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Abstract: Hybrid power systems for off-grid sites are commonly designed using simulation. Operating rules for the controller dispatch strategy are defined, and a simulation uses site-specific data to find the minimum-cost system composition that satisfies the site's electricity demand. The resulting design is strongly influenced by the a priori choice of strategy. We present a new approach to design isolated sites: off-grid electricity supply optimization (OGESO). In our approach, the dispatch rules are not fixed, and we simultaneously optimize the composition and the controller strategy. A mixed integer programming model finds the optimal system composition and the optimal dispatch based on one year of deterministic hourly data. Because the optimal dispatch is complex, it is analyzed using data mining to find a practical controller strategy. Computational results on diesel-wind-battery hybrid systems demonstrate the benefits of the proposed approach.

Key Words: Optimization, wind, diesel, battery, hybrid power system, remote site, mixed integer linear programming, data mining.

1 Notation

Sets:

$s \in S$	Sources with diesel: d , wind: w and battery: b
$t \in T$	Time steps
$y \in Y$	Years of project lifetime $\|Y\|$

Parameters:

a_d	Diesel consumption slope (1)
b_d	Diesel consumption constant (1)
c^f	Diesel liter cost (\$/L)
c_s^i	Unit source s initial cost (\$)
c_s^o	Unit source s O&M cost (\$)
c_s^r	Unit source s replacement cost (\$)
$d(t)$	Length of time step t (h)
e_b	Battery efficiency (%)
e_{bsd}	Battery self-discharge (%)
E_b^{max}	One battery module maximal energy (Wh)
i	Annual actualization rate (%)
l_s	Element s lifetime ($year$ or h)
P_{bc}^{max}	Maximal charge power for a battery module (W)
P_{bd}^{max}	Maximal discharge power for a battery module (W)
P_d^{max}	Maximal power for a diesel generator (W)
$P_l(t)$	Electricity load at time t (W)
$P_w^c(w)$	Wind turbine power at wind velocity w (W)
$P_w^1(t)$	Power of a wind turbine at time t (W)
r_s^1	Number of source s replacements (1)
r_s^2	Percent of element unused (%)
u_d^{min}	Minimum use of diesel generator (%)
u_b^0	Percent of battery initial energy (%)
$w(t)$	Wind velocity at time t (W)

Variables:

$A_d(y)$	Diesel generator replacement at year y (1)
C	Annualized cost of project(\$)
C^e	Cost of evacuated power (\$)
C^f	Cost of diesel consumption (\$)
C_s^i	Initial (capital) cost of source s (\$)
C_s^o	Operation and maintenance cost of source s (\$)
C_s^r	Replacement cost of source s (\$)
C_s^s	Salvage cost of source s (\$)
D_d	Number of diesel generator operating hours (h)
E_b	Battery energy level (Wh)
$f_g(t)$	Diesel consumption at time t (L)
N_s	Number of installed units of source s (1)
$N_d(t)$	Number of diesel generators used at time t (1)
$P_s(t)$	Power exchanged at time t with source s (W)
$P_e(t)$	Power evacuated at time t (W)

2 Introduction

Isolated sites such as remote communities, factories, and military bases often need a local and autonomous power supply system because it is too expensive to connect them to the power grid. Their power supply is normally provided using diesel generation. While straightforward to implement, this technology is expensive and polluting; moreover, fuel availability may be limited and/or expensive. The recent progress in photovoltaic and wind-turbine technologies and the increasing concern for the environment motivate the use of renewable sources in such diesel-generator systems to reduce diesel consumption and to take advantage of local resources. In 1992 Vera [1] carried out a techno-economic study and concluded that a hybrid wind and diesel system could be suitable for an isolated Mexican site. After the Rio Earth Summit of 1992, the U.S. Department of Energy subsequently began the development of the HOMER simulation software [2] for the design of hybrid power systems. Wind-diesel systems are common in isolated Alaskan and Canadian sites, and they have proved their reliability and effectiveness. Kotzebue, St. Paul, and Wales in Alaska are three examples of wind-diesel systems where the kWh price is around \$0.55 compared to \$0.70 for diesel-only generation [3]. More recently, battery technology has been introduced to create diesel-wind-battery systems [4]. Although this type of hybrid system has been only rarely implemented and has yet to prove its viability, it is currently considered to have good potential for isolated Nordic sites. The site of Fairbanks in Alaska is a demonstrative successful project of a powerful saft liquid-filled Ni-Cd battery operating since 2004 and able to supply 27 MW continuously for up to five minutes [5]. Most HPS research focuses on finding the minimum-cost design able to satisfy the site's electricity demand. In this paper we consider a diesel-wind-battery (DWB) system as illustrated in Figure 1.

