PV/FC/WIND HYBRID SYSTEM OPTIMAL SIZING USING PSO MODIFIED ALGORITHM

BY

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Abstract. Renewable energy sources in energy generation can decrease the costs of system fuel and also can have desirable impact on reliability of system. Therefore a suitable combination between the system reliability indices level and system capital investment costs is required. In this paper a hybrid system consisting of a wind turbine, photovoltaic (PV) arrays and fuel cell (FC) is designed so as to provide a specific pattern of load. The aim of this design is minimizing the cost of overall 20-year energy generation system in considering and not considering reliability indices constraints. Data’s relation to load, solar irradiance and wind speed are considered deterministic. It is assumed that there is emergency outage probability of three main units through system components. These units include wind turbines, PV arrays and DC/AC converter. System costs include investment cost, cost of maintenance and repair and also costs associated with loss of load. A modified PSO algorithm is used for system optimization and the results are compared with common PSO algorithm. Combining a modified intelligent algorithm with reliability evaluation leads to an increase in the volume of computations and consequently in the calculation time. An approximate model is presented to estimate system reliability which caused a significant decrease in calculation time.

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1. Introduction

The fast process of industrialization and growing population during the past years caused the increase of electricity consumption. Limitation of space and the slow improvement of the networks also caused some areas with high load density which could result in declining of power quality and voltage collapse. At the same time, non-urban areas are witnessing poor performance of the networks like high voltage drops and high losses along the distribution lines (Rahman et al., 2004). In contrast, despite limitations in networks and available financial resources, utilities are also hardly trying to expand and boost networks. In this way, distribution generation could be one of the suitable options. One of the solutions for increasing economic efficiency in renewable system is using different hybrid systems. The sun and wind are two main sources in renewable energies which seem to devote a large portion of generating energy in future.

The supplied energy from these resources is predictable and as a result the power of these systems and their storage systems will be considered much more than the amount of load power demand, to increase load reliability and availability. In hybrid systems, the generation predictability with combining the several resources is increased and in fact these resources cover each other’s deficits (Bagen & Billinton, 2005). From this perspective, the wind and the sun have presented suitable overlap for each other, so the power of units and also necessary storages in combining wind-sun units compared to only wind units or sun units have been significantly reduced.

Various definitions are presented for reliability, but the definition that is widely accepted is as follows: Reliability is the probability of a system or a component correct operation under exploitation conditions in specified time (Billinton & Allan, 1992). Reliability calculations represent major issues which should be considered along with economic and environmental evaluations resulting from using energy renewable sources. Accurate evaluation of economic profit used from these units needs investigation of rate of systems’ reliability. Obviously, available energy limitation in renewable energy sources and also its discontinuous behavior reduces level of system reliability (Karki & Billinton, 2001).

For minimization of hybrid system costs many methods are presented. A wide range of optimization methods, from classical combination like linear and non-linear, analytical and numerical programming, mainly based on partial derivatives calculation, to applying modern intelligent algorithms like Genetic
algorithm and Particle Swarm Optimization (PSO), are used in different researches.

In (Ntziachristos et al., 2005) a hybrid system consisting of a wind turbine and an FC is studied for improving profitability of wind power. In another study, wind farm equipped with Superconductor Magnetic Energy Storage (SMES) is studied (Nomura et al., 2005). SMES is suitable for improving power quality. In (Monai et al., 2002) hybrid system consists of PV array, FC and SMES is investigated. Unit sizing determination and PV/Wind/FC hybrid system costs analysis is analyzed in (Nelson et al., 2006). In other studies the performance and sizing of PV/Wind/FC hybrid system is considered (Kim et al., 1997; Vafaei, 2011; Waqas, 2011; Bilal et al., 2012; Garcia & Weisser, 2006). Paper (Koutroulis et al., 2006) optimizes the capacity of diesel generator with wind turbine.

