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# Optimising the use of a battery in a wind-diesel-battery hybrid island grid using power prediction and day-ahead optimisation

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**Abstract.** Using demand and local renewable generation data, the performance of a hybrid wind-diesel-battery island grid was assessed for a range of scheduling approaches, ranging from simple prioritising of the battery over diesel, through a simple assessment of expected day-ahead demand-wind generation balance to a day-ahead optimisation.

A key factor in the performance assessment was a nonlinear cost of using the battery, where the cost depended on the state of charge of the battery, reflecting how the life time of many batteries depends on their depth of discharge. The results suggested that a simple assessment of the day-ahead balance may increase the operational costs compared to immediate battery prioritisation but combining forecasts with optimisation can lead to reliable operational cost savings.

## Key words

Hybrid grid, Wind energy, optimisation, forecasting.

## 1. Introduction

Island communities or remote communities with no or only a weak connection to a distribution or transmission system are often highly dependent on local fossil-fuel based generation. Not only does the fuel need to be imported, posing a reliability risk, but also the fuel prices are higher than elsewhere due to the added transportation costs. For that reason, such communities could benefit substantially from using local resources for generation such as wind or PV.

A key challenge for relatively small communities is that the demand profile through a day is much more volatile than typical national profiles since individual user behaviour has a stronger influence on the overall load, in particular if there is a small number of large consumers. In addition, most renewable energy sources have their own substantial variability, which might or might not be correlated with demand. Again, the variability of renewable power is much larger if it is extracted from a small region, compared to renewable power fed into a larger network, e.g., [1]. For that reason, adding renewable generation to a small grid will pose increased requirements both, for immediate balancing as well as managing seasonal variation from demand and renewable power.

One common way to develop renewable energy for island communities is to combine renewable energy systems with diesel generators, with the aim to reduce the overall fuel consumption. This works well if the renewable contribution is fairly small and does not exceed demand too frequently. However, as typical renewable systems operate with capacity factors of well below 50% (e.g., 20 - 30% for wind turbines), this limits the net renewable contribution to a fairly moderate proportion. For more significant renewable installed capacities, one will encounter periods of residual need as well as times of substantial excess power generation. As a result, some form of energy storage is required [2]. One difficulty is that energy storage is expensive. In simple terms of hierarchy, diesel generators are cheap to acquire, Wind turbines or PV panels are more expensive but affordable, while batteries are expensive where the price is affected by both, the power rating of the battery and the energy capacity [3].

Common energy storage technologies for smaller grids are batteries as they are easy to install and among the cheapest options in terms of installation costs. However, the lifetime of many battery types depends strongly on battery usage as well as environmental conditions [4]. For example, discharging a battery to only little below capacity will have virtually no effect on the life of the battery but discharging by more than about 50% (depending on type) will reduce the life time substantially, where that deterioration of battery life is faster than linear. Therefore, exploiting a battery to its potential, even if staying within the maximum depth of discharge specified by the manufacturer, will age the battery relatively quickly and necessitate a replacement sooner. Since the battery is the most expensive component, any premature replacement will increase the total project cost substantially.

Based on this argument, it is therefore possible that it might be cheaper at a particular time of day to use the diesel generator and preserve available battery charge; or even to keep the diesel generator running even when sufficient wind power is available to charge the battery so that it can be used later on when the battery power is more valuable.

Optimisation techniques have long been used for Renewable and hybrid energy systems, though most frequently for their design and less for their day-to-day scheduling, e.g., [5,6]. However, they are frequently based on historical data and therefore assume 'perfect knowledge' whereas scheduling always occurs with imperfect knowledge of the near future. As a result, scheduling optimisation has to be coupled with stochastic modelling [7] or forecasts.

### A. Aims and objectives

The aims of this paper are to explore how likely such events are, how much they affect the hybrid system performance, and how the performance can be optimised. Considering that smaller communities have to operate a fairly small system where using expensive expert scheduling would not be possible, one of the guiding principles was that the operation of the hybrid system should only be based on readily available local information.

