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C.D. Barley, C.B. Winn,
L. Flowers, H.J. Green

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OPTIMAL CONTROL OF REMOTE HYBRID POWER SYSTEMS PART I: SIMPLIFIED MODEL

C. Dennis Barley,[1,2,3] C. Byron Winn,[1] Larry Flowers,[2] and H. James Green[2]
1. Mechanical Engineering Department, Colorado State University, Fort Collins, CO 80523, USA.
2. Wind Technology Division, National Renewable Energy Laboratory,
1617 Cole Boulevard, Golden, CO 80401, USA.
3. e-mail: dbarley@lance.colostate.edu

ABSTRACT

In this two-part study, time-series models are used to determine optimal dispatch strategies, in conjunction with optimally-sized components, in remote hybrid power systems. The objective of the dispatch optimization is to minimize the costs associated with diesel fuel, diesel starts, and battery erosion, based on a thorough economic analysis of present worth life-cycle cost. An ideal predictive control strategy is used as a basis of comparison. In Part I (reported here), a simplified time-series model is used to obtain preliminary conceptual results. These results illustrate the nature of the optimal dispatch strategy and indicate that a simple SOC setpoint strategy can be practically as effective as the ideal predictive control. In Part II (at a later date), a more detailed model will be used to obtain more accurate, quantitative results. We anticipate that these results will be correlated to dimensionless economic, design, and performance parameters, rendering them useful as design guidelines over a wide variety of load profiles, climates, equipment specifications, and economic variables.

INTRODUCTION

Billions of people in small villages in developing countries currently lack a supply of electricity. In many cases, utility grid extension is impractical due to dispersed population, rugged terrain, or both; thus small (village-scale), stand-alone power systems are likely to be the most viable option. Various "hybrid" combinations of wind turbine generators (WTG), photovoltaic arrays (PV), and/or diesel generators, with or without rechargeable batteries, are currently being proposed, researched, and marketed as the most cost-effective and ecologically sound solution. Such systems are referred to as Remote Hybrid Power Systems (RHPS).

When one or more renewable resources are augmented with both hour-to-hour energy storage (batteries) and fueled backup power (diesel gensets), the issue of dispatch strategy arises. As used here, the term "dispatch" refers to that aspect of control strategy which pertains to the sources and destinations of energy flows. Of particular interest and controversy is the possibility of using diesel power to charge batteries. Benefits of such "cycle-charging" include (1) maximizing diesel generating efficiency by operating at full rated power and (2) minimizing the frequency of diesel starts. Adverse effects of cycle-charging include (1) battery erosion (i.e., shortening of service life), (2) electrical losses in the battery and in power conversion (depending on the AC/DC bus arrangement) which detract from the improved generating efficiency, and (3) lost opportunities for storing renewable energy in the batteries. Various hybrid systems currently on the market feature the extremes of no battery use at all versus full charging of batteries every time diesel genset(s) run. More sophisticated control schemes, including the use of meteorological forecasts, neural networks, fuzzy logic, and adaptive control, have been proposed.

In this two-part study, time-series models are used to determine optimal dispatch strategies, in conjunction with optimally sized components, in RHPS with hour-to-hour energy storage. The objective of the dispatch optimization is to minimize the costs associated with diesel fuel, diesel starts, and battery erosion, based on a thorough economic analysis of present worth life-cycle cost. The strategies range from a load-following diesel (no hour-to-hour diesel energy storage) to full charging of batteries every time the diesel starts. An ideal predictive control strategy is used as a benchmark.

In Part I, reported in this paper, a simplified time-series model is used to develop valuable insights and to obtain preliminary results. Features of this model include: quasi-steady-state conditions within each time step, no power conversion losses, no battery losses, and unlimited rates of battery charge and discharge. The following conclusions have emerged and are discussed in subsequent sections:

1. An ideal dispatch strategy, based on perfect prediction of future conditions, has been identified and modeled.
2. A simple (non-predictive) state-of-charge (SOC) setpoint strategy can be practically as effective as the ideal control. Efforts to develop predictive controllers are *not* supported by this study.
3. Optimal control strategy and optimal component sizing are interdependent; they must be determined jointly.
4. Diesel startup cost is typically insignificant in the control optimization.
5. Full charging of batteries with diesel energy is quite *un*likely to be cost-effective.
6. High battery cost and high renewable energy penetration tend to favor a load-following diesel dispatch strategy in which batteries are not charged with diesel energy.
7. Low battery cost and low renewable energy penetration tend to favor a strategy of charging batteries to roughly 10% of their allowed SOC range - *not* to a relatively high SOC.

