Microgrid Supplier Selection Problem Considering Euclidean Distance and Ideal Vector System

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Abstract

In the present research two new methods to select optimal suppliers considering component replacement policies for a micro-grid were developed, the main objectives considered in the replacement problem are to minimize the overall system costs (operation cost, maintenance cost), as well as maximize the overall system efficiency. Once the replacement schedules are generated, we propose two methods, a) Euclidean Distance and b) Ideal Vector System) to select suppliers to replace components in the system. The methods are applied to a previously designed micro-grid, the Euclidean Distance method looks for solutions (vectors) defined by the closest distance that most closely resembles the desired (ideal) vector (solution), which is the one with a smaller distance to the ideal vector, the closest solution, as defined by the Euclidean distance, will be the one the one that offers in this case a more efficient condition to the characteristics of efficiency and system cost, among others. The second method proposed in the present work, the ideal vector system, considers the gains that exist between the characteristics of the participating vectors (solutions), for example, cost is a characteristic for which the negative gain becomes a positive gain for this algorithm, and characteristics such as component life considering the longer components' life the better for the system. The final solution is found in the vector that defines the highest gain; all characteristics are converted into a vector in values per unit referenced to a desired vector established by the decision maker. The proposed methods are applied to a microgrid previously generated by using a microgrid design allocation algorithm and after running a component replacement analysis model. Finally, the two proposed methods are applied to a microgrid and both methods converge to select the same suppliers to replace components in the micro-grid.

Keywords
Micro-Grid, Euclidean Distance. Supplier Selection

1. Introduction
Nowadays, there is a growing demand for electric energy and one of the the major challenges is to reduce climatic warming due in large part to emissions released by fossil fuels (Abdelkader et al. 2018). U.S. Energy consumption for generating electricity Fifty years ago was self-sufficient in its supply of petroleum. Today, it imports more than half of its petroleum and consumes 25% of the world's supply (Salameh, 2014). Oil is a limited resource that will eventually run out, at least as an economically viable energy source (Salameh, 2014 and Dawoud et al. 2018). The exponential increase in global energy demand is the primary cause of rapid depletion of fossil fuels and increased greenhouse gas emissions of conventional generators (Adefarati and Bansal, 2017). Natural options are offered by the Earth to produce electricity such as photovoltaic, concentrated solar energy, wind energy, fuel cells, and many others. Not only governments around the world are worried about the climate changes but also researchers from developed countries are investing many time and money to create or improve green energy strategies. In 2015, global energy consumption increased by 1.0% and in 2014 increased by 1.1%, while in the last ten years the average energy consumption was 1.9%. This result is one of the consequences of energy savings efforts made by governments and citizens. The power grid consists of three distinct divisions namely, the generating station, the transmission network, and the distribution network, so the focus of this job it is after distribution network called load center. The load center is categorized by different terms such as public or private no large areas and public or private massive areas. The specific focus of this job is centered on private or public buildings. According to Dan Arvizu, director of National Renewable Lab., buildings consume 38% of the total energy produced in which 71% is electricity. For instance, the energy demand for hotels is on average higher than that of commercial buildings. A typical hotel's annual power

consumption ranging from 250 to 350 kWh/m^2 versus a typical commercial building at 30–152 kWh/m^2. Additionally, large-scale accommodation operations have unique operational characteristics in comparison to their smaller counterparts, demanding even larger load capacities due to increased air-conditioning requirements and more extensive comfort facilities. Average annual energy consumption figures for large hotels range from 450 to 700 kWh/m^2 (Dalton et al. 2008). Energy building supply is based on two distinct forms, external electricity supply, which is connected to an electric city company or by itself, which known as a micro-grid. A micro-grid into a building consists of generating enough energy for its consumption through renewable energies. The first stage is to complete the project by installing the whole elements to produce green energy based on solar photovoltaic and/or wind power. However, every system is constituted by assets that have a limited lifetime, so it is important to optimize the system cost by considering costs associated with asset replacement. Component replacement analysis consists of determining the correct time or schedules to replace certain components in the system such that some total cost function is minimized. Given a level of output or service expected from a component over some time since its installation in the system a decision is required to be made periodically to either keep that component for one more planning period. Replacing component with a new component or doing some maintenance on the existing component, as it wears out with the aging process. This work is based on the selection of components of the micro-grid solar panel stand-alone once they must be selected to replace an existing component that in theory will be out of service. The proposed algorithm is based on the creation of vectors using the characteristics of the potential components provided considering a finite number of providers, these vectors will be compared using Euclidean distances against a desired vector. The vector that keeps the least distance against the desired or ideal vector will be the vector to be selected by the algorithm.

