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POWER STORAGE MODELING FOR RENEWABLE ENERGY SYSTEMS

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ABSTRACT

Renewable energy production is increasing, and the cost of power storage is decreasing, enabling users to exercise control over their power consumption from the electricity grid. To achieve partial or complete energy independence, consumers need to be able to calculate the energy storage required to cover periods when renewable power is not being produced. To address this need, a model is introduced which determines energy storage characteristics from a single simulation of an energy production system. From this model, the optimal storage size necessary for a required level of grid-independence can be calculated quickly, to a high degree of accuracy. By using existing data, no user estimation of demand parameters is required, making this model accessible to non-specialists. The optimal battery size for a domestic photovoltaic - battery system under varying demand and production scenarios is analysed and the accuracy and computational performance of the model assessed.

1 INTRODUCTION

Renewable energy production and storage is increasing world-wide. This is a phenomenon occurring at all levels of energy use: at a domestic level by individuals and families; at a company level, including factories; and across geographic regions and nationally (D'Aprile et al. 2016; Ren et al. 2016). This trend has been driven by many factors, including environmental and energy security concerns, and the steady decrease in the cost of technologies required to produce and store power.

The most prominent mode of renewable energy production is photovoltaic (PV). The steady decrease in production cost of solar panels, improvements in PV technology over the past decade (Razykov et al. 2011) have lead to a proliferation of this technology amongst consumers at all levels of consumption. Additionally, the cost of battery production has decreased steadily, (Bilgili et al. 2015) and the introduction of consumer-oriented products, for example, the Tesla Power Wall (Tesla Inc. 2018), has enabled consumers to exercise more control over their consumption of electricity from national power grids. This includes selective connection (for example, to augment personal energy production by renewable energy) to complete energy self-sufficiency, that is, disconnection from the national grid, in the most extreme case.

A fundamental question for any consumer contemplating partial or total energy independence is battery size. This is a non-trivial problem as it depends on the magnitude, variability, and covariance of energy production and consumption. Production is a function of system size, location and climate, as well as being subject to the vagaries of weather, including day-to-day as well as seasonal fluctuations. Daily demand patterns also influence battery size. For example, household demand typically peaks after sunset, necessitating larger storage than would be the case if demand were to peak during daylight hours - as may be the case for an office or factory. A consequence of these factors is that it is not possible to express the variables required to determine battery size in a simple enough functional form in order to derive a tractable stochastic model for battery size.

To address this limitation, this paper introduces a simulation-based model to determine the battery size required for a chosen level of system independence (reliability). The model integrates energy production, storage and consumption by a discrete-event simulation of an *unconstrained* production - demand process. Modeled in this way, the energy shortfall resulting from this system is identified. That is, periods when current energy production is insufficient to meet demand and would be met by battery or other energy storage. Random sampling of this process enables the energy shortfall distribution to be evaluated quickly, to a high degree of accuracy. The amount of energy storage (battery size) for a required level of energy reliability can then be determined efficiently from this shortfall distribution.

Inputs to the model for real (existing systems) are historical energy consumption, and energy production time series. For example, energy use data would typically be recorded by a Smart Meter. If an energy production system was in place, historical production data could be used. In this situation, no user modeling of any system parameters is required. For more speculative systems, such as during the project planning stage, production data could be estimated or imputed from other sources. For example, the data used to model to photovoltaic energy production for the example and analysis in this paper was calculated from public domain climate and solar data repositories.

Using the energy shortfall model, a user can evaluate the necessary investment in energy storage based on: their demand profile, investment in energy production capability, and proportion of user demand to be met by the system. In this way, a user can optimise their investment in renewable energy based on preference and cost, subject to constraints imposed by consumption pattern, climate and geographic location.

The following section describes current approaches to determining energy storgage requirements and energy supply reliability. The production - inventory model underpinning the energy storage model, and the adaptation of this for energy modeling is presented in Section 3. Specific adaptations for a domestic photovoltaic - battery system, and computational experiments illustrate the model in Section 4, and the accuracy and computational performance of the model discussed. Section 5 summarises the research and presents future research directions.

2 ENERGY STORAGE MODELING

The design and implementation of energy storage systems has received increased attention in recent years, in line the uptake of renewable energy production. Many novel approaches for the large scale storage of electrical energy are currently undergoing research and development, including gravitational, mechanical, thermal, and chemical systems (Letcher 2016). For smaller industrial and domestic applications, battery technologies have become the major form of energy storage due to decreasing cost, as well as their relative compactness and modularity, and ease of integration with existing power systems (Leadbetter and Swan 2012b). Models for energy storage sizing vary in their motivation, but include concerns such as demand smoothing, peak load reduction, economic concerns (such as cost minimisation) for grid integrated systems, or energy supply reliability for independent (grid disconnected) systems. A common concern for all energy systems is service reliability. That is, the ability to provide power when it is required. The means by which this currently addressed in system size planning is now briefly discussed.

