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Power Management Strategy Based on Weather Prediction for Hybrid Stand-alone System

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Abstract

This paper presents an intelligent strategy for optimal power management of stand-alone hybrid system. The designed management strategy aims at regulating the power flow between the generated and the consumed powers of a wind/solar/battery stand-alone system in order to satisfy the load (one family house). The chosen strategy considers the wind generator (WG) and the photovoltaic panel (PV) as the main energy sources and the battery bank (BS) as storage system. For the power source emergency, it uses the diesel engine (DE) as an additional source. Indeed, the optimal management strategy consists of generating power references for each subsystem. Based on the prediction of weather conditions, these power references are generated with taking into account some constraints related to the reliability of each subsystem.

In order to validate the proposed strategy under real situations, measurements of the weather conditions and the power consumption data of an individual house are considered. The simulation results are highlighted to demonstrate the feasibility of our approach.

Keywords: Power Management, Renewable Energy, Prediction, ANFIS.

1. Introduction

The current global energy situation is becoming increasingly critical. This situation is induced, on the one hand by the increased energy consumption due to the population’s growth and on the other hand, by the considerable technological development of a variety of energy dependent systems. Moreover, these energy requirements largely come from fossil fuels that emit greenhouse gases, and whose reserves are largely weakened during decades. The excessive use of fossil fuels threatens the availability of its world reserve since most machines and engines are fueled with it [1]. Considering the current global petroleum resources are expected to be used up within 50 years if they are consumed with the present consumption rates [2], new technologies of energy production from renewable sources, like solar or wind energy are receiving much high attention worldwide.

Recently, there have been many proposed technical projects in the development of the combination of different renewable energy sources which are mutually complementary in order to maximize efficiency and ensure supply without...
intermittence of the isolated areas; resulting in the popularity of the use of hybrid systems in recent years as those proposed in [1,3–6]. The hybrid renewable energy systems have been introduced as green and reliable power systems for remote areas. It depends therefore on the geographical and meteorological conditions of the target region. There is a steady increase in usage of hybrid renewable energy systems and consequently, optimal strategies for power flow management of the system are required. With respect to the literature, several works deal essentially with sizing or economics study and management of stand-alone hybrid systems [3,4], [7,8]. In [9], the authors are focused on the control of $dc – dc$ converters which are linking the multi-source system with the $dc$ bus. As a control strategy, a sliding mode control has been used in order to regulate the $dc$ bus and track power references of each source.

In this paper, we propose to design an optimal management algorithm based on prediction of the wind-solar energy potential and the power consumption of the load over a time horizon. The prediction power allows to take good decisions according to weather conditions and load consumption. Based on these predictions, the management algorithm searches for the solutions which can satisfy the cost function of a suitable optimization problem subject to some constraints over the time horizon. To do this, a power management strategy for the hybrid wind/solar based system is designed. Moreover, the use of only wind and photovoltaic system with battery storage may not track the load demand. Another kind of source must be added [10,11], in our case, a diesel engine is chosen as emergency source.

2. Hybrid System description

Stand-alone hybrid generation systems are usually used to supply remote areas or locations interconnected to a weak grid. They combine several generation modules, typically assimilating different renewable energy sources. In this work, a wind-solar system is considered as main energy source. A lithium-ion battery bank is used to overcome the periods of poor production. In fact, the battery operates as secondary source for supplying the power deficit caused by the dynamic power balance [12]. In addition to these sources a $DE$ is used as backup source. The considered system is illustrated by figure 1. As it is previously mentioned, this topology uses $WG$ and $PV$ subsystems as the main energy sources. These subsystems operate in parallel to inject the converted power into the $dc$ bus. The $WG$ used in our case is based on a permanent magnet synchronous generator ($PMSG$). This type of generator has become popular for wind conversion systems especially for small variable-speed turbines due to their advantages over other types of wind turbines [13]. Furthermore, due to the intermittence of the wind and solar energies taken separately, the association of this sources offers a good solution for this kind of isolated system. However, a storage system like a battery or a superconductor remains indispensable to ensure power supply of the load without interruption. Consequently, the storage system based on lithium-ion battery is considered. Due to their advantages like light weight, low self-discharge rate, and high specific energy, Lithium-ion batteries have become one of the most popular type of batteries in various applications such as portable devices, electric vehicles and renewable energy systems [14,15].