2. Literature Review

Component replacement is an active research area that has attracted researchers in recent years who have developed novel methods to address component replacement problems in areas such as transportation, energy, manufacturing etc., For example, Tabriz et al. (2016) present age-based replacement models subject to shocks and failure rate to determine the optimal replacement cycle. As a result, according to system reliability, maintenance costs of the system are to be minimized. Parthanadee et al. (2012), Stasko and Oliver (2012), Bazargan and Hartman (2012), and Chang-Ing Hsu et al. (2011) developed algorithms to determine the optimal replacement decision over a time horizon. Based on cost-benefit analysis considering age, maintenance, preferences, repair cost, retrofit, purchasing, and other constraints they develop algorithms based on stochastic dynamic programming approach to optimize decisions regarding purchasing, leasing, or disposing of their components: vehicles for the first two and aircraft for the last two paper mentioned. Espiritu and Coit (2008), proposed a new replacement analysis methodology by developing and demonstrating how to determine system-level component replacement schedules for electricity distribution systems composed of sets of heterogeneous assets. The proposed model is an iterative combined dynamic programming and integer programming approach to obtain cost-efficient system-level component replacement schedules to minimize the total net present value of unmet demand (considering the system availability), maintenance, and purchase costs over a finite planning horizon. There is an annual budget limiting total expenditures for maintenance and replacement costs that limit the selection of component replacement schedules. Golovin (2016), introduces the concept of the replacement matrix and unconditional and conditional rules. The replacement matrix facilitates the maintenance procedure in terms of content, clarity and cost structure. One of the benefits of the matrix is the ability to see quickly how and when maintenance actions are performed. Formalization of the replacement rule in the form of a matrix is a universal tool and simplifies the notation of the maintenance policy, as well as allowing the programming of a mathematical model of the repair process (renewal process) in a computer simulation. Seif and Rabbani (2014) have published based on the failure rates of the components of a machine, the life cycle cost is assessed, mathematically modeled, and incorporated to the parallel machine replacement problem with capacity expansion consideration. The problem is modeled as mixed integer programming which intends to minimize the total costs incurred during a planning horizon of several periods for the machines of the same type with different ages. In the present research, a novel algorithm is developed to address a component replacement problem considering microgrids. Component replacement schedules indicate when is the best time to replace a component in the future considering different characteristics of the system, as it has been solved by previous researchers, but once the replacement schedule is determined, there is still the need for an analysis or methodology to determine the best supplier to select to replace components in the system.

2.1 Supplier selection

One challenge after defining replacing times between components in a micro-grid is to choose a best supplier among a finite number of suppliers offering similar products from different brands. Product traits can be characterized in a algebraic vector considering the most important elements to be compare among different products of the same component finding the best choice related to a desired vector. Draisma et al. (2015), state that the nearest point map of a real algebraic variety with respect distance is an algebraic function. The Euclidean distance degree of a variety is the number of critical points of the squared distance to a general point outside the variety. Also they express that a real algebraic variety X C Rn, they consider the following problem: given *u* Є Rn, compute *u**Є X that minimizes the squared Euclidean distance du(x) = n, i=1(u_i-x_i) from the given point u. This optimization arises in diverse. J. Ma. et al. (2020), write in a interesting article that with the development of technology and sciences, data collection and processing data have become more important every day. They mention that a Support vector machine (VSM) proposed by Vapnik, has emerged as an excellent pattern recognition tool over the last decades. SVM is to seek an optimal decision boundary via maximizing the margin between two parallel support hyperplanes. SVM has been used in various real-world problems, such as fault diagnosis, least square classification and more. Our proposed methods ra aimed to solve the supplied selection problem once the component replacement schedules have been generated, in sections 3 and 4 the proposed methods are presented.

3. Model development

The general configuration of the micro-grid model based on solar energy stand alone is presented in figure 3.1.

