

Optimal Sizing of a Reliable Hydrogen-based Stand-alone Wind-Fuel Cell System

Seyed Mehdi Hakimi*, Mohammad Manthouri†

A hybrid wind/ fuel cell generation system is designed to supply power demand. The aim of this design is to minimize the total cost of the hybrid system over an expected 20 years of operation. The optimization problem is solved aimed at providing a reliable supply for the consumer's demand. The system consists of fuel cells, some wind units, some electrolyzers, a reformer, an anaerobic reactor and some hydrogen tanks. The system is assumed stand-alone and uses the biomass as an available energy source. Also, wind speed and load data are assumed completely deterministic. System costs are mainly due to the investments, replacement, operation, and maintenance as well as loss of load costs. The prices are provided empirically, and the system components are commercially available. An advanced upgrade of Particle Swarm Optimization algorithm is used to solve the optimization problem. Results are analyzed to illustrate the impact of component outages on the reliability and the system costs, so it is shown that they are directly dependent on each component's reliability (e.g. the outages result in a need for a generating system bigger in size to provide the load with an acceptable reliability of supply).

Keywords: Index Terms—wind Turbine, Fuel Cell, Optimal Sizing, Particle Swarm Optimization, Reliability.

Received Jan. 2016; Revised May 2016; Accepted June 2016.

I INTRODUCTION

Wind turbines and fuel cells are widely used for feeding the consumer's demand for the out land areas. Considering that these systems act complementary, so they usually use as combined units. Fig. 1 shows the hybrid system block diagram that is used in this article. The output of each unit is connected to a common DC bus bar. Also in this hybrid pattern, a fuel cell stack, an electrolyzer and a hydrogen storage tank are used to store energy (Energy Storage System). Hydrogen is a suitable choice to store energy that is recently considered seriously [1–3]. This system can do short time and long time storage simultaneously. Although it seems that using diesel generator is economically beneficial but it has weaknesses such as pollution and dependence on fuel. On the other hand, hydrogen-based storage systems; in addition to cleanness, do not need any fossil fuel when combining with the electrolyzer and hydrogen tank. Also, it will be expected that, in future, using hydrogen-based systems will become economically more desirable because fossil fuel costs are increasing whereas fuel cell costs are decreasing [4]. As another point, wind-diesel systems do not provide any storage for the excessive produced wind energy. On the other hand, the proposed system can store the excessive energy. This stored capacity could be used to supply the load when the wind velocity decreases or when the load reaches its peak [5]. Also, fuel cell can produce load from hydrogen that is emanated from waste materials. Paying attention to the intermittent characteristics of

wind power, the important problem is to design grid independent wind systems providing a sufficient reliability in various climate conditions, in addition to considering the relative investment and utilization costs. In [32] an update literature review on optimization techniques used for the sizing and energy management of hybrid photovoltaic/wind/battery energy systems is presented.

This study presents the minimization of the total cost of the hybrid system. The system consists of fuel cells, some wind units, some electrolyzers, a reformer, an anaerobic reactor and some hydrogen tanks. The system is assumed stand-alone and uses the biomass as an available energy source. Also, wind speed and load data are assumed completely deterministic. System costs are mainly due to the investments, replacement, operation, and maintenance as well as loss of load costs. The prices are provided empirically, and the system components are commercially available. An advanced upgrade of Particle Swarm Optimization algorithm is used to solve the optimization problem. Results are analyzed to illustrate the impact of component outages on the reliability and the system costs, so it is shown that they are directly dependent on each component's reliability.

This paper is organized as follows: in section 2 the model of the wind-fuel cell system is explained. Operation strategy is introduced in section 3. Section 4 is investigated evaluation of reliability-cost. In section 5 problem statement is explained. Section 6 presents particle swarm optimization. In section 7 the results of the simulation are presented. Finally, in section 8 conclusion of the proposed method is presented.

*sm_hakimi@damavandiau.ac.ir PhD Assistant Professor 09124798639 Department of Electrical Engineering, Damavand Branch, Islamic Azad University, Damavand, (Corresponding author)

†PhD Assistant Professor +989128387235 Electrical and Electronic Engineering Department, Shahed university, Persian Gulf Highway Tehran/Iran, mmanthouri@shahed.ac.ir

