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Research paper

Hybrid Solar Wind Power System Dimensioning based on a Fuzzy Global Performance Index

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Abstract

In the paper, an automatic design procedure to design a grid connected Hybrid Solar Wind Power System (HSWPS) is proposed. It is based on a fuzzy global performance index taking into account both technical and economical objectives. The technical objective, related to system reliability, is expressed by the Energy Index of Reliability (EIR), whereas the economical objective is expressed by means Relative Unit Electricity cost (RUEC). The HSWPS model is based on a closed form solution approach which allows to treat the power produced by the hybrid system as a probabilistic variable. The procedure aims at finding the optimal size of the two subsystems (i.e. Photovoltaic System (PVS) and Wind Energy Conversion System (WECS)).

***Keywords**: Grid connected systems, Photovoltaic power plants, Wind power plants, Fuzzy Performance Index.*

1. Introduction

Many countries are developing different mechanisms to deploy as much as possible the diffusion of Renewable Energy Systems (RESs). In particular for photovoltaic systems, due to the low energy density of solar radiation, the micro (up to 20 kW) distributed generation is particularly incentivized by means mechanisms such as feed in tariff and net metering. At the same time, other forms of micro generation are encouraged such as hydro and wind turbines. In particular, the wind technology for urban and suburban application is today in rapid expansion and ad hoc wind turbine technology for such applications are in progress.

Based on this scenario the interest for hybrid photovoltaic and wind systems is growing very fast. The design of grid-connected hybrid renewable energy systems, including economical objectives, requires the assessment of long-term system performance in order to reach the best compromise between reliability and cost. Previous studies on Hybrid Solar Wind Power System (HSWPS) [1], [2], [3] use a deterministic approach for the system modelling. Kellog et al. [4] proposed a numerical solution to obtain the optimal unit sizing of HSWPS, the modelling approach is based on energy balance. Markvart proposes a procedure [5] that theoretically determines the sizes of the PV arrays and wind turbines in an HSWPS through a effective graphical construction that satisfies the energy demand during the year. For determining the performance of a hybrid system with energy storage, Karaki, Chedid and Ramadan proposed in [6] a general numerical probabilistic approach. The authors and Raiti in [7] presented a probabilistic model, able to evalute the long-term system performance in terms of Energy Index of Reliability (EIR).

The present paper paper is focused on the considerations that the dimensioning of HSWPS is, in general, a multi-objective problem. A fuzzy global performance index is used to determine the area of the PV modules, the modules tilt angle, and the rated power of the wind turbine, taking into account the Energy Index of Reliability (EIR) and the total plant cost expressed by the Relative Unit Electricity Cost (RUEC). To carry out the optimal sizing of HSWPS a probabilistic model has been used [7]. The procedure has been tested taking into account different scenarios, characterized by the yearly load demand, the time pattern of load demand and two different unit cost for PVS and WECS.

2. Problem statement

Fuzzy Logic has shown to be a useful tool in the definition of decision making schemes allowing to obtain fuzzy global quality indexes. An example is given in [8] where fuzzy logic is applied to off-grid PV systems. In this paper Fuzzy Logic is applied to develop an automatic dimensioning procedure for HSWPS considering two conflicting objectives.

The goals of the optimisation problem, that are computed by means a probabilistic model of HSWPS for the evaluation of energy system performance, are:

• the maximization of the EIR;
• the minimization of the RUEC.

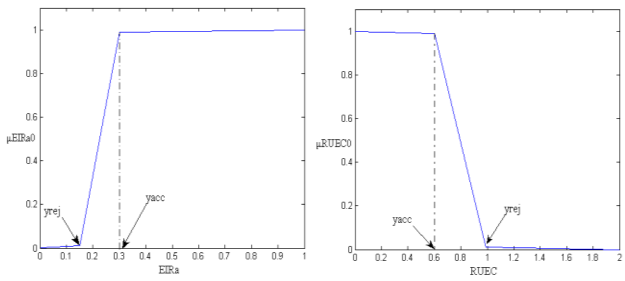
The control variables taken into account are:

• the photovoltaic module surface A, that strongly influences the overall cost of the Photovoltaic System (PVS);
• the tilt angle β, on which the optimal compromise between the amount of supplied energy, and its uniform distribution during the year depends;
• the rated power of Wind Energy Conversion System (WECS) PR;
The required inputs variables are:
• site characteristics and meteorological data;
• PVS and WECS characteristics;
• load demand;
• economical data.