In Part II (at a later date), we will use a more detailed model to obtain more accurate, quantitative results. We anticipate that these results will be correlated to dimensionless economic, design, and performance parameters, rendering them useful as design guidelines over a wide variety of load profiles, climates, equipment specifications, and economic variables.

THE SIMPLE MODEL

Accurate models of RHPS's, such as HYBRID1 [1], SOMES [2], and WDILOG [3], include complexities such as:

1. Statistical treatment of load and resource fluctuations within a time step, either analytically or by a Monte Carlo approach;
2. Battery models which account for resistive losses, voltage variations, and chemical reaction rates;
3. Power conversion losses, which depend on the AC/DC bus configuration;
4. Strategic staging of multiple diesels;
5. One or several preprogrammed dispatch strategies.

Reworking one of these models to perform predictive control and comparisons with various simpler dispatch schemes would be a major task, especially in the exploratory stage of developing an understanding of the role of prediction in an optimal control strategy. This is the reason for Part I of this study, in which a simple, easy-to-manipulate model is used to formulate a predictive algorithm, gain insights, study first-order effects, and plan a more detailed follow-on study. This approach has in fact proven very fruitful.

Features of the Simple Model used in Part I include the following:

1. Quasi-steady-state (QSS). It is assumed that the village electrical load and the renewable resource are constant within each one-hour time step. Because the systems considered feature substantial battery capacity, and because power conversion losses are not yet considered, the QSS assumption should not undermine the results.
2. A time step of one hour is used throughout this study. In view of the battery bank sizes and the frequency of diesel starts that result from the optimizations, as discussed below, this time step appears to be adequate.
3. Ideal battery model. The battery model is simply a tally of kWh of energy in and out, between a lower and an upper limit. There are no losses, and charge and discharge rates are unlimited. These unrealistic assumptions would tend to bias the results toward more use of battery storage. Because the qualitative conclusions at this stage of the study are conservative with respect to battery use, the ideal battery model is deemed adequate at this stage. A more detailed model will be used in Part II. Note that battery SOC is relative; 0% SOC is the minimum allowed, which might correspond to a lower limit of 25% or 40% absolute SOC. The battery capacity corresponds to the range of SOC permitted.
4. A single diesel genset is sized to match the peak village electrical load. Its fuel curve is assumed to be linear, with slope and intercept per Skarstein and Uhlen's relation [4] (Equation 2, Figure 1). It is permitted to operate within a range of 0% to 100% of its rated power. A non-zero minimum operating power is a parameter for future study.
5. The only renewable energy source modeled is a WTG. A PV model is to be included in Part II. The same general principles will apply; however, the diurnal cycle of sunlight in conjunction with the load profile is expected to influence the optimizations of battery sizing and usage.
6. The AC/DC bus configuration is not addressed; power conversion losses and limits are neglected.

