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Abstract: Sustainable processes have recently awaked an increasing interest in the process systems engineering literature. In industry, this kind of problems inevitably required a multi-objective analysis to evaluate the environmental impact in addition to the economic performance. Bio-based processes have the potential to enhance the sustainability level of the energy sector. Nevertheless, such processes very often show variable conditions and present an uncertain behavior. The approaches presented for solving multi-objective problems under uncertainty have neglected the potential effects of different quality streams on the overall system. Here, it is presented an alternative approach based on a State Task Network formulation capable of optimizing under uncertain conditions, considering multiple selection criteria and accounting for the material quality effect. The resulting set of Pareto solutions are then assessed using the Elimination and Choice Expressing Reality-IV method, which identify the ones showing better overall performance considering the uncertain parameters space.

Cover letter

Departament d'Enginyeria Química

UNIVERSITAT POLITÈCNICA DE CATALUNYA

Barcelona, January 25th 2017

Prof. Dr. Mohamed Al Nimr
Editor in Chief
Energy Conversion and Management

Dear Editor,

Please consider the revised version of the manuscript entitled "Systematic Approach for the design of sustainable Supply Chains under quality uncertainty" that we are re-submitting for its eventual publication in the SDEWES2016 special issue of Energy Conversion and Management (EC&M) as a research paper. The paper proposes a novel strategy for the sustainable coordination of multi-scenario supply chain (SC) problem subjected to an uncertain biomass quality and using multiple criteria as a decision tool. We have taken into account all suggestions / comments received from the Editors and reviewers, in a separate file, which have contributed substantially to the paper improvement, thus we believe that now it is ready for publication.

We believe that the paper is appropriate for EC&M because it addresses the optimization of energy SCs. Using the proposed strategy, it is possible to manage multiple quality biomass streams in order to increase/ensure the sustainability of the process through the use of biomass as alternative energy source. These relevant issues perfectly fit within the scope of the journal. So we are confident that the paper meets the expectations of EC&M and wish it can be considered for its publication.

Cordially yours,

Prof. Luis Puigjaner
Corresponding author

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Highlights

- This methodology allows taking profit of the uneven biomass quality in the management of energy Supply Chains.
- The proposed strategy allows the solution selection considering multiple decision criteria.
- The proposed strategy facilitates decision-making avoiding subjectivity in the solution selection.
- The resulting base model is generic and the strategy is flexible enough to be implemented in other real cases.

*Revised Manuscript with no changes marked
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Systematic Approach for the design of sustainable Supply Chains under quality uncertainty

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ABSTRACT.

Sustainable processes have recently awaked an increasing interest in the process systems engineering literature. In industry, this kind of problems inevitably required a multi-objective analysis to evaluate the environmental impact in addition to the economic performance. Bio-based processes have the potential to enhance the sustainability level of the energy sector. Nevertheless, such processes very often show variable conditions and present an uncertain behavior. The approaches presented for solving multi-objective problems under uncertainty have neglected the potential effects of different quality streams on the overall system. Here, it is presented an alternative approach based on a State Task Network formulation capable of optimizing under uncertain conditions, considering multiple selection criteria and accounting for the material quality effect. The resulting set of Pareto solutions are then assessed using the Elimination and Choice Expressing Reality-IV method, which identify the ones showing better overall performance considering the uncertain parameters space.

Keywords: Uncertainty, State Task Network, Sample Average Approximation, Sustainability, quality, Industrial symbiosis.

1. Introduction

During the last decade, industrial globalization have been continuously changing the business behavior, thus making it difficult to remain competitive in the global market for current processes/industries [1]. Additionally, the increasing government pressure on designing green processes has led to the need for developing more sophisticated strategies to design and manage industrial processes. The above jointly with the recent improvements in environmental analysis techniques has stimulated the emergence of sustainability strategies in process systems engineering (PSE) literature [2]. Here, one major challenge concerns how to combine multi-objective (MO) [3] approaches (maximize economic performance while minimizing environmental impacts) with uncertainty strategies for a reliable/quick response against unpredictable situations (including demands, prices, availability and quality uncertainties) [4].

Along these lines, industrial symbiosis (IS) appears as a promising strategy to bring together companies from different sectors in order to share resources (such as energy, materials and water) and provide stability to the markets [5]. The concept of IS covers multiple important gaps in the current PSE literature [6], since it attempts to enhance the process sustainability as well as the financial and social benefits for all the participants [7]. Nevertheless, in practice the application of IS strategies is a hard task to carry out, mainly due to the limited flow of information within industries, the lack of integration strategies, the complexity of synergy identification and the dynamic behavior associated to IS networks. In fact, several authors agree that in order to meet the highest sustainability standards, the synthesis and operation of robust industrial symbiosis systems should be improved in parallel with solution strategies for highly complex design and planning optimization problems [8]. Therefore, robust and flexible mathematical formulation should be developed to address IS problems using a PSE approach.

In the PSE literature, bio-based processes can be mentioned as one of the most representative example of IS, especially because of their structural and conceptual similarities. Actually, in the field of bio-based processes, multiple works can be found focusing on operating conditions, equipment units' efficiency, and raw material properties, among others. For example, Mikulandrić et al. [9] use an Artificial Neural Networks (ANN) method to predict the variability of the operational conditions (i.e., output temperatures) and model the dynamic behavior of a biomass gasification unit for its use in on-line applications. The above study uses a surrogate model which requires experimental training data. In parallel, Sepe et al. [10] combine traditional gasification techniques with a solar-assisted steam gasification unit in order to increase the quality of the resulting syngas stream (1.4 times more than the traditional value). Recently, Mirmoshtaghi et al. [11] study the impacts of different parameters on the gas quality and gasifiers performance for a biomass gasification unit. Even if those detailed studies increase the efficiency of the process, their improvements are constrained by the available infrastructure. In order to address such an issue, Liu et al. [12] optimize the production pathway of a biofuel supply chain (SC) evaluating the economic, energy and environmental performance applying simultaneously MO and environmental methods (ε-constraint and Life Cycle Assessment (LCA), respectively). In 2012, Gebreslassie [13] optimize the design of a bio-refinery supply chain under demand uncertainty and multiple objectives using decomposition strategies.

In addition to the mentioned works, other contributions ranging from a complete review on stochastic programming [14] to a study on stochastic applications for green supply chains [15] focus on improving MO models under uncertainty [16] in order to enhance the robustness of the final solution [17]. The main limitation here is the large CPU time associated with these strategies [18]. Furthermore, all those strategies disregard the flexibility of the model formulation limiting the management and evaluation of the flows (as function of their properties), which has an important impact on the operating efficiency [19]. In this line, Pérez-Fortes et al. [20] extended the State Task Network (STN) formulation, typically used in scheduling problems, in order to solve the design and planning problem of a regional bio-based energy SC. The formulation proposed by Pérez-Fortes [20] also considers multiple objectives, including economic, environmental and social performance in an attempt to increase the sustainability of the final solution while maintaining the model flexibility. This formulation was later extended by Laínez et al. [21] in which a decomposition algorithm is proposed in order to handle a large and complex model. This model evaluates the performance of a co-combustion process over the electricity distribution network of Spain, considering multiple biomass kinds (forest wood residues and agricultural woody residues) to partially substitute coal as main power resource. To the best of our knowledge, although there are methodologies to assist in the design of green processes, there is still a gap in the evaluation of the influence of the quality of the raw material on the process' performance which is attempted to be fulfilled in this work.

The proposed approach is based on a STN formulation under uncertainty. A bio-based energy production SC is used as a test bed case study in which different energy consumers and their respective SCs as well as their interactions will be studied. Multiple criteria shall be considered, including economic, environmental and social aspects, ensuring the robustness and sustainability of the solutions for all the participating actors. Given that locally available agro-industrial waste is used, it should be subject to uncertainty caused by climate variations. Thus, the impact on biomass availability across the time as well as the corresponding variability for the processes prior to the biomass collection will be considered in the model here presented [22]. Additionally, the combination of different raw material sources with varied qualities will be analyzed in order to evaluate their effects over the energy generation efficiency, thus making the final solution more realistic. To tackle the resulting model, a solution strategy, based on the Sample Average Approximation (SAA) algorithm, is used for optimization under uncertainty, in order to reduce the computational effort. Finally, the

ELimination and Choice Expressing REality (ELECTRE-IV) method will be used as multi-criteria decision-making tool in order to identify the solution that best reflects the decision-makers preferences.

2. Problem statement

This paper tackles the design and planning of a centralized multi-echelon bio-based energy production supply chain subject to raw material uncertainties. Here, two main actors will be considered (the supplier and the manufacturer). Both actors are considered in a single SC management problem, however the exchange of resources between them is allowed. More precisely, food industry will provide the raw material for energy production, while the power generation plant will meet the energy needs of the food industry. Uncertain behaviors in raw material availability and quality properties are addressed through a tailor-made approach. To illustrate the capabilities of the proposed approach, a conveniently modified version of the case study modelled by Pérez-Fortes et al. [20] is used. Additionally to the original process data (i.e. potential sites, material states, tasks, equipment's, etc.), a set of actors composed by suppliers $(\boldsymbol{e}|\boldsymbol{e}=\mathbf{1},\dots,\boldsymbol{E})$ which provide the biomass; the consumers $(\boldsymbol{m}|\boldsymbol{m}=\mathbf{1},\dots,\boldsymbol{M})$ as markets; and the manufacturers $(\boldsymbol{f}|\boldsymbol{f}\neq\boldsymbol{e}\ \boldsymbol{and}\ \boldsymbol{f}\neq\boldsymbol{m})$ as energy producers are defined. Also a given expected raw material availability profiles is defined for each short-term period and supplier.

The goal is to optimize the following decisions concerning the design and planning of the SC, including the eventual installation of a pre-processing unit with its corresponding capacity and location, distribution links among facilities (suppliers, manufacturer and consumers), sizing of installed equipment units and biomass utilization at any period. Those decisions are taken in order to achieve the decision maker objectives which includes the expected net present value, expected environmental impact and the social performance (quantified via the creation of job opportunities) as economic, environmental and social metric respectively.

For further details about the process data, equipment description and its capacity, the readers are addressed to Pérez-Fortes et al. [20] and to the Appendix A of this paper.

3. Methods

The proposed solution strategy is a modification of the approach recently proposed by Medina-González et al. [23]. The method's approach comprises three main steps as shown in Fig. 1. A stochastic multi-objective optimization (MOO) model is developed in step 1. Step 2 solves the stochastic MOO problem using a customized strategy that provides as output a set of solutions that are then evaluated in step 3 to select the optimal design that best satisfies the decision maker preferences. A detailed description of each step (including the specific methods/algorithms used) is provided in the following subsections.

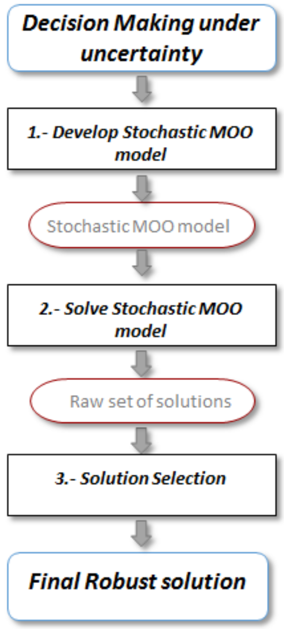

Fig. 1. Algorithm for the proposed method.

3.1. *Multi-scenario two-stage stochastic programming model.*

A general scheme of the bio-based SC under study is shown in Fig. 2. Particularly, this model assumes fixed locations for supplier sites where biomass is produced (as a waste of food industry). The final product can be produced at several potential processing sites. The properties of the raw biomass as well as its availability are considered uncertain since they highly depend on the unpredictable weather conditions as well as on the specific treatments at each generation site. Consequently, pretreatment units must be installed aiming to reach homogeneous conditions required by subsequent steps in the SC. The equipment capacity of each production site is constrained by its nominal production rate (i.e. the number of working hours per year and the type of equipment used). On the other hand, the storage and transportation capacities are modelled taking into account the limits of the corresponding equipment (physical limitations). Materials flows appear only if selecting such a flow improves the performance of the SC despite its associated cost. All the SC decisions will be taken by optimizing the three objectives defined before.

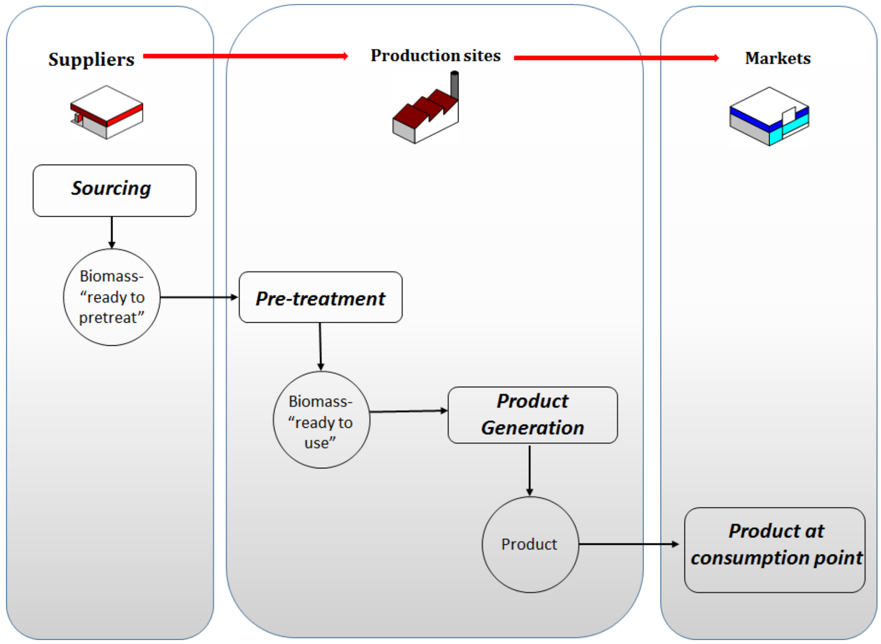

Fig. 2. General scheme for bio-based Supply Chain.

The original mathematical formulation is described in detail in Perez-Fortes et al. [20], including the most relevant mass and energy balances, associated constraints, and also the required equations that describe the technologies involved. However, in this work, the original model has been modified in order to manage the associated uncertainty described later in this paper. Hence, the original MO problem has been reformulated into a multi-scenario two-stage stochastic problem of the following form (Eq.(1)), henceforth known as Model P:

$$
\begin{array}{ll}
(P) & \max_{x\,y} \{f_1(x, y_c, \lambda_c), \dots, f_{ob}(x, y_c, \lambda_c), \dots, f_{|OB|}(x, y_c, \lambda_c)\} \\
 & h(x, y_c, \lambda_c) \quad \forall c \in \mathrm{C} \\
s.t. & g(x, y_c, \lambda_c) \quad \forall c \in \mathrm{C} \\
 & x \in \mathrm{X}, y_c \in \mathrm{Y}
\end{array} \tag{1}
$$

Here, x represent the first-stage decision variables, whereas y_c, λ_c denote the second-stage decision variables and uncertain parameters values that belong to the space ϕ of uncertain parameters, respectively. The solution space ϕ is described through λ_c, which is the vector of the values taken by the uncertain parameters in the scenarios c of the set C. First stage decisions may contain integer variables due to allocation requirements. $f(x, y_c, \lambda_c)$ represents the multi-dimensional objective function; $h(x, y_c, \lambda_c)$ and $g(x, y_c, \lambda_c)$ are vectors of equality and inequality constraints.

Model P can be interpreted as follows. First stage decision variables (x) must be taken before a realization of the random vector (λ_c) becomes known (here and now decisions). However, such a decision needs to satisfy as well the second-stage set of constraints. Therefore, recourse actions need to be taken (second-stage decision variables y_c) with an associated impact over the objective function. Hence, given a first-stage decision x, each realization of λ_c leads to recourse costs given by the value of the second-stage function (y_c). Finally in Eq. (1) f_{ob} represents the different objective functions of the problem ($f_1 = ENPV$, $f_2 = -Impact_{overall}^{2002}$ and $f_3 = ESoC$.). A detailed description of the expected profit calculation and the other criteria is provided in Appendix B of this work. Notice that even if this formulation is used, our approach is general enough to accommodate more sophisticated objective definition as well as additional criteria.

3.2. Solution strategy (Sample Average Approximation algorithm)

The solution of Model P is challenging due to the number of scenarios, objectives and variables required in the STN formulation. In order to expedite the solution and reduce the computational effort, a solution strategy based on the well-known SAA algorithm is used. First, optimize Model P for a deterministic case (considering only one scenario) and maximizing the economic performance (single objective). Then, fix the design decision variables obtained for the first-stage variables and optimize again the profit in Model P, but this time considering all the scenarios ($|C|$). This procedure will be repeated recursively by replacing the scenario used in the first part by another one until the designs of the supply chain (for the different scenarios) are generated. The overall algorithm is graphically described in Fig. 3.

Further details on SAA can be found in [24] while a useful application for solving stochastic problems in Bioethanol and Sugar Production problems is reported in [25].

Note that even if Model P is a multi-objective model, in this step of the algorithm only one objective function is considered. More precisely, the economic performance ($ENPV$) is used as optimization objective while environmental and social impacts are calculated in parallel during the process, but they never act as objective functions. The reason for this is that the explicit consideration of multiple objectives under uncertainty leads to large CPU times, even using tailored decomposition strategies such as Lagrangean decomposition [21] and discrete differential dynamic programming [26]. Hence, the remaining objectives are assessed in a post-optimization step.

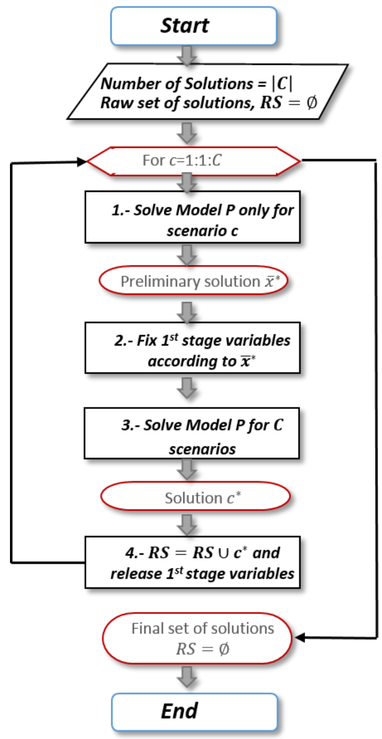

Fig. 3. Algorithm that represents the detail of the particular strategy used in the present work.

3.1. Solution selection procedure (ELECTRE-IV algorithm)

The selection of a unique and robust solution that guarantees the decision makers satisfaction and simultaneously avoids subjectivity sources for multiple criteria problems is a very hard task. In this work, the application of the ELECTRE-IV method is proposed to overcome this limitation. This method is a derivation of the ELECTRE method, which was first introduced by Roy [27]. In general, those methods perform a systematic analysis of the relationship between all possible pairings of multiple options (solutions) considering multiple and common criteria. As a result, this method provides a hierarchically ordered list of solutions according to their performance compared to the others. In other words, this method quantifies the extent to which each option outranks all others.

Following this method, one solution (Sol_a) is said to outrank another option (Sol_b) if and only if Sol_a is at least as good as option Sol_b for all the criteria and strictly better in at least one. The main difficulty/disadvantage of almost all the ELECTRE methods is that an outranking relation must be constructed beforehand and this implies a strong source of subjectivity as commented by [28] and later on confirmed by [29]. However, this difficulty is totally overpassed in ELECTRE-IV method as described in [30] and proved by Shanian et al. [31] by using four parameters to systematically construct fuzzy outranking relationships. Those parameters express the thresholds at which the option will be considered preferred, indifferent, undesirable or infeasible for each criterion. Making use of those thresholds, the outranking relationships define the dominance of each solution over the remaining ones for each criterion under evaluation. Indeed in Fig. 4, a graphical description of the solution selection procedure is illustrated.

After applying the thresholds, one solution (Sol_a) can be classified as strictly and weakly preferred, indifferent or equal compared with another solution (Sol_b). After defining the preference relationships for each pair of options, they are traduced to its numerical equivalence, following the traditional assumption: 1, 0.8, 0.6 and 0.4 for strictly, weakly, indifferent and equally preferred, respectively. Therefore, a new normalized matrix is obtained and a ranking procedure is applied as follows:

- Construct a partial preorder KO_1 and KO_2
- Construct the complete preorder KO $=\mathrm{KO}_1 \cap \mathrm{KO}_2$ as the final result.

KO_1 and KO_2 are constructed through a descending and ascending distillation procedure, respectively [28].The combination of these two partial preorder alternatives provides a unique and robust descending desirability hierarchical ordered list. For more details regarding the ELECTRE methodologies (Including ELECTRE-IV) and its application the reader should refer to [28] and [29]. Without loss of generality, ELECTRE-IV method is applied to identify the most appealing solution from the set of solutions obtained after solving Model P by applying the SAA solution strategy.

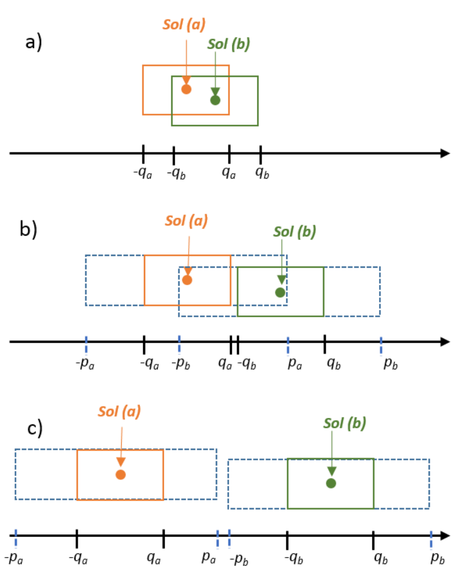

Fig. 4. Representation of thresholds application: a) represents an indifference situation since the indifference area (orange and green line) overlap the solution point. b) represents a weakly preference relation, since their indifference areas do not overlap, but the preference area does (blue dotted line). c) represents a strict preference relation since the preference and indifference thresholds are clearly distinguishable.

4. Case study

The design-planning problem is formulated as a two-stage Mixed Integer Linear Program (MILP) based on a real case study first studied by Pérez-Fortes et al. [20]. Particularly, this case study is related to a bio-based energy supply chain located in Ghana, using gasification technology. It consists of an energy generator system with several units and energy consumers under uncertain conditions (biomass availability and quality). More precisely, the nine small communities of the Atebubu-Amantin district (rural area of Ghana, Africa) constitute the supply chain case study. This case study includes 40 different biomass states (s) and six different equipment technologies (j), which represent the different treatment, pre-treatment and means of transportation. The set of activities i comprises 79 elements for each pair of biomass state-processing and biomass state-transportation activities. The set f consists of 31 locations, including nine suppliers, nine possible pre-treatment/treatment sites, nine markets sites and four potential sites in which a treatment unit can be installed. The project is evaluated along a planning horizon of 10 years with an annual interest rate of 15%. Detailed description about the technologies used in this work can be found in Appendix A. It is also important to mention that the scope of this paper is to propose a useful strategy to overcome the challenges associated to a MOO problem under uncertainty. Therefore, technical challenges related to temporal electricity supply (e.g., electricity storage, switching on/off the transfer grid, availability of power supply in a certain hours of a day etc.) are out of the scope of the paper. Additional studies extending this formulation and including electricity supply challenges are required to explore the effect on the economic, environmental and social performances.

Cassava crop is a common tropical crop mainly used to provide food. Currently cassava waste is widely used for multiple purposes including fertilization, ethanol and biogas production. In this work the use of cassava rhizome for energy production will be evaluated. Cassava availability, Lower Heating Value and moisture content (LHV and MC respectively) are the main properties under analysis. Their average values for each community are shown in Table 1 and were obtained through historical data. Those parameters were considered as the uncertain parameters and modeled through a normal distribution. Particularly, 50 scenarios were generated via Monte Carlo sampling in order to discretize the normal distributions, assuming the mean values in Table 1 and a variance of 30%. It is important to highlight that Monte Carlo sampling is less efficient than other sampling techniques. However, here it is used as a crude method to illustrate the generation of scenarios. It is important to mention that parameters values are highly dependent to climate conditions. For example, for a dry season, the total availability decreases as well as the water content, however in the same environment the LHV is expected to increase. Hence, uncertain parameters are assumed to be correlated.

Table 1. Average values for biomass properties at each community in Atebubu-Amantin district.

	Water*	LHV(MJ/kg)	Availability (t)
Senso	0.425	10.61	12.74
Old Konkrompe	0.426	10.56	24.39
Fakwasi	0.427	10.51	81.10
Kunfia	0.429	10.46	122.18
Trohye	0.431	10.40	16.22
Bompa	0.432	10.34	22.07
Nwunwom	0.434	10.28	5.272
Boniafo	0.436	10.22	21.08
Abamba	0.438	10.15	28.15

* These values are expressed as a weight fraction

The geographic characteristics of this community allow us to define drying and chipping as the potential pre-treatments since they are more suitable for rural areas in developing countries. Cassava waste is pre-processed before gasification to obtain the required shape and MC for further processing steps. Each community represents one single supplier-production-consumer site. However, pretreatment and/or treatment sites can be installed in each community and at the same time this community acts as energy consumer (customer). Those communities could be connected to a specific-built low voltage or medium voltage micro grid (LV and MV respectively). The main difference among them is that LV supplies energy within the community and the MV connects different communities considering the associated investment cost.

Without loss of generality the LCA indicator Impact 2002+ was quantified using data from the Ecoinvent database [32] in accordance with the technical report used in the based paper [33]. In order to produce a representative value from the environmental analysis, the main environmental impacts under analysis includes the traditional 15 mid-point categories (including carcinogens, non-carcinogens, respiratory inorganics, ionizing radiation, ozone layer depletion, respiratory organics, aquatic ecotoxicity, terrestrial ecotoxicity, terrestrial acid, land occupation, aquatic acidification, aquatic eutrophication, global warming, non-renewable energy and mineral extraction) associated to biomass production (cassava waste obtaining), transportation by tractors, pre-treatments (chipper and dryer) and generation of electricity through biomass gasification. For further details on LCI values, see [34]. Additionally, detailed information about the environmental analysis of this case study can be found in [20].

The mathematical model has been written in GAMS and solved using CPLEX 11.0 on a PC Intel(R) Core(TM) i7-2600M CPU 2.70 GHz and 16.00 GB of RAM. The deterministic model contains 17,328 equations, 144,703 continuous variables and 186 binary variables, while the stochastic one with 50 scenarios has 708,444 equations, 5,108,277 continuous variables and 186 binary variables. Each iteration of the algorithm (each solution of the deterministic model) entails a CPU time of approximately 2,700 seconds. It is important to remember that the stochastic model that includes all the scenarios and maximize the expected profit as unique criterion cannot be solved in less than 24h (86,400s) due to CPU limitations (i.e., after this CPU time, CPLEX is unable to close the optimality gap below 5% even when optimizing only the expected profit; consequently, larger CPU times are expected when dealing with multiple objectives). Details on the SC are provided next.

The aim of the proposed formulation is to select the most suitable processing units (including their capacity and location), the best way to interconnect the various elements of the supply chain (i.e., providers, intermediates and consumers), and adequate biomass cycle storage and transport flows in order to make the best use of biomass as feedstock. In order to perform a feasible comparison, the model described in this work (Model P) is solved under deterministic and stochastic conditions (i.e. for average values of the uncertain parameters and also considering all the uncertain scenarios simultaneously, respectively). The above will allow us to promote a discussion and highlight the effect of the new elements now considered under a fair comparison environment.

4.1. First case. Deterministic solution analysis

In this case the biomass availability and properties are assumed known beforehand (See Table 1) and constant across the entire time horizon (i.e. no solution generation is required). Multi-objective optimization (MOO) is carried out in this case, including economic, environmental and social performance ($NPV, Impact_{overall}^{2002}$ and SoC respectively) using the well-known ε-constraint formulation. Accordingly, lower and upper values for each objective are obtained through their individual optimization and displayed in Table 2. Note that the results while optimizing NPV are highly similar to those in the environmental friendly scenario. Particularly, the economic performance corresponding to the configuration that maximizes the NPV is $\$2.35\text{x}10^5$, which represents the maximum NPV that can be obtained in this case study. This value drops to 8% (Table 2) for the environmental friendly network while, for the socially friendly network the economic performance is reduced to \$0. Logically, this result is highly undesirable and provides a lower bound on the economic performance. While optimizing NPV, the value of $Impact_{overall}^{2002}$ keeps a considerably low value since this is reduced just in a 3%, compared with their best performance ($Impact_{overall}^{2002}$ optimization). On the contrary, while optimizing SoC, the environmental impact and economic objective reach both their worst performance. The above is mainly because of the highly transportation and production emissions, as well as to the costs, associated with such a solution.

Table 2. Individual performances at each single objective optimization

	Optimization		
	Economic	Environmental	Social
NPV (\$)	235853	19919	0
$Impact_{overall}^{2002}$	0.657	0.636	0.9
SoC	15	19	27

It is important to notice that in the case of SoC the maximum value considered was 27. This is because the social impact considered only those pretreatment/treatment units installed at the community points and not in external sites. The associated networks of each individual optimization are presented in the Figs. 5-7. In general four types of matter and energy flows are presented disregarding the time period when the distribution is performed. Those flows represent the distribution of raw material, dried and chipped matter, and finally the energy among sites.

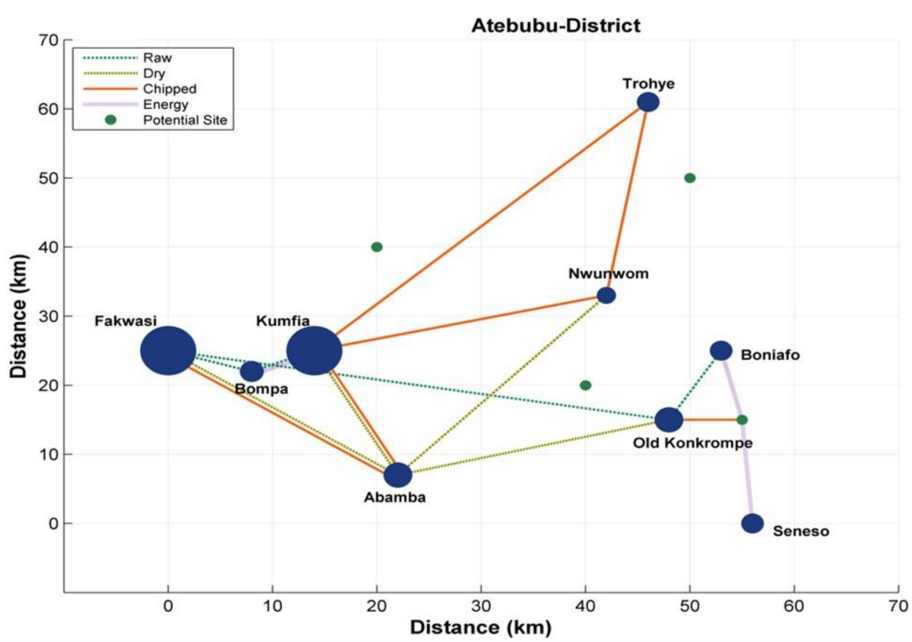

Fig. 5. Optimum network configuration for the economic criteria (NPV). Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

Fig. 5 depicts the network among communities that maximizes the NPV, while Table 3 describes the units installed at each site. The model decides to install an energy generation system (G-ICE) in almost all the communities (6 of the 9 communities), while pre-processing facilities were allocated in only four sites. Those sites are strategically located to best handle the biomass of all the communities, thereby reducing the transportation costs. According with Table 3, the minimum chipping capacity is installed in all the communities (0.1t/h), which is enough to process all the needed cassava waste. Therefore, fluxes of raw material allow to centralize the pretreatment sites in the largest communities, which positively contributes to minimize the $Impact_{overall}^{2002}$.

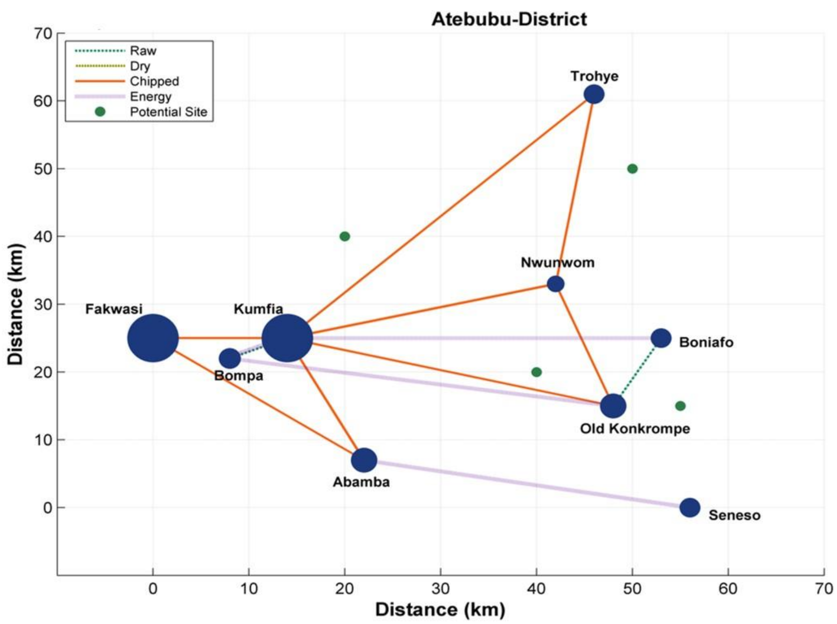

Fig. 6. Optimum network configuration for the environmental criteria ($Impact_{overall}^{2002}$). Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

The network associated to the minimization of $Impact_{overall}^{2002}$ is displayed in Fig. 6. It can be noticed that this network reduces the material and energy exchanges among facilities, since this option only distributes chipped material (orange lines). Therefore, the reduction of environmental impact is due to the reduction in transportation tasks (emissions) and this, consequently, leads to a necessity of more pre-treatment/treatment units, thereby increasing the overall installation cost (almost one per site, reaching an investment cost higher than \$1.2x10^5). This is clearly illustrated in Table 3, in which more installation of pretreatment and treatment units is displayed if compared with the best NPV network. Additionally, Table 3 shows the installed capacity at all the sites, which take similar values than those in the maximum NPV case, except for the case of Kumfia which increase the G-ICE capacity.

Finally, the network associated to the maximum SoC is the most complex due to the large mass flows between locations (see Fig. 7). The model installs each type of unit at each location, and even if their capacities are much lower than those in the previous cases, the economic performance is highly affected due to unnecessary installation/transportation costs. Here, the maximum value for the social criterion (27) was obtained installing three units per community site. Therefore, it can be highlighted that pretreatment/treatment units are installed and then operated to meet the demand. Thus, an inefficient management and use of resources is obtained providing a negative impact on the sustainability of the network (i.e. worst performance for economic and environmental objectives). Even if cassava waste is produced by each community and, in this design all the communities have pretreatment/treatment sites (partially energy sufficient), there is a considerable amount of distributed material. This is due to the flexibility of the proposed formulation in which a combination of different quality materials from different sites is allowed. The above proves that the material distribution for mixing purposes is cheaper than pretreating the material at each site, ultimately leading to better economic performance. This positive impact due to the explicit consideration of raw material quality is also present in the NPV and $Impact_{overall}^{2002}$ networks (Fig. 5 and 6, respectively), nevertheless its presence is not as evident as in this last design.

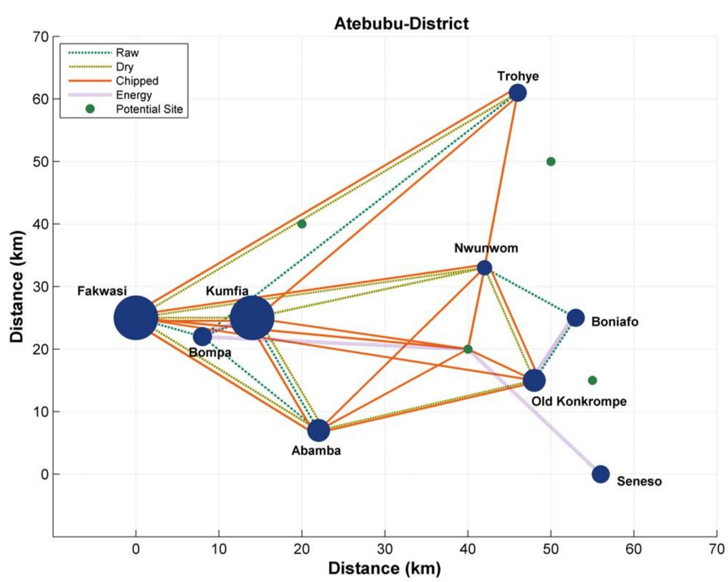

Fig. 7. Optimum network configuration for the social impact (SoC). Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

Table 3. Equipment capacity for the optimum networks configurations obtained for the three selected criteria.

	NPV Optimization			Impact Optimization			Social Optimization		
	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)
Senso							0.1	0.1	18.0
Old Konkrompe	0.1	0.1	18.0	0.1	0.1	18.0	0.1	0.1	37.7
Fakwasi	0.2	0.1	63.6	0.2	0.1	63.5	0.1	0.1	63.5
Kumfia	0.3	0.1	101.3	0.3	0.1	122.0	0.2	0.1	132.0
Trohye			18.0	0.1	0.1	18.0	0.1	0.1	18.0
Bompa							0.1	0.1	18.0
Nwunwom		0.1	18.0		0.1	18.0	0.1	0.1	75.0
Boniafo							0.1	0.1	18.0
Abamba	0.1		18.0	0.1	0.1	28.5	0.1	0.1	18.0
Extrasite1									18.0
Extrasite2									
Extrasite3			31.86						
Extrasite4									

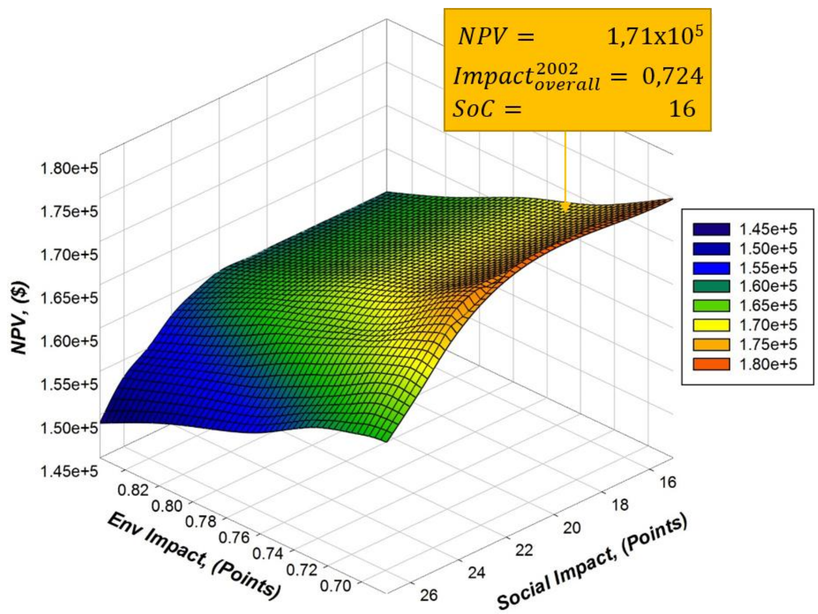

Fig. 8. 3-D representation of the Pareto solutions for the three objectives including the allocation of the overall solution in the feasible solution space.

In the last part of this section, the analysis of the extreme solutions is presented. In order to produce a meaningful solution comparison, the three objectives were analyzed simultaneously using the well-known ε-constraint method. After applying the ε-constraint method, 65 solutions networks were found. As a result, a Pareto frontier was built representing a feasible surface space for the NPV vs $Impact_{overall}^{2002}$ vs SoC problem (see Fig. 8). It is important to highlight that each point in this surface represents a potential feasible optimal solution. From Fig. 8, it is evident that as the SoC objective increases, the NPV decreases while $Impact_{overall}^{2002}$ increases as well, proving their conflicting behaviors. When the social criteria range from 15 to 22, there is no significant change in the economic and environmental performance. However, for values greater than 22 in the social criteria, the performance of the others gradually decreases. It is worth to mention that this surface ranges from $\$1.49 \times 10^5$ to $\$1.73 \times 10^5$ and from 0.68 to 0.86 for the economic and environmental performance, respectively.

Ranking solutions

An infinite number of feasible solutions exist. To select the preferred solution, the ELECTRE-IV method has been applied in accordance with the procedure described in section 4.3. The preference, indifference and infeasible thresholds for each one of the criteria used in this work are presented in Table 4.

Table 4. Thresholds values for the three objectives considered in this case study.

Thresholds	Criteria		
	NPV (\$)	$Impact_{overall}^{2002}$	SoC
Indifference (q)	149667.79	0.65	15.00
Preference (p)	168687.72	0.70	24.00
Veto (v)	173442.70	0.85	27.00

The thresholds must reflect the preferences of a decision maker under realistic conditions. In this particular case, the indifference threshold for the NPV corresponds to its lowest feasible value. The preference threshold for the NPV is set as 80% of its maximum value, while the veto thresholds is set as the maximum NPV value. Similar assumptions were used for the thresholds definitions for the remaining criteria. Using the above thresholds, the ELECTRE-IV method was next applied to evaluate the 65 resulting feasible optimal solutions. Table 5 illustrates the solutions sorted according to their desirability as a function of the preference thresholds.

Table 5. Ranked solutions according to its dominance for this case study.

Ranking	Solution
1	2
2	48
3	47
4	1, 6, 7, 8, 16, 17, 18,,21, 22, 26, 27, 31, 32, 36, 37, 41, 42, 50, 52-63, 65
5	11, 48
6	3, 5, 9, 10, 13, 15, 19, 20 ,23, 28, 29, 30, 33, 35, 38, 40, 43, 45, 49
7	4, 14, 24
8	34, 39, 44

From Table 5, solution 2 was found as the overall dominant solution according to the decision makers' preferences. For this solution, the NPV value is $\$ 1.71 \times 10^5$, and the environmental and social impact are 0.724 and 16, respectively. The above solution entails a reduction of 2%, 15% and 40% form the best possible economic, environmental and social performance values, respectively. From an overall perspective, solution

2 represents a good performance. Fig. 8 shows the selected solution within the solution space. Additionally, Fig. 9 shows the network associated to solution 2.

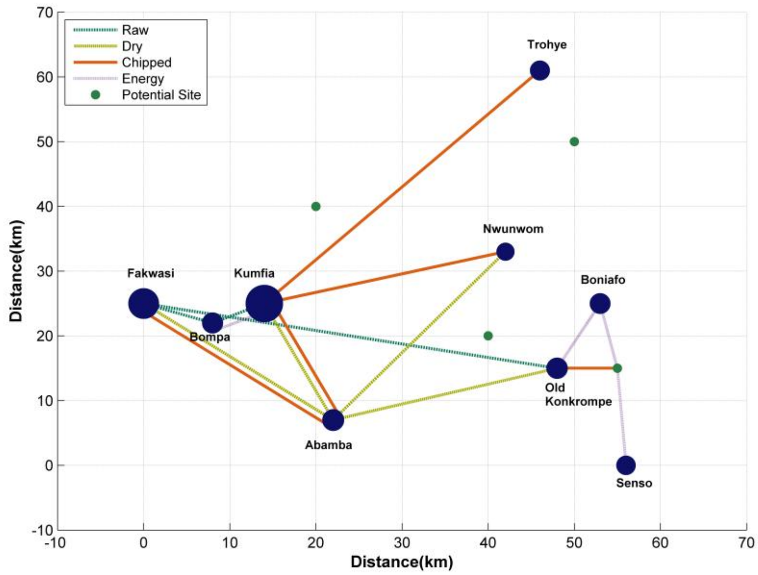

Fig. 9. Optimum network configuration selected using ELECTRE-IV method. Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

It is important to highlight that this design highly depend on the definition of the thresholds for each criteria, therefore, another global overall solution can be found using different thresholds. From Fig. 9 it can be noticed that the final network is slightly different to that one associated to the best economic performance by reducing the amount of material distributed (Raw and chipped) at the expenses of treating that material at each particular site. Even with this small reduction in the final profit the use of this approach reduces the subjectivity in the selection procedure, since the solution comparison is carried out under fair and equal conditions.

4.2. Second case. Stochastic solution approach.

In this section, Model P is solved via the SAA algorithm described in sections 3.1 and 3.2. More precisely, for this model 50 scenarios were defined to model the MC, LHV and availability uncertainties. Hence, 50 different SC´s designs were obtained. The economic performance was expressed through its associated expected value ($ENPV$), while the environmental performance was represented as the worst environmental scenario, and social objective as the sum of the binary variables regarding unit installation.

The 50 solutions obtained after applying the proposed approach were evaluated through the ELECTRE-IV method in order to compare all the solutions with each other. As in the first case, ELECTRE-IV method provides a ranking for the 50 possible solutions as a function of the thresholds parameters defined by the decision maker (See Table 6).

Table 6. Ranked solutions according to its dominance for this case study

Ranking	Solution
1	9
2	18
3	4
4	12, 37
5	29
6	1-3, 5-11, 13-17, 19-28, 30-36, 38-50

The following Fig. 10 shows the scheme associated to best overall solution obtained after applying the proposed solution selection strategy.

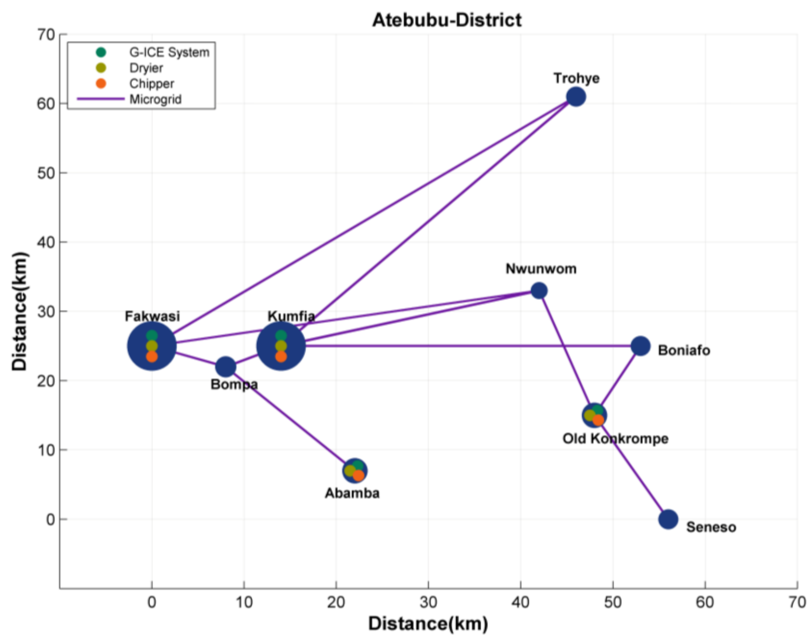

Fig. 10. Resulting robust network. A golden and orange dot represents the dryer and chipper pretreatments units, respectively. Similarly, green point represents the energy production system, while a purple line represents the micro-grid in order to allow the energy exchange among communities.

From Fig. 10, it can be noticed how all the pretreatment activities are performed at strategic locations. Those activities are highlighted in a color scheme. Additionally, Table 7 shows the capacities installed at each equipment unit to provide a robust structure for the complete uncertain solution space. This solution centralizes the treatment/pre-treatment units in just 4 sites. More precisely, Chipper units are installed near to its lower capacity (0.1 t/h), while Dryer ones shows a larger capacity in three cases. On the other hand, the G-

ICE systems capacity installed vary according to its localization. For example, gasifiers with low capacity are installed near the smallest communities, while the two gasifiers with highest capacity are located close to the largest communities in order to property satisfy the energy demand and minimize at the same time the transportation tasks. It is important to remember that the material flows highly depend on the conditions of each scenario.

Table 7. Equipment capacity for the robust networks configuration.

	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)
Senso			
Old Konkrompe	0.17	0.1	168.98
Fakwasi	0.24	0.1	241.74
Kumfia	0.31	0.12	316.93
Trohye			
Bompa			
Nwunwom			
Boniafo			
Abamba	0.1	0.1	97.48
Extrasite1			
Extrasite2			
Extrasite3			
Extrasite4			

The above superstructure has an expected profit of \$ $1.54x10^5$, while the remaining objectives achieve a value of 0.73 and 12, which represents a deterioration of 10%, 1% and 25% for the economic, environmental and social objectives, respectively, if compared with the solution with the best overall performance seen in the first case (i.e. Deterministic solution obtained using the ELECTRE-IV method). Note that this direct comparison might not be very insightful, as both designs are evaluated under different conditions. Hence, a more sophisticate comparison is described in the next section.

4.3. *Deterministic and Stochastic design comparison.*

A value of information analysis (VIA) was performed to quantify the performance reduction associated with a particular decision [35]. Let us consider the expected performance resulting from the solution for the second case (i.e. stochastic solution) and the solution for the first case (i.e. deterministic solution). Then, the difference between the stochastic and deterministic objectives represents the impact associated to neglecting uncertainties.

In order to properly apply the VIA, the designs obtained under deterministic and stochastic conditions in the first and second case studies must be fixed. Then, the problem has to be solved for their counterpart conditions (i.e. deterministic design under uncertain conditions and vice versa). The optimal values for each objective are shown in Table 8.

From Table 8, it can be seen how the deterministic design under stochastic conditions reach a deterioration of 8.57% and 4.16% for the economic and environmental performance. This means that the deterministic design is efficient only for specific and known parameters, however, when the situation change this network performs under suboptimal conditions (reducing the net revenues). On the contrary, the stochastic design evaluated under deterministic conditions reach a reduction of 52% and 36% for economic and environmental performance. This reduction seems important, however, it means that the stochastic design reduces the potential benefits under certain unfavorable conditions of uncertainty, but entails an increase in its average performance for the entire uncertain space. Therefore, this analysis demonstrated the utility of explicit and uncertain formulation when some of the required parameters are unknown.

Table 8. Equipment capacity for the robust networks configuration.

	Deterministic Design				Stochastic Design		
	$NPV(\$)$	$Impact_{overall}^{2002}$	SoC		$NPV(\$)$	$Impact_{overall}^{2002}$	SoC
Deterministic conditions	171,007	0.72	16	Deterministic conditions	101,729	1.15	12
Stochastic conditions	156,341	0.75	16	Stochastic conditions	154,836	0.73	12
Value of Information*	8.57	-4.16	0		-52.48	36.52	0

- This value is expressed in %

5. Conclusions

In this work, a systematic method to support the supply chain optimal design under uncertain raw material conditions has been proposed. This strategy allows optimizing a stochastic multi-criteria problem considering the quality of different streams. Our method consists of a STN formulation combined with a decomposition strategy to produce a flexible formulation while reducing the computational effort required to solve the problem. Additionally, the ELECTRE IV method was presented as a tool to take a final decision in a quick and systematic way, thus facilitating decision-making tasks and avoiding subjectivity in the selection of the final solution.

The capabilities of this approach have been successfully proved using as a test bed a multi-scenario multi-objective design and planning of a bio-based supply chain problem. It has been found that this method allows managing different material flows with different properties in a sustainable way, thus ensuring an energy supply and reducing operational costs.

Furthermore, this approach can be used in different engineering problems in which material flows quality must be considered explicitly. In the future, the combination of this method with alternative decomposition strategies and scenarios reduction methods will be explored. Besides, additional works involving energy supply issues will be further investigated to increase the robustness of the final solution in real life energy supply chains.

Nomenclature

Abbreviations	
MO	Multi-objective
SC	Supply chain
MOO	Multi-objective optimization
MILP	Mixed integer linear programming
PSE	Process system engineering
SAA	Sample average approximation
STN	State Task Network
LCA	Life Cycle Assessment
LCI	Life Cycle inventory
IS	Industrial Symbiosis
G-ICE	Gasifier internal combustion engine
LV	Low voltage
MV	Medium voltage
LHV	Lower heating value
MC	Moisture content
O&M	Operation and maintenance
MILP	Mixed integer linear programming
VI	Value of information
MFP	Micronized food products
ANN	Artificial Neuronal Network
Indices	
s	Material State
j	Technology (Treatment/Pre-treatment equipment's)
i	Task
f	Origin sites
f'	Destination sites
t	Time period
c	Scenarios
k	Interval for Piecewise approximation (Economies of scale)
e	Supplier site
m	Market site
a	Midpoint environmental category
g	Endpoint damage category
Sets	
T_s	Task that produce material *s*
$\bar{T}_s$	Task that consume material *s*
C	Set of scenarios
E_{rm}	Suppliers *e* that provide raw materials
$\hat{E}_{prod}$	Suppliers *e* that provide production services
$\bar{E}_{tr}$	Suppliers *e* that provide transportation services
FP	Materials *s* that are final products
$\bar{I}$	Task *i* with variable input

I_j	Tasks *i* that can be performed in technology *j*
$\bar{J}_e$	Technology *j* that is available at supplier *e*
$\bar{J}_f$	Technology that can be installed at location *f*
J_i	Technology that can perform task *i*
J_{Stor}	Technologies to perform storage activities
Mkt	Market locations
Ntr	Not transport tasks
RM	Materials *s* that are raw materials
Sup	Supplier locations
Tr	Distribution tasks
RS	Raw set of solutions
$\bar{x}^*$	Optimal set of solutions for scenario c
ϕ	Space of uncertain parameters
KO_1	Ascending pre-ordered set of solutions
KO_2	Descending pre-ordered set of solutions
Parameters	
A_{sftc}	Maximum availability of raw material *s* in period *t* in location *f* and for scenario *c*
Dem_{sft}	Demand of product *s* at market *f* in period *t*
$Distance_{ff'}$	Distance from location *f* to location *f'*
$FCFJ_{jft}$	Fixed cost per unit of technology *j* capacity at location *f* in period *t*
FE_{jfk}^{limit}	Increment of capacity equal to the upper limit in interval *k* for technology *j* in facility *f*
$rate$	Discount rate
$Invest^{MV}$	Investment required for medium voltage
M	Big positive number
$NormF_g$	Normalizing factor of damage category *g*
$Price_{sft}$	Price of product *s* at market *f* in period *t*
$Price_{jfk}^{limit}$	Investment required for an increment of capacity equal to the upper limit of interval *k* for technology *j* in facility *f*
$Tortuosity$	Tortuosity factor
$Water_{sc}$	Moisture for material *s* and scenario *c*
$Water_{ij}^{max}$	Maximum moisture for task *i* performed in equipment *j*
α_{sij}	Mass fraction of task *i* for production of material *s* in equipment *j*
$\bar{\alpha}_{sij}$	Mass fraction of task *i* for consumption of material *s* in equipment *j*
β_{jf}	Minimum utilization rate of technology *j* capacity that is allowed at location *j*
ζ_{ag}	*g* endpoint damage characterization factor for environmental intervention *a*
$\theta_{ijff'}$	Capacity utilization rate of technology *j* by task *i* whose origin is location *f* and destination location *f'*
$\rho_{eff't}^{tr}$	Unitary transportation costs from location *f* to location *f'* during period *t*
τ_{sfet}^{ut1}	Unitary cost associated with task *i* performed in equipment *j* from location *f* and payable to external supplier *e* during period *t*
τ_{sfet}^{ut2}	Unitary cost associated with handling the inventory of material *s* in location *f* and payable to external supplier *e* during period *t*
χ_{est}	Unitary cost of raw material *s* offered by external supplier *e* in period *t*
$\psi_{ijff'a}$	Environmental category impact CF for task *i* performed using technology *j* receiving materials from node *f* and delivering it at node *f'*
ψ_{ija}^{T}	Environmental category impact CF for the transportation of a mass unit of material over a length unit
λ_c	Uncertain parameters vale
q	Indifference threshold
p	Preference thresholds
v	Veto thresholds
$Prob_c$	Probability of occurrence of scenario *c*
Variables	
$DamC_{\mathrm{gftc}}$	Normalized endpoint damage *g* for location *f* in period *t* and scenario *c*
$DamC_{gc}^{SC}$	Normalized endpoint damage *g* along the whole SC for scenario *c*
$EPurch_{etc}$	Economic value of sales executed in period *t* during scenario *c*
$ESales_{tc}$	Economic value of sales executed in period *t* and scenario *c*
$FAsset_{tc}$	Investment on fixed assets in period *t* and scenario *c*

$FCost_{ftc}$	Fixed cost in facility *f* for period *t* and scenario *c*
F_{jftc}	Total capacity technology *j* during period *t* at location *f* and scenario *c*
FE_{jftc}	Capacity increment of technology *j* at location *f* during period *t* and scenario *c*
HV_{sc}	Lower heating value for material *s* during scenario *c*
IC_{aftc}	Mid-point *a* environmental impact associated to site *f* which rises from activities in period *t* and scenario *c*
$Impact_{fc}^{2002}$	Total environmental impact for site *f* and scenario *c*
$Impact_{overa}^{2002}$	Total environmental impact for the whole SC
NPV_c	Economic metric for a deterministic case (just one scenario *c*)
$P_{ijff'tc}$	Specific activity of task *i*, by using technology *j* during period *t*, whose origin is location *f* and destination is location *f'* and scenario *c*
$Profit_{ftc}$	Profit achieved in period for each facility *f* at time period *t* and scenario *c*
Pv_{sijftc}	Input/output material of material *s* for activity of task *i* with variable input/output, by using technology *j* during period *t* in location *f* and scenario *c*
$Purch_{et}^{pr}$	Amount of money payable to supplier *e* in period *t* associated with production activities
$Purch_{et}^{rm}$	Amount of money payable to supplier *e* in period *t* associated with consumption of raw materials
$Purch_{et}^{tr}$	Amount of money payable to supplier *e* in period *t* associated with consumption of transport services
$Sales_{sff'tc}$	Amount of product *s* sold from location *f* in market *f'* in period *t* and scenario *c*
S_{sftc}	Amount of stock material *s* at location *f* in period *t* and scenario *c*
SoC_c	Surrogate social metric at each scenario *c*
x	First stage decision variables
y_c	Second stage decision variables
Sol_a	Solution 1 performance to compare in ELECTRE-IV
Sol_b	Solution 2 performance to compare in ELECTRE-IV
$ENPV$	Expected net present value
$ESoC$	Expected social performance
Binary Variables	
V_{jftc}	Technology installed at location *f* in period *t* and scenario *c*
$Z_{ff'c}$	Facilities *f* and *f'* interconnected by a medium voltage line during scenario *c*
SOS2 variable	
ξ_{jfkt}	Variable to model the economies of scale technology *j* in facility *f* at period *t* as a piecewise linear function

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Appendix A

Technologies characteristics

The gasifier requires that the inlet material strictly satisfies a physical homogeneity (chipped) and a MC lower than 20% (dried). It is assumed that chipper and dryer work an average of 8 h/d while the gasifier works in average 16 h/d. The project has a lifespan of 10 years which is a typical length in this type of SC`s [36]. On-field storage is allowed only before chipping and gasification. This kind of storage represents an economic and simple option providing assurance of biomass availability against seasonality, as well as aims to reducing pre-treatment/treatment capacities. It is important to notice that this kind of storages is only applicable for primary waste and if secondary waste is considered other type of storage may be required.

The capacities of chipper and dryer are assumed to have the same range than those capacities employed while processing maize in micronized food products (MFP) during one day. Those capacity ranges, the investment and operation and management (O&M) costs are taken from the literature. The required parameters and physical limitations used to model the activities in the mathematical formulation are described below.

1. Biomass generation. The cassava is harvested and subjected to different treatments in Food Industries which produce a cassava waste with unpredicted properties.
2. Drying. A rotatory drum is the equipment used to decrease the inlet MC to the desire value of 20%w/w. This unit has an energy efficiency of 99% and use diesel as utility. The diesel price is defined as $1133.31/t and the available capacities for rotatory drums are assumed in the range of 0.1-5 t/h [39]. In this task biomass changes its MC and LHV values proportionally to the water removed.
3. Chipping. Chipping task is mandatory, placed after drying one. It consumes electricity which is directly taken from the G-ICE system. Chippers have 96% energy efficiency and, similarly to dryer units, their available capacities range from 0.1 to 5 t/h [37].
4. G-ICE system. As has been commented, in this model the key parameter to control is the MC, since complementarily with the amount of inlet air highly influence the producer gas composition/performance. The gasification production capacity range between 5-100 kWe. The main parameters and outputs associated to this equipment are shown in Table A.1. Here, the equipment efficiency represents the main parameter and will impact in the amount of Biomass required [38].

5. Transportation. Solid biomass should be distributed from its origin point to a storage place or to pre-treatment/treatment sites by tractors. The capacity of this equipment (Tractors) was set at 10t, which represents the upper level of tractor capacity. The price of transport task depends on the amount of material transported and the distance among sites. Lineal distances among nodes expressed in km are corrected through a tortuosity factor of 1.8 [39].
6. Distribution grids. This task represent another type of transportation, but this time is energy transportation and not material. LV and MV are considered as "equipment". The LV distribution line has 6% losses in energy terms while MV distribution line losses are proportional to the power demand, as indicated in [40].

Table A.1. Principal output values and specification for the - G-ICE system.

Parameters	Values
Tgasif(°C)	702
Flowrate (kg/h)	35.33
LHV(MJ/kg)	6.32
CGE(%)	68
Power(kW_e)	15.8
η(%)	17

It is considered that the electricity demand should be partially or totally satisfied. The demand has been estimated for each community considering a direct relationship with its population density. Particularly, the highest gross demand is set to be 448.65 kWh/d, while the lowest is 21.17 kWh/d, as shown in Table A.2.

Table A.2. Energy demand and population distribution in Atebubu-Amantin district.

Community	Population (2010)	Net demand (kWh/d)	Gross demand LV (kWh/d)	Gross demand MV (kWh/d)
Senso	296	42.43	45	61.63
Old Konkrompe	566	88.6	93.96	119.48
Fakwasi	1881	333.2	353.35	393.67
Kunfia	2834	423.05	448.64	501.92
Trohye	376	58.65	62.2	78.84
Bompa	512	69.88	74.11	114.43
Nwunwom	122	19.97	21.17	31.57
Boniafo	489	84.86	89.99	115.51
Abamba	653	91.1	96.61	122.13

Appendix B

In order to ease the understanding of the model, the variables and constraints are classified in four groups. The first one describes process constraints, which provides the topology of the SC. The second one deals with the economic metric applied, while the third refers to the environmental model used. Finally the fourth group describes the objective function for this formulation.

5.1. Process model

As commented before, this model is an adaptation of the model presented by Pérez-Fortes et al. [20].which use an extended STN model representation adapted to the design and planning SC problem. The basis of this formulation is that a node is defined for each activity (transportation, pretreatment and treatment) collecting all the information through a single variable set. Therefore the key variable in this formulation is $P_{ijff'tc}$, which represents the specific activity of task i performed using technology j receiving input materials from site f and delivering output materials to site f' at time t and for scenario c. Treatment and pre-treatment activities are modeled considering that facility f and f' are the same since those activities must receive and deliver material within the same site (P_{ijfftc}). Otherwise, for distribution activity, facilities f and f' must be different. This feature eases the economic and environmental metrics formulation and also facilitates the control of inputs and outputs materials for all the activities. Notwithstanding, multiple meaningless variables are produced increasing the required computational effort.

The SC material balances were modelled by a single equation set for all materials and echelons as stated in the STN formulation. Those balances must be satisfied at each node of the network. The expression that balances each material s consumed at each potential facility f in every time period t and every scenario c is given in Eq. (B.1). Parameter α_{sij} is defined as the mass fraction of material s that is produced by task i performed using technology j; T_s set refers to those tasks that have material s as output, while $\bar{\alpha}_{sij}$ and $\bar{T}_s$ set refer to a task consuming s material.

$$S_{sftc} - S_{sft-1c} = \sum_{f'} \sum_{i \in T_s} \sum_{j \in (j_i \cap \bar{J}_{f'})} \alpha_{sij} P_{ijf'ftc} - \sum_{f'} \sum_{i \in \bar{T}_s} \sum_{j \in (j_i \cap \bar{J}_f)} \bar{\alpha}_{sij} P_{ijff'tc} \qquad \forall s, f, t, c \qquad (B.1)$$

Notice that the material coefficients (consumption/production factors) for a given activity are fixed and represented by the α_{sij} , $\bar{\alpha}_{sij}$ parameters; however, there are activities for which the model should define an inputs mixture in order to achieve a given value for a specific biomass property (i.e., moisture content). In order to account for those activities the mass balance must be modified as shown in Eq. (B.2).

$$S_{sftc} - S_{sft-1c} = \sum_{f'} \sum_{i \in T_s} \sum_{j \in (j_i \cap \bar{J}_{f'})} \alpha_{sij} P_{ijf'ftc} - \sum_{f'} \sum_{i \in \bar{T}_s} \sum_{j \in (j_i \cap \bar{J}_f)} \bar{\alpha}_{sij} P_{ijff't} c + \sum_{i \in (T_s \cap \bar{I})} \sum_{j \in (j_i \cap \bar{J}_{f'})} Pv_{sijftc} - \sum_{i \in (\bar{T}_s \cap \bar{I})} \sum_{j \in (j_i \cap \bar{J}_{f'})} Pv_{sijftc} \qquad \forall s,f,t,c \quad (B.2)$$

In order to ensure the energy balance Eq. (B.3) is defined. Here, the heating value (HV_{sc}) for material s and scenario c changes in activity i if this task is a pretreatment one and explicitly modifies the biomass properties or if it is a task that just changes the shape of biomass but it is receiving different kinds of biomass as input.

$$\sum_{s \in T_s} HV_{sc} * Pv_{sijftc} = \sum_{s \in \bar{T}_s} HV_{sc} * Pv_{sijftc} \qquad \forall i \in \bar{I}, f, t, c \quad (B.3)$$

Notice that the heating value for the feedstock depends on the properties of the raw material, and specifically on their moisture content, therefore Eq. (B.4) must be satisfied. In this constraint $Water_{sc}$ and $Water_{ij}^{max}$ represents the moisture content for material s and scenario c and the maximum moisture content permitted for task i performed in equipment j, respectively.

$$\sum_{s \in S_i} Water_{sc} * Pv_{sijftc} \leq Water_{ij}^{max} \sum_{s \in \bar{S}_i} Pv_{sijftc} \qquad \forall i \in \bar{I}, j, f, t, c \quad (B.4)$$

The combination of Eq. (B.3) and Eq. (B.4) allows reducing the energy required to dry the biomass allowing the mixture of different quality biomass feedstocks. Therefore both the design and retrofit of SCs will be affected by those mixtures. In this sense, Eq. (B.5) and Eq. (B.6) select the installation of the equipment technology in the potential locations as well as its temporal capacity increase. In order to skip a complex non-linear formulation while calculating the capacity expansion, a piecewise linear approximation in k different intervals was applied. This formulation uses the so-called SOS2 variable (ξ_{jfktc}), in which at most two consecutive variables are non-zero. The FE_{jfk}^{limit} represents the limit of capacity expansion for interval k while V_{jftc} is a binary variable indicating if the capacity of technology j is expanded at site f in period t and scenario c or not. Eq. (B.7) describes the total capacity F_{jftc} bookkeeping taking into account the amount increased during planning period t (FE_{jftc}).

$$\sum_{k} \xi_{jfktc} * FE_{jfk}^{limit} = FE_{jftc} \qquad \forall\, j \in \bar{J}_f, f, t, c \qquad (B.5)$$

$$\sum_{k} \xi_{jfktc} = V_{jftc} \qquad \forall\, j \in \tilde{J}_f, f, t, c \qquad (B.6)$$

$$F_{jftc} = F_{jft-1c} + FE_{jftc} \qquad \forall\, j \in \tilde{J}_f, f, t, c \qquad (B.7)$$

In order to ensure the total production rate at each plant, Eq. (B.8) defines the boundaries for the production rate being bigger than a minimum level (β_{jf}) and lower than the available capacity. This capacity is expressed as equipment j available time during one planning period, then $\theta_{ijff'}$ represents the time required to perform task i in equipment j per unit of produced material. Since operation times are determined, this parameter can be readily approximated beforehand.

$$\beta_{jf} F_{jft-1c} \leq \sum_{f'} \sum_{i \in I_j} \theta_{ijff'} * P_{ijff'tc} \leq F_{jft-1c} \qquad \forall\, j \in \tilde{J}_f, f, t, c \qquad (B.8)$$

Eq. (B.9) guarantees that the amount of biomass s purchased from site f at each time period t is lower than an upper bound given by physical availability A_{sftc} which is different at different scenarios (e.g., seasonality, crop/plantation yield in a specific region). Eq. (B.10) aims to stablish the electrical network (i.e. if locations f' and f are interconnected). The binary variable $Z_{f'fc}$ has a value equal to one if f' and f are interconnected at scenario c, and 0 otherwise; while M represents a big positive number. Additionally, the model assumes that part of the demand can be left unsatisfied because of limited production or supplier capacity. Thus, Eq. (B.11) forces the sales of product s carried out in market f during time period t to be less than or equal to maximum demand.

$$\sum_{f'} \sum_{i \in \bar{T}_s} \sum_{j \in \bar{J}_i} P_{ijff'tc} \leq A_{sftc} \qquad \forall\, s \in RM, f \in Sup, t, c \qquad (B.9)$$

$$P_{ijff'tc} \leq M * Z_{f'fc} \qquad \forall\, s \in FP, i \in Mkt, f' \notin Mkt, t, c \qquad (B.10)$$

$$\sum_{f'} \sum_{i \in T_s} \sum_{j \in \bar{J}_i} P_{ijf'ft,c} \leq Dem_{sft} \qquad \forall\, s \in FP, f \in Mkt, t, c \qquad (B.11)$$

For further model details the reader should refer to [20].

5.2. Economic model.

The expression representing the operation costs, the total capital investment, and NPV are next described in detail. The total expected revenue obtained in any period t can be easily modelled as stated in Eq. (B.12).

$$ESales_{ftc} = \sum_{s \in FP} \sum_{f' \in Mkt} Sales_{sff'tc} * Price_{sf't} \qquad \forall\, f \notin (Mkt \cup Sup), t, c \qquad (B.12)$$

Overall operating cost can be computed by means of the estimation of indirect and direct costs. The total fixed operating cost for a given SC structure can be represented as Eq. (B.13), where $FCFJ_{jft}$ is the fixed unitary capacity cost of using technology j at site f.

$$FCost_{ftc} = \sum_{j \in \bar{J}_f} FCFJ_{jft} * F_{jftc} \qquad \forall f \notin (Mkt \cup Sup), t, c \qquad (B.13)$$

The Eq. (B.14) describes the cost of purchases from supplier$e$, considering raw material purchases, transportation, and production resources at any scenario c.

$$EPurch_{etc} = Purch_{et}^{rm} + Purch_{et}^{tr} + Purch_{et}^{pr} \qquad \forall e, t, c \qquad (B.14)$$

The purchases of raw materials ($Purch_{etc}^{rm}$) made to supplier e are evaluated in Eq. (B.15). The variable X_{est} represents the cost associated with raw material s purchased to supplier e. Transportation and production variable costs are determined by Eq. (B.16) and Eq. (B.17), respectively. The provider unitary transportation cost from location f to location f' during period t is represented by $\rho_{eff't}^{tr}$. Similarly, τ_{ijfet}^{ut1} signifies the unitary production cost associated to perform task i using technology j, whereas τ_{ijfet}^{ut2} represents the unitary inventory costs of material s storage at site f. The parameter τ_{ijfet}^{ut1} and τ_{ijfet}^{ut2} entails similar assumptions to the ones considered with regard to α_{sij} and $\overline{\alpha}_{sij}$, since the amount of utilities and labor required by an activity are proportional to the amount of material processed.

$$Purch_{etc}^{rm} = \sum_{s \in RM} \sum_{f \in F_e} \sum_{i \in \bar{T}_s} \sum_{j \in J_i} P_{ijfftc} * X_{est} \qquad \forall f \in E_{rm}, t, c \qquad (B.15)$$

$$Purch_{etc}^{tr} = \sum_{i \in Tr} \sum_{j \in (J_i \cap \bar{J}_e)} \sum_{f} \sum_{f'} P_{ijfftc} * \rho_{eff't}^{tr} \qquad \forall e \in \bar{E}_{tr}, t, c \qquad (B.16)$$

$$\begin{aligned} Purch_{etc}^{pr} = & \sum_{f} \sum_{i \notin Tr} \sum_{i \in \bar{T}_s} \sum_{j \in (J_i \cap \bar{J}_e)} P_{ijfftc} * \tau_{ijfet}^{ut1} \\ & + \sum_{s} \sum_{f \notin (Sup \cup Mkt)} S_{sftc} * \tau_{ijfet}^{ut2} \end{aligned} \qquad \forall e \in \tilde{E}_{prod}, t, c \qquad (B.17)$$

The total capital investment is calculated by means of Eq. (B.18) and Eq. (B.19). Investment costs include those required to expand the technology's capacity j in facility site f in period t as well as to connect two different locations f and f' by using a medium voltage network ($Invest^{MV}$). Recall that an economy of scale for technologies capacity is considered in which $Price_{jft}^{limit}$ is the investment for a capacity expansion equal to the limit of interval k (FE_{jfk}^{limit}).

$$FAsset_{tc} = \sum_{j} \sum_{f} \sum_{k} Price_{jft}^{limit} * \xi_{jfktc} + \sum_{f} \sum_{f'} Invest^{MV} Distance_{ff'} Z_{ff'c} \quad \forall t = 0, c \qquad (B.18)$$

$$FAsset_{tc} = \sum_{j}\sum_{f}\sum_{k} Price_{jft}^{limit} * \xi_{jfkt}c \qquad \forall\, t > 0, c \qquad (B.19)$$

The calculation of profit at each time period is represented at Eq. (B.20). Finally, the rate of return used in a discounted cash flow analysis to determine the *NPV* is computed by means of Eq. (B.21).

$$Profit_{ftc} = ESales_{ftc} - \left(FCost_{ftc} \ + \sum_{e} EPurch_{eftc} \right) * X_{est} \qquad \forall\, f, t, c \qquad (B.20)$$

$$NPV_c = \sum_{f}\sum_{t} \left(\frac{Profit_{ftc} - FAsset_{ftc}}{(1+rate)^t} \right) \qquad (B.21)$$

Finally the expected NPV is defined as in Eq. (B.22), considering the probability of occurrence $prob_c$.

$$ENPV = \sum_{c} NPV_c * prob_c \qquad (B.22)$$

5.3. Environmental model.

In accordance with the LCA method, environmental interventions are translated into environmental impact through a characterization factors which are represented in Eq. (B.23). The environmental impact associated with site f, as a consequence of carrying out activities in period t under scenario c is calculated through the variable IC_{aftc}. Parameter $\psi_{ijff'a}$ represents a characterization factor for the environmental impact associated to a specific task i performed using technology j, receiving materials from node f and delivering them at node f' for each environmental category a.

$$IC_{aftc} = \sum_{j \in \tilde{J}_f}\sum_{i \in I_j}\sum_{f'} \psi_{ijff'a} * P_{ijff'tc} \qquad \forall\, a, f, t, c \qquad (B.23)$$

Since all environmental impacts are assumed linearly proportional to the activity performed ($P_{ijff'tc}$), parameter $\psi_{ijff'a}$ should be fixed and constant. The value of the environmental impact factor $\psi_{ijff'a}$ is associated with transport and therefore it is calculated for each pair of nodes as is formulated in Eq. (B.24). Here Parameter ψ_{ija}^{T} represents the a characterization factor of the environmental impact associated to the amount of material transported over a given distance. In order to correct the estimated distance between nodes, a $Tortuosity$ factor was defined. In this work the environmental impact in distribution activities is assigned to the origin node.

$$\psi_{ijff'a} = \psi_{ija}^{T} * distance_{ff'} * Tortuosity \qquad \forall\, i \in Tr, j \in J_i, a, f, f' \qquad (B.24)$$

Eq. (B.25) introduces $DamC_{gftc}$ variable, which is a weighted sum of all environmental interventions. They are combined using g endpoint damage factors ζ_{ag}, normalized with $NormF_g$ factors, as the LCA method indicates [41]. Moreover, Eq. (B.26) calculates g normalised endpoint damage along the SC ($DamC_{gc}^{SC}$).

$$DamC_{gftc} = \sum_{a \in A_g} NormF_g * \zeta_{ag} * IC_{aftc} \qquad \forall g,f,t,c \qquad (B.25)$$

$$DamC_{gc}^{SC} = \sum_f \sum_t DamC_{gftc} \qquad \forall g,c \qquad (B.26)$$

Eq. (B.27) sums the endpoint environmental damages for each site f while Eq. (B.28) calculates the expected environmental impact as a function of the probability of occurrence of scenario c.

$$Impact_{fc}^{2002} = \sum_g \sum_t DamC_{gftc} \qquad \forall f,c \qquad (B.27)$$

$$Impact_{overall}^{SC} = \sum_f \sum_t \sum_g \sum_c DamC_{gftc} * prob_c \qquad (B.28)$$

For further details about the operational and environmental formulation the interested reader is referred to [42].

5.4. *Objective function.*

Without loss of generality the social impact is associated to the amount of working places which promote the economic activation and will lead to an improvement in the lifestyle of the community around the industry. Therefore, social criterion is the number of sites that have a treatment or pre-treatment system installed as shown in Eq. (B.29). The binary variable V_{jftc} characterizes the number of units installed per site, this criterion assigns a value of 1 to each unit installed per site f.

$$SoC_c = \sum_j \sum_f \sum_t V_{jftc} \qquad \forall c \qquad (B.29)$$

It is very important to comment that in order to ease the formulation of the MO problem, Eq. (B.30) introduces the expected SoC impact as a function of the probability of occurrence $prob_c$.

$$ESoC = \sum_c SoC_c * prob_c \qquad (B.30)$$

It is important to highlight that the proposed social performance calculation is less efficient than other methods, such as social life cycle assessment. However, here the social performance is used as a crude assessment to illustrate its effect on the solution's selection in the proposed method. In this particular model $ESoC$ and $Impact_{overall}^{2002}$ will be optimized (maximized and minimized respectively) together with the economic criteria ($ENPV$). The overall optimization problem can be posed mathematically as follows:

$$\max_{\mathcal{X},\mathcal{Y}} \{ENPV, -Impact_{overall}^{2002}, ESoC\} \qquad (B.31)$$

Where, $\mathcal{X}$ denotes the binary variables set, while $\mathcal{Y}$ corresponds to the continuous variable set.

$$\mathcal{X} \in \{0,1\};\ \mathcal{Y} \in \mathbb{R}^+ \qquad (B.32)$$

***Detailed Response to Reviewer Comments**

Manuscript No. ECM-D-16-05575, Energy Conversion & Management

Title: Systematic Approach for the design of sustainable Supply Chains under quality uncertainty

Authors: Sergio Medina-González, Moisés Graells, Gonzalo Guillén-Gósalbez Antonio Espuña and Luis Puigjaner

Response to Editor and reviewer's comments

Dear Editor,

We would like to thank you and the reviewers for going through our manuscript, and providing valuable suggestions for improvement. Our responses and actions taken to address the concerns of the reviewers follow. They are highlighted in yellow in the revised manuscript.

Answers to the Editor

Comment 1
Do not use abbreviations and acronyms in the title. Avoid using abbreviations and acronyms in abstract and highlights.

Response
Definitely, we wish to present a manuscript totally congruent with the edition policies and objectives of the journal. To address this issue, the content of the manuscript has been modified substantially, as detailed in the following:

Actions
- No abbreviation/acronyms are used in the present title, "supply chain" instead of (SC) has been used in the Highlights. No acronym is used in the abstract. Please, see the file "ECM-D-16-05575 revised manuscript highlighted in yellow"

Comment 2
Avoid lumping references as in [2-4], [5, 6] and all other. Instead summarize the main contribution of each referenced paper in a separate sentence.

Response
Thanks for this suggestion

Actions
- Lumping references have been avoided. Instead, the main contribution of each referenced paper is summarized in a separate sentence. Please, see the file "ECM-D-16-05575 revised manuscript highlighted in yellow"

Comment 3
Avoid using first person.

Response
Thanks for this suggestion

Actions
- Using first person has been avoided.

Comment 4
Shorten the paper, up to 35 pages.

Response
See actions

Actions
- The manuscript is now shortened, up to 35 pages.

Comment 5
The first time you use an acronym, please write the full name and the acronym in brackets.

Response
See actions

Actions
- Done, in the revised manuscript.

Comment 6
The word 'Methodology' should be 'Materials and Methods' or 'Methods'

Response
See actions

Actions
- The Editors are right. Notwithstanding, since appropriate sophisticated algorithms and a powerful computer are used along the methods envisaged, even a more proper title of this Section of the manuscript would be "Methods and Tools". However, the authors have strictly kept the suggestion made by the Editors. So, now this Section is labelled "Methods". Additionally, all "methodology/methodologies" appearing along the text have been duly replaced by "method/methods", as they can be identified highlighted in yellow in the revised manuscript (revised manuscript document highlighted in yellow) where appropriate.
- .

Answers to reviewer 1

Comment 1

It is an interesting paper with valid approach to design bio-based energy supply chain using MMO model and MC decision making method. Existence of uncertainty of some parameters (in this case quality and availability of the raw materials) calls to consider stochastic modeling. Comparison of results with deterministic and stochastic approach, given on a real-case, provides valuable insights into this problem after a lot of work in modeling, generating solutions and selecting the optimal one.

Response

Thanks to this reviewer for these positive comments.

Comment 2

The paper is quite long (40 pages with appendixes), and might be reduced. Since deterministic model is already published, authors might simply use the reference while give focus more on explaining their proposed stochastic model given in appendix B. Also ELECTRE method is known, so no need to give details. They can use ref. [33, 34] while giving only short description in chapter 3.3 up to line 14 on page 9 and lines 20-21 on page 10.

Response

Thanks for the suggestions made.

Actions

- The manuscript is now shortened, up to 35 pages (in accordance with Editors' comments).
- The detailed information of the case study in section 2 has been reduced since is practically the same information used in reference [20]
- Authors consider that ELECTRE method is known but still a brief description of the method is required for the reader's smooth reading and understanding. Therefore, the section 3.3 has been reduced as much as possible following the suggestions made by the reviewer.

Comment 3

Also, although this will not shorten but enlarge paper, authors might present optimal solution for deterministic case (solution 2) with graphical representation, so it would be easier to compare this solution with the optimal solution 9 for the stochastic case.

Response

Thanks for these suggestions. This modification will certainly increase the quality of the paper.

Actions

- The Fig. 9 has been included into the final version of the manuscript. Additionally, a brief description of the comparison among optimal solutions has been inserted in the final manuscript (See Page 18 Line 8-13).

Comment 4

One observation is regarding the results in Table 8. We can see that result for deterministic model (solution 2) for stochastic conditions is very similar to the result for stochastic model (solution 2) for same stochastic conditions. So I would say stochastic model is better to derive expected values for uncertain parameters (using deterministic model expected values are to be expected only if parameters are known). Was solution 2 generated with deterministic model also one generated with stochastic model? Doesn't look like 50 scenarios were the same, so looking into results in Table 8 I got impression that ELECTRE IV would rank solution 2 for deterministic case the best or next to the best to the solution 9 generated for the stochastic case. Could authors provide some explanation to this?

<u>Response</u>

Thanks for this interesting comment. Certainly this give place for an stimulating discussion.

<u>Actions</u>

- First of all let us clarify the purpose of this comparison. The deterministic design (i.e. SC design for the first case) and the stochastic design (i.e. SC design for the second case) were obtained under different conditions, therefore the performances of those designs cannot be compared directly. As a consequence the deterministic design (optimal design for an average value in quality and availability parameters) must be evaluated under stochastic conditions (i.e. 50 scenarios representing the uncertain quality and availability) which will allow us to determine if the deterministic design works under optimal/suboptimal conditions when uncertainty is considered (more likely under suboptimal conditions). In the same way, and in order to complete the comparison, the stochastic design (i.e. optimal design considering 50 scenarios representing the uncertain quality and availability) must be evaluated under deterministic conditions (i.e. considering an average value in quality and availability parameters). So in summary, the deterministic and stochastic designs are obtained under different conditions. Indeed, due to this different calculation conditions "solution 2" for case 1 and case 2 may lead to different designs. Additionally the solution selection is carried out separately (between cases) by applying ELECTRE-IV method. After that, the cross evaluation is produced and shown in Table 8.

- In this particular work, and going into the numerical results, it is true that for the deterministic and stochastic designs under stochastic conditions (Considering uncertainty), their performances are similar, but still, the one associated to stochastic design is better in overall perspective (considering simultaneously the 3 objectives). This means that in fact both designs can provide acceptable overall results, but the ELECTRE-IV method selects the best one as a function of the threshold parameters (i.e. decision making criteria).

- This discussion appears, in compact form, in the page 21, lines 3-11 of the revised manuscript.

Answers to reviewer 2

Comment 1

The paper "Systematic Approach for the design of sustainable Supply Chains under quality uncertainty" describes an interdisciplinary research study proposing an application of advanced decision support system for optimisation of regional energy supply chains. Thus it corresponds to the topics of the journal and is suitable for publication.

The paper is novel in terms of proposed methodological approach. The methodology combines optimisation tasks under uncertainty conditions with multi-objective approaches and minimisation of subjectivity during selection of the optimal solution. In addition, the authors claim to be able to account for the material quality effect by using the proposed methodology. Introduction, Problem statement, Methodology and Conclusions are clearly presented and well organised in the paper and prospective impact on the future research is sufficiently described.

The paper does not contain material that could be omitted. All parts contain important information which is essential for the understanding of proposed methodology and presentation of results.

Response

Thanks for these positive comments.

Comment 2

The application of methodology is demonstrated on a case study where regional supply chains in Ghana (Africa) for transformation of cassava waste to electricity. Pre-treatment, gasification and energy transfer processes are evaluated. The information about the case study is not detailed enough. In particular, it is not clear what type of cassava waste is assessed? Is it primary waste - residues from field activities (e.g., leaves, stalk) or secondary waste - residues from food processing industries (e.g., peels, pulp)? From the description it is not clear, how the storage of cassava waste is meant to be organised. Authors mention that on-field storage is foreseen, but it is likely not realistic when residues from food processing industries are concerned.

Response

Thanks for this comment. Indeed there was a lack of detailed description about the type of Cassava waste considered.

Actions

- The type of Cassava waste used is primary waste. This issue has been corrected and is presented in the manuscript on the Page 10, lines 19-22 and Appendix A, page 28, lines 5-9 of the manuscript.

Comment 3

Regarding energy conversion part it is mentioned that gasifier works in average 16 h/day, meaning that gasification will be organised as a batch process. Consequently, the electricity production is not continuous. Are the technical *challenges related to temporal electricity supply taken into account (e.g., need for electricity storage, switching on/off the transfer grid, availability of power supply in a certain hours of a day etc.) and how they will affect the economic, environmental and social performance of the provided solutions?*

Response

The reviewer points out a clear limitation in the technical challenges associated to the electricity supply.

Action

- This limitation has been explicitly recognized in the manuscript and can be found on the page 10, lines 15-18 of the revised manuscript.

Comment 4

Conclusions related to the application of methodology are clear and refer to important findings. However, the lack of important details in case study description is raising concerns if the proposed robust methodology is able to capture the challenging nature of the real life energy supply chains and to provide optimal solution not only theoretically, but also practically.

Response

The reviewer points out a clear limitation in the concluding remarks.

Actions

- This comment is directly connected with the comment 2, and its explanation is merged with the answer of comment 2. The answer can be found on the page 22, lines 3-7 of the manuscript.
- This scenario will be the subject of our further research

Comment 5

The English of the paper is satisfactory. Only some minor spelling and terminology corrections are needed. For example, authors sometimes use term "raw matter", sometimes "raw material". This should be aligned through the text. In Page 11, row 9 instead of "whit", "with" should be used. LHV is described as "Latent Heat Value". The correct term is "Lower Heating Value" or Net Calorific Value. Some grammatical errors are found also on Page 20 rows 5 and 11.

Response

Thanks to the reviewer for its accurate observation.

Actions

- A detailed English revision in the full manuscript has been performed.

Comment 6

Regarding units, it is not clear what is meant on Page 31, rows 21 and 35.

Response

Thanks to the reviewer for its accurate observation.

Action

- The typo mistakes were corrected. As can be seen in page 28, line 18 and page 29, line 2 of the revised manuscript.

Comment 7

The Abstract of the paper is informative and concise.

Response

Thanks to the reviewer for this positive comment.

Comment 8

The Highlights reflect the content of the paper. It would be better to avoid using abbreviations in the Highlights, since they should be understood as stand-alone without reading the whole paper. Thus I suggest replace "SC" with "supply chains" in the first bullet point of Highlights.

Response

Thanks for this suggestion.

Action

- No abbreviation/acronyms are used in the present Highlights, "supply chain" instead of (SC) has been used. Please, see the file "ECM-D-16-05575 revised manuscript highlighted in yellow"

Comment 9

All cited references are included in the text and related mostly to recent research publications. One typing error should be corrected for reference on Page 31, row 22.

Response

Thanks for this accurate observation.

Actions

- This issue has been corrected in the reviewed manuscript.

Comment 10

Illustrations and Tables are informative and well presented. Probably Figure 8 and Figure 9 could be joined, since Figure 9 contains the same information as the Figure 8.

Response

Thanks for this suggestion.

Action

- Figs. 8 and 9 have been joined and as a consequence a new Fig. 9 now appears (following also the recommendation by another reviewer).

Answers to reviewer 3

Comment 1

-page 4 line 19

As the manuscript subject is on Sustainable SCs, when one considers energy production from biomass, social performance should not be quantified only via job creation, but also taking into account that an edible plant such as cassava, probably important for feeding the local population since ever, is submitted to a large scale use as energy feedstock. There are well known examples on how it may cause price fluctuations, water shortage and famine. In case the social dimension is not properly treated (via a social life cycle assessment), it would be better to consider a less broad scope, from "sustainable" to "green" SCs or another equivalent term. In case the social dimension is further considered, and sustainability scope is kept, a robust, objective definition of sustainability should be included as the basis to the whole analytical approach.

Response

Thanks to the reviewer for this accurate observation. The reviewer suggests a modification that certainly would eventually increase the quality of the paper.

Actions

- The introduction of a sophisticate assessment (such as social life cycle assessment) will definitely increase the quality of the manuscript, however the main scope of the paper was to present a tool to solve sustainable MO problems under uncertainty and select the best overall solution. Indeed, in the present work the social objective is poorly represented but this doesn't affect the performance of the method. In fact, the method will perform equally well when using other sophisticated assessments. The reviewer suggests modifying the definition from "sustainable" to "green" SCs, notwithstanding, this method is planned to be used as a tool for sustainable problems, therefore even if the objective definition is crude the performance of the method cannot be properly evaluated unless we evaluate and consider all the 3 objectives simultaneously. This clear limitation is described in the revised manuscript page 7, Lines 6-7 and page 35, Lines 19-21.
- An additional comment is that our research group is investigating "level of satisfaction" as the main social objective component. Although difficult to quantify, progress is being made, which for the reasons indicated above is out of the scope of this manuscript.

Comment 2

- *page 12 line 11*

All main environmental impacts from the operation of the biomass-based energy system should be presented and discussed in the manuscript. In case they are limited to the few ones described in this sentence, LCA should be expanded to consider water use in plantations, waste from gasification, energy usage by the industrial process, etc. as important factors for a sustainable SC. I would suggest that a systemic LCA methodology (such as SLCA - Sustainability

Life Cycle Assessment) should be applied to check materiality levels of the multiple potential environmental and social impacts.

<u>Response</u>
Thanks to the reviewer for this suggestion. Indeed this comment is directly linked with the previous one.

<u>Action</u>

-The traditional 15 mid-point categories (including carcinogens, non-carcinogens, respiratory inorganics, ionizing radiation, ozone layer depletion, respiratory organics, aquatic ecotoxicity, terrestrial ecotoxicity, terrestrial acid, land occupation, aquatic acidification, aquatic eutrophication, global warming, non-renewable energy and mineral extraction) are used as environmental impacts. This issue has been properly detailed in the revised manuscript Page 11, Lines 15-19.

*Revised Manuscript with changes marked

Systematic Approach for the design of sustainable Supply Chains under quality uncertainty

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ABSTRACT.

Sustainable processes have recently awaked an increasing interest in the process systems engineering literature. In industry, this kind of problems inevitably required a multi-objective analysis to evaluate the environmental impact in addition to the economic performance. Bio-based processes have the potential to enhance the sustainability level of the energy sector. Nevertheless, such processes very often show variable conditions and present an uncertain behavior. The approaches presented for solving multi-objective problems under uncertainty have neglected the potential effects of different quality streams on the overall system. Here, it is presented an alternative approach based on a State Task Network formulation capable of optimizing under uncertain conditions, considering multiple selection criteria and accounting for the material quality effect. The resulting set of Pareto solutions are then assessed using the Elimination and Choice Expressing Reality-IV method, which identify the ones showing better overall performance considering the uncertain parameters space.

Keywords: Uncertainty, State Task Network, Sample Average Approximation, Sustainability, quality, Industrial symbiosis.

1. Introduction

During the last decade, industrial globalization have been continuously changing the business behavior, thus making it difficult to remain competitive in the global market for current processes/industries [1]. Additionally, the increasing government pressure on designing green processes has led to the need for developing more sophisticated strategies to design and manage industrial processes. The above jointly with the recent improvements in environmental analysis techniques has stimulated the emergence of sustainability strategies in process systems engineering (PSE) literature [2]. Here, one major challenge concerns how to combine multi-objective (MO) [3] approaches (maximize economic performance while minimizing environmental impacts) with uncertainty strategies for a reliable/quick response against unpredictable situations (including demands, prices, availability and quality uncertainties) [4].

Along these lines, industrial symbiosis (IS) appears as a promising strategy to bring together companies from different sectors in order to share resources (such as energy, materials and water) and provide stability to the markets [5]. The concept of IS covers multiple important gaps in the current PSE literature [6], since it attempts to enhance the process sustainability as well as the financial and social benefits for all the participants [7]. Nevertheless, in practice the application of IS strategies is a hard task to carry out, mainly due to the limited flow of information within industries, the lack of integration strategies, the complexity of synergy identification and the dynamic behavior associated to IS networks. In fact, several authors agree that in order to meet the highest sustainability standards, the synthesis and operation of robust industrial symbiosis systems should be improved in parallel with solution strategies for highly complex design and planning optimization problems [8]. Therefore, robust and flexible mathematical formulation should be developed to address IS problems using a PSE approach.

In the PSE literature, bio-based processes can be mentioned as one of the most representative example of IS, especially because of their structural and conceptual similarities. Actually, in the field of bio-based processes, multiple works can be found focusing on operating conditions, equipment units' efficiency, and raw material properties, among others. For example, Mikulandrić et al. [9] use an Artificial Neural Networks (ANN) method to predict the variability of the operational conditions (i.e., output temperatures) and model the dynamic behavior of a biomass gasification unit for its use in on-line applications. The above study uses a surrogate model which requires experimental training data. In parallel, Sepe et al. [10] combine traditional gasification techniques with a solar-assisted steam gasification unit in order to increase the quality of the resulting syngas stream (1.4 times more than the traditional value). Recently, Mirmoshtaghi et al. [11] study the impacts of different parameters on the gas quality and gasifiers performance for a biomass gasification unit. Even if those detailed studies increase the efficiency of the process, their improvements are constrained by the available infrastructure. In order to address such an issue, Liu et al. [12] optimize the production pathway of a biofuel supply chain (SC) evaluating the economic, energy and environmental performance applying simultaneously MO and environmental methods (ε-constraint and Life Cycle Assessment (LCA), respectively). In 2012, Gebreslassie [13] optimize the design of a bio-refinery supply chain under demand uncertainty and multiple objectives using decomposition strategies.

In addition to the mentioned works, other contributions ranging from a complete review on stochastic programming [14] to a study on stochastic applications for green supply chains [15] focus on improving MO models under uncertainty [16] in order to enhance the robustness of the final solution [17]. The main limitation here is the large CPU time associated with these strategies [18]. Furthermore, all those strategies disregard the flexibility of the model formulation limiting the management and evaluation of the flows (as function of their properties), which has an important impact on the operating efficiency [19]. In this line, Pérez-Fortes et al. [20] extended the State Task Network (STN) formulation, typically used in scheduling problems, in order to solve the design and planning problem of a regional bio-based energy SC. The formulation proposed by Pérez-Fortes [20] also considers multiple objectives, including economic, environmental and social performance in an attempt to increase the sustainability of the final solution while maintaining the model flexibility. This formulation was later extended by Laínez et al. [21] in which a decomposition algorithm is proposed in order to handle a large and complex model. This model evaluates the performance of a co-combustion process over the electricity distribution network of Spain, considering multiple biomass kinds (forest wood residues and agricultural woody residues) to partially substitute coal as main power resource. To the best of our knowledge, although there are methodologies to assist in the design of green processes, there is still a gap in the evaluation of the influence of the quality of the raw material on the process' performance which is attempted to be fulfilled in this work.

The proposed approach is based on a STN formulation under uncertainty. A bio-based energy production SC is used as a test bed case study in which different energy consumers and their respective SCs as well as their interactions will be studied. Multiple criteria shall be considered, including economic, environmental and social aspects, ensuring the robustness and sustainability of the solutions for all the participating actors. Given that locally available agro-industrial waste is used, it should be subject to uncertainty caused by climate variations. Thus, the impact on biomass availability across the time as well as the corresponding variability for the processes prior to the biomass collection will be considered in the model here presented [22]. Additionally, the combination of different raw material sources with varied qualities will be analyzed in order to evaluate their effects over the energy generation efficiency, thus making the final solution more realistic. To tackle the resulting model, a solution strategy, based on the Sample Average Approximation (SAA) algorithm, is used for optimization under uncertainty, in order to reduce the computational effort. Finally, the

ELimination and Choice Expressing REality (ELECTRE-IV) method will be used as multi-criteria decision-making tool in order to identify the solution that best reflects the decision-makers preferences.

2. Problem statement

This paper tackles the design and planning of a centralized multi-echelon bio-based energy production supply chain subject to raw material uncertainties. Here, two main actors will be considered (the supplier and the manufacturer). Both actors are considered in a single SC management problem, however the exchange of resources between them is allowed. More precisely, food industry will provide the raw material for energy production, while the power generation plant will meet the energy needs of the food industry. Uncertain behaviors in raw material availability and quality properties are addressed through a tailor-made approach. To illustrate the capabilities of the proposed approach, a conveniently modified version of the case study modelled by Pérez-Fortes et al. [20] is used. Additionally to the original process data (i.e. potential sites, material states, tasks, equipment's, etc.), a set of actors composed by suppliers $(\boldsymbol{e}|\boldsymbol{e} = \mathbf{1}, \ldots, \boldsymbol{E})$ which provide the biomass; the consumers $(\boldsymbol{m}|\boldsymbol{m} = \mathbf{1}, \ldots, \boldsymbol{M})$ as markets; and the manufacturers $(\boldsymbol{f}|\boldsymbol{f} \neq \boldsymbol{e}\ \boldsymbol{and}\ \boldsymbol{f} \neq \boldsymbol{m})$ as energy producers are defined. Also a given expected raw material availability profiles is defined for each short-term period and supplier.

The goal is to optimize the following decisions concerning the design and planning of the SC, including the eventual installation of a pre-processing unit with its corresponding capacity and location, distribution links among facilities (suppliers, manufacturer and consumers), sizing of installed equipment units and biomass utilization at any period. Those decisions are taken in order to achieve the decision maker objectives which includes the expected net present value, expected environmental impact and the social performance (quantified via the creation of job opportunities) as economic, environmental and social metric respectively.

For further details about the process data, equipment description and its capacity, the readers are addressed to Pérez-Fortes et al. [20] and to the Appendix A of this paper.

3. Methods

The proposed solution strategy is a modification of the approach recently proposed by Medina-González et al. [23]. The method's approach comprises three main steps as shown in Fig. 1. A stochastic multi-objective optimization (MOO) model is developed in step 1. Step 2 solves the stochastic MOO problem using a customized strategy that provides as output a set of solutions that are then evaluated in step 3 to select the optimal design that best satisfies the decision maker preferences. A detailed description of each step (including the specific methods/algorithms used) is provided in the following subsections.

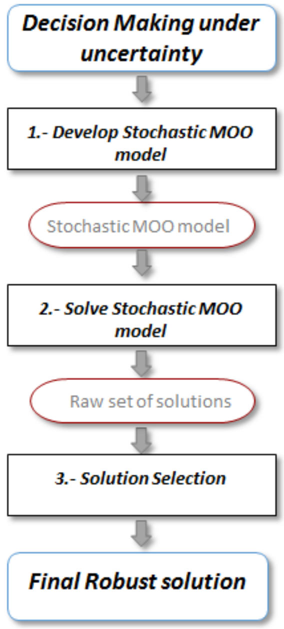

Fig. 1. Algorithm for the proposed method.

3.1. Multi-scenario two-stage stochastic programming model.

A general scheme of the bio-based SC under study is shown in Fig. 2. Particularly, this model assumes fixed locations for supplier sites where biomass is produced (as a waste of food industry). The final product can be produced at several potential processing sites. The properties of the raw biomass as well as its availability are considered uncertain since they highly depend on the unpredictable weather conditions as well as on the specific treatments at each generation site. Consequently, pretreatment units must be installed aiming to reach homogeneous conditions required by subsequent steps in the SC. The equipment capacity of each production site is constrained by its nominal production rate (i.e. the number of working hours per year and the type of equipment used). On the other hand, the storage and transportation capacities are modelled taking into account the limits of the corresponding equipment (physical limitations). Materials flows appear only if selecting such a flow improves the performance of the SC despite its associated cost. All the SC decisions will be taken by optimizing the three objectives defined before.

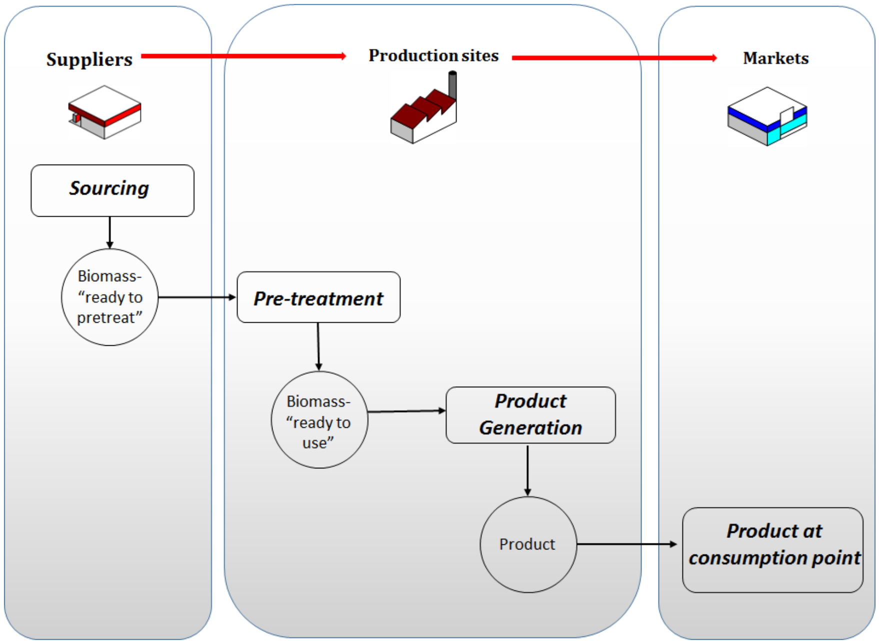

Fig. 2. General scheme for bio-based Supply Chain.

The original mathematical formulation is described in detail in Perez-Fortes et al. [20], including the most relevant mass and energy balances, associated constraints, and also the required equations that describe the technologies involved. However, in this work, the original model has been modified in order to manage the associated uncertainty described later in this paper. Hence, the original MO problem has been reformulated into a multi-scenario two-stage stochastic problem of the following form (Eq.(1)), henceforth known as Model P:

$$
\begin{array}{lll}
(P) & \max\limits_{x\,y} \{f_1(x, y_c, \lambda_c), \dots, f_{ob}(x, y_c, \lambda_c), \dots, f_{|OB|}(x, y_c, \lambda_c)\} & \\
 & h(x, y_c, \lambda_c) \quad \forall c \in \mathrm{C} & \\
s.t. & g(x, y_c, \lambda_c) \quad \forall c \in \mathrm{C} & (1) \\
 & x \in \mathrm{X}, y_c \in \mathrm{Y} &
\end{array}
$$

Here, x represent the first-stage decision variables, whereas y_c, λ_c denote the second-stage decision variables and uncertain parameters values that belong to the space ϕ of uncertain parameters, respectively. The solution space ϕ is described through λ_c, which is the vector of the values taken by the uncertain parameters in the scenarios c of the set C. First stage decisions may contain integer variables due to allocation requirements. $f(x, y_c, \lambda_c)$ represents the multi-dimensional objective function; $h(x, y_c, \lambda_c)$ and $g(x, y_c, \lambda_c)$ are vectors of equality and inequality constraints.

Model P can be interpreted as follows. First stage decision variables (x) must be taken before a realization of the random vector (λ_c) becomes known (here and now decisions). However, such a decision needs to satisfy as well the second-stage set of constraints. Therefore, recourse actions need to be taken (second-stage decision variables y_c) with an associated impact over the objective function. Hence, given a first-stage decision x, each realization of λ_c leads to recourse costs given by the value of the second-stage function (y_c). Finally in Eq. (1) f_{ob} represents the different objective functions of the problem ($f_1 = ENPV$, $f_2 = -Impact_{overall}^{2002}$ and $f_3 = ESoC$.). A detailed description of the expected profit calculation and the other criteria is provided in Appendix B of this work. Notice that even if this formulation is used, our approach is general enough to accommodate more sophisticated objective definition as well as additional criteria.

3.2. Solution strategy (Sample Average Approximation algorithm)

The solution of Model P is challenging due to the number of scenarios, objectives and variables required in the STN formulation. In order to expedite the solution and reduce the computational effort, a solution strategy based on the well-known SAA algorithm is used. First, optimize Model P for a deterministic case (considering only one scenario) and maximizing the economic performance (single objective). Then, fix the design decision variables obtained for the first-stage variables and optimize again the profit in Model P, but this time considering all the scenarios ($|C|$). This procedure will be repeated recursively by replacing the scenario used in the first part by another one until the designs of the supply chain (for the different scenarios) are generated. The overall algorithm is graphically described in Fig. 3.

Further details on SAA can be found in [24] while a useful application for solving stochastic problems in Bioethanol and Sugar Production problems is reported in [25].

Note that even if Model P is a multi-objective model, in this step of the algorithm only one objective function is considered. More precisely, the economic performance ($ENPV$) is used as optimization objective while environmental and social impacts are calculated in parallel during the process, but they never act as objective functions. The reason for this is that the explicit consideration of multiple objectives under uncertainty leads to large CPU times, even using tailored decomposition strategies such as Lagrangean decomposition [21] and discrete differential dynamic programming [26]. Hence, the remaining objectives are assessed in a post-optimization step.

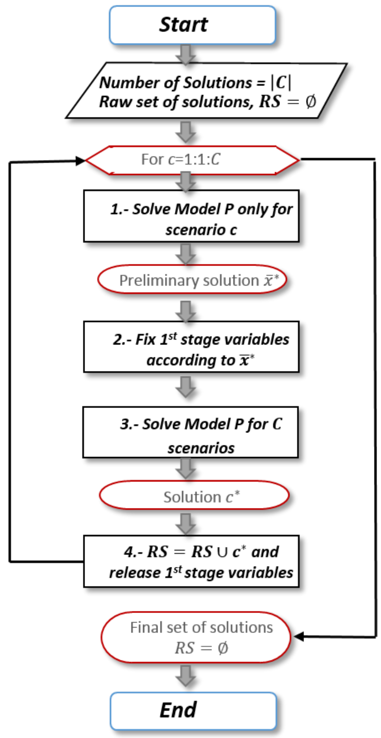

Fig. 3. Algorithm that represents the detail of the particular strategy used in the present work.

3.1. Solution selection procedure (ELECTRE-IV algorithm)

The selection of a unique and robust solution that guarantees the decision makers satisfaction and simultaneously avoids subjectivity sources for multiple criteria problems is a very hard task. In this work, the application of the ELECTRE-IV method is proposed to overcome this limitation. This method is a derivation of the ELECTRE method, which was first introduced by Roy [27]. In general, those methods perform a systematic analysis of the relationship between all possible pairings of multiple options (solutions) considering multiple and common criteria. As a result, this method provides a hierarchically ordered list of solutions according to their performance compared to the others. In other words, this method quantifies the extent to which each option outranks all others.

Following this method, one solution (Sol_a) is said to outrank another option (Sol_b) if and only if Sol_a is at least as good as option Sol_b for all the criteria and strictly better in at least one. The main difficulty/disadvantage of almost all the ELECTRE methods is that an outranking relation must be constructed beforehand and this implies a strong source of subjectivity as commented by [28] and later on confirmed by [29]. However, this difficulty is totally overpassed in ELECTRE-IV method as described in [30] and proved by Shanian et al. [31] by using four parameters to systematically construct fuzzy outranking relationships. Those parameters express the thresholds at which the option will be considered preferred, indifferent, undesirable or infeasible for each criterion. Making use of those thresholds, the outranking relationships define the dominance of each solution over the remaining ones for each criterion under evaluation. Indeed in Fig. 4, a graphical description of the solution selection procedure is illustrated.

After applying the thresholds, one solution (Sol_a) can be classified as strictly and weakly preferred, indifferent or equal compared with another solution (Sol_b). After defining the preference relationships for each pair of options, they are traduced to its numerical equivalence, following the traditional assumption: 1, 0.8, 0.6 and 0.4 for strictly, weakly, indifferent and equally preferred, respectively. Therefore, a new normalized matrix is obtained and a ranking procedure is applied as follows:

- Construct a partial preorder KO_1 and KO_2
- Construct the complete preorder KO $=KO_1 \cap KO_2$ as the final result.

KO_1 and KO_2 are constructed through a descending and ascending distillation procedure, respectively [28].The combination of these two partial preorder alternatives provides a unique and robust descending desirability hierarchical ordered list. For more details regarding the ELECTRE methodologies (Including ELECTRE-IV) and its application the reader should refer to [28] and [29]. Without loss of generality, ELECTRE-IV method is applied to identify the most appealing solution from the set of solutions obtained after solving Model P by applying the SAA solution strategy.

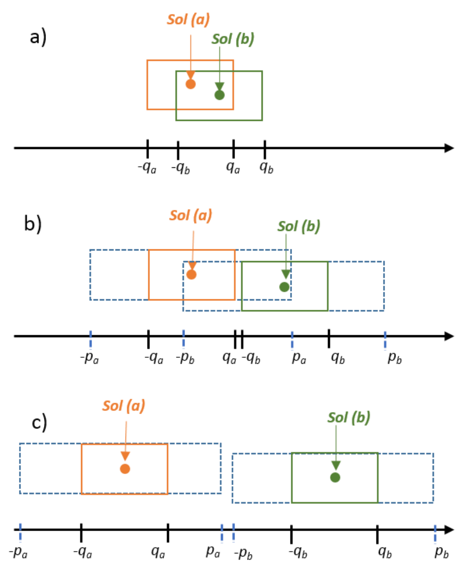

Fig. 4. Representation of thresholds application: a) represents an indifference situation since the indifference area (orange and green line) overlap the solution point. b) represents a weakly preference relation, since their indifference areas do not overlap, but the preference area does (blue dotted line). c) represents a strict preference relation since the preference and indifference thresholds are clearly distinguishable.

4. Case study

The design-planning problem is formulated as a two-stage Mixed Integer Linear Program (MILP) based on a real case study first studied by Pérez-Fortes et al. [20]. Particularly, this case study is related to a bio-based energy supply chain located in Ghana, using gasification technology. It consists of an energy generator system with several units and energy consumers under uncertain conditions (biomass availability and quality). More precisely, the nine small communities of the Atebubu-Amantin district (rural area of Ghana, Africa) constitute the supply chain case study. This case study includes 40 different biomass states (s) and six different equipment technologies (j), which represent the different treatment, pre-treatment and means of transportation. The set of activities i comprises 79 elements for each pair of biomass state-processing and biomass state-transportation activities. The set f consists of 31 locations, including nine suppliers, nine possible pre-treatment/treatment sites, nine markets sites and four potential sites in which a treatment unit can be installed. The project is evaluated along a planning horizon of 10 years with an annual interest rate of 15%. Detailed description about the technologies used in this work can be found in Appendix A. It is also important to mention that the scope of this paper is to propose a useful strategy to overcome the challenges associated to a MOO problem under uncertainty. Therefore, technical challenges related to temporal electricity supply (e.g., electricity storage, switching on/off the transfer grid, availability of power supply in a certain hours of a day etc.) are out of the scope of the paper. Additional studies extending this formulation and including electricity supply challenges are required to explore the effect on the economic, environmental and social performances.

Cassava crop is a common tropical crop mainly used to provide food. Currently cassava waste is widely used for multiple purposes including fertilization, ethanol and biogas production. In this work the use of cassava rhizome for energy production will be evaluated. Cassava availability, Lower Heating Value and moisture content (LHV and MC respectively) are the main properties under analysis. Their average values for each community are shown in Table 1 and were obtained through historical data. Those parameters were considered as the uncertain parameters and modeled through a normal distribution. Particularly, 50 scenarios were generated via Monte Carlo sampling in order to discretize the normal distributions, assuming the mean values in Table 1 and a variance of 30%. It is important to highlight that Monte Carlo sampling is less efficient than other sampling techniques. However, here it is used as a crude method to illustrate the generation of scenarios. It is important to mention that parameters values are highly dependent to climate conditions. For example, for a dry season, the total availability decreases as well as the water content, however in the same environment the LHV is expected to increase. Hence, uncertain parameters are assumed to be correlated.

Table 1. Average values for biomass properties at each community in Atebubu-Amantin district.

	Water*	LHV(MJ/kg)	Availability (t)
Senso	0.425	10.61	12.74
Old Konkrompe	0.426	10.56	24.39
Fakwasi	0.427	10.51	81.10
Kunfia	0.429	10.46	122.18
Trohye	0.431	10.40	16.22
Bompa	0.432	10.34	22.07
Nwunwom	0.434	10.28	5.272
Boniafo	0.436	10.22	21.08
Abamba	0.438	10.15	28.15

* These values are expressed as a weight fraction

The geographic characteristics of this community allow us to define drying and chipping as the potential pre-treatments since they are more suitable for rural areas in developing countries. Cassava waste is pre-processed before gasification to obtain the required shape and MC for further processing steps. Each community represents one single supplier-production-consumer site. However, pretreatment and/or treatment sites can be installed in each community and at the same time this community acts as energy consumer (customer). Those communities could be connected to a specific-built low voltage or medium voltage micro grid (LV and MV respectively). The main difference among them is that LV supplies energy within the community and the MV connects different communities considering the associated investment cost.

Without loss of generality the LCA indicator Impact 2002+ was quantified using data from the Ecoinvent database [32] in accordance with the technical report used in the based paper [33]. In order to produce a representative value from the environmental analysis, the main environmental impacts under analysis includes the traditional 15 mid-point categories (including carcinogens, non-carcinogens, respiratory inorganics, ionizing radiation, ozone layer depletion, respiratory organics, aquatic ecotoxicity, terrestrial ecotoxicity, terrestrial acid, land occupation, aquatic acidification, aquatic eutrophication, global warming, non-renewable energy and mineral extraction) associated to biomass production (cassava waste obtaining), transportation by tractors, pre-treatments (chipper and dryer) and generation of electricity through biomass gasification. For further details on LCI values, see [34]. Additionally, detailed information about the environmental analysis of this case study can be found in [20].

The mathematical model has been written in GAMS and solved using CPLEX 11.0 on a PC Intel(R) Core(TM) i7-2600M CPU 2.70 GHz and 16.00 GB of RAM. The deterministic model contains 17,328 equations, 144,703 continuous variables and 186 binary variables, while the stochastic one with 50 scenarios has 708,444 equations, 5,108,277 continuous variables and 186 binary variables. Each iteration of the algorithm (each solution of the deterministic model) entails a CPU time of approximately 2,700 seconds. It is important to remember that the stochastic model that includes all the scenarios and maximize the expected profit as unique criterion cannot be solved in less than 24h (86,400s) due to CPU limitations (i.e., after this CPU time, CPLEX is unable to close the optimality gap below 5% even when optimizing only the expected profit; consequently, larger CPU times are expected when dealing with multiple objectives). Details on the SC are provided next.

The aim of the proposed formulation is to select the most suitable processing units (including their capacity and location), the best way to interconnect the various elements of the supply chain (i.e., providers, intermediates and consumers), and adequate biomass cycle storage and transport flows in order to make the best use of biomass as feedstock. In order to perform a feasible comparison, the model described in this work (Model P) is solved under deterministic and stochastic conditions (i.e. for average values of the uncertain parameters and also considering all the uncertain scenarios simultaneously, respectively). The above will allow us to promote a discussion and highlight the effect of the new elements now considered under a fair comparison environment.

4.1. First case. Deterministic solution analysis

In this case the biomass availability and properties are assumed known beforehand (See Table 1) and constant across the entire time horizon (i.e. no solution generation is required). Multi-objective optimization (MOO) is carried out in this case, including economic, environmental and social performance ($NPV, Impact_{overall}^{2002}$ and SoC respectively) using the well-known ε-constraint formulation. Accordingly, lower and upper values for each objective are obtained through their individual optimization and displayed in Table 2. Note that the results while optimizing NPV are highly similar to those in the environmental friendly scenario. Particularly, the economic performance corresponding to the configuration that maximizes the NPV is \$2.35x10^5, which represents the maximum NPV that can be obtained in this case study. This value drops to 8% (Table 2) for the environmental friendly network while, for the socially friendly network the economic performance is reduced to \$0. Logically, this result is highly undesirable and provides a lower bound on the economic performance. While optimizing NPV, the value of $Impact_{overall}^{2002}$ keeps a considerably low value since this is reduced just in a 3%, compared with their best performance ($Impact_{overall}^{2002}$ optimization). On the contrary, while optimizing SoC, the environmental impact and economic objective reach both their worst performance. The above is mainly because of the highly transportation and production emissions, as well as to the costs, associated with such a solution.

Table 2. Individual performances at each single objective optimization

	Optimization		
	Economic	Environmental	Social
NPV (\$)	235853	19919	0
$Impact_{overall}^{2002}$	0.657	0.636	0.9
SoC	15	19	27

It is important to notice that in the case of SoC the maximum value considered was 27. This is because the social impact considered only those pretreatment/treatment units installed at the community points and not in external sites. The associated networks of each individual optimization are presented in the Figs. 5-7. In general four types of matter and energy flows are presented disregarding the time period when the distribution is performed. Those flows represent the distribution of raw material, dried and chipped matter, and finally the energy among sites.

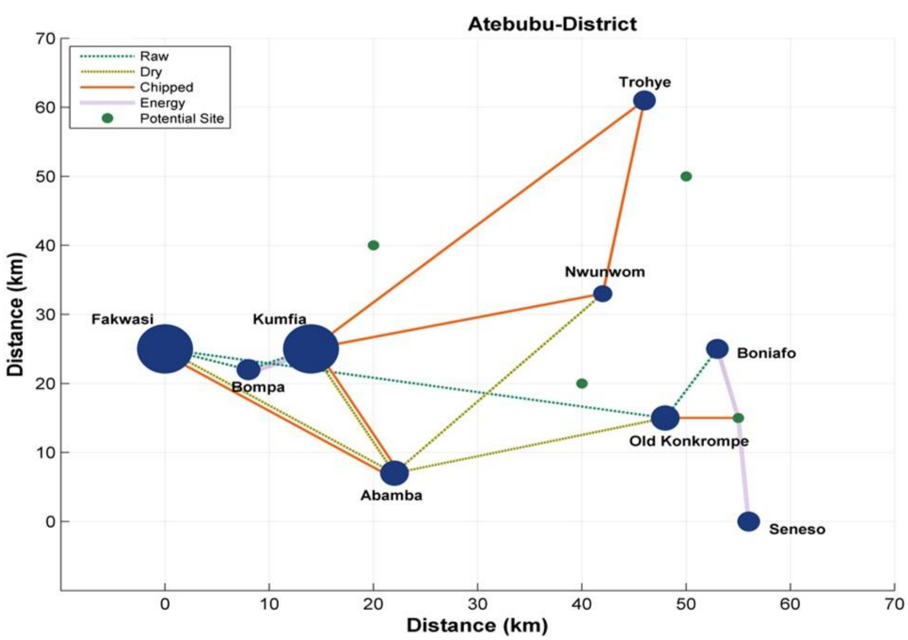

Fig. 5. Optimum network configuration for the economic criteria (NPV). Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

Fig. 5 depicts the network among communities that maximizes the NPV, while Table 3 describes the units installed at each site. The model decides to install an energy generation system (G-ICE) in almost all the communities (6 of the 9 communities), while pre-processing facilities were allocated in only four sites. Those sites are strategically located to best handle the biomass of all the communities, thereby reducing the transportation costs. According with Table 3, the minimum chipping capacity is installed in all the communities (0.1t/h), which is enough to process all the needed cassava waste. Therefore, fluxes of raw material allow to centralize the pretreatment sites in the largest communities, which positively contributes to minimize the $Impact_{overall}^{2002}$.

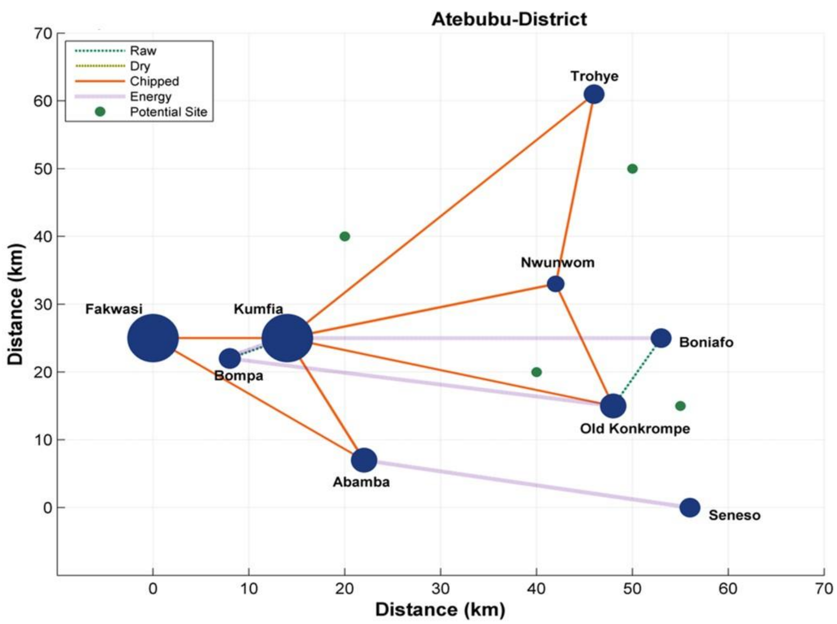

Fig. 6. Optimum network configuration for the environmental criteria ($Impact_{overall}^{2002}$). Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

The network associated to the minimization of $Impact_{overall}^{2002}$ is displayed in Fig. 6. It can be noticed that this network reduces the material and energy exchanges among facilities, since this option only distributes chipped material (orange lines). Therefore, the reduction of environmental impact is due to the reduction in transportation tasks (emissions) and this, consequently, leads to a necessity of more pre-treatment/treatment units, thereby increasing the overall installation cost (almost one per site, reaching an investment cost higher than $1.2x10^5). This is clearly illustrated in Table 3, in which more installation of pretreatment and treatment units is displayed if compared with the best NPV network. Additionally, Table 3 shows the installed capacity at all the sites, which take similar values than those in the maximum NPV case, except for the case of Kumfia which increase the G-ICE capacity.

Finally, the network associated to the maximum SoC is the most complex due to the large mass flows between locations (see Fig. 7). The model installs each type of unit at each location, and even if their capacities are much lower than those in the previous cases, the economic performance is highly affected due to unnecessary installation/transportation costs. Here, the maximum value for the social criterion (27) was obtained installing three units per community site. Therefore, it can be highlighted that pretreatment/treatment units are installed and then operated to meet the demand. Thus, an inefficient management and use of resources is obtained providing a negative impact on the sustainability of the network (i.e. worst performance for economic and environmental objectives). Even if cassava waste is produced by each community and, in this design all the communities have pretreatment/treatment sites (partially energy sufficient), there is a considerable amount of distributed material. This is due to the flexibility of the proposed formulation in which a combination of different quality materials from different sites is allowed. The above proves that the material distribution for mixing purposes is cheaper than pretreating the material at each site, ultimately leading to better economic performance. This positive impact due to the explicit consideration of raw material quality is also present in the NPV and $Impact_{overall}^{2002}$ networks (Fig. 5 and 6, respectively), nevertheless its presence is not as evident as in this last design.

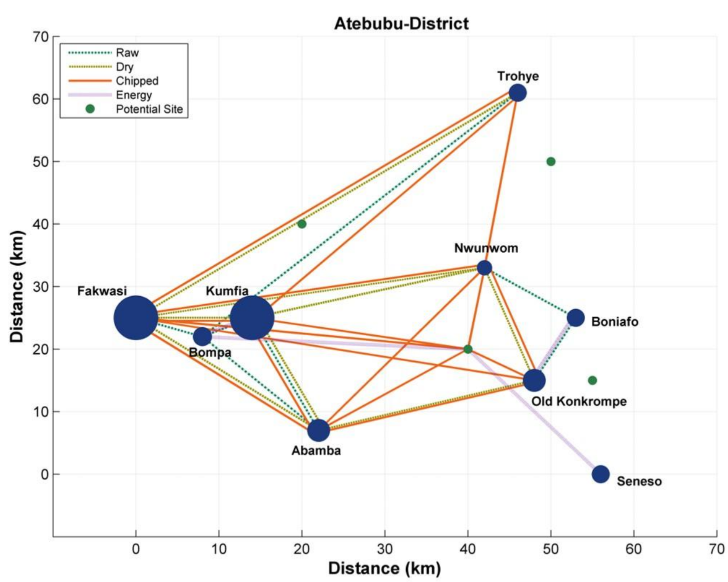

Fig. 7. Optimum network configuration for the social impact (SoC). Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

Table 3. Equipment capacity for the optimum networks configurations obtained for the three selected criteria.

	NPV Optimization			Impact Optimization			Social Optimization		
	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)
Senso							0.1	0.1	18.0
Old Konkrompe	0.1	0.1	18.0	0.1	0.1	18.0	0.1	0.1	37.7
Fakwasi	0.2	0.1	63.6	0.2	0.1	63.5	0.1	0.1	63.5
Kumfia	0.3	0.1	101.3	0.3	0.1	122.0	0.2	0.1	132.0
Trohye			18.0	0.1	0.1	18.0	0.1	0.1	18.0
Bompa							0.1	0.1	18.0
Nwunwom		0.1	18.0		0.1	18.0	0.1	0.1	75.0
Boniafo							0.1	0.1	18.0
Abamba	0.1		18.0	0.1	0.1	28.5	0.1	0.1	18.0
Extrasite1									18.0
Extrasite2									
Extrasite3			31.86						
Extrasite4									

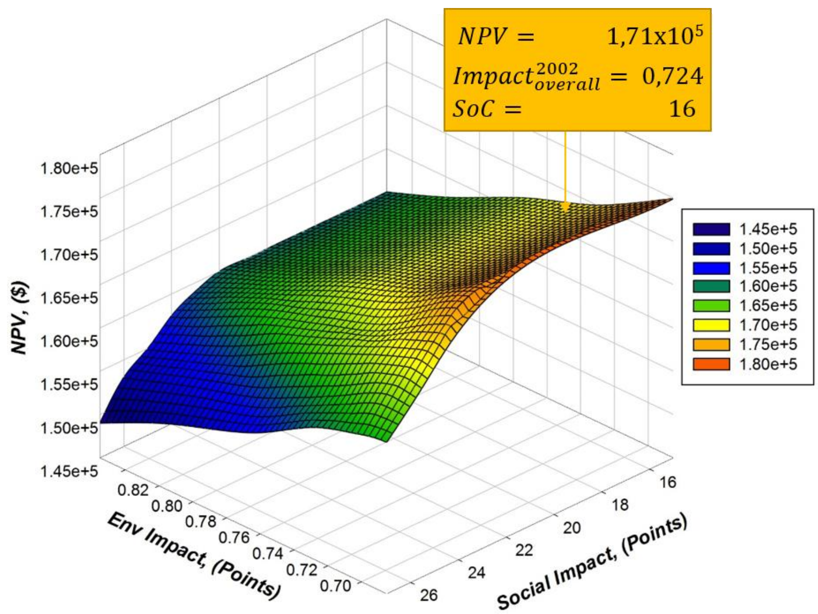

Fig. 8. 3-D representation of the Pareto solutions for the three objectives including the allocation of the overall solution in the feasible solution space.

In the last part of this section, the analysis of the extreme solutions is presented. In order to produce a meaningful solution comparison, the three objectives were analyzed simultaneously using the well-known ε-constraint method. After applying the ε-constraint method, 65 solutions networks were found. As a result, a Pareto frontier was built representing a feasible surface space for the NPV vs $Impact^{2002}_{overall}$ vs SoC problem (see Fig. 8). It is important to highlight that each point in this surface represents a potential feasible optimal solution. From Fig. 8, it is evident that as the SoC objective increases, the NPV decreases while $Impact^{2002}_{overall}$ increases as well, proving their conflicting behaviors. When the social criteria range from 15 to 22, there is no significant change in the economic and environmental performance. However, for values greater than 22 in the social criteria, the performance of the others gradually decreases. It is worth to mention that this surface ranges from \$1.49x10^5 to \$1.73x10^5 and from 0.68 to 0.86 for the economic and environmental performance, respectively.

Ranking solutions

An infinite number of feasible solutions exist. To select the preferred solution, the ELECTRE-IV method has been applied in accordance with the procedure described in section 4.3. The preference, indifference and infeasible thresholds for each one of the criteria used in this work are presented in Table 4.

Table 4. Thresholds values for the three objectives considered in this case study.

Thresholds	Criteria		
	NPV (\$)	$Impact_{overall}^{2002}$	SoC
Indifference (q)	149667.79	0.65	15.00
Preference (p)	168687.72	0.70	24.00
Veto (v)	173442.70	0.85	27.00

The thresholds must reflect the preferences of a decision maker under realistic conditions. In this particular case, the indifference threshold for the NPV corresponds to its lowest feasible value. The preference threshold for the NPV is set as 80% of its maximum value, while the veto thresholds is set as the maximum NPV value. Similar assumptions were used for the thresholds definitions for the remaining criteria. Using the above thresholds, the ELECTRE-IV method was next applied to evaluate the 65 resulting feasible optimal solutions. Table 5 illustrates the solutions sorted according to their desirability as a function of the preference thresholds.

Table 5. Ranked solutions according to its dominance for this case study.

Ranking	Solution
1	2
2	48
3	47
4	1, 6, 7, 8, 16, 17, 18,,21, 22, 26, 27, 31, 32, 36, 37, 41, 42, 50, 52-63, 65
5	11, 48
6	3, 5, 9, 10, 13, 15, 19, 20 ,23, 28, 29, 30, 33, 35, 38, 40, 43, 45, 49
7	4, 14, 24
8	34, 39, 44

From Table 5, solution 2 was found as the overall dominant solution according to the decision makers' preferences. For this solution, the NPV value is \$ 1.71x10^5, and the environmental and social impact are 0.724 and 16, respectively. The above solution entails a reduction of 2%, 15% and 40% form the best possible economic, environmental and social performance values, respectively. From an overall perspective, solution

2 represents a good performance. Fig. 8 shows the selected solution within the solution space. Additionally, Fig. 9 shows the network associated to solution 2.