To explore these aims, the paper has the following objectives:

- To define a realistic island grid using measured consumption from a community, modelled wind power contribution using a local weather station, and a choice of battery and diesel installations to meet demand.
- To define a generic objective function to capture the effect of nonlinear battery costs in a clear way without getting distracted by specifying a particular technology in great detail (such as [8,9,10]).
- To provide forecasts of demand and wind power at each point of time in the operational period with a forecasting horizon of 24 hours.
- To apply various decision-making tools for adjusting the battery and diesel operation, including absolute priority of battery, very simple decision criteria based on the day-ahead energy balance, and identifying the optimum choice for the predicted supply and demand for the following 24 hours.

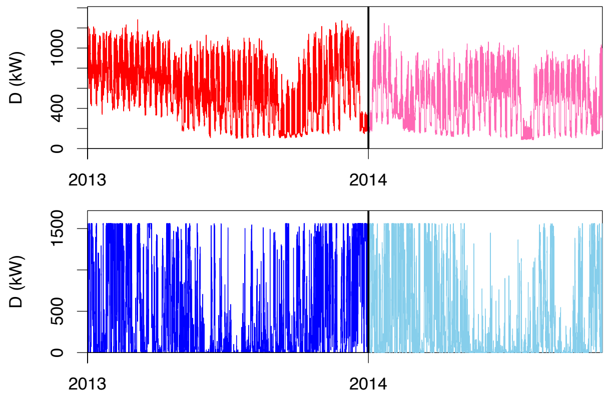


Fig. 1. Time series of (a) demand and (b) wind power.

## 2. Model description

In this section, the model will be described following the order of the objectives stated above.

### A. Data source

The available load data were a set of half-hourly consumption data for the entirety of 2013 and January 2014 to the end of October 2014, with a maximum peak demand of 1300 kW, a minimum of around 100 kW and a mean demand of 600 kW. Figure 1 shows the demand in the upper panel and the wind power in the lower panel, where the darker colours are the 2013 data used for setting up the system and for training the forecasting model, while the lighter colours show the operational period.

The available resource data were a set of hourly wind speed measurements from an anemometer 10 m above ground at a UK Meteorological Office weather station at the location of that community. To convert the single-point wind speed data to a representative wind power profile from a portfolio of small, medium and large turbines, the wind speed time series was scaled to nine hub heights between 10 m and 70 m. To each of the nine wind speed series, a random perturbation was added consistent with the spatial extent of the area available to the community, using the wind aggregation procedure from [1].

Every wind speed created in this way was then fed through a generic wind turbine performance curve with unit installed capacity, and finally averaged across the nine representations to arrive at a normalised power at each time. The overall capacity factor of this portfolio of wind was found to be $C_C$ = 30 % during 2013 and 24% during 2014.

### B. System configuration and constraints

In the present set-up, the wind energy was expected to provide around two-thirds of the consumption, of which half would be used directly, and half via the battery with a round-trip efficiency of $\eta_{rt}$ = 72%. Based on this, the installed capacity was set at

$$G_W = \frac{\langle D \rangle}{C_C}\left(\frac{1}{3} + \frac{1}{3\eta_{rt}}\right) = 1560\ \mathrm{kW} \qquad (1)$$

where $<D>$ is the mean demand and $C_C$ the capacity factor from the design/training year 2013.

The battery power rating was limited to the maximum demand while the energy capacity was one of the parameters changed in the analysis, ranging from 0.5 hours to 8 hours at full power. The diesel generator was also limited at the maximum demand.

*C. Power balancing and objective functions*

Given the demand, $D$, and relative wind power, $p_w$, the power and energy balances were ensured by

$$D = G_W p_w + P_B + P_D \qquad (2)$$

and

$$E_B(t) = E_B(t - 1h) - \begin{cases} P_B/\eta_d & , \quad P_B > 0 \\ P_B\ \eta_c & , \quad P_B < 0 \end{cases} \qquad (3)$$

where $P_B$ and $P_D$ are the battery and diesel power, respectively, $E_B$ the charge level of the battery, $\eta_d$ the discharge efficiency and $\eta_c$ the charging efficiency of the battery ($\eta_{rt} = \eta_c\eta_d$). The sign convention is such that the battery power is positive when the battery discharges and provides power to meet demand, and negative when it absorbs power from the grid. While the diesel power should always be positive, we allowed negative diesel power as a proxy of wind curtailment.