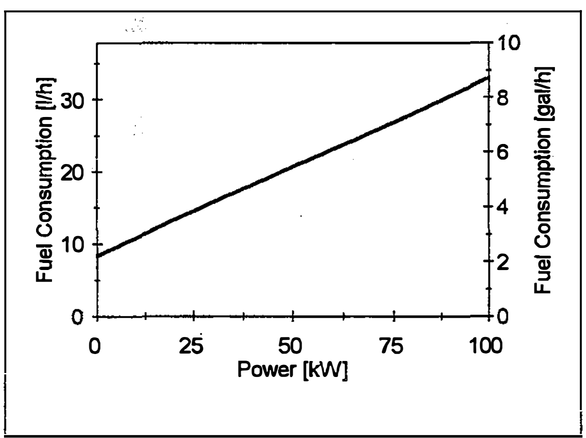

FIGURE 1: HOURLY DIESEL FUEL CONSUMPTION

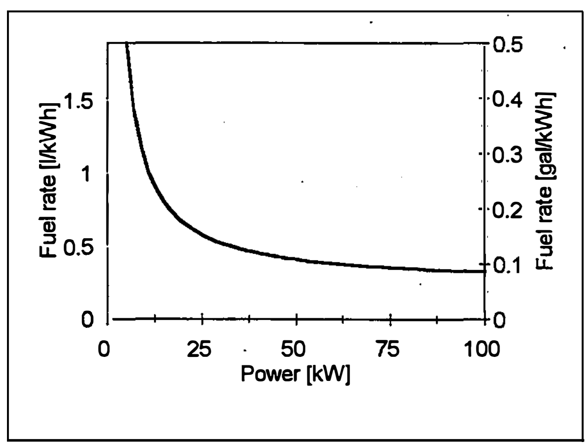

FIGURE 2: DIESEL FUEL CONSUMPTION PER KWH

THE IDEAL DISPATCH STRATEGY

As was mentioned in the Introduction, one incentive for cycle-charging is operation of the diesel genset at its maximum efficiency. In Figure 1, diesel fuel consumption in liters/hr (gal/h) is plotted against electrical power output. In Figure 2, the same relationship is plotted in terms of liters (gal) per kWh. Note that the fuel consumption per kWh is lowest at full load and approaches infinity at no load. Contrariwise, a *disincentive* for cycle-charging is the possibility that a subsequent opportunity to use the batteries for storage of renewable energy will be sacrificed. In that case, the value of generating electricity at the highest possible diesel genset efficiency is overshadowed by the fact that the energy could have come from a renewable resource. This is illustrated in Figure 3, in which the effects of three dispatch strategies are superimposed:

(dotted curves)	"zero-charge," or "load-following diesel," in which batteries are never charged with diesel energy.
(thin solid curves)	"full cycle-charge," in which batteries are charged to 100% of their capacity every time the diesel is started.
(bold solid curves)	predictive control - judicious charging of batteries based on knowledge of future conditions.

The top curve in Figure 3 is "Net Renewable" power, i.e., power output of wind turbine minus village electrical load. A positive value of Net Ren. is power that is available for storage in the battery; a negative value is a demand for power from the battery or the diesel genset. This synthetic data was tailored to illustrate the dispatch strategies, and it applies to all three cases. The second (triple) trace depicts the output of the genset for the three strategies. The bottom traces depict battery SOC history, and the third set of traces, marked "Spillage," depict excess renewable energy that was wasted because the batteries were already fully charged. Diesel fuel usage for the three strategies is as follows:

Zero-charge:	606 liters (160 gal)
Full-charge:	753 liters (199 gal)
Predictive:	496 liters (131 gal)

This example illustrates the role of prediction in optimal dispatch. The zero-charge strategy used more fuel than the predictive control because the genset was not run at its maximum efficiency; the full-charge strategy used more fuel than the predictive control because some of the energy that was stored in the battery was destined to be wasted as spilled energy. Note also that the diesel run time is a minimum with the predictive strategy. The predictive strategy may be summarized as follows:

(Partial result, subject to consideration of battery erosion cost)
Once the diesel is started, it should be run at full power until any further battery charging would lead to spillage of renewable energy that could have been utilized.

In this model, perfect prediction is obtained by using load and resource data for future hours in the dispatch algorithm. A real-time controller, of course, does not have this capability. Practical control schemes are discussed in the next section, using the ideal dispatch strategy as a benchmark.

An additional disincentive for cycle-charging is battery erosion. The cost of batteries in a RHPS has two components: (1) the capital cost, which depends on the sizing of the battery bank but not on the dispatch strategy, and (2) the replacement cost, due to battery erosion, which does depend on the dispatch strategy. Battery lifetime is rated in terms of the number of cycles to failure versus depth of discharge (DOD = 1 - absolute SOC); such data from a number of sources is plotted in Figure 4.[1] In Figure 5, this same data is replotted in terms of total lifetime energy flow, computed as (number of cycles) x (DOD). The shapes of these curves vary; some appear constant over the entire range of DOD; for others, the variation is small within a broad range of DOD, say 20% to 80%. The NiCd battery is an exception. In the current study, a fixed

[1]Battery test are usually based on complete, periodic charge/discharge cycles; the actual performance of batteries in a RHPS, in which the SOC may meander, needs further study.

