optimisation.

1.1. *Problem Statement*

1.1.1. *Temporal Resolution in PV Battery Scheduling Optimisation*

Currently there are no PV and consumption benchmark datasets for PV battery power scheduling optimisation. As a result, different PV and load datasets are used in optimisation studies and their temporal resolutions are dependent on the applied sampling rates of electricity meters and weather stations.

For most optimisation studies related to PV battery power scheduling, the granularity of input PV and consumption data will determine the temporal resolution of an optimisation cost function. This is because most models have a single fixed-length horizon with constant resolution and formulation of the optimisation problem is more straight-forward when the input data to an optimisation model has the same granularity as the output control signals.

As indicated in Table 1, which provides a summary of applied temporal resolutions for the optimisation models used in our reviewed PV battery scheduling literature, most studies use PV and consumption data at a relatively low resolution.

Table 1: Temporal resolution applied in PV battery scheduling optimisation studies

Temporal Resolution	References
1 minute	(Venayagamoorthy et al. 2016)
4 – 5 minutes	(Koohi-Kamali et al. 2014; Wang et al. 2014)
10 minutes	(Bennett et al. 2015; Riffonneau et al. 2011)
15 minutes	(Braam et al. 2015; Hanna et al. 2014; Keerthisinghe et al. 2014; Li & Danzer 2014; Nottrott et al. 2013; Olaszi & Ladanyi 2017; Syed & Raahemifar 2016)
30 minutes	(Abdulla et al. 2016; Abdulla et al. 2017; Keerthisinghe et al. 2016; Ratnam et al. 2015a; Ratnam et al. 2015b; Zhang et al. 2015)
1 hour	(Aghajani et al. 2015; Chang et al. 2013; Fuselli et al. 2013; Liu et al. 2015; Lorenzi & Silva 2016; Lu & Shahidehpour 2005; Luna et al. 2016; Ming et al. 2017; Nunez-Reyes et al. 2017; Pezeshki et al. 2014; Ranaweera & Midtgård 2016; Shang et al. 2016; Su et al. 2014; Teng et al. 2013; Wu et al. 2014; Zhang & Jia 2015)

The use of low temporal resolution in an optimisation's objective function may lead to errors in estimated costs as realised costs are derived instantaneously in a real-time scenario. A few approaches in the literature have compared various granularities used in Distributed Generation (DG) optimisations and some explorations have been conducted to evaluate the impacts of applying input data with various resolutions.

In Hawkes & Leach's analysis on the impacts of temporal resolution on combined production of heat and power (CHP) modelling (2005), they found using coarse demand data has a noticeable impact on the optimal capacity, carbon dioxide emission reduction and lifetime costs of a CHP system. An analysis was done to explore the effects of data granularity on the imports and exports of a DG system, the study concluded that low resolution data leads to underestimations of imports and exports (Wright & Firth 2007). Hoevenaars & Crawford (2012) investigated impacts of data resolution on the optimal sizes of components such as PV, wind, battery and diesel in a renewable system, they found the impacts are strongly related to system configuration and it is difficult to make a simple granularity recommendation. A study completed by Ried et al. (2015) explored effects of applying low resolution data on the modelling of residential PV battery system, the results showed coarse load data could cause overestimations of battery lifetime and underestimations of a battery's contribution to PV self consumption. The impact of data granularity on DG capacity and estimated losses were investagted by Kools & Phillipson (2016), they recommended a resolution finer than 1 hour is not necessary as differences in results are negligible when using high resolution data. Beck et al. (2016) conducted an analysis on the influence of PV and load data granularity on self-consumption and sizing of a PV battery system. They found temporal precision of load data is more critical to the estimation of self-consumption rate and for a system with a relatively low and stable demand profile, 15-minute data is sufficient for determination of self-consumption rate. Moreover, their study concluded that 1 hour resolution is sufficient for sizing of PV battery systems. Abdulla et al. (2017) demonstrates that for a residential PV storage system, the estimations of storage value can be influnced by the temporal resolution of input PV and load data. An average of 17% difference was found between using 1 minute and 30 minute data for a simulated site configuration in which the battery is controlled by a rule-based algorithm designed to maximise self consumption of PV.

From the literature, it remains unclear how low temporal precision could impact the optimised costs of objective functions in a PV battery power scheduling model. Moreover, a resolution finer than 1 minute has not yet been explored by DG optimisation analysis. Therefore, it is worthwhile to look more closely at temporal resolution, to understand how the optimised costs are affected.

1.1.2. *Storage Efficiency Settings in PV Battery Scheduling Optimisation*

Storage efficiency plays an important role in the system setup of a PV battery power scheduling optimisation problem as it not only affects the system energy losses but can also influnence the State of Charge (SOC) constraints in the optimisation formulation.

Most studies in power scheduling optimisation of PV and battery systems tend to assume the battery conversion loss is linear to the energy flows of a battery. Battery efficiency settings used by reviewed literature can be categrised into three main types, as shown in Table 2.

Table 2: Battery Efficiency Settings applied in existing PV battery scheduling optimisation studies

Storage Efficiency Setting	References
Perfect Conversion Efficiency	(Hubert & Grijalva 2012; Leo et al. 2014; Luna et al. 2016; Luna et al. 2017; Miyazato et al. 2016; Nottrott et al. 2013; Pezeshki et al. 2014; Ratnam et al. 2015a; Ratnam et al. 2015b; Suzuki 2012; Venayagamoorthy et al. 2016; Zhang