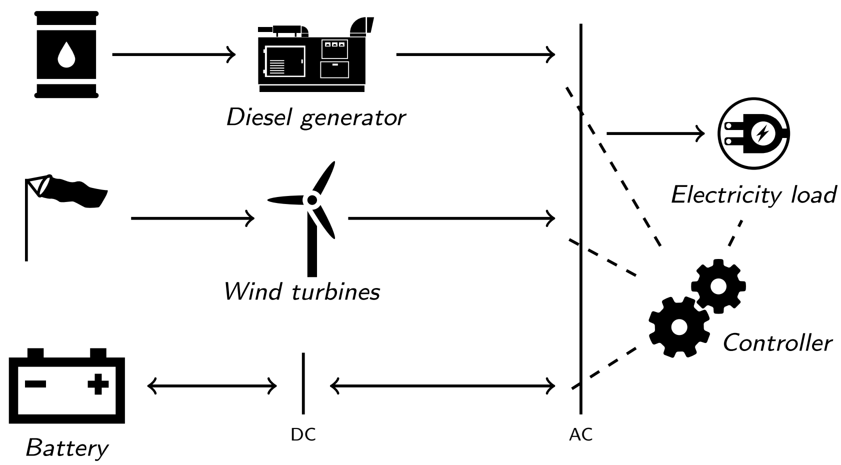

Figure 1: Structure of a diesel-wind-battery system

We classify previous studies of DWB systems into three groups depending on the design approach. Strategic models have the longest horizons. Their computation is not expensive because the time steps are years and the calculations are based on averages. In these models, there is no simulation of the controller strategy and we neglect hourly variations in the wind or demand. To find the wind-turbine or battery contribution, some ratios must be defined. Based on a statistical or deterministic wind analysis such as that in [6], we find the ratio of wind-power penetration to determine the wind-energy production for each year. An analysis such as that in [7] gives the battery-capacity factor and indicates how much energy can be stored to partly satisfy the annual demand. An annualized lifetime project cost is then calculated based on the capital, maintenance, fuel, and other costs. We can compare the cost of several designs and select the best. Retscreen, developed by Natural Resources Canada [8], is the best known strategic model. It is able to directly determine the wind-energy and battery ratios based on site-specific wind and demand data.

Operational models have the shortest horizons, with time steps of seconds or milliseconds. The primary goal of such models is to design stable systems. These models simulate a system in detail using dynamic equations. They study special stability events such as the start of generators or full-wind production to check the frequency/voltage stability and the active/reactive power balance [9–11]. These models cannot be used for long horizons because the computation becomes too expensive. Moreover, they do not simulate the controller strategy. Such short-term studies are mandatory before implementation. Sometimes they change the design or determine a need for stability elements such as flywheels.

Finally, tactical models have medium-term horizons with time steps of minutes or hours. They often use a simulation approach because it simultaneously allows good model accuracy and long-term computation [12,13]. A controller is mandatory for any DWB system because it handles the dispatch of the power sources in the system. DWB systems are normally modeled with a fixed controller strategy [14–16]. The simulation can explore several designs and is usually based on annual wind and demand data. If we know the system composition and demand for every step of the annual data, we can calculate the cost of every design and return the least expensive. The HOMER software developed by NREL [17] is the best known simulation model; it can simulate a wide range of hybrid systems. An alternative to simulation is linear programming (LP) which does not need to fix the controller strategy [18]. Given hourly wind and demand data, usually for one year, the LP model can find the optimal design and the optimal hourly dispatch. The annual data can be deterministic [19,20] or stochastic [21].

The optimization of the dispatch strategy is often overlooked despite its fundamental role in the performance of an HPS. Simulation approaches simply fix the strategy a priori. Some LP models give the dispatch for one year but typically do not specify an implementable strategy. Garcia and Weisser [22] use LP to find the OPP for a year; they use it as a reference to benchmark and improve the controller strategies defined by the user. This is one of the first studies that tries to optimize the controller strategy for a given HPS design.

In this paper we propose a new tactical approach for designing a DWB system. The proposed approach, called off-grid electricity supply optimization (OGESO), inspired by the work of Garcia and Weisser [22]. OGESO uses mixed-integer linear programming (MILP) to simultaneously optimize the composition of a DWB system and its dispatch strategy. Because the optimal dispatch is too complex to use in practice, it is analyzed using data mining to find a practical controller strategy. We provide a comparison of the results obtained using OGESO with those obtained from HOMER for the same sites.

This paper is structured as follows. In Section 3 we give an overview of OGESO (Off-Grid Electricity Supply Optimization), our proposed approach to DWB system design. In Section 4 we introduce the OGESO MILP model giving optimal design and strategy. We then explain in Section 5 how we obtain a practical dispatch strategy by data mining of the optimal dispatch. A comparison with the well-known simulation software HOMER is presented in Section 6 for some scenarios. Section 7 concludes the paper.