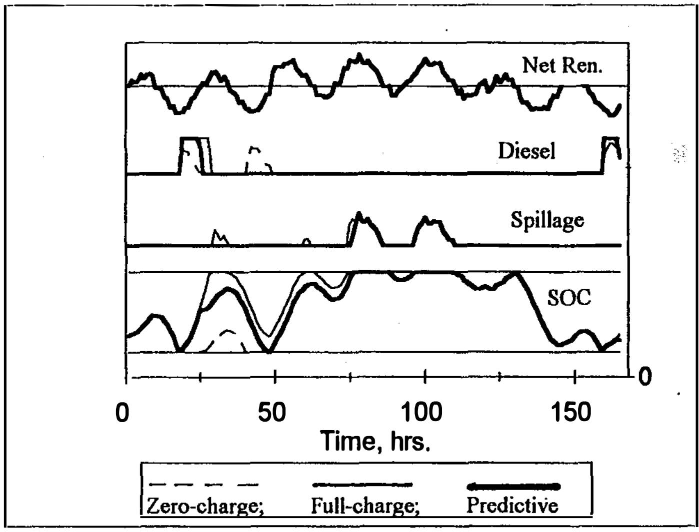

FIGURE 3: THE ROLE OF PREDICTION IN DISPATCH

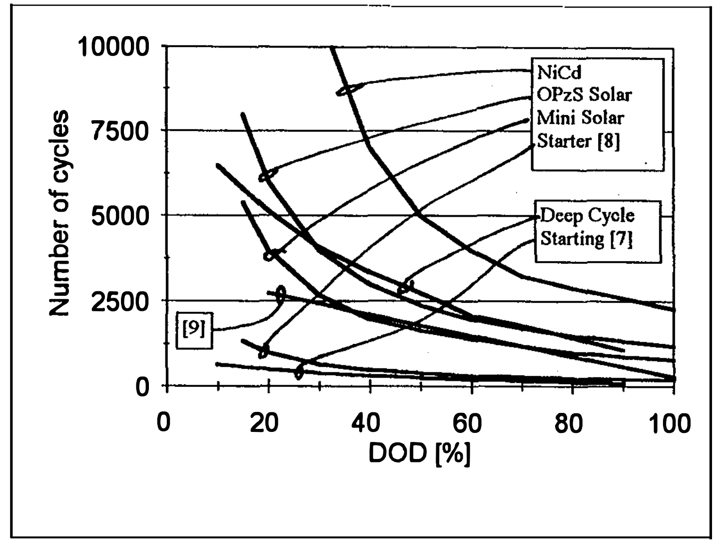

FIGURE 4: LIFETIME BATTERY CYCLES VS. DOD

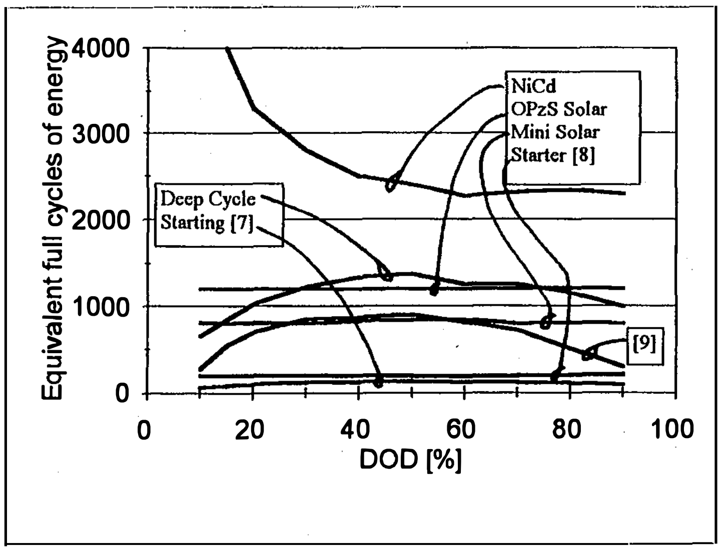

FIGURE 5: LIFETIME BATTERY ENERGY VS. DOD

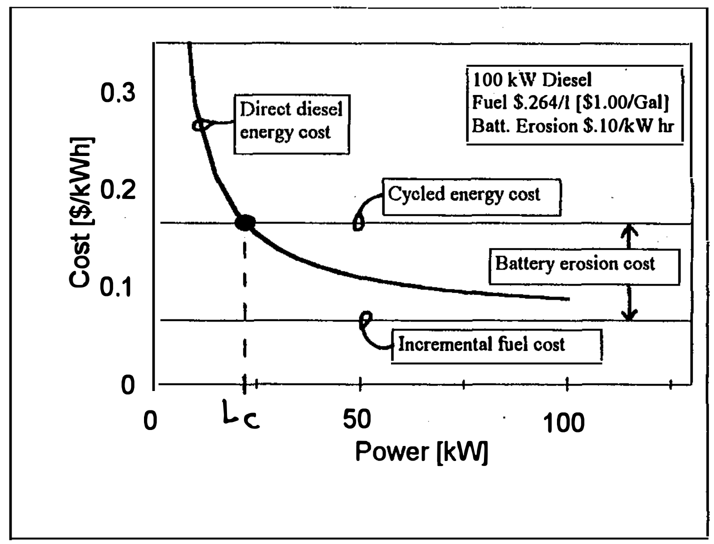

FIGURE 6: DETERMINATION OF CRITICAL LOAD

number of equivalent full cycles, i.e., a fixed number of kWh, is assumed in the life of a battery, leading to a fixed cost of battery erosion in \$/kWh of energy flow.