	& Jia 2015; Zhu & Hug 2014)
Constant Charging/Discharging Efficiency	(Abdulla et al. 2016; Abdulla, Steer, Wirth, De Hoog, et al. 2017; Aghajani et al. 2015; Barnes et al. 2015; Bennett et al. 2015; Braam et al. 2015; Chang et al. 2013; Fuselli et al. 2013; Georges et al. 2017; Gitizadeh & Fakharzadegan 2013; Hanna et al. 2014; Hoevenaars & Crawford 2012; Hoke et al. 2013; Hong & Lin 2013; Koohi-Kamali et al. 2014; Kusakana 2016; Li & Danzer 2014; Liu et al. 2015; Lorenzi & Silva 2016; Lu & Shahidehpour 2005; Mahanty & Gupta 2004; Ming et al. 2017; Olaszi & Ladanyi 2017; Ranaweera & Midtgård 2016; Ranaweera et al. 2017; Reddy 2016; Ren et al. 2016; Schibuola et al. 2017; Su et al. 2014; Syed & Raahemifar 2016; Teng et al. 2013; Torreglosa et al. 2015; Wang et al. 2014; Wu et al. 2014; Zhang et al. 2015)
Efficiency derived from quadratic curves	(Keerthisinghe et al. 2014; Keerthisinghe et al. 2016; Riffonneau et al. 2011; Tischer & Verbic 2011)

From Table 2, we can see several studies assume perfect battery conversions (i.e. the efficiency is assumed to be 100%). The majority of approaches incorporate a constant charging/discharging efficiency. Several studies have adopted a quadratic battery efficiency curve where the battery charging/discharging efficiency is dependent on the input/output power.

To the best of the authors' knowledge, there is no published research looking at evaluating the impacts of various battery efficiency settings in a PV battery optimisation model. Furthermore, there is a need to investigate the data from real PV battery systems to assess whether a linear battery efficiency model is sufficient.

1.2. Contributions and Structure of the paper

In this study, we aim to conduct a sensitivity study to investigate the impacts of temporal resolution and battery efficiency settings on the optimised costs of PV battery scheduling models using high resolution real site data collected from Australian residential PV and battery systems. The contributions are to:

- Investigate the errors related to various granularities in optimised costs of a rule-based battery scheduling algorithm and a linear programming (LP) optimisation model designed to minimise household electricity costs.
- Using real-time high resolution PV battery site data, evaluate the errors in estimated optimised costs for a rule based optimisation model with linear battery efficiency settings.
- Propose a linear regression model to track state of charge (SOC) in a rule-based optimisation model. Investigate whether a linear regression model is sufficient to achieve an adequate accuracy for estimating SOCs and optimised costs.

2. Methodology

2.1. Data

Three main datasets collected from Solar Analytics' residential customers are used in this work: (1) One year of 5 second PV and consumption data collected from 45 Australian residential customers. (2) Up to one year of 30 second PV, consumption and battery energy data collected from 36 Australian residential battery customers who all have the same battery model. (3) Up to one year of 30-minute battery application programming interface (API) data collected from the 36 residential battery customers mentioned above. The API data is directly provided by the battery's manufacturer and it includes information such as the maximum usable capacity, 30-minute SOC, charge and discharge.

2.2. Optimisation Models

2.2.1. Nomenclature

Table 3: Variables

Variable	Definition	Variable	Definition
pv_t	PV energy output during interval *t* (kWh)	$energy_{out}$	Energy flow out of the battery (kWh)
l_t	Household load during interval *t* (kWh)	$\boldsymbol{a}$	Intercept for the linear regression model
d_t	Excess demand during interval *t* (kWh)	$\boldsymbol{b}$	Slope for the linear regression model
soc_t^{usable}	Usable capacity during interval *t* (kWh)	T_t	30-minute ambient temperature (°C)
P_t^c	Maximum charging/discharging rate (kW)	b_t	30-minute battery AC energy flow (kWh)
b_t^{ch}	Energy transferred to battery during interval *t* (kWh)	g_t^{import}	Grid import during interval *t* (kWh)
b_t^d	Energy transferred from the battery during interval *t* (kWh)	g_t^{export}	Grid export during interval *t* (kWh)
soc_t	State of Charge at start of interval *t* (kWh)	h	Number of intervals in 24 hours
$cost_t^{pv}$	Electricity Cost during interval *t* ($AUD) for a PV system with no battery	**m**	Number of intervals in one year
$cost_t^{batt}$	Electricity Cost during interval *t* ($AUD) for a PV system with installed battery	ΔC_{30min}	30-minute capacity change (kWh)
p_t^{export}	Export Tariff during interval *t* ($AUD/kWh)	$energy_{in}$	Energy flow into the battery (kWh)
p_t^{import}	Import Tariff during interval *t* ($AUD/kWh)		

Table 4: Model Parameters

Parameter	Definition	Value used in granularity analysis	Value used in efficiency analysis
C_{total}	Total Battery Size (kWh)	Unique optimal size, one for each site	8.4
P_{max}	Rated maximum charging/discharging power (kW)	$0.4\times C_{total}$	2.0
SOC_{min}	Minimum value for state of charge	20%	Site specific value derived from

			API data, one for each site
$degrad_c$	Degradation rate in total capacity (kWh/interval)	0	Site specific value derived from API data
$degrad_p$	Degradation rate in maximum charging/discharging power (kW/interval)	0	Site specific value derived from API data
SOC_{start}	State-of-charge when we start our simulation	50%	Site specific value collected from API data
η_{ch}	Charging efficiency	90%	Site specific value derived from API and energy flow data
η_d	Discharging efficiency	90%	Site specific value derived from API and energy flow data
η_{single}	Single efficiency same for both charging & discharging	90%	Site specific value derived from API and energy flow data

2.2.2. *Rule-based (RB) Model*

The rule based model used in this work is a simple control algorithm which aims to maximise PV self-consumption. It has been considered and implemented for some studies (e.g. in Abdulla et al. 2017) and is used in practice at many installed battery sites due to its simplicity and ease of implementation. Another reason to include this model is that all the real battery systems included in this study are controlled by this algorithm so adopting this model allows us to make an empirical sensitivity analysis on battery efficiency by comparing real and estimated optimised costs. A pseudo code of this algorithm is presented in Table 5.