A fuzzy set is defined for each design Objective Function (OF). The piecewise linear Membership Functions (MF) are fixed by two values (y_{acc}, y_{rej}) representing the lower acceptability limit and the upper acceptability limit respectively, as shown in Fig. 1.
If the values of each objective are below y_{rej} they are considered not satisfactory and are rejected; on the contrary, if they are beyond y_{acc} they are fully acceptable. These two values are determined according to the design specifications. This method uses as few restrictions as possible on the configuration of the photovoltaic/wind system and on the time distribution of the load and, therefore it is suitable for a wide variety of applications.
A global performance index can be specified by the intersection (min operator) of the fuzzified objectives.
For a defined system configuration, yielding a given value of the single objective, $y_i(x)$, and the related MF, $\mu_i(y_i(x))$, the optimization procedure provides a value of the fuzzy global objective function $O(x)$ given by:

$$O(x) = \min_{i=1\ldots n} \left\{ \mu_i \left(y_i (x) \right) \right\} \tag{1}$$

where n is the number of OFs.



(a) (b)

Fig. 1: Membership functions: µEIRa0 (a) and µRUEC0 (b)

3. The technical objective: EIR

The power P_h created by an HSWPS is the sum of the power P_w of the WECS and the power P_{pv} of the PVS. Then taking into account that P_w and P_{pv} are statistically independent, the *pdf* of the random variable $f_{Ph}(P_h)$ can be obtained as:

$$\boldsymbol{f}_{\boldsymbol{P_h}}(P_h) = \boldsymbol{f}_{\boldsymbol{P_w}}(P_w) * \boldsymbol{f}_{\boldsymbol{P_{pv}}}(P_{pv}) \tag{2}$$

where * represents the convolution operator.
Depending on the system working conditions, the pdf of the Ph and the integration extremes of the convolution integral of expressions (2) will vary as [7]:

$$\boldsymbol{f}_{\boldsymbol{P_h}}(\boldsymbol{P_h}) = \int_{max\left(0,\boldsymbol{P}_h - \boldsymbol{P_{pv}}(k_{tu})\right)}^{min(\boldsymbol{P}_h, P_R)} \boldsymbol{f}_{\boldsymbol{P_{pv}}}\left(\boldsymbol{P_h} - \boldsymbol{P_w}\right) \cdot \boldsymbol{f}_{\boldsymbol{P_w}}\left(\boldsymbol{P_w}\right) dP_w \tag{3}$$

where PPV(ktu) is the maximum power generated by the PVS.
The Expected not Supplied Energy (ENSE) is a probabilistic index applied in reliability analysis of power systems utilizing random renewable energy sources. The ENSE is the awaited value of energy that will not be supplied when the load demand exceeds the available production.
The ENSE for the HSWPS can takes different forms according to the load and generating conditions [7]. Normalizing the EENS index with respect to the load, it is possible to compute the EIR index. On the yearly basis EIR is given by:

$$EIR_y = 1 - \frac{\sum_{m=1}^{12} EENS_m}{\sum_{m=1}^{12} L_m} \tag{4}$$

where L_m is the monthly average daily energy of the local load.

4. The economical objective: RUEC

The alternatives among different electricity generating systems implies a careful evaluation of both the incurred costs and benefits obtained when utilizing a given source instead of some alternatives. These costs and benefits can be evaluated using economic criteria, even though evaluations connected to subjective choices of committees or the designer, and social or environmental impact assessments cannot be always expressed by economic values alone. Among the possible economic analyses, the Life-Cycle Costing (LCC) method has been applied, it is well-known for its completeness and it is widely used for economical evaluations in technical applications [9]. The analysis period must be the lifetime of the longest-lived system. LCC can then be annualized, i.e., expressed in terms of a cost per year, obtaining the so-called Annualized Life-Cycle Cost (ALCC):

$$ALCC = \frac{I_o + E_{pn} \cdot P_a}{P_a} [€ / year] \tag{5}$$

where *Pa* is the Present Worth Factor calculated for a given discount rate, excess inflation rate and number of years (analysis period), *Io* is the total investment and *Epn* are yearly operation and maintenance expenses.
The total investment (*I0*) of an HSWPS is computed as the sum of the investment of each part of the system taking into account packaging, transportation and installation:

$$I_0 = I_{0pv}\left(P_{pv}\right) + I_{0W}\left(P_R\right) \tag{6}$$

where *I0pv* and I0W are respectively the investment for PVS and for WECS. The relationships between the unit cost of PVS (*Cpv*) and WECS (*Cw*) and between the Peak Power (*Ppv*) and the Rated Power (PR) are considered linear according to the following:

$$I_0 = C_{pv} \cdot P_{pv} + C_W \cdot P_R \tag{7}$$

where:
Cpv is the unit cost of PVS varying the system peak power [€/kWp];
Ppv is the PVS peak power [kWp];
Cwis the unit cost of WECS varying the rated power of wind turbine [€/kW];
PR is the rated power of wind turbine [kW].
The yearly operation and maintenance expenses (*Epn*) are usualy referred as an annual fixed charge rate on the up-to-date value of capital as follows:

$$E_{pn} = m_{pv} \cdot C_{pv} \cdot P_{pv} + m_W \cdot C_W \cdot P_R \tag{8}$$

where *mpv* and *mW* are the annual fixed charge rate for PVS and WECS respectively.
In addition to the ALCC, the other approach for weighting two electricity-generating systems refers to the Unit Electricity Cost (UEC) that consists in the net cost of generating each kWh during the lifetime of each system; the UEC can be obtained as it follows:

$$UEC = \frac{ALCC - E_{year} \cdot p}{E_{year}} [€ / kWh] \tag{9}$$

where E_{year} is the expected average electrical energy produced in a year by HSWPS (*kWh*) and *p* is the electrical energy price *(€/kWh)*.
In the this paper it has been chosen to refer the UEC of the energy cost of HSWPS supplied loads with the electrical energy price p of grid supplied loads, in this way it is possible to define the RUEC (Relative Unit Electricity Cost). In this case, the life-cycle costing process provides a relatively straightforward way to make a valid economic comparison between different options. Taken with other non-economic factors, these evaluations form the core of the decision making process.

5. The case of study

The proposed procedure has been applied to the case of an HSWPS placed in Acireale, Italy (latitude 37°36'27"72 N, altitude 161 *m*). In Fig. 2 it is possible to see the daily average monthly energy generated by an HSWPS in which the two subsystems have an unitary power rating.
After a first look of meteorological data, it has been noted that the site taken into consideration is characterized by a certain anti-correlation between solar time patterns and wind, as shown in Fig. 3. Indeed, this fact provides a basic condition for exploitation of HSWPS generation systems potential (e.g. it reduces energy storage requirement [9]). For the development of the probability distribution of irradiance and wind speed, data measured locally are used, in fact due to the local nature of windiness the cross correlation analysis of meteorological data should not be overlooked [10].
The optimal design procedure has been applied on different system configurations derived by varying the electrical load demand time patterns with the same yearly value and varying the yearly load demand. Six typical load demand time patterns have been used with the same total energy as shown in Table 1. The applied membership functions are µEIRa0 and µRUEC0 (see fig.1). The economical data used for the performed evaluations are given in Table 2.

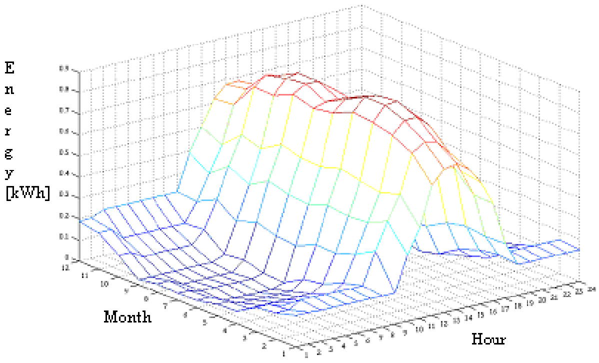


Fig. 2: Daily average monthly energy generated by an HSWPS with PR= 1 kW, VC=3 m/s VR=12 m/s, VF=60 m/s, Ppv=1kWp, η=0.093, β=39°.

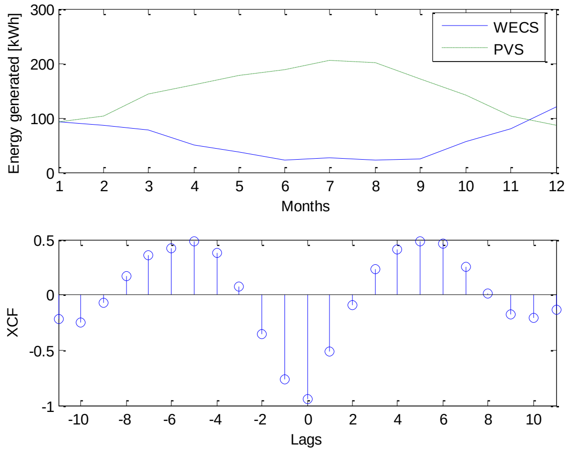


Fig. 3: Monthly average energy generated by a PVS with Ppv=1kWp (dash-dotted line) and by a WECS with PR= 1kW (solid line) and related cross-correlation