Optimisation models form the basis for the design and planning the operation of many large integrated energy production - storage systems. In these models, failure to supply is introduced into the objective function as a cost, either as a penalty, or as the expense of obtaining power from an alternative source. For example, Sigrist et al. (2013) model the energy storage systems requirements for isolated, primarily wind power generation, systems using mixed integer linear optimisation. The objective is to make weekly plans that minimize energy storage costs, subject to hourly demand and production requirements using a mix of storage technologies. For this isolated system supply security (reliability) is represented as a cost in the optimisation model to obtain energy from alternative sources. In a similar vein, (Berrada and Loudiyi 2016) use non-linear optimization to calculate the storage and production capacity of grid-integrated solar/wind energy farms. The objective function is revenue maximisation, and service in this model is the amount of stored energy available for sale into the power grid. In this case the cost of failure to supply is opportunity loss. In these and similar models, the probability the system fails to supply can be derived from the optimal plan. However, these models require complex optimisation, which is computationally intensive and accessible only to specialists.

Discrete-event simulation-based optimisation is an alternative approach for evaluating the reliability of energy production - supply systems. Ekren and Ekren (2008) model the storage capacity required to obtain energy self-sufficiency for an isolated solar and wind powered installation. The objective function is total power cost minimisation (taking into account plant cost and operation). Service reliability is factored into this model as a cost premium for providing energy from an external source weighted by a loss of load probability. System operation is evaluated across a variety of parameter combinations using discrete-event simulation, from which an optimal parameter combination is found using response surface methodology, or simulated annealing (Ekren and Ekren 2010). Leadbetter and Swan (2012a) model the battery capacity necessary to reduce peak demand (peak shaving). Service reliability is calculated from instances of failure, that is, when the household is unable to meet demand using stored energy. Multiple simulation trials of household operation at varying battery/inverter settings enable the construction of iso-failure plots, from which optimal system characteristics can be determined for a desired level of peak demand offset. A limitation of using simulation models in this way for optimisation is the inability of the simulation model to be used as a basis for determining the functional form for the factors controlling supply reliability without resorting to multiple trials to evaluate the input parameter space. This requires multiple trials, again making the modeling also computationally expensive. In the model developed in this paper, a method requiring only single simulation of the production-supply system is introduced, making the optimisation highly efficient.

Schneider et al. (2016) analyse the energy storage requirements of an apartment building from an inventory modeling perspective. Residual load data, (energy produced from renewable sources, less user demand) to be supplied from the grid, is collected over one year. This forms the basis for constructing an empirical shortfall distribution from which storage size can be optimised based on the costs of energy production, storage and alternative energy supply using a single period (Newsvendor type) inventory model (Hopp and Spearman 2011). Although this approach captures the volatility of energy production and demand, every day starts anew under the assumptions of a single period model, therefore energy stored day to day is not captured, and the effect on storage of successive days of under production, for example, is not captured. To address this, a multi-period model is implemented, which provides a better estimation of energy shortfall. to eliminate the need to estimate demand parameters we simulate directly from user data.

3 PRODUCTION-INVENTORY MODEL FOR ENERGY STORAGE

The model for energy production and storage developed in this paper is based on a multi-period constrained production-inventory system intended, at least implicitly, for physical systems. This section introduces the fundamental discrete-event model and then presents adaptations for approximating energy production and storage systems, where demand and production are continuous and likely to be time-phased. The complete algorithm for simulating this system is then described.

3.1 Constrained Production-Inventory Model

The constrained production-inventory model for physical systems is based on the protocol that at each discrete time period, customer demand is supplied either by production during that time period, or by a combination of production and stock from inventory. If production during any period exceeds demand, then that excess can be put into inventory for future use. Production is constrained, with the consequence that if demand in any period is sufficiently large that it cannot be serviced by current production and stock held in inventory then a *stockout* results. This may result in either a lost sale, or a backorder for supply in a later period. A typical approach to managing these systems is to determine a *target level*, or ideal maximum inventory level, in order that an acceptable level of service is achieved (Muckstadt and Sapra

2010). To calculate the required target level, for a desired level of service in a production system, it is necessary to model the probability distribution of the *inventory shortfall*. This is the amount by which the safety stock falls short of the target level at the end of each production-supply cycle.

In a multi-period system, the inventory shortfall, V, is defined by the recursive relationship

$$V_t = \max(V_{t-1} + D_t - P_t, 0), \tag{1}$$

where D_t and P_t are demand and production at time t respectively. Demand at each period D_t, is an independent random variable. Production at each period is determined as the amount required to supply demand in the current period, and restore the end of period inventory to the target level, subject to a constraint, C, thus $P_t < C$. The condition that $E(D) < C$ means that an infinite backlog of unmet demand does not build up, hence the process is ergodic, and a steady state distribution exists for V (Muckstadt and Sapra 2010).