3 Overview of the Proposed Approach

OGESO requires hourly information about the wind and demand forecasts for a period of one year. Using this information, it simultaneously optimizes the site design and determines the optimal hourly dispatch, i.e., it specifies how much power each source must supply or the battery must charge or discharge to meet the demand. The optimization is done on the basis of minimizing the total cost of the project. This total cost includes the operating costs and the design cost. A significant part of the operating cost (and hence the total cost) is the cost of the fuel for the diesel generator. This cost can be reduced by optimizing the controller strategy that will depend on the selected design.

The OGESO approach is illustrated in Figure 2. It consists of two steps:

1. The first step, presented in Section 4, solves an MILP model representing the DWB system. The objective function minimizes the total project cost. the MILP uses deterministic hourly data for the wind and demand. The MILP solution includes the hourly dispatch corresponding to the minimum project cost; no controller strategy is specified.
2. The second step, presented in Section 5, performs a data-mining analysis of the optimal hourly dispatch to find the best controller strategy. The data-mining uses a decision tree to find a robust and practical controller strategy for the specific site.

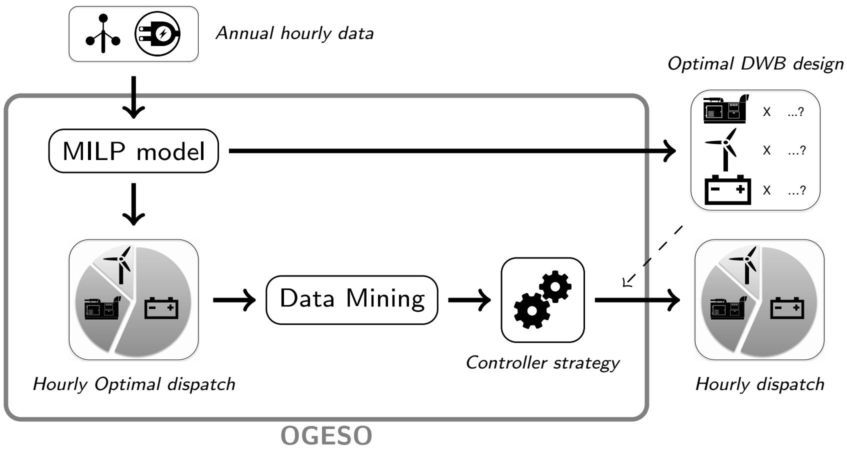

Figure 2: The OGESO approach

4 Optimal Design and Dispatch

In this section we present the OGESO MILP model. The number of time steps in the model is 8760, equal to the number of hours in one year.

4.1 Modeling the power sources

A first constraint specifies the electrical load supply $P_l(t)$ at each time step t:

$$P_d(t) + P_w(t) + P_b(t) - P_e(t) = P_l(t) \quad \forall t \in T \tag{1}$$

Battery energy and powers are superior or equal to zero but not $P_b(t)$ which can be negative for charge. Next we model each of the terms on the left-hand side of (1).

4.1.1 Wind-turbine power $P_w(t)$

The wind-turbine power parameter $P_w^1(t)$ is calculated at each time step t using the wind speed data $w(t)$ and the characteristic curve for the wind turbine (shown in Figure 3) that gives the electricity output $P_w^c(w)$ for integer wind speeds in the production range (w^i to w^o). We determine $P_w^1(t)$ for each hour t by interpolating between the closest integer wind speeds in the characteristic curve:

$$P_w^1(t) = \begin{cases} P_w^c(\lceil w(t) \rceil) \cdot (w(t) - \lfloor w(t) \rfloor) & \\ \quad + P_w^c(\lfloor w(t) \rfloor) \cdot (\lceil w(t) \rceil - w(t)), & \text{if } w^i \le w(t) \le w^o \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The total wind power $P_w(t)$ is then obtained by multiplying $P_w^1(t)$ by the number of wind turbines:

$$P_w(t) = N_w \cdot P_w^1(t) \quad \forall t \in T \tag{3}$$

4.1.2 Diesel-generator power $P_g(t)$

The variable $N_d(t)$ is the number of generators used at each hour t, which is at most the total number of generators N_d:

$$N_d(t) \le N_d \quad \forall t \in T \tag{4}$$

Each generator cannot supply more than P_d^{max} units of electricity (we assume they are all the same). The diesel power $P_d(t)$ at each hour t is therefore