Table 1: Load demand time pattern

	Daily time pattern		
	Constant (1)	Midday Peak (2)	Midnight Peak(3)
Summer Peak (A)	A1	A2	A3
Winter Peak (B)	B1	B2	B3

Table 2: Economical data

Parameter	Value
Period of analysis	30 [years]
Excess inflation	0.022
Excess inflation energy cost	0.03
Discount rate	0.05
Annual fixed charge rate PVS (m_{pv})	1%
Annual fixed charge rate WECS (m_W)	1%
C_{pv}	6000 [€/kWp]
C_w	1500 [€/kW].
Electrical energy price *p*	0.15 [€/kWh]

Fig. 4 provides the outputs of the OP, related to the various configurations, showing the optimal values of control variables (*A*, *PR*, *β*).

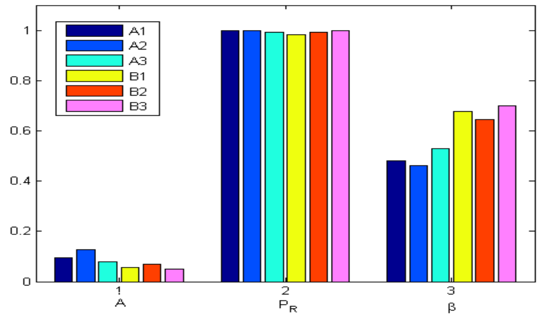


Fig.4: Normalized optimal values of the control variables varying the load demand time patterns (yearly load demand of 20 MWh)

Figures 5 shows the optimal values of control variables, while in Figure 6 the objectives varying the yearly load demand (the time pattern used is A1) is repored. It is possible to note that the control variables A and β will vary and PR is at maximum value. This result relies on the cost functions used for WECS and PVS.
It can be observed that to satisfy the load demand the PV surface increases, as a consequence the RUEC objective increases too, due to the fact that PVS is the most expansive system, at the same time the EIRa objective decreases due to the PVS generation profile (absence of generation during night time).The procedure has been tested considering three different MFs for each OF. Some options have been fixed, such as: time pattern A1, the yearly load demand 20 MWh, and the electrical energy price has been assumed to be 0.1 €/kWh. The two values (y_{acc}, y_{rej}) for each MF are reported Table 3 and 4, the MFs are reported in fig. 7.

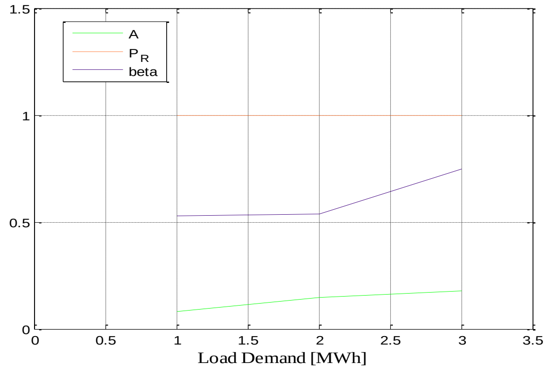


Fig. 5: Normalized optimal values of the control variables varying the yearly load demand (time pattern A1)

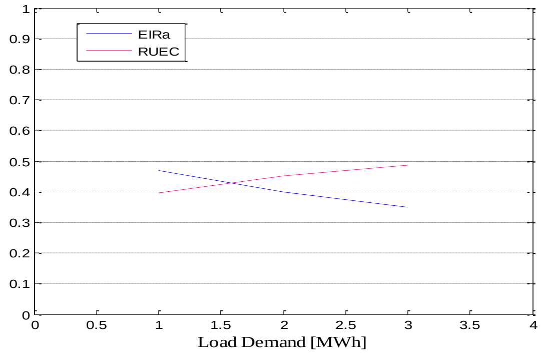


Fig.6: Normalized optimal values of the objectives varying the yearly load demand (time pattern A1)

Table 3: Membership functions for EIRA objective

	yrej	*yacc*
μEIRa0	0.15-0.01	0.3-0.99
μEIRa1	0.05-0.01	0.2-0.99
μEIRa2	0.05-0.01	0.3-0.99