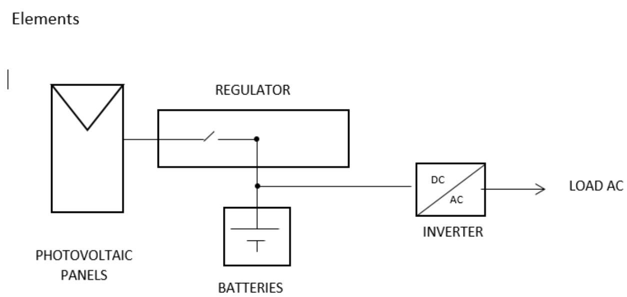

Figure 3.1 General configuration of a micro-grid solar panel stand alone

As a preliminary work of this study, a micro-grid based on solar energy was designed from the data given on the need for load, geographic data for information on solar irradiation, as well as the general characteristics of electrical components such as solar panels, regulators, batteries. and inverters. With this information, a specific configuration of the micro-grid (Figure 3.2) was selected that considers the specific number of solar panels, batteries, regulators and inverters.

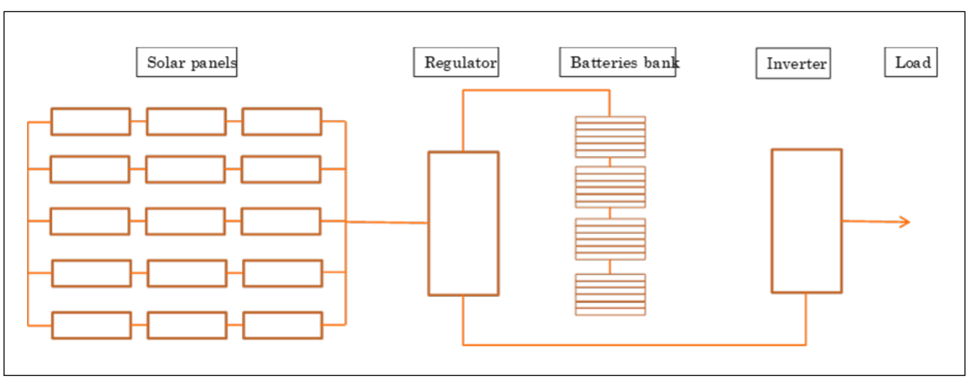

Figure 3.2 Solar panel stand-alone micro-Gird

A multi-objective GA was developed to determine the best components based on "*n*" number of suppliers, there were two objectives considered in the study, The first objective is based on the solar panel efficiency, and the second objective considers the minimization of the total annualized component cost, the objectives considered were to maximize the Average Solar Panel Efficiency subject to a nominal efficiency (13%)and to minimize the total annualized component cost

$$\text{Average Solar Panel Efficiency} = \sum_{i=1}^{n} \frac{Eff_{pi}}{n}$$

$$\text{Annualized Component Cost} = \sum_{i}^{n} \frac{C_i}{Ul_i} + Cm_i$$

$$Eff = \frac{I_{nom} x\, V_{nom}}{G\, x\, A}$$

Subject to:
Ftss1 >= X
Ftss2 >= Budget

Where:

Eff ------------------ Solar panel efficiency
G ------------------ Irradiance Kwh/m2
A ------------------ Area of solar panel m2
Inom ---------------- Nominal current
Vnom --------------- Nominal voltage
C_i ------------- Cost of element *i*
Ul_i ------------- Useful life in years of component *i*
Cm_i ------------ Maintenance cost of element *i*

After running 30 iterations the algorithm shows through a pareto set (Figure 3.3) different options of supplier combinations. As it can be observed, higher solar panel efficiency solutions are seen in the right upper corner while lower cost solutions are shown in the left lower corner.

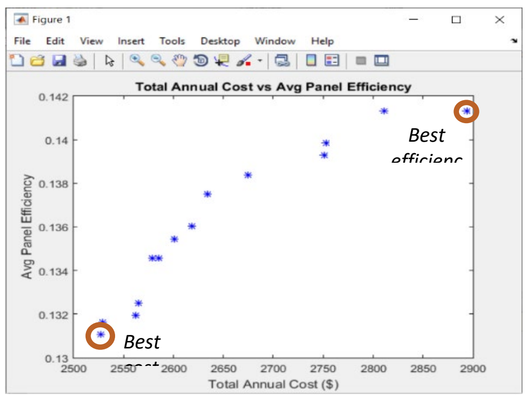

Figure 3.3 Pareto Optimal Solution for micro-grid configuration

Once the Pareto-Optimal solutions have been obtained, a solution for system implementation has to be obtained, in the present example, one solution to design the micro-grid, Is selected and the replacement algorithm is run allowing to establish probabilistic replacement dates for each of its components as shown in figure 3.4.