In Figure 6, the cost of cycled (stored diesel) energy is compared to the cost of energy supplied directly by the genset. When the diesel is running, the cost of generating additional energy for cycle-charging is related to the slope of the fuel curve (see Figure 1); this cost is shown as "Incremental fuel cost" in Figure 6. To this cost is added the battery erosion cost associated with storing the energy; the sum is indicated as "Cycled energy cost." The intersection of this line with the direct diesel energy cost (the cost of running the genset to meet the load directly; cf. Figure 2) defines a "critical load," L_c. The critical load may be calculated directly as follows (linear fuel curve assumed):

$$L_c = C_f F_0 / C_{be}, \text{ where:} \tag{1}$$

C_f = Cost of fuel, \$/liter (\$/gal)
F_0 = Diesel no-load fuel consumption, liters/hr (gal/h)
C_{be} = Cost of battery erosion, \$/kWh

By applying Skarstein and Uhlen's relation [4] for fuel consumption q [l/h] as a function of diesel rated power P_r [kW] and operating power P [kW]:

$$q = 0.246\ P + 0.08415\ P_r \tag{2}$$

Equation 1 is further developed as:

$$L_c/P_r = (C_f/C_{be}) \times 0.08415\ \text{l/kWh}, \quad \text{or} \tag{3a}$$

$$L_c/P_r = (C_f/C_{be}) \times 0.02223\ \text{gal/kWh} \tag{3b}$$

When the net load (village electrical load - renewable power) is greater than the critical load, it is more economical to meet the load by running the diesel and using the power directly. When the load is less than the critical load, it is more economical to use energy that was previously stored in the battery by diesel operation in excess of the load at that time. Note in Equations 1 and 3 that the critical load depends on the ratio of the fuel cost to the battery erosion cost.

The use of the critical load in the predictive dispatch scheme is illustrated in Figure 7. The objective is to eliminate diesel operation for loads less than L_c by storing energy during a prior diesel run. The thin curves show the effects of a load-following (zero-charge) strategy. The arrows indicate how this energy is time-shifted with the predictive dispatch, shown with bold curves. This time-shifting is subject to the constraint previously illustrated in Figure 3, regarding spillage of energy due to the limited storage capacity of the battery.

The cost of starting a diesel genset, which was mentioned in the Introduction as an incentive for cycle-charging, has been treated informally in the above analysis by storing as much energy as is cost-effective whenever the diesel is started. A more explicit treatment does not seem to be warranted. Bleijs et al. [5] have determined that the wear penalties associated with a diesel start are "equivalent to 1-4 minutes of continuous high-load operation." In preliminary studies of joint optimization of component sizing and dispatch strategy, in which the cost of diesel starts is ignored, and which are discussed below, the frequency of diesel starts is on the order of one per day. It is evident that an explicit treatment of diesel start cost would not make a significant difference.

CASE STUDIES

The ideal dispatch strategy, as developed above, requires exact knowledge of future conditions. Of course, in a real system such information is not available. A simple strategy that does *not* require prediction is the SOC setpoint strategy, in which batteries are charged to a prescribed SOC every time the diesel must be started. The load-following, or zero-charge strategy is a special case for which the setpoint is 0%; the full-charge strategy is a special case for which the setpoint is 100%. By exercising the simple model, an optimal setpoint (within the range 0-100%) may be determined for which the fuel and battery erosion costs are a minimum, and the following questions may be answered:

1. What setpoint optimizes performance with the SOC setpoint strategy?
2. How does the performance of the optimized setpoint strategy compare to that of the ideal predictive control?

The answer to the first question may serve as a design guideline; the answer to the second question may serve as an estimate of how much improvement in performance might be expected by developing practical predictive control schemes.

For the purpose of these comparisons, hourly wind data from DOE Candidate Wind Sites (summarized in the Wind Energy Resource Atlas of the United States [6]) was selected for five locations representing various climate types: Amarillo, TX (southern Midwest), Block Island, RI (Atlantic coastal), Culebra, PR (trade wind), Finley, ND (northern Midwest), and Mt. Holyoke, MA (New England mountain). For each location, several years' data with numerous gaps (periods of missing data) was edited. For each of the 12 calendar months, a 3-week period of continuous data was selected (when possible) from among the years for which the data was good enough, thus avoiding gaps. These 12 three-week intervals were then strung together into a pseudo 'year' of 252 days of real wind data without gaps. This editing procedure was chosen as an alternative to synthesizing data to fill gaps. A realistic hourly load profile, based on one month's data from Cuttyhunk Island was used. A single 24-hour load series was compiled by averaging across the 31 days of the month and normalizing to an average load of 50 kW; the resulting profile, shown in Figure 15, was applied for each day of the simulation year. Results for three different assumed battery erosion costs are shown in Figure 8 ($.00/kWh), Figure 9 ($.05/kWh), and Figure 10 ($.20/kWh). In these three figures, the abscissa is the wind:load ratio (WLR), computed as (yearly average power available from the WTG) / (yearly average load). This corresponds to varying the number of WTGs installed, treating this as a continuous (rather than stepwise) variable. A low WLR corresponds to a "weak" renewable energy system, a low wind penetration, and a long-term tendency for batteries to become discharged in the absence of diesel operation. A high WLR corresponds to a "strong" renewable energy system, a high wind penetration, and a long-term tendency for batteries to become fully charged in the absence of diesel operation. Wind data from Finley was used in generating Figures 8-10; similar results leading to the same conclusions were obtained for Amarillo, Block Island, Culebra, and Mt. Holyoke.