Table 4: Membership functions for RUEC objective

	yrej	*yacc*
μRUEC0	0.6-0.99	0.99-0.01
μRUEC1	0.3-0.99	0.7-0.01
μRUEC2	0.3-0.99	0.99-0.01

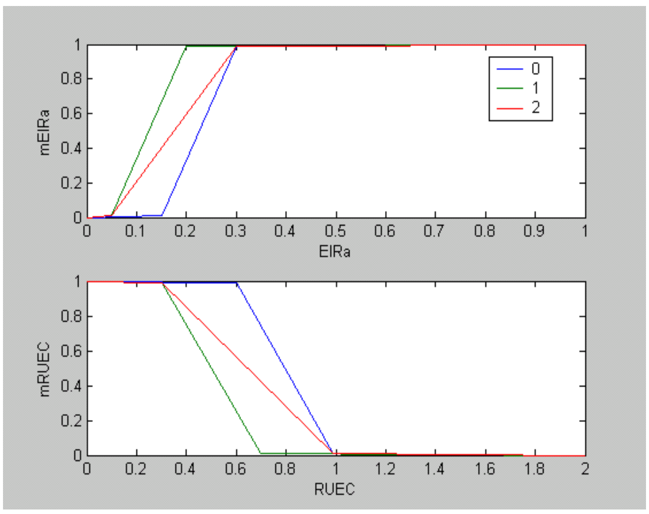


Fig. 7: The three Membership functions for EIRa and for RUEC

Table 5 and Table 6 provide the outputs of the OP, related to the various configurations, showing the optimal values of the objectives and the corresponding values of the control variables, for the time pattern A2 and yearly load demand 20 MWh.
Depending on the choice of the combination of the MFs respectively for EIRa and RUEC is possible to weight the objectives in the global fuzzy global quality index. For example the combination of μ_{EIRa0} and μ_{RUEC0} determines the prevalence of reliability objective, whereas the combination of μ_{EIRa1} and μ_{RUEC1} determines the prevalence of economical objective.

Table 5: Results for the objectives for different membership functions (yearly Load demand 20 MWh, time pattern A2)

	μEIRa0	μEIRa1	μEIRa2
μ*RUEC0*	A=92.531 m^2 P_R=20 kW β=43.4622	A=83.2915 m^2 P_R= 20 kW β=42.6507	A=83.2915 m^2 P_R=20 kW β=42.6507
μ*RUEC1*	A=56.5709 m^2 P_R=19.7918kW β=44.2408	A=53.3587m^2 P_R=20 kW β=42.6415	A=53.3587 m^2 P_R=20 kW β=42.6415
μ*RUEC2*	A=92.5312 m^2 P_R= 20 kW β=43. 4622	A=83.2915 m^2 P_R=20 kW β=42.6507	A=83.2915m^2 P_R=20 kW β=42.6507

Table 6: Results for the objectives for different membership functions (yearly Load demand 20 MWh, time pattern A2)

	μEIRa0	μEIRa1	μEIRa2
μ*RUEC0*	RUEC=0.2577 EIRa=0.6993	RUEC=0.2315 EIRa=0.691	RUEC=0.2315 EIRa=0.691
μ*RUEC1*	RUEC=0.1477 EIRa=0.6551	RUEC=0.132 EIRa=0.648	RUEC=0.132 EIRa=0.648
μ*RUEC2*	RUEC=0.2577 EIRa=0.6993	RUEC=0.2315 EIRa=0.691	RUEC=0.2315 EIRa=0.691

7. The optimization procedure evaluation

To evaluate the goodness of the solution provided by the fuzzy logic OP many tests have been carried out. As evaluation criteria the control variables has been reduced to one, in such as way to observe the behavior of the objectives EIRa and RUEC as a function of the control variable chosen. In fig 8 it is possible to observe the plots of EIRa(β) and RUEC(β) in which βopt indicates the optimal results calculated by means the OP. As expected the optimal result is equal to the minimum value of RUEC(β) and it is close to the maximum value for EIRa. In this test the values of the other two variables are respectively: $A=200\ m^2$ and $PR=20\ kW$. Other assumptions has been done: the membership functions are μ_{EIRa2} and μ_{RUEC0}, the yearly load demand is *30 MWh* and the load demand time pattern is B3.

