Abstract: This study quantifies the benefits of implementing model predictive control on residential solar PV and energy storage systems considering a time-of-use demand tariff, feed-in tariff and varying PV system sizes and battery life-cycle costs. The control system analysed makes use of economic model predictive control (EMPC) whereby the objective function is directly tied to the economics of the system. Using residential load and PV data from an Australian distribution network service provider, the EMPC controller is compared to a rule-based controller, highlighting the benefits of EMPC in regards to annual economic performance and battery energy throughput. The EMPC algorithm is then tested using 10 residential customers at the low voltage feeder level showing the capacity for the EMPC controller to shift peak demand and flatten the aggregated load profile of 30 residential customers.

Nomenclature

\( k \) discrete-time step
\( P_{\text{load}}(k) \) gross household electrical load
\( P_{\text{pv}}(k) \) gross household PV production
\( P_{\text{ch}}(k) \) energy storage charging power
\( P_{\text{dis}}(k) \) energy storage discharging power
\( P_{\text{in}}(k) \) net power imported from the grid
\( P_{\text{export}}(k) \) net power exported from the grid
\( \text{SoC}(k) \) energy storage state-of-charge
\( C(k) \) time-varying import tariff
\( C_f \) feed-in tariff
\( C_{\text{ch}} \) energy storage life-cycle cost
\( C_{\text{es}}(k) \) total net cost to the customer
\( C_{\text{ES}} \) energy storage unit cost
\( \Delta t \) length of time step \( k \) in hours
\( \eta \) energy storage charging/discharging efficiency
\( n_{\text{cycles}} \) energy storage unit rated cycles over lifetime
\( P_{\text{max}} \) energy storage maximum charging power in kW
\( P_{\text{max}} \) energy storage maximum discharging power in kW
\( \text{SoC}_{\text{max}} \) energy storage maximum state-of-charge in kWh
\( \text{SoC}_{\text{min}} \) energy storage minimum state-of-charge in kWh

1 Introduction

Distribution networks are currently experiencing rapid change, primarily due to the increasing prevalence of distributed energy resources (DERs), such as solar photovoltaic (PV) systems, smart appliances, electric vehicles (EVs) and electrical energy storage (ES) such as batteries. When controlled intelligently, DERs can provide several benefits to distribution network service providers (DNSPs) and the associated customers such as reduced costs, improved reliability and aiding the increase of renewable energy resources in electrical networks [1].

Solar PV systems, in particular, have seen significant adoption in the residential sector. This has been attributed to rising electricity prices, incentivised feed-in tariffs and the rapid reduction in the cost of PV modules [2]. In Australia alone, over 2 million solar PV systems (ranging in size up to 100 kW) have been installed on residential homes as of the end of 2018 [3]. That accounts for 20% of Australian houses.

While solar PV has become widespread throughout distribution networks, electrical ES has just begun to spread throughout the residential energy sector. A study on residential and commercial ES undertaken in [4] suggests that Australia may have between 150,000 and 450,000 by 2020. The Australian Energy Market Operator (AEMO) conducted a study on the projected uptake of small-scale PV and ES systems. While these systems are not currently economically viable at the residential level, AEMO expects a sharp reduction in the price of batteries over the coming years due to economies of scale. This will, in turn, lead to an increase in the uptake of residential ES with a cumulative battery storage capacity of 11,755 MWh by 2037/38 [5].

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While battery prices are expected to fall, the ability to add additional revenue streams for residential customers will greatly increase the economical viability of ES. These additional revenue streams include tariff arbitrage (purchasing energy when prices are low and using it when prices are high) and demand response through participation in a virtual power plant (VPP). Through dispatching VPPs, DNSPs can mitigate issues related to frequency instability and peak demand requirement.

The ability to add these additional revenue streams to a residential solar PV and ES system requires a control system that is capable of predicting future load, PV generation and electricity prices. Using this information, the control system can optimally control the charging and discharging of the ES to ensure the technical and economic objectives of the system are met. A review of different control systems for DERs is presented in [6]. Four main control strategies are identified throughout the literature; rule-based control (RBC), optimal control, agent-based modelling and model predictive control (MPC). MPC has been identified as one of the more popular control strategies for DERs in research due to its ability to consider the current state of a system and its predicted future states subject to disturbances such as varying electricity prices and the stochastic nature of renewable energy resources.