Table 5: Pseudo Code for the rule-based model

input parameters
Input $pv_t, l_t, P_{max}, C_{total}, SOC_{min}, p_t^{import}, p_t^{export}, SOC_{start}, degrad_c, degrad_p$
import charging/discharging efficiencies
Input η_{ch}, η_d
Set initial SOC to SOC_{start}
$soc_0 \leftarrow SOC_{start}$
# for loop starts
for t in (1, 2, …, m):
    $soc_t^{usable} \leftarrow C_{total} \times (1 - SOC_{min}) - t \times degrad_c$
    $P_t^c \leftarrow P_{max} - t \times degrad_p$
    $d_t \leftarrow l_t - pv_t$
    if $d_t < 0$:
    # when there is excess solar, charge battery until full
        $b_t^{ch} \leftarrow \min(-d_t, P_t^c, (soc_t^{usable} - soc_{t-1})/\eta_{ch})$
        $g_t^{export} \leftarrow -d_t - b_t^{ch}$
        $cost_t^{pv} \leftarrow d_t \times p_t^{export}$
        $cost_t^{batt} \leftarrow -g_t^{export} \times p_t^{export}$
        $soc_t \leftarrow soc_{t-1} + b_t^{ch} \times \eta_{ch}$
    else:
    # when there is excess demand, discharge battery until depleted
        $b_t^d \leftarrow \min(d_t, P_t^c \times \eta_d, soc_{t-1} \times \eta_d)$
        $g_t^{import} \leftarrow d_t - b_t^d$
        $cost_t^{pv} \leftarrow d_t \times p_t^{import}$
        $cost_t^{batt} \leftarrow g_t^{import} \times p_t^{import}$
        $soc_t \leftarrow soc_{t-1} - b_t^d/\eta_d$
Output $\sum_{t=1}^{m} cost_t^{pv}, \sum_{t=1}^{m} cost_t^{batt}$

2.2.3. *Linear Programming Model*

Linear Programming (LP) has been applied by some researchers in this area as it can converge at a low computational cost and guarantee the solution is optimal if the optimisation problem is linear (Hanna et al. 2014; Hoke et al. 2013; Lorenzi & Silva 2016; Lu & Shahidehpour

2005; Nottrott et al. 2013; Ratnam et al. 2015b; Wu et al. 2014). In this work we are running simulations at a high temporal resolution, therefore LP is favoured to minimise computational costs. Table 6 demonstrates the mathematical cost function and convex constraints used in our LP formulation.

Table 6: Formulation of the LP model

Objective Function	$Minimise\ J = \sum_{t=1}^{h}(g_t^{import} \times p_t^{import} \text{-} g_t^{export} \times p_t^{export})$
Variables	$b_t^{ch}, b_t^{d}, g_t^{export}, g_t^{import}$
Equality constraints	$pv_t + b_t^d + g_t^{import} = l_t + b_t^{ch} + g_t^{export}$
	$soc_t = soc_{t\text{-}1} + b_t^{ch} \times \eta_{ch} \text{-} b_t^d / \eta_d$
Inequality constraints	$b_t^{ch} \geq 0;\ b_t^d \geq 0;\ g_t^{export} \geq 0;\ g_t^{import} \geq 0$
	$b_t^{ch} \leq P_t^c; b_t^d \leq P_t^c$
	$0 \leq soc_t \leq soc_t^{usable}$

2.3. *Sensitivity Analysis*

2.3.1. *Analysis on Temporal Resolution*

2.3.1.1. RB Approach

5 second residential PV and consumption data is first resampled into a few other lower resolutions (30 second, 1 minute, 2 minute, 5 minute, 15 minute, 30 minute and 60 minute) and then are fed into the RB model mentioned in Section 2.2.2. The RB model outputs two values which are the year electricity cost without installing battery and the situation with installed battery, the yearly savings of operating the battery are found by subtracting $\sum_{t=1}^{m} cost_t^{batt} \sum_{t=1}^{m} cost_t^{pv}, \sum_{t=1}^{m} cost_t^{batt}$ from $\sum_{t=1}^{m} cost_t^{pv}$. Further, we estimate the error of savings which would be estimated if data were only available at lower temporal resolutions. We then use Equation (1) and Equation (2) to determine the relative errors to our finest resolution (i.e. 5 second) by comparing costs and savings of 5 second data with other coarser temporal resolutions.

$$Relative\ error\ in\ optimised\ costs = \frac{costs\ for\ lower\ resolution \text{ - } costs\ for\ highest\ resolution}{costs\ for\ highest\ resolution} \tag{1}$$

$$Relative\ error\ in\ savings = \frac{savings\ for\ lower\ resolution \text{ - } savings\ for\ highest\ resolution}{savings\ for\ highest\ resolution} \tag{2}$$

2.3.1.2. LP Approach

A similar simulation framework is implemented for our LP model however instead of inputting all the PV and load data for a year, we include an optimisation planning horizon of 24 hours assuming perfect foresights of PV and consumption. Theoretically, the optimisation horizon of a PV battery system control problem is the lifetime of the system however this is not adopted in this study for two reasons: (1). Longer horizons will exponentially increase the computational cost for optimisation algorithms such as LP. (2). For optimisation models that require forecasts of PV and load, it is not feasible to get forecasted data with an adequate accuracy for a horizon equal to the lifetime of a system.

The Gurobi Optimiser (Gurobi Optimization, Inc. 2016) is used in Python to solve the 24-hour planning horizon, then the derived control signals are implemented in the next day. Due to the high computational demands on solving 5 second and 30 second, in this paper we only perform our analysis on data with 1-minute temporal resolution, and coarser. Moreover, we only consider the ToU tariff structure for the LP model due to the reason that under a flat tariff structure, it is not viable to charge from the grid at a lower rate or perform other types of price arbitrage so maximising self-consumption like what we do in the RB model is already the optimal control scheme.