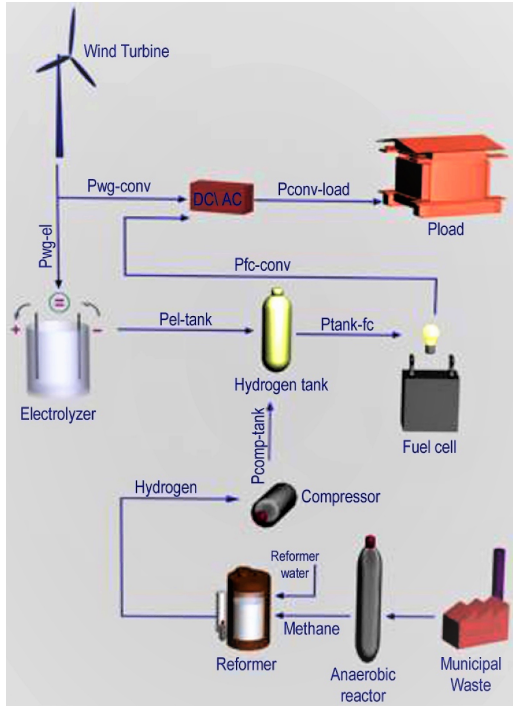


Figure 1: Hybrid system block diagram

II WIND- FUEL CELL SYSTEM MODELING

A Wind turbine:

The output power of turbine that is used in this study is shown in Fig. 2.

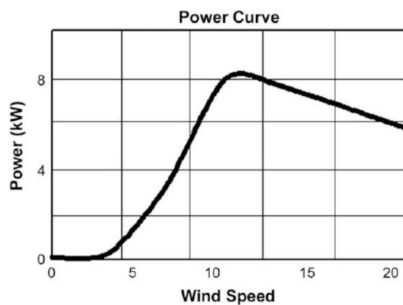


Figure 2: The output power of wind turbine specification in accordance with wind speed [4].

Usually, the builder factory presents this curve and it presents the real power that transfers from the turbine to bus bar. Same as [4] the utilized turbine in this article is BWC Excel-R/48. The nominal turbine power is 7.5KW, and its output voltage is equal to 48 VDC. Its output power (P_{WG}) specification in accordance

with wind velocity (ν_W) can be estimated as below:

$$P_{WG} = \begin{cases} 0 & ; \nu_W \leq \nu_{cut-in}, \nu_W \geq \nu_{cut-out} \\ P_{WG,max} \times \left(\frac{\nu_W - \nu_{cut-in}}{\nu_{rated} - \nu_{cut-in}} \right)^m & ; \nu_{cut-in} \leq \nu_W \leq \nu_{rated} \\ P_{WG,max} + \frac{P_{furl} - P_{WG,max}}{\nu_{cut-out} - \nu_{rated}} \times (\nu_W - \nu_{rated}) & ; \nu_{rated} \leq \nu_W \leq \nu_{furl} \end{cases} \quad (1)$$

Where, ν_{cut-in} , $\nu_{cut-out}$ and ν_{rated} are respectively cut in wind speed (m/s), cut out in wind speed and nominal wind speed (m/s) of the turbine, $P_{WG,max}$ and P_{furl} are wind turbine output power at rated and cut out speeds, respectively. In this study, the exponent m is equal to 3. Also, in above equation, ν_W refers to wind speed at the height of wind turbine hub. Measured data at any height can be converted to installation height through exponent law [6]:

$$\nu_w = \nu_w^{measure} \times \left(\frac{h_{hub}}{h_{measure}} \right)^\alpha \quad (2)$$

Where, α is the exponent law coefficient. This value varies from less than 0.10 for very flat land, water or ice to more than 0.25 for heavily forested landscapes. The one-seventh power law (0.14) is a good reference number for relatively flat surfaces such as open terrain of grasslands away from tall trees or buildings [7].

B Electrolyzer

Electrolyzer works based on the simple process of water electrolysis: a direct current is passed through two electrodes submerged in water, which thereby decomposes into hydrogen and oxygen. The hydrogen can then be collected from the anode. Most electrolyzers produce hydrogen at a pressure around 30 bars [8]. On the other hand, the reactant pressures within a Proton Exchange Membrane FC (PEMFC) are around 1.2 bars (a bit higher than atmosphere pressure) [9]. As a result, in most studies, electrolyzer's output is directly injected to a hydrogen tank [4, 7, 9, 10, 11 and 12]. However, in some cases, for raising the density of stored energy, a compressor may pressurize electrolyzer's output up to 200 bars. Also, in another study, for reducing the compressor's energy consumption, two hydrogen tanks are used [5]. In this configuration, electrolyzer's output is directly injected to a low-pressure tank and when this tank is fully charged, compressors pump the hydrogen into a second high-pressure tank. Thus, the compressor does not work continuously and, as a result, it consumes lower amount of energy. In this paper, the electrolyzer is directly connected to the hydrogen tank; however, the developed software is sufficiently flexible to handle the compressor model. Transferred power from electrolyzer to hydrogen tank can be defined as follows:

$$P_{el-tank} = P_{wg-el} \times \eta_{el} \quad (3)$$

C Hydrogen tank

The tank energy storage for each time step t can be calculated from the below equation

$$E_{\tan k}(t) = E_{\tan k}(t-1) + P_{el-\tan k}(t) \times \Delta t - \left(\frac{P_{\tan k-fc}(t) \times \Delta t}{\eta_{storage}} \right) + P_{comp-\tan k} \times \Delta t \quad (4)$$

$$P_{comp-\tan k} = \frac{H_{2-total} \times HHV}{24} \quad (5)$$

$$H_{2-total} = Population(800) \times Waste_{ave} \times H_{2-waste} \quad (6)$$