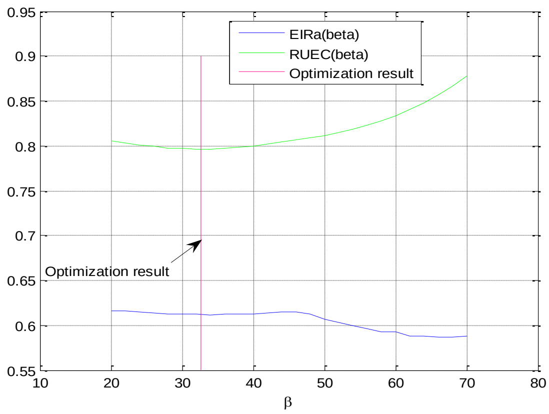


Fig. 8: Comparison between the optimal value for β obtained trough OP and the OFs EIRa(β) and RUEC(β) yearly load demand 30 MWh and time pattern B3

Another test has been conducted varying the initial values for the control variables. The following simulations have been performed:
a) minimum values (A=1 m2-PR=0.1 kW-β=20°)
b) maximum values (A=200 m2- PR=20 kW-β=70°)
c) central values (A=100 m2- PR=10 kW-β=45°)
As shown in fig. 9 the fuzzy global objective function O(x) doesn't change varying the initial values for the control variables.

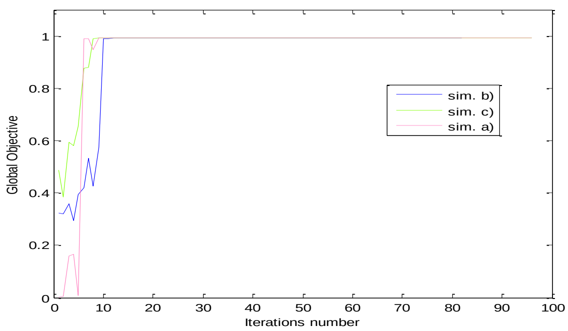


Fig. 9: Normalized global objectives for different initial values of control variables (load demand 30 MWh and time pattern B3) On the other hand figs. 10 and 11 show that different configurations are equivalent.

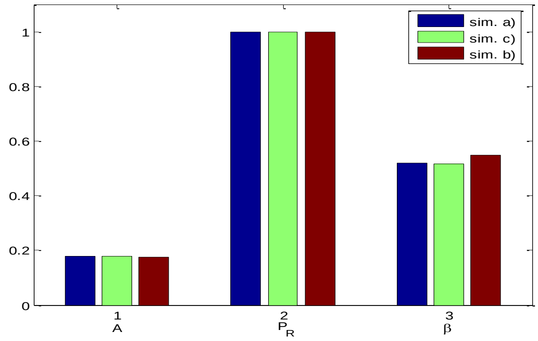


Fig. 10: Normalized optimal values for the control variables for different initial value of control variables (load demand 30 MWh and time pattern B3)

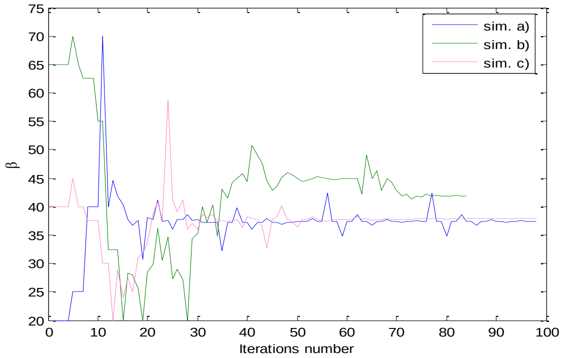


Fig. 11: Normalized optimal values for β obtained for different initial values of control variables (load demand 30 MWh and time pattern B3).

In particular, the tilt angle β, that is important to determine the best compromise between the quantity of the supplied energy and its uniformity during the year; is the most sensitive control variable; whereas rated power of WECS PR cannot change due to its saturated value. In fact, due the availability of wind (in the considered case) and the reduced cost for unit of power of the WECS systems compared with the PVS, the solutions always present a maximization of the rating of the wind turbine, so in the different considered case only the tilt angle and the surface of the PV modules are the sensitive values.

8. Conclusion

In this paper the problem of the optimal dimensioning of HSWPSs has been considered. With this in view a closed form probabilistic model that allows to estimate the long-term average performance of a HSWPS has been used as a core of a fuzzy based multi-objective performance index.
The design procedure has been applied to many different system configurations obtained by varying the electrical load demand, the load demand time pattern, the membership functions and the cost functions. The tests results show excellent flexibility in finding the optimum size of the HSWPS plants when there are uncertainties to determine the optimal compromise between reliability and cost.
Additional issues will deserve future investigations, such as the addition of the hub height of the wind turbine as a new control variables and the development of more effective cost functions that take into account other incentives.

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