In Figure 8, with an assumed battery erosion cost of $0.00/kWh, it may be observed that:

1. For WLR=0, the setpoint-100% strategy is the same as the ideal predictive control. Because there is no wind energy, cycle-charged energy is never spilled. Over the range 0<WLR<0.5, the effects of the two strategies are practically indistinguishable.
2. For WLR>1.5, the setpoint-0 strategy is practically as effective as the ideal predictive control. In such a strong system, it is almost inevitable that the wind will soon charge the batteries, so any cycle-charging would be wasted.
3. For moderate systems (0.5<WLR<1.5), an optimal setpoint between 0% and 100% yields performance that is so close to that of the ideal predictive control that the two curves appear as one in the figure.

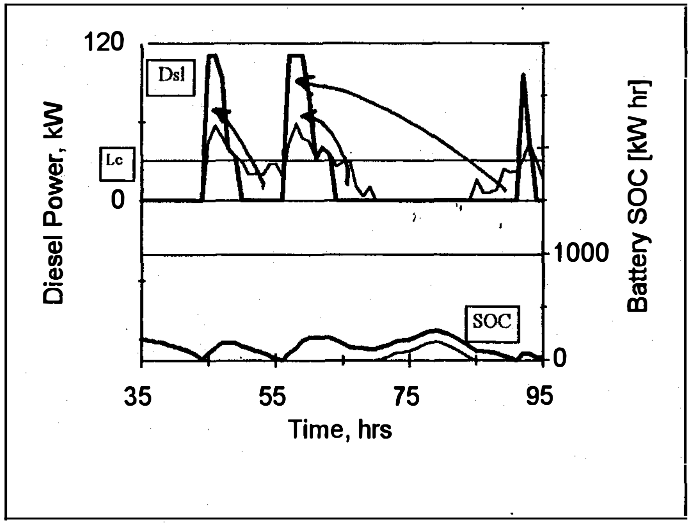

FIGURE 7: THE ROLE OF CRITICAL LOAD IN DISPATCH

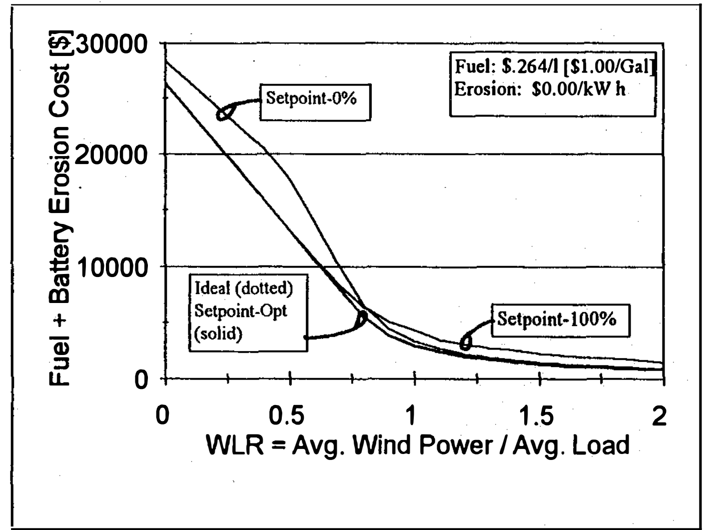

FIGURE 8: CASE STUDY WITH ZERO EROSION COST

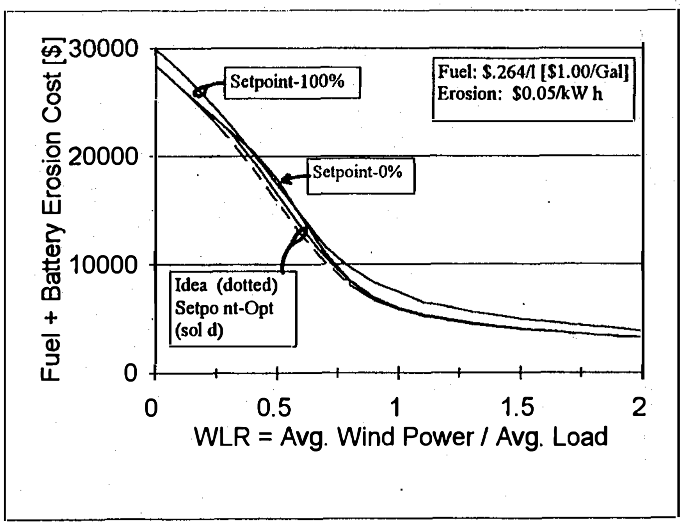

FIGURE 9: CASE STUDY WITH LOW EROSION COST

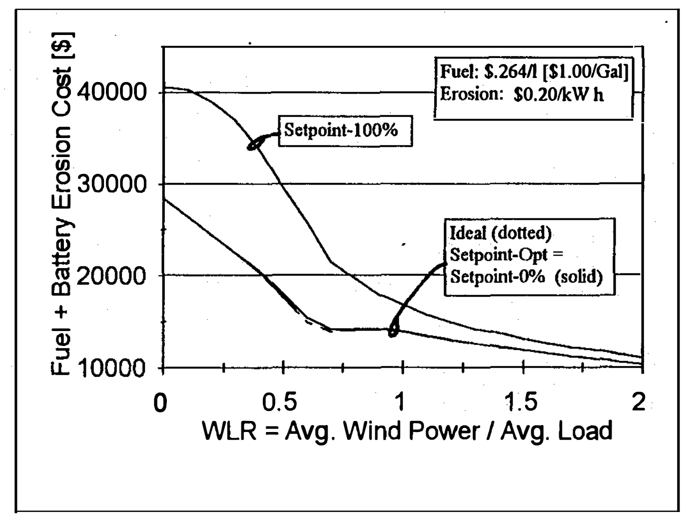

FIGURE 10: CASE STUDY WITH HIGH EROSION COST

In Figures 11-13, fuel and erosion cost is plotted vs. SOC for three systems corresponding to Figure 8:

Figure 11: WLR = 0.0. Optimal setpoint is 100%, although little variation in cost is observed in the range 10% to 100%.[2]
Figure 12: WLR = 0.8. Optimal setpoint is approximately 10%.
Figure 13: WLR = 2.0. Optimal setpoint is approximately 10%.

An interpretation of these results is as follows: By increasing the setpoint from 0% to 10% (the smallest increment used in this computation), the diesel is permitted to run at full-rated power in nearly every hour of operation.[2] As the setpoint is further increased from 10% to 100%, (1) no further gain in diesel efficiency is achieved, (2) more of the cycled energy is destined to be spilled (if the WLR is high enough that the wind energy ever exceeds the load), and (3) the interval between diesel starts is increased. Because the diesel start cost is typically negligible, the predominate effect is item (2), i.e., the wasting of diesel energy.