The mass exponential distribution has been shown to be a highly accurate approximation of the shortfall distribtion under a wide variety of demand distributions (Glasserman 1997; Roundy and Muckstadt 2000; Muckstadt and Sapra 2010). This is defined for $V \geq 0$ as $P(V = 0) = P_0$, and the remainder being exponentially distributed with mean γ^{-1}, that is, $P(V = v) = \overline{P}_0 \gamma e^{-\gamma v}$. The complementary cumulative distribution function, defining the probability that the shortfall will exceed v, is

$$\overline{F}_V(v) = \begin{cases} \overline{P}_0 e^{-\gamma v}, & v > 0. \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

This enables the target inventory level necessary to give a required service level (the probability that demand in any period is not met - Type I service) to be calculated as

$$\text{Target Inventory Level} = -\gamma \cdot ln\left(\frac{1 - \text{Service Level}}{\overline{P}_0}\right), \overline{P}_0 \neq 0.$$

Analytical methods for evaluating the parameters of Equation 2 are given by Glasserman (1997) and Roundy and Muckstadt (2000), which are accurate when the coefficient of demand variation is less than 2, and the probability distribution function for demand is expressible in analytical form. Recent research by Betts (2014) introduced a highly efficient method for parameter estimation in which the shortfall distribution is created empirically by random sampling from a single unconstrained simulation of production system. Calculating service levels directly from the modeled shortfall distribution is a much faster form of simulation-optimisation than simulating the system under varying target levels to find the one that achieves the desired service.

The parameters of the mass exponential distribution are estimated using efficient computational methods. This approach eliminates the need to express the demand distribution in analytical form by simulating demand directly from the data. The new model also been shown to remain highly accurate at very high levels of demand variability. These factors make this new simulation-based model highly suitable for energy production systems modeling, where highly variable demand *and* production result in high process variability, and where historical demand and production are known, but in many cases impossible to express in a tractable functional form. Adaptations of this model for energy systems are now introduced.

3.2 Adaptations for Renewable Energy Systems Modeling

To better model renewable energy production and storage, the following modifications to the original discrete-event simulation of a physical production and inventory system are proposed:

- **Shorter discrete-event time intervals** achieved by subdividing the typically daily time steps in physical production inventory systems more closely approximate the continuous time-varying process of power production and consumption.

- **Stochastic production** typical of renewable energy systems (for example solar, wind, wave) replaces constrained production in the original model. Thus, P_t is now a random variable. This does not materially affect the behavior of Equation 1 and the resulting shortfall distribution despite increasing the variance of the modified process to $Var(D) + Var(P)$, compared with $Var(D)$ previously.

- **Time-phased demand and production** reflect periodic (typically daily) patterns of energy consumption and production violates the assumptions that D_t is an i,i,d random variable. To avoid this bias in modeling the shortfall distribution, the sampling rate of the inventory shortfall in the simulation model is set low enough to ensure that consecutive sampled variables are effectively independent.

- **Storage losses** in power systems mean that, compared with using energy directly, as it is created, only a proportion of the energy stored can be retrieved. This is the *round trip efficiency* of the storage system, B. Taking this into account, Equation 1 becomes

$$V_t = \begin{cases} \max(V_{t-1} + D_t - P_t, 0), & D_t \geq P_t \\ \max(V_{t-1} + B(D_t - P_t), 0) & D_t < P_t. \end{cases}$$

- **Latency** in the conversion of stored energy to usable power is typical of many non-battery energy storage systems. However, assumptions of the original model remain valid even under stochastic production delay (Muckstadt and Sapra 2010), enabling these technologies to be modeled.

3.3 Simulation Model for Energy Storage Level

Figure 1, presents the complete model for determining the parameters of the energy shortfall distribution by simulation directly from power production and demand data. This distribution is then used to calculate the storage level necessary to provide a power supply at a specified reliability. The assumptions underpinning the discrete-event simulation model are first described:

- **Time resolution** of the simulation is determined by the granularity of the demand or production input data streams, whichever is the finest. In the model following, the time frame evaluated is assumed to be composed of an arbitrary number of *days*, each of which consists of *n* discrete *time intervals*. Inputs to the model are either historical time series data of consumption and production, or modeled data.

- **The daily cycle** of energy production and consumption is reflected in, the model by simulating each day as time sequenced iterations through the course of the day at the finest resolution of the data.

- **Daily demand and production** are sampled randomly and independently to capture the systematic interaction between these factors over the longer term in the presence of day-to-day variation. That is, *days* for production are chosen at random, and independently of *days* for consumption.

- **Energy storage time evolution** is determined by the succesive daily production-supply cycles. The model implicitly assumes that all demand can be supplied, thus an infinite shortfall is theoretically possible. Demand is either supplied from energy produced during the current period, or from stored energy, or a combination of the two. Excess energy produced is stored, reducing the energy shortfall. Storage is capped (by convention, at 0, reflecting the as yet unknown energy target level) so that excess energy produced is discarded. This reflects energy that could be sold to the energy grid.

- **The shortfall distribution sampling** occurs at random, at a sufficiently low rate to eliminate correlation between successive sampled points.