While MPC has been researched extensively for the control of DERs, there exists the need to quantify the benefits that MPC has on a range of residential customers with varying daily energy consumption, solar PV production and battery life-cycle costs. This research provides a framework that will allow DNSPs and residential customers alike to quantify the potential technical and economic benefits of implementing economic MPC (EMPC) for ‘typical’ residential customers using real residential load and PV...
data considering a time-of-use demand tariff and feed-in tariff. The key contributions of the proposed research are as follows:

- Development of an EMPC algorithm for the control of a residential ES unit considering time-varying tariffs and battery life-cycle cost in the optimisation.
- Statistical analysis of residential load and PV data to determine typical daily energy consumption and production characteristics for residential energy consumers.
- Evaluation of the proposed EMPC algorithm against RBC. The EMPC controller itself will also be evaluated considering the effect varying PV system size and the inclusion of a battery life-cycle cost in the optimisation has on annual electricity bills and battery energy throughout for a typical residential house.
- Evaluating the ability of the proposed EMPC algorithm to reduce peak demand across a low voltage (LV) distribution feeder when optimising for a time-of-use (TOU) tariff.

The remainder of this paper is organised as follows: Section 2 provides a background on the use of EMPC for the optimal control of DERs. Section 3 outlines the mathematical derivation of an EMPC algorithm to control a residential ES system. In Section 4, a statistical analysis of 442 residential customers with solar PV is undertaken to determine typical load consumption and PV production profiles that will be used for simulations. The EMPC controller is then simulated in Section 5 over the course of a year, highlighting the economic benefits of the controller, and it's the ability to shift peak load on a feeder with 30 residential customers. Finally, Section 6 provides a conclusion and recommendations for future work.

2 EMPC of DERs

The use of MPC for the optimal control of DERs has been extensively studied over the last several years. In general, MPC is used to optimally track a predetermined set point subject to system constraints. Examples of this classical MPC include [7], where MPC is used to optimise the operation of a residential heating, ventilation and air conditioning system with on-site thermal energy generation and storage. Another example of classical MPC is implemented in [8] to coordinate residential ES systems and on-load tap changers for voltage regulation in distribution networks. Both of these examples aim to optimally steer the system towards a set point (temperature in [7] and voltage in [8]); however, in some instances the objective may not be to track a set point but to reduce the overall operational costs of the system.

Unlike classical MPC, EMPC is used to minimise the economic costs of a system directly as opposed to deviations from a set point [9]. For this reason, EMPC has been researched extensively to control DERs for optimal economic dispatch subject to time-varying tariffs. Thermal and electrical ES are excellent candidates to apply EMPC as energy can be stored when prices are low and subsequently dispatched when prices are high.

EMPC is applied to domestic hot water systems (DHWs) in [10] for demand response and peak demand reduction. By operating the DHWS during off-peak periods when the cost of electricity is low, the EMPC is able to minimise the annual cost of the system while reducing daily peak demand and meeting the required daily demand for hot water.

Electrical ES such as batteries has garnered significant interest in the potential of optimal dispatch at the transmission, distribution and household level using EMPC. A study was undertaken in [11] for the potential of massive ES in the presence of renewable energy sources such as wind to be dispatched at the transmission level using EMPC.

The optimal control of ES using EMPC in microgrids is proposed in [12–14]. In [12], mixed-integer linear programming is utilised to reduce electrical usage costs in a microgrid while including battery operating costs and utility-oriented goals such as peak demand reduction and load smoothing. A central controller in [13] uses EMPC to control large-scale storage in a microgrid in the presence of multiple renewable generators. The EMPC controller was able to guarantee the 20-year lifetime of the battery with significant reductions in costs due to energy consumption. A distributed EMPC strategy for battery ES in microgrids is proposed in [14], whereby a microgrid power market is used to coordinate local self-interested EMPC battery controllers.

EMPC has also been used at the household level with the goal of reducing electricity bills for residential customers. Multiple optimal charge strategies for residential PV and battery ES are presented in [2]. Among the strategies was a cost minimisation strategy that utilised EMPC. This strategy was shown to provide the greatest annual reduction in electricity bills for the household. A similar strategy is presented in [15] with the added objective of peak shaving of the residential load. This is achieved by the EMPC algorithm optimising the use of ES around a TOU demand tariff. An EMPC strategy is presented in [16] to optimise combined thermal and electrical systems in a residential house. The model included a PV system, battery ES, residential building, heat pump and thermal ES. The EMPC controller was shown to reduce annual operational costs, reduce electricity consumption and increase the self-consumption of renewable energy compared to the reference PID controller.