$$P_d(t) \le N_d(t) \cdot P_d^{max} \quad \forall t \in T \tag{5}$$

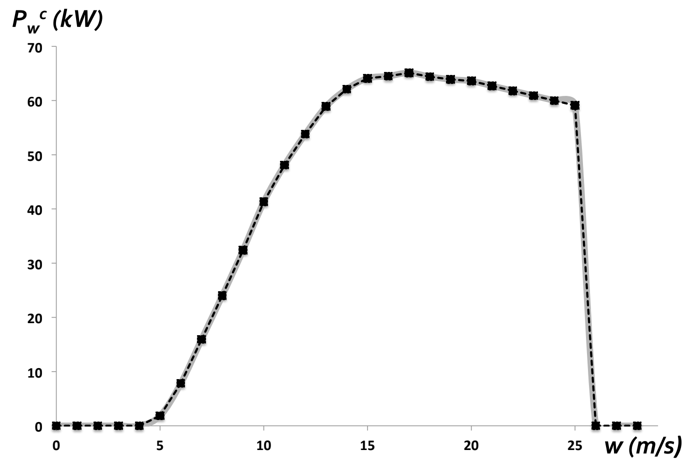

Figure 3: Characteristic curve $P_w^c(w)$ of an AOC 15/50 wind turbine

Each generator must supply at least u_d^{min}% of P_d^{max}. Below this value, usually around 30%, the generator lifetime is compromised and consumption is high. Therefore,

$$P_d(t) \geq u_d^{min} \cdot N_d(t) \cdot P_d^{max} \quad \forall t \in T \tag{6}$$

4.1.3 Battery power $P_b(t)$

The charge is limited by the maximum charge P_{bc}^{max} and depends on the number of batteries, N_b. Therefore,

$$P_b(t) \geq -N_b \cdot P_{bc}^{max} \quad \forall t \in T \tag{7}$$

The discharge is limited by the maximum hourly discharge P_{bd}^{max}:

$$P_b(t) \leq N_b \cdot P_{bd}^{max} \quad \forall t \in T \tag{8}$$

Charging and discharging will change the battery energy $E_b(t)$, which must respect the following continuity equation:

$$P_b(t) \leq \frac{E_b(t) - E_b(t-1)}{d(t)} \cdot e_b \cdot e_{bsd}^{d(t)} \quad \forall t \in T \tag{9}$$

where e_b is the efficiency of charging and discharging and e_{bsd} is the hourly self-discharging percentage. The time step $d(t)$ is equal to one hour in our model. The battery energy is limited by the maximum capacity E_b^{max}:

$$E_b(t) \leq N_b \cdot E_b^{max} \quad \forall t \in T \tag{10}$$

4.1.4 Extra power generated $P_e(t)$

Extra power not stored in the battery must be evacuated.

4.2 Objective function and costs

We now determine the costs in order to calculate the objective function:

$$\min\ C = C^e + C^f + \sum_{s \in S} C_s^i + C_s^o + C_s^r - C_s^s \tag{11}$$

We include several positive costs: initial, replacement, operation and maintenance (O&M), salvage, and fuel detailed below.

4.2.1 Extra power cost C^e

depends on the maximum power to evacuate (see Remark at part 4.2.6).

4.2.2 Initial cost C_s^i

This is the purchase cost of each element:

$$C_s^i \geq N_s \cdot c_s^i \quad \forall s \in S \tag{12}$$

where c_s^i is the price of one element $s \in S$.

4.2.3 O&M cost C_s^o

This is an annualized cost for wind and batteries:

$$C_s^o \geq \sum_{y \in Y} \frac{N_s \cdot c_s^o}{(1+i)^y} \quad \forall s \in \{w, b\} \tag{13}$$

where c_s^o is the price of O&M for one element s and for one year. For the diesel generator we have to calculate the number of operating hours in a year:

$$D_d \geq \sum_{t \in T} N_d(t) \cdot d(t) \tag{14}$$

We then multiply this number by a hourly cost and annualize the result:

$$C_d^o \geq \sum_{y \in Y} \frac{D_d \cdot c_d^o}{(1+i)^y} \tag{15}$$

4.2.4 Replacement cost C_s^r

We must determine how often we replace each source. For the wind turbine and batteries:

$$r_s^1 = \left\lfloor \frac{|Y|}{l_s} \right\rfloor \quad \forall s \in \{w, b\} \tag{16}$$

where $|Y|$ is the project lifetime. Then

$$C_s^r \geq \sum_{y=1}^{r_s^1} \frac{N_s \cdot c_s^r}{(1+i)^{y \cdot l_s}} \quad \forall s \in \{w, b\} \tag{17}$$

For the diesel generator this cost depends on the number of operating hours. We must ensure that there are enough hours for all the years:

$$N_d \cdot l_d + \sum_{i=1}^{y} A_d(y) \cdot l_d \geq D_d \cdot y \quad \forall y \in Y \tag{18}$$

