Adaptive Fuzzy Logic Controller Based Energy Management for a Stand-alone PV Hybrid System with Battery and Hydrogen Storage Path

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Abstract. The paper describes a novel adaptive fuzzy logic controller based energy management concept (A-FLC-EM) for a stand-alone photovoltaic (PV) hybrid system with battery and hydrogen storage path. The reference application is a single family home. The basic idea is to switch and optimally adjust the energy management parameters according to identified changes of distinct long-term energy supply and/or demand situations. Key elements of the offline learning phase are the analysis of the energy time series and the automatic determination of distinct energy situations on the basis of a segmentation algorithm and a vector of suitable statistical features calculated for a short-term, sliding observation window. A bottom-up approach is used, ranking and selecting statistical features that are particularly good at distinguishing certain long-term energy situations. The selected features form the basis for a clustering algorithm to detect and describe distinct energy situations. For each energy situation, the calculation of optimal energy management parameters is performed for a training data set employing particle swarm optimization (PSO). The performance of the novel A-FLC-EM is demonstrated compared to a conventional fuzzy logic controller based energy management (FLC-EM) with an all-year fixed parameter setting. Qualitative and quantitative improvements as well as further challenges are discussed.

Keywords: photovoltaics (PV) · stand-alone hybrid system · hybrid energy storage system (HESS) · adaptive energy management · fuzzy logic controller (FLC) · particle swarm optimization (PSO)

1 Introduction

In order to achieve the CO_2 reduction targets of the Paris Climate Protection Agreement, a rapid shift away from fossil fuels and a rapid expansion of renewable energies, in particular photovoltaics and wind energy, is essential [1]. According to [2], short-term and long-term energy storage systems play an important role in stabilizing the energy system and efficiently and economically balancing fluctuations in energy supply and demand at different time scales. With the further rapid expansion of photovoltaics, which are particularly flexible, less location-dependent and can be easily integrated in a decentralized

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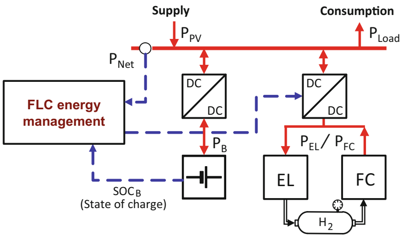

Fig. 1. Structure of the investigated PV hybrid system

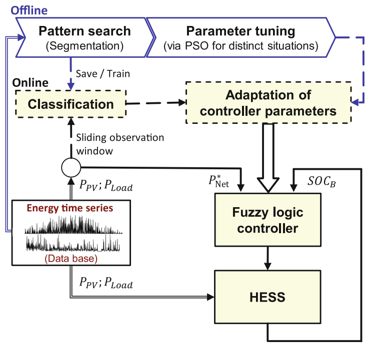

Fig. 2. Structural overview of the novel, adaptive fuzzy logic controller based energy management (A-FLC-EM).

manner, seasonal energy storage tasks are becoming increasingly relevant in addition to the use of battery storage for self-consumption optimization and as day-night balancing.

Hybrid energy storage solution consisting of a lithium-ion battery and a hydrogen storage path are well known in the field of off-grid electrification and stand-alone power supply systems [3].

In this paper we chose a simple reference application of a stand-alone photovoltaic (PV) hybrid system with battery and hydrogen storage for a single family home (s. Figure 1). Numerous example applications demonstrate the great potentials of this HESS configuration [3–6] and point out both the necessity of a good, adapted design and sizing [5] of installed capacities and powers of the energy storage components and the importance of an intelligent energy management (EM) for the optimal control of the power flows within the HESS [4]. There are energy management concepts [4, 6, 7], with fuzzy logic controller based approaches being commonly used. This paper describes a novel adaptive fuzzy logic controller based energy management concept (A-FLC-EM) for stand-alone photovoltaic (PV) hybrid system with battery and hydrogen storage path (s. Figure 2).