Fig. 1: Architecture of the power hybrid system
3. Supervisory and power management strategy

3.1. Problem Formulation

The main objective of this study is to propose an optimal management strategy for the multi-source system in order to ensure energy autonomy of an isolated house of European type. To achieve our objective, a management strategy based on three steps to control this multi-source system is considered. The first step consists of the prediction of both renewable potential energy available to the location site and the power consumption of the house over a given prediction time horizon. The prediction of weather conditions is important to ensure uninterrupted power supply of the load. Indeed, it takes into account the future changes of climatic conditions that can affect the good working of the system and also to anticipate critical situations. This prediction also allows to reduce the needless solicitations of the backup source which is represented by the DE and consequently extends its lifetime. The second step consists in generating the power references for the PV, the WG and the BS sub-systems in order to generate enough energy to satisfy the load demand by taking into account the potential energy available for each source. The power reference generation depends on many parameters such as available energetic potential, maximum power variation supported by the conversion system, charge and discharge battery current, etc. The third step is to design a controller for each subsystem allowing to track the power references. Note that this part is not discussed in this paper, but the readers can refer to our previous works for details [16–18]. In order to give an overview of the control tools presented in this paper, figure 2 shows a general view of the considered strategy.

Where \( P_{ch} \), \( P_W \) and \( P_{PV} \) represent respectively the load power, the wind generated power and the photovoltaic generated power. The symbol (\(^\hat{}\)) is used to indicate the predicted values.

3.2. Power prediction using ANFIS algorithm

3.2.1. ANFIS algorithm

The Adaptive neuro-fuzzy inference system network (ANFIS) is a kind of artificial neural network that is based on the Takagi-Sugeno fuzzy inference system. It integrates both of neural network and fuzzy logic principles in order to integrate benefits of both in a single network.

The ANFIS network is composed of two parts like fuzzy systems. The first part is the antecedent part and the second part is the conclusion part that is connected to each other by rules, in network form. If ANFIS in network structure is shown, that is demonstrated in five layers, it can be described as a multi-layered neural network as shown in figure 3. Where the first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions (MFs), the fourth layer executes the consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summing up the outputs of fourth layer [19].
The neuro-fuzzy predictor (NF) is a system based on a fuzzy neural network. The reasoning of the prediction is achieved by fuzzy logic. The structure of fuzzy inference is determined by expertise, while its MFs are optimized using neural networks. ANFIS can be seen as a loopless neural network for which each layer is a component of a neuro-fuzzy system.

3.2.2. Prediction using ANFIS

A good prediction of weather conditions like solar irradiance, ambient temperature and wind speed is required in most hybrid system applications, especially in the energy management [20]. Different models are introduced in the literature to predict weather conditions [21–23]. Indeed, the artificial intelligence models such as neuro and fuzzy nets have gained more attention regarding their capability in predicting unknown parameter systems and their easiest to establish model. In this research, an ANFIS (Adaptive neuro fuzzy inference system) model [24] is used to estimate the weather conditions [25][26]. The idea consists of using the meteorological data with local measurement data for short-term prediction of ambient conditions. Based on the analysis of the locally collected data, an ANFIS algorithm is used for solar radiation, temperature and wind speed prediction.

Thereafter, based on these prediction results, the power potentials noted by \( \hat{P}_{pv} \) and \( \hat{P}_w \) are obtained using respectively WG and PV dynamic models while \( \hat{P}_{ch} \) is directly predicted.