In the current paper, unlike many of the latest researches, the effect of considering reliability indices is investigated along with the economic factors, for designing an optimal combination of stand-alone systems consisting of PV and Wind resources, with minimum cost and maximum of response to load power demand. Obtaining an optimal design using an intelligent algorithm seems very effective, due to the extent of variables and the magnitude of objective function. In this paper a modified PSO algorithm (MPSO) is proposed. It is used for the optimization of a case study system in order to show its convergence and effectiveness. The solutions obtained with MPSO algorithm are compared with the ones provided by common PSO algorithm.

2. Problem Formulation

In this paper optimal sizing of system components, that is the number of wind turbines, number and angle of PV arrays installation, EL capacity, hydrogen tank, FC and DC/AC convertor, is determined. Also the availability rate of system components on costs and system reliability indices is investigated. System costs contain net present-value cost (NPC), maintenance and repair cost and replacement cost of devices plus the associated cost to load curtailment during 20 years. The system under study, having an FC energy storage system, is outlined in Fig. 1. In this scheme a combination of an FC, an EL, and an HS tank has been used. In principle, an FC operates like a battery. Unlike a battery, an FC does not run down or require recharging. It will produce energy in the form of electricity and heat as long as fuel is supplied.

The nomenclature utilized in our paper is presented in Table 6 from the Appendix.
Fig. 1 – A hybrid Wind/PV plant with hydrogen energy storage system.

2.1. Objective Function

The net preset-value cost (NPC) for a specific component can be calculated as follow (Elhadidy & Shaahid, 1999):

\[
NPC_i = N_i \left( CC_i + RC_i \times K_i + MRC_i \times PWA(\text{ir}, R) \right).
\]

The net-present-value cost (NPC) of load loss can be obtained as:

\[
NPC_{\text{loss}} = LOEE \times C_{\text{loss}} \times PWA
\]

Finally, the objective function of the minimization problem is defined by:

\[
Total\text{Cost} = \sum_i NPC_i + NPC_{\text{loss}}.
\]

According to (Hakimi et al., 2007), the expressions that can be calculated for costs and calculation of components power according to wind and solar data are

\[
P_{PV} = 0.001G \times P_{PV, \text{rated}} \times \eta_{PV, \text{conv}},
\]

\[
G(t, \theta_{PV}) = G_v(t) \cos(\theta_{PV}) + G_H(t) \sin(\theta_{PV})
\]

The turbine used in this paper is the BWC Excel-R/48 model applied in (Kashefi Kaviani et al., 2007).
The wind speed in installation height can be calculated using the relation:

\[
V_{w_h}^v = V_{w}^{ref} \times \left( \frac{h}{h_{ref}} \right)^\alpha
\]  

(7)

In order to consider the outage probability of units (e.g. forced outages or scheduled outages), the generated power by renewable units is defined by:

\[
P_{ren(\text{fail})} = \left(N_{WG} - n_{WG}^{\text{fail}}\right) P_{WG} + \left(N_{PV} - n_{PV}^{\text{fail}}\right) P_{PV}
\]  

(8)

\[
P_{el-tank} = P_{ren-el} \eta_{el}
\]  

(9)

The stored energy in the hydrogen tank for each step-time can be calculated by means of

\[
E_{tank}(t) = E_{tank}(t-1) + P_{el-tank}(t) \Delta t - P_{tank-FC}(t) \Delta \eta_{storage}
\]  

(10)

\[
m_{storage}(t) = \frac{E_{storage}(t)}{HHV_{H_2}}
\]  

(11)

\[
P_{FC-inv} = P_{tank-FC} \eta_{FC}
\]  

(12)

\[
P_{inv-load} = (P_{FC-inv} + P_{ren-inv}) \eta_{inv}
\]  

(13)

2.2. Constraints

The objective function must be optimized under the following constraints:

\[
E[ELF] \leq ELF_{max}
\]  