From the literature, it is evident that significant research has been undertaken relating to the development of EMPC algorithms for the economic dispatch of DERs. However, there is still further need to evaluate the techno-economic benefits for both customer and DSNP of EMPC compared to off the shelf rule-based ES controllers. There exists a gap in understanding the benefits of EMPC when considering varying battery costs, varying PV system generating capacities and how these factors, when considering real network load and PV data, effect annual electricity cost ES longevity for residential customers.

3 MPC formulation

The following section presents an EMPC controller used to optimise the charging and discharging of residential ES under time-varying tariffs. Along with the EMPC formulation is the presentation of a simple energy model that will be used in conjunction with the EMPC and RBC controllers to evaluate the techno-economic benefits of EMPC for both customers and DSNPs alike.

3.1 Classical MPC

As was discussed in Section 2, classical MPC aims to steer a given system optimally towards a specified set point subject to various constraints. In classical MPC, linear time-invariant systems are typically represented as a state-space model in the form

\[ \dot{x}_k = Ax_k + Bu_k \]

\[ y_k = Cx_k + Du_k \]

where state vector \( x_k \in \mathbb{R}^n \), input vector \( u_k \in \mathbb{R}^m \) and output vector \( y_k \in \mathbb{R}^o \). The state matrix \( A \in \mathbb{R}^{n \times n} \), input matrix \( B \in \mathbb{R}^{n \times m} \), output matrix \( C \in \mathbb{R}^{o \times n} \) and input-output feed through the matrix \( D \in \mathbb{R}^{o \times m} \).

The objective of a model predictive controller is to obtain an optimal set of control inputs \( u_k \) that steer the system towards a reference trajectory over a finite prediction horizon (\( N \)). The performance of control inputs is quantified using a cost function, usually in the form

\[ J(x_0, u_0, u_1, \ldots, u_N) = \sum_{k=0}^{N} \left( \| x_k \|^2 + \| u_k \|^2 \right) \]

Here \( Q \) and \( R \) are the weighting matrices that relate to the input and output state vectors, respectively. Only the first optimal control action \( u_k \) is applied to the system; the rest are discarded until the next time step \( k + 1 \), when the process is repeated.
3.2 Economic MPC

When considering classical MPC, the cost function described by (3) tracks a pre-determined target. This formulation is not always suitable when a controller is aiming to optimise the economic performance of a process. For this reason, EMPC was developed [17].

EMPC employs a general cost function that allows for optimal control that is inherently tied to the system economics using the following general equation:

\[
\min \sum_{j=0}^{N-1} l_j(\tilde{x}(j), u(j)) + V_f(\tilde{x}(j + N)) \quad (4a)
\]

Subject to:

\[
\tilde{x}(j + 1) = f_d(\tilde{x}(j), u(j), 0) \quad (4b)
\]

\[
\tilde{x}(k) = x(t_k) \quad (4c)
\]

\[
(\tilde{x}(j), u(j)) \in \mathcal{Z}, \quad j = k, k + 1, \ldots, k + N - 1 \quad (4d)
\]

\[
\tilde{x}(k + N) \in \mathcal{X}_f \quad (4e)
\]

The cost function related to the economic performance of the system at a given time \( k \) along the prediction horizon \( N \) is defined by \( l_j \) in (4a). Equation (4b) is used to predict the future state \( \tilde{x} \) of the system given a dynamic system model \( f_d \) and the initial state measurement defined by (4c). Equation (4d) represents the constraints on the system states and input variables. The terminal cost \( V_f \) in (4a) represents costs that extend beyond the prediction horizon with the terminal constraint defined by (4e) contained in the terminal set \( \mathcal{X}_f \).