The principle of the proposed ANFIS prediction consists of using the measurement \( m(t) \) of weather conditions (solar irradiance, temperature and wind speed) presented as time-series. In time-series prediction, we need to know the values of time-series up to time \( t \) to predict the value at some point in the future \( t + p \). The principle of this prediction is to create a mapping data sample every \( p \) units of time, to predict \( m_{t+p} \). The input training data for ANFIS algorithm is four-dimensional (4 inputs) vector as: \( E(t) = [m(t-3)p), m(t-2)p), m(t-p), m(t)] \) and the output which corresponds to the prediction value is \( s(t) = m(t+p) \). For each \( t \), the training inputs/outputs data is structured whose first components is the four-dimensional input \( E \) and whose second component is the output \( s \). If two fuzzy sets are associated to each input variable, the ANFIS algorithm is constituted from 16 inference rules \( R_j \) (\( j = 1, ..., 16 \)). These rules are represented as follows:

\[
R_j: \text{IF} \ (m_{t-3} \text{ is } A^j_1) \text{ AND} \ (m_{t-2} \text{ is } A^j_2) \text{ AND} \ (m_{t} \text{ is } A^j_4) \text{ AND} \ (m_{t} \text{ is } A^j_4) \\
\text{ THEN } m_{t+p} = a^j_1m_{t-3} + a^j_2m_{t-2} + a^j_3m_{t-p} + a^j_4m_t + a^j_0
\]  \hspace{1cm} (1)

With considering the first \( n \) of \( N \) measurements with time step \( p \) up to time \( t \), \( [m(t-N), m(t-(N-p)), ..., m(t-(N-n))] \) as training data and \( [m(t-(N-n-p)), ..., m(t), m(t+p)] \) as testing data, to estimate during a sliding time interval the \( N-n \) step ahead future values of the time series \( [\hat{m}(t-(N-n)), ..., \hat{m}(t), \hat{m}(t+p)] \). Note that \( m(t+p) \) here is fixed arbitrarily at any value in order to achieve the ANFIS testing process. The retained output estimated value is \( \hat{m}(t+p) \). Based on the predicted data of solar irradiance, temperature and wind speed, the power potentials of photovoltaic \( \hat{P}_{pv} \) and of wind \( \hat{P}_w \) can be obtained using mathematical models of each energy conversion system. The operation principle of this technique is illustrated in figure 4. Where \( G = [G_t, ..., G_{t-N}] \), \( T_a = [T_{a,t}, ..., T_{a,t-N}] \), \( V_W = [V_{W,t}, ..., V_{W,t-N}] \) and \( P_{ch} = [P_{ch,t}, ..., P_{ch,t-N}] \) are respectively the measurement data of solar irradiance, ambient temperature, wind speed and load consumption.
In order to predict the weather conditions like solar irradiance, temperature and wind speed, we used the ANFIS method previously presented. To achieve this goal and test the performances of our prediction algorithm, measurements data of the weather parameters during three different months is used. These measurements are done by a French weather agency (Météo-France) near our laboratory in Amiens in the months of January, March and June 2013 with a sampling time equal to 1 minute. Note that it is assumed that the irradiation and the cell temperature are homogeneous over all panel. These measurements are used for the training data and designing the ANFIS model. In order to validate this algorithm, simulation tests using the real measurement data are carried out in section 5.

Using this prediction of weather conditions and based on the mathematical models of each energy conversion system (wind turbine and photovoltaic panels), it is possible to calculate the potential energy available of each source during the prediction horizon. By doing so, we can anticipate critical situations and take appropriate decisions with the management algorithm.

### 3.2.3. Simulation results for weather prediction

In order to validate the proposed prediction method, simulation results using real measurement are highlighted bellow. These measurement are provided by Météo-France Agency [27] which measured each 1 minute. measurement of 10 days in a row are chosen as scenario to carry out the simulation results witch begin from $1^{st}$ to $31^{th}$ March 2013 with a sampling time equal to 1 minute.

