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Research article

Planning stand-alone electricity generation systems, a multiple objective optimization and fuzzy decision making approach

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ABSTRACT

This paper presents a fuzzy-multiple objective optimization methodology to plan stand-alone electricity generation systems. The optimization process considers three main objectives, namely technology cost, environmental and societal impacts. For each feasible solution of the Pareto set, a system reliability index is evaluated along the lifetime of the project. As a key contribution, the decision making process is carried out by applying a fuzzy satisfaction method (FSM). The FSM accounts simultaneously four key performance indexes (KPI): technical, economic, environmental and social. The novelty of the proposal lies on the inclusion of societal impact (local wealth creation) in the FSM used here to select the more appropriate solution. Previous contributions on FSM only accounts two of four indexes considered in this paper. The methodology was applied in a Colombian case study. The results show the importance of the simultaneous consideration of technical, economic, environmental and social objectives in the evaluation of off-grid energization solutions.

1. Introduction

Planning stand-alone electricity systems in rural areas is a topic of great interest for policy makers in developing regions. Energy planners should consider different technic-economic, environmental and social aspects to assess off-grid solutions. The planning problem can be addressed by means of an optimization model with several objectives. In practice these objectives are conflicting and multiple-objective optimization models must be solved to find out the more appropriate combination of resulting objectives.

The challenge is how to specify an affordable, cost effective and sustainable solution for stand-alone electricity generation systems since isolated communities lack economic conditions to cover the real cost of service. Furthermore, it is necessary to consider alternative strategies to improve the coverage, mainly if the expansion of the distribution network is unacceptable from a technic and/or economic point of view [1, 2]. As a result, the problem of selecting and sizing the technologies for a stand-alone electricity generation systems must be analyzed from the broader context.

A series of contributions can be found in literature about how to optimize stand-alone electricity generation systems [3]. In general, many of these valuable optimization approaches are based on multiple objective deterministic models. Some of them include specific strategies to perform decision making tasks once the set of feasible solutions are identified and ranked. In order to introduce uncertainty in the decision making-process, vast majority of methodologies use statistics to select the appropriate solution [4].

However, when statistics are not available, some few contributions resort to fuzzy modelling to represent the vagueness associated to the reliability of each possible solution is some extent. For instance, a fuzzy satisfaction method (FSM) has been previously applied in Malaysia [5]. This proposal characterizes solutions for stand-alone systems but only accounting only two objectives: economic (system cost) and environmental (carbon dioxide emissions) in the FSM. Including other aspects such as societal and system reliability indexes in the FSM could be worth. Indexes such as local economic impacts or expected energy not supplied can be useful to get a sustainable electricity off-grid solution [6].

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Table 1
Review of key performance indexes (KPI) according objectives of the planning problem.

Objective	Index	Description	Reference
EC	NPV	Net Present Value	[7, 8, 9, 10, 11]
EC	TIC	Total Investment Cost	[12, 13]
EC	LCC	Life Cycle Cost	[14, 15, 16, 17]
EC	LCOE	Levelized Cost of Energy	[18, 19, 20, 21, 22]
EC	TAC	Total Annual Cost	[23, 24, 25]
TC	LPSP	Probability of Loss of Power Supply	[21, 24]
C	LOLP	Probability of Loss of Power	[26]
TC	EIR	Energy Index Reliability	[5]
TC	LOLR	Risk of Load Loss	[27]
TC	LOLE	Expected Load Loss	[28]
TC	DPSP	Probability of Supply Deficiency	[29]
TC	ENS	Energy Not Supplied	[30]
TC	ELF	Load Loss Factor	[15, 31]
TC	WRE	Unused Renewable Energy	[19]
TC	REP	Penetration of Renewable Energy	[16]
TC	P (R)	Probability of Risk Status	[20]
EV	E	TotalCO_2 Emissions	[10, 15, 23]
EV	EE	Embodied Energy	[32]
EV	LCA	Life Cycle Emissions	[14, 23]
SC	EA	Energy acceptance	[7]
SC	HDI	Human developing	[8]
SC	HDI	Job creation	[8]
SC	LWC	Local Wealth Creation	[6]

After careful review of literature, we did not find decision-making strategies for stand-alone electricity generation systems planning based on fuzzy satisfaction methods accounting simultaneously economic, environmental and societal and technical (reliability) impacts. In order to demonstrate the novelty of the proposal, a exhaustive list of existing contributions in this topic is provided in Section 2 where generation technologies, performance indexes, optimization techniques and decision making strategies are classified and analyzed.

To fill the research gap, this document presents a multi-objective optimization model whose decision-making strategy is based on a fuzzy satisfaction method.

The optimization process considers three main objectives, namely technology cost, environmental and societal impacts through the concept of local wealth creation [6]. For each feasible solution of the Pareto set, a fourth index (system reliability) is evaluated along the lifetime of the project. The feasible set of efficient solutions are weighted with the fuzzy satisfaction method in order to select the best alternative from the Pareto set. The authors deem the application of a fuzzy approach can provide increased insight into energy planning decision making processes. The proposal has been applied in a off-grid zone of Colombia.

This document is organized as follows. Section 2 is devoted to review the state of art. The methodology is presented in Section 3. In Section 4 the results obtained from a Colombian case-study are presented and analyzed. Conclusions are drawn in Section 5.

2. Background

The planning problem of stand-alone electricity generation systems have been widely treated in literature. Existing references on the topic can be classified according to three different scopes: 1) key performance indexes (KPI) used to valuate feasible solutions (Table 1), 2) optimization methodologies used to screen out feasible solutions (Table 2) and 3) decision-making procedures to select and recommend the best option (Table 3).

2.1. Key performance indexes

Table 1 lists a classification of key performance indexes (KPI) depending on economic (EC), technical (TC), social (SC) and environmental (EV) dimensions of the planning problem.

The majority of existing planning methodologies are related with the economic performance (EC) dimension: net present value, total investment cost, life cycle cost, levelized cost of energy and total annual cost. Some specific contributions deal with technic aspects (TC) such as reliability (probability of loss of supply, energy not supplied, etc) and penetration levels of renewable-based generation (unused renewable energy, penetration of renewable energy, etc.). Recent trends on low carbon energization are introducing performance indexes according to environmental considerations (EV) such as total emissions, embodied energy and life cycle assessment.

It is worth to highlight that the social aspect (SC) has been previously included in the decision making analysis from a qualitative perspective [20, 33, 34] but not incorporated as a performance index relating societal impacts in the optimization stage. Recently, [7, 8] considered societal indexes at the optimization stage. In this paper, the local wealth creation (LWC) index proposed by [6] is incorporated both in the optimization stage and the decision-making stage.

2.2. Multiple-objective optimization stage

Since foregoing indexes are relevant to assess the suitability of an effective solution, the evaluation of the problem as a whole requires to pose a mathematical optimization problem with multiple objectives (MO) [35]. This kind of optimization allows to identify the set of strategies for an appropriate design solution.

The methodology of selection and sizing of stand-alone generation systems can be written as a MO optimization problem.

The solution of the MO problem is then described by the Pareto front, a set of non-dominated solutions [44] obtained by conventional, heuristic or hybrid methods and use of specific software [45]. Table 2 in a general way the main MO optimization methods reported in literature applied to plan stand-alone electricity generation systems. The methods are classified by the corresponding optimization technique [46].

There are a number of commercial/open source software tools suitable to be used in the planning process. The Standard optimization microgrid design software HOMER [9] and Clean Energy Management software RetScreen [45] use conventional linear-programming optimization methods to get feasible solutions. The Hybrid Optimization by Genetic Algorithms (iHOGA) is based on heuristic methods [8].

In this paper, we use a genetic algorithm [39] to screen out feasible solutions of the MO problem considering economic (EC), environmental (EV) and societal (SC) objectives. Technical performance (TC) is calculated a posteriori. A reliability index, Energy not supplied (ENS), is evaluated for each solution of the Pareto set.

Table 2
Multiple objective optimization models for stand-alone generation systems planning.

Type	Method	Description	Reference
Conventional	LP	Linear Programming	[36]
Conventional	MILP	Mixed Integer Linear Programming	[13, 37]
Conventional	NLP	Non Linear Programming	[33, 34, 38]
Heuristics	GA	Genetic Algorithms	[39]
Heuristics	MPSO	Modified Particle Swarm Optimization	[12]
Heuristics	SPEA	Strength Pareto Evolutionary Algorithms	[22]
Heuristics	MOEA	Multi-Objective Evolutionary Algorithm	[7]
Heuristics	ABC	Artificial Bee Colony	[18]
Heuristics	NSGA II	Non-Sorting Genetic Algorithm	[29, 32, 40]
Heuristics	MLUCA	MOA of Alignment Competition	[23]
Hybrid	IPF	Iterative Fuzzy Pareto	[5]
Hybrid	SA-TS	Hybrid Tabu-Search Simulation-annealing	[41]
Hybrid	PSOMCS	PSO and Monte Carlo Simulation	[42]
Hybrid	HTGA-ES	Hybrid GA and Exhaustive Search	[43]

Table 3
Review of decision making strategies to define stand-alone electricity generation systems.

Objectives	Technologies	Decision making method	References
EC-EV	PV-DG-FC-B	AHP	[14]
EC-EV	PV-WT-T-B	Ranking	[10, 22, 23]
EC-EV	PV-WT-B	Topsis	[19]
EC-EV	PV-WT-B	Single Objective Optimization	[15, 47]
EC-TC	PV-WT-B	Single Objective Optimization	[17, 26]
EC-TC	PV-WT-B	Single Objective Optimization	[24, 25]
EC-TC	PV-WT-B	Ranking	[29, 48]
EC-TC	PV-WT-T-B	Single Objective Optimization	[16, 28, 49]
EC-TC	PV-WT-FC	Single Objective Optimization	[21, 27, 50]
EC-EV-TC	PV-WT-B	Ranking	[32]
EC-EV-TC	PV-WT-FC-HT	Ranking	[31]
EC-SC	PV-WT-T-B	Ranking	[7]
EC-TC	PV-WT-T-B	Ranking	[20]
EC-TC	PV-WT-T-BM-B	Ranking	[33]
EC-TC	PV-WT-T-B	AHP	[34]
EC-TC	PV-WT-T-HG-BM-B	Single Objective Optimization	[51]
EC-TC	PV-WT-B	Fuzzy Satisfaction	[5]
EC-TC-EV-SC	PV-WT-T-B	Fuzzy Satisfaction	This paper

2.3. Decision-making stage

Once the multiple objective optimization problem is stated with the performance indexes listed in Table 1 and later solved using any technique listed in Table 2, it is necessary to select the more appropriate solution accounting all aspects under consideration. Therefore, the decision-making process is carried out using a number of strategies. Table 3 presents different decision making procedures applied to select efficient solutions. The list of contributions on this topic is classified according to economic, technical, environmental and societal objectives (EC, TC, EV and SC) and also by technologies considered wind (WT), solar photovoltaic (PV), combined with battery banks (B), thermal solutions (including diesel reciprocating engines and natural gas micro-turbine) (T), fuel cells (FC), small-scale hydraulic generation (HG), biomass (BM) and hydro tank (HT).

Some contributions in Table 3 pose planning problem as a single objective optimization problem. In this case, only one solution is get and no decision making process is carried out.

Contributions based on multiple objective optimization can rank the set of efficient solutions (Pareto front) according decision maker preferences. In this case qualitative aspects are included to guide the best choice.

Other contributions select the best option according to a given methodology such as Topsis, Analytical Hierarchal Processing (AHP) or Fuzzy Satisfaction methods (FSM).

Notice that the economic objective is clearly predominant in decision making process. In some contributions such as [14, 19, 23], the environmental or technical objectives are also included. Contributions [20, 33, 34] deal with economic and technical objectives at the same time.

In this review we found only one contribution that applies the fuzzy satisfaction method (FSM) in the decision making process [5]. However only two objectives are considered economic (EC) and technical (TC).

In this paper we improve the approach proposed in [5] by including the environmental (EV) and societal (SC) objectives [6]. Last row of Table 3 shows how this contribution makes the difference with respect to existing decision making procedures used in literature to select the more appropriate solution for the stand-alone generation systems planning problem.

3. Methodology

In this section the statement of the multiple objective optimization problem and the proposed decision-making process is described in detail. The multiple objective problem can be solved using any suitable technique based on traditional mathematical programming or heuristic algorithms. In this paper, the multiple objective problem is solved using a Genetic Algorithm. Each solution of the Pareto set includes specific figures for economic (EC), environmental (EV) and societal (SC) objectives.

System reliability - Expected Energy Non Supplied - regarded here as a technical objective (TC) is determined *a posteriori* for each element of the Pareto set. The decision-making process – selecting the best option from the Pareto set – is carried out through the fuzzy satisfaction method (FSM) considering all four objectives stated above: EC, EV, SC and TC.

3.1. The multiple-objective optimization model

The optimization problem is defined as a three-objective constrained model in Eq. (1).

$$\min F(x) = [f_1(x), f_2(x), -f_3(x)] \quad (1)$$
$$\text{subject to} \quad g_i(x) = 0 \quad i = 1, ..., m$$
$$h_j(x) \leq 0 \quad j = 1, ..., p$$

The first objective $f_1(x)$ corresponds to the minimization of life cycle costs (LCC) of the project. Life Cycle Cost (LCC) is an important economic (EC) performance index that account the impact both pending and future costs of the project. It compares initial investment options and identifies the least operational cost over a given period.

The second objective $f_2(x)$ – the environmental (EV) one – corresponds to the minimization of the life cycle of carbon dioxide CO_2 emissions (LCE).

Finally, the third objective $f_3(x)$ accounts a societal benefit (SC). The inclusion of this societal objective in the planning process of stand-alone generation systems constitutes the main contribution of the paper. This objective comprises the maximization the social benefit associated to economic growth and job creation in the life cycle of local wealth creation (LWC) [6].

The vector of decision variables is given by four elements:

$$x = [x_1, x_2, x_3, x_4]^T = [A_{PV}, A_{WT}, P_T, P_B]^T \quad (2)$$

where,

A_{PV} is the total surface area of the photovoltaic system (PV) in m^2,

A_{WT} is the total sweep area of the wind turbine(WT) system turbines in m^2,

P_T is the average power output of the thermal (T) reciprocating engine in kW.

P_B is the charge level of the battery bank (B) in Ah.

The aforementioned objective functions are constrained to one ($m = 1$) equilibrium equation (energy balance) and four ($p = 4$) capacity constraints associated to admissible upper and lower bounds for the dispatch of each technology: photovoltaic (PV), wind (WT), diesel (T) and battery storage (B).

In the following, each objective of the multiple objective optimization problem written in Eq. (1) is defined.

3.1.1. Economic objective: Life Cycle Cost (LCC)

The Life Cycle Cost (LCC) of the stand-alone generation system evaluates for each technology the net present value of capital and maintenance expenditure (CAPEX) and operational costs (OPEX).

$$f_1(x) = C_f(l_t, \gamma, \nu) + C_m(l_t, \gamma, \nu) + C_O(l_t, \gamma, \nu) - I_{CO_2}(l_t, \gamma, \nu) \quad (3)$$

where,

l_t is the project lifetime in years,

γ is the annual discount rate in percent,

ν is the annual inflation rate in percent,

C_f is the present value of capital costs in \$ (Colombian currency),

C_m is the present value of maintenance costs of system elements in \$,

C_O is the present value of operating costs of the system (fuel) in \$,

I_{CO_2} is the present value of the income from avoided CO_2 emissions in \$.

The capital expenditure or fixed cost (C_f) corresponds to the overnight cost of the generation system as well as the present value of battery replacements in the future. The cost of replacement of the associated electronic equipment such as regulator and inverter are not considered, taking into account that the life span of these equipments commercially is higher than 25 years. The fixed cost also includes the engineering, procurement and construction (EPC) expenditures. The maintenance cost (C_m), operating cost (C_O) and avoided emission cash flows (I_{CO_2}) are given by their net present value cost along l_t years project and an annual discount rate γ expressed in percent.

The fixed cost C_f can be decomposed in four components: the fixed cost of photovoltaic (C_{PV}), wind (C_{WT}), diesel plant (C_T) and battery solutions (C_B). The fixed cost of batteries is calculated at present value considering a number of replacements along the project lifetime.

$$C_f = C_{PV} + C_{WT} + C_T + C_B \quad (4)$$

$$C_f = c_{PV} \cdot P_{PV} + c_{WT} \cdot P_{WT} + c_T \cdot B_T + \quad (5)$$
$$\textstyle\sum_{i=1}^{Y_B} c_B \cdot P_B \cdot (\frac{1+\nu}{1+\gamma})^{(i-1)b_l} \quad (6)$$

where,

c_{PV} is the fixed cost of the photovoltaic panels per unit of installed area in \$/m^2,

c_{WT} is the fixed cost of the wind turbine system per unit of swept area in \$/m^2,

c_B is the fixed cost of the battery banks in \$/Ah,

c_T is the fixed cost of the thermal reciprocating engine in \$/kW,

b_l is the battery lifetime in years,

Y_B is the number of battery replacement along the project lifetime: l_f/b_l

Where, b_l is the battery bank lifespan and l_f is the project lifetime.

Depending on the technology used (photovoltaic, wind, storage and diesel) the net present value of the maintenance cost is determined as:

$$C_m = \textstyle\sum_{i=1}^{l_t} c_{mPV} \cdot A_{PV} \cdot (\frac{1+\nu}{1+\gamma})^i + \sum_{i=1}^{l_t} c_{mWT} \cdot A_{WT} \cdot (\frac{1+\nu}{1+\gamma})^i \quad (7)$$
$$+ \textstyle\sum_{i=1}^{l_t} c_{mB} \cdot P_B \cdot (\frac{1+\nu}{1+\gamma})^i + \sum_{i=1}^{l_t} c_{mT} \cdot P_T \cdot (\frac{1+\nu}{1+\gamma})^i$$

where,

c_{mPV} is the maintenance cost of photovoltaic system in \$/m^2,

c_{mWT} is the maintenance cost of the wind solution in \$/m^2,

c_{mB} is the maintenance cost of the batteries in \$/Ah,

c_{mT} is the maintenance cost of the thermal reciprocating engine in \$/kW.

The net present value of the operational cost is given by

$$C_O = \sum_{i=1}^{l_t} \frac{T \cdot P_T \cdot c_{fuel} \cdot H_R}{H_{fuel}} \cdot (\frac{1+\nu}{1+\gamma})^i \quad (8)$$

where,

c_{fuel} is the fuel cost, given in \$/m^3 for GLP and \$/l for diesel,

H_R is the heat rate of thermal component in Btu/kWh,

T is the average operation time in hr/year, this is established by the planner,

H_{fuel} is the specific heat value by fuel, given in Btu/m^3 for GLP and Btu/l for diesel.

The net present value of the income due to avoided CO_2 emissions is estimated by comparing the emissions of the system with the virtual emissions obtained if the energy was obtained from the network. This is given by:

$$I_{CO_2} = \lambda \cdot [\epsilon_n \cdot (\mathcal{W}_{PV} + \mathcal{W}_{WT} + \mathcal{W}_B + \mathcal{W}_T) \cdot l_t - (\epsilon_T \cdot \frac{T \cdot B_T}{1 \cdot 10^3} \cdot lt)] \quad (9)$$

where,

λ is price of avoided emissions in \$/tCO_2,

ϵ_n is the emissions factor with reference to the network in tCO_2/MWh,

ϵ_T is the emissions factor of CO_2 produced by the thermal reciprocating engine in tCO_2/MWh,

$\mathcal{W}_{PV}$ is the annual real energy produced by the photovoltaic system in MWh/year,

$\mathcal{W}_{WT}$ is the annual real energy produced by the wind system in MWh/year,

$\mathcal{W}_B$ is the annual real energy stored in the battery bank in MWh/year,

$\mathcal{W}_T$ is the annual energy produced by the reciprocating engine in MWh/year.

The energy produced by the photovoltaic generation system in kWh is a function of the average solar irradiation in the area, assuming an operating time in the year of 8760 hours.

$$\mathcal{W}_{PV} = 8760 P_{PV} = 8760 \cdot \eta_{PV} \cdot \eta_{inv} \cdot A_{PV} \cdot S_I \tag{10}$$

where,

P_{PV} is the annual average output of the photovoltaic system in kW,
η_{PV} is the total efficiency of the photovoltaic system in per unit,
η_{inv} is the total efficiency of the inverter system in per unit,
S_I is the average solar irradiance in kW/m^2.

The efficiency of the wind conversion process is determined according to [32] as:

$$\eta_{WT} = C_P \cdot \eta_{GB} \cdot \eta_G \tag{11}$$

where,

C_P is the wind turbine conversion efficiency,
η_{GB} is the efficiency of the gear box,
η_G is the efficiency of the electric generator.

The density of the air relies on the height in (kg/m^3) of the wind turbines and its value is estimated according to [32] as:

$$\rho = \frac{354.049}{T_a} \cdot e^{-0.034 \cdot \frac{z}{T_a}} \tag{12}$$

where,

z is the average height of the wind turbine hub in meters,
T_a is the average temperature of the environment in C°.

For the simplification of the model, the energy produced by the wind unit is obtained from average wind speed in the area, assuming an operating time in the year of 8760 hours:

$$\mathcal{W}_{WT} = 8760 P_{WT} = 8760 \cdot \eta_{WT} \cdot \frac{\rho}{2} \cdot A_{WT} \cdot v^3 \tag{13}$$

where,

P_{WT} is the annual average output of the wind system in kW,
η_{WT} is the total efficiency of the wind conversion,
ρ is the density of the air kg/m^3,
v is the average wind speed m/s.

The energy stored in battery bank is a function of the operational voltage. Using a reduced battery model for optimization model simplicity, assuming an average state of charge (SOC).

$$\mathcal{W}_B = \frac{\%SOC}{1 \cdot 10^6} \cdot \eta_{inv} \cdot P_B \cdot V_B \tag{14}$$

where,

$\%SOC$ is the percentage of average battery state of charge,
P_B is the battery bank capacity in Ah,
V_B is the operating voltage of the battery bank in V.

The energy produced by the thermal reciprocating engine is a function of the average time of operation T in hours and given by

$$\mathcal{W}_T = \frac{1}{1000} \cdot P_T \cdot T \tag{15}$$

3.1.2. Environmental objective - Life Cycle Emissions (LCE)

The second objective function of the multiple objective optimization problem accounts the CO_2 emissions produced during the operation of the system. The emissions comprise the carbon footprint produced during the construction process, installation and commissioning of each technology including the emissions generated in the manufacturing of the components, transporting of the components from the factory to the place of the system.

Photovoltaic and wind turbine technologies have a foot-print associated with emissions produced during the manufacturing process. In this way, a broad context of the environmental emissions and impacts generated by the stand-alone electricity energy system is considered. Thus, total emissions are determined through specific emission factors for the installed capacity of each technology that should be added to the emissions produced by the operation of the thermal reciprocating engine. The emission factors applied in this paper were taken from [22]. The overall objective function for the Life Cycle Emissions (LCE) is given by the following expression:

$$f_2(x) = \epsilon_{PV} \cdot P_{PV} + \epsilon_{WT} \cdot P_{WT} + \epsilon_B \cdot P_B + \epsilon_{TG} \cdot P_T + \gamma_T \cdot W_T \tag{16}$$

where,

P_B is the average charge level of the battery bank in Ah,
P_T is the average power output by the thermal reciprocating engine kW,
ϵ_{PV} is the emission factor for the photovoltaic system kgCO_2/kW,
ϵ_{WT} is the emission factor for the wind turbine system kgCO_2/kW,
ϵ_B is the emission factor associated with battery installation kgCO_2/Ah,
ϵ_T is the emission factor associated with reciprocating engine manufacturing kgCO_2/kW,
γ_T is the emission factor for thermal operation kgCO_2/kWh.

3.1.3. Societal objective - Local Wealth Creation (LWC)

The third objective to be considered in the optimization problem accounts the social impact of the stand-alone energy supply in the area. The inclusion of this objective constitutes the main contribution of the paper. The concept of Local Wealth Creation (LWC) is applied [6]. This concept combines economic growth with job creation accounting the acceptance and appropriation of the project by the community. This function considers the job creation during the life cycle [33]. The contribution of the stand-alone generation system to economic growth is determined considering the energy intensity and the job creation related to each component of the system. The local wealth creation function is expressed as:

$$f_3(x) = \epsilon_{eng} \cdot (\mathcal{W}_{PV} + \mathcal{W}_{WT} + \mathcal{W}_B + \mathcal{W}_T) \cdot l_t + \alpha \cdot J_C(x) \tag{17}$$

where,

ϵ_{eng} is the local energy intensity in \$/MWh,
α is the contribution factor to the LWC for job created in \$/Jobs
$J_C(x)$ is the job creation function. The job creation function is defined by unitary factors that relate the jobs created during to the construction, transportation and installation of hybrid generation system technologies. Job requirements for operation and maintenance are also included. Given by the number of jobs created during the life cycle and based on the job creation factors presented in [7] and [33], the function of job creation is expressed as:

$$J_C(x) = J_{PV} \cdot P_{PV} + J_{WT} \cdot P_{WT} + J_B \cdot P_B + J_{TG} \cdot P_T + J_g \cdot W_T \tag{18}$$

where,

J_{PV} is the job creation factor for photovoltaic system in Jobs/kW,
J_{WT} is the job creation factor for WT system in Jobs/kW,
J_B is the job creation factor for installation of the batteries in Jobs/kW,
J_{TG} is the job creation factor for thermal installation in Jobs/kW,
J_g is the job creation factor for the operation of the reciprocating engine in Jobs/kWh.

3.1.4. Optimization model constraints

The three objectives detailed above are constrained to the energy balance of the system as well as the lower and upper bounds of the decision variables. Thus, one energy balance equation and four capacity constraints are recognized.

System energy balance in kWh/yr is given by

$$\mathcal{W}_{PV} + \mathcal{W}_{WT} + \mathcal{W}_B + \mathcal{W}_T = \mathcal{W}_D \tag{19}$$

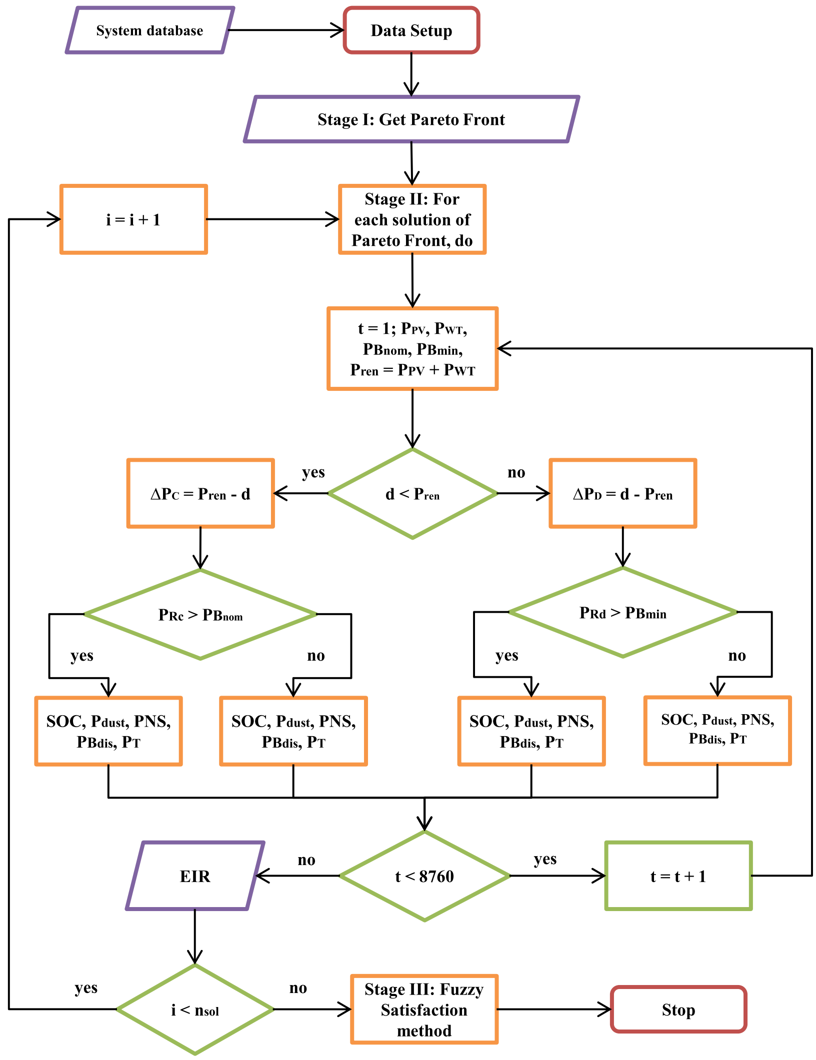

Fig. 1. General planning algorithm.

where photovoltaic ($\mathcal{W}_{PV}$), wind ($\mathcal{W}_{WT}$), storage ($\mathcal{W}_B$) and diesel generator ($\mathcal{W}_T$) generated energy flows expressed in kWh per year. These energy contributions are determined according to equations (10)-(15). Energy demand ($\mathcal{W}_D$) in kWh/yr is previously defined by the energy planner. For the sake of simplicity, the amount of energy wasted from renewable sources is considered negligible when it exceeds the demand and the battery bank is charged. The system capacity constraints are given by

$$A_{PV}^{min} \leq A_{PV} \leq A_{PV}^{max} \tag{20}$$

$$A_{WT}^{min} \leq A_{WT} \leq A_{WT}^{max} \tag{21}$$

$$P_B^{min} \leq P_B \leq P_B^{max} \tag{22}$$

$$P_T^{min} \leq P_T \leq P_T^{max} \tag{23}$$

where lower and upper capacity bounds are specified by each technology.

For the sake of simplicity, this model does not include distribution lines since generation facilities and loads are located in the same place. For this reason, a restriction on distribution losses is not included and no associated cost is added in the objective function of the economic aspect.

The average power output of each kind of renewable units depends on the decision variables A_{PV} and A_{WT} and a scaling factor k_{PV} and k_{WT} in kW/m^2, respectively.

$$P_{PV} = A_{PV} \cdot k_{PV} \tag{24}$$

$$P_{WT} = A_{WT} \cdot k_{WT} \tag{25}$$

3.2. Solution approach

The planning problem is solved in three different stages. In the first stage I, the multiple objective optimization problem is solved with a Genetic Algorithm (MOGA) and the Pareto front (containing LCC, LCE and LWC performance indexes) is identified from the set of the feasible solutions. In the second stage II, the energy reliability index (EIR) is determined for each solution of the Pareto front. The most appropriate solution is selected at third stage III by applying the proposed fuzzy satisfaction method (FSM) according to the three objectives obtained in stage I (LCC, LCE and LWC performance indexes) and the energy reliability index (EIR) evaluated in stage II. The complete solution approach is described in detail in the ten-step algorithm depicted in Fig. 1.

3.2.1. Data setup

Step 1: Input parameters of the optimization algorithm are settled: the load curves, the annual irradiance curve, the annual wind speed curve, technology costs (CAPEX, OPEX), technical parameters of each technology, emission factors, job creation factors, project parameters such as interest rates and life cycle time, maximum demand and consumption. Upper and lower limits of decision variables are also established.

3.2.2. Stage I: MOGA solution and Pareto front identification

Step 2: The mathematical problem is solved. A multiple objective genetic algorithm (MOGA) is run to solve the optimization problem stated in Eqs. (3)-(18) subject to Eqs. (19)-(25). Technical solutions for economic, environmental and societal objectives are identified. This approach is based on a variation of the algorithm NSGA-II (Non-Sorting Dominated Genetic Algorithm) with elitist selection of non-dominance [32]. The algorithm favors individuals with a higher value that help increase the diversity of the population, even if they have a lower fitness value. It is important to assure the diversity of the population for the convergence of the Pareto optimal front and to identify the number of elite members (Pareto non-dominated solutions) in the iterative process. There are two options for elite identification in the search of the Pareto optimal front: Pareto fraction and distance function. The fraction function limits the number of individuals on the Pareto front (elite members) and the distance function helps maintain sufficient diversity to favor individuals who are far from the optimal front

The optimization problem yields the Pareto front with $i = 1, \ldots, n_{sol}$ solutions in the form $\mathbf{x_i} = [A_{PV}, A_{WT}, P_B, P_T]^T$. Each solution is evaluated at objective function f_i^{obj}, $obj = 1, \ldots, n_{obj}$. The average power output of renewable, charge level and thermal reciprocating engines are determined (P_{PV}, P_{WT} and P_T) from decision variables.

3.2.3. Stage II: energy reliability index evaluation

Step 3: Each solution of the Pareto front $i = 1, \ldots, n_{sol}$ is setup for initial time. Technical attributes of the system are calculated at hour $t = 1$: 1) Power output of renewable sources ($0 \le P_{PV}(t) \le P_{PV}$, $0 \le P_{WT}(t) \le P_{WT}$) is determined according to equations (10) and (13), 2) State of charge (SOC) of the batteries is given by ($SOC_B^{min} \le P_B(t) \le SOC_B^{nom}$) for batteries: $SOC = P_B(t)/P_B^{nom}$, 3) the base output of thermal reciprocating engines $P_T(t)$ is also fixed to give voltage-frequency support to the system. In order to promote the use of renewable resources and use the thermal resource as a reliability support only, the base output of the fossil-based plant is adjusted as 15% of the peak load $P_T^{base} = 0.15 d^{max}$.

Step 4: (Conditional): At hour $t = 1$ it is verified if the available renewable resource can satisfy the demand. Depending on the difference between the load demand ($d(t)$) and the available renewable resource ($P_{ren}(t) = P_{PV}(t) + P_{WT}(t)$), it is defined whether the batteries are suitable to be charged.

Step 5.1: If the batteries are charging, then the stored energy (ΔP_C) in kWh is given by:

$$\Delta P_C(t) = P_{ren}(t) - d(t) \tag{26}$$

Thus, the total charge level $P_{Rc}(t)$ is given by:

$$P_{Rc}(t) = \Delta P_C(t) + SOC(t) \tag{27}$$

(Conditional) If the total charge P_{Rc} is greater than the nominal level P_B^{nom}, the batteries are charged at its nominal value, and the excess power (P_{ren}^{dust}) is dissipated through a resistance. The output of the reciprocating engine $P_T(t)$ remains at its base value. Then, power balance is given by:

$$SOC(t+1) = P_B^{nom}(t) \tag{28}$$

$$P_{ren}^{dust}(t) = 0, \tag{29}$$

$$PNS(t) = 0, \tag{30}$$

$$P_T(t) = P_T^{base} \tag{31}$$

(Conditional) If the total charge P_{Rc} is lower than the nominal level P_B^{nom}, the batteries are loaded with the available power.

$$SOC(t+1) = SOC(t) + \Delta P_C, \tag{32}$$

$$P_{ren}^{dust}(t) = 0, \tag{33}$$

$$PNS(t) = 0, \tag{34}$$

$$P_T(t) = P_T^{base} \tag{35}$$

The output of the thermal reciprocating engine remains at its base value P_T^{base}.

In both cases, no load shedding is required, then power not supplied $PNS(t)$ is zero.

Step 5.2: If the batteries are discharging $P_{ren} \le d(t)$ and $\Delta P_D \ge 0$

$$\Delta P_D(t) = d(t) - P_{ren}(t) \tag{36}$$

It is verified if the total charge P_{Rd}.

$$P_{Rd}(t) = SOC(t) - \Delta P_D \tag{37}$$

(Conditional) If P_{Rd} is greater than P_B^{min}, batteries are going to be discharged and a new $SOC(t)$ is established for the next hour $t+1$.

$$SOC(t+1) = SOC(t) - \Delta P_D, \tag{38}$$

$$P_{dust}(t) = 0, \tag{39}$$

$$P_{ns}(t) = 0, \tag{40}$$

$$P_T(t) = P_{Tbase} \tag{41}$$

The output of the thermal reciprocating engine P_T remains at its base value.

(Conditional) If P_{Rd} is lower than P_B^{min}, battery charge level reaches its minimum value and the total battery discharge is given by

$$P_B^{dis}(t) = \Delta P_D + P_{Bmin}(t) - SOC(t) \tag{42}$$

The battery discharge output $P_B^{dis}(t)$ is then compared with the available thermal output P_T.

(Conditional) If the total discharge output $P_B^{dis}(t)$ is lower than thermal based output P_T, the thermal output should be increased to meet the balance:

$$SOC(t) = SOC_B^{min}, \tag{43}$$

$$P_B^{dust}(t) = 0, \tag{44}$$

$$PNS(t)) = 0, \tag{45}$$

$$P_T(t) = P_B^{dis}(t), \tag{46}$$

(Conditional) If the total discharge output $P_B^{dis}(t)$ is greater than P_T, the thermal reciprocating engine is dispatched to its nominal output value but it cannot provide enough power to cover the peak demand and load shedding is required:

$$SOC(t) = SOC_B^{min}, \tag{47}$$

$$P_B^{dust}(t) = 0, \tag{48}$$

$$PNS(t) = P_B^{dis}(t) - P_T, \tag{49}$$

$$P_T(t) = P_T. \tag{50}$$

In this case, the load shedding is $PNS(t) = P^{dis}(t)$-P_T.

Step 6: The sequential simulation for the estimation of the reliability of the technical arrangement is executed for a period of one year. This reliability analysis is carried out assuming that annual solar irradiance and annual wind speed conditions do not change significantly across the project lifespan. Then, Step 5 is repeated for each hour of the year from $t = 1$ to $t = 8760$ according to the annual load curve, the wind sped and irradiance annual curves.

Step 7: The annual Energy Reliability Index (EIR) is determined from power not supplied (PNS) figures obtained in Step 5.2 from hour $t = 1$ to hour $t = 8760$:

$$EIR = 1 - \frac{\sum_{t=1}^{8760} PNS}{\mathcal{W}_D} \tag{51}$$

where $\sum_{t=1}^{8760} PNS$ is the annual energy not supplied in kWh/year and $\mathcal{W}_D$ is the annual load consumption in kWh/year.

$$\mathcal{W}_D = \sum_{t=1}^{8760} d(t) \quad (52)$$

Step 8: Steps 3 to 7 are repeated for every solution of the Pareto set.

Step 9: At this point, all three optimized objectives – economic (LCC), environmental (LCE) and societal (LWC) – were characterized with a corresponding energy reliability index (EIR) for every feasible solution in the Pareto set.

3.2.4. Stage III: decision making: fuzzy satisfaction method FSM application

Step 10: Accounting the four objectives per Pareto solution summarized at Step 9, the decision-making process is carried out in order to select the best option. In this paper a fuzzy satisfying method is used for this purpose.

The method is described as follows: for each feasible solution $i = 1, ..., n_{sol}$ of the Pareto set, a membership function ρ_{f-i}^{obj} is defined for each objective $obj = 1, ..., n_{obj}$. The magnitude of the membership function ranges from 0 to 1 reflecting the level upon which a given solution belongs or not to the set that minimizes the objective function f_i^{obj}. All solutions should be evaluated in order to select the best one that equitably reconciles all the three objectives of the optimization problem. The method takes two formulations depending on whether the objective function f_i^{obj} is minimized (Eq. (53)) or maximized (Eq. (54)).

On one hand, when the objective function f_i^{obj} is minimized, a linear membership function is used for all objective functions as follows:

$$\rho_{f-i}^{obj} = \begin{cases} 1 & f_i^{obj} \le f_{min}^{obj} \\ \frac{f_{max}^{obj} - f_i^{obj}}{f_{max}^{obj} - f_{min}^{obj}} & f_{min}^{obj} < f_i^{obj} < f_{max}^{obj} \\ 0 & f_i^{obj} \ge f_{max}^{obj} \end{cases} \quad (53)$$

where

ρ_{f-i}^{obj} is the weight assigned to the i-th solution of a minimization objective;

f_{max}^{obj} It is the maximum value of the minimization objective obtained;

f_{min}^{obj} It is the minimum value of the minimization objective obtained;

f_i^{obj} It is the value of the minimization objective obtained by the i-th solution.

On the other hand, when the objective function f_i^{obj} is maximized, a linear membership function is used for all objective functions as follows:

$$\rho_{f-i}^{obj} = \begin{cases} 1 & f_i^{obj} \ge f_{max}^{obj} \\ \frac{f_i^{obj} - f_{min}^{obj}}{f_{max}^{obj} - f_{min}^{obj}} & f_{min}^{obj} < f_i^{obj} < f_{max}^{obj} \\ 0 & f_i^{obj} \le f_{min}^{obj} \end{cases} \quad (54)$$

where

ρ_{f-i}^{obj} is the weight assigned to the i-th solution of a maximization objective;

f_{max}^{obj} is the maximum value of the maximization objective obtained;

f_{min}^{obj} is the minimum value of the maximization objective obtained;

f_i^{obj} is the value of the maximization objective obtained by the i-th solution.

The normalized weight of each solution (ρ_i) combines the weights obtained for all the objectives considered in the decision making process. This normalized weight makes it possible to compare solutions.

$$\rho_i = \frac{\sum_{obj=1}^{n_{obj}} \rho_{f-i}^{obj}}{\sum_{i=1}^{n_{sol}} \sum_{obj=1}^{n_{obj}} \rho_{f-i}^{obj}} \quad (55)$$

where, ρ_i is the normalized weight for each solution.

When calculating the normalized weights ρ_i for all n_{sol} solutions, it is possible to obtain the best solution within the Pareto set by selecting highest normalized weight.

Table 4
Data setup.

Parameter	Value
Average inflation rate, v	9%
Battery bank lifespan, b_l	6 years
NG init cost, C_T	6000 M$/kW
WT init cost, C_{WT}	600 M$/m^2
NG maint cost, C_{mT}	120 M$/kW
WT maint cost, C_{mWT}	10.4 M$/m^2/yr
Battery replac, Y_B	4
CO_2 price, λ	5 k$/tCO$_2$
Voltage bat bank, V_B	48 [V]
Inverter efficiency, η_{inv}	95%
Wind generator eff, η_G	80%
NG em. fact, ϵ_T	800 gCO$_2$/kWh
Specific Heat fuel, H_{fuel}	35315 Btu/m^3
Discount rate, γ	12%
Project lifetime, l_f	25 yr
PV init cost, C_{PV}	180 M$/m^2
Batt init cost, C_B	150 M$/Ah
PV maint cost, C_{mPV}	16.4 M$/m^2/yr
Batt maint cost, C_{mB}	40 M$/Ah/yr
NG fuel cost, C_{fuel}	1500 M$/m^3/yr
Em. factor Net, ϵ_n	370 gCO$_2$/kWh
PV Efficiency, η_{PV}	16%
Wind conv eff, η_{WT}	60%
Gear box eff, η_{GB}	70%
Wind turb conv eff, η_{TC}	60%
NG Heat Rate, H_R	11.2 Btu/kWh

3.3. System data

The input parameters for the algorithm are summarized in Table 4. All costs and prices are given in Colombian currency \$. $J_{PV} = 2.7 \times 10^{-3}$, job creation factor for photovoltaic system in Jobs/kW, $J_{WT} = 1.1 \times 10^{-3}$, job creation factor for WT system in Jobs/kW, $J_B = 0.01 \times 10^{-3}$, job creation factor for installation of the batteries in Jobs/kW, $J_{TG} = 12 \times 10^{-6}$, job creation factor for thermal installation in Jobs/kW, $J_g = 0.14 \times 10^{-4}$, job creation factor for the generator operation in Jobs/kWh. $\epsilon_{PV} = 1392$, CO_2 em. factor for the photovoltaic system kgCO_2/kW, $\epsilon_{WT} = 675$, CO_2 em. factor for the wind turbine system kgCO_2/kW, $\epsilon_B = 55.3$, CO_2 em. factor associated with battery installation kgCO_2/kW, $\epsilon_T = 400$, CO_2 em. factor for manufacturing kgCO_2/kW, $\gamma_T = 252$, CO_2 em. factor for diesel/gas operation gCO_2/kWh. ϵ_{eng} is the local energy intensity in \$/MWh, and α is the contribution factor to the LWC for job created in \$/JobsLC

4. Results

The proposed methodology was applied into a village located in the municipality of Guican, department of Boyacá (Colombia). According to [53] by 2013 the department had a total of 382,416 households and a coverage index (ratio of number of users with energy service to number of households) of 96.43%. According to the statistics presented in [53] a coverage growth of up to 97.6% was estimated for 2017. This means that 9,178 homes lack electricity. The village under study is located in a rural off-grid zone at the north of the department (715059 786264 18N UTM). The distance between the village and Tunja (the capital of the department) is 255 km, with an average altitude of 2983 m.a.s.l. and a total population of 6,909 inhabitants. A share of 75% (5197 inhabitants) are located in rural zones.

Results of the application of the step-by-step planning algorithm depicted in Fig. 1 is presented.

Step 1 - Data Setup: The average annual load to serve is 2 MW, 17.47 GWh/year with a peak load of 3.25 MW. The estimation of the wind and solar irradiance potential was obtained from the NREL [52] according to the GPS location of the village under study. Annual demand, solar irradiance, wind speed curves are depicted in Fig. 2.

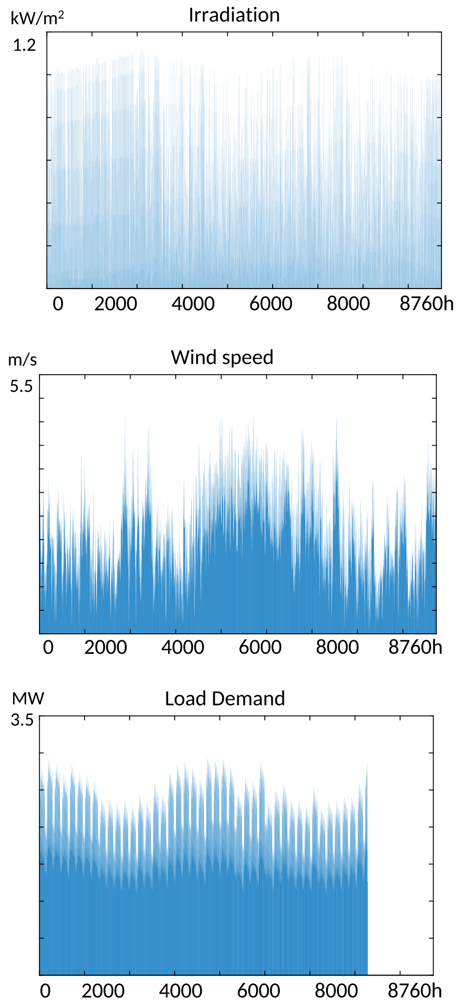

Fig. 2. Annual load demand curve d (MW), annual solar irradiance curve, S_I (kW/m^2), speed curve v (m/s), NREL-NRSDB Data, 2014 [52].

Technology and fuel costs consider particular conditions to build and operate off-grid solutions in rural areas of developing countries such as Colombia.

Optimization model constraints are defined as follows:

$$0 \le A_{PV} \le 8000 \text{ m}^2 \tag{56}$$

$$0 \le A_{WT} \le 15000 \text{ m}^2 \tag{57}$$

$$1000 \text{ Ah} \le P_B \le 3000 \text{ Ah} \tag{58}$$

$$1000 \text{ kW} \le P_T \le 6000 \text{ kW} \tag{59}$$

Stage I, Step 2, optimization results: Fig. 3 depicts the results of the optimization process. The Pareto front comprises 133 non-dominated solutions. Thus, the Pareto set size is 133. The optimization process was carried out in a PC computer with the following characteristics: Intel (R) Core (TM) i7-5500U CPU @ 2.40 GHz, 8.00 GB (RAM). The optimization method was coded in Matlab using the *gamultiobj* function. The genetic algorithm runs with a population size of 380 and with 120 generations. The processing time obtained was 204.15 seconds. The resulting 3-dimension graphs show that cost in the life cycle cost (LCC) ranges between 25 and 40 billion \$ (approx. US\$8.6 and 10.3 million). This result implies an average LCC cost of US\$0.27-0.32 per kWh. The life cycle of emissions (LCE) objective varies between 60 and 85 $MtCO_2$. Finally, the local wealth creation (LWC) ranges between 22 and 28 billion \$ (approx. US\$ 13.6 and 15.3 million).

Stage II, Steps 3-9, reliability analysis: Once obtained the set of non-dominated solutions in Stage I, the energy reliability index (EIR) is calculated for each optimal solution of the Pareto, the results are presented in Fig. 4. The calculated EIR ranges 0.83 and 0.91. This means that load shedding is required in all solutions with different degree of severity.

Table 5
Best solution - Solution 109.

	kW/Ah		GWh	Objective	Value
P_{PV}	523.3	$\mathcal{W}_{PV}$	4.58	LCC [Bi \$]	32.9
P_{WT}	341.8	$\mathcal{W}_{WT}$	3.00	LCE [$MtCO_2$]	81.9
P_B	1460	$\mathcal{W}_B$	12.78	LWC [bi\$]	26.6
P_T	1264.4	$\mathcal{W}_T$	11.07	EIR [%]	91

Stage III, Step 10, decision making using a fuzzy satisfaction method FSM: In the top-right hand of Fig. 3 it is showed the results obtained for the normalized weights computed using Eq. (55). The highest normalized weight is $0.009625 * 10^{-3}$. The best normalized weight corresponds to the non-dominated solution number 109 of the pareto set. Table 5 lists the attributes of the best option. The best solution 109 is highlighted as a red bullet in the Pareto set shown in Fig. 3.

It is worth to note that the fuzzy satisfaction method (FSM) seeks the best solution in the around of the middle of the Pareto front. This result is consistent with the fact that in this area the four objectives are well balanced. The best solution represents a reduction of 4248 kTon CO_2 year with respect to the emissions that would have been obtained if the energy had been taken from the grid.

The resulting dispatch profile of renewable and fossil-based technologies for the best solution 109 is depicted in Fig. 5.

The resulting capacity specifications by technology are determined according to the results for best solution 109 displayed in Table 5. The recommended nominal sizes of the system are $P_{PV}^{nom} = 700$ kW, $P_{WT}^{nom} = 400$ kW, $P_B^{nom} = 1500$ Ah, $P_T^{nom} = 1500$ kW. We can observe from Fig. 5 that the thermal reciprocating engine can represent around 40% of the annual load demand. The use of storage is really limited in Colombia due to its higher costs. Solar PV and wind WT output have a share of almost 60% the annual load demand. Particular conditions of Colombia such as moderate fuel cost and high renewable potential suggest to limit the use of storage as a solution to tackle renewable energy intermittency. Regarding the inclusion of societal considerations such as local wealth creation (LWC), the results show the importance of off-grid energy solutions to improve local economy.

The planning process for a stand-alone electricity system in Colombia has considered three optimized objectives (economic EC, environmental EV and social SC) and evaluated a reliability index (technical TC). Four technologies are considered: solar PV, wind WT, thermal reciprocating engines (T) and batteries (B). The optimization process was carried out taking into account the costs on-site (a rural area) for every technology.

We obtained a design specification (solution 109) that reconciles the trade-offs among the four key performance indexes (LCC, LCE, LWC and EIR). The state of art in this topic is improved by including societal objectives – strongly dependent on local economies – in both the optimization and decision making processes. As a key contribution, the proposed methodology enhances the decision making process by applying a fuzzy satisfaction method considering economic, technical, societal and environmental attributes at once.

5. Conclusions

This paper presents a fuzzy-multiple objective optimization methodology to plan stand-alone electricity generation systems. The novelty of the proposal lies on the inclusion of societal impact (local wealth creation) in the FSM used here to select the more appropriate solution. We conclude that the use of decision-making processes based upon fuzzy satisfaction methods (FSM) in stand-alone system specification produces satisfactory solutions accounting simultaneously four key

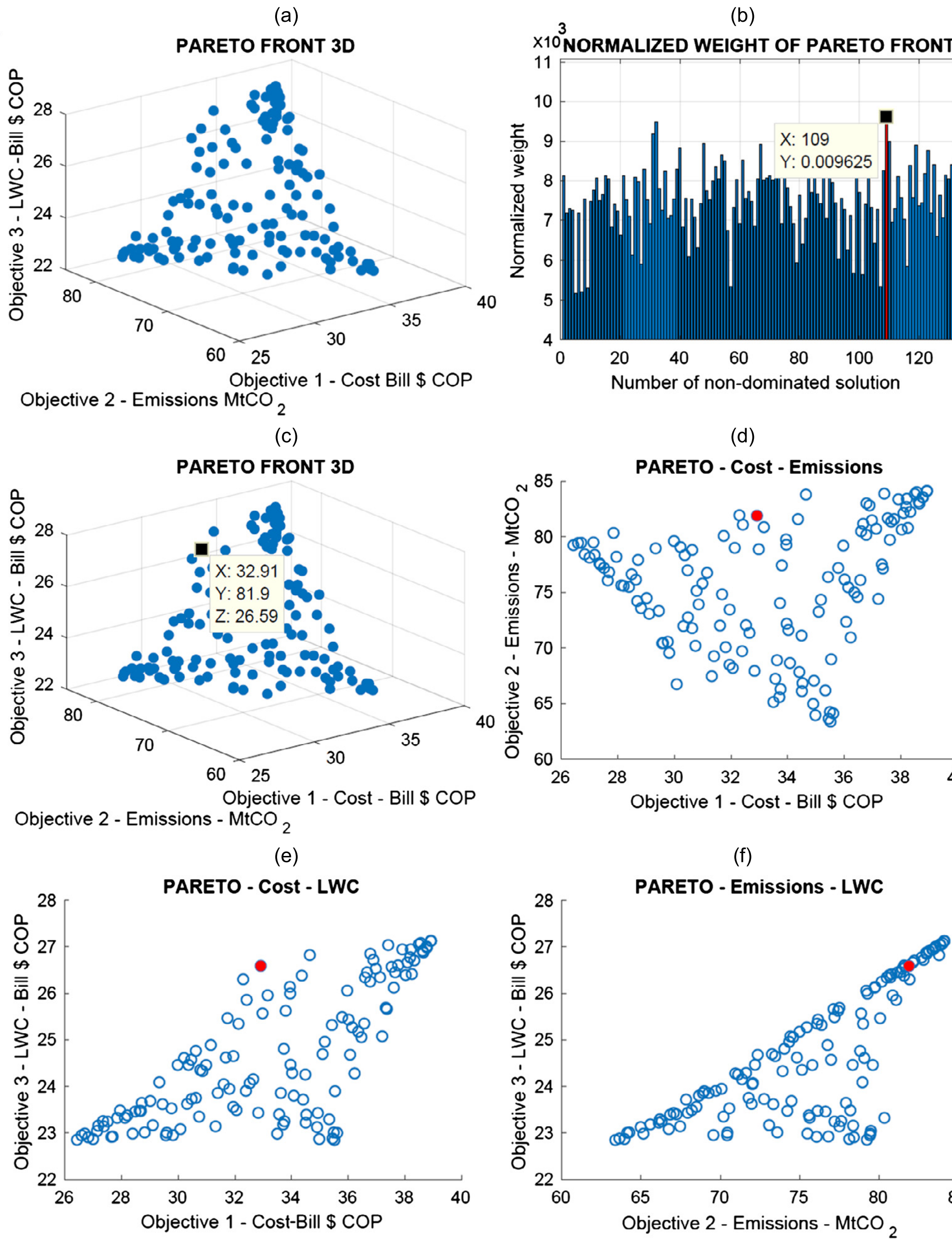

Fig. 3. Case study Pareto optimal set.

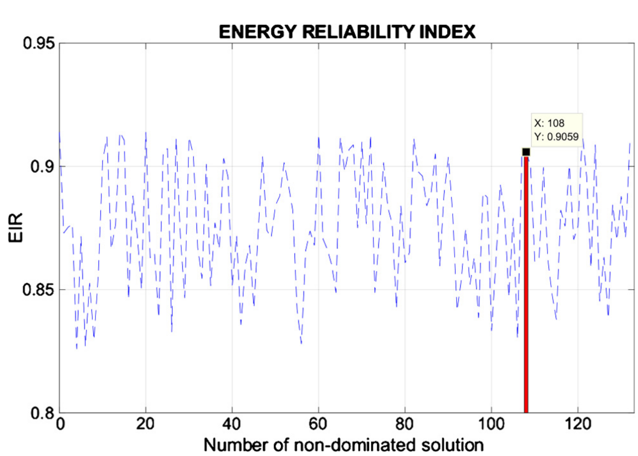

Fig. 4. Energy Index Reliability (EIR).

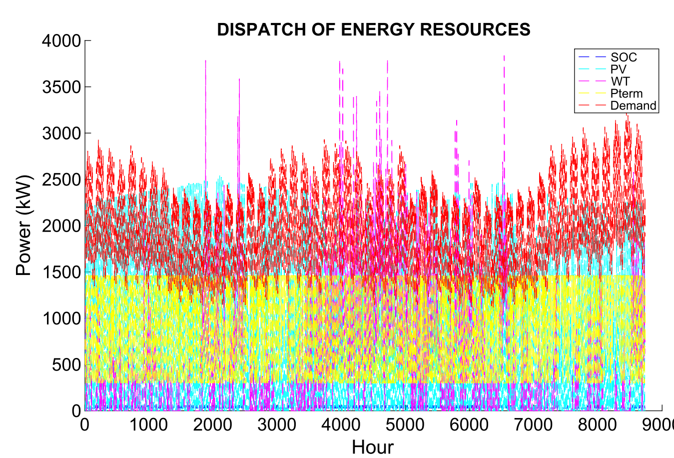

Fig. 5. Hourly dispatch by technology to cover the system load.

performance indexes (KPI): technical, economic, environmental and societal. Real-world application in Colombia suggests a fossil-renewable mix of 40-60% with a local health creation income of $26 Billion per year and a environmental impact of 80 MtCO2 per year. Finally, one of the recommendations to improve the model and to consider in future works, can be the inclusion of the losses in distribution lines, taking into account the magnitude of the power of the system and that the consumers can be at a significant distance from the generation node of the microgrid. With this factor it is necessary to reformulate the cost function and the calculation of CAPEX and OPEX of the project would change.

Declarations

Author contribution statement

J. D. Rivera-Niquepa: Performed the experiments; Analyzed and interpreted the data.

P. M. De Oliveira-De Jesus: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

J. C. Castro-Galeano & D. Hernandez-Torres: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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