(14)
2.3. Exploitation Strategy

The exploitation mode of the system is determined in terms of operating conditions. Basically, in each time step, one of the following conditions may exist:

\[- P_{\text{ren}}(t) = \frac{P_{\text{load}}(t)}{\eta_{\text{inv}}}: \text{all the generated power by renewable sources is} \]
\[\text{injected through DC/AC converter to load.}\]

\[- P_{\text{ren}}(t) > \frac{P_{\text{load}}(t)}{\eta_{\text{inv}}}: \text{extra generated power by wind and PV units is} \]
\[\text{delivered to EL for hydrogen production. In spite of extra power injected to EL} \]
\[\text{from its nominal capacity or filling of HS tank, extra power is lost in dump} \]
\[\text{load.}\]

\[- P_{\text{ren}}(t) < \frac{P_{\text{load}}(t)}{\eta_{\text{inv}}}: \text{the deficit of load power demand is supplied by} \]
\[\text{FC. If this deficit is more than FC power or there is not enough hydrogen in} \]
\[\text{tank, some of the load is not supplied which causes loss of load.}\]

Under above circumstances, the constraints should be considered and all system equations should be taken into consideration.

3. Reliability/Cost Evaluation

For simulation we consider the wind and radiation annual data related to one of the northwest region of Iran and also the load pattern related to IEEE reliability test system (RTS) (Khan & Iqbal, 2005) with a 50 kW annual peak load. Test system is stimulated for one year with one hour step-time with considering reliability/cost evaluation. The results are extended for a 20 year period considering deterministic data sets and economical factors.

3.1. Reliability Indices

In this paper we apply the reliability indices expressed by the following equations (Billinton & Allan, 1992; Karki & Billinton, 2001; Choe et al., 2010; Dursun & Kilic, 2012):

\[0 \leq N_i\]
\[0 \leq \theta_{PV} \leq \frac{\pi}{2}\]
\[E_{\text{tank}}(0) \leq E_{\text{tank}}(8760)\]
3.2. System Reliability Model

The reliability calculations are done by considering the outage probability of generation units, that is wind turbines and PV array, and also the outage probability of DC/AC converter.

\[
f_{\text{ren}} \left(n_{\text{fail}}^{\text{inv}}, n_{\text{fail}}^{\text{inv}}\right) = \left[N_{\text{WG}}^{\text{inv}} - n_{\text{fail}}^{\text{inv}}\right] A_{\text{WG}}^{N_{\text{WG}}^{\text{inv}} - n_{\text{fail}}^{\text{inv}}} \left(1 - A_{\text{WG}}\right)^{n_{\text{fail}}^{\text{inv}}} \times \left[N_{\text{PV}}^{\text{inv}} - n_{\text{fail}}^{\text{inv}}\right] A_{\text{PV}}^{N_{\text{PV}}^{\text{inv}} - n_{\text{fail}}^{\text{inv}}} \left(1 - A_{\text{PV}}\right)^{n_{\text{fail}}^{\text{inv}}}
\]

\[
f_{\text{system}} \left(n_{\text{fail}}^{\text{inv}}, n_{\text{fail}}^{\text{inv}}, n_{\text{fail}}^{\text{inv}}\right) = f_{\text{ren}} \left(n_{\text{fail}}^{\text{inv}}, n_{\text{fail}}^{\text{inv}}, n_{\text{fail}}^{\text{inv}}\right) \times A_{\text{inv}}^{N_{\text{inv}}^{\text{inv}} - n_{\text{fail}}^{\text{inv}}} \left(1 - A_{\text{inv}}\right)^{n_{\text{inv}}^{\text{fail}}}
\]

In the above equation, \(A_{\text{inv}}\) refers to probability of DC/AC convertor availability which equals 98-99\% (Billinton & Allan, 1992).
3.3. Proposed Approximate Method

For system reliability evaluation, all the system statuses are considered and reliability indices are calculated in respect with the probability of system in each status and the corresponding loss of load rate.