Same as the RB approach, the simulation framework produces yearly electricity costs with and without battery along with yearly savings. Relative errors are also computed using Equation 1 and Equation 2.

2.3.1.3 Battery Size

For the temporal resolution analysis, we determine an optimal battery size for each residential PV customer without battery by feeding their 5 minute PV and consumption data into a battery sizing model proposed by Tang et al. (2015).

2.3.2. Sensitivity Analysis on Battery Efficiency Settings

2.3.2.1. Single Efficiency and Dual Efficiency

The first step of the battery efficiency analysis is to determine errors in estimated optimised costs and savings using a constant efficiency.

Single efficiency is referred as the situation when we assume charging efficiency equal to discharging efficiency (i.e. $\eta_{ch} = \eta_d$) and dual efficiency is when $\eta_{ch} \neq \eta_d$. Both efficiency settings have been previously applied in the literature list summarised in Table 2. In this study, we examine both scenarios separately by following these steps:

I. Apply a linear curve fit on the 30-minute battery AC energy flows and capacity changes and then derive a single charging/discharging efficiency (see Equation 3) and separate charging and discharging efficiencies (see Equation 4) for an individual battery customer.

For single efficiency setting:

$$\Delta C_{30min} = energy_{in} \times \eta_{single} \text{-} energy_{out} / \eta_{single} \tag{3}$$

For dual efficiency setting:

$$\Delta C_{30min} = energy_{in} \times \eta_{ch} \text{-} energy_{out} / \eta_{d} \tag{4}$$

II. Derive a linear capacity and charging/discharging power degradation rate ($degrad_c$, $degrad_p$) for each battery site by fitting a linear curve on the time since a battery is installed and changes in the rated maximum usable capacity (C_{total}) and charging/discharging power (P_{max}).

III. Determine the true electricity costs and savings in various resolutions by applying battery, PV and load data of 36 residential battery customers.

IV. Feed PV and consumption data from 36 battery customers and the parameters listed in Table 4 into our RB model to determine our estimated costs and savings.

2.3.2.2. Linear Regression SOC Tracking Model

A linear regression model formulated in Equation 5 is proposed to evaluate whether we could train a linear SOC tracking model using limited amount of SOC and battery energy data instead of using data from a whole year like what is done in Section 2.3.2.1. Another initiative for this approach is that we suspect other features such as temperature and previous SOCs could enhance our results. So instead of just doing a linear curve fit for all the data we have for one site, we add features including previous SOCs, 30-minute ambient temperature and AC battery energy flows for 90 days and then implement the trained linear regression model in our RB simulation model for the rest of the data period. Therefore, instead of updating our SOC with constant efficiencies, we use the trained linear regression model. Finally estimated optimised SOCs and optimised costs are compared against true costs and battery API SOCs to see if we could obtain a satisfactory level of accuracy in estimated SOCs, electricity costs and savings.

$$SOC_t = \boldsymbol{a} + \boldsymbol{b}\begin{bmatrix} SOC_{t-1} \\ T_t \\ b_t \\ hour \end{bmatrix} \tag{5}$$

2.4. Tariff Structure

A flat tariff and a time-of-use (ToU) have been considered for both temporal resolution and battery efficiency analyses. The adopted tariff rates are shown in Table 7.

Table 7: Tariff Rates for Flat and ToU

Flat Tariff ($AUD/kWh)	**ToU Tariff ($AUD/kWh)**		
	Peak (3pm to 9pm on weekdays)	Off-peak (10 pm to 7 am on weekdays & weekends)	Shoulder (all other times)
0.30	0.45	0.15	0.25

3. Results and Discussion

3.1. Impacts of Temporal Resolution on Optimised Costs and Savings

Relative errors in optimised costs and savings which are illustrated in Figure 1 and Figure 2 for various granularities, clearly show underestimations in both optimised costs and savings derived from lower resolutions for RB and LP models. At an hourly resolution, compared to results with 5 second time interval, approximately 3% mean relative error is found in optimised costs across all included sites for the three explored scenarios. The RB model with ToU tariff seems to be slightly more sensitive to temporal precision compared to the flat tariff scenario but overall it can be observed that the relative errors caused by coarser resolutions are consistent across both investigated optimisation models.

On the other hand, the influence of granularity is much higher on the yearly electricity bill savings. As indicated in Figure 2, the mean relative errors in savings for 30-minute and 60-minute temporal resolutions could be as high as 9.11% and 12.6% for the RB model with flat tariff. The savings computed from the LP model are less sensitive to data granularity compared to the results from our RB model.

The results demonstrated in Figure 1 and Figure 2 give confidence in applying PV and consumption data of 5 minute or other finer temporal resolutions in PV battery scheduling optimisations. For our included residential sites, 5-minute data results in less than 1% and less than 4% underestimations in optimised costs and savings respectively. Given that 5-minute data will not exceed the bandwidth limits of most smart meters in the current market, we recommend that 5-minute sampling rate is a viable option for PV battery power scheduling optimisation models.