We annualize the replacement of the diesel generators:

$$C_d^r \geq \sum_{y \in Y} \frac{A_d(y) \cdot c_d^g}{(1+i)^y} \tag{19}$$

4.2.5 Salvage cost C_s^s

This is the reselling cost that applies at the end of the project:

$$r_s^2 = \frac{|Y|}{l_s} - r_s^1 \quad \forall s \in \{w, b\} \tag{20}$$

We annualize this at the end of the project:

$$C_s^s \geq N_s \cdot \frac{(1 - r_s^2) \cdot c_s^r}{(1+i)^{|Y|}} \quad \forall s \in \{w, b\} \tag{21}$$

For the diesel generator:

$$C_s^s \geq \left(N_d + \sum_{y \in Y} A_d(y) - \frac{D_d \cdot |Y|}{l_d} \right) \cdot \frac{c_d^i}{(1+i)^{|Y|}} \tag{22}$$

4.2.6 Fuel cost C^f

We assume a linear consumption that depends on the power, so the consumption at each time t is:

$$f_d(t) \geq a_d \cdot P_d(t) + b_d \cdot N_d(t) \quad \forall t \in T \tag{23}$$

We annualize and sum up to obtain the total fuel cost:

$$C^f \geq \sum_{y \in Y} \sum_{t \in T} \frac{f_d(t) \cdot c^f}{(1+i)^y}. \tag{24}$$

Remark: The MILP model presented here was designed so as to be comparable with HOMER. It could in principle be made more realistic, for example by introducing battery cycling, nonlinear diesel consumption, and the cost of extra power evacuation.

4.3 Procedure for Solving the MILP Model

The MILP model is a challenging large-scale problem because of the presence of general integer variables, the large number of time steps (8760), and the time-step dependency of most the variables. Our initial solution attempts (using CPLEX 12.0) stopped after one hour of CPU time with a solution that was far from optimal with an optimality gap of about 13%. Increased CPU times gave only small improvements: for example, a gap of 7% after four hours.

We therefore developed a specialized procedure that exploits the model structure to reduce the computational time. The procedure is shown in Figure 4.

The procedure works as follows. We initially assume that a DWB site design able to handle the demand for several months will suffice for one year. Preliminary experiments showed that the values of the variables $N_d/N_w/N_b$ were generally close to the optimal solution for a whole year after only 1000 time steps ($|T| = 1000$) (1a). This time-restricted solution is obtained in less than 3 minutes because of the smaller value of T. Let $N_d'/N_w'/N_b'$ denote the optimal values of the variables for this time-restricted problem (1b).

Next we fix the design $N_d'/N_w'/N_b'$ and solve the resulting MILP problem for the $|T| = 8760$ time steps (2). The optimal solution and its objective function z' are obtained in a few seconds.

The value of z' is an upper bound on the true global optimal solution. Using this value and the $N_d'/N_w'/N_b'$ design, we apply Algorithm 1 to reduce the feasible set of the MILP by eliminating designs that would yield solutions with objective value worse than z' (3). After approximately 10 minutes we have new constraints on the design variables $N_w/N_g/N_b$ that must hold for the global optimal solution of the MILP model.

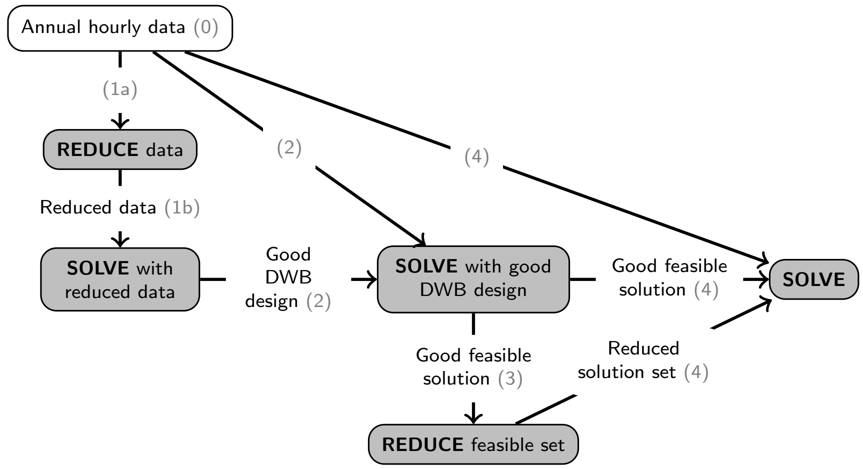

Figure 4: Procedure to efficiently solve the MILP problem

Algorithm 1: Feasible set reduction

for $s \in \{d, w, b\}$ **do**
  $i = 0$
  $pruning = False$
  while $pruning = False$ **do**
    Add constraint: $N_s \geq N'_s + i$
    Solve with time limit = 200 s
    Remove constraint: $N_s \geq N'_s + i$
    if $z \geq z'$ **then**
      Add constraint: $N_s \leq N'_s + i - 1$
      $pruning = True$
    else
      $i = i + 1$

Finally we call CPLEX to solve the full MILP model giving it the best-known integer solution (corresponding to z') and the new constraints on $N_d/N_w/N_b$ (4). The optimal solution with an integrality gap less than 1% is now computed in a few minutes.