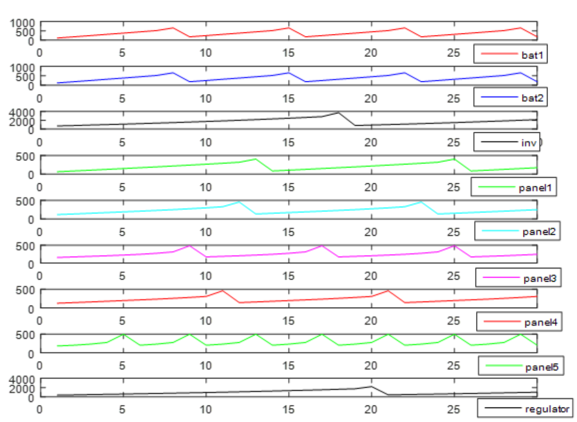

Figure 3.4 Replacement policy for every component in tem micro-grid

3.1 Vector Generation using Euclidean distance and the Ideal vector information

Two different methods to select suppliers to select suppliers to replace and upgrade components in the microgrid configuration obtained previously (Shown in Figure 3.4) are developed. The models are run for each subsystem in the microgrid (Solar Panels, Regulator, Batteries and Inverter) to determine the best supplier to be selected for system upgrade at the time when the component replacement is required. The first method is based on generating Euclidean Distances and the second is based on selecting solutions close to the ideal vector, both methods are described next.

a) Euclidean Distance Method. A vector for every supplier *i* is generated and compared with the desired vector, the algorithm finds the shorter distance between vectors and the best vector to determine the solution who is to nearest to the desired vector.

Supplier vector:

$$vi = (x_1 + x_2 + x_3 + \cdots + x_n)$$

Desired vector:

$$vbi = (x_{b1} + x_{b2} + x_{b3} + \cdots + x_{bn})$$

Euclidean distance:

$$di = \sqrt{\sum_{i=1}^{n} \left(1 - \frac{v_i}{v_{bi}}\right)^2}$$

b) Ideal Vector system. A vector is generated for every supplier *i* and it is compared with the ideal vector finding the closest solutions between vectors.

Supplier vector:

$$v_i^{+,-} = \left(x_1^{+,-} + x_2^{+,-} + x_3^{+,-} + \cdots + x_n^{+,-}\right)$$

Desired vector:

$$vb_i^{+,-} = \left(x_{b1}^{+,-} + x_{b2}^{+,-} + x_{b3}^{+,-} + \cdots + x_{bn}^{+,-}\right)$$

Maximum and minimum values as better:

x_i^+-----------------------------→ A characteristic that high value is better.

x_i^------------------------------→ A characteristic that low value is better.

$v_{si}^+ = [v_i^+ - v_{bi}^+]$ or $v_{si}^- = [v_{bi}^- - v_i^-]$

$$vw_i = \sum_{i=1}^{n} vw_i = 1$$

Where:
vw_i-------→ Is the weigh vector, values given according to the importance of each characteristic.

$$d_1 = \sum_{i=1}^{n} vw_i \left(\frac{v_{si}^{+}}{v_{bi}^{+}} \right)$$

$$d_2 = \sum_{i=1}^{n} vw_i \left(\frac{v_{si}^{-}}{v_{bi}^{-}} \right)$$

$$f_n = d_1 + d_2$$

f is the result for every supplier, the results are compared among them, and the best value obtained will be the most positive number.

4 Numerical Results

The data considered in the present study for each component in the system (Fig. 3.2) is shown in Tables 4.1 through 4.8 along with the results obtained.

a) Euclidean Distances result: After running the algorithm considering Euclidean distances, the supplier number three has been considered the best supplier for solar panels because the distance is the lowest value (0.5181). As shown in Table 4.2, the best supplier for Regulators is supplier number two because the distance is the lowest value (0.2025). The best supplier for the battery subsystem in the micro-grid shown in Figure 3.4 is supplier number three the distance is the lowest value (0.2693) and finally for the Inverter, supplier number one has been considered the best supplier, the distance is the lowest value (0.0000) as shown in Table 4.4.