*C. Costs and objective functions*

For the final assessment of the system performance, a system cost was calculated based on annualised capital costs, annual operation and maintenance costs and diesel fuel costs. For the battery, a cost based on the required power and current level of discharge when power was drawn from the battery. For the day-ahead optimisation of the diesel and battery scheduling, only the diesel fuel costs and the battery discharge costs were considered.

Table I. – Costs for the system components

| | | units |
|---|---|---|
| Wind Turbine | | |
| Installation | 1000 | £ / kW |
| O & M | 2% | |
| Wind curtailment | 0.0025 | £ / kWh |
| diesel | | |
| Installation | 200 | £ / kW |
| O & M | 4% | |
| Fuel | 0.0025 | £ / kWh |
| Battery | | |
| Power rating | 500 | £ / kW |
| Storage size | 500 | £ / kWh |
| O & M | 4% | |
| Battery discharge | $(1 - E_B/V_B)^4$ x 0.025 | £ / kWh |
| Battery charging | 0 | £ / kWh |

Assuming a project life of 25 years, typical capital costs for wind, diesel and battery components were taken and divided by 25 years. These costs are specified as £/kW installed for wind and diesel, while the battery had a contribution to the costs in terms of £/kW as well as £/kWh of installed storage capacity. The operation and maintenance costs were specified as a percentage of the capital costs.

Rather than being concerned with accurate figures, the choice of the cost components was mainly to represent the relative costs for the components, with diesel the cheapest and the battery the most expensive. For the operational costs, the main consideration was that the fuel cost for the diesel generator was a fixed value per kWh produced while that for the battery varied from much less than diesel per kWh at high levels of available charge to more than diesel as the state of the battery approached its limit of the depth of discharge. These relative costs are summarised in Table 1.

*D. Forecasting demand and wind power*

As the variability of demand is fundamentally different from that of wind power, two different approaches were used to represent demand and wind power forecasting. Demand depends strongly on well-known behavioural patterns through the day and week, where the daily mean demand does not vary rapidly from one week to the next. It is therefore possible to simulate demand forecasting based on the smoothed actual demand of the next 24 hours, using a 3-hour moving average, but introduce a forecasting error by adding a uniformly distributed random perturbation between – 30 and + 30 kW to each hour. In effect, this turns perfect foresight into an imperfect forecast.

The wind power prediction was based on a Singular Systems Analysis (SSA) of the 2013 data [11]. The predictor was created through a Principal Component Analysis of the 2013 data using a lag window of 12 hours and then defined as the three leading Singular Vectors. This could then be used at each current time point in 2014 by taking the most recent 12 hours of wind power measurements and projecting them onto the Singular Vectors. Once in the Singular vector coordinates, dynamically similar observations from the 2013 data could be evolved forward for the forecasting horizon of 24 hours, and then re-transformed to actual wind power predictions.

*E. Scheduling approaches*

Four different scheduling approaches are compared in this analysis

1) *Priority*. During this scheduling approach no forecast of either demand or wind power is used. Instead, the use of the battery is prioritised. If there is a current surplus of wind power and the battery is not full, then that surplus is used to recharge the battery. Conversely, if the wind power is not sufficient, the battery is used first to complement the wind power,

and the diesel generator is only used if the battery is not sufficient.