Figure 1 shows the algorithm for Discrete-Event simulation model of the energy shortfall distribution parameters P_0 and γ, the following terminology is used: the time interval to be evaluated, I, consists of a number of *days*, with each day consisting of *n periods*. Production and demand days are independently chosen at random. Days are subdivided into n time periods. Thus demand and production over each day are $D_{d,t}$, $P_{d',t}$ respectively. N samples are obtained. k sets threshold for sampling, and is set at 0.001 in the trials that follow, so that samples are taken every 1000 iterations on average. The shortfall array is then sorted into ascending order. To estimate P_0 and γ, binary division is used to find the break point, X, where the lower group, $V_0, \ldots, V_X$, are the zeros from which P_0 is calculated. γ is determined from the the upper group $V^H = V_{X+1}, \ldots V_N$ by fitting a regression of V_H against its log-transformed fractiles with intercept ≈ 0 and finding the gradient (Fraile and Garca-Ortega 2005; Betts 2014).

Initialize: $V_t = 0$; Initialize array to store V_t: $\mathbf{V}[\,] = \emptyset$; $s = 1$
repeat
randomly choose demand day: $D_d, d \in I$
randomly choose production day: $P_{d'}, d' \in I$
  for $t = 1$ to n **do**
    $$V_t = \begin{cases} \max(V_{t-1} + D_t - P_t, 0), & D_t \geq P_t \\ \max(V_{t-1} + B(D_t - P_t), 0) & D_t < P_t. \end{cases}$$
    if $\text{rand}(0,1) < k$ then $\mathbf{V}[s] = V_t$; $s = s + 1$
  next
until $s = N$
sort $\mathbf{V}[\,]$ into ascending order
if all $\mathbf{V}[\,] = 0$ then $P_0 = 0, \gamma = 0$
else set $x_{low} = 1$, $x_{high} = N$, $x_{mid} = trunc((x_{low} + x_{high})/2)$
repeat
  if intercept $V^H(X_{low}) < 0$ and intercept $V^H(X_{mid}) < 0$ **then**
    $X_{low} = X_{mid}$
  else
    $X_{high} = X_{mid}$
$x_{mid} = trunc((x_{low} + x_{high})/2)$
until $X_{low} = X_{mid}$ or $X_{high} = X_{mid}$
$P_0 = X_{mid}/N$ and γ = gradient $V^H(X_{mid})$

Figure 1: Discrete-Event simulation model of the energy shortfall distribution parameters P_0 and γ.

4 EXPERIMENTAL RESULTS FOR A DOMESTIC PHOTOVOLTAIC-BATTERY SYSTEM

The model is now illustrated by modeling the battery requirements for a domestic photovolatic energy system. For this simplified system, electrical energy collected by solar panels is either used directly, or stored in (lithium-ion type) batteries for later use. Power is delivered to household via an inverter, which converts DC power to AC at the voltage required for domestic use. The system is managed by a simple controller.

Energy consumption data is based on historical use. Energy production and storage is based on a theoretical PV system, using publicly available solar exposure data and typical system characteristics. Data sources and characteristics of the data are first outlined. The specific adaptations to Figure 1 to implement theoretical solar production and storage are then described. Experimental design and results are then discussed.

The performance of the simulation model was evaluated by measuring the accuracy of predicted battery size necessary to achieve a specified service level for 10 households, based on desired service reliability (grid independence), historical energy consumption (shown in Figure 2), and PV system size. Because solar exposure varies greatly over the year, as shown in Figure 3, the model was tested over shorter periods, corresponding high, low or transitional solar exposure. Battery size was calculated over “seasons” based on the solar cycle. Each season was approximately 91 days in duration centered on the southern hemisphere summer and winter solstices (December 22 and June 22 respectively), and autumnal and vernal equinoxes (March 22 and September 22 respectively).

4.1 Demand and Production Data

Historical household consumption used in the experiments that follow, was extracted from a publicly available data set released as part of the Govhack Australia (2016) hackathon. The data consists of household consumption recorded at 30 minute intervals, daily over one year (2015), for 10 households in the Sydney region, Australia. Figure 1 shows total daily consumption (kWh), by season, for each of these households. Both the average consumption and seasonal use patterns vary between households with peak demands typically occurring during summer or winter. Intraday power consumption (not shown) also varies, with morning and evening peaks in demand being typical.

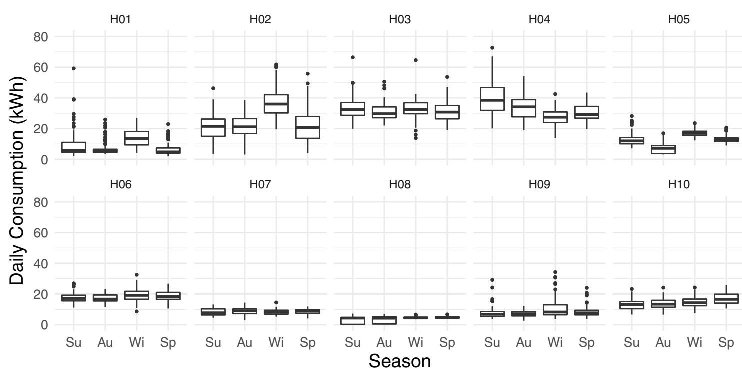

Figure 2: Total daily household consumption (kWh) by season, for 10 households.

