OPTIMAL SCHEDULING OF HYBRID ENERGY SYSTEMS USING LOAD AND RENEWABLE RESOURCES FORECAST

Sami H. Karaki, Ayman Bou Ghannam, Fuad Mrad, Riad Chedid

American University of Beirut, P.O. Box: 110236, Beirut, Lebanon
skaraki@aub.edu.lb

ABSTRACT

In this paper, the integration of an optimizer and a forecaster into the energy management system (EMS) of a hybrid renewable energy system is studied. The role of the optimal EMS is to select the best decision set for the operation of the system based on a 24-hour forecast, reducing power conversion losses and unnecessary battery charge discharge cycles. Different forecast methods have been chosen for the 24-hour forecast of load, wind speed, and solar irradiance. A Genetic Algorithm is used for the optimizer. The cost function for evaluating system performance accounts for the fuel consumed, battery degradation, the amount of load shed, and the startups of the diesel engine. The results of the simulation have shown about 50% reduction in the number of battery cycles while preserving the same level of diesel engine fuel consumption as compared to classical EMS.

Keywords: Energy management systems, renewable energy, hybrid energy system, load forecast, wind speed forecast, solar irradiance forecast, and genetic algorithms

1. INTRODUCTION

The basic components found in a typical hybrid renewable energy system include: a photovoltaic (PV) generator, a wind turbine (WT), a diesel engine, a storage battery, an electric load, and a dump load. The EMS controls the energy required from the sources to balance the connected loads. Thus, it turns on or off the diesel engine, charges or discharges the battery, connects or disconnects the dump load, or even sheds some load. For optimal performance, it should maximize the power utilized from renewable energy resources, minimize fuel consumption, minimize load shed, while operating the system safely within its operational constraints. Authors have investigated and discussed EMS of hybrid systems.

Soni and Ozveren (2006) proposed a model that gives the PV array and wind turbine the highest priority to supply the load. The battery supply balances the deficiency in RE resources. When the battery state of charge level falls below 20% of its rated value, the diesel generator is turned on. Wichert et al (2001) described an EMS for a system consisting of PV cells, batteries and a diesel engine. The diesel generator is operated at 80% of its rated output to maximize its efficiency. A predictive three hour distribution of the net load minus the PV is used. Seeling-Hochmuth (1998) proposed optimized fixed system control strategies that consist of certain predetermined control settings from offline optimization by running a genetic algorithm on a simulator of the system. Scrivani (2005) proposed an energy management technique for sea water reverse osmosis (RO) desalination plant, PV cells, batteries, and a diesel engine. To reduce fuel consumption, the proposed algorithm forecasts the expected levels of solar irradiance for the next 12 hours to determine whether to start the RO plant or not. The hourly average of the irradiance for the last 5 days is used as a forecast for the future values.

In this paper, we investigate the integration of a load and resource forecast and an optimizing algorithm into the EMS to increase the life of battery storage and reduce the switching of supplies and loads, and energy wasted in dump loads. Load is forecasted using established short term load forecast methods that divide the load into weather sensitive and base load (Karaki, 1999). The wind forecast uses weighted least squares to fit past observed data and expected weather stations' forecast to a polynomial. The solar irradiance forecast uses the statistical model of Perez et al. (2007) relating it to clear solar irradiance and sky cover parameter available from weather forecasts. The optimal decisions in the EMS are obtained by a Genetic Algorithm (GA) that evaluates system performance using a cost function accounting for the fuel consumed, the battery degradation, the amount of load shed, and the number of starts of the diesel engine.

2. SYSTEM COMPONENTS

The different components of the system are shown in Fig. 1, and the EMS coordinates their operation by calculating the power output levels to be supplied based on data recorded and the expected forecast of weather and load. Power is then dispatched among loads and supplies.

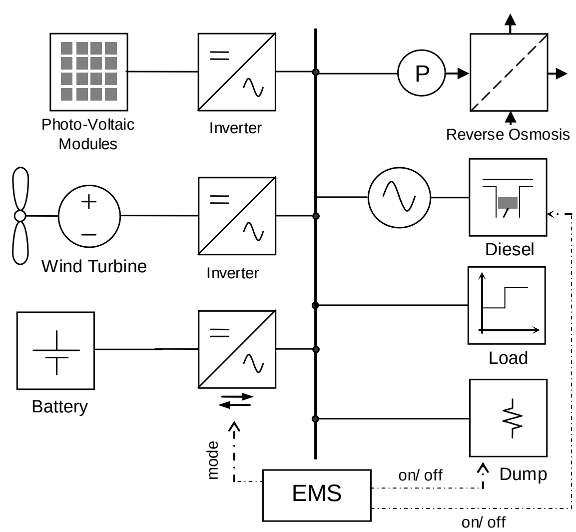

Figure 1: Hybrid renewable energy system

Renewable energy (RE), delivered by the solar modules and the wind turbine, is non-dispatchable and must be supplied at its available power level. Dispatchable units have a slack capability to maintain power balance at the busbar. These units may be the diesel engine (DE) when it is on, or alternatively, the battery and dump load when the DE is off. Load shedding may also used as a form of slack in the balance of power but only in extreme cases, e.g. the diesel fuel has run out. So, the classical EMS strategy to match RE and load is:

- If power from RE resources exceeds demand, then charge the battery until it is full, and supply the dump load with the excess; the DE is off.
- Else if RE power and battery discharge power exceed demand, then discharge the batteries, and turn off the dump load; the DE is off
- Else if RE power and DE power exceed demand then turn on the DE (if not already on); charge batteries if SOC is less than 80%.
- Else we have to shed load, since all available resources are not enough.

Based on this logic, the EMS can turn on and off the diesel engine, specify the battery charge/ discharge level, and connect and disconnect loads (load shed) or dump loads. The grid forming unit is specified at a lower control level; thus, if the DE is on then it is the grid forming unit, else it is the battery inverter. This logic is, however myopic and cannot tell if the sun will be up in two hours, for example, or that the wind resource is likely to be lost.

An optimizing EMS should contain a resource and load forecast and integrate their result in the decision making process, as shown in Figure 2. The optimal EMS bases its decision on forecasted values of load and renewable energy resources. But since forecasting and analyzing data is a slow and computationally demanding process, the EMS will be divided into three independent parts: a forecaster, an optimizer, and a dispatcher, each running at a different rate.

3. LOAD AND RESOURCE FORECASTS

Short-term forecasts of load and renewable energy resources for the next 24 hours are provided by a process that runs once per half-hour. Different forecast mechanisms are used for wind speed, solar irradiance, and load. The method used for short term forecast splits the load into a base load, a weather sensitive component, and special events (Karaki 1999).

On the other hand, the estimate of the net power flow (renewable energy power minus load power) in the system for the next hour is highly dependent on the most recently observed values, and it will vary each time the forecaster runs. Thus another very short term forecaster function is run each time the optimizer or dispatcher runs. Its inputs are the short term forecast, and the most recent readings of the net power flow; and its output is a forecast over a 1 hour horizon of the net power flow at intervals of 6 minutes.

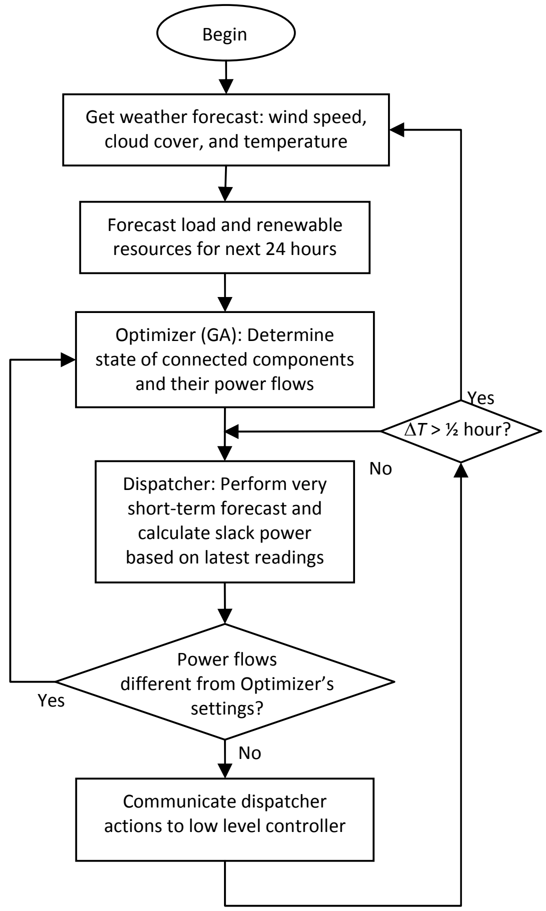

Figure 2: The optimal EMS algorithm

3.1 Wind Forecast

The method consists of finding a polynomial that fits the past data points and future wind speeds available from weather forecast data using the least squares method. Suppose that the current value of measured wind speed is y_0, the previous ones are y_{-1}, y_{-2} ..., and future values are y_4, y_8 ..., then y as a polynomial function of time is:

$$y_i = a_0 + a_1 t_i + a_2 t_i^2 \tag{1}$$

By considering equally spaced samples y_i at times $t_i = i\,dt$ the equations (1) in matrix form become:

$$\begin{bmatrix} y_4 \\ y_0 \\ y_{-1} \\ y_{-2} \\ y_{-3} \\ y_{-4} \\ y_{-5} \end{bmatrix} = \begin{bmatrix} 1 & 4dt & (4dt)^2 \\ 1 & 0 & 0 \\ 1 & -dt & (-dt)^2 \\ 1 & -2dt & (-2dt)^2 \\ 1 & -3dt & (-3dt)^2 \\ 1 & -4dt & (-4dt)^2 \\ 1 & -5dt & (-5dt)^2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix}$$

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{a}$$

Since older data points are less relevant than more recent ones, the weighted least square method is used to take this factor into consideration. The coefficients $\boldsymbol{a}$ are given by: $\boldsymbol{a} = (\boldsymbol{H^T W H})^{-1}\boldsymbol{H^T W}\,\boldsymbol{y} = \boldsymbol{X}\,\boldsymbol{y}$, where $\boldsymbol{W}$ is a diagonal matrix of measurement weights. Exponential smoothing is used on the weights starting from a value of 1 for the current reading and decreasing by 25% at -5. As we can see $\boldsymbol{X}$ is a constant matrix, and it needs to be calculated only once. Thus all the forecast algorithm has to calculate is the matrix product $\boldsymbol{X}\,\boldsymbol{y}$.

3.2 Solar Irradiance Forecast

It uses the empirical model of Perez et al (2007) relating solar irradiance to that of a clear sky using the sky cover parameter available from the weather forecast. The ratio of irradiance to that of clear sky irradiance is given by:

$$\frac{GHI}{GHI_{clear}} = 1 - 0.87SK^{1.9}$$

Where GHI is the average hourly irradiance, GHI_{clear} is the hourly clear sky irradiance, and SK is the forecasted sky cover parameter, which is a nine-level number between 0/8 and 8/8 with 0 corresponds to clear sky and 1 corresponds to total overcast.

The hourly average clear sky irradiance is obtained from historical data assuming that it is reached at least once in a week. So for any hour, the clear sky irradiance is equal to the maximum irradiance of the previous 7 days at the same hour. Here the variation in the maximal solar irradiance level throughout a week is assumed negligible. This method of estimation of clear sky irradiance level doesn't need any pre-setting and adapts to the location in which it is installed.

3.3 Very Short Term Forecast

The very short term net power forecast is carried out by a least squares method based on past five data points and future data points (forecasted by the short term forecaster). A second order polynomial is used to forecast the net power at the next step, i.e., 6 minutes ahead, by fitting past data points at -6, -12, -30 and -60 minutes together with the 60 minutes ahead obtained earlier from short term forecast.

4. THE OPTIMIZER

The optimizing methodology is based on a genetic algorithm with an appropriate representation of the possible solutions and has a method to calculate the fitness of these solutions. The input of this function is the short term forecast of load and resources, and its outputs are the diesel engine state (on/off), the battery power level, and load shed levels. In the operation of the system the following rules are considered:

- The dump load is not connected if the batteries are discharging or if the diesel engine is running,
- Supplying the load has a higher priority than charging the battery and fuel consumption considerations.

With these rules, we are left with two parameters to control: the power of the diesel engine and the power of the batteries. But due to power flow balance constraints, only one of these needs to be determined. We have chosen the diesel engine power since this variable is a composite of a discrete variable stating whether the engine is on or off and a continuous one specifying its power when running.

So the diesel engine (DE) power is divided into discrete levels to reduce the computational complexity without major degradation of performance. A reasonable approach is to divide the operation range of the DE power into eight levels within the permitted zone of operation. The selected levels are: 0, 60%, 65%, 70%, 80%, 90%, 95%, and 100%. A higher level of accuracy has been chosen near the limits to allow for smoother behavior of the system. Thus the DE generator power levels are represented as a string of 24 bits corresponding to 8 hours with 3 bits each representing the 8 levels of the diesel engine.

The heuristic used to speed up the solution process was to divide the 24 hour horizon into 3 periods of 8 hours each. This was found to be sufficient since he optimizing process is being repeated progressively at half-hour intervals. Increasing the horizon to 24 hours simply increased the computations without any noticeable improvement in the quality of decisions reached. The Cost function defined below is used as a fitness measure of the represented solutions. Reproduction was based on a single crossover point, and selection is based on tournament stochastic polling with an elite count of 5 in a generation population of 50. The mutation rate had a uniform distribution from 0 to 0.3.

4.1 Cost Function

The GA algorithm uses the system cost function as an individual fitness evaluation. The system cost function has the following form:

$$L = \sum_{i=1}^{N} u_i F_{DE}(P_{DEi}) + S_{DE}(u_i, u_{i-1}) + F_{LS}(LS_i) + F_{BT1}(SOC_i, \Delta T) + F_{BT2}(\Delta W)$$

Where:

- u_i is a Boolean defining the state of generator (on/off)
- $F_{DE}(P_{DEi}) = C_{DE}\, P_{DEi}$ is the cost of operating the diesel engine in \$/h, with P_{DEi} being the power delivered in kW in time interval i, C_{DE} is the cost of energy obtained from the diesel generator in \$/kWh; a typical value is 0.17 \$/kWh for the selected 20kW diesel generator.
- $S_{DE}(u_i, u_{i-1}) = 5C_{DE}\, u_i(u_i - u_{i-1})$ is the cost of starting the diesel engine, which is essentially a penalty factor selected heuristically to limit the number of start-ups to 8 per day as a maximum. In addition to that, the minimal time to run the diesel engine is 18 minutes. Violating this limit is penalized by a large cost of $10C_{DE}$.
- $F_{BT1}(SOC_i, \Delta T) = C_{BT} Q_{BT}(1 - SOC)k\Delta T$ is the cost of prolonged discharge of the battery, which is proportional to the depth of discharge of the battery and its duration; where C_{BT} is the cost of replacing the battery, ΔT is the discharge time in days, and k is a constant calculated considering that a battery should

be recharged to its full capacity once every 4 days (Mattera et al, 2003) to avoid sulfation. For a battery of 10 years lifetime when kept at full charge, and 50% reduction if kept at 40%, k would be equal to 0.022.

- $F_{LS}(P_{LSi}) = 50\ C_{DE}\ P_{LSi}$ is the cost of load shedding, which represents the social cost of not serving the load arbitrarily set at 50 times the cost of supplying it from the diesel engine.
- $F_{BT2}(\Delta W)$ is the cost of battery degradation (ΔW) that accounts for the limited number of charge/ discharge cycles. This item is further explained below.

4.2 Battery Degradation

The number of discharge cycles that a battery can undergo over its lifetime is specified by manufacturer's curves for different discharge levels. Scrivani (2005) suggested that the total power a battery can supply over its life is nearly constant irrespective of the depth of discharge if the SOC of a battery is kept above 40%. A somewhat related approach is used here. The degradation in battery life for each cycle is calculated as the inverse of the number of cycles the battery can undergo at a given discharge level. Thus, if ΔW is the degradation of the battery due to one cycle from full charge to a depth DOD and back to full charge, then

$$\Delta W = \frac{1}{N_{DOD}}$$

Where N_{DOD} is the number of cycles the battery can undergo for the given discharge level, read from the manufacturer's curve. For a partial discharge from SOC_1 to SOC_2 , ΔW is then taken as:

$$\Delta W = \frac{1}{N_{DOD_2}} - \frac{1}{N_{DOD_1}}$$

Thus, the lifetime W of the battery is started at 1 and is updated as $W = W_{old} - \Delta W$; total degradation of the battery occurs when W becomes zero. Thus the cost of the battery degradation is simply:

$$F_{BT2}(\Delta W) = \Delta W\ \ C_{BT}$$

4.3 Constraints

The diesel engine operation levels are confined to 8 discrete levels, the diesel engine will always operate within its permissible limits, and thus there are no additional constraints on the optimization variable. As for the batteries, the power that can be delivered (P_{BT}) and the state-of-charge (SOC) have upper and lower bounds:

$$-P_{BT}^{\max} < P_{BT} < P_{BT}^{\max}$$

$$0.4 < SOC < 1$$

The other variables are computed from the power balance equation:

$$P_{LS} - P_{DL} = P_{load} - P_{RE} - P_{DE} - P_{BT}$$

Where $P_{LS} \geq 0$ and $P_{DL} \geq 0$

Thus any solution produced by the optimizer would be feasible.

5. THE DISPATCHER

The role of the Dispatcher is to check if the profile assigned by the optimizer is valid for the current data readings. In case it is consistent with observed data, the assigned values will be applied; else, the optimizer will be called to recalculate the optimal profile using the latest readings. The Optimizer having specified the state of the DE and the power flow into the different components, the Dispatcher operates as follows:

- If the diesel engine is on then it is the grid forming unit; if DE power is much different than the one specified by the optimizer, or bus frequency has deviated from its reference value (power mismatch), then run the optimizer again; else set battery, load shed, and dump load to their assigned values.
- Else if the DE is off, the battery (BT) is the grid forming unit; if BT power is much different than the one specified by the optimizer, or bus frequency has deviated from its reference value (power mismatch), then run the optimizer again; else set load shed, and dump load to their assigned values.

6. SIMULATION AND RESULTS

The methodology was applied to the system being installed at Bourj Cedria, Tunis, with the sizes of the different subsystems given as: wind turbine size is 15 KW, the PV generator size is 15 kW, the battery size is 3.6 kWh, the reverse osmosis plant is 4 kW, and the general electrical load has a peak of 11 kW. Wind speed and solar irradiance data for one year starting on 12/12/2007 was used in the evaluation.

Data from a weather station at Bourj Cedria in Tunis has been used in testing the methods. Forecasts from weather stations were not available, and were simulated from average values over 4 hours with the addition of 25% perturbation. The solar irradiane forecast error is about 8% and is almost constant over the 24 hours forecast range.

A second order polynomial has been used for the very short term forecast of net load. Past data points corresponding past 6, 12, 30 and 60 minutes have been chosen together with the 1 hour ahead short term forecast. The error in the six minutes forecast is about 8% and increases to about 10% for the 1 hour forecast.

A typical week in winter and another in spring have been selected for the simulation. The winter week has insufficient renewable energy resources contributing to about 50% of load demand. Spring days on the other hand have more abundant renewable energy resources of about 94%.

The EMS has been tested in two different configurations. In the first case, a classical if-then-else static EMS similar to the one used in commercial controllers has been used (Chedid et al, 2008), which is considered as a reference for comparison. In the second case, the performance of the forecaster and the optimizer are tested together.

Figure 3 shows the power flow of diesel engine and that of the battery. We can see that the diesel engine is always running near its rated power, and thus at its highest efficiency. Nevertheless, the efficiency gained from running diesel engine at a high load factor is wasted in the unnecessary charge discharge cycles of the battery (Figure 4) and reducing the life of the batteries due to a relatively high frequency of cycling. This could be seen clearly in the interval from 60 to 140 hours. The net load is always positive all over this zone meaning that there is no surplus of resources to be stored, and thus the battery need not be discharged.

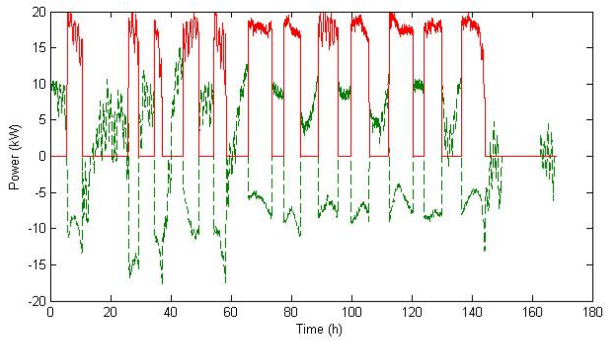

Figure 3: Diesel engine (continuous) and battery (dashed) power flows for the winter week: classical EMS

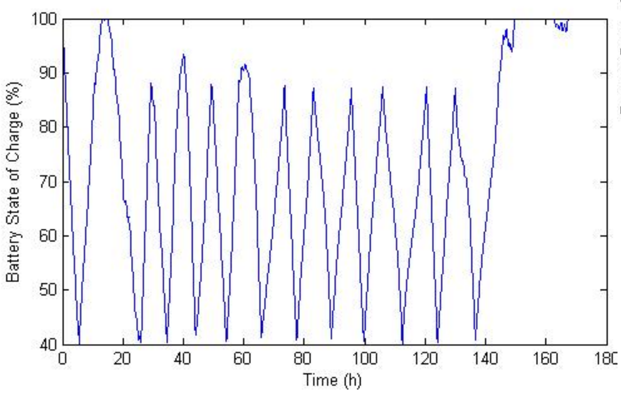

Figure 4: Battery State of Charge in the winter week: classical EMS

For the optimal EMS, the diesel and battery power flows are shown in Figure 5. In this case, the diesel engine runs for prolonged intervals at a lower load factor, and the power supplied to the battery is small. The latter takes the form of discrete steps set by the optimizer as a compromise between diesel engine efficiency and battery charging efficiency. As a result the battery is cycled less often (Figure 6), thus prolonging its useful life. There are some spikes in the diesel engine operation due to high perturbations in the wind power or load, but within the imposed limits (t_{on} >18 minutes).

The results of the simulation of the system using the Classical EMS and the proposed optimal EMS are given in Table 1 for typical weeks in winter and in spring. The number of runs per hour of the optimizer for the 7 winter days was monitored and the mean was found to be one call every about half an hour and its decision set remains valid for that period. As can be seen in the table below, there is a considerable reduction of in the number of charge discharge cycles of the batteries is reduced by more than 50%, which indicates that the battery life would be more than doubled.

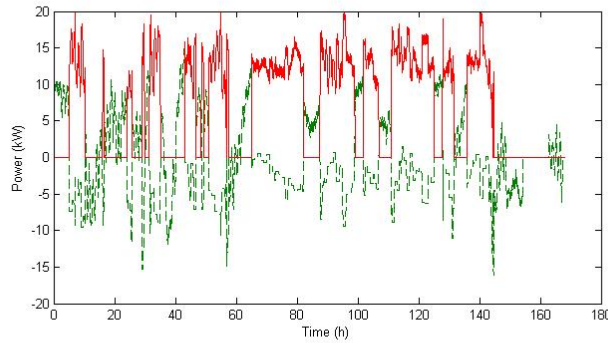

Figure 5: Diesel engine (continuous) and battery (dashed) power flows for the winter week: optimal EMS

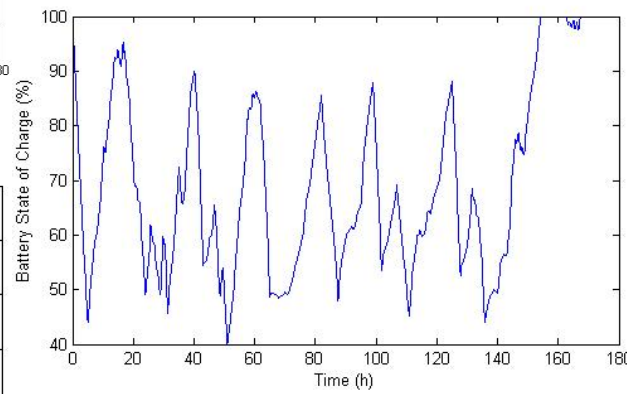

Figure 6: Battery State of Charge in the winter week: optimal EMS

Table 1: Simulation Results for a Winter and Spring Week

	Winter Week		Spring Week	
EMS Type	Classical	Optimal	Classical	Optimal
Demand (kWh)	1959	1959	1959	1959
RE Supply (kWh)	1032	1032	2085	2085
Dumped (kWh)	89	62	462	463
Diesel (kWh)	1181	1105	391	389
Fuel (liters)	384	368	127	130
DE Starts	12	16	5	15
Battery Cycles	12	7	5	1

There is a reduction in the required power from the diesel engine (about 6%) and in the fuel consumption (about 4%) for the winter week, whereas the diesel engine power is almost the same in spring with a slight increase in fuel consumption. This is due to the fact that the optimal EMS doesn’t always run the diesel engine at its peak load, which would introduce some losses. Using two diesel engines would however solve this problem. The number of diesel engine starts is limited to about 2 per day, which is less than the permissible value. Overall, the optimal EMS has achieved almost the same level of fuel consumption but with a major decrease in the number of cycles of the batteries.

The response of the system in different configurations has been simulated to analyze the effect of variations in system size on the EMS performance. For a battery size reduced by 10%, the results are shown in Table 2, cols. 1 and 2. The classical EMS shows a slight reduction in fuel cost but an increase in the number of battery cycles (from 12 to 15), when compared to cols. 1 and 2 in Table 1. On the other hand, the optimal EMS has produced a slight increase in fuel consumption (1%) but a lower increase in the number of cycles (7 to 8).

Since the battery is needed to store excess energy, its size reduction should lead to an increase in the dump load power. The results show that this is true for the optimal EMS, but not for the classical one, which is an indication of the bad management of battery storage by the classical EMS that has more dump load energy and more fuel consumption in base case. On the other hand, the optimal EMS performance has degraded a little with the decrease in the battery size indicating that the system is capable of handling the extra storage. However, it remains better in terms of fuel consumption and battery life taken together.

Table 2: Winter Week Reductions: Battery Capacity (10%), PV generator (10%), and Diesel Engine (25%)

	Battery		PV		DE	
EMS Type	C[1]	O	C	O	C	O
Demand (kWh)	1959	1959	1959	1959	1959	1959
RE Supply (kWh)	1032	1032	993	993	1032	1032
Dumped (kWh)	81	85	77	60	57	59
Diesel (kWh)	1177	1117	1200	1131	1102	1056
Fuel (liters)	382	371	390	376	360	350
DE Starts	13	14	12	18	9	14
Battery Cycles	15	8	12	4	8	1

Note 1: C for classical and O for optimal

When the PV generator size is reduced by 10% results are shown in Table 2, cols 4 and 5. The fuel consumption with the classical EMS has increased by 1.5%, whereas the number of battery cycles is the same. In the optimal system the fuel consumption is increased by 2.2% but the number of battery cycles is reduced from 7 to 4. This is expected since battery storage is less useful in systems with low renewable energy resources. Here also overall system performance with the optimal EMS remains significantly better than that of a classical EMS.

The performance of the system with a 25% reduction in the Diesel engine rated power has also been analyzed (Table 2, cols 6 and 7). Here we note a 3% reduction in the fuel consumption with a large drop in the number of battery cycles. System efficiency has improved for both the Classical and Optimal EMS which indicates that there is a need for a smaller diesel engine.

The performance of the system is dependent on both, the component sizes and the EMS logic, by using an “optimal” EMS logic the dependence of system performance on the EMS is thus ideally eliminated but practically reduced. Thus the performance is more dependent on the component sizes when using an “optimal” EMS as compared to a classical if-then-else EMS logic.

7. CONCLUSIONS

This paper has investigated the integration of a reconfigurable optimizer and a forecaster into the Energy Management System (EMS) as compared to a classical EMS of a hybrid energy system. The results of the simulation have shown about 50% reduction in the number of battery cycles while preserving the same level of diesel engine fuel consumption as compared to a classical EMS. This reduction should elongate the life of the batteries up to 100%, thus introducing a major reduction in the operation cost of the system. The effect of the optimal EMS on the size of system components has been studied. Sensitivity analysis has shown that the system operating with an optimal EMS is more sensitive to changes in system component sizes, because it is operating near its peak efficiency boundary.

ACKNOWLEDGEMENTS

The work described in this paper was inspired and partly carried out as Work Package 3 in the Open Gain Project funded by the EC under FP6 (Contract No. 32535). The Open Gain project is carried out by a consortium of MENA institutions led by Prof. Essam Badreddin, head of the Automation Lab at the University of Heidelberg, Germany.

REFERENCES

Chedid R, S. Karaki, D. Fares, E. Azar, K. Kabalan, 2008, Open Gain Integrated Energy Management System Design, *AUB Progress Report Document (WP3)*.

Karaki S., 1999, Weather Sensitive Short Term Load Forecasting using Artificial Neural Networks and Time Series, *International Journal of Power and Energy Systems*, Vol. 19, No. 3, pp. 251-256.

Mattera F., D. Benchetrite, D. Desmettre, J. Martin, E. Potteau, 2003, Irreversible Sulfation in Photovoltaic Batteries, *Journal of Power Sources* 116, 248–256.

Perez R. et al, 2007, Forecasting solar radiation–Preliminary evaluation of an approach based upon the national forecast database, *Solar Energy* 81, 809–812.

Scrivani A., 2005, Energy management and DSM techniques for a PV-diesel powered sea water reverse osmosis desalination plant in Ginostra, Sicily, *Desalination* 183, 63–72.

Seeling-Hochmuth G., 1998, *Optimization of Hybrid Energy Systems Sizing and Operational Control*, PhD Dissertation, University of Kassel.

Soni A., Ozveren C., 2006, Improved Control of Isolated Power System by the Use of Feeding Technique, *Proceedings of the 41st International Universities Power Engineering Conference* (UPEC '06), September 2006.

Wichert B., M. Dymond, W. Lawrance, and T. Friese, 2001, Development of a Test Facility for Photovoltaic-Diesel Hybrid Energy Systems, *Renewable Energy* 22, 311-319.