Figure 5 shows the solar irradiance prediction result using the proposed ANFIS method. Since the solar irradiation has an important dynamic variation in this month (March) especially in our region (north of France) where the sky is often cloudy, an accuracy prediction with small time horizon (10 minutes) becomes very difficult. Unlike solar irradiance, ambient temperature has a slow dynamic which makes the prediction less difficult as we can see in figure 6. Figures 7 and 8 present respectively the prediction results of the wind speed and load demand. According to these result, we can conclude that the quality of the prediction decreases when the dynamic variation of the wind
speed or the load increases. According to these results, we can see that the high dynamic of weather parameters can affect the robustness of the prediction. Indeed, solar irradiance and wind speed can vary significantly within a span of time, consequently their short-term prediction becomes more difficult. Despite the high variation in of all these parameters, the prediction is done with sufficient precision. In order to illustrate this aspect, figures 9 and 10 shows the influence of the high variation of the meteorological parameter on the prediction precision by using two different days measurement.

According to figures 9 and 10 we can see that the prediction algorithm gives a better result when the dynamic variation of irradiance is low (July, 9th, 2013). Indeed, the mean absolute error is near to 6.67 for January 1st, 2013 day, while it is equal to 17.90 for the January 1st, 2013 day.

It is useful to note that the time horizon of the prediction has an important influence in the prediction prediction. In order to carry out the influence of the time horizon in the quality of prediction we carry out some tests and the results are highlighted in Table 1. Indeed, the quality of the prediction is quantified by some indices like mean absolute error (MAE), mean absolute percentage error (MAPE) or the Akaike information criterion (AIC) [28]. Note that the smaller these indices are, the better the prediction is.

With $NI$ is number of the ANFIS input, $MF$ the number the ANFIS membership function, $HP$ is the time horizon in minutes. From this table, we can see that the prediction quality decreases with the time horizon. Indeed, a compromise must be found between the quality of prediction and the needs of the management algorithm. Therefore, in our study we chose a prediction horizon of 10 minutes which gives in the first case, an acceptable prediction error, and in the second one, satisfies the needs of the management algorithm.
Table 1: Prediction horizon’s influence on the prediction accuracy

| Tests          | MAE   | MAPE  | AIC   |
|---------------|-------|-------|-------|
| NI=4;MF=2,HP=1 | 3.014 | 2.486 | 5.043 |
| NI=4;MF=2,HP=5 | 6.798 | 3.736 | 6.556 |
| NI=4;MF=2,HP=10| 10.308| 7.187 | 7.131 |
| NI=4;MF=2,HP=20| 15.133| 13.864| 7.565 |
| NI=4;MF=2,HP=30| 20.889| 19.175| 7.737 |

3.3. Power management strategy design

3.3.1. Algorithm presentation

The purpose of the management algorithm proposed in this paper is to generate optimal references for the each PV, WG and BS subsystems in order to satisfy the load demand. The idea is presented as follows: using the prediction algorithm, the estimated powers $\hat{P}_{pv}$, $\hat{P}_w$ and $\hat{P}_{ch}$ over the prediction horizon are obtained. Then, the management strategy takes some decisions in order to optimally manage the power flow between the different parts of the system with respecting imposed constraints. These constraints primarily aim at ensuring uninterrupted energy supply of the load, and also guaranteeing good functioning of the multi-source system over a long time. Precisely, the management strategy aims at modifying the operating points of the WG and the PV systems in order to produce enough power to satisfy the load requirements while favouring the wind source at the expense of the photovoltaic. This choice is taken according to the interesting wind potential of the site. Another objective of the management strategy is to exploit the storage battery in order to maximize its lifetime. Indeed, a good supervision of the battery’s state of charge and also its charge and discharge current is required. Of course we should minimize its solicitation i.e. promote the power produced by renewable sources. Furthermore, in adverse situations of production, the diesel generator turns on. However, the management strategy attempts to use this conventional source as least as possible to reduce the diesel consumption and give priority to renewable energies.