Solar energy production is calculated from daily solar exposure during sunlight hours. This data was all obtained from public sources. Daily solar exposure for the Sydney region is published by the Australian Government, Bureau of Meteorology (2015). Daily sunrise and sunset times are published by Geoscience Australia (2015). Solar data for the year 2015 was used in the experiments that follow. Figure 3 shows daily solar exposure in (MJm^{-2}) over the year. In the modeling that follows it is assumed that solar intensity varies over the day as a sinusoidal function from sunrise to sunset. Analysis of total daily household demand

and total daily exposure showed that these had a very low correlation, in the range $|r| < 0.2$. Accordingly in the experiments following, daily demand and solar exposure are sampled independently.

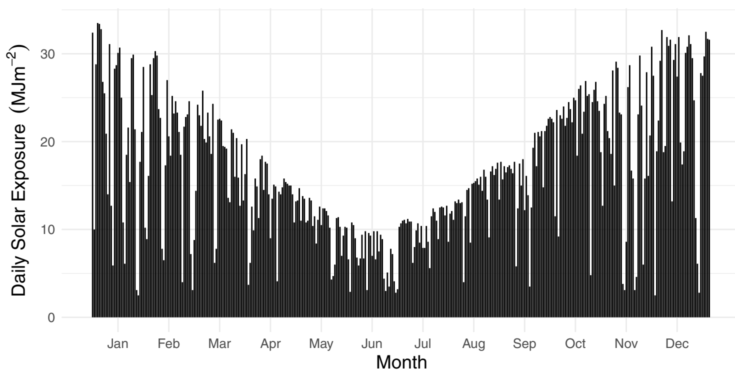

Figure 3: Daily solar exposure (MJm^{-2}) over one year.

4.2 Modeling Solar Energy Production and Storage

Solar energy production (kWh) is calculated as a function of the following inputs: the day of the year, d; the time of day, t, solar radiation over the whole day, R_d, (MJm^{-2}), latitude, L°, solar panel tilt, T°, system energy production capacity, Z, (kW); and system solar to electrical energy conversion efficiency $E\%$.

Daily solar exposure relative to latitude and panel tilt is

$$R^*_d = \frac{R\, sin(\alpha) Sin(\alpha + T)}{sin(\alpha)}, \text{ where } \alpha = 90 - L + 23.45^\circ\, sin(\frac{360^\circ}{365}(284 + d))$$

(Pveducation.Org 2018). Total daily solar exposure is calculated at 30 minute intervals between sunrise, and sunset, SR_d and SS_d respectively, since this is the time resolution set by the consumption data, assuming a sinusoidal intensity over the day.

$$R^*_{d,t} = \begin{cases} R^*_d \cdot sin\left(\frac{(t - SR_d) \cdot 180^\circ}{SS_d - SR_d}\right) \cdot \frac{\pi}{4 \cdot (SS_d - SR_d)}, & SR_d < t < SS_d \\ 0, & \text{otherwise.} \end{cases}$$

Thus, for a system of size ZkW, total energy (kWh) produced over each 30 minute time interval is

$$P_{d,t} = R^*_{d,t} \cdot Z \cdot E.$$

4.3 Design of Experiments

The factors varied between trials were: desired service reliability (the probability that power demanded would be supplied), which was set at 90%, 95%, 99% and 99.9%; and PV system sizes, at $Z = 5$, 10 and 20kW. Trials were not run when the expected production capacity of the PV system was not sufficient to meet expected household demand over a particular season. 150 repetitions were run at each feasible parameter combination. System parameters determining production and storage efficiency were not varied between trials. These were: the latitude of Sydney $L = -33.50^\circ$; panel tilt toward north $T = 33.50^\circ$

(giving maximum energy production over the year). Solar energy to electrical energy conversion efficiency, $E = 0.15$; and battery round trip efficiency, $B = 0.85$, were estimated to be values typical of current PV-battery systems. See, for example, National Renewable Energy Laboratory (2018).

The following simulation run length and sampling parameters were adopted from Betts (2014) as values giving a high level of accuracy, beyond which only a small increase in accuracy could be obtained at a high computational cost. 10,000 samples were collected to model the shortfall distribution (V) in each trial. The sampling rate was $k = 0.001$, that is, one sample was obtained every 1000 iterations, on average. This equates to a run length of approximately 10,000,000 iterations of the production - demand cycle in the initial simulation, from which the shortfall distribution parameters are estimated (figure 1). A second (test) simulation of the system, to measure the accuracy of the predicted battery size was run for 10,000 iterations. At these parameter setting, the total time to run the simulation - optimisation model, including accuracy testing, was of the order of 30 seconds on a 2.4 Ghz iMac.