3.2. Impacts of Constant Efficiency Settings on Optimised Costs and Savings

Table 8 illustrates the errors relative to the "true" cost calculated from 30 second real battery site import and export data (more detailed boxplots are shown in Appendix A). Although the real-time costs are derived instantaneously instead of every 30 second, from the results shown above in Figure 1 and Figure 2, we believe the resulting costs and savings from 30 second data can still be quite close approximations to the real-time costs. Underestimations and overestimations can be observed respectively in estimated costs and savings computed from our RB simulation model for both single and double efficiency settings. A few pronounced points are summarised below:

- Applying constant efficiency settings results in significant errors in estimated costs and savings across all temporal resolutions.
- Underestimations in optimised costs are larger with coarser input data which is consistent to what we found in Figure 1 and Figure 2, however the overestimations in savings are interestingly lower when we apply data with longer time intervals. We think this trend is caused by underestimations due to lower temporal resolutions cancelling out the overestimations effects of using constant efficiencies.
- To examine our hypothesis on the cancelling effects, we recompute the relative errors shown in Table 9 (more detailed boxplots are shown in Appendix B) by comparing simulated costs and savings with the true results generated from real imports and exports aggregated to each tested temporal resolution. So instead of comparing all the results to 30 second true costs and savings, we generate 1, 2, 5, 15, 30 and 60 minute "true" costs and savings from real imports and exports at these temporal resolutions to allow comparisons within the same temporal resolution so that we could minimise the impacts of temporal resolution in our efficiency analysis. As demonstrated in Table 9, we are now observing higher relative errors in savings and lower errors in optimised costs for coarser temporal resolutions.
- It can be observed that the two efficiency settings (single and dual) make small differences in terms of errors in optimised costs and savings.
- The included ToU tariff produces larger underestimations in optimised costs and smaller overestimations in savings compared to the results with flat tariff.

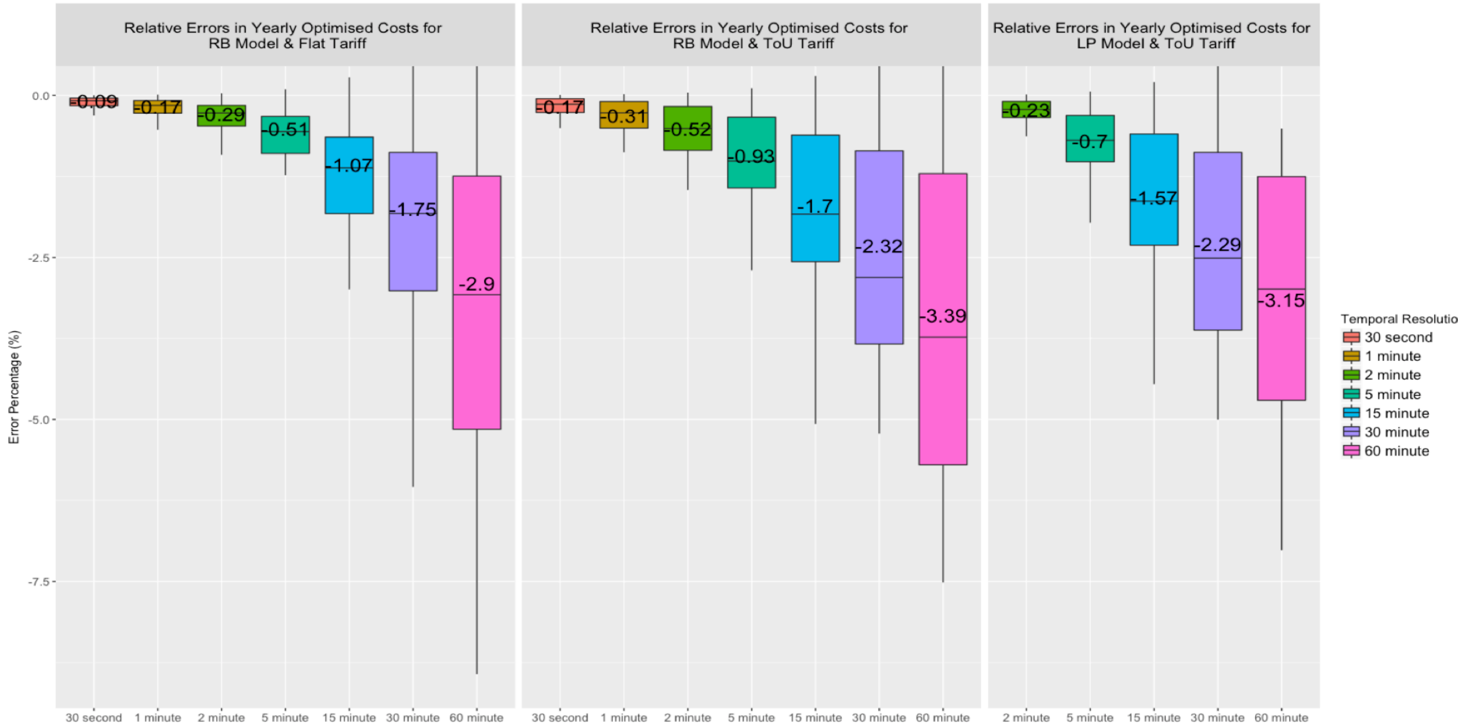

Figure 1: Percentage Relative Errors in Yearly Optimised Costs for RB model with Flat (left), ToU (middle) and LP Model with ToU (right) (numbers inside boxplots are the mean errors after excluding outliers).