Where, $H_{2-total}$ is totally daily produced hydrogen [kg], $Waste_{ave}$ is average waste per each person [kg], $H_{2-waste}$ is produced H_2 per each kg of waste [kg], Δt is step time length that is assumed 1 hour, $\eta_{storage}$ is storage system efficiency that represents the losses from the leakage and is assumed 95% [13] and HHV is hydrogen Higher Heating Value that is assumed 39.7 kWh/kg [14]. Other specifications could be found in [4].

D Fuel cell

Proton exchange membrane (PEM) fuel cells provide a reliable function in discontinuous operating conditions and its relevant industrial models are produced on a wide scale and are available commercially [8]. This kind of fuel cell is suitable for big usages and has a nearly fast dynamic response, around 1 to 3 seconds [8]. Its output power can be calculated as a function of its input hydrogen power and the efficiency η_{fc} that can consume it constantly.

$$P_{fc-conv} = P_{\tan k-fc} \times \eta_{fc} \quad (7)$$

E DC/AC Converter

Finally, for load consumption, a DC/AC converter, converts DC electrical power to AC with suitable load frequency. The effect of converter losses can be modeled by its efficiency.

$$P_{conv-load} = (P_{fc-conv} + P_{wg-conv}) \times \eta_{conv} \quad (8)$$

The costs, lifetime and specifications of components could be found in [4].

III OPERATION STRATEGY

The procedure for the desired system operation is selected based on its working conditions. Primarily in each step of time, one of the below conditions could be set:

- $P_{WG}(t) = \frac{P_{load}(t)}{\eta_{conv}}$ In this state, all of the produced power from wind units is fed to load via DC/AC converter.
- $P_{WG}(t) > \frac{P_{load}(t)}{\eta_{conv}}$ In this state, extra power produced by the wind units is injected into the electrolyzer to produce hydrogen. When the injected power to the electrolyzer was out of its nominal capacity or when the hydrogen tank was over-filled, the extra power is taken away from the system by being wasted in resistance.
- $P_{WG}(t) < \frac{P_{load}(t)}{\eta_{conv}}$ In this state, load requirements are supplied from the fuel cell. If the requirements exceed the nominal capacity of the cell, or in case, there is not enough hydrogen, some parts of the load should be cut out considered as a loss of load.

In all the above conditions, the limitations of the devices should be considered by using Esqs. (1)–(7).

IV EVALUATION OF RELIABILITY-COST

Annual wind speed data from a region in the northwest of Iran and the load pattern related to the reliability test system IEEE [15] with an annual peak of 500KW are used to simulate the whole system. This simulation is for one year time period, the resolution is one hour, and the reliability-cost is calculated by neglecting both the load growth and the uncertainty in wind speed. Results are calculated over a 20 year period to take proper account of the economic factors.

A Reliability indexes

Different indexes for calculation of system reliability are presented in references [8, 15, 16, 17, and 18]. Loss of energy expectation (LOEE), expected energy not supplied (EENS), equivalent loss factor (ELF) are samples of such indexes. These indexes are explained with below relations:

$$LOEE = EENS = \sum_{t=1}^N E[LOE(t)] \quad (9)$$

That N is the number of time steps in which system's reliability is evaluated (here, $N = 8760$). $E[LOE(t)]$ is the expected value of the loss of load in t^{th} time interval that is described with below equation:

$$E[LOE] = \sum_{s \in S} Q(s) \times P(s) \quad (10)$$

$Q(s)$ is the amount of loss of load (kWh) in situation s and $P(s)$ is the probability of standing in State s and S is all of the possible situations for the system. Assuming that $D(t)$ is equal to the amount of load request (kWh) in time interval t , finally, equivalent load rupture coefficient can be defined as below:

$$ELF = \frac{1}{N} \sum_{t=1}^N \frac{Q(t)}{D(t)} \quad (11)$$

Whereas ELF consists of more information about both the numbers and the magnitudes of the outages [11], in this article, it is used as the main criterion of reliability. In [8] the allowable maximum ELF in advanced countries is equal to 0.0001, although, for grid-independent systems that were studied in [8], this restriction is considered 0.01.