4.4 Results

The accuracy of the predicted battery size was tested by re-running the simulation of the system described in figure 1, but with a battery of the recommended size in place, and recording the Type I service level obtained. The mean absolute error (MAE) between predicted service level (desired reliability), and calculated service reliability (from the test simulation), by PV system size, season, desired service reliability and household, is shown in Table 1. Empty cells correspond to parameter combinations where expected energy production was insufficient to meet expected energy demand.

Model validity was evaluated by comparing the battery size recommendations of the current model against those published by a variety of vendors and consumer information services including Tesla (Tesla Inc. 2018) and Solar Choice (James Martin II 2018). Although these resources could not evaluate battery size at the level of specificity of the trials reported (for example, with respect to service level, seasonal effect, PV system size and demand variation), trial results were in agreement with their general recommendations. Model stability was evaluated by calculating the coefficient of variation of the recommended battery size over all repetitions at each parameter combination. This was 0.015 on average for all trials reported, indicating a high level of stability across the parameter values evaluated.

Table 1 shows that service level prediction accuracy decreases as the constraint of the energy production system decreases, that is, for a given service level, increasing the size of the PV system reduces the accuracy of predictions. This is because the approximation of the energy shortfall by the mass exponential distribution becomes more accurate towards the tail of the distribution, which is achieved at higher service level fractiles, or under increased production constraint (Glasserman 1997; Roundy and Muckstadt 2000). At the lowest level of service reliability tested, 90% the MAE of the predicted reliablity is quite low, of the order of 3%,(0.029), thus storage system recommendations made at this level of reliability would need to exercise caution. However, for tests at 95% service reliability and above, the predictions have a MAE of of 0.005, or 0.5%. At the highest levels of service reliability, model accuracy is greatest. Thus, the model is most useful for situations where grid-equivalent supply reliability (greater than 99.99%) is required. Differences in model accuracy between households at all factor levels suggests that the effect of intra-day demand variation on the shortfall distribution should be explored further.

5 SUMMARY AND CONCLUSION

This paper has introduced a discrete-event simulation-based model to determine the storage level required to achieve a desired level energy service reliability for a renewable energy system. The parameters of the energy shortfall distribution are estimated by sampling from a single simulation of the demand - production system, from which the energy storage required for a required level of service reliability can be calculated directly. Computational testing of the service reliability given by the predicted battery size shows that the accuracy of the model increases with desired service reliability. The model is highly accurate at service levels approaching grid reliability. Because the output of the model describes the parameters of the energy shortfall distribution, a user can evaluate the performance of a battery of any size. In this way the service level given by a battery of a fixed size can be calculated over the year, enabling the relative costs and benefits of an investment in batteries to be evaluated.

Table 1: Mean Absolute Error: predicted *vs* actual service reliability, by PV system size, season, desired service reliability (SR) and household (HH).