2) *Persistence.* In this scenario, the demand forecast as described in §2.D is used, but it is expected that the wind power generation is constant for the next 24 hours. Using these two predictions, the residual load, $L_R = D - G_w p_w$, is calculated and then accumulated into a net electricity surplus or deficit over the next 24 hours, $E_R = \Sigma\ L_R$. If a net deficit is expected, the diesel generator is initially set to meet that deficit: $P_{D,0} = E_R$ / 24h. Then the battery is used to meet the remaining demand as far as possible, up to maximum depth of discharge, $P_B = L_R - P_{D,0}$, subject to sufficient battery power rating and remaining charge.
3) *Prediction.* The approach is the same as for the *Persistence* approach, except that the wind power prediction from the SSA predictor is used instead of assuming constant wind power.
4) *Optimised.* In this final scheduling approach, the demand prediction and SSA wind power prediction are used in a Limited-memory Broyden-Fletcher-Goldfarb-Shanno with box constraints (L-BFGS-B) optimiser [12] implemented in R through the optim() function [13]. The objective function for the optimisation was the sum of the wind curtailment, diesel fuel and battery discharge/charge costs as given in Table I over the optimisation horizon. The current residual load was then set to the values recommended for the current time step of the optimised scheduling.

### F. *Post-optimisation analysis*

After every available time step for 2014 had been scheduled according to each of the four scheduling approaches, the total usage costs for that period was calculated as the sum of the wind curtailment, diesel fuel and battery usage costs. To provide a comparable performance measure for all battery sizes explored, the operational costs for the different scheduling approaches were compared against the *Priority* scheduling and expressed as percentage differences.

As the diesel generator was only limited to the maximum demand, it was effectively unconstrained. For that reason, the maximum diesel power actually used was also evaluated, as this would affect the total system costs if the installation were tailored to that maximum. The effect of adjusting the installed diesel capacity on the overall costs was measured through the total annualised system costs using all the elements from Table I.

## 3. Results

In this section, the results from the scheduling with the battery with an available storage capacity of one hour's worth of generating at maximum demand, i.e., 1300 kWh, is presented in detail, followed by a comparison of the operational and total costs for all battery sizes explored here.