The basic idea is to switch and optimally adjust the energy management parameters according to identified changes of distinct long-term energy supply and/or demand situations. The basis for the novel A-FLC-EM is, in a first step, the offline identification of characteristic energy situations in historical measurement and training data of PV and load profiles using methods of unsupervised data mining. In a second step, the determination of suitable energy management parameters for the respective segments and the respective energy situation is performed employing particle swarm optimization. During online operation, the energy situations described in advance are identified with the help of a classification algorithm. On this basis, decisions are made for the adaptation of the energy management parameters.

The paper is structured as follows. Section 2 gives an overview of the reference application, PV and load time series, component models and the conventional FLC-EM. Section 3 presents the developed methodology for identifying distinct energy situations by analyzing statistical features over a short-term, sliding observation window. The overall methodological concept for pattern recognition in energy time series including feature extraction and feature evaluation is presented and demonstrated for the PV and load profiles of the reference application. Section 4 introduces the novel A-FLC-EM, describes the tuning and optimization of the EM-parameters, explains the Cluster-then-predict classification concept for online-use and presents results from performance tests and comparison of the novel A-FLC-EM with a conventional FLC-EM (with constant energy management parameters for the whole year). Section 5 summarizes the results and gives a brief outlook on current and future research and application.

2 Reference Application

2.1 System Structure and Component Models

Figure 1 shows the coupling structure of the reference application. While the power of the lithium-ion battery storage P_B can provide the instantaneous net power P_{Net} between the PV system with power P_{PV} and the load power P_{Load}, the control of the electrolyzer power P_{EL} or fuel cell power P_{FC} leaves degrees of freedom for a higher-level energy management. Power converter modules connect the voltage variable component side with a common high voltage DC-bus, on which the sum of all power flows is balanced:

$$P_B(t) = P_{PV}(t) - P_{Load}(t) + P_{FC}(t) - P_{EL}(t) \tag{1}$$

For the technical optimization of the HESS, the efficiency and the stress of the components are considered in particular. The criterion for good efficiency in a stand-alone PV system with a hydrogen storage path is the relative hydrogen surplus compared to the initial value, in particular through utilization of the PV generation power by an increase of the self-consumption q_{SC}, which is defined as the ratio between the amount of PV energy used and the amount of total PV energy generated:

$$q_{SC} = \frac{E_{PV,used}}{E_{PV}} \tag{2}$$

The evaluation of the energy throughput and the cyclic stress of the lithium-ion battery is based on the criterion of equivalent full cycles k_{FEC}, which is calculated from the total cyclic energy $E_{B,acc}$, the nominal voltage U_{nom} and the nominal capacity $Q_{B,nom}$ of the battery:

$$k_{FEC} = \frac{E_{B,acc}}{2U_{nom}Q_{B,nom}} \tag{3}$$

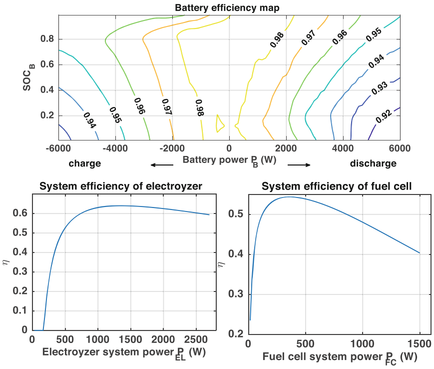

Fig. 3. Efficiency maps for modeling the loss behavior of battery, electrolyzer and fuel cell.

For a good utilization of the battery, k_{FEC} should not be too small. However, to achieve a high overall efficiency of the HESS, unnecessary conversion and transfer of energy from the hydrogen storage to the battery should be avoided. The energy of the hydrogen storage path should be supplied directly to the load if possible. To maximize the lifetime of electrolyzer and fuel cell, it is important to reduce the number of their start-stop cycles. This can be achieved by continuous operation with only slight modulation of the output power. The simulation studies in this paper work with a coarse temporal resolution of 10 min. Therefore, the loss behavior of battery, electrolyzer and fuel cell is modeled by the efficiency maps shown in Fig. 3. The sizing of battery, electrolyzer and fuel cell is based on preliminary investigations and the available components of the experimental system. For the lithium-ion battery (AKASOL neeoRack) the efficiency map was experimentally determined [25]. Six battery modules with a total energy content of 33 kWh are used. The C-rate of the battery is limited to $1\frac{1}{h}$. . The rated power of the electrolyzer is 2700 W and of the fuel cell 1500 W. The efficiency curves of the hydrogen conversion components have also been determined experimentally (s. Fig. 3).