B Cost of loss of load

The cost of interruption in supplied electrical energy can be calculated in different ways. For example, it can be calculated by the client tendency toward spending more money to develop the grid or the detrimental effects caused by the source interruption in the generation process. Calculated quantities in several cases are usually identical: around 5 to 40 US\$/kWh for industrial consumers and around 2 to 12 US\$/kWh for domestic subscribers [8]. In this article, the cost of consumers' dissatisfaction, caused by loss of load, is approximately considered 5.6 US\$/kWh, like [8].

V PROBLEM STATEMENT

The aim of this article is to find the optimum size of the system components, i.e. number of wind turbines, electrolyzer capacity, hydrogen tank, fuel cell, reformer, anaerobic reactor, compressor and DC/AC converter. System costs comprise investment net present cost value, maintenance and operation cost, replacement cost and also the cost of interruption in load supplement in 20 years system duration.

The net present cost of the i^{th} equipment can be calculated via below equation [12]:

$$NPC_i = N_i \times (CC_i + RC_i \times K_i + O \& MC_i \times PWA(ir, R)) \quad (12)$$

That N is the number(unit) or the capacity(kW or kg)of the equipment, CC (US\$/unit) is the capital cost, RC is the replacement cost (US\$/unit), $MC\&O$ is the maintenance and operation cost (US\$/unit-yr) and R is the project lifetime (equal to 20 years in this article), ir is the real interest rate(equal to 0.08 in this research) that is determined based on the Nominal interest rate ($ir_{nominal}$) and the Annual inflation rate (f) according to the below equation[19]:

$$ir = \frac{(ir_{nominal} - f)}{(1 + f)} \quad (13)$$

PWA and K are Annual Payment Present Worth and Single Payment present worth respectively those are defined as below:

$$PWA(ir, R) = \frac{(1 + ir)^R - 1}{ir(1 + ir)^R} \quad (14)$$

$$K_i = \sum_{n=1}^{y_i} \frac{1}{(1 + ir)^{n \times L_i}} \quad (15)$$

y and L are the numbers of replacement and lifetime of the equipment, respectively.

Equation (8) presents the lost load expectation then cost of loss of load can be obtained from below equation:

$$NPC_{loss} = LOEE \times C_{loss} \times PWA \quad (16)$$

Where, C_{loss} is the cost of customer's dissatisfaction (US\$/kWh). Finally, the objective function is defined as below:

$$F_{opt} = \min_x \left\{ \sum_i NPC_i + NPC_{loss} \right\} \quad (17)$$

The number of equipment is represented as i and x is a 5 element vector consists of the optimization variables that the above-mentioned objective function is optimized on the below constraints:

$$E[ELF] \leq ELF_{max} \quad (18)$$

$$0 \leq N_i \quad (19)$$

$$E_{tan k}(0) \leq E_{tan k}(8760) \quad (20)$$

Constraint (19) demonstrates that in tank stored energy in end of the year ought not to be less than initial energy. This constraint ensures that reliability calculations are done for the worst case.

VI PARTICLE SWARM OPTIMIZATION

PSO is a population-based algorithm that exploits a population of individuals to probe promising region of the search space. In this context, the population is called swarm and the individuals are called particles. Each particle moves with an adaptable velocity within the search space and retains in its memory the best position it ever encountered. The global variant of PSO the best position ever attained by all individuals of the swarm is communicated to all the particles [20]. The general principles for the PSO algorithm are stated as follows.

Suppose that the search space is n -dimensional, then the i th particle can be represented by an n -dimensional vector, $X_i^{\frac{1}{4}}[x_{i1}, x_{i2}, \dots, x_{in}]T$, and velocity $V_i^{\frac{1}{4}}[v_{i1}, v_{i2}, \dots, v_{in}]T$, where $i^{\frac{1}{4}}1, 2, \dots, N$ and N is the size of the population. In PSO, particle i remembers the best position it visited so far, referred to as $P_i^{\frac{1}{4}}[p_{i1}, p_{i2}, \dots, p_{in}]T$, and the best position of the best particle in the swarm is referred as $G^{\frac{1}{4}}[g_1, g_2, \dots, g_n]T$ [21]. Each particle i adjusts its position in next iteration $t+1$ with respect to Eqs. (20) And (21) [20]:

$$V_i(t+1) = w(t)V_i(t) + c_1 r_1 (P_i(t) - X_i(t)) + c_2 r_2 (G(t) - X_i(t)) \quad (21)$$

$$X_i(t+1) = X_i(t) + \chi V_i(t+1) \quad (22)$$

Where, $w(t)$ is the inertia coefficient which is employed to manipulate the impact of the previous history of velocities on the current velocity. χ is constriction factor which is used to limit velocity, here $\chi = 0.7$. c_1 and c_2 denote the cognitive and social parameters and r_1 and r_2 are random real numbers drawn from the uniformly distributed interval $[0, 1]$. $w(t)$ resolves the trade-off between the global and local exploration ability of the swarm. A large inertia coefficient encourages global exploration while small one promotes local exploration. Experimental results suggest that it is preferable to initialize it to a large value (here, 1), giving priority to the global exploration of search space, and gradually decreasing to a small value about zero (here, 0) as to obtain refined solution [20].