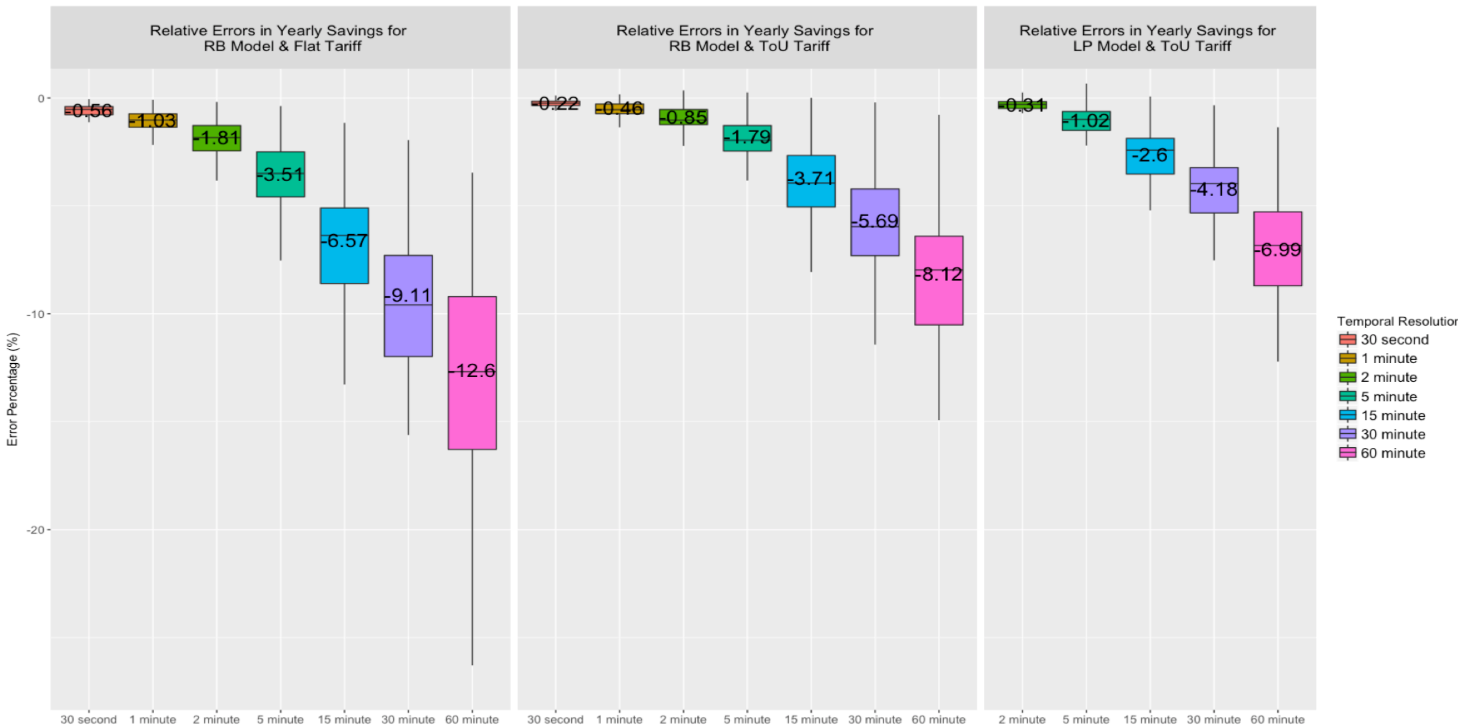

Figure 2: Percentage Relative Errors in Yearly Savings for RB model with Flat (left), ToU (middle) and LP Model with ToU (right) (numbers inside boxplots are the mean errors after excluding outliers).

Table 8: Mean Percentage Errors relative to True Yearly Costs & Savings

Tariff Structure	*Flat*		*ToU*	
Efficiency Settings	Single Efficiency	Dual Efficiency	Single Efficiency	Dual Efficiency
Mean percentage relative errors in optimised costs for various temporal resolutions (%)				
30 second	-8.01	-8.88	-9.51	-8.47
1 minute	-8.24	-8.28	-10.04	-8.92
2 minute	-8.58	-8.58	-9.84	-9.54
5 minute	-9.23	-9.16	-11.05	-10.69
15 minute	-10.35	-10.2	-13.1	-13.79
30 minute	-11.29	-11.11	-14.98	-15.66
60 minute	-12.79	-12.56	-17.45	-18.11
Mean percentage relative errors in savings for various temporal resolutions (%)				
30 second	19.06	20.46	14.27	15.31
1 minute	18.9	20.32	14.38	15.42
2 minute	18.64	20.08	14.5	15.57
5 minute	17.97	19.48	14.55	15.68
15 minute	16.48	18.03	14.19	13.92
30 minute	15	16.52	13.06	13.42
60 minute	12.64	14.12	10.88	11.86

Table 9: Mean Percentage Errors relative to True Yearly Optimised Costs & Savings with corresponding resolutions

Tariff Structure	*Flat*		*ToU*	
Efficiency Settings	Single Efficiency	Dual Efficiency	Single Efficiency	Dual Efficiency
Mean percentage relative errors in optimised costs for various temporal resolutions (%)				
30 second	-8.01	-8.88	-9.51	-8.47
1 minute	-8.05	-8.1	-9.76	-8.67
2 minute	-8.21	-8.24	-9.35	-9.08
5 minute	-8.64	-8.63	-10.31	-9.99
15 minute	-9.49	-9.41	-12.05	-12.74
30 minute	-10.2	-10.09	-13.66	-14.35
60 minute	-11.08	-10.92	-15.49	-16.15
Mean percentage relative errors in savings for various temporal resolutions (%)				
30 second	19.06	20.46	14.27	15.31
1 minute	19.06	20.5	14.5	15.57
2 minute	19.46	20.92	15.16	16.24
5 minute	20.7	22.16	16.79	17.85

15 minute	23.36	25.94	19.82	20.87
30 minute	25.9	28.53	22.63	23.7
60 minute	29.57	32.25	26.32	28.4

3.3. Evaluation of Linear Regression Model

As illustrated in Table 10 (more detailed boxplots are shown in Appendix C), a few error metrics have been implemented to evaluate the accuracy of our proposed SOC tracking model. Based on the mean absolute error (MAE) and median absolute error (MDAE), overall the linear regression has a relatively satisfactory accuracy on tracking SOCs. On the other hand, the mean square error (MSE), root mean square error (RMSE) and r-squared value suggest the model makes a noticeable amount of predictions that are quite far from the SOC labels collected from API. Errors in optimised costs and savings are mostly comparable to what can be observed in Table 9 however large overestimations which average at 44.24% are found in estimated yearly savings with flat tariff so there are not any noticeable improvements of including more input features.

Overall, there is still room for improvements in SOC tracking. It also appears that our model is performing quite well at low SOC values but fails to make accurate estimations of high SOCs. As a result, significant overestimations are found in estimated savings.