2.2 Conventional FLC-EM

Several studies highlight the use of conventional fuzzy logic controllers (FLC) as an effective means of controlling power flows in HESS [4–14]. Conventional energy management concepts for stand-alone applications are mainly based on two input variables, the state of charge of the battery storage SOC_B, which should stay within certain limits in order to guarantee security of supply and the net power P_{Net} to be balanced on the energy bus. The input and output variables of the FLC-EM are described by membership functions (MSF) and linked by the fuzzy rule base and inference mechanism. For a detailed description of conventional FLC-EM the reader is referred to [15]. In this work a fuzzy logic controller according to Mamdani is used (s. Fig. 4). The numbers of membership functions and associated rules are chosen as little as possible in order to keep the overall energy management comprehensible and the search space for the optimization based tuning algorithm small. The number of membership functions for the input variables are chosen to be three for SOC_B [*low*, *good*, *high*], two for the normalized net power

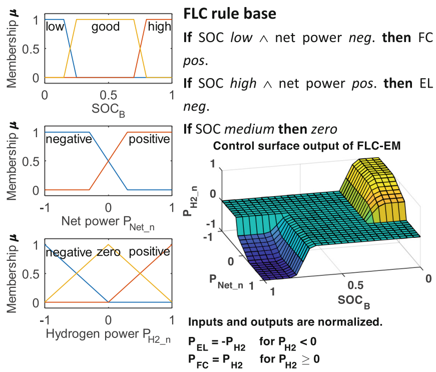

Fig. 4. Conventional FLC-EM with only three rules, a reduced number of MSFs and MoM aggregation

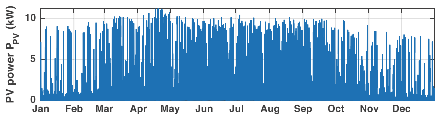

Fig. 5. PV power profile of reference application (installed PV peak power is 12 kW).

P_{Net_n} [*negative*, *positive*] and three for the output variable the normalized power of the hydrogen converters P_{H2_n} [*negative*, zero, *positive*]. Negative output values indicate operation of the electrolyzer and positive values operation of the fuel cell. The relatively smooth characteristic diagram of the reduced FLC implementation (s. Fig. 4) is achieved by choosing the mean of the maximum instead of the often proposed centroid defuzzification method.

2.3 PV and Load Profiles

The determination and description of typical energy situations is based on learning data with a duration of one year each. For the testing of the new A-FLC-EM, validation data of four other comparable annual cycles are used, which were not used in the learning process. The PV generation capacities are calculated on the basis of a single-diode equivalent circuit model. Measured data of global radiation and temperature at a site in Berlin from 2017 to 2020 are used for this purpose. The orientation of the PV plant is 35° south. The JAM60S20 polycrystalline PV module with a peak power of 380 W was used. The measurement data are made freely available by the Berlin University of Applied Sciences [26].

Figure 5 shows an example of the calculated power profile of a PV system with an installed peak power of 12 kW for the year 2017, which was used for the further investigations. The load profiles used in the paper are based on a set of measured data from 74 private households, which is also freely available [16]. For the validation phase, a load profile with a length of four years was constructed. For this purpose, selected load profiles that were similar in terms of maximum peak power (∅ 8.03 kW), annual

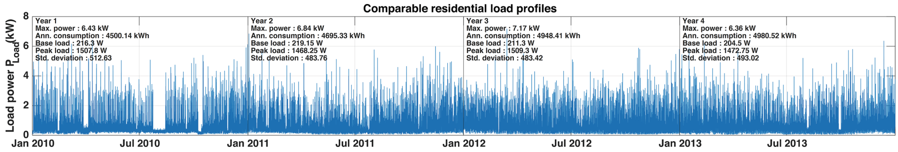

Fig. 6. Load power profiles and characteristic values of four representative, similar single-family households (from a database of 74 profiles, [16]).