In this method, it is suggested to use average power of wind turbine and PV arrays instead considering all statuses related to outage of wind turbines and PV arrays and finally to calculate the mathematical expectation of system reliability indices. We suggest to consider the output power of renewable resources equal to the mathematical expectation of their output power, leading to

\[
E[P_{ren}] = \sum_{s \in S} P_{ren}(s) \times f_p(s).
\]  
(26)

Replacing eqs. (8) and (24) in eq. (26), we get

\[
E[P_{ren}] = \sum_{n_{WG}} \sum_{n_{PV}} \left[ P_{ren} \left(n_{\text{fail}}^{\text{WG}}, n_{\text{fail}}^{\text{PV}}\right) \times f_p \left(n_{\text{fail}}^{\text{WG}}, n_{\text{fail}}^{\text{PV}}\right) \right].
\]  
(27)

It can be easily proved that

\[
E[P_{ren}] = N_{WG} P_{WG} A_{WG} + N_{PV} P_{PV} A_{PV}.
\]  
(28)

4. Proposed Algorithm

4.1. PSO Algorithm

Particle Swarm Optimization (PSO) is a group algorithm in which a set of particles move into the problem space in order to find an optimum solution of the objective function. Each individual of the population (called swarm) moves around in the search-space with adjustable velocity and keeps in its memory the best position gained ever. The best position obtained by all the individuals of the population is transferred between all particles. In fact it is supposed that each particle in each moment knows about the best positions obtained by all the individuals of the population until that moment, fact which is expected to move the swarm towards the best solution of the optimization problem. The general principles of the algorithm are explained further on.

Considering an \(n\)-dimensional search space, and a population consisting of \(N\) particles, the \(i^{th}\) particle is an \(n\)-dimensional vector which can be defined by (29) and the corresponding velocity of this particle is also an \(n\)-dimensional vector expressed by (30):
where $i = 1, 2, 3, \ldots, N$.

In the PSO algorithm, the $i^{th}$ particle saves the best position ever obtained under the name vector $P_i = [p_{i1}, p_{i2}, \ldots, p_{in}]^T$ in its memory and the vector $G = [g_1, g_2, \ldots, g_n]^T$ refers to the best position which is ever obtained by all the individuals of the population. The position of the $i^{th}$ particle in iteration $(t+1)$ is defined by the following equations (Parasopoulos & Vrahatis, 2004):

\begin{align*}
V_i(t+1) &= \omega(t)V_i(t) + c_1(t) r_1 (P_i(t) - X_i(t)) + c_2(t) r_2 (G(t) - X_i(t)) \quad (31) \\
X_i(t+1) &= X_i(t) + \chi V_i(t+1) \quad (32)
\end{align*}

In the above equations, $\omega$ refers to inertia coefficient which indicates the impact of previous velocity vector on the current iteration. $\chi$ represents the constriction factor which enters in the above equations in order to limit velocity vector impact, $c_1$ and $c_2$ – the cognitive parameter (local acceleration) and the social parameter (global acceleration), respectively $r_1$ and $r_2$ – random numbers, uniformly distributed within the interval $[0,1]$.

The larger the product $c_1 \times r_1$ is, the $i^{th}$ particle moves more quickly toward the best position gained by it. The velocity of the particle is affected under product $c_2 \times r_2$ by all the individuals of population toward the best position obtained.

$\omega$ is responsible for providing desired tradeoff between the global and local search capability of the population. The bigger inertia coefficient persuades the set to search in a larger area. Now smaller inertia coefficient causes accuracy increase of set in local search. Based on experiments, it is suggested that at the beginning of the search a substantial value be specified to $\omega$ (here 1) so that global search be in priority to local search, then in order to obtain the best possible solution, the size gradually moves toward the small size like zero (Parasopouloos & Vrahatis, 2004).

$c_1$ and $c_2$ accelerate looking for the best local and group position, respectively. In earlier papers, these two values were considered equal to a constant value (usually 2) (Kennedy & Eberhart, 1995; Parasopoulos & Vrahatis, 2004). But further studies suggest that these two parameters also to be
adjusted dynamically (Tripathi et al., 2007). Experiments show that you can get the best results, in spite of adjusting $c_1$ on 2.5 at the beginning of the search and then its gradual reduction toward 0.5. In contrast, it is better that the value of $c_2$ also to be increased on a reversed route from 0.5 to 2.5. The PSO operation is shown in Fig. 2 in 3D space.

Fig. 2 – Definition of search in PSO algorithm.