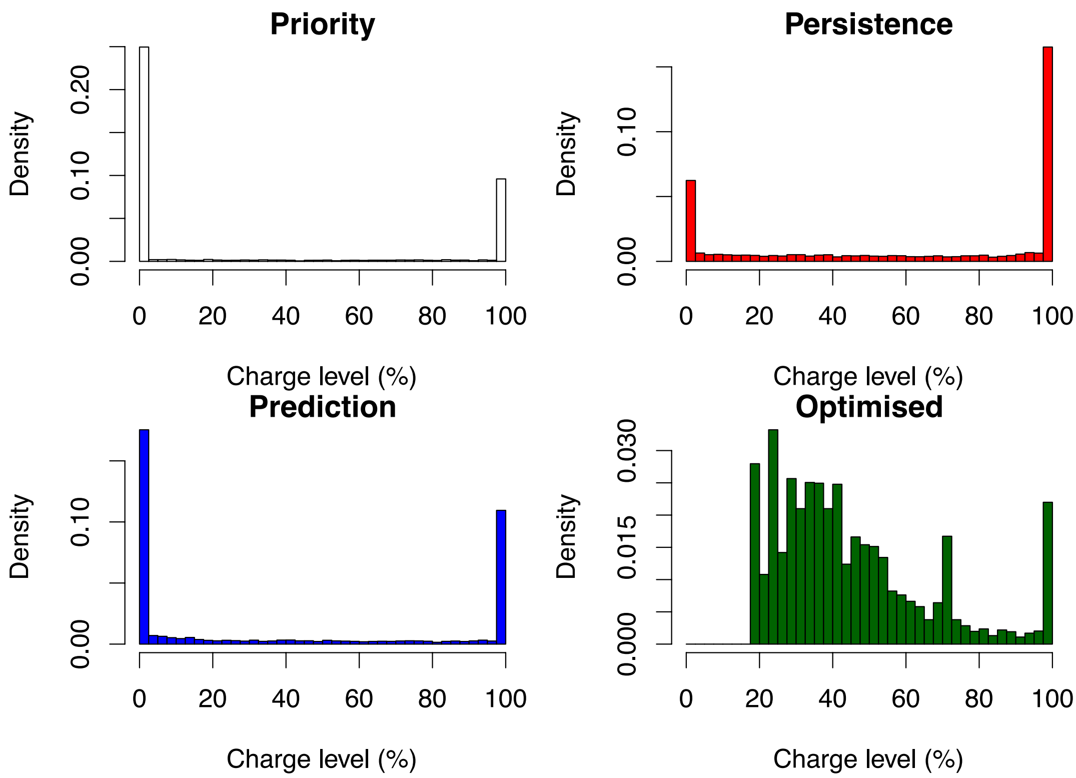

Fig. 2. Battery usage profiles as histograms of observed state of charge of small battery.

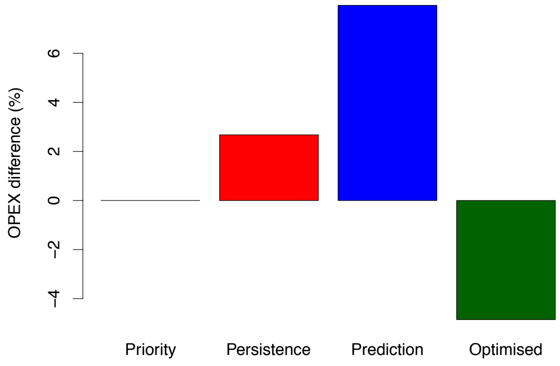


Fig. 3. Changes in operational costs relative to Priority.

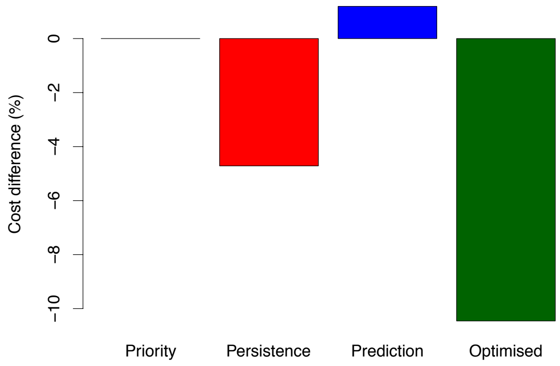


Fig. 4. Changes in total costs relative to prioritising the battery.

The pattern of the battery usage for the four different scheduling patterns is shown in Figure 2. As one might expect, prioritising the battery over diesel at all times results in a profile where the battery tends to be utilised to its capacity very quickly, so that it is either full or empty (discharged to its maximum depth of discharge) for most of the time (Fig. 2a). Specifically, the battery is empty for much more of the time than it is full. Attempting to incorporate expectations of future needs over the next 24 hours affects the balance between empty and full but does little to change the overall pattern. Here, assuming constant wind power in the *Persistence* scheme results in the battery being discharged much less frequently (Fig. 2b), whereas using the SSA predictor results in a more balanced profile (Fig. 2c).

Using optimised scheduling alters the profile substantially (Fig. 2d). As the cost of discharging the battery increases rapidly as it approaches maximum depth of discharge and exceeds the diesel costs at a state of available charge of 44%, it is not surprising that the scheduler avoids low charge levels. There appears to be almost a hard lower limit for the charge level of around 20%, but there is also a broader range of observed charge levels between that self-imposed lower limit and a full battery.

The consequences of these scheduling approaches on the operational costs are shown in Figure 3, which suggest that attempting to balance battery and diesel on expected future demand but without optimising actually increases operational costs by 2% or 8%, respectively. In contrast, combining forecasts and optimisation result in operational savings of around 5%.

In terms of total system costs, Figure 4 shows that *Persistence* decreases the annualised total costs, while the SSA prediction increases them slightly. Optimised scheduling would have resulted in total costs savings of over 10%. The savings using *Persistence* can be traced back to less demand on the battery power as well as the required installed capacity of the diesel generator. The overall savings using optimised scheduling are due to the operational savings as well as smaller power rating of the battery needed.