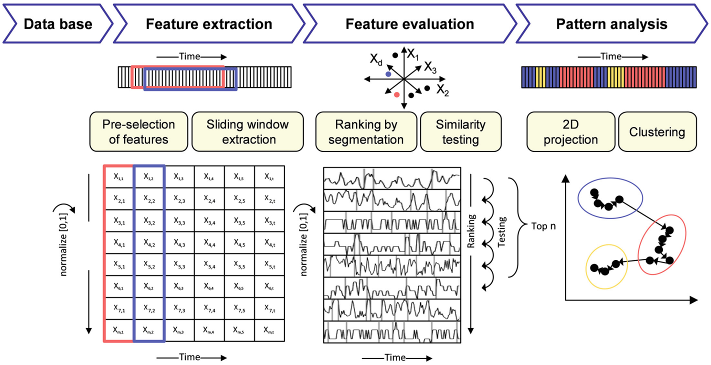

Fig. 7. Concept for automatic data processing and detection of long-term energy situations in energy time series.

energy consumption (∅ 4335.5 kWh), base load (∅ 213 W), peak load (∅ 1.42 kW), and standard deviation (∅ 488.4) were combined (s. Fig. 6).

3 Pattern Search Concept

3.1 Methodological Concept

The proposed method for identifying long-term energy situations belongs to the domain of unsupervised learning and is a hybrid algorithm of segmentation and pattern recognition shown in Fig. 7. Direct subsequence time series clustering is controversial [17]. In this paper, the goal is to examine energy time series in a shorter sliding observation window for a variety of statistical features that behave consistently over long periods of time and thus allow conclusions to be drawn about homogeneity intervals and distinct energy situations (as well as phases of transition in between). A bottom-up segmentation algorithm adapted from [18] can be used to rank the most informative features by evaluating the number of changing points according to a constant error criterion. In order to avoid features with very similar characteristics (without additional information gain), in a second step of the feature evaluation, after defining the quality of individual features, the similarities to neighboring features are checked in a descending order. The top-n features obtained in this way form the basis for a more in depth pattern analysis. A visual representation of a two-dimensional projection of the feature space using principal component analysis can provide initial indications of the number of distinct patterns

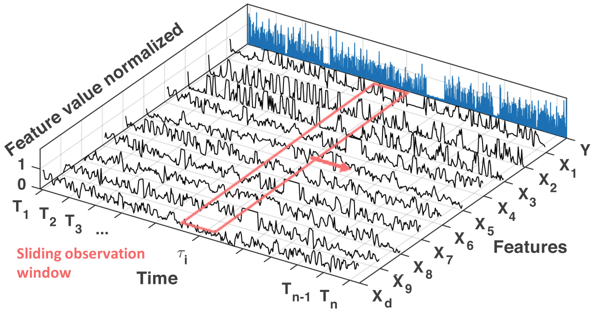

Fig. 8. Multivariant description of the original energy time series by a vector of features for a short-term sliding observation window.

present. In an iterative process, features and patterns are evaluated both graphically and according to evaluation criteria using clustering algorithms to separate different energy situations from each other.

3.1.1 Feature Extraction

In the first step, the proposed pattern recognition works by transferring the original time series to symbolic sequences described by a vector of statistical features. With the help of a short-term, sliding observation window of defined length, a multidimensional representation of the original data is achieved (s. Fig. 8). In this context, time series are defined in general form as a set of n observations of d-dimensional vectors $Y = [y_1, \ldots, y_n]$ with $y_i \in \mathbb{R}^d$, $i = 1 \ldots n$ corresponding to temporally ordered observations. Each window is bounded by its length with the two parameters start point $\tau_{i,start}$ and end point $\tau_{i,end}$ be chosen. Two adjacent segments are separated by a defined step size i (in the course of this study one day) and can then be moved overlapping in time ($\tau_{i-1,end} > \tau_{i,start}$). As a representation of a time period, a feature vector is determined in multivariant form, resulting in an $i \times d$ matrix X of features as a discretized multivariant description of the original time series Y.