		PV System Size (kW)											
		5				**10**				**20**			
		Season											
HH	**SR**	**Su**	**Au**	**Wi**	**Sp**	**Su**	**Au**	**Wi**	**Sp**	**Su**	**Au**	**Wi**	**Sp**
H01	**0.9**	0.0692	-	-	-	0.0126	0.0051	0.0143	0.0137	0.0199	0.0329	0.0826	0.0643
	0.95	0.0355	-	-	-	0.0026	0.0068	0.0033	0.0083	0.0113	0.0082	0.0085	0.0135
	0.99	0.0074	-	-	-	0.0017	0.0020	0.0018	0.0011	0.0014	0.0077	0.0081	0.0072
	0.999	0.0012	-	-	-	0.0004	0.0004	0.0005	0.0004	0.0006	0.0009	0.0010	0.0009
H02	**0.9**	0.0257	0.0059	-	0.0093	0.0176	0.0265	0.0068	0.0102	0.0226	0.0448	0.0629	0.0117
	0.95	0.0123	0.0026	-	0.0033	0.0077	0.0038	0.0051	0.0092	0.0071	0.0134	0.0024	0.0048
	0.99	0.0032	0.0016	-	0.0023	0.0014	0.0045	0.0020	0.0049	0.0014	0.0054	0.0070	0.0020
	0.999	0.0008	0.0004	-	0.0004	0.0005	0.0027	0.0005	0.0004	0.0007	0.0030	0.0009	0.0008
H03	**0.9**	-	-	-	-	0.0207	0.0249	-	0.0243	0.0186	0.0036	0.0588	0.0038
	0.95	-	-	-	-	0.0102	0.0127	-	0.0118	0.0058	0.0098	0.0306	0.0084
	0.99	-	-	-	-	0.0024	0.0029	-	0.0022	0.0030	0.0026	0.0062	0.0009
	0.999	-	-	-	-	0.0006	0.0006	-	0.0005	0.0008	0.0004	0.0009	0.0003
H04	**0.9**	-	-	-	-	-	-	-	-	0.0128	0.0069	0.0149	0.0261
	0.95	-	-	-	-	-	-	-	-	0.0062	0.0050	0.0108	0.0130
	0.99	-	-	-	-	-	-	-	-	0.0012	0.0022	0.0030	0.0050
	0.999	-	-	-	-	-	-	-	-	0.0004	0.0005	0.0005	0.0007
H05	**0.9**	-	-	-	-	-	-	-	-	0.0237	0.0144	0.0224	0.0320
	0.95	-	-	-	-	-	-	-	-	0.0120	0.0079	0.0025	0.0161
	0.99	-	-	-	-	-	-	-	-	0.0024	0.0023	0.0029	0.0033
	0.999	-	-	-	-	-	-	-	-	0.0006	0.0004	0.0006	0.0007
H06	**0.9**	0.0554	0.0143	-	0.0363	0.0178	0.0029	0.0101	0.0238	0.0218	0.0136	0.1872	0.0418
	0.95	0.0279	0.0073	-	0.0189	0.0040	0.0062	0.0078	0.0104	0.0116	0.0062	0.0147	0.0087
	0.99	0.0061	0.0013	-	0.0042	0.0025	0.0023	0.0026	0.0046	0.0011	0.0039	0.0076	0.0085
	0.999	0.0010	0.0003	-	0.0007	0.0009	0.0004	0.0006	0.0007	0.0014	0.0009	0.0010	0.0010
H07	**0.9**	-	-	-	-	0.0137	0.0105	-	0.0268	0.0050	0.0594	0.0791	0.0426
	0.95	-	-	-	-	0.0084	0.0027	-	0.0060	0.0071	0.0064	0.0048	0.0072
	0.99	-	-	-	-	0.0023	0.0026	-	0.0042	0.0032	0.0076	0.0068	0.0084
	0.999	-	-	-	-	0.0005	0.0005	-	0.0007	0.0006	0.0010	0.0009	0.0010
H08	**0.9**	0.0146	0.0164	0.0229	0.0150	0.0113	0.0258	0.0640	0.0464	0.0324	0.0451	0.0603	0.0519
	0.95	0.0050	0.0084	0.0133	0.0126	0.0109	0.0124	0.0033	0.0085	0.0055	0.0024	0.0015	0.0051
	0.99	0.0015	0.0024	0.0036	0.0031	0.0011	0.0065	0.0077	0.0085	0.0067	0.0095	0.0097	0.0098
	0.999	0.0004	0.0005	0.0006	0.0006	0.0003	0.0008	0.0009	0.0010	0.0009	0.0010	0.0010	0.0010
H09	**0.9**	0.0110	0.0301	0.0625	0.0363	0.0309	0.0532	0.0686	0.0429	0.0442	0.0555	0.0578	0.0493
	0.95	0.0071	0.0059	0.0142	0.0028	0.0021	0.0088	0.0020	0.0089	0.0149	0.0141	0.0066	0.0095
	0.99	0.0012	0.0048	0.0053	0.0072	0.0045	0.0086	0.0078	0.0092	0.0076	0.0091	0.0080	0.0090
	0.999	0.0004	0.0006	0.0009	0.0009	0.0006	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
H10	**0.9**	0.0260	0.0103	-	0.0203	0.0399	0.0207	0.0052	0.0193	0.0419	0.0333	0.0085	0.0150
	0.95	0.0093	0.0094	-	0.0087	0.0114	0.0092	0.0047	0.0076	0.0215	0.0035	0.0134	0.0129
	0.99	0.0044	0.0026	-	0.0010	0.0031	0.0066	0.0015	0.0007	0.0022	0.0078	0.0013	0.0020
	0.999	0.0007	0.0005	-	0.0004	0.0037	0.0009	0.0004	0.0006	0.0043	0.0010	0.0007	0.0002

Variations in service level accuracy between households, especially at lower service reliability levels, indicates that further research into the effect of intra-day demands on the form of the shortfall distribution at lower fractiles may improve prediction accuracy. The sensitivity of model accuracy to the parameter settings for the computational trials, which were adopted from Betts (2014) for a physical production - inventory system, should be investigated more fully.

For the experiments in this paper, real household consumption data was used, eliminating the need to model this input. The solar energy production from solar panels was modeled, for this theoretical system, using Australian Government data from the public domain. However, for an existing PV system, time series of actual solar production could be used for simulating the shortfall distribution. In such a situation, no user estimation of any demand or production data would be required. Data from other types of renewable energy production, for example, wind generation, could be incorporated with no loss of accuracy. Because the original multi-period inventory model and subsequent simulation optimisation is robust to stochastic production delay and scale independent, the current modeling could be applied to many newer energy large scale storage technologies such as mechanical, thermal and chemical storage systems.

The current model could form the basis of web-based resource to calculate energy storage requirements, based on energy consumption data, and real or modeled energy production. The computational trials in Section 4 could be adapted for many locations in the world where solar exposure, sunrise and sunset data are routinely recorded. The ubiquity of Smart Meters means that consumption data is now recorded by energy suppliers, with this data also available to users. At the time of writing, the authors could not identify any battery size calculators available using real consumption data for individualised modeling. However, the demand for calculators, such as the National Renewable Energy Laboratory (2018) pvwatts resources for PV systems, and current interest in battery technology indicate that a calculator based on the current research may have a wide audience among renewable energy adopters.