The total computational time for this procedure depends on the data, but it is around 20 minutes for all our instances.

5 Dispatch strategy

The MIP model of OGESO provides an optimal design and a corresponding OPP. The second step of OGESO analyzes this profile using data mining to find an implementable controller strategy.

5.1 Power profiles and information matrix

As an example, consider the optimal design for site 1 with $N_g = 5$, $N_w = 8$, and $N_b = 2$, and the following portion of optimal dispatch at $t = 37$:

$$P_d(37) = 70 \text{ kW}, P_w(37) = 190 \text{ kW}, \text{ and } P_b(37) = 50 \text{ kW}.$$

The corresponding initial data are:

$$P_l(37) = 310 \text{ kW}, w(37) = 10 \text{ m/s}, \text{ and } E_b(37) = 50 \text{ kW}.$$

In this example the controller strategy used diesel generation, wind turbines, and battery discharge to satisfy the demand. This is one of ten possible cases (Table 1) and is labeled dwb.

Table 1: Possible Dispatch Options

1	Diesel generator only	d
2	Wind turbine only	w
3	Battery discharge only	b
4	Diesel generator and wind turbine	dw
5	Diesel generator and battery charge	db*
6	Diesel generator and battery discharge	db*
7	Wind turbine and battery charge	wb
8	Wind turbine and battery discharge	wb
9	Diesel generator, battery charge, and wind turbine	dwb*
10	Diesel generator, battery discharge, and wind turbine	dwb*

** Need equation to completely determine power profile*

The choice of the power profile may be obvious depending on the system information received. For example, cases 2 and 7 are typically selected in high-wind conditions. The decisions are more complicated when the controller uses both diesel generators and batteries. We can for example either decide to have more diesel generation to charge the batteries for future use or to have less generation and to meet part of the demand via battery discharge. Almost all controller strategies carefully consider this case.

For this case, Equation 1 does not suffice and we have to introduce the value $\alpha(t)$ to completely characterize the power profile:

$$\forall P_d(t) \neq 0 \qquad \alpha(t) = \frac{|P_l(t) - P_w(t)|}{P_d(t)}. \tag{25}$$

In our example, $\alpha(t) = 1.714$ and represents a subcase of the dwb case (battery discharge). In our data mining we must have a finite and reasonable number of power profiles, so when necessary we round $\alpha(t)$ to combine similar profiles. For our example, $\alpha(t) = 1.7$ and the case is labeled $dwb1.7$. We use $\alpha(t)$ to determine if the battery is charged ($\alpha(t) \leq 1$) or discharged ($\alpha(t) > 1$).

Finally, we transform all the power profiles into a finite case and form a decision vector. The goal of the data mining is to predict the power profiles from the system information available, so we build an information matrix corresponding to the decision vector. As in a real controller, we must use past system information to determine future power profiles. We define two columns for the information matrix:

- Ratio of wind power to demand calculated with real-time wind information (wl in Figure 6);
- Charge of battery calculated with battery energy for the previous hour (soc in Figure 6).

5.2 Data mining

We use the Matlab statistical toolbox. We form our decision tree by applying the *classregtree* function to the information matrix and the corresponding power profile decision. The tree is binary. The resubstitution error is the predicted percentage of errors in the data used to build the tree, and the cross-validation error is based on unused data (10-fold method [23]) and better represents the tree robustness.

Our initial decision tree had low errors (12% resubstitution and 17% cross-validation) but too many nodes (about 300) to be implemented in a real controller. Pruning was necessary, and Figure 5 shows a plot of both errors versus the number of nodes. The errors increase slowly. We decided to prune the tree at the point (18 nodes) where the resubstitution and cross-validation errors are equal, and this led to the tree of Figure 6.

Our final decision tree has sixteen nodes, with resubstitution and cross-validation errors of 16.7%. These errors do not necessarily have a direct effect on the cost, and for each scenario we have to simulate the corresponding controller strategy to find the new DWB project cost.