In (Tan, 2007), in order to prevent local optimal algorithm premature convergence, the mutation operator which is used in Genetic algorithm (GA) is combined with PSO, fact that substantially improves the algorithm efficiency. Despite optimization variables not being binary and according to the positive effect of mutation in last researches, this operator is also used in this paper. The philosophy of this operator is that first each variable in particle is given a random number between zero and one with normal probability distribution function (PDF). If the given number to a variable is less than the supposed value (like 0.05), then mutation operator is imposed to that variable. So, the variable is considered equal to a random value in its acceptable domain.

4.2. Modified PSO Algorithm

This algorithm contains two steps. In the first step, the classic PSO algorithm is applied and, in each iteration the best position of the particles is saved in an array; after finishing the iterations of the first step, these arrays are classified as the first member of arrays contains the first member of particles and the last member of arrays contains the last one. So, the number of arrays is equal to the number of the particles. These arrays are used as the primary assumption for the second step. In the second step, there are two nested cycles in which the following algorithm is applied:

1) First cycle: $t := t + 1$. 
2) Second cycle: \( j := j + 1 \) (we divide the field into some parts with equal desired dimensions).

* For \( i = 1, 2, ..., pop \), the velocity of each particle is calculated for related part (remaining dimensions are constant) and the next position of the particles is determined (\( X = X + rand \times V \)). Actually, we make some other particles around the positions that we found for each particle in the first step.

* For \( i = 1, 2, ..., pop \), the particles are distributed in related dimension (remaining dimensions are constant), then the limits related to velocity and variables are checked.

* We calculate the function according to variables and particles and then we chose the best particle. In fact, for each particle’s position in the first step and its group that is made in the second step, we try to find a position with the most accuracy between them.

* End of cycle \( j \)
* End of cycle \( t \)

5. Results and Discussions

The case study system is optimized using the MPSO algorithm implemented under MATLAB environment. The system data, including solar radiation and annual wind speed, related to one of the northwest regions of Iran is captured with one sample per hour precision. The specifications of system components are depicted in Table 1. The curves of annual wind speed at 15 m height and vertical/horizontal radiation are shown in Figs. 3 and 4, respectively. Fig. 5 illustrates the IEEE RTS load pattern with 50 kW annual peak load. Load curtailment cost also is considered in case study with 5.6 US$/kWh.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Turbine</td>
<td>19400</td>
<td>15000</td>
<td>75</td>
<td>96</td>
<td>–</td>
<td>20</td>
</tr>
<tr>
<td>PV Array</td>
<td>7000</td>
<td>6000</td>
<td>20</td>
<td>96</td>
<td>–</td>
<td>20</td>
</tr>
<tr>
<td>EL</td>
<td>2000</td>
<td>1500</td>
<td>25</td>
<td>100</td>
<td>75</td>
<td>20</td>
</tr>
<tr>
<td>Hydrogen Tank</td>
<td>1300</td>
<td>1200</td>
<td>15</td>
<td>100</td>
<td>95</td>
<td>20</td>
</tr>
<tr>
<td>FC</td>
<td>3000</td>
<td>2500</td>
<td>175</td>
<td>100</td>
<td>50</td>
<td>5</td>
</tr>
<tr>
<td>Converter DC/AC</td>
<td>800</td>
<td>750</td>
<td>8</td>
<td>99.89</td>
<td>90</td>
<td>15</td>
</tr>
</tbody>
</table>
Fig. 3 – Annual wind speed in 15 m height.

Fig. 4 – Annual horizontal/vertical radiation.

Fig. 5 – Curve of annual load IEEE with peak 50 KW.
The net present-value cost considering and not considering reliability for MPSO and PSO algorithm are presented in Table 3. According to the obtained results in Table 3, the cost in MPSO algorithm is less than PSO algorithm. Optimization results including the costs and reliability indices are presented as in Table 4. The optimal combination for the case study system is shown in Table 5.

Table 2
Case Study System Assumptions

<table>
<thead>
<tr>
<th>System Lifetime</th>
<th>Real Interest Rate</th>
<th>( E_L)</th>
<th>Load Pattern</th>
<th>Peak Load</th>
<th>Load Curtailment Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 Years</td>
<td>6%</td>
<td>0.01</td>
<td>IEEE RTS</td>
<td>50 kW</td>
<td>5.6 US$/kWh</td>
</tr>
</tbody>
</table>

Table 3
Comparison between Results Obtained by MPSO as Compared with PSO Algorithm

<table>
<thead>
<tr>
<th>( \sum_i NPC_i ) considering reliability</th>
<th>MPSO (MUS$)</th>
<th>PSO (MUS$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.316</td>
<td>3.1370</td>
</tr>
</tbody>
</table>

| \( \sum_i NPC_i \) not considering Reliability | 2.1485 | 2.9510 |

Table 4
Case Study System Reliability/Cost Evaluation

<table>
<thead>
<tr>
<th>Investment Cost (MUS$)</th>
<th>( \sum_i NPC_i ) (MUS$)</th>
<th>( NPC_{loss} ) (MUS$)</th>
<th>( ELF ) (MW yr)</th>
<th>( LOEE ) (MWh yr)</th>
<th>( LOLE ) (h yr)</th>
<th>LPSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.688</td>
<td>2.316</td>
<td>0.148</td>
<td>0.0033</td>
<td>1.0540</td>
<td>334.73</td>
<td>0.0091</td>
</tr>
</tbody>
</table>

Table 5
System Optimal Combination in Case Study System

<table>
<thead>
<tr>
<th>( N_{WG} )</th>
<th>( N_{PV} )</th>
<th>( P_{el} )</th>
<th>( M_{tank} )</th>
<th>( P_{FC} )</th>
<th>( P_{lev} )</th>
<th>( \theta_{PV} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>223</td>
<td>119.45</td>
<td>143.4</td>
<td>43.5</td>
<td>45.9</td>
<td>33.7</td>
</tr>
</tbody>
</table>

The important point that can be seen in Table 4, is equivalent loss factor index (ELF) obtained in the optimal point. As it was suggested earlier, part of objective function defined with (3) indicates the loss imposed to customers because of load curtailment. Moreover, the objective function constraint (14) also affected level of load curtailment and so limits its level, as a result system reliability is preserved in an optimal level. According to the obtained results which are shown in Table 4, it can be observed that system reliability constraint is not enabled in an optimal point and has conformed to the standard and is less than predetermined value (0.01) which expresses the validity of the results. In fact, because of high loss of load costs compared to costs of system reliability improvement, increasing replacement costs, and system repair and maintenance (designing more expensive system) are more cost efficient economically.
6. Conclusions

1. In this paper, a hybrid system consisting of Wind turbine, PV array, FC, EL and AC/DC convertor was used considering reliability indices for provision of IEEE reliability test load.
2. To provide a time-efficient solution process for the optimization problem, a reliability model was applied for reliability evaluation.
3. The optimal size of system components was determined using a computer program which is written in Matlab environment.
4. The overall cost of hybrid system, such as investment cost, operation and maintenance cost, and the cost associated with loss of load, was optimized considering reliability indices.
5. The results obtained by the MPSO algorithm were compared with the ones provided by the common PSO method.
6. Present-value cost (NPC) of energy generation was calculated with and without considering reliability indices using common PSO and modified PSO. Rate of this cost in MPSO algorithm concluded less than PSO algorithm. Also this cost in MPSO considering reliability indices was concluded more than not considering reliability indices.
7. The proposed hybrid solution procedure (MPSO) gained better results than PSO with respect to capital investment costs minimization and system reliability indices level.

APPENDIX

Table 6: Nomenclature

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Definition</th>
<th>Nomenclature</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPC&lt;sub&gt;i&lt;/sub&gt;</td>
<td>Net present value cost for a specific device</td>
<td>N&lt;sub&gt;WG&lt;/sub&gt;</td>
<td>Total number of installed wind turbines</td>
</tr>
<tr>
<td>N&lt;sub&gt;i&lt;/sub&gt;</td>
<td>Number of units and/or unit capacity, [kW or Kg]</td>
<td>N&lt;sub&gt;PV&lt;/sub&gt;</td>
<td>Total number of installed PV arrays</td>
</tr>
<tr>
<td>CC&lt;sub&gt;i&lt;/sub&gt;</td>
<td>Capital investment cost, [US$/unit]</td>
<td>P&lt;sub&gt;el−tank&lt;/sub&gt;</td>
<td>EL output power</td>
</tr>
<tr>
<td>RC&lt;sub&gt;i&lt;/sub&gt;</td>
<td>Replacement cost, [US$/unit]</td>
<td>P&lt;sub&gt;rew−el&lt;/sub&gt;</td>
<td>Delivered electric power to EL</td>
</tr>
<tr>
<td>K</td>
<td>Single payment present worth</td>
<td>η&lt;sub&gt;el&lt;/sub&gt;</td>
<td>EL efficiency</td>
</tr>
<tr>
<td>O &amp; MC&lt;sub&gt;i&lt;/sub&gt;</td>
<td>Maintenance and repair cost, [US$/unit-yr]</td>
<td>E&lt;sub&gt;tank&lt;/sub&gt;(t)</td>
<td>Stored energy in the hydrogen tank for each step-time</td>
</tr>
<tr>
<td>PWA</td>
<td>Annual payment present worth</td>
<td>Δ&lt;sub&gt;t&lt;/sub&gt;</td>
<td>Duration of each step-time (one hour)</td>
</tr>
<tr>
<td>NPC&lt;sub&gt;loss&lt;/sub&gt;</td>
<td>Net present-value cost of load loss</td>
<td>P&lt;sub&gt;tank−FC&lt;/sub&gt;(t)</td>
<td>Transferred power from the hydrogen tank to the FC</td>
</tr>
<tr>
<td>C&lt;sub&gt;loss&lt;/sub&gt;</td>
<td>Equivalent cost of load curtailment per kWh, [US$/kWh]</td>
<td>η&lt;sub&gt;storage&lt;/sub&gt;</td>
<td>Efficiency of storage system (95%)</td>
</tr>
<tr>
<td>P&lt;sub&gt;PV&lt;/sub&gt;</td>
<td>Array output power</td>
<td>m&lt;sub&gt;storage&lt;/sub&gt;(t)</td>
<td>Mass of stored hydrogen in the tank</td>
</tr>
</tbody>
</table>
Table 6  
Continuation

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Definition</th>
<th>Nomenclature</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G$</td>
<td>Perpendicular radiated power on the surface of each array, [W/m²]</td>
<td>$E_{storage}(t)$</td>
<td>Stored energy in tank</td>
</tr>
<tr>
<td>$P_{PV,\text{rated}}$</td>
<td>Rated power of each array, such that $G = 1000$ W/m²</td>
<td>$HHV_H2$</td>
<td>Higher heating value of hydrogen (39.7 kWh/kg)</td>
</tr>
<tr>
<td>$\eta_{PV,\text{conv}}$</td>
<td>Efficiency of DC/DC converter between each array and DC bus</td>
<td>$P_{\text{FC-inv}}$</td>
<td>FC output power</td>
</tr>
<tr>
<td>$G_v(t)$</td>
<td>Rate of vertical radiations in the $t^{th}$ step-time, [W/m²]</td>
<td>$\eta_{\text{FC}}$</td>
<td>FC efficiency</td>
</tr>
<tr>
<td>$\theta_{PV}$</td>
<td>PV panel tilt angle</td>
<td>$P_{\text{inv-load}}$</td>
<td>Delivered power to load</td>
</tr>
<tr>
<td>$G_h(t)$</td>
<td>Rate of horizontal radiations at step-time $t$, [W/m²]</td>
<td>$P_{\text{inv-inv}}$</td>
<td>Delivered power to inverter from renewable unit</td>
</tr>
<tr>
<td>$P_{WG}$</td>
<td>WT output power</td>
<td>$\eta_{\text{inv}}$</td>
<td>Inverter efficiency</td>
</tr>
<tr>
<td>$v_W$</td>
<td>Wind speed</td>
<td>$E[X]$</td>
<td>Mathematical expectation</td>
</tr>
<tr>
<td>$v_{\text{cut-in}}$</td>
<td>Cut-in speed of turbine, [m/s]</td>
<td>$ELF_{\text{max}}$</td>
<td>Maximum equivalent loss factor index</td>
</tr>
<tr>
<td>$v_{\text{cut-out}}$</td>
<td>Cut-out speed of turbine, [m/s]</td>
<td>$P_{\text{load}}(t)$</td>
<td>Load power</td>
</tr>
<tr>
<td>$P_{WG,\text{max}}$</td>
<td>Maximum output power of WT, [kW]</td>
<td>$LOL(t)$</td>
<td>Loss of load at step-time $t$</td>
</tr>
<tr>
<td>$v_{\text{rated}}$</td>
<td>Rated speed of turbine, [m/s]</td>
<td>$LOLE$</td>
<td>Loss of load expectation</td>
</tr>
<tr>
<td>$PWG,\text{ max}$</td>
<td>Maximum output power of turbine, [kW]</td>
<td>$LOEE$</td>
<td>Loss of energy expectation</td>
</tr>
<tr>
<td>$P_{\text{fuel}}$</td>
<td>Output power at cut-out speed</td>
<td>$EENS$</td>
<td>Energy not supplied expectation</td>
</tr>
<tr>
<td>$v_W^k$</td>
<td>Wind speed at a specific height</td>
<td>$LOE(t)$</td>
<td>Loss of energy at step-time $t$</td>
</tr>
<tr>
<td>$v_W^{\text{ref}}$</td>
<td>Wind speed at the reference height</td>
<td>$Q_s$</td>
<td>Amount of loss of energy</td>
</tr>
<tr>
<td>$h_{\text{ref}}$</td>
<td>Reference height</td>
<td>$LPSP$</td>
<td>Loss of power supply probability</td>
</tr>
<tr>
<td>$P_{\text{ren}}(\eta_{WG,\text{ fail}}, \eta_{PV,\text{ fail}})$</td>
<td>Injected power of renewable units to DC bus</td>
<td>$D(t)$</td>
<td>Load demand (kWh) in time step $t$</td>
</tr>
<tr>
<td>$n_{\text{fail, WG}}$</td>
<td>Number of wind turbines being out of the grid</td>
<td>$A_{WG}$</td>
<td>Availabilities of each WG</td>
</tr>
<tr>
<td>$n_{\text{fail, PV}}$</td>
<td>Number of PV arrays being out of the grid</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
REFERENCES


OPTIMIZAREA UNUI SISTEM HIDRBID DE GENERARE A ENERGIEI UTILIZÂND UN ALGORITM PSO MODIFICAT

(Rezumat)

Utilizarea surselor de energie regenerabile poate determina scăderea costurilor de producţie şi la creşterea fiabilităţii sistemului. În acest scop este necesară determinarea unei combinaţii optime între nivelul indicatorilor de fiabilitate şi a costurilor de capital corespunzătoare. În această lucrare este proiectat un sistem hibrid ce constă dintr-o turbină eoliană, un câmp de generatoare fotovoltaice şi celeule de combustibil, în scopul furnizării unei sarcini prescrise. Scopul proiectării îl constituie minimizarea costurilor totale de generare a energiei pe o perioadă de 20 de ani în două ipoteze: cu luare în considerare sau nu a indicatorilor de fiabilitate. Se presupune că este posibilă apariţia unor situaţii de urgenţă în componentele sistemului. Funcţia de cost considerată include investiţii, costuri de întreţinere şi reparaţii, precum şi costuri legate de pierderea de sarcină. Pentru optimizarea sistemului se consideră un algoritm PSO modificat, implementat în Matlab. Rezultatele furnizate de acesta sunt comparate
cu cele obținute în urma aplicării algoritmului PSO clasic. Combinarea unui algoritm de inteligență artificială cu evaluarea unor indicatori de fiabilitate determină creșterea volumului de calcule și, în consecință, a duratei de calcul. Pentru a depăși acest neajuns în lucrare este utilizat un model aproximativ pentru estimarea indicatorilor de fiabilitate, ceea ce determină o scădere substanțială a duratei de calcul.