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A Decision Support Approach to Provide Sustainable Solutions to the Consumer, by Using Electrical Appliances

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Abstract: The diversity of energy efficiency appliances existent on the market, with all its different issues, contributes to the existence of several tradeoffs (e.g., energy and water consumption vs. initial investment), which make the consumer's choices in the market difficult. This becomes even more relevant, by knowing that nowadays a consumer tries to get a solution from the market, with a good compromise between the economic, social and environmental dimensions, and according to its priorities and specific needs, which can be different from other consumers. By adopting a multicriteria approach, combined with an optimization technique, based on evolutionary algorithms (EA), it will be possible to provide a set of sustainable solutions from the market to the consumer, that respects the compromise referred before. In this work, it will be presented an approach to support a decision-agent (DA) (consumer), by performing a set of sustainable choices based on electrical appliances, from the market and suitable to its needs. The method will be applied to a case study, to demonstrate its application. Regarding the obtained solutions, several savings are achieved (electrical and water consumption, CO_2 emissions) by taking into account the consumer's relative importance, regarding each dimension considered.

Keywords: sustainable development; energy efficiency; electrical appliances; life cycle cost analysis (LCCA); multi-attribute value theory (MAVT); multi-objective optimization; NSGAII

1. Introduction

Nowadays, energy plays an important key role on our society, where energetic necessities, are highly associated with issues such the growth of population, the economic development and the progress of technology [1].

Despite the technology progress, the energy demand has risen in the last years, especially regarding the last decade, threatening therefore, the last commitments made on behalf of the reduction of greenhouse gas emissions (GEE) in the atmosphere, given the high dependency of the electrical energy production, in the use of fossil fuels [2].

According to [3,4] and more recently [5] the reduction of energy consumption is necessary to get sustainability, with buildings accounting 40 percent (approx.) of the final energy consumed [6].

From that percentage, the residential sector, represents about 14% of the final world's electric energy consumed [7], representing thus an important sector to improve energy efficiency, by achieving sustainable solutions/measures.

Recently, there were made some energy efficiency improvements regarding electrical household appliances, not only in the European region, but in other regions around the world, such as Asia, America and Africa [8]. One of such measures is mandatory labeling [8–10], which provides relevant information to the consumer, related to each electrical appliance (e.g., noise (air conditioner), energy consumption, cloth capacity (washing machine), etc.), promoting therefore a suitable use, adjusted to its needs [11].

However, and given the several options available in the market (brands and models) as well as an appliance's own features, it is difficult to analyze their benefit–cost ratio and, therefore, which solution is better to the consumer [12–16].

In this sense, multiple-attribute value theory (MAVT), could be used as a method, to define the space decision and both objective functions.

Furthermore, the use of optimization techniques, combined with MAVT, can support the decision-agent (consumer), by achieving sustainable solutions, through the household appliances to be acquired.

Given the previous work from [17], evolutionary algorithms (EA), more specifically genetic algorithms, have been successfully applied to solve optimization problems with less time than other algorithms, given their stochastic nature and global search ability [18–23].

Therefore, this work aims to contribute with an integrated approach, based on MAVT and Non-Dominated Sorting Genetic Algorithm II (NSGAII), by providing the consumer with sustainable solutions from the market, considering its different needs.

2. Literature Review and Contribution

2.1. Literature Review

Methods like simulation (e.g., [24]), based on what if analysis, are commonly employed to simulate a limited set of options.

Some approaches, however, are mainly economical, allowing consumers therefore to obtain the highest energy savings, for the same initial investment (e.g., [24,25]). Other approaches explore issues such as benefit-cost analysis, initial investment costs, GEE emission savings, among others, regarding retrofitting measures (e.g., [26]), where some of them are even combined with technologies too (e.g., [25]).

Although, these approaches are considered limited, since they don't account other important factors (e.g., environment, labelling, legal, social, among others) to find solutions, that are suitable to the occupant's needs. They also don't consider the criteria related to each electrical appliance, exist on market, which varies according to the number of household occupants.

Nowadays, some works have developed multi-criteria decision-making (MCDM) models to support decision-agents to solve problems regarding building's retrofits, by considering energy efficiency and building's internal comfort (e.g., [22]), although others, were performed through the ranking of diferent options (e.g., [23]).

In the same context, there are also other MCDM models, as well as multiple-attribute value theory (MAVT) methods found in the literature that joins optimization with multicriteria methods to obtain feasible solutions through a set of measures/solutions, chosen according to a set of criteria (e.g., [24–26]).

Although, such methods don't take into consideration the different criteria related to each electrical appliance, existed on the market, suitable to the occupants' needs.

Metaheuristics have been also considered to solve energy problems as method to provide a set of feasible solutions, such as particle swarm optimization (PSO) (e.g., [15]) as well as genetic algorithms (GA's) (e.g., [19]), among others.

However, none of these methods have been integrated into a combined approach that allows selection of sustainable appliances by a decision-agent, according to a set of criteria.

2.2. Contribution

The literature, discussed above, shows one gap, regarding the retrofit measures for buildings, that allows to support a household consumer to choose a set of sustainable solutions (electrical appliances) from the market.

To fill the gap discussed before in the literature, this paper presents a decision support method, which allows the decision agent to be provided with a set of household appliances, existed in the market, by considering each energy service to be acquired.

The obtained solutions allow promotion of sustainability by acting on its tree dimensions, i.e., economical (e.g., consumption savings, savings regarding initial investment costs), environmental (GEE emissions and water consumption savings), and social. The approach includes economical (e.g., budget restrictions) as well as environment (e.g., noise) restrictions, regarding each energy service considered in the case study.

3. Materials and Methods

3.1. Problem Statement

This problem will take into account a household consumer, that wants to buy from the market, a set of household appliances. In this case, it was considered that seven different energy services were to be acquired; lighting, air conditioner, washing machine, dish washing machine, electric oven, dryer machine and refrigerator.

The DA has a limit budget to perform such decision (2100 € in the case study), and he wants to achieve a set of sustainable solutions, not only good from the social point of view (by pre-selecting the appliances according to its needs), but a set of solutions that allows them to achieve a good compromise between its economic and environment concerns, which are expressed as a set of two relative importance factors (weights), respectively ω_A (economics) and ω_B (environment). In this case, it was considered (respectively) 0.7 and 0.3.

The building has four occupants (decision-agent included). Given his intention into acquire an air conditioner (and based on the well-known room area to be climatized), the corresponding heating and cooling needs were calculated. Such value, as well as the remain criteria to pre-select the appliances from the market, regarding the number of 4 occupants, is presented on Table 1.

Table 1. Criteria used to pre-select the appliances from the market (applied to case study).

Electrical Appliance	Criteria Used	Characteristics
Air conditioner	types of air conditioner considered: heated/cooled zone minimum capacity required	wall (mono split) wall (multi split) Portableliving room 9905.6 BTU
Washing machine	Capacity according to the number of household's occupants [9]	7 kg
Dishwasher	load capacity.	12 cutlery
Oven	volume, based on the nr. of occupants [9]	47 cm × 68 cm
Dryer machine	type of dryer machines load capacity from [9]	by exhaust 7 kg
Lighting	technology	halogen Compact Fluorescent Light (CFL) Fluorescent
Refrigerator	capacity of the refrigerators [9] type of refrigerator according to the number of occupants [9]	150 L refrigerator Combined type

The remaining assumptions are shown on Tables 2 and 3, as well as the correspondent consumption profile (Table 3).

Table 2. Tariffs used and other assumptions considered.

Emission Factor [gCO_2/kWh]	675	Discount Factor [%]	7
Life cycle (usage phase) [years]:	10	Annual Factor	7.02
Electrical Energy tariff [€/kWh]	0.162	Water tariff [€/m^3]	1.19

Table 3. Consumer usage profile (considered).

Emission Factor [gCO_2/kWh]	675	Discount Factor [%]		7
Life cycle (usage phase) [years]:	10	Annual Factor		7.02
Electrical Energy tariff [€/kWh]	0.162	Water tariff [€/m^3]		1.19
Energy Service	Usage Profile (h)			
	Daily	Weekly	Monthly	Annual
Air Conditioner	2	12	48	576
Washing Machine	1	4	16	192
Dryer Machine	1	4	16	192
Refrigerator	11	77	330	4015
Electric Oven	1	2	8	96
Dish Washing Machine	1	4	16	192
Lighting	5	35	150	1825
Energy Service	Usage Profile (Frequency)			
	Daily	Weekly	Monthly	Annual
Air Conditioner	1	6	24	288
Washing Machine	1	4	16	192
Dryer Machine	1	4	16	192
Refrigerator	1	7	30	365
Electric Oven	1	2	8	96
Dish Washing Machine	1	4	16	192
Lighting	1	7	30	365

The consumption profile was performed, by making a set of assumptions based on the hours, which was then extrapolated to a weekly and year base. However, the decision-agent (consumer) can also define its usage profile, according to its needs, or by using the profile, presented here, as a default.

The data, from Table 3, will be adopted to perform a life cycle cost analysis (LCCA), considering each individual solution, as will be described in the next section.

3.2. Data Set

Additionally to the data referred to before, regarding the criteria used (Table 1) and consumer usage profile (Table 2), data regarding the electricity consumption were considered, according to the consumer usage profile assumed in Table 2, i.e., on an hourly, daily, monthly and yearly basis, even then extrapolated for the lifecycle considered in this case study (10 years), performing a LCCA, regarding each appliance from each energy service, during the usage phase (Annex I).

Data regarding the initial investment, as well as the criteria referred above and the remain data (brand and model) regarding each appliance, was also considered (Annex I).

3.3. Proposed Approach

The approach presented here, was developed to support a DA who wants to buy a set of household appliances existed on market.

This set of appliances, regarding each energy service, are potential solutions, provided by the proposed approach, presented on Figure 1.

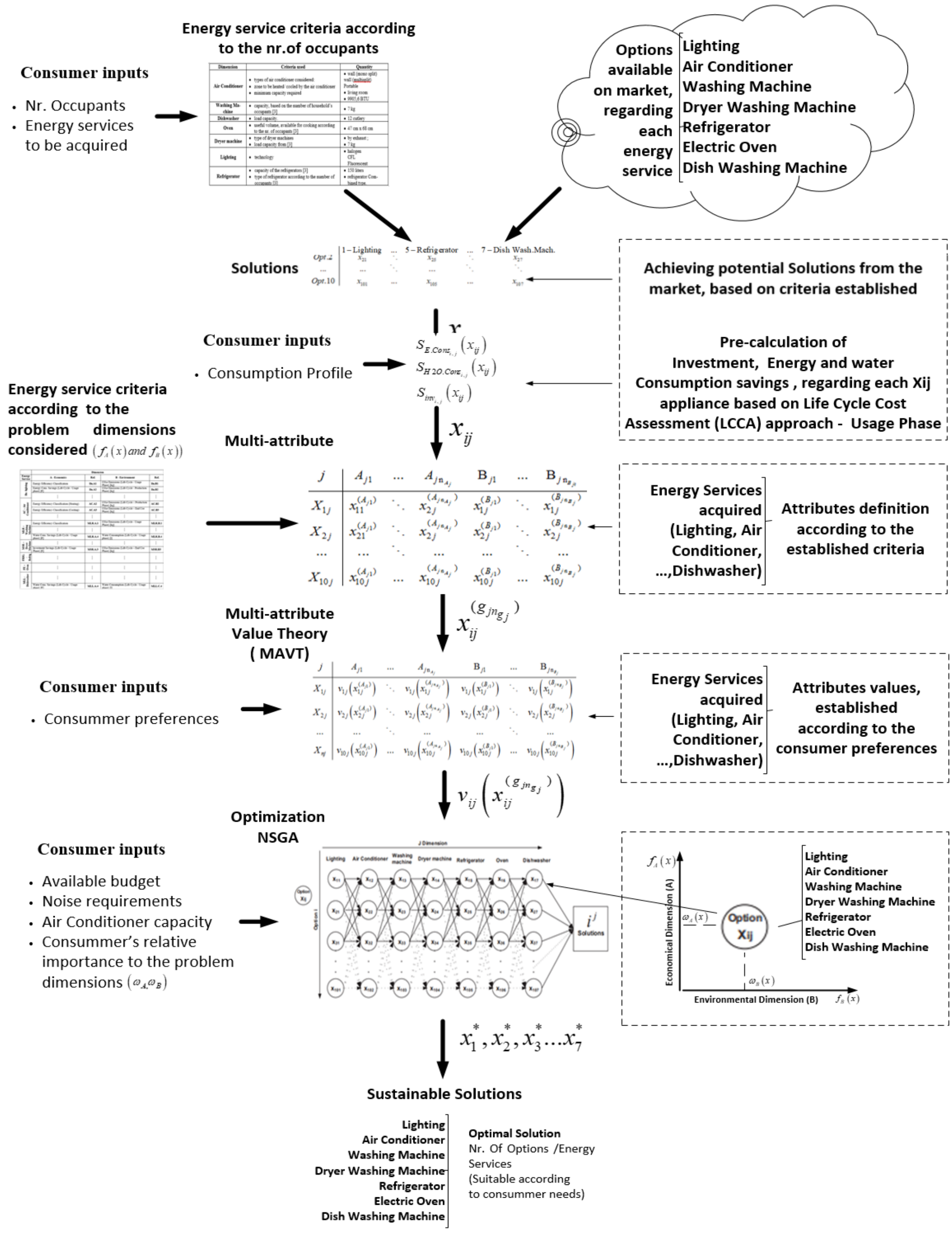

Figure 1. Model proposed.

At first, a set of potential solutions (x_{ij}) are pre-selected from the market, according to specific criteria, according to building occupants. The criteria are the same, although the value of the correspondent attributes can change according to the building number of occupants. An example of such a table is presented in Table 1 regarding the case study presented here.

This pre-selection allows to reduce the decision space, accounting only the solutions, suitable to the consumer needs, as well as to increase NSGAII efficiency, by achieving optimal solutions with less time.

Each one of these potential solutions (x_{ij}), is then formulated as an option i, regarding energy service j, to be acquired by the DA (consumer) from the market.

Given a DA consumption profile (e.g., Table 2), LCCA is then preformed to achieve, for each appliance, the corresponding savings, regarding energy consumption ($S_{E.Cons_{i,j}}(x_{ij})$), water consumption ($S_{H2O.Cons_{i,j}}(x_{ij})$) as well as the initial investment ($S_{inv_{i,j}}(x_{ij})$). Both parameters, are savings, obtained from the comparison between the efficient and the correspondent "standard solution" (less efficient one).

Given the diversity of features, regarding each solution, as well as the DA's economic, social and environmental concerns, a set of attributes was defined according to the consumer preferences and regarding each energy service, for the two problem dimensions considered; A-Economics, B-Environment. These attributes are presented on Table 4.

Table 4. Attributes used to define problem dimensions, regarding each energy service considered.

Energy Service	Dimension			
	A-Economics	**Ref.**	**B-Environment**	**Ref.**
Ilu—lighting	Energy Efficiency Classification	Ilu.A1	CO_2e Emissions (Life Cycle—Usage Phase) [kg]	Ilu.B1
	Energy Cons. Savings (Life Cycle—Usage phase) [€]	Ilu.A2	CO_2e Emissions (Life Cycle—Production Phase) [kg]	Ilu.B2
	⋮	⋮	⋮	⋮
AC—Air Conditioner	Energy Efficiency Classification (Heating)	AC.A2	CO_2e Emissions (Life Cycle—Production Phase) [kg]	AC.B2
	Energy Efficiency Classification (Cooling)	AC.A3	CO_2e Emissions (Life Cycle—End Use Phase) [kg]	AC.B3
	⋮	⋮	⋮	⋮
MLR—Washing Machine	Energy Efficiency Classification	MLR.A.1	CO_2e Emissions (Life Cycle—Usage Phase) [kg]	MLR.B.1
	⋮	⋮	⋮	⋮
	Water Cons. Savings (Life Cycle—Usage phase) [€]	MLR.A.4	Water Consumption (Life Cycle—Usage phase) [3]	MLR.B.4
MSR—Dryer Machine	⋮	⋮	⋮	⋮
	Investment Savings (Life Cycle—Usage Phase) [€]	MSR.A.3	CO_2e Emissions (Life Cycle—End Use Phase) [kg]	MSR.B3
FRIG.—Refrigerator	⋮	⋮	⋮	⋮
FE—Oven	⋮	⋮	⋮	⋮
MLL—Dishwasher	⋮	⋮	⋮	⋮
	Water Cons. Savings (Life Cycle—Usage phase) [€]	MLL.A.4	Water Consumption (Life Cycle—Usage phase) [3]	MLL.C.4

Apart from the energy efficiency classification (Table 4), regarding each energy label, belonging to each energy service, all the adopted attributes can be applied into other regions. In this case, the EU's Energy Labelling framework Regulation (2017/1369) was adopted, although, and with the correspondent adjustments referred before, it can be applied in other world regions.

The consumption profile was performed, by making a set of assumptions based on the hours, which was then extrapolated to a weekly and year base. However, the decision-agent (consumer) can also define its usage profile according to its needs, or by using the profile, considered in the case study presented here, as a default.

As referred to before, MAVT is used to support the DA, by evaluating a set of alternative solutions, according to a set of criteria/attributes established (Table 1).

Based on criteria from Table 1, it was defined $x_{ij}^{(g_{jt})}$, as the attribute regarding each alternative solution i, associated to a certain energy service j, stablished according to criteria t, associated to energy service j and problem dimension g considered (A-Economical; B-Environmental), i.e.,

$$g_{jt} \in \left\{ \left\{ A_{j1}, A_{j2}, ..A_{jn_{A_j}} \right\} \cup \left\{ B_{j1}, B_{j2}, ..B_{jn_{B_j}} \right\} \right\} \tag{1}$$

with:

$$g = \{A\,, B\} \wedge j = \{1,\ 2, .., 7\} \wedge t = \left\{ \left\{ 1,\ 2, ..n_{A_j} \right\} \cup \left\{ 1,\ 2, ..n_{B_j} \right\} \right\} \wedge n_{A_j}, n_{B_j}, \mathrm{t}, j \in \mathbb{N} \tag{2}$$

By following the notation described above and based on criteria established in Table 1, as well as the assumptions presented on Tables 2 and 3 for the considered case study, the correspondent attribute $\left(x_{ij}^{(g_{jt})} \right)$ behavior/pay-off was defined, regarding each option i, belonging to energy service j. On Figure 2a), an example of this table, regarding the energy service "Lighting", is presented.

Lighting	$A.1_{.1}$	...	$A.n_{.1}$	$B.1_{.1}$	...	$B.n_{.1}$
X_{11}	$x_{11}^{(A.1.)}$	$\ddots$	$x_{1n_1}^{(A.n_{A1}.)}$	$x_{11}^{(B.1)}$	$\ddots$	$x_{11}^{(B.n_{B1})}$
X_{21}	$x_{21}^{(A.1.)}$	$\ddots$	$x_{1n_1}^{(A.n_{A1}.)}$	$x_{21}^{(B.1)}$	$\ddots$	$x_{21}^{(B.n_{B1})}$
...	...	$\ddots$	...	...	$\ddots$	...
X_{101}	$x_{101}^{(A.1.)}$	...	$x_{1n_1}^{(A.n_{A1}.)}$	$x_{101}^{(B.1)}$	...	$x_{101}^{(B._{B1})}$

(**a**)

Lighting	$A.1_{.1}$	...	$A.n_{.1}$	$B.1_{.1}$	...	$B.n_{.1}$
X_{11}	$v_{11}\left(x_{11}^{(A.1.)}\right)$	$\ddots$	$v_{11}\left(x_{1n_1}^{(A.n_{A1}.)}\right)$	$v_{11}\left(x_{11}^{(B.1)}\right)$	$\ddots$	$v_{11}\left(x_{11}^{(B.n_{B1})}\right)$
X_{21}	$v_{21}\left(x_{21}^{(A.1.)}\right)$	$\ddots$	$v_{21}\left(x_{2n_1}^{(A.n_{A1}.)}\right)$	$v_{21}\left(x_{21}^{(B.1)}\right)$	$\ddots$	$v_{21}\left(x_{21}^{(B.n_{B1})}\right)$
...	...	$\ddots$	...	...	$\ddots$	...
X_{101}	$v_{101}\left(x_{101}^{(A.1.)}\right)$	...	$v_{101}\left(x_{101}^{(A.n_{A1}.)}\right)$	$v_{101}\left(x_{101}^{(B.1)}\right)$	...	$v_{101}\left(x_{101}^{(B.n_{B1})}\right)$

(**b**)

Figure 2. Example of evaluation table (lighting energy service)): (**a**) $x_j^{(g_{jt})}$; (**b**) $v_{ij}\left(x_j^{(g_{jt})}\right)$.

Therefore, and according to MAVT, there is a value $v_{ij}^{(g_{jt})}\left(x_{ij}^{(g_{jt})}\right)$, associated to the attribute $x_{ij}^{(g_{jt})}$, such as:

$$x_{ij}^{(g_{jt})} \longrightarrow v_{ij}^{(g_{jt})}(x_{ij}^{(g_{jt})}) \tag{3}$$

Given the 2 objectives considered, different attributes are used to define the performance regarding the set of objectives defined.

Therefore, in order to transform the criteria to follow the same scale and units, an expression was used to establish the relationship between the new and the previous value of $x_{ij}^{(g_{jt})}$, respectively $\left(v_{ij}^{(2)}\left(x_{ij}^{(g_{jt})}\right)\right)$ and $\left(v_{ij}^{(1)}\left(x_{ij}^{(g_{jt})}\right)\right)$, by using also the corresponding worst and better results, for a given criteria g_{jt}, i.e.,

$$v_{ij}(x_{ij}^{(2)}) = \frac{\left(v_{ij}^{(1)}(x_{ij}^{(g_{jt})}) - v_{worst.ij}(x_{ij}^{(g_{jt})})\right)}{\left(v_{\mathrm{better}.ij}(x_{ij}^{(g_{jt})}) - v_{worst.ij}(x_{ij}^{(g_{jt})})\right)} \tag{4}$$

The new values of each $x_{ij}^{(g_{jt})}$ $\left(v_{ij}\left(x_{ij}^{(g_{jt})}\right)\right)$, fills a new evaluation table, belonging to each energy service j. On Figure 2b), it's shown an example for a table regarding energy service "Lighting".

Based on the value attributes, previously achieved, it was used the additive model to aggregate them, referred to each option i, regarding energy service j, which was further improved, by applying optimization techniques, by using NSGAII algorithm.

The consumer will face a problem of the type of a combinatorial (Figure 1), where the number of combinations is dependent on the number of individual solutions to be considered, related to each energy service (23 million combinations in the case study considered here). This number of combinations can be reduced by assuming that the consumer cannot perform any choices (x_{ij}), given his limited budget (Figure 1).

Constraints like the air conditioner capacity and appliances noise maximal requirements will also be accounted for to suit consumer needs in order to improve its social wellbeing.

After defining the value attributes of each potential solution, and by using the additive model, the problem presented here can be formulated as follows:

$$\begin{array}{ll} \max \quad V_m(x), & c/\ m = A, B \\ subject\ to\ x \in X & c/V_m(x) = [V_A(x), V_B(x)]^T \end{array} \quad (5)$$

where x is the decision variable vector, defined as:

$$x \in \mathrm{X} : x \in \left\{ x_{ij}^{(A_{jt})}, x_{ij}^{(B_{jt})} \right\} \wedge \mathrm{t}, \mathrm{i}, j \in \mathbb{N} \quad (6)$$

with,

$$j = \{1, \ldots, 10\} \wedge j = \{1,\ 2, \ldots, 7\} \wedge t = \left\{ \left\{1, \ldots, n_{A_j}\right\} \cup \left\{1, \ldots, n_{B_j}\right\} \right\} \wedge n_{A_j}, n_{B_j} \in \mathbb{N} \quad (7)$$

where $V_A(x)$ and $V_B(x)$, are the aggregate objective functions, regarding each dimension considered (A-Economics; B-Environment):

$$V_g(x) = \sum_{j=1}^{n_j} \sum_{t=1}^{n_{g_j}} v_j(x_j^{(g_{jt})})\ w/g = \{A\ , B\} \wedge v_j(x_j^{(g_{jt})}) \wedge n_j, n_{g_j}, \mathrm{t}, j \in \mathbb{N} \quad (8)$$

Therefore, and based on (8), the objective functions are:

$$Economic\ Well-being : \max V_A(x) = \sum_{j=1}^{n_j} \sum_{t=1}^{n_{A_j}} v_j(x_j^{(A_{jt})}) \quad (9)$$

$$Environment\ Well-being : \max V_B(x) = \sum_{j=1}^{n_j} \sum_{t=1}^{n_{B_j}} v_j(x_j^{(\mathrm{B}_{jt})}) \quad (10)$$

The first objective function is based on the work of [20].

By using the additive model from MAVT, the aggregated function results in a unique objective function, weighted by the decision-agent relative importance (ω_g) as follows:

$$V(V_A(x), V_B(x)) = \omega_A.V_A(x) + \omega_B.V_B(x) = \sum_{j=1}^{n_j} \left(\omega_A \sum_{t=1}^{n_{A_j}} v_j(x_j^{(A_{jt})})\ + \omega_B \sum_{t=1}^{n_{B_j}} v_j(x_j^{(\mathrm{B}_{jt})}) \right) \quad (11)$$

The constraints, regarding economic and environment well-being/dimensions, are:

Economic–Budget:

$$r_1 : \sum_{j=1}^{n_{\dim}} I_j(x_j) \leq\ available\ budget\ (\eta_{disp.}) \Leftrightarrow \sum_{j=1}^{n_{\dim}} x_j^{(A_{jt})}\ \leq\ \eta_{disp.} \quad (12)$$

with

$$A_{jt} = \{A_{14}\ , A_{26}, A_{35}, A_{44}, A_{54}, A_{64}, A_{75}\} \wedge n_{\dim}, \mathrm{t}, j \in \mathbb{N} \quad (13)$$

Environment–Noise:

$$r_j : Noise_j \leq Max.Noise_j \Leftrightarrow x_j^{(B_{jt})} \leq Max.Noise_j \quad (14)$$

With:

$$B_{jt} = \{B_{24}\ , B_{35}, B_{44}, B_{54}, B_{64}, B_{75}\} \wedge n_{\dim}, \mathrm{t}, j \in \mathbb{N} \tag{15}$$

The NSGAII individual framework, is presented as follows on Figure 4.

As referred to before, NSGAII's codification used was real so that it can only be chosen in one individual solution, regarding each type of appliance at the time.

The model will be applied, using the case study presented before, and by considering a consumer (DA), who wants to buy seven energy services.

3.4. Strengths and Weakness of the Presented Model

The presented approach deals with the LCCA concept by predicting, according to a given consumption profile, the costs associated with the usage phase, corresponding to each electrical appliance (energy service) to be considered. The consumer's needs (e.g., cloth dryer machine, fridge and air conditioner capacities, among others) are also considered, to provide the decision-agent with more suitable appliances existing in the market.

Besides the Environment dimension, the preferences regarding the consumer's relative importance corresponding to each dimension (Environment and Economics) are also considered in this work.

Given its advantages in getting several optimal (sustainable) and different solutions, the approach presented here allows use to prevent an eventual unavailability of a specific appliance.

The social dimension, although implicit through consumer preferences and needs, needs to be more explicit, which will be one of the improvements of this work.

The LCCA only accounts the usage phase in this work. Therefore, further developments will be included in future, given this issue.

3.5. Non-Dominated Sorting Genetic Algorithm II (NSGAII)

Given GA's successful in guaranteeing optimal solutions, as well as its advantages faced other methods [27], we decided to use it in this study.

Therefore, the approach proposed here, will use the NSGAII as an optimization method to deal with the potential solutions, resulting from the multicriteria analysis.

In general, NSGAII presents good performance on optimizing two objective functions, with efficiency, by making use of two approaches; a non-domination rank and crowding distance. The first one allows to reduce the time of computation, while the second one, guides in the selection process [28].

In a maximization problem (for both objective functions), if a fitness value of solution j is more than the correspondent one from solution i, then solution j dominates solution i, with j having a better ranking.

When both solutions, have the same rank, the solution placed in the region with less crowd, is selected [28] (Figure 3). We used NSGAII in our study, to create diverse solutions for the two objectives considered.

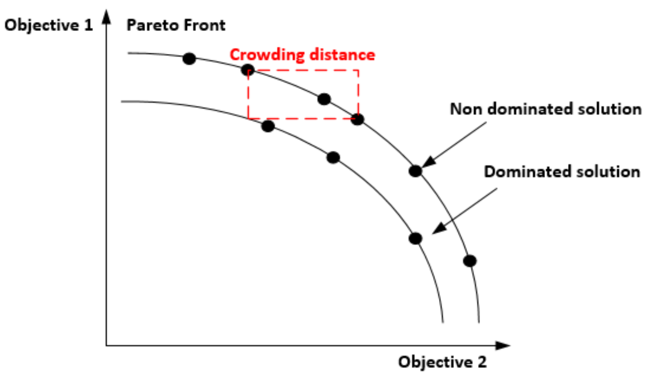

Figure 3. Crowding distance and non-dominated solutions.

As it was referred before, NSGAII's codification used, was real, so it can only be chosen as one individual solution, regarding each type of appliance at the time.

The NSGAII individual framework is presented as follows in Figure 4:

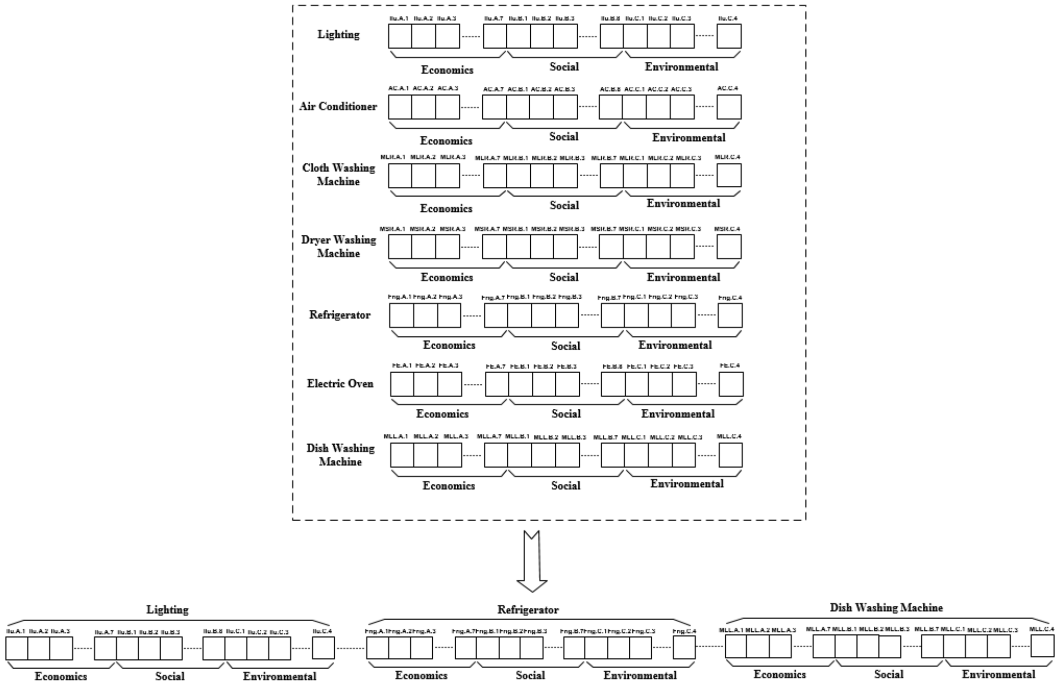

Figure 4. GA's individual framework.

The GA's iteration process, applied here, makes use of several steps, which includes initialization, crossover, and selection (Figure 5). Parameters like the population size, iteration size, and crossover rate, were determined experimentally.

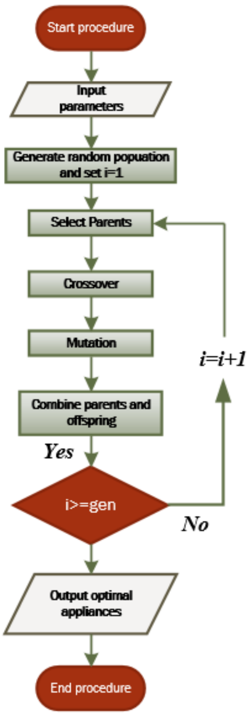

Figure 5. Non-dominated sorting genetic algorithm II (NSGAII) individual framework.

Initialize population

The first generation is formed by the randomized generation of a number *n* of individuals, which is called the population size. In this work, each solution carries the information of a potential aggregated solution formed by a set of appliances desired by the DA.

Evaluate fitness

The fitness function allows us to perform a continuous evolutionary search by NSGAII, with the fitness values of each individual solution, being calculated and evaluated.

Each individual is then ranked, selected and determined.

Selection, crossover and mutation

The next generation is achieved by the selection, crossover and mutation operators. Individuals are randomly selected by Tournament into a group, where the best ones, are selected for crossover [17]. Therefore, it's introduced by this operator, the randomness and certainty characteristics.

The best solutions/individuals are selected from the parents and offspring. The last one, is obtained through the individuals generated from the crossover and mutation operators. The iteration process finishes, after the maximum iteration is satisfied, by finding the correspondent Pareto frontier.

4. Results and Discussion

NSGAII was implemented by using Matlab code, by considering the following parameters:

- Selection method: tournament
- Crossover method: single point
- Mutation used: normal random mutation

The remaining NSGA-II parameters (initial population, crossover and mutation rate) were defined after several runs.

The max generations parameter was tested at first, where it was selected a maximum generation number of 90 to show that if 90 iterations were enough to find the Pareto curve. Other parameters were also tested, such as the population size (100 individuals), the tournament size (10), the crossover rate (0.9), and the mutation rate (0.3). The results obtained, regarding the 90th and 100th generations, are presented on Figure 6, where it can be seen that both cases have a similar Pareto frontier. In this sense the max number of iterations/generations of 90 were selected. Then, several combinations of crossover and mutation rates of NSGA-II were performed (Table 5).

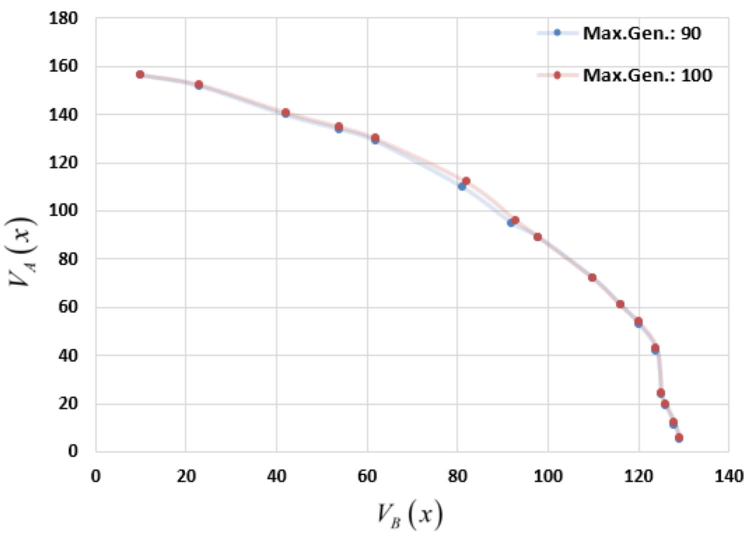

Figure 6. Pareto frontier for 90th and 100th generations.

Table 5. Combinations of crossover and mutation rates used.

Experiment	Crossover Rate	Mutation Rate
1	0.8	0.1
2	0.8	0.3
3	0.9	0.1
4	0.9	0.3

The combinations, presented on Table 4, were performed by setting a max iteration of 90. The correspondent results are shown on Figure 7, where it's noted that the small change on parameters, has a reduced effect in the results. Thus, NSGAII's parameters were used to show the results of the present case: population size (100), max iteration (90), tournament size (10), crossover rate (0.9) and mutation rate (0,1).

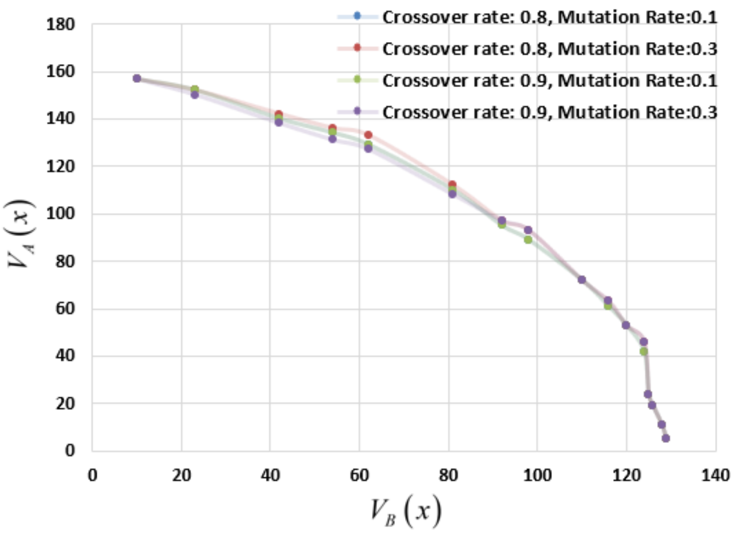

Figure 7. Pareto frontier for different parameters of NSGAII.

NSGA-II is applied on resolution of multi-objective problems. Therefore, the correspondent solution, is a Pareto frontier, which is gradually formed through an iteration process, where is an increase in the number of solutions of Pareto frontier in the first generations. Once the frontier was formed, improved results regarding each solution were founded in further generations (Figure 8).

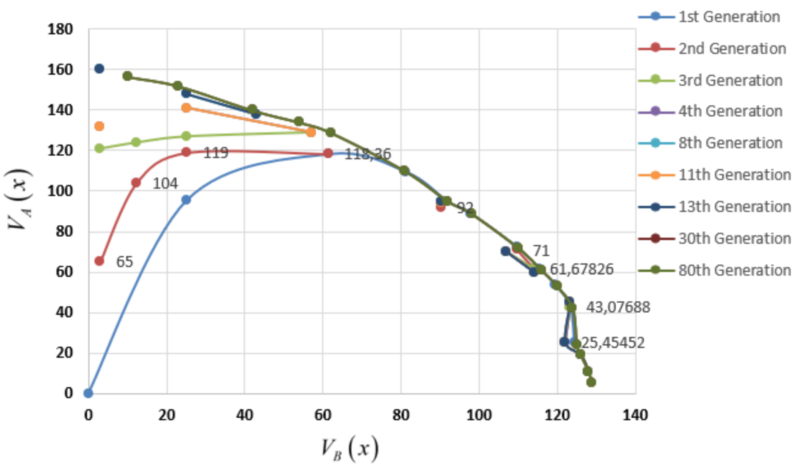

Figure 8. Pareto frontier for different generations of the selected parameters.

After NSGAII calculations, the Pareto frontier in Figure 9 is thereby obtained, where each node represents a potential solution of the problem, i.e., a set of sustainable solutions (appliances) regarding each energy service required.

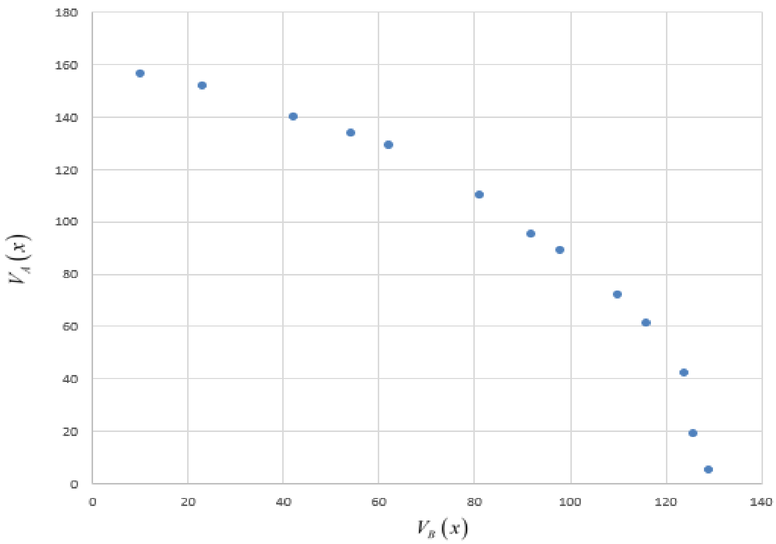

Figure 9. Pareto frontier of the last generation.

Although the economic well-being decreases, the environmental well-being increases here.

One of these nodes are presented on Table 3, as an example of a feasible solution obtained, considering a budget of 2100 €.

Thirteen potential solutions were selected regarding the last generation by the algorithm, as an example of a Pareto frontier.

One of these nodes are presented in Table 6, as an example of a feasible solution, considering a budget of 2100 € and a life cycle (usage phase) of 10 years.

Table 6. Example of a sustainable solution obtained.

Electrical Appliance	Stand. Solution Total Invest. (€)	Effic. sol. Total Invest (€)	Invest. Saving (€)	Energy Consum. Savings (€)	Water Consum. Savings (l)	CO_2 Savings (kg)	Brand	Model
Lighting	15.89	09.53	5.34	59.40	-	28.90	GE	EFL23W
Air Conditioning	368.00	299.00	69.00	1320.60	-	1315.70	Whirlpool	PACW9HP
Refrigerator	250.00	529.00	−279.00	708.10	-	8.70	Candy	CFET 6182W
Dishwasher Machine	310.00	349.00	−39.00	3.20	423.00	6.90	Bosch	SMS25AI00E
Washing Machine	262.00	294.00	−32.00	6.90	317.00	94.80	Siemens	WI12A222ES
Oven	170.00	199.00	−29.00	1.70	-	2.20	Zanussi	ZZB21601XV
Clothes dryer	349.00	419.00	−70.0	12.30	-	1.70	Electrolux	EDP2074PDW
Total	1724.90	2099.60	−374.70	2112.30	740.00	1458.90	-	-

The CO_2 savings are also presented, compared with the less efficient one (standard solution).

Based on Table 6, if the consumer opts for the solutions set provided by this approach, he can save up to 2112.3 €, further contributing to a 1458.9 kg of CO_2 and 740 L of water, both savings/years, based on the life cycle considered.

5. Conclusions and Further Work

In this paper, an approach to provide sustainable electrical household appliances from the market to the decision-agent (consumer) was presented, considering two problem dimensions (objectives), regarding sustainability; environment and economic well-being.

Both solutions were pre-selected, based on a set of specific criteria, related to each type of appliance, considered by the case study.

Criteria were used to pre-select the appliances from the market adjusting therefore, the method to the case study presented here.

Other criteria were also used combined with MAVT to model the consumer preferences, according to the two problem dimensions presented here.

The main objective was to maximize consumer well-being (environment and economics). Social wellbeing was also promoted, by suit the obtained solutions to the consumer needs.

The relative importance, given by the DA (consumer), was also considered, in order to weight the DA decision through both dimensions.

NSGAII were then applied here to obtain optimal solutions by maximizing both dimensions, considering the environmental impact (CO_2 and water savings), as well as the economic rationality (initial investment and energy consumption savings) regarding the lifecycle of each appliance, during its usage phase.

The results show that this method provides alternative (and sustainable) appliances that attend the consumer's needs.

We test different parameters (max number of iterations, crossover and mutation rates) and their correspondent values, are not quite sensitive to the results. Additionally, NSGAII can also find the Pareto frontier of the solutions, providing therefore several alternative solutions to the consumer.

The achievements presented on this work, allows to proceed in a way of getting a more completed approach that maximizes all the dimensions of sustainability: economical, environmental and social.

Therefore, the social dimension, although implicit through consumer preferences and needs, will more explicit, by being expressed through a third dimension to be included in the model.

As referred to before, the LCCA only accounts the usage phase in this work, bringing up the need to include the remaining LCCA phases (Production and Final Disposal) as further developments to be considered in this work.

As referred to in Section 1, there are several regions around the world, where energy efficiency measures have been applied.

Therefore, and based on what was referred to in Section 3, apart from energy efficiency classification, all the adopted attributes can be applied into other regions. In this work, it was adopted the EU's Energy Labelling framework Regulation (2017/1369) for energy efficiency classification, although, and with the correspondent adjustments referred before, it can be applied into other world's regions, adjusted to each consumer's individual needs, as referred to above.

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