3.3 Residential energy modelling

The following model is developed considering a residential system at a given time instant \( k \) to optimise the economic performance of the system, including battery charging and discharging power in kW, respectively. This introduces a non-linearity in the model as the SoC of the battery at time \( k + 1 \) is a function of the previous SoC at time instant \( k \) and the power supplied to or drawn from the battery. This is described using the following equation:

\[
P_{\text{load}}(k) = P_{\text{e}}(k) + P_{\text{ch}}(k) = P_{\text{dis}}(k) = P_{\text{ex}}(k) \quad (8)
\]

3.3.2 ES model: The state-of-charge (SoC) of an ES unit at time instant \( k + 1 \) is a function of the previous SoC at time instant \( k \) and the power supplied to or drawn from the battery. This is described using the following equation:

\[
\text{SoC}(k + 1) = \text{SoC}(k) - \left(\frac{P_{\text{ch}}(k) + P_{\text{dis}}(k)}{\eta_{\text{bat}}}\right)\Delta t \quad (9)
\]

SoC\((k + 1)\) is the predicted SoC of the battery at time \( k + 1 \), SoC\((k)\) is the current SoC at time \( k \), \( \eta_{\text{bat}} \) is the battery charging or discharging efficiency and \( \Delta t \) is the duration of time step \( k \) in hours.

3.3.3 Constraints: The EMPC controller must also adhere to the following inequalities:

\[
-P_{\text{ch,max}} \leq P_{\text{ch}}(k) \leq 0 \quad (10a)
\]

\[
0 \leq P_{\text{dis}}(k) \leq P_{\text{dis,max}} \quad (10b)
\]

\[
-\infty \leq P_{\text{ex}}(k) \leq 0 \quad (10c)
\]

\[
0 \leq P_{\text{im}}(k) \leq \infty \quad (10d)
\]

\[
\text{SoC min} \leq \text{SoC}(k) \leq \text{SoC max} \quad (10e)
\]

where \( P_{\text{ch,max}} \) and \( P_{\text{dis,max}} \) represent the ES unit maximum charging and discharging power in kW, respectively. SoC\(_{\text{max}}\) and SoC\(_{\text{min}}\) represent the maximum and minimum ES unit SoC in kWh, respectively.

3.4 ES life-cycle cost

The cost of importing and exporting electricity at the residential level is determined by the customers’ energy retailer. However, there exists a need to also quantify the operational costs of using an ES unit. The ES unit is quite often the most expensive asset in residential energy systems, so it is paramount to include this cost in the EMPC objective function.

The inclusion of a life-cycle cost associated with the ES unit also increases system stability, as it reduces the possibility of excessive charging and discharging of the battery, which will rapidly reduce its expected life. This is particularly important when considering the stochastic nature of residential energy consumption and solar PV output along with time-varying electricity prices.

To account for this in the control system, a $/kWh value \( C_b \) is assigned to the use of an ES unit at each time step of the prediction horizon. The equation for calculating \( C_b \) is presented in (11).

\[
C_b = \frac{C_{\text{ES}}}{2 n_{\text{cycles}}(\text{SoC}_{\text{max}} - \text{SoC}_{\text{min}})} \quad (11)
\]

\( C_b \) is required to be calculated on a case-by-case basis where \( C_{\text{ES}} \) is the total capital investment associated with the ES system, \( n_{\text{cycles}} \) is the total rated cycles of the ES unit (multiplied by 2 as a cycle is considered to be a full charge then discharge) and \( \text{SoC}_{\text{max}} \) and \( \text{SoC}_{\text{min}} \) are the maximum battery SoC and minimum SoC in kWh, respectively.

3.5 EMPC cost function

The total economic cost \( C_e \) for a residential house with solar PV and ES at any time instant \( k \) is defined using the following equation:

\[
P_{\text{load}} = P_{\text{e}}(k) + P_{\text{ch}}(k) + P_{\text{dis}}(k) + P_{\text{ex}}(k)
\]

\[
C_e(k) = P_{\text{load}}(k) + C_b
\]
\[
C_e(k) = \frac{P_{\text{im}}(k)\Delta t \times C_t(k) + P_{\text{ex}}(k)\Delta t \times C_f(k)}{+(P_{\text{dis}}(k) + P_{\text{ch}}(k))\Delta t \times C_b(k)} \tag{12}
\]

where \(C_t(k)\) is the tariff associated with importing electricity from the grid and \(C_f(k)\) is the feed-in tariff received for exporting energy to the grid.