In Figure 10, a high battery erosion cost ($0.20/kWh) is assumed. In this case the storage cost is so high that the optimal setpoint is 0% regardless of the WLR. Again, the optimal setpoint strategy is practically as effective as the ideal predictive control.

In Figure 9, a low battery erosion cost ($0.05/kWh) is assumed. In this case, the optimal setpoint is 10% in the range $0.4 \leq \text{WLR} \leq 0.8$, and 0% otherwise.

These results support the conclusions listed in the Introduction.

JOINT SIZING/DISPATCH OPTIMIZATION

By now it is apparent that the optimal dispatch strategy for a given electrical load depends on the sizing of the WTG(s) and on the battery erosion cost. It also depends on the sizing of the battery bank, which was arbitrarily set at 1000 kWh (20 hours of average load) in the computations discussed above. So final conclusions, useful as design guidelines, must be based on joint optimization of component sizing and dispatch strategy. The outcome, of course, will depend on equipment specifications and capital cost, on fuel and battery erosion costs, on load profile, on climate, and on financial parameters (e.g., discount rate). A sample computation is illustrated in Figure 14, based on assumptions too numerous to list in this paper. Each point on the graph is already optimized with respect to dispatch strategy. The point marked indicates the optimal combination of battery size, WTG sizing, and SOC setpoint. In this example, the optimal setpoint is 10%, and the average number of diesel starts per day is 0.7. This typical result of roughly one diesel start per day when the diesel start cost is neglected supports the conclusion that the start cost is typically not significant in the optimization. A more accurate and thorough set of computations is planned for Part II of this study. As mentioned in the Introduction, we anticipate that these results will be correlated to dimensionless economic, design, and performance parameters, rendering them useful as design guidelines over a wide variety of climates, equipment specifications, load profiles, and economic variables.

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[2]The smaller irregularities are caused by random amounts of energy left in the battery at the end of the simulation year, as well as by part-load diesel operation in the last hour of a charge cycle. Otherwise, the curve in Figure 11 should be flat from 10% to 100% SOC.

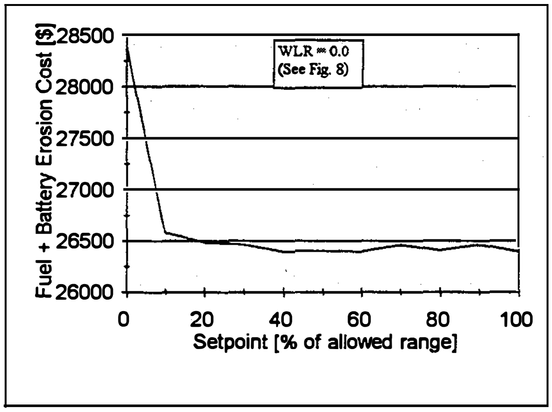

FIGURE 11: SETPOINT OPTIMIZATION FOR WLR=0.0

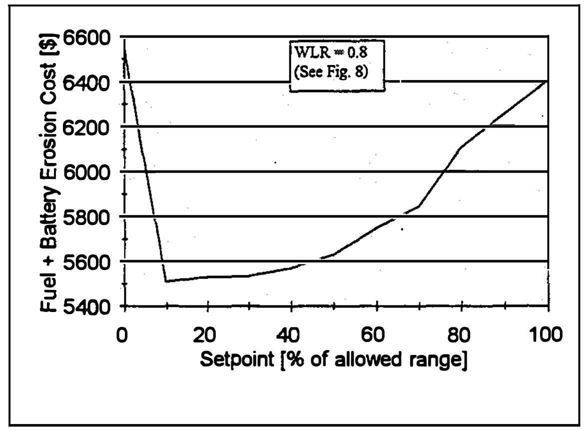

FIGURE 12: SETPOINT OPTIMIZATION FOR WLR=0.8

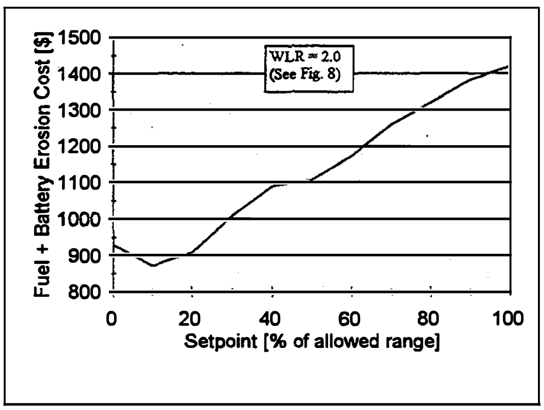

FIGURE 13: SETPOINT OPTIMIZATION FOR WLR=2.0

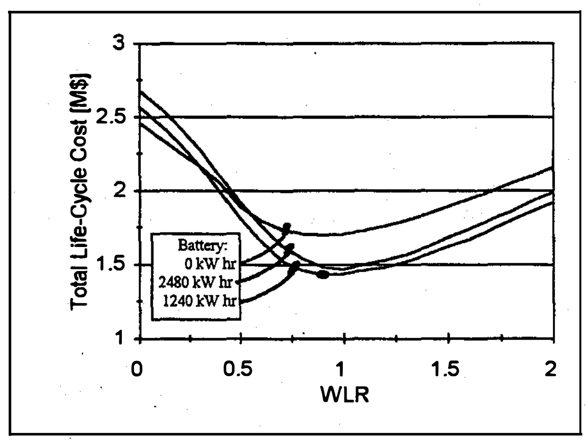

FIGURE 14: JOINT SIZING/DISPATCH OPTIMIZATION

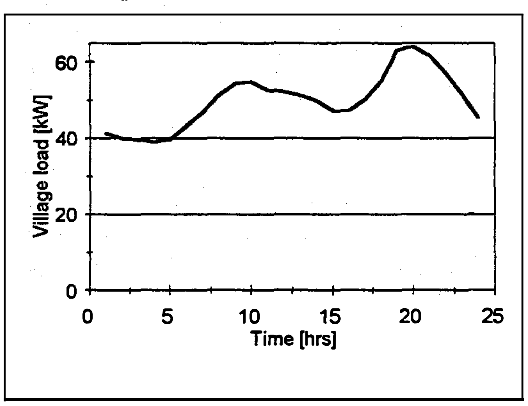

FIGURE 15: VILLAGE ELECTRICAL LOAD USED IN CASE STUDIES

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