c_1 And c_2 accelerate the search toward local and global best directions, respectively. In earlier studies both of these parameters were set on a constant value, e.g. $c_1 = c_2 = 2$ [20–30]. But, advanced literature recommends adjusting these parameters dynamically [21]. Experiments indicate to initialize c_1 to 2.5 and decrease it monotonically to 1.5 during optimization procedure. On the other hand, it is better to track c_2 on an inverse trajectory. In order to prevent premature convergence to suboptimal solutions, Raymond R. Tan augmented a binary PSO with a GA based mutation operator and achieved significant improvement in the rate of successful convergence [31]. Therefore, in the current study, we incorporate mutation operator into our continuous-space PSO algorithm. This mutation operator reinitiates the value of each continuous variable into its feasible range by a predefined probability (e.g. 5%).

In this study, the number of population is set to 60, and for preventing an explosion of the swarm, maximum allowable velocity along each dimension is set to half of its feasible range. Results show that, in this application, for a different number of switching angles, the algorithm converges within 100–150 iterations. Hence, in a conservative manner, the number of iterations

Table 1: Assumed conditions for the base state.

Cost of lost demand	Peak of the load	Load pattern	ELF _{max}	Interest rate	Lifetime of project
5.6US\$/kWh	500kw	IEEE RTS	0.01	8 percents	20 years

is set to 200. Also, for enhancing the PSO's ability in escaping from local minima, a mutation operator is incorporated into the algorithm. Results indicate that it is better to utilize this operator in discrete iteration intervals with different probabilities. In this study, mutation probabilities for iteration intervals of [30, 90] and [110, 170] are 1% and 3%, respectively. Other iteration intervals are not influenced by mutation.

VII RESULTS

In this article, the optimum combination of the considered hybrid system that is shown in Fig. 1 is calculated. This system is optimized using PSO algorithm. The software uses Matlab programming. The system data consists of the annual wind data which belongs to a region in the northwest of Iran that is sampled every 1 hour. The annual wind speed at 15m hob height is shown in Fig. 3 and the annual load curve that is actually an IEEE standard curve with 500 kW peak, is shown in Fig. 4. For basis state (Table 1), the system is optimized and the results are obtained as below (table 2). The sizes of the reactor, reformer and compressor are assumed fixed and equal to 750kg/day, 31.2kgH₂/day and 50kw respectively.

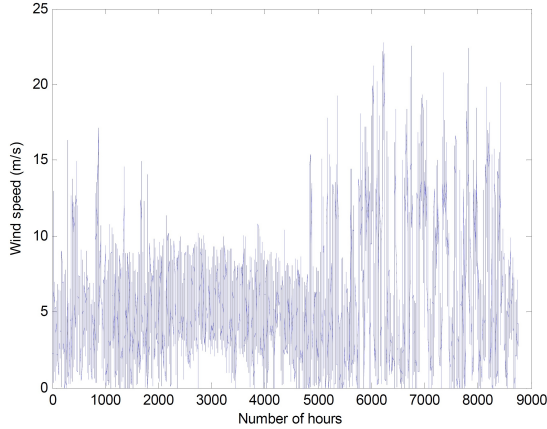


Figure 3: Wind speed in a year.

For optimization, a Pentium PC with 3.2 IV GHz CPU and 512 MB Ram is used. Required time for optimization is about 6 hours. Calculated optimum structure and optimum cost are shown in Table 2 and the system reliability indexes are shown in Figs. 5–8.

Table 2: Optimal cost and combination of components.

$F_{opt}(\$)$	N_{wg}	N_{el}	N_{tank}	$N_{fuelcell}$
4.29×10^7	1069	2137	8506	434

In addition to the objective function, constraint No. 17 also applies to the amount of ruptured load and bounds which, consequently maintains the system reliability at an acceptable value.