Therefore, considering (4) and ignoring terminal costs, the EMPC objective function that is to be solved at each time interval \(k\) is described using (13). The goal of the objective function is to steer the system towards the lowest cost by controlling the \(P_{\text{ch}}(k)\) and \(P_{\text{dis}}(k)\) decision variables.

\[
J = \min_{u_k, u_{k+1}, \ldots, u_{k+N-1}} \sum_{j=k}^{N-1} C_e(k) \tag{13}
\]

Subject to: (10a)–(10e).

4  Residential customer data for analysis

To determine the benefits of EMPC for both customers and DNSPs considering varying customer PV system sizes and ES cost, network data were required. The network data obtained consists of residential gross electrical load and gross solar PV generation from an Australian DNSP. The dataset is comprised of 442 residential customers with 30 min interval data from 01/07/2018 to 30/06/2019.

Evaluating the economic benefit of the proposed EMPC controller for all 442 customers across the electrical network is infeasible due to the computational complexity of such a task. For this reason, a statistical analysis was undertaken to determine an appropriate case study customer. The statistical analysis involved summing the total energy produced and consumed for each customer over the year and subsequently dividing that value by 365 to yield the average daily energy consumption/production of each customer. This data was then used to produce the histograms presented in this section.

4.1 Load and solar PV analysis

The average daily energy consumption and production for each customer was calculated using the 30 min interval data. A histogram with 45 bins was then produced, showing the distribution of average load consumption and solar PV production across all 442 customers. The histograms for energy consumption and production are presented in Figs. 2 and 3, respectively. From the analysis, the average load consumption was 25.23 kWh with a standard deviation of 13.26 kWh and the average daily solar PV production was 27.77 kWh with a standard deviation of 7.58 kWh.

4.2 Excess PV energy

It was also important to understand the average amount of excess energy produced by the solar PV system that was not used locally. This provides an indication of how much energy is available each day to charge an ES unit. Fig. 4 shows the average excess PV energy produced daily by the set of customers is 16.02 kWh with a standard deviation of 5.85 kWh. Considering the average daily total PV production of 27.77 kWh indicates that, on average, 57.7% of the energy produced by a PV system is exported to the grid. This indicates the customers considered in this study have sufficient excess PV energy that could be used to charge an ES unit.

4.3 Energy production versus energy consumption

The ratio between the average daily energy produced and daily consumed for each customer was also analysed. This ratio assists in understanding how much energy the PV system produces in comparison to their daily energy consumption. A ratio >1 indicates that on average, the house produces more energy than it consumes; conversely, a ratio <1 indicates the house uses more energy on average than it produces.
5.1 Initial conditions and assumptions

The technical data related to the ES unit used in the simulations is shown in Table 1. The data for the residential ES unit were obtained from [18]. This particular ES unit was chosen due to its commonality throughout the DNSP’s network.

It is also assumed that the EMPC controller has a perfect prediction of the measured disturbances along the prediction horizon. That is, the EMPC controller can perfectly predict solar PV generation and customer load 24 h ahead. In a real-world implementation, these predictions would be subject to error, which in turn would affect the overall benefits of an EMPC controller. However, the purpose of this research is to highlight the maximum benefit EMPC can provide compared to other control systems subject to the same load, PV, and ES unit data.

5.2 System costs

The TOU tariff considered for the simulations is the ‘Home Time-of-Use’ tariff from [19]. The tariff consists of a morning and evening peak of 0.2869 $/kWh, midday and evening shoulder period of 0.2052 $/kWh and an off-peak period of 0.1613 $/kWh. The feed-in tariff for any energy exported to the grid is fixed at 0.11 $/kWh.

This cost for using the ES is determined using (11) with data from Table 1. The result for $C_b$ was calculated to be 0.1076 $/kWh. However, this battery life-cycle cost causes the EMPC controller never to use the ES, as it is more economically viable to export any excess solar PV energy to the grid for a feed-in tariff of 0.11 $/kWh.

Nevertheless, to highlight the effect the inclusion of battery life-cycle cost has on the usage of an ES unit over the course of a year, simulations were undertaken with a battery life-cycle cost 50% lower than the cost of 0.1076 $/kWh. Graphical representation of the system costs as a function of time is shown in Fig. 6.