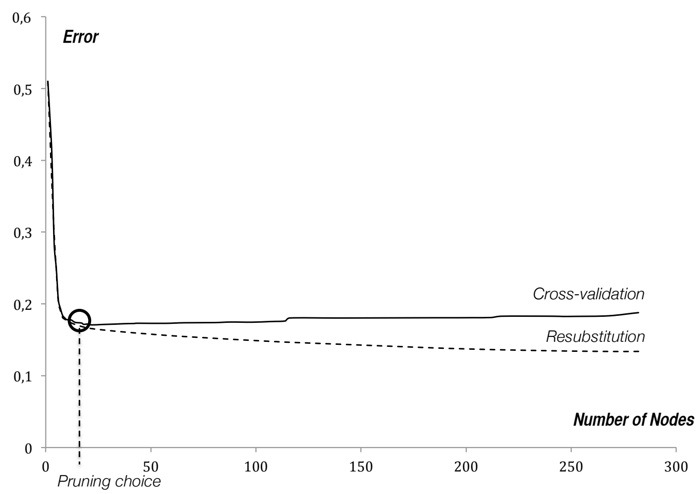

Figure 5: Errors vs. number of nodes

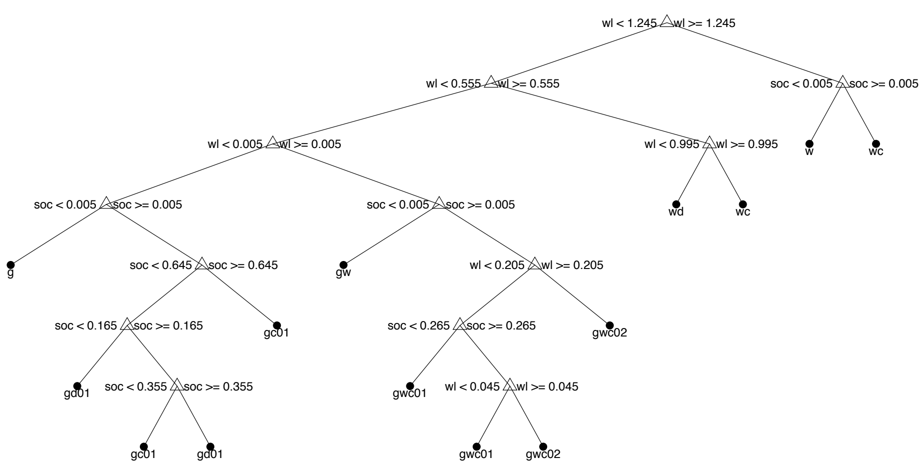

Figure 6: Final decision tree

6 Computational Results

We validate the OGESO approach by comparing its results with those obtained using HOMER.

HOMER simulates many site designs and calculates the total cost for each design based on the corresponding dispatch. The dispatch is obtained by applying the fixed controller strategy to the hourly data for the wind and demand. The site giving the minimum-cost design is selected. The approach of HOMER is illustrated in Figure 7.

We constructed 4 scenarios corresponding to all possible combinations between the two sets of wind data (W1 and W2) and two sets of demand data (L1 and L2) shown in Table 2. We used a Zn-Br flow battery, 65 kW nominal-power wind turbines and 75 kW maximum-power diesel generators.

To reliably compare HOMER and OGESO, we provide them with the same wind and demand data. They each return a site design and its corresponding dispatch. We then calculate the total project cost for each solution using the independent cost module illustrated in Figure 8 which is based on HOMER's cost computation and also checks the validity of the solution in terms of meeting the demand.

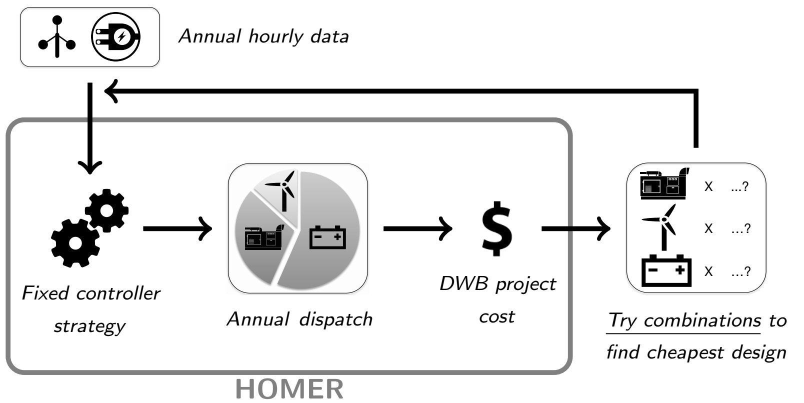

Figure 7: The HOMER approach

Table 2: Wind and Load Datasets

Data		Average	Max	Min	Change
Wind	V1	8.7 m/s	21 m/s	0 m/s	7%
	V2	8.7 m/s	25.5 m/s	0 m/s	15%
Demand	L1	167 kW	310 kW	70 kW	7%
	L2	167 kW	420 kW	50 kW	15%