The overall pattern of operational percentage savings from the differing scheduling approaches does not change significantly across the range of batteries installed. This is illustrated in Figure 4 for the savings achieved through optimised scheduling, which result in relatively constant savings of between 5 and 3%.

The percentage system cost savings in Figure 5, on the other hand, depend strongly on the storage capacity of the battery. While the battery is relatively small, the savings made during the operational optimisation, together with savings from only needing a smaller power rating of the battery can be substantial. As the battery storage size increases, the battery can contribute more to the balancing over the optimisation horizon. As a consequence the optimisation utilises the battery more for the power balancing, with the consequence that the power rating increases with increasing storage volume. At some point, the increased installation costs outweigh the operational savings leading to a higher system cost.

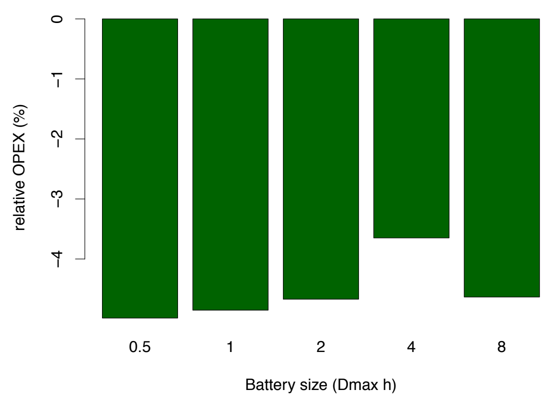


Fig. 5. Operational cost savings through optimised scheduling relative to prioritising the battery.

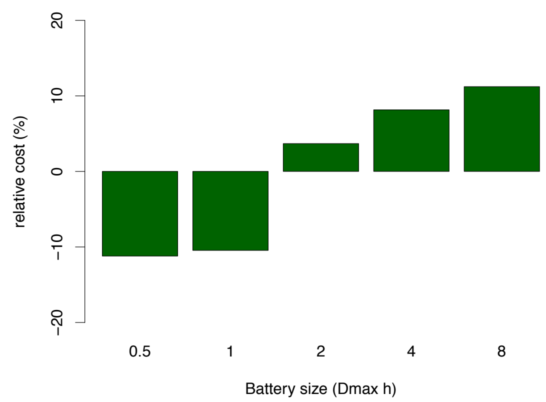


Fig. 6. Total system cost savings through optimised scheduling relative to prioritising the battery.

## 4. Conclusion

Optimum design of a hybrid Renewable Energy system is based on completely known historical resource data. Operating a hybrid system, however, takes place under conditions where both, the immediate future is not completely known, and the annual demand-resource balance may be very different from that used for the system design. The analysis of a system here, where the usage of the energy storage component is nonlinear, has shown that the short-term scheduling of such a hybrid system can be effectively optimised when combining forecasts of demand and resource with a day-ahead optimisation.

While the analysis presented here was based on measured demand and resource data, the hybrid system components and costs were highly idealised to demonstrate the principle. The key principle investigated here was that the energy storage cost varied such that the cost balance between using stored energy or fossil fuel depended on the state of the energy storage device. One aspect of this study to be refined in further work is that the capacities of the back-up generator and the energy storage power rating were effectively unconstrained. However, this allowed a post-hoc cost analysis to identify how different scheduling approaches would require different initial investments. To investigate the sensitivity of both, the total system costs and operational costs, on limited installed capacities, the next step in this analysis will be to progressively reduce the maximum power of the battery and/or the diesel generator.

Despite the generic nature of the study, the following observations appear to be robust; using demand and/or generation forecasts alone does not lead to any reliable cost savings. Operational savings are only reliably achieved across the different system designs if the forecasts are coupled with an optimisation of the scheduling according the forecasts to determine the current scheduling decisions. One important aspect of the methodologies used here are that they are fully accessible to small communities, as the forecasting and optimisation only requires locally available data, such as electricity consumption and wind energy production and can be carried out at little computational expense.


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