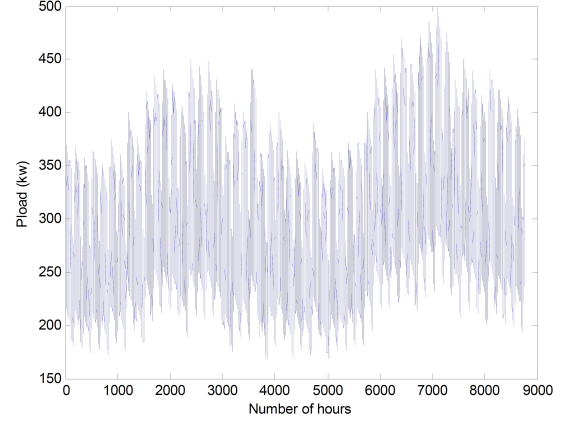


Figure 4: Hourly load in the year.

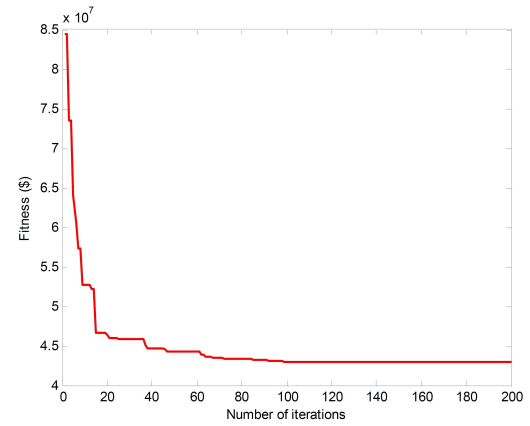


Figure 5: PSO algorithm Convergence curve.

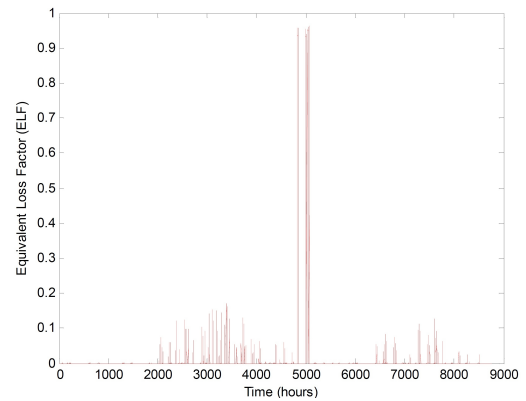


Figure 6: Equivalent loss factor.

Results show that the reliability inequality constraint, i.e. Eq. 17, isn't active at the optimum point. In fact, because of high loss of load costs (cost of customer's dissatisfaction), designing a reliable and, therefore, the expensive system is economically

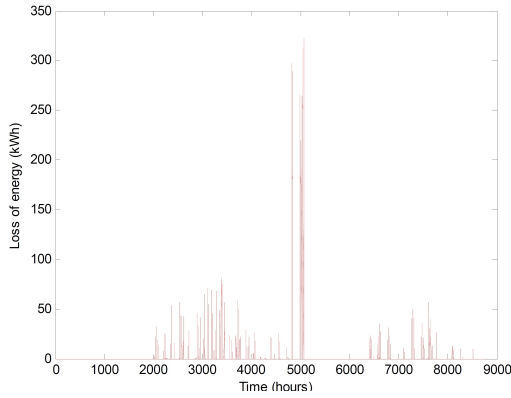


Figure 7: Loss of energy expectation.

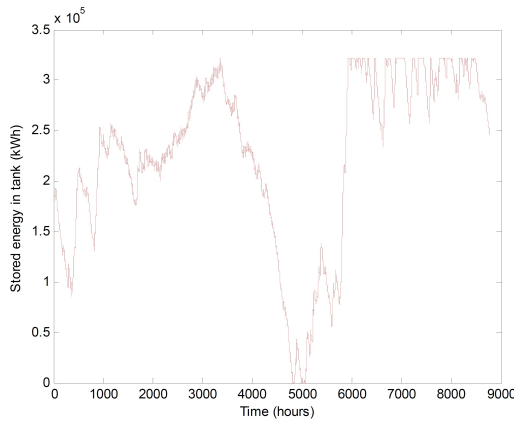


Figure 8: Stored energy in tank expectation during a year.

reasonable. As it is shown in Fig. 6, the ELF has its maximum amount in 5000 hours, maybe because the wind speed is low in this hour (Fig. 3) and the amount of reservation in hydrogen tank is very low (Fig. 8), so loss of load in this hours occurred more than other hours in the year.

The load feeding, as an index for the system reliability in each hour of the year, is more sensitive to the amounts of the stored energy in the hydrogen tank; therefore, the expectation factor of the stored energy in the hydrogen tank in each hour of the year is shown in Fig. 8. Fig. 6 shows the ELF and Fig. 7 demonstrate the loss of energy expectation (LOEE) in various hours in the year.