The description of time series segments is based on a vector of features. Those features can be found in different areas of data processing, from basic and descriptive statistics, to studies from signal processing in the image domain, to descriptive parameters from probabilistics in model building. A comprehensive collection of such functions is provided by the toolbox hctsa (highly comparative time-series analysis) [19] especially developed for analyzing time series in MATLAB. Within full scope more than 7700 different characteristic feature calculations are implemented. However, as the number increases, the programmed computational effort increases sharply and it seems reasonable to make a preselection for the specific use case:

- Features from descriptive statistics, such as mean, standard deviation, kurtosis, skewness, form the basis for the quantitative description of time series sections and are comparatively easy to interpret.
- Due to the fluctuating energy supply and the periodicity of energy time series, both in the PV and load profile, further information content can be inferred in an image

domain. The fast Fourier transformation as well as the wavelet transformation and decomposition are computational methods used to analyze the power spectrum. Features can be calculated from certain ranges of the spectra of Fast Fourier or Wavelet Transform.

- Entropy measures from information theory and symbolic transforms further extend the search range. However, the interpretability of the features can sometimes become difficult. At this point, we should point out the strength of unsupervised learning methods, which provide concise results in the presence of unknown results in a defined search space.

With these considerations in mind, a standard set of 362 features was selected for the study of the energy time series, although individual features are also run with different sets of input parameters. For example, different wavelet basis functions can be used for the wavelet decompositions, or the level of decomposition can be varied.

3.1.2 Feature Evaluation

The goal of the feature evaluations is to find out from the broad field of possible features those that are particularly well suited for the following clustering. Classical approaches of feature subset selection problems can be found in the literature [20–23], but are hardly considering temporal causality of data points in time series or are related to classification rather than clustering tasks. For this reason, feature selection is formulated for the present study according to its own stationarity criterion. The evaluation of a bottom-up segmentation algorithm with uniform error criterion is based on the thesis: the fewer segments are found, the more homogeneous are the identified energy situations – the informative value about long-term energy situations increases with the output of a low value. The coefficient of variation is subsequently used with a threshold value to exclude features with a nearly constant course from consideration. Similarly, the Euclidean distance measure compares the similarity between two adjacent features, after which those with nearly identical trajectories are grouped.

3.1.3 K-Means Pattern Analysis

Unsupervised pattern recognition methods are used to explore local and global structures in the energy time series data. k-Means is a clustering algorithm that can assign a number of data points N to a number of clusters K. The objective function minimizes the within-cluster sum of squares

$$J_m = \sum\nolimits_{i=1}^{K} \sum\nolimits_{k \epsilon X_i}^{N} \|x_k - c_i\|^2 \tag{4}$$

where X_i is a set of data points of the i-th cluster and c_i is the mean for that points over cluster i. After randomly initializing the cluster centers, during an iterative process the center of each cluster is determined according to Eq. (5):

$$c_i = \frac{\sum\nolimits_{k=1}^{N_i} x_k}{N_i}, x_k \epsilon X_i \tag{5}$$

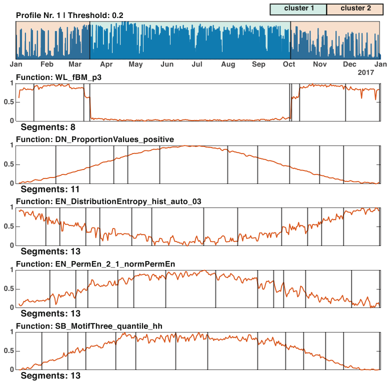

Fig. 9. Top-5 features for PV profile segmentation.

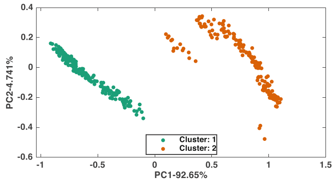

Fig. 10. Principle component analysis of five dimensional feature vector of PV profile with clusters of distinct energy situations.