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REFERENCES

Australian Government, Bureau of Meteorology 2015. "Climate Information For Solar Energy". http://www.Bom.Gov.Au/Climate/Data-Services/Solar-Information.Shtml. Accessed April 14th, 2018.

Berrada, A., and K. Loudiyi. 2016. "Operation, Sizing, and Economic Evaluation of Storage For Solar and Wind Power Plants". *Renewable and Sustainable Energy Reviews* 59:1117–1129.

Betts, J. M. 2014. "Calculating Target Inventory Levels For Constrained Production: A Fast Simulation-Based Approximation". *Computers & Operations Research* 49:18–27.

Bilgili, M., A. Ozbek, B. Sahin, and A. Kahraman. 2015. "An Overview of Renewable Electric Power Capacity and Progress In New Technologies In The World". *Renewable and Sustainable Energy Reviews* 49:323–334.

D'Aprile, P., J. Newman, and D. Pinner. 2016. "The New Economics of Energy Storage". Technical report, Mckinsey & Company.

Ekren, O., and B. Y. Ekren. 2008. "Size Optimization of A Pv/Wind Hybrid Energy Conversion System With Battery Storage Using Response Surface Methodology". *Applied Energy* 85(11):1086–1101.

Ekren, O., and B. Y. Ekren. 2010. "Size Optimization of A Pv/Wind Hybrid Energy Conversion System With Battery Storage Using Simulated Annealing". *Applied Energy* 87(2):592–598.

Fraile, R., and E. Garca-Ortega. 2005. "Fitting An Exponential Distribution". *Journal of Applied Meteorology* 44(10):1620–1625.

Geoscience Australia 2015. "Compute Sunrise, Sunset & Twilight Times". http://www.Ga.Gov.Au/Geodesy/Astro/Sunrise.Jsp. Accessed April 14th, 2018.

Glasserman, P. 1997. "Bounds and Asymptotics For Planning Critical Safety Stocks". *Operations Research* 45(2):244–257.

Govhack Australia 2016. "2016 Year In Review". https://www.Govhack.Org/Competition/2016-Year-In-Review/. Accessed April 14th, 2018.

Hopp, W. J., and M. L. Spearman. 2011. *Factory Physics*. Waveland Press.

James Martin II 2018. "Sizing Residential Solar & Battery Systems: A Quick Guide". https://www.solarchoice.Net.Au/Blog/Residential-Solar-Battery-System-Sizing-Quick-Guide. Accessed June 13th, 2018.

Leadbetter, J., and L. Swan. 2012a. "Battery Storage System For Residential Electricity Peak Demand Shaving". *Energy and Buildings* 55:685–692.

Leadbetter, J., and L. G. Swan. 2012b. "Selection of Battery Technology To Support Grid-Integrated Renewable Electricity". *Journal of Power Sources* 216:376–386.

Letcher, T. M. 2016. *Storing Energy*. Elsevier, Oxford.

Muckstadt, J. A., and A. Sapra. 2010. *Principles of Inventory Management*. Springer Series In Operations Research and Financial Engineering. Springer-Verlag, New York.

National Renewable Energy Laboratory 2018. "Pvwatts Calculator". http://pvwatts.Nrel.Gov/. Accessed April 14th, 2018.

Pveducation.Org 2018. "Solar Radiation On A Tilted Surface". http://www.pveducation.org/pvcdrom/properties-of-Sunlight/Solar-Radiation-On-a-tilted-surface. Accessed April 14th, 2018.

Razykov, T., C. Ferekides, D. Morel, E. Stefanakos, H. Ullal, and H. Upadhyaya. 2011. "Solar Photovoltaic Electricity: Current Status and Future Prospects". *Solar Energy* 85(8):1580 – 1608.

Ren, Z., G. Grozev, and a. Higgins. 2016. "Modelling Impact of Pv Battery Systems On Energy Consumption and Bill Savings of Australian Houses Under Alternative Tariff Structures". *Renewable Energy* 89:317–330.

Roundy, R. O., and J. A. Muckstadt. 2000. "Heuristic Computation of Periodic-Review Base Stock Inventory Policies". *Management Science* 46(1):104–109.

Schneider, M., K. Biel, S. Pfaller, H. Schaede, S. Rinderknecht, and C. H. Glock. 2016. "Using Inventory Models For Sizing Energy Storage Systems: An Interdisciplinary Approach". *Journal of Energy Storage* 8:339 – 348.

Sigrist, L., E. Lobato, and L. Rouco. 2013. "Energy Storage Systems Providing Primary Reserve and Peak Shaving In Small isolated Power Systems: An Economic Assessment". *International Journal of Electrical Power & Energy Systems* 53:675–683.

Tesla Inc. 2018. "Meet Powerwall, Your Home Battery". https://www.Tesla.com/en_au/powerwall. Accessed April 14th, 2018.

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