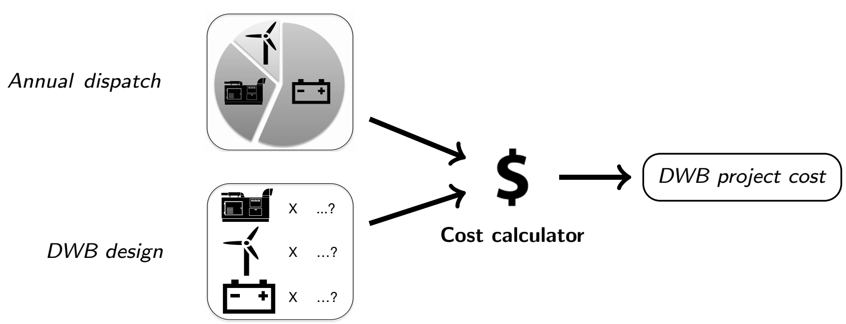

Figure 8: Independent cost calculator for HOMER and OGESO comparison

The results are reported in Table 3. As expected, the DWBHS project cost is lower than the HOMER cost. However, the results are not fully comparable because the OPP does not specify a controller strategy. We conclude that we could potentially find a better controller strategy than that of HOMER.

The simulation of the controller strategy obtained by data mining gives a different dispatch than the optima design found by the MIP. We can now fairly compare HOMER and OGESO, and the results for the four scenarios are reported in Table 3.

For all four scenarios, the cost is worse than the OGESO MILP result but better than that of HOMER. Our OGESO approach is effective because the strategy found by data mining is appropriate for each specific site. It takes into account the DWB design specificities, and local demand and weather features. The main difference is in the diesel consumption, with a reduction in the diesel generation and an increase in the battery use, as shown in Figure 9.

For sites with no wind or demand features, our approach is less effective. However, such local features are common, and even without them our approach is sufficiently robust to give results similar to those of HOMER. For example, suppose we consider changes in the wind distribution and re-apply the controller strategy found by data mining for scenario 1. For small adjustments the cost comparison with HOMER

Table 3: HOMER / OGESO for four isolated sites

Scenario		1	2	3	4
Data	Demand	D1	D2	D1	D2
	Wind	V1	V1	V2	V2
Design ($N_d/N_w/N_b$)	HOMER	5-8-2	6-8-4	9-5-3	6-9-4
	OGESO	5-8-2	6-7-3	5-8-2	6-8-4
Cost ($k)	HOMER	4320	4521	4411	4548
	MILP	4195	4356	4030	4318
		2.8%	*3.6%*	*8.6%*	*5.0%*
	OGESO	4261	4441	4136	4474
		1.3%	*1.7%*	*6.2%*	*1.6%*

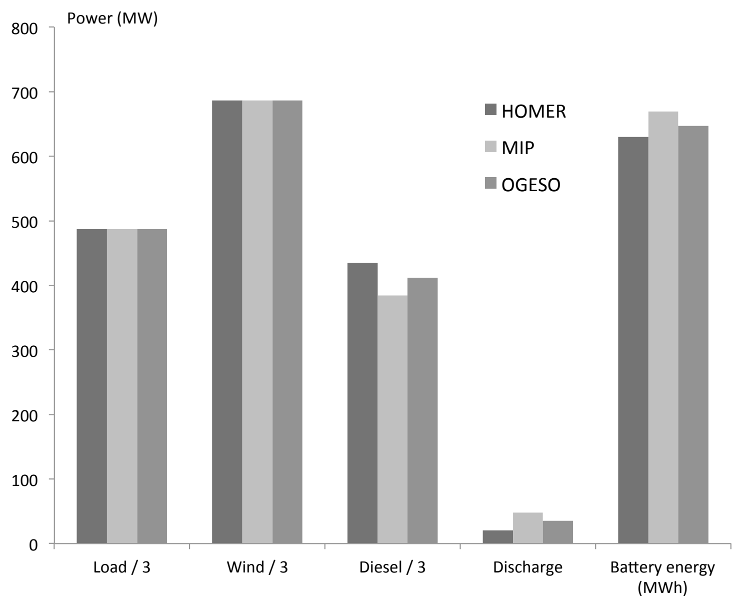

Figure 9: Total power for isolated site 1

changes from 1.4% to 0.4%, and for large adjustments it changes to -0.5% (i.e., HOMER is better). However, such changes in the climate are not realistic, and we can use OGESO to calculate an updated controller strategy.

7 Conclusion

We propose OGESO, a new approach to design power systems for isolated sites. OGESO solves an MILP problem using annual deterministic data to determine an optimal DWB design and a corresponding hourly dispatch. We use data mining and a decision tree to determine a practical controller strategy. The MILP problem in OGESO is a large-scale problem and challenging to solve to optimality. We therefore developed an algorithm that solves it in around twenty minutes to global optimality. The computational results for 4 realistic scenarios shows that OGSEO gives a lower total cost than HOMER for all of them. Future research will look at ways to increase the accuracy of the model, for example by introducing for example battery cycles or nonlinear diesel consumption.

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