Table 4.1 Method one. Solar panel analysis vectors. Lower distance better.

SOLAR PANEL	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Maximum power (w)	250	250	250	250	1.0000	1.0000	1.0000	0.0000	0.0000	0.0000
S.C. power (kw)	335	326	350	335	0.9731	1.0448	1.0000	0.0007	0.0020	0.0000
Eficiency (%)	15.34	16	14.87	16	1.0430	0.9694	1.0430	0.0019	0.0009	0.0019
Cost (Dlls)	220	222	280	200	1.0091	1.2727	0.9091	0.0001	0.0744	0.0083
Warranty (years)	10	4	6	15	0.4000	0.6000	1.5000	0.3600	0.1600	0.2500
Maintenance cost (Dlls)	22	22	28	20	1.0000	1.2727	0.9091	0.0000	0.0744	0.0083
Useful life (years)	25	40	15	25	1.6000	0.6000	1.0000	0.3600	0.1600	0.0000
								0.7227	0.4717	0.2684
								0.8501	0.6868	0.5181

Table 4.2 Method one. Regulator analysis vectors. Lower distance better.

REGULATOR	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Maximun power input (w)	4850	4850	5000	4500	1.0000	1.0309	0.9278	0.0000	0.0010	0.0052
Own energy consumption (w)	1	1.5	1	2.5	1.5000	1.0000	2.5000	0.2500	0.0000	2.2500
Efficiency (%)	97.5	97	98	96	0.9949	1.0051	0.9846	0.0000	0.0000	0.0002
Cost (Dlls)	687	750	690	750	1.0917	1.0044	1.0917	0.0084	0.0000	0.0084
Maintenance cost (Dlls)	70	75	70	80	1.0714	1.0000	1.1429	0.0051	0.0000	0.0204
Warranty (years)	5	4	6	5	0.8000	1.2000	1.0000	0.0400	0.0400	0.0000
								0.3035	0.0410	2.2843
								0.5509	0.2025	1.5114

Table 4.3 Method one. Batteries analysis vectors. Lower distance better.

BATTERIES	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Useful Life (years)	20	8	12	18	0.4000	0.6000	0.9000	0.3600	0.1600	0.0100
Deep discharge (%)	20	15	12	25	0.7500	0.6000	1.2500	0.0625	0.1600	0.0625
Cost (Dlls)	1600	1400	1500	1600	0.8750	0.9375	1.0000	0.0156	0.0039	0.0000
Maintenance cost (Dlls)	160	140	180	160	0.8750	1.1250	1.0000	0.0156	0.0156	0.0000
								0.4538	0.3395	0.0725
								0.6736	0.5827	0.2693

Table 4.4 Method one. Inverter analsis vectors. Lower distance better.

INVERTER	DESIRED	SUP1	SUP2	SUP3	VALUE PU1	VALUE PU2	VALUE PU3	(base-data)^2	(base-data)^2	(base-data)^2
Nominal power (w)	4500	4500	5000	4000	1.0000	1.1111	0.8889	0.0000	0.0123	0.0123
Peak power (w)	10000	10000	12000	8000	1.0000	1.2000	0.8000	0.0000	0.0400	0.0400
Efficiency (%)	95	95	94	92	1.0000	0.9895	0.9684	0.0000	0.0001	0.0010
Cost (Dlls)	1600	1600	1800	1500	1.0000	1.1250	0.9375	0.0000	0.0156	0.0039
Maintenance cost (Dlls)	160	160	180	150	1.0000	1.1250	0.9375	0.0000	0.0156	0.0039
Warranty time (years)	5	5	4	4	1.0000	0.8000	0.8000	0.0000	0.0400	0.0400
								0.0000	0.1237	0.1012
								0.0000	0.3517	0.3180

b) Ideal Vector System Results: After running the algorithm considering the ideal vector, as shown in Table 4.5, the supplier number three has been considered the best supplier for solar panels because the distance is the lowest value (0.1498) to the ideal vector. As shown in Table 4.6, the best supplier for Regulators is supplier number two because the distance is the lowest value (0.0219). The best supplier for the battery subsystem in the micro-grid shown in Table 3.4 is supplier number three the distance is the lowest value (0.0000) and finally for the Inverter, supplier number one has been considered the best supplier, the distance is the lowest value (0.0000) as shown in Table 4.8
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Table 4.5 Method two. Solar panels analysis vectors. Highest gain better.

SOLAR PANEL	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Maximum power (w)	250	250	250	250	0	0	0	0.0000	0.0000	0.0000	IGUAL				
S.C. power (kw)	335	326	350	335	-9	15	0	-0.0269	0.0448	0.0000	HIGH BETTER	0.0500	-0.0013	0.0022	0.0000
Eficiency (%)	15.34	16	14.87	16	0.66	-0.47	0.66	0.0430	-0.0306	0.0430	HIGH BETTER	0.1000	0.0043	-0.0031	0.0043
Cost (Dlls)	220	222	280	200	-2	-60	20	-0.0091	-0.2727	0.0909	LOW BETTER	0.4000	-0.0036	-0.1091	0.0364
Warranty (years)	10	4	6	15	-6	-4	5	-0.6000	-0.4000	0.5000	HIGH BETTER	0.2000	-0.1200	-0.0800	0.1000
Maintenance cost (Dlls)	22	22	28	20	0	-6	2	0.0000	-0.2727	0.0909	LOW BETTER	0.1000	0.0000	-0.0273	0.0091
Useful life (years)	25	40	15	25	15	-10	0	0.6000	-0.4000	0.0000	HIGH BETTER	0.1500	0.0900	-0.0600	0.0000
												1			
								0.0162	-0.7859	0.5430	HIGH BETTER		-0.0270	-0.1408	0.1043
								-0.0091	-0.5455	0.1818	LOW BETTER		-0.0036	-0.1364	0.0455
								0.0071	-1.3313	0.7248			-0.0307	-0.2772	0.1498

Table 4.6 Method two. Regulator analysis vectors. Highest gain better.

REGULATOR	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Maximun power input (w)	4850	4850	5000	4500	0	150	-350	0.0000	0.0309	-0.0722	HIGH BETTER	0.1000	0.0000	0.0031	-0.0072
Own energy consumption (w)	1	1.5	1	2.5	-0.5	0	-1.5	-0.5000	0.0000	-1.5000	LOW BETTER	0.0500	-0.0250	0.0000	-0.0750
Efficiency (%)	97.5	97	98	96	-0.5	0.5	-1.5	-0.0051	0.0051	-0.0154	HIGH BETTER	0.1000	-0.0005	0.0005	-0.0015
Cost (Dlls)	687	750	690	750	-63	-3	-63	-0.0917	-0.0044	-0.0917	LOW BETTER	0.4000	-0.0367	-0.0017	-0.0367
Maintenance cost (Dlls)	70	75	70	80	-5	0	-10	-0.0714	0.0000	-0.1429	LOW BETTER	0.2500	-0.0179	0.0000	-0.0357
Warranty (years)	5	4	6	5	-1	1	0	-0.2000	0.2000	0.0000	HIGH BETTER	0.1000	-0.0200	0.0200	0.0000
												1.0000			
								-0.2051	0.2361	-0.0875	HIGH BETTER		-0.0205	0.0236	-0.0088
								-0.6631	-0.0044	-1.7346	LOW BETTER		-0.0795	-0.0017	-0.1474
								-0.8683	0.2317	-1.8221			-0.1001	0.0219	-0.1562

Table 4.7 Method two. Batteries analysis vectors. Highest gain better.

BATTERIES	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Useful Life (years)	20	8	12	18	-12	-8	-2	-0.6000	-0.4000	-0.1000	HIGH BETTER	0.25	-0.1500	-0.1000	-0.0250
Deep discharge (%)	20	15	12	25	-5	-8	5	-0.2500	-0.4000	0.2500	HIGH BETTER	0.1000	-0.0250	-0.0400	0.0250
Cost (Dlls)	1600	1400	1500	1600	200	100	0	0.1250	0.0625	0.0000	LOW BETTER	0.4000	0.0500	0.0250	0.0000
Maintenance cost (Dlls)	160	140	180	160	20	-20	0	0.1250	-0.1250	0.0000	LOW BETTER	0.2500	0.0313	-0.0313	0.0000
												1			
								-0.8500	-0.8000	0.1500	HIGH BETTER		-0.1750	-0.1400	0.0000
								0.2500	-0.0625	0.0000	LOW BETTER		0.0813	-0.0063	0.0000
								-0.6000	-0.8625	0.1500			-0.0938	-0.1463	0.0000

Table 4.8 Method two. Inverter analysis vectors. Highest gain better.

INVERTER	DESIRED	SUP1	SUP2	SUP3	Vs	Vs	Vs								
Nominal power (w)	4500	4500	5000	4000	0	500	-500	0.0000	0.1111	-0.1111	HIGH BETTER	0.1	0.0000	0.0111	-0.0111
Peak power (w)	10000	10000	12000	8000	0	2000	-2000	0.0000	0.2000	-0.2000	HIGH BETTER	0.0500	0.0000	0.0100	-0.0100
Efficiency (%)	95	95	94	92	0	-1	-3	0.0000	-0.0105	-0.0316	HIGH BETTER	0.1000	0.0000	-0.0011	-0.0032
Cost (Dlls)	1600	1600	1800	1500	0	-200	100	0.0000	-0.1250	0.0625	LOW BETTER	0.4000	0.0000	-0.0500	0.0250
Maintenance cost (Dlls)	160	160	180	150	0	-20	10	0.0000	-0.1250	0.0625	LOW BETTER	0.2500	0.0000	-0.0313	0.0156
Warranty time (years)	5	5	4	4	0	-1	-1	0.0000	-0.2000	-0.2000	HIGH BETTER	0.1000	0.0000	-0.0200	-0.0200
												1			
								0.0000	0.1006	-0.5427	HIGH BETTER		0.0000	0.0001	-0.0443
								0.0000	-0.2500	0.1250	LOW BETTER		0.0000	-0.0813	0.0406
								0.0000	-0.1494	-0.4177			0.0000	-0.0812	-0.0036

Accordingly, to results previously shown table number 4.9 shows a comparison between both methods. In this specific exercise both methods yield the same results

Table 4.9 Comparison between both methods

Component	Method 1	Method 2
Solar panel	Supplier three	Supplier three
Regulator	Supplier two	Supplier two
Batteries	Supplier three	Supplier three
Inverter	Supplier one	Supplier one

As it can be seen in the results, both methods convert the characteristics of each of the electrical component separately into vectors that are positioned in a plane, in the case of method number one the comparison is with a desired vector, this desired vector is composed of the values expected by the decisions maker. This method defines by closest distance the provider vector that most closely resembles the desired vector, that is, the vector with a smaller distance to the desired vector is the one that offers in this case a more efficient condition to the characteristics of efficiency, cost of life useful, among others. In the case of methodology number two, the decision is found in the vector that defines the highest gain, all characteristics are converted into a vector in values per unit referenced to a desired vector established by the person concerned. It is understood that values of higher better are opposed to the values of lower better, for this reason a change of sign is established in the values lower better so that the positive response of the lower side is shown as a positive gain of the upper side, therefore event, the vector with the highest gain becomes the most efficient vector with respect to the vector previously set as the desired vector.

6. Conclusion

This work is based on the selection of components of the micro-grid solar panel stand-alone once they must be selected to replace an existing component that in theory will be out of service. This algorithm is based on the creation of vectors using the characteristics of the potential components provided in a finite number of providers, these vectors will be compared in distances against a desired vector. The vector that keeps the least distance against the desired vector will be the vector to be selected by the algorithm. Another algorithm contemplates the gains that exist between the characteristics of the participating vectors, such as cost is a characteristic of greater better, for which the negative gain becomes a positive gain for this algorithm, as well as characteristics such as life It is useful that larger populations are better, it is a characteristic that does not change sign, it remains positive throughout the process, so the vector that offers the highest gain will be the vector selected by this algorithm. In this particular work, it was found that both methodologies converge at the same provider selection points based on a desired vector. Despite this example is limited by only three providers and a specific number of characteristics to evaluate, this work can be taken to more complex instances of selection contemplating variable elements of the components that are involved in the operation of the same components. Perhaps, where the geographical areas with variation in solar irradiation are present as parts of the estimation variables. Considering international suppliers in the process with variation in the monetary values that are involved in the costs of the elements.

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