Since the estimated energy potential of wind and solar subsystems and the future load of the system, for prediction horizon, are known. The objective function (equation (2)) designed for this control and the summarized constraints (equation (3)) related to the optimal operating of the system are as follows:

$$\min_{P_{w,ref}, P_{pv,ref}, P_{bat,ref}} \int_{t_0}^{t_{HP}} (\alpha(P_{ch} - P_{w,ref} - P_{pv,ref} - P_{bat,ref})^2 + \beta P_{pv,ref}^2 + \gamma P_{bat,ref}^2 + \xi \Delta P_{bat,ref}) dt \quad (2)$$

Subjected to:

$$P_{w,ref} \leq \hat{P}_{w} \quad (3a)$$

$$P_{pv,ref} \leq \hat{P}_{pv} \quad (3b)$$

$$P_{w,ref}(t + \delta) - P_{w,ref}(t) \leq dP_{w,max} \quad (3c)$$

$$P_{pv,ref}(t + \delta) - P_{pv,ref}(t) \leq dP_{pv,max} \quad (3d)$$

$$20\% < SOC < 80\% \quad (3e)$$

$$3C \text{ maximum during } 1\text{ min}, \text{ and } 1C \text{ maximum in the rest of time.} \quad (3f)$$

$$P_{gen} = \begin{cases} 
550W, \text{ if } (SOC < 25\%) \&(\hat{P}_w + \hat{P}_{pv} < \hat{P}_{ch}) \\
0W, \text{ else}
\end{cases} \quad (3g)$$

The equation 2 aims at ensuring the power balance between sources and load with favouring wind source at expense of photovoltaic and battery bank sources. Indeed, $\alpha$, $\beta$, $\gamma$ and $\xi$ are parameters representing weight factors. Parameter $\alpha$ aims at ensuring the power balance between generated and consumed that allows to track load demand. Parameter weighting $\beta$ represents a small constraint for the PV source so it aims at furthering the wind source. The choice of
favouring wind source at the expense of the photovoltaic source is justified by the fact that the wind energy potential is more important in the system location area. Note that this choice can be changed according to the energetic potential of a specified site or according to the specifications. \( \gamma \) factor aims at preserving the battery unnecessary solicitations. Indeed, the battery is considered as the weak element of this multi-source system. Hence, a specific treatment reserved to the battery is more than desirable. Therefore, this factor allows to limit the use of battery source. Finally, the \( \xi \) factor aims at limiting the abrupt variations in the power exchanged with the battery. Indeed, the requested instantaneous deep changes can affect the battery lifetime considerably.

Furthermore, the constraints (3a) and (3b) require that the solution obtained by the management algorithm must be smaller than the available powers within each sampling time. Equations (3c) and (3d) impose constraints of increasing rate of wind and solar power references between two sampling times \((t \text{ and } t + \delta)\). Equations (3e) and (3f) represent the constraints on state of charge and the maximum charge/discharge acceptable current by the battery respectively. Finally, (3g) represents the diesel generator activation conditions.

The optimization problem presented by equations 2 and 3 is solved using nonlinear constraints programming algorithm under Matlab/Simulink software. In order to validate the proposed management strategy, a scenario of 10 days with real measured data is considered.

### 3.3.2. Simulation results for the management algorithm

Once the predicted powers are known, the second part of the simulation is focused on the management algorithm results. The curves of the obtained power references are given in the figures below. The simulation results are carried out using real weather condition (figure 11) profiles and real load profile (figure 12). These profiles are obtained by measurements from 1st to 10th March 2013 in the region of Amiens by the weather agency France.

![Fig. 11: Measured weather’s conditions: (a) solar irradiance, (b) cells temperature and (c) wind speed](image)

![Fig. 12: Consumption profile](image)

Note that the cell’s temperature \( T_c \) is obtained by using the model given by the equation (4):  

\[
T_c = T_a + (NOCT - T_{ref}) \frac{G}{G_{ref}}
\]  

(4)

with \( T_a \) is the ambient temperature, \( T_{ref} = 20^\circ C \) and \( G_{ref} = 1000 \text{ W/m}^2 \) are the standard conditions and \( NOCT \) is given by the manufacture in the PV datasheet [29].

The power references obtained in simulation using the previous weather conditions are shown in figures 13 and 14. These weather condition profiles are very interesting to test our management algorithm because it may include most of the scenarios that our system can handle as situation during its operation. That means that it includes situations where all the sources can not track the load demand, one single source can satisfy the load alone, or there is an excess production. This is the reason why we choose to test our algorithm with real data. The simulation results that summarize all these scenarios can be fond below.

Figure 13 illustrates the power delivered by all subsystems that constituted the hybrid system. Indeed, in order to ensure energy autonomy of the load while respecting the constraints defined earlier, each subsystem (WG, PV, BS
and $DE$) must generate as much power as indicated by the corresponding power trajectory. In this case, the main goal defined in the specification is achieved as shown in figure 15 (the balance of power is balanced).

As illustrated in figures 13, 14 and 15; the main objective of our management strategy is achieved. That means that the generated power can satisfy the load demand despite unfavourable climatic conditions in some cases. As shown in figure 14 (zoom on the third day), the decision of favouring the $WG$ instead of the $PV$ is verified. Indeed, we can see that when the $WG$ can satisfy the load, and when the $SOC$ is high, the $PV$ production becomes zero.

Furthermore, figure 16 and figure 17 show the battery $SOC$ and diesel engine power respectively. Indeed, the battery state of charge remains always between 20% and 80% as imposed by the management strategy.

Figure 18 represent the contribution parts of $WG$ and $PV$ respectively. We can also deduce from these figures that the $WG$ acts as the main source while $PV$ operates as complement if necessary. It can be noted that the choice of promoting $WG$ at the expense of $PV$ can be changed depending on wind and photovoltaic energetic potential site.
Remark: Normally, for the most types of battery technologies, the optimal operating range of these is 25%–80%. However, for the chosen battery technologies (LiFePO₄) the operating range can be between 20% and 90%. This choice allows us to minimize the switching-on duration of the DE. Indeed, the total switching-on duration of the DE goes from 25.6 hours if 25% < SOC < 80% to 22.15 hours if 20% < SOC < 85%. In other words, we can save 3.45 hours of fuel for DE switching-on. In addition, the number of turning on over simulation period goes from 16 to 14. Given that the lifetime of the DE strongly depends on the number of its switching on, therefore we can claim to extend its life by minimizing the number of its switched on over a year. However, a good SOC estimation is required in order to avoid excessive over charge/discharge of the battery.

4. Conclusions

In this paper, an optimal management strategy based on the prediction of weather conditions is proposed and applied to a wind/PV/battery/diesel stand-alone system. The prediction of the weather conditions is very important for our management algorithm in the sense that it allows to anticipate the critical situations and take appropriate decisions at the right time. Therefore, it preserves our system and extends its lifetime.

The presented management algorithm consists of minimizing a proposed cost function under some constraints reflecting the good operating of the system and taking into account the physical characteristics of all the energy conversion systems. The minimization process is done while computing power references for the wind, solar and battery subsystems.

The performances of the proposed management strategy and the prediction method are validated under real weather conditions and real load consumption data. Indeed a scenario of 10 continuous days data is used in order to carry out several simulations with the Matlab/SIMULINK software. Future work will include tests of large time span behavior of the hybrid system and implement this strategy in practice using the test bench of our laboratory.

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Appendix A. Systems parameters

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### Table A.2: Systems parameters

| Systems                | Characteristic |
|------------------------|----------------|
| Wind generator         | 1 kW           |
| PV generator           | 1.5 kW         |
| Battery Capacitance    | 120 Ah         |
| Bus voltage            | 100 V          |

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