5.3 Rule-based controller

To provide a benchmark to compare the EMPC controller, a rule-based controller was developed. The RBC consists of a series of conditional statements that dictate when to charge or discharge the ESU. The primary aim of the controller is to make the net consumption at the customers’ point of common coupling equal to 0 kW. Put simply, the RBC charges the battery with excess energy from the PV system and subsequently uses that energy whenever there is a net load on the house. The RBC does not take into account the varying price of electricity or battery life-cycle cost when determining whether or not to use the battery. This control methodology is generally how most off-the-shelf residential ES systems operate.

Pseudocode for the charging and discharging decisions made by the RBC controller at each time step $k$ are shown in Fig. 7.
5.4 Individual day open-loop simulations

To understand the different control actions observed between RBC and EMPC with and without a cost assigned to the battery, open-loop simulations were undertaken for a single day of the year. Using load and PV data for Customer 308 on 02/06/2019, the resultant power curve for each system in the house, as described by (8) was obtained for each control scenario. Each ES unit began the simulation with 1 kWh of charge. The resultant power curves for the RBC are presented in Fig. 8, EMPC with $C_b = 0.0$ $$/kWh is presented in Fig. 9 and finally, EMPC with $C_b = 0.0538$$ / kWh is presented in Fig. 10.

Figs. 8–10 give some key insights into how each control system dictates the charging and discharging of the ES unit. The RBC in Fig. 8 simply charges from the excess solar during the day, and then uses the ES unit to meet the evening load, even into the lowest pricing period.

The EMPC with $C_b = 0.0$ $$/kWh in Fig. 9 can be seen participating in tariff arbitrage, i.e. the ES unit charges from the grid early in the morning when the price of energy is low and subsequently uses that energy during the morning peak price between 7:00 and 9:00. Then similar to RBC, it charges using excess solar energy and discharges the battery into the evening. While energy arbitrage provides substantial financial benefits, it leads to significantly higher battery energy throughput, which could have a negative effect on battery longevity.

Finally, the EMPC with $C_b = 0.0538$$ / kWh in Fig. 10 can be seen only charging with the excess solar energy that it predicts is required to meet the evening peak period between 17:00 and 20:00. The rest of the solar PV energy is simply exported to the grid. This result is due to the controller limiting the energy throughput of the ES unit to ensure it’s longevity, a direct result of including the battery life-cycle cost in the optimisation problem.

5.5 Annual closed-loop simulations

To determine the annual costs for the customer, both the EMPC controller and the RBC controller were then simulated between 01/07/2018 and 30/06/2019 using 30 min load and PV interval data for Customer 308. A daily supply charge of $1.3958$/day [19] was considered for each scenario.

Along with varying the battery life-cycle cost, the size of Customer 308’s PV power output was scaled according to the PV/load ratio histogram in Fig. 5. Simulations were undertaken with a PV/load ratio of 1.34 ($\mu$), 2.0 (+$\sigma$) and 0.68 ($-$$\sigma$). The RBC and EMPC simulations were also compared with the annual cost of the system with just PV and no ES.

The simulations and data handling were executed using python [20]. The EMPC was executed with a time step of 30 min and a prediction and control horizon equal to 24 h. The optimal solution of the EMPC cost function (13) was calculated using the general algebraic modelling system (GAMS) software [21]. A python script would generate and execute GAMS code and then would subsequently retrieve the results of the optimisation applying the control actions to the system. The optimal results were stored and compared with the RBC results.

5.5.1 Results: Fig. 11 shows the annual electricity bill for Customer 308 across all simulation scenarios. Note that this figure reflects the cost paid by the customer to their energy retailer; therefore, the monetary cost associated with using the ES is not included in this figure. Key observations from the results are as follows:

- The EMPC controller considering $C_b = 0.0$ led to higher annual savings in all scenarios compared to the other scenarios. This is a result of the controller participating in tariff arbitrage, as shown in Fig. 9.
- The EMPC controller provides greater annual savings to customers with a less PV/load ratio. This is evident from the EMPC with a PV/load ratio of 0.68 and $C_b = 0.0$ achieving an annual saving of $102 compared to the RBC. Comparing to the...
EMPC with a PV/load ratio of 2.0 and $C_b = 0.0$, only a saving of $19 was achieved annually compared to the RBC.