The properties of the algorithm, a strict partitioning of all data points assuming spherical clusters, must be considered in the evaluation, as well as the need for further evaluation criteria to find the optimal number of patterns. The use of normalized data must also be considered. Otherwise, unequal weighting will occur during calculation of distances between data points.

3.2 Analysis of PV Profile

To analyze and describe typical situations in the PV profile (reference year 2017), the first step is to calculate a selection of 362 suitable features for a rolling window of width three days according to the algorithm described in Sect. 3.1. The reconstruction error as a stop criterion for segmentation was set to 0.2. The five best rated features in descending order are shown in Fig. 9 with their feature names. A detailed interpretation of the features would go beyond the scope of this study. Reference is made to the hctsa toolbox [19], whose documentation lists the function names and other sources.

The clustering results particularly follow the first feature *WL_fBM_p3*, which strongly influences the principle component PC1 (s. Fig. 10) and indicate a seasonal change in energy situation to be considered for the energy management. Although the exact interpretation is excluded, it should be mentioned, that the value *WL_fBM_p3* is calculated via a wavelet decomposition and the estimated standard deviations of detail coefficients.

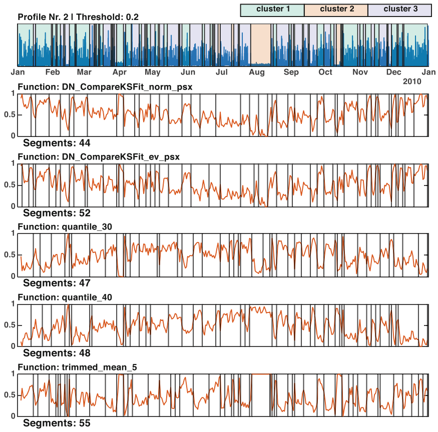

Fig. 11. Top-5 features for load profile segmentation.

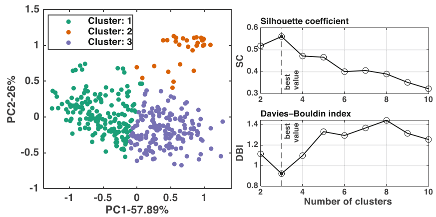

Fig. 12. Principle component analysis of load profile segmented into three clusters using top-5 features and k-Means clustering algorithm.

It can be summarized that with the help of the algorithm it was possible to identify features for persistent, slowly changing energy situations. The distinction between summer and winter operation is described surprisingly accurately by a single feature. In contrast, the dynamic courses of the other features in the ranking, which follow the smoothed course of the annual generation potential, appear less unexpected.

3.3 Analysis of Load Profile

Analogous to the recognition of energy situations in annual profiles of PV generation, the pattern search method is also applied to the load profiles of the household year 2010 described in Sect. 3.2. The same set of statistical features from Sect. 3.1 is calculated over an annual cycle over a sliding observation window with a length of three days. The segmentation runs for all features with the same reconstruction error of 0.2. The five best features obtained are shown in Fig. 11 below.

For the load profiles the principal component analysis shows less pronounced clusters (s. Figure 12, left), which have to be evaluated in a differentiated way.

While the silhouette coefficient (SC) measures how similar a point in its own cluster is compared to points in another cluster, the Davies-Bouldin index (DBI) is based on a ratio between the distances within a cluster and the distances between clusters (s.

Fig. 12, right). The two criteria are evaluated for a number of clusters from 2 to 10. The optimum number of three clusters for the present data set is obtained for the highest SC value and the lowest DBI value. Based on an initial qualitative observation, it is possible to match the patterns with statements about the load demand in base load operation, at medium consumption and at high consumption. A concrete assignment to distinct energy situations cannot be made easily.

4 Adaptive Fuzzy Logic Controller Based Energy Management

In this section, the implementation of the A-FLC-EM concept based on identified energy situations and descriptive features is presented. On the one hand, global parameter optimization can be performed on distinct segments, on the other hand, the selection and switching of EM parameters is encountered by a classification procedure. After an offline learning phase, the concept is tested in a simulation-based online operation.