Table 10: Error metrics for estimations of SOCs & errors in optimised costs and savings

Error metrics for estimations of SOCs	Mean Value	Errors in optimised costs and savings	Mean Error Percentage
Mean absolute error	4.79	Error in yearly optimised costs with flat tariff	-14
Root mean square error	12.34	Error in percentage for yearly savings with flat tariff	44.24
Median absolute error	1.25	Error in percentage for yearly optimised costs with ToU tariff	-16.98
R squared value	0.82	Error in percentage for yearly savings with ToU tariff	29.75
Mean square error	126.31		

Conclusion and Future works

In this paper we perform a sensitivity analysis on the influences of applying coarser PV/consumption data and constant battery efficiencies in a PV battery power scheduling optimisation model. We have shown that low temporal precisions can lead to noticeable underestimations in both optimised costs and savings for all optimisation scenarios explored in our approach. Then we conclude 5-minute temporal resolution is sufficient to compute results with a good level of accuracy. Furthermore, the sensitivity investigation on applying constant battery efficiencies demonstrates significant underestimations in estimated electricity costs and even larger overestimations in electricity bill savings. It should also be noted that a cancelling effect is found when implementing both coarser data and constant efficiencies, the resulting errors in savings are reduced. Furthermore, the linear regression model that includes more features such as temperature and previous SOCs did not make any noticeable improvements on reducing relative errors of optimised costs and savings.

For future works, as we only include a RB and a LP model with a single objective of minimising electricity costs in our approach, it would be worthwhile to evaluate the impacts of temporal resolutions in other optimisation models such as dynamic programming, quadratic programming, mixed integer linear programming, evolutionary algorithms and reinforcement learning. Other optimisation objectives such as reducing peak demands, minimising battery degradation can also be considered for a more detailed granularity sensitivity study. In terms of battery efficiency and SOC tracking, we believe there is a need to extract more input features for our existing model or to develop more advanced non-linear models to improve efficiency and SOC estimations in a PV battery optimisation model.

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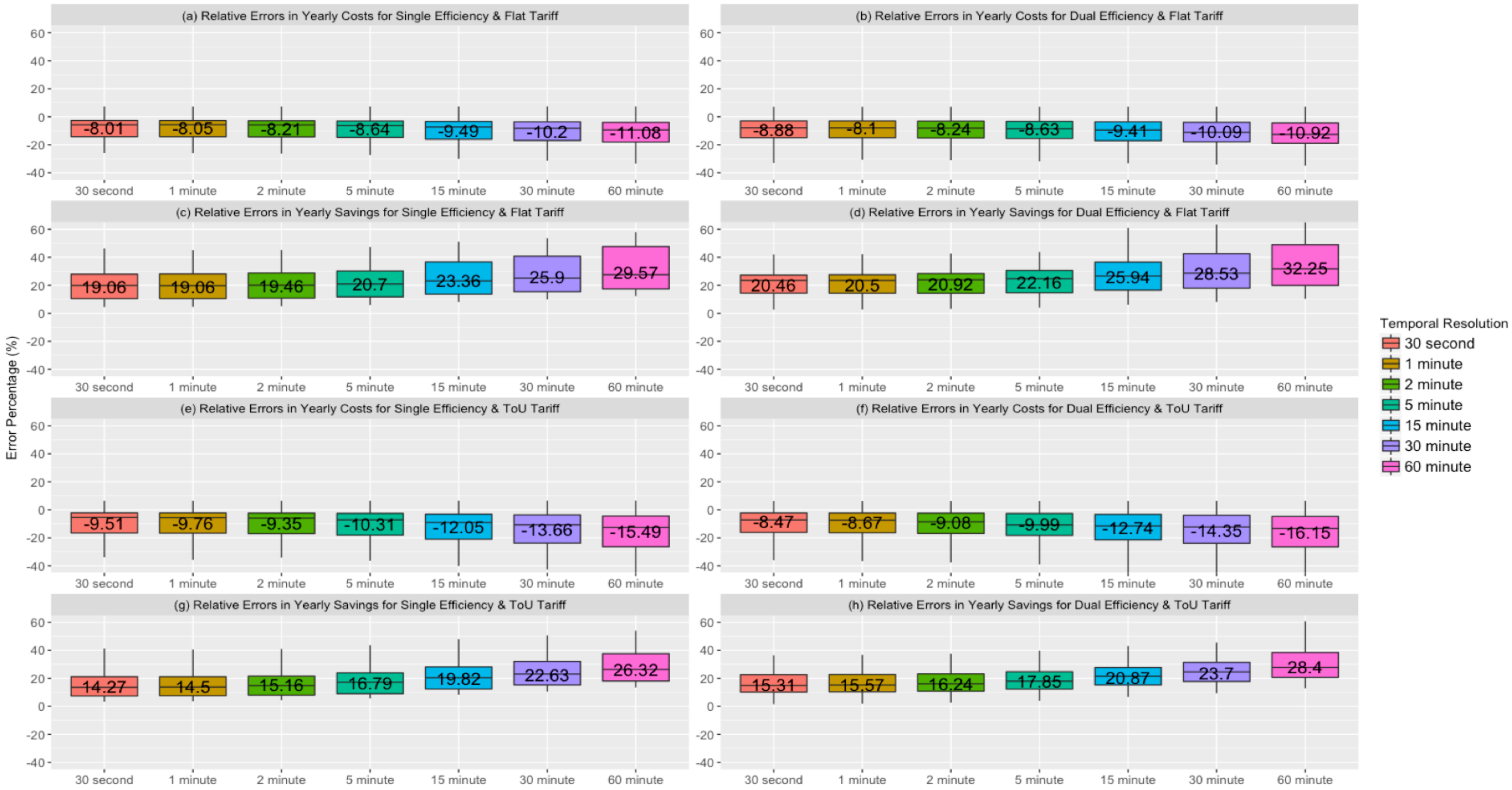
Appendix A: Mean Percentage Errors relative to 30 Second True Yearly Optimised Costs & Savings (numbers inside boxplots are the means after excluding outliers).

(a) relative errors in optimised costs with flat and single efficiency setting (numbers inside boxplots are the means after excluding outliers). (b) relative errors in optimised costs with flat and dual efficiency setting. (c) relative errors in savings with flat and single efficiency setting. (d) relative errors in savings with flat and dual efficiency setting. (e) relative errors in optimised costs with ToU and single efficiency setting. (f) relative errors in optimised costs with ToU and dual efficiency setting. (g) relative errors in savings with ToU and single efficiency setting. (h) relative errors in savings with ToU and dual efficiency setting.

Appendix B: Mean Percentage Errors relative to True Yearly Optimised Costs & Savings with corresponding resolutions (numbers inside boxplots are the means after excluding outliers).

(a) relative errors in optimised costs with flat and single efficiency setting (numbers inside boxplots are the means after excluding outliers). (b) relative errors in optimised costs with flat and dual efficiency setting. (c) relative errors in savings with flat and single efficiency setting. (d) relative errors in savings with flat and dual efficiency setting. (e) relative errors in optimised costs with ToU and single efficiency setting. (f) relative errors in optimised costs with ToU and dual efficiency setting. (g) relative errors in savings with ToU and single efficiency setting. (h) relative errors in savings with ToU and dual efficiency setting.



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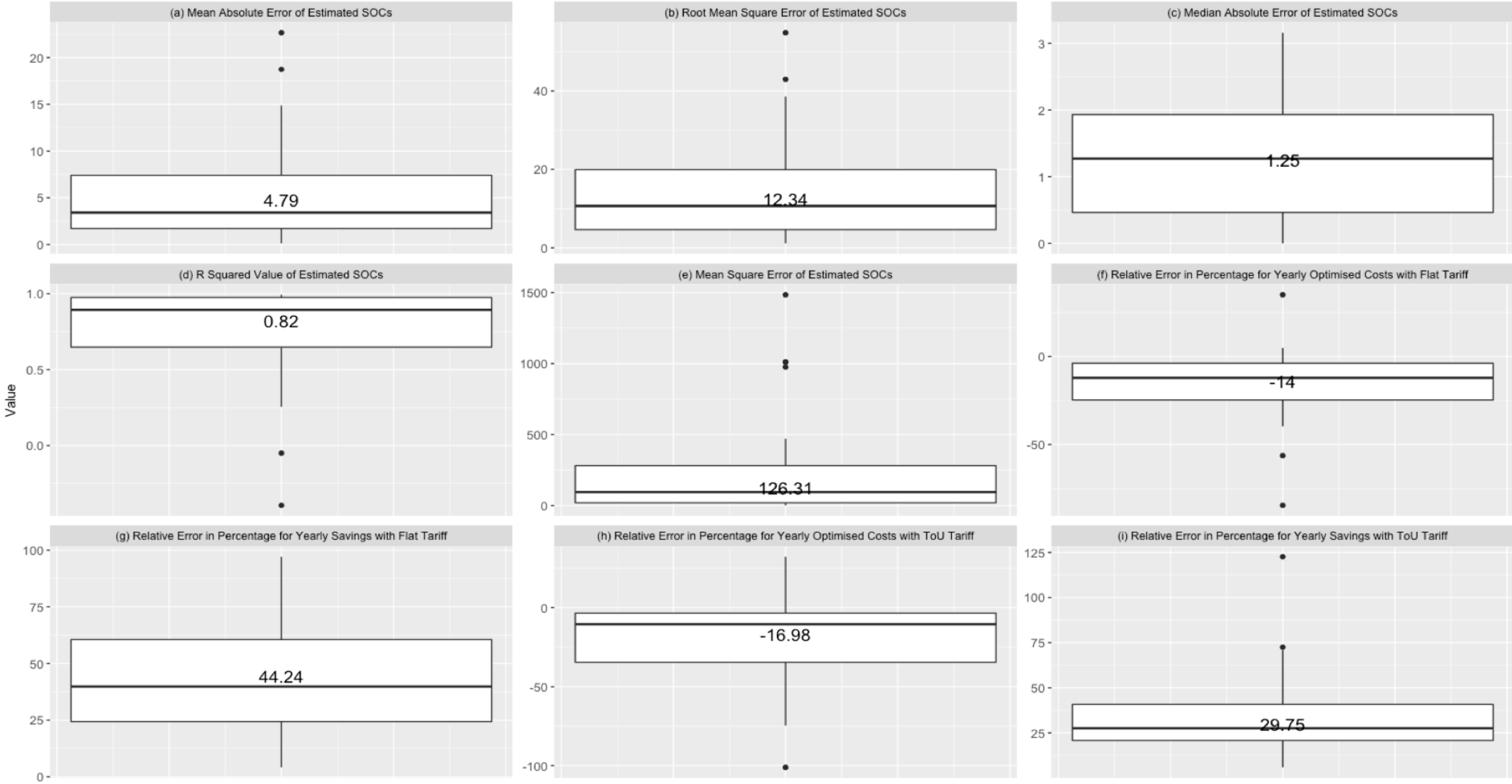
Appendix C: Error metrics for estimations of SOCs, errors in optimised costs and savings relative to 30 minute true costs and savings (numbers inside boxplots are the means after excluding outliers

(a) Mean Absolute Error of Estimated SOCs. (b) Root Mean Square Error of Estimated SOCs. (c) Median Absolute Error of Estimated SOCs. (d) R Squared Value of Estimated SOCs. (e) Mean Square Error of Estimated SOCs. (f) Relative Error in Percentage for Yearly Optimised Costs with Flat Tariff. (g) Relative Error in Percentage for Yearly Savings with Flat Tariff. (h) Relative Error in Percentage for Yearly Optimised Costs with ToU Tariff. (i) Relative Error in Percentage for Yearly Savings with ToU Tariff.



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