Another key aspect of the simulations was comparing the usage of the ES unit in each scenario. Fig. 12 shows the annual energy throughput of the ES unit for each scenario that included ES. Key observations from the results are as follows:

- Energy throughput, when considering EMPC leads to comparable energy throughput for PV/load ratios regardless of PV system size.
- The inclusion of battery life-cycle cost $C_b = 0.0538$ in the optimisation problem led to a significant reduction of annual energy throughput compared to both RBC and EMPC with $C_b = 0.0$.
- Energy throughput considering RBC increases with PV system size and saturates when large PV systems are considered.

Combining the annual electricity costs from Fig. 11 and the ES energy throughput from Fig. 12 (applying the ES cost of 0.0538 $/kWh) yields Fig. 13, the total annual costs for the customer. From these results, the key observations were

- Applying EMPC with an associated battery life-cycle cost provides the greatest annual savings across all simulation scenarios.
- While EMPC with $C_b = 0.0$ appears to provide the greatest economic benefit in Fig. 11, when considering the operational costs of the battery, it leads to similar, and in the $-\sigma$ case, a worse performance than RBC. This highlights the importance of incorporating the battery life-cycle cost in the EMPC formulation for residential ES.

5.6 LV feeder level simulations

Along with quantifying the potential economic benefits of EMPC for individual customers, this research set out to touch upon the potential benefits that EMPC could provide DNSPs at the LV feeder level. One key benefit of optimising the use of ES around a TOU tariff is the ability to shift load outside of peak demand periods.

To demonstrate the ability for EMPC to shift peak load, 30 customers in a similar geographic location were chosen from the Australian DNSP's network data to represent an LV feeder in a distribution network. Of the 30 customers, 10 were assigned solar PV and an ES unit. While only ten customers were considered for this simulation, the control could be scaled to any number of customers and also make use of any time-varying tariff.

It was chosen to run a simulation using data from the 27/05/19 as this day had a large evening aggregated peak load across the 30 customers. Again using Python and GAMS, EMPC was applied to each of the 10 customers with an ES unit to obtain their net load. All ES units started the simulation with an SoC of 1 kWh and utilised the ES technical data from Table 1. The TOU tariff and feed-in tariff presented in Fig. 6 are used in the optimisation. The optimal net load obtained from GAMS for each customer was added to the net load of the 20 customers without solar PV and an ES unit to represent the total aggregated feeder load as seen by the upstream distribution transformer. Observations were then made comparing RBC across all ten ES units and EMPC across all ten ES units.

5.6.1 Results: The aggregated feeder load with RBC and the aggregated feeder load with EMPC are shown in Fig. 14.

From Fig. 14, it is evident the EMPC has significantly lower peak demand in the evening than the RBC. During the peak demand period between 17:00 and 20:00, the EMPC controller had, on average, a reduction in aggregated demand across the 30 customers of 22% compared to the RBC. The maximum daily peak demand was reduced from 84 kW in the RBC case to 70 kW in the EMPC case. The reduction in peak demand was achieved by the EMPC algorithm predicting the large evening peak load and
subsequently pre-charging the ES units in the morning between 0:00 and 7:00. This effectively shifted the peak load and flattened the aggregated load profile across the 30 customers.

Implementing EMPC on ES units in distribution networks could assist DNSPs in deferring the need for network augmentation due to increased demand. These savings could subsequently be passed on to their customers, providing further financial benefits compared to off-the-shelf, uncoordinated RBC.

6 Conclusion
This paper evaluated the benefits of an EMPC controller for residential ES systems. The controller was shown to provide a greater reduction in annual electricity costs for all PV/load ratios (0.68, 1.34, 2.0) compared to standalone PV systems and ES systems that utilise RBC.

When considering battery life-cycle cost, the EMPC controller was shown to provide a significant reduction in battery energy throughput with the average (µ) scenario, showing a 55% reduction in throughput compared to RBC, highlighting the ability for the EMPC algorithm to increase battery longevity. When including the annual operational costs of using the battery along with the customer annual electricity bill, EMPC, with the battery cost included in the objective function, provides the greatest annual savings across all scenarios.

When the EMPC algorithm was implemented across 10 customers in a 30 customer dataset, it was shown to effectively flatten the aggregated feeder demand profile, with an evening peak demand reduction of 22% compared to RBC.

Future work for this research includes coordinating multiple ES units and PV generators to participate in voltage regulation and demand response at the network level. Also, the inclusion of deferrable loads such as air conditioning systems and EV chargers into the EMPC formulation.

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