4.1 Optimization of EM Parameters

Due to the unsupervised learning methods used to detect energy situations and due to a lack of understanding of the location of characteristic change points, it can be difficult to perform FLC-EM typical expert-based adjustment of energy management parameters. However, segmented time series of energy supply and/or demand give the opportunity to compensate for these weak spots through algorithmic tuning of membership functions locally. Metaheuristic optimization algorithms such as particle swarm optimization are primarily suitable for solving such problems.

In this work, a particle swarm of size $N_S = 20$ represents possible solutions to the problem by multidimensional vectors that are iteratively adjusted. The search in the solution space is described by Eqs. (7) and (8), which determine a position x_i and velocity v_i of the particles. $\epsilon_{1,2}$ are random values between [0, 1] and α, β parameters of a given learning rate, usually between [0, 2], here set equal to 1. After each iteration k, the global best solution g^* of the entire swarm is stored in addition to the individual best solution of each particle x^* [24].

$$v_i^{k+1} = v_i^k + \alpha\epsilon_1\left[g^* - x_i^k\right] + \beta\epsilon_2\left[x_i^* - x_i^k\right] \tag{6}$$

$$v_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

Besides the parameter settings of the PSO, a suitable fitness function f is introduced to evaluate the operational objectives. This is minimized in favor of high system efficiency and low component stress under the condition of supply security.

With a weighted sum, the relative hydrogen surplus at the end of the year $k_{H2,Sur}$ in kg, the equivalent full cycles of the battery k_{FEC} and the start-stop cycles of the electrolyzer $N_{Cyc,EL}$ and the fuel cell $N_{Cyc,FC}$ are taken into account:

$$f = \frac{1}{2}k_{H2,Sur} + \frac{1}{4}k_{FEC} + \frac{1}{8}N_{Cyc,EL} + \frac{1}{8}N_{Cyc,FC} + E_{shed}^3 \tag{8}$$

A penalty-term E_{shed} increases the costs exponentially in case of load shedding due to lack of energy reserves.

4.2 Cluster-Then-Predict Classification

Centroid-based clustering algorithms such as k-Means can label new observations based on the model created. At the same time, assigning new points to a cluster algorithm seems misleading because the results of a clustering algorithm are imperfect – they represent only a snapshot of a segmentation of the current data. How well they generalize to new data is an open question. Also, it should be noted that the k-Means algorithm does not fit all data bases, as it tends to detect only spherical structures with an approximately uniform distribution of observations across patterns. The indications of patterns in this paper are based on observations of the principle component analysis plots and on statistics such as the Davies-Bouldin index or the silhouette coefficient. Despite the ambiguity of a good clustering, in the case of PV time series, describable situations, in particular a summer and winter operation, could be identified and their cluster centroids stored. In online classification, new data points from a trailing window are assigned to the existing clusters and used to select the EM parameter set. This very simple form of classification is chosen because of the strong dependencies on the previous clustering results and is called the cluster-then-predict approach. For each new data point in the form of a feature vector x_d the degree of membership to a pattern K_i is calculated based on the distance to its centroids:

$$\mu_{Ki}(x) = \frac{1/(x - c_{Ki})^2}{1/(x - c_1)^2 + \cdots + 1/(x - c_{Ki})^2} \tag{9}$$

4.3 Performance Tests and Comparison

A brief presentation and discussion of the simulation results focuses on the comparison between the conventional all-year fixed fuzzy logic controller based energy management (FLC-EM) and the novel adaptive fuzzy logic controller based energy management (A-FLC-EM) for the distinction between summer and winter operation. Based on the pattern recognition segments in PV power profiles, controller parameters are optimized separately employing a particle swarm optimization algorithm. Figure 13 shows the resulting nonlinear output maps. The quantitative comparison in Table 1 shows slight improvements in the evaluation criteria for each additional reference year 2 to 4. The main indicator of improved system utilization is the increase in the relative hydrogen surplus at the end of the simulation year $k_{H2,Sur,a}$, corresponding to increases in the PV self-consumption quota q_{SC}. Annual load shedding $E_{Shed,a}$ as well as start-stop cycles of the electrolyzer $N_{Cyc,EL}$ and fuel cell $N_{Cyc,FC}$ were reduced. The increase in full equivalent cycles k_{FEC} again indicates that the battery in the adaptive approach has an increased energy throughput in order to use it for the increasingly longer operation times of the electrolyzer.

A more detailed view in Fig. 14 shows on summer days (right) this larger cyclic discharge margin of the battery to absorb the PV power peak, while on winter days (left) an average higher SOC with adaptive fuzzy logic controller based energy management is positively noticeable to buffer short-term load peaks.

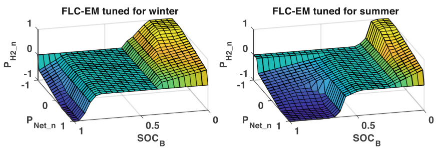

Fig. 13. Optimized controllers of A-FLC-EM for distinct energy situations in winter and summer.

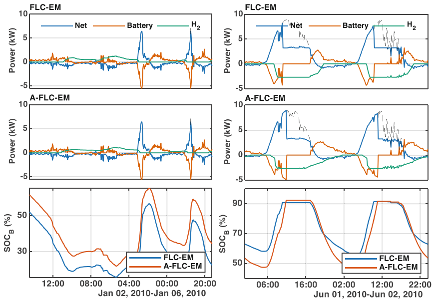

Fig. 14. Qualitative comparison of A-FLC-EM and conventional FLC-EM for two typical days in summer and in winter.

Table 1. Comparison of the performance of the conventional FLC-EM with the novel A-FLC-EM.

Evaluation criteria		**FLC-EM**			**A-FLC-EM**		
Year		**2**	**3**	**4**	**2**	**3**	**4**
q_{SC}	(%)	77.24	80.26	79.61	78.88	81.89	82.62
$E_{Shed,a}$	(kWh)	9.19	7.01	3.38	4.75	1.10	1.19
$k_{H2,Sur,a}$	(%)	19.39	17.68	21.96	20.68	19.00	24.46
$N_{Cyc,FC}$		59	75	86	51	81	84
T_{FC}	(h)	1572	1449	1440	1703	1611	1582
η_{FC}	(%)	50.03	50.4	50.81	51.45	50.98	52.02
$N_{Cyc,EL}$		328	273	282	269	259	254
T_{EL}	(h)	2496	2331	2301	3439	3137	3238
η_{EL}	(%)	59.7	60.04	59.76	60.22	59.64	60.23
k_{FEC}		120.0	128.2	124.7	131.7	137.3	137.1

5 Summary and Outlook

A novel adaptive fuzzy logic controller based energy management concept for a stand-alone photovoltaic hybrid system with battery and hydrogen storage path was presented in this paper. A single-family house was selected as the reference application and described on the basis of several years of measurement data for PV- and load profiles. The basic idea of the new energy management concept to switch the energy management parameters depending on identified changes of a pronounced long-term energy supply and/or energy demand situation could be successfully demonstrated. In this context, the concept was first introduced in the offline learning phase to analyze the energy time series and automatically identify different distinct energy situations based on a segmentation algorithm and a vector of appropriate statistical features over a short-term sliding observation window. For each identified energy situation, particle swarm optimization was used to calculate the optimal energy management parameters of an FLC for a training data set. The performance of the novel A-FLC-EM was evaluated in comparison to a conventional FLC-EM with parameters fixed for the entire year. Significant qualitative and quantitative improvements were achieved.

Further investigations are concerned with the introduction of more complex classification methods (e.g. based on fuzzy pattern classification) with a better separation of classes in the high dimensional feature space. Furthermore, continuing investigations on the suitability and application of different features are to be carried out. Also, the adaptation law shall be extended and developed and investigated by smoothly fading and not switching between controller parameters or their control outputs. Furthermore, the presented methodology shall be investigated for other energy management concepts (not only based on FLC) and shall be demonstrated also for other HESS configurations in other application fields.

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