A Sensitivity analysis toward reliability constraint

In this article, the ELF index is considered as a reliability constraint for the studied system, also it is mentioned that this constraint is equal to 0.01 for grid independent systems and equal to 0.0001 for advanced systems. The ELF constraint is chosen 0.0001 in the simulation program. The results are shown in the Table 3. As it is seen, in case that $ELF_{max} = 0.0001$, system costs increased, because in this case the amount of loss of load is lower and the system has higher reliability in comparison with the primary state. In case that reliability constraint isn't applied ($ELF = 0$), the costs of the system increased, because in this case, the load must be supplied in all hours a year.

Table 3: Sensitivity analysis toward reliability constraint.

ELF_{max}	$F_{opt}(\$)$	N_{wg}	N_{el}	N_{tank}	$N_{fuelcell}$
0.01	4.29×10^7	1069	2137	8506	434
0.0001	4.61×10^7	1069	2518	9742	483
0	4.71×10^7	1069	3179	9951	525

VIII CONCLUSION

The studied system includes (Fig. 1 wind turbine, fuel cell, electrolyzer, hydrogen tank, anaerobic reactor, reformer, and converter. Wind and local rubbish are used as a renewable source of energy production. The aim of this article is finding the optimum sizes of the system components. System costs include capital cost, replacement cost, maintenance and operation cost and costs due to the interruptions in the load feeding during 20 years system life. Also, the problem constraint is chosen to be the maximum allowable value for the ELF index. The system simulation applies constraints such as the maximum and the minimum power observance and the produced energy by the equipment. The optimal combination of the components is achieved by a novel version of the particle swarm optimization, which efficiently converges to the global, or near to the global, optimum combination.

As it is proved, if the system reliability increases, the system size and cost will increase.

Other advantages of such systems are: lower investment cost for developing the transmission grid, improvement in the power quality, the higher reliability of energy production, besides, the area will no longer need the large power plants.

REFERENCES

- [1] G. C. Ghosh, B. Emonts, D. Stolen, "Comparison of Hydrogen Storage with Diesel-generator System in a PV-WEC Hybrid System", *Sol. Energy* 75(2003) 187-198.
- [2] T. Bak, J. Nowotny, M. Rekas, C.C. Sorrell, "Photo-electrochemical Hydrogen Generation from Water using Solar Energy: Materials-related Aspects", *Int. J. of Hydrogen. Energy* 27(2002) 991-1022.
- [3] A. Kashefi Kaviani, H.R. Baghaee, G.H. Riahy, "Design and Optimal Sizing of a Photovoltaic/Wind-generator System Using Particle Swarm Optimization", *Proceedings of the 22nd Power system Conference (PSC)*, Tehran, Iran, December 19-21 2007.
- [4] M.J. Khan, M.T. Iqbal, "Pre-feasibility Study of Stand-alone Hybrid Energy Systems for Applications in Newfoundland", *Renew. Energy* 30(2005) 835-854.
- [5] A. Mills, S. Al-Hallaji, "Simulation of Hydrogen-based Hybrid Systems Using Hybrid2", *Int. J. of Hydrogen. Energy* 29(2004) 991-999.
- [6] E. Koutroulis, D. Kolokotsa, A. Potirakis, K. Kalaitzakis, "Methodology for Optimal Sizing of Stand-alone Photovoltaic/Wind-generator Systems using Genetic Algorithms", *Sol. Energy* 80(2006) 1072-1088.
- [7] H. Yang, W. Zhou, L. Lu, Z. Fang, "Optimal sizing method for stand-alone hybrid solar-wind system with LPSP technology by using genetic algorithm", *Sol. Energy* 82(2008) 354-367.
- [8] R.S. Garcia, D. Weisser, "A Wind-diesel System with Hydrogen Storage: Joint Optimization and Dispatch", *Renew. Energy* 31(2006) 2296-2320.
- [9] T.F. El-Shatter, M.N. Eskander, M.T. El-Hagry, "Energy Flow and Management of a Hybrid Wind/PV/Fuel Cell Generation System", *Energy Convers. and Management* 47(2006) 1264-1280.
- [10] M.J. Khan, M.T. Iqbal, "Dynamic Modeling and Simulation of a Small Wind-Fuel Cell Hybrid Energy System", *Renew. Energy* 30(2005) 421-439.

- [11] D.B Nelson, M.H. Nehrir, C. Wang, "Unit Sizing and Cost Analysis of Stand-alone Hybrid Wind/PV/Fuel cell Power Generation System", *Renew. Energy* 31(2006) 1641-1656.
- [12] S.M. Hakimi, S.M. Moghaddas-Tafreshi, A.Kashefi, Unit Sizing of a Stand-alone Hybrid Power System Using Particle Swarm Optimization (PSO)", *Proceeding of the International Conference on Automation and Logistics, Jinan, China, August 2007.* 3107-3112
- [13] M.Y. El-Sharkh, M. Tanrioven, A. Rahman, M.S. Alam, "Cost-Related Sensitivity Analysis for Optimal Operation of a Grid-parallel PE Fuel Cell Power Plant", *J. of Power Sources* 161(2006) 1198-1207
- [14] K. Strunz, E.K. Brock, "stochastic Energy Source Access Management: Infrastructure-integrative Modular Plant For Sustainable Hydrogen-electric Cogeneration, *Int. J. of Hydrogen. Energy* 31(2006) 1129-1141.
- [15] R. Billinton, R.N. Allan, "Reliability Evaluation of Power Systems", Plenum Press, New York, 1984
- [16] Bagen, R. Billinton, "Evaluation of Different Operating Strategies in Small Stand-alone Power Systems", *IEEE Trans. on Energy Convers.* Sept. 2005, Vol.20, Issue: 3, 654-660.
- [17] R. Karki, R.Billinton, Reliability/cost Implications of PV and Wind Energy Utilization in small Isolated Power systems", *IEEE Trans. on Energy Convers.* Vol.16, Issue 4, Dec. 2001 368-373.
- [18] D. Xu, L. Kang, L. Chang, B. Cao, "Optimal Sizing of Stand-alone Hybrid Wind/PV Power Systems Using Genetic Algorithm", *Canadian Conference on Electrical and Computer Engineering*, 2005, 1-4 May 2005, 1722-1725.
- [19] A.H. Shahirinia, S.M. Moghaddas-Tafreshi, A.H. Gastaj, A.R. Moghadamjoo, "Optimal Sizing of Hybrid Power System Using Genetic Algorithm", *Int. Conf. on Future Power Sys.* 2005, 16-18 Nov. 2005.
- [20] Parasopoulos KE, Vrahatis MN. On the computation of all global minimizers through particle swarm optimization. *IEEE Trans. Evol Comput* June 2004; Volume: 8, Issue: 3, 211-224.
- [21] Tripathi PK, Bandyopadhyay S, Pal SK. Multi-objective particle swarm optimization with time variant inertia and acceleration coefficients. *Inf Sci* 2007, 177, 5033-49.
- [22] Bagen, Billinton R. Evaluation of different operating strategies in small standalone power systems. *IEEE Trans. Energy Convers.* September 2005;20(3):654-60.
- [23] Karki R, Billinton R. Reliability/cost implications of PV and wind energy utilization in small isolated power systems. *IEEE Trans. Energy Convers.* Dec 2001;16(4):368-73.
- [24] Nomura S, Ohata Y, Hagita T, Tsutsui H, Tsuji-Iio S, Shimada R. Wind farms linked by SMES systems. *IEEE Trans. Appl Supercond* 2005:1951-4.
- [25] Marchesoni M, Savio S. Reliability analysis of a fuel cell electric city car. In: *IEEE 2005 European Conference on Power Electronics and Applications*; 11-14 September 2005, 0-10.
- [26] Khairil MK, Javanovic S. Reliability modeling of uninterruptible power supply systems using fault tree analysis method. *Eur. Trans. Electr. Power* 2007. Volume 19 Issue 6, Pages 814 - 826
- [27] Karki R, Billinton R. Cost-effective wind energy utilization for reliable power supply. *IEEE Trans. Energy Convers.* June 2004; 19:435-40.
- [28] Tina G, Gagliano S, Raiti S. Hybrid solar/wind power system probabilistic modeling for long-term performance assessment. *Sol. Energy* 2006; 80:578-88.
- [29] Eberhart RC, Kennedy J. A new optimizer using particle swarm theory. In: *Proceeding of sixth symposium on micro machine and human science, Nagoya, Japan*; 1995, 34-44.
- [30] Kennedy J, Eberhart RC. Particle swarm optimization. In: *Proceeding of IEEE Int. Conf. on Neural Networks, Perth, Australia, vol. IV*; 1995. 1942-1948.
- [31] Jarbouli B, Damak N, Siarry P, Rebai A. A combinatorial particle swarm optimization for solving multi-mode resource-constrained project scheduling problems. *Appl Math Comput* 2008; 195:299-308.
- [32] Nadjemi O, Nacer T, Hamidat A, Salhi H. Optimal hybrid PV/wind energy system sizing: Application of cuckoo search algorithm for Algerian dairy farms. *Renewable and Sustainable Energy Reviews.* 2017 Apr 1;70:1352-65.