Storage system scheduling effects on the life of lead-acid batteries

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***Abstract*—Storage systems are a key element to take advantage of renewable energy due to its ability to transfer energy consumption from one time period to another. With high charge/discharge ratios one can increase the short term revenue stream from a renewable energy system whereas with a low charge/discharge ratios one can increase the long term benefits. Hence, when compared against nominal charge or discharge operation, the storage system life can be increased/reduced with a low/high charge or discharge ratios. In order to quantify this fact for different storage management strategies, this work analyze the effect on the life of a lead-acid battery system of three scheduling strategies: linear programming, crisp logic and fuzzy logic. The three cases will be compared against a reference strategy which consist on solving a linear optimization problem with perfect forecast of load, energy price and renewable availability. A photovoltaic system is taken as the renewable source and historic values for eight months are used to study the trend in the life of the storage system. it can be concluded that higher storage capacity leads to higher overall benefits, however, this cannot be said for the maximum storage system power, even when considering only the costs benefits, which suggest that a proper strategy and parameter selection can be better than high power ratio.**

***Index Terms*—Energy storage management systems, fuzzy logic systems, linear programming, smart grids.**

I. Introduction

The storage management plays a key role in power distribution networks with renewable sources. For example, by shifting generation from light-load/low-price time periods to peak-load/high-price time periods [1, p.262]. Depending on the available storage devices and local generation equipment the storage management can be composed by only a battery or several storage devices.

Battery storage systems are typically composed by lead-acid batteries. Battery systems are a sensible element because «how [it] performs over its lifetime is highly dependent upon how it is operated in real-time during each charge and discharge cycle.» [2, p.2]. Two main approaches have appeared to handle this: Rule-based methods and Fuzzy Logic methods.

A rule-based approach depending on weather conditions is presented in [3]. There, Chakraborty *et al*. propose five energy storage programs which are activated depending on today's and tomorrow's weather. The philosophy is intuitive, for example, «If the next day is going to be cloudy and the present day's generation is good, the [storage system] should be able to store more energy during the present day» [3, p.5].

The fuzzy logic approach of [4] consists on a membership function for the battery state of charge, electricity price, load demand, renewable energy generation, actual solar daily generation and next day solar availability to derive a charge or discharge signal. On the other side, storage system in [5] depends mainly in the «charging price»: the difference between the maximum daily price and minimum daily price. The fuzzy logic is employed to derive changes in charging price, subject to local generation price and storage device accumulated participation –until actual time slot. For Mahmoud *et al*. storage charging/discharging rates are constraints in the optimization problem, while storage dispatch depends on comparing the charging price with local generation costs.

Colson *et al*. in [2] developed a cost-efficient index for optimal operation of the storage system that in addition it offers a user interface to decide if battery health is more important than revenue stream. However, still is not clear if changing the storage management strategy itself makes such adjustment useless, because the strategy is to aggressive or in turn, because the strategy already cares about the discharge rates. This paper will analyze battery life effects of three storage management strategies in order to explore a possible way to optimize system performance according to battery life.

This document is organized as follows: section 2 describes the scheduling strategies used; section 3 the battery lifetime model; then, in section 4, the results are presented, to later in section 5 end with some concluding remarks.

II. Scheduling strategies

A one bus system was selected for testing the storage system scheduling. The cases to be analyzed are:

Reference case Solve a linear optimisation problem with a rolling horizon of 48 hours [6], knowing in advance the energy demand, price and solar irradiance.

Average case Solve a linear optimisation problem with a rolling horizon of 48 hours, assuming an average energy demand, price and solar irradiance curve.

Crisp logic case Calculate the required charging/discharging power of the battery using a function which depend on a demand, price and solar irradiation signal at the beginning of the period t.

Fuzzy logic case Calculate the required charging/discharging power of the battery using a fuzzy logic inference system [4], for a demand, price and solar irradiation signal at the beginning of the period t and a solar signal for next-day solar irradiance.

In each case is analyzed the battery life according to the model proposed in [2]. Battery life consumed will be taken as an index of the overall effect of each strategy. Simulations are run for a total observation time of 8 months (1 month taken as 30 days), which includes a one-week holiday season. Details of each strategy are presented below.

A. Linear optimization

The scheduling of a storage system can be stated as a linear optimization problem with the following objective function:

$$\max. \left\{\pi_{\text{in}}^T P_{\text{in}} - \pi_{\text{out}}^T P_{\text{out.}}\right\} \tag{1}$$

With:

$$P_{\text{in}} = P_{\text{ss,in}} + P_{\text{pv,grid}} \tag{2}$$

$$P_{\text{out}} = P_{\text{ss,out}} - P_{\text{pv,load}} + L \tag{3}$$

Where $L = [L(1), L(2), \dots L(t_n)]^T$ is the column vector of the energy consumed at each time period t within the time window T, which in turn is composed of n time periods, i.e. $T = \{1, 2, \dots t, \dots t_n\}$. $P_{\text{pv,grid}}$ is the column vector of the energy injected to the grid and $P_{\text{pv,load}}$ is the column vector of the energy used to satisfy the demand, both from the photovoltaic (PV) system for each $t \in T$. $P_{\text{ss,in}}$ and $P_{\text{ss,out}}$ are column vectors of the energy injected/withdrew at the connection point from the storage system for each $t \in T$. π_{in}^T and π_{out}^T are the row vectors with the energy price for injecting and withdrawing energy into and out of the power distribution system for each $t \in T$.

This objective is constrained to the following inequality constraints:

$$0 \leq P_{\text{ss,in}} \leq r \times \varepsilon_{\text{in}} \tag{4}$$

$$0 \leq P_{\text{ss,out}} \leq r / \varepsilon_{\text{out}} \tag{5}$$

$$SOC^{(\text{min.})} \leq SOC \leq SOC^{(\text{max.})} \tag{6}$$

$$P_{\text{pv,load}} \leq L + P_{\text{ss,out}} \tag{7}$$

$$P_{\text{pv,grid}} \geq 0 \tag{8}$$

$$P_{\text{pv,load}} \geq 0 \tag{9}$$

Where SOC is the column vector of the state of charge of the storage for each time $t \in T$, $SOC^{(\text{min})}$ and $SOC^{(\text{max.})}$ are the SOC minimum and maximum limits; r is the maximum charging/discharging limit of the storage system; and ε_{in} and ε_{out} are the discharge and charge efficiency of the storage system.

The objective is also restricted to the following equality constraints:

$$P_{SS} = P_{\text{ss,in}} / \varepsilon_{\text{in}} - P_{\text{ss,out}} \times \varepsilon_{\text{out}} \tag{10}$$

$$P_{PV} = P_{\text{pv,grid}} + P_{\text{pv,load}} \tag{11}$$

$$P_{SS}(t) = (SOC(t-1) - SOC(t)) \times P_{SS}^{(\text{max.})} / \Delta t \tag{12}$$

$$SOC(t_n) = SOC(1) \tag{13}$$

Where P_{SS} is the column vector with the total power flowing from or to the storage system for each time period $t \in T$, $P_{SS}^{(\text{max.})}$ is the maximum capacity of the storage system and Δt is the duration of each time period $t \in T$.

Since all vectors on equation 7 are constrained to positive values, this inequality force the PV system to first supply all the energy requirements before injecting energy into the grid. On the other hand, equations 4, 5 and 10 are used to force storage system operation into two states for each time period: charging or discharging. So, if $P_{\text{ss,in}} \neq 0$ then $P_{\text{ss,out}} = 0$. This is possible only if $\varepsilon_{\text{in}} \varepsilon_{\text{out}} \leq 1$ and if in the objective function this values have opposite signs. For further information please refer to [7].

This linear optimisation problem is used to compute the answer of two cases: Perfect information case and average case. Perfect information case solve the problem using the values of L, π_{in}, π_{in} and P_{PV} measured during the observation time (8 months). The average case solve the problem using an average from historical values of L, π_{in}, π_{out} and P_{PV}. L average takes into account the differences between week days, saturday and sunday/holidays; average taken on π_{in} and π_{out} do not make any difference between days; and P_{PV} average is scaled depending on the total energy of the analyzed days within the time window. So if the average solar irradiance sums to x kWh, the present day irradiance sums to y kWh and the next day irradiance sums to z kWh, the average solar irradiance data for each $t \in T$ is scaled by y/x for $t \in \{1, 2...24\}$ and z/x for $t \in \{25, 26, ...48\}$. When different, energy price π_{in} is taken as a sclaled version of π_{out} due to the lack of information.

B. Crisp logic

The crisp logic control is composed of a price-to-power function defined as:

$$P_{SS}(\pi')\big|_t = \begin{cases} r, & \pi' \leq \pi'^{(\text{min})} \\ m\pi' - \left(m\pi^{(\text{min})} - r\right) & \pi'^{(\text{min})} < \pi' \leq \pi'^{(\text{max})} \\ -r, & \pi' > \pi'^{(\text{max})} \end{cases} \tag{14}$$

With:

$$m = \frac{2r}{\pi'^{(\min)} - \pi'^{(\max)}} \tag{15}$$

Where π' is a price signal calculated as the ratio between the actual price (at time t) and the maximum price of the last 12 hours. Here, r is also the maximum charging/discharging limit of the storage system. $\pi'^{(\min)}$ and $\pi'^{(\max)}$ are function parameters which correspond to the minimum and maximum saturation prices.

This storage management system calculate a charge signal when: $P_{SS}(\pi')|_t \geq 0$ or $L - P_{PV} < 0$ –The final charge signal is the higher one. Conversely, a discharge signal is calculated when: $P_{SS}(\pi')|_t < 0$ and $L - P_{PV} \geq 0$. At each step the SOC limits are checked, and if violated, the corresponding signal is corrected. Besides, if SOC falls below a threshold, the system will prioritize the charging signal until a selected SOC is achieved. Those values do not coincide with the minimum and maximum SOC limits.

C. Fuzzy logic

A fuzzy logic system is a kind of expert system which transform the real world variables to a semantic space in order to take decisions under uncertainty. One of the advantages of this kind of transformation is that the semantic space allow a definition of the relationships between the inputs and outputs through terms near to natural-language, and so, it results in intuitive definitions. But this comes with a great effort in calibration and testing of the system parameters if the problem to be solved through this tool is on early stages of research [8].

For the present work, the fuzzy system consist on three major inputs: present load ($L(t)$), reference price ($\pi'(t)$) and total irradiance ($S(t)$). The storage system power injected/withdrew to/from the grid ($P_{SS}(t)$) constitute the only output. At each t the signals are read and processed to derive an output signal. The price signal is the same used in the crisp logic system: it is the ratio between the present price and the maximum price of the last 12 hours. The total irradiance is calculated as the sum of the observed irradiance at each time t for the day.

The semantic space for each one of the variables is the same: low, medium and high. However, the membership functions for each fuzzy variable are not the same. All fuzzy system parameters are described in the annex. There, Table II summarize the membership functions for each fuzzy variable following the nomenclature depicted in Figure 5 and Table III show the set of rules implemented (Those rules are product of a empirical tuning process, It is left for future works the optimal fuzzy system parameter selection problem).

From Table II, it can be observed that the load signal is processed depending on the day in order to account for differences between week days, Saturdays and Sundays/holidays. Besides, two total irradiance signals are treated as inputs by the fuzzy inference system: present day and next day total irradiance – Although both inputs have the same membership function.

The fuzzy inference is done with two sets of signals: One depending on the reference price and load, and other depending on the present day and next day irradiance. Any of these signals give a pair of possible charge and discharge ratios. The charge ratio depending on price and load are added to the charge ratio depending on total irradiance; the same is applied to the discharge ratio signal. The biggest between the two signals is selected to go through the defuzzification process [4]. Like in the case of the crisp logic system, the SOC limits are always checked and the power output of the storage system is corrected if it is necessary.

III. Battery life

The calculation of the lead-acid battery life is based on the modeling presented in [2]. There, Colson *et al.* present a lead-acid battery model to quantify the round-trip efficiency and costs on a real time basis. The costs are calculated by determining the remaining life of the battery, which in turn depends on the discharge current. The discharge current allow to calculate the Depth Of Discharge (DOD), and with this latter one can compute the remaining life of a battery ($L_{\text{remaining}}$). The equation is here reproduced from [2] for the sake of reference:

$$L_{\text{remaining}} = L_{\text{rated}} \left(1 - \frac{\sum_{t<=n} d_{\text{eff.}}}{\Gamma_{\text{rated}}}\right) \tag{16}$$

With:

$$\Gamma_{\text{rated}} = L_{\text{rated}} D_{\text{rated}} C_{\text{rated}} \ \text{[Ah]}$$

$$d_{\text{eff.}} = d_{\text{actual}} \left(\frac{C_{\text{rated}}}{C_{\text{actual}}}\right) (D')^{u_0} \exp\left[u_1 (D' - 1)\right] \ \text{[Ah]} \tag{17}$$

$$D' = \frac{DOD_{\text{actual}}}{DOD_{\text{rated}}} \tag{18}$$

Where DOD_{actual} is the DOD at current time t, DOD_{rated} is the rated DOD, d_{actual} is the discharged energy at time t, $d_{\text{eff.}}$ is the effective discharged energy («corrected for the depth and rate of discharge» [2]), C_{rated} is the battery rated capacity, C_{actual} is the battery capacity at time t and L_{rated} is the life of the battery in cycles at rated DOD and rated current and Γ_{rated} is the life of the battery in Ah. As stated in [2], $\Delta DOD = d_{\text{actual}}/C_{\text{actual}}$, so the above equations can be expressed completely on terms of the DOD. Actually, it was found that the dynamic model of the battery presented by Colson *et al.* is equivalent in terms of the SOC to the computed by the scheduling strategies. Therefore, as the DOD can be computed from the SOC, it was employed the results of the scheduling strategies.

IV. RESULTS

A demand with a peak load rounding 35 kW, an storage system with a capacity of 240 kWh and maximum charge/discharge power ratio of 34 kW and a solar availability of 70 to 100 kW at noon was simulated. The choose of the eight months corresponds to the period of time on which there are several holidays. In fact, it covers Christmas holidays and the Colombian Easter week, called «Semana Santa». All the storage system parameters can be consulted in [2] and [9]. Figure 1 depicts the behavior of the four strategies analyzed.

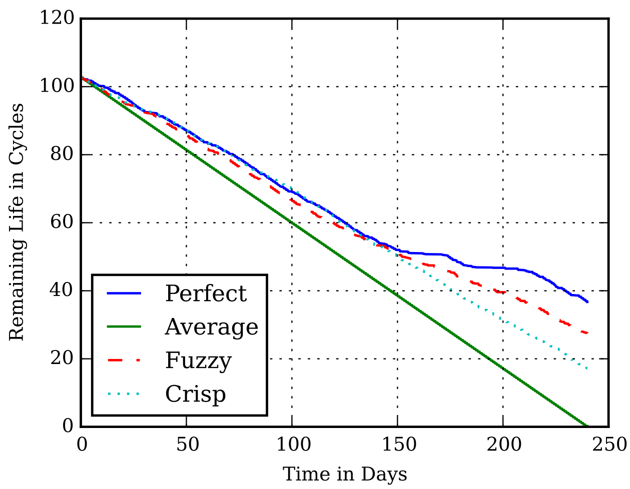


Figure 1. Remaining life of the storage system in terms of cycles. The initial value of the remaining life cycles are 103 cycles, and for the average strategy the remaining life is less than 1 cycle.

First it is concluded that the reference case, which is the case of linear programming strategy with perfect information, is the better strategy. This behavior is explained as the result of better control over the solar irradiance, which in turn yields to less cycles. It worth noticing that even with data limitations the fuzzy and crisp strategies have a well performance. In particular, the fuzzy strategy is about ten cycles of the perfect information strategy. Since the average strategy is the worst of the three, the following analysis do not include more data about it.

As stated before for high charge/discharge ratios, one may expect lower values on battery life. However, this is somehow related to the capacity of the storage system too, so a variation over the capacity and power ratio of the storage system was done. The methodology is the following: Taking as a base case the original simulation, the capacity was changed from 1/4 of the total capacity to 8/4 of the total capacity in steps of 1/4. For each capacity it was simulated a maximum power charge/discharge ratio of 1/10, 1/7, 1/3 and 1/2 of the total capacity. It worth noticing that due to the change of storage system maximum power from simulation to simulation, the membership function must be rewritten as described in Table I.

Table I
STORAGE SYSTEM MEMBERSHIP FUNCTIONS AS A PERCENTAGE OF ITS MAXIMUM CHARGE/DISCHARGE POWER.

	S.S. output [%]			
low	-	6	6	30
med.	6	30	70	94
high	70	94	94	-

A first result for the perfect and fuzzy logic strategies, was that the remaining life is almost the same for each capacity if the power to capacity proportion is held constant, e.g. it was the same to simulate with 1/4 of capacity with 1/2 of the capacity as the power to capacity proportion than 8/4 of capacity with the same power to capacity proportion. By looking the charge and discharge power of the storage system, it was noticed that the difference between cases were only by a scalar, and overall, the same cycles were observed for each t. In contrast, the crisp logic strategy do not have this property. This is because the crisp logic depends more directly over the prices than the other two strategies, and because for the other two strategies there a more discrete steps between one signal and other, i.e. for the crisp logic strategy a little variation on the price signal lead to a small variation on the power charge/discharge ratio signal, whereas for the fuzzy logic and the perfect information strategy this might not be the case.

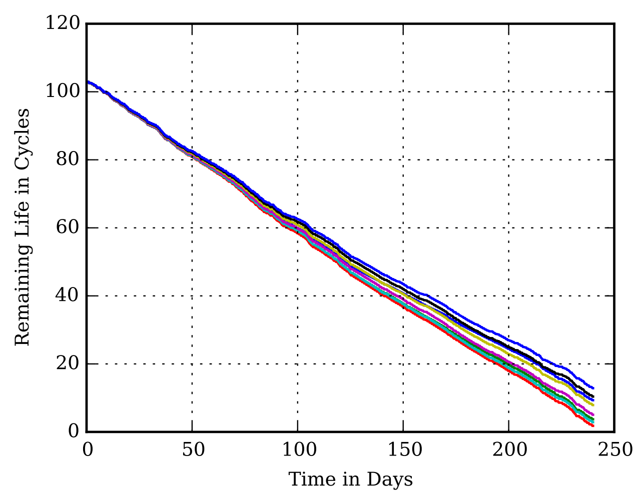


Figure 2. Remaining life of the crisp strategy for different battery capacities taking as the maximum power ratio of the storage system half of the capacity. For the fuzzy and perfect information strategy there is no difference on the life remaining if the power to capacity ratio is constant.

In Figure 2, it is shown the crisp strategy for 8 capacities and a maximum charge/discharge ratio of half the capacity. It was expected that better results came from small capacities and worst results from big capacities, since preliminary simulations allowed to observe that small capacities have slower cycles. However, the worst performance is from a capacity corresponding to 3/4 of the reference capacity, and surprisingly enough, the capacity corresponding to 8/4 of the reference capacity was just ten cycles of the better case, which was the smallest capacity. This behavior is quite similar to the observed in Figure 3. There are depicted 4 life cycles curves, each one corresponding to a power to capacity proportion for the same capacity. The smallest charge/discharge ratios get the better performance, as expected, however 1/2 power to capacity proportion outperforms 1/7. This can be observed on Figure 4 where total energy costs are plotted as a function of the remaining life in cycles.

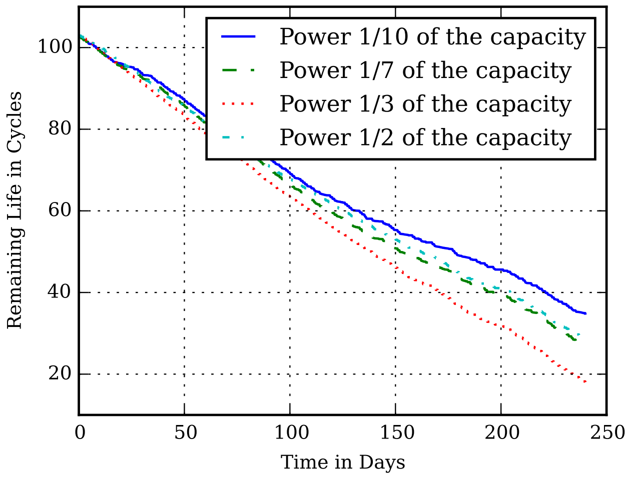
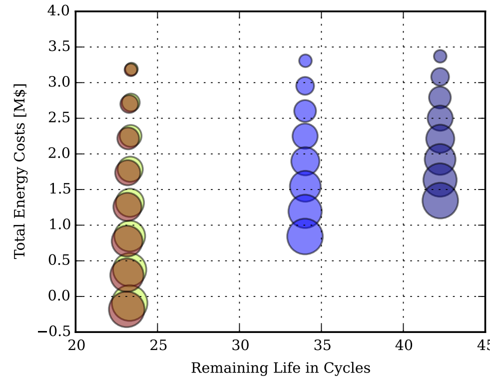
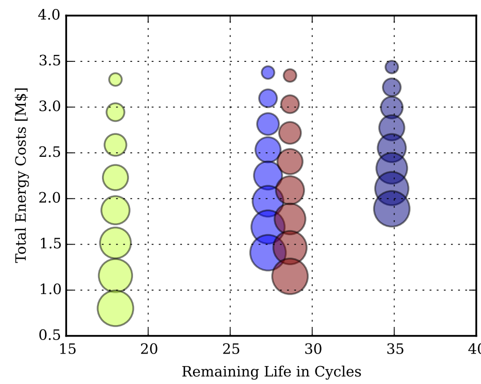


Figure 3. Remaining life for the fuzzy logic strategy for different maximum charge/discharge power ratio for the reference capacity.

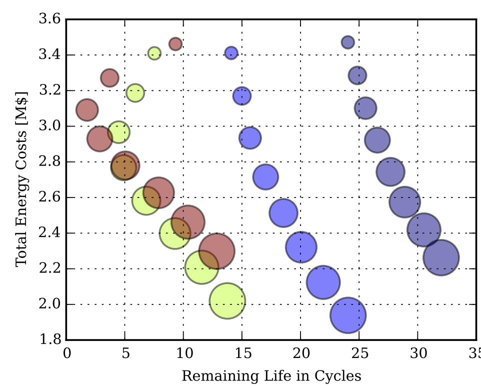
From there it is also observed that higher capacity points always dominates lower capacity points, since always an increment on capacity yields at least a diminish on costs –for the crisp logic strategy, such increment also leads to a higher value of remaining cycles. Besides, it is immediately noted that the change in storage system power output changes with the strategy chosen: For the perfect information case, 1/3 and 1/2 of the capacity have almost the same values; as noted before, for the fuzzy logic case, the 1/2 power to capacity ratio outperforms the 1/7 ratio; and for the crisp logic case, the maximum capacity with 1/7 and 1/10 of power to capacity ratio dominates all other points. Interestingly enough, it can be seen that for this latter strategy, a reduction of 25% in capacity and almost 70% in power to capacity ratio, results on a better battery-life performance without sacrificing cost performance. Further analysis on battery lifetime modeling, strategy selection and parameter tuning must be done to properly explain this behavior.



(a) Linear programming with perfect information



(b) Fuzzy logic



(c) Crisp logic

Figure 4. Total energy costs as a function of the life remaining for the analyzed strategies. The lower the wavelength color the bigger the power, and the wider the area, the bigger the capacity.

V. Conclusions

On this paper four storage management systems scheduling strategies are simulated in order to see the impact on battery lifetime. From this study is observed again the importance of information, since the reference strategy –linear optimization with perfect information– outperforms all other strategies. Fuzzy logic strategies, even with its limitations show a good performance, reaffirming the importance of this kind of tool for real applications. The linear optimization strategy with average information is the worst of all four strategies, so further tuning and parameter testing is recommended. It is observed that for different capacities, if the proportion between capacity and maximum charge/discharge ratio is conserved, the remaining life of the battery will not change. This is true only for the case of the linear optimization strategy with perfect information and the fuzzy logic strategy. In general, it can be concluded that higher storage capacity leads to higher overall benefits, however, this cannot be said for the maximum storage system power, even when considering only the costs benefits, which suggest that a proper strategy and parameter selection can be better than high power ratio. However, this behavior can be also due to the fact that the battery life model only consider the DOD to calculate the remaining life. So, even if the DOD comes from a third order model the information regarding the losses and temperature must be used directly in the lifetime model in order to see a change in behavior.

VI. Appendix: Fuzzy system description

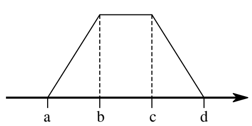


Figure 5. Membership functions standard shape used.

Table II
Membership functions for each fuzzy variable.

	a	b	c	d		a	b	c	d
Load week days [kW]					T. Irradiance [kWh]				
low	-	21	21	25	low	-	400	400	450
med.	21	33	33	35	med.	400	450	450	500
high	33	35	35	-	high	450	500	500	-
Load Saturdays [kW]					Ref. Price [%]				
low	-	21	21	25	low	-	30	20	30
med.	21	29	29	31	med.	20	30	70	80
high	29	31	31	-	high	70	80	80	-
Load Sundays/holidays [kW]					S.S. output [kW]				
low	-	17	17	18	low	-	2	2	10
med.	17	18	25	27	med.	2	10	24	32
high	25	27	27	-	high	24	32	32	-

Total irradiance is calculated as the sum of the observed irradiance at each time t for the day. The reference price is the ratio between the present energy price and the maximum price of the last 12 hours.

Table III
Fuzzy rules implemented for the storage management system.

	And		Then
	Input	Input	Output
	Load	R. Price	Charge
R1	Low	Low	High
R2	Med.	Low	High
R3	Low	Med.	High
	Load	R. Price	Discharge
R4	Med.	High	High
R5	High	High	High
R6	Med.	Med.	Low
	Present I.	Next day I.	Charge
R7	Low	Low	Med.
R8	Low	High	Low
R9	High	Low	High
R10	High	High	High
	Present I.	Next day I.	Discharge
R11	Low	High	Med.
R12	Med.	Med.	Med.

It must be read as «If Input And Input, Then, Output», e.g. rule R1 says «If Load is Low And R. Price is Low, Then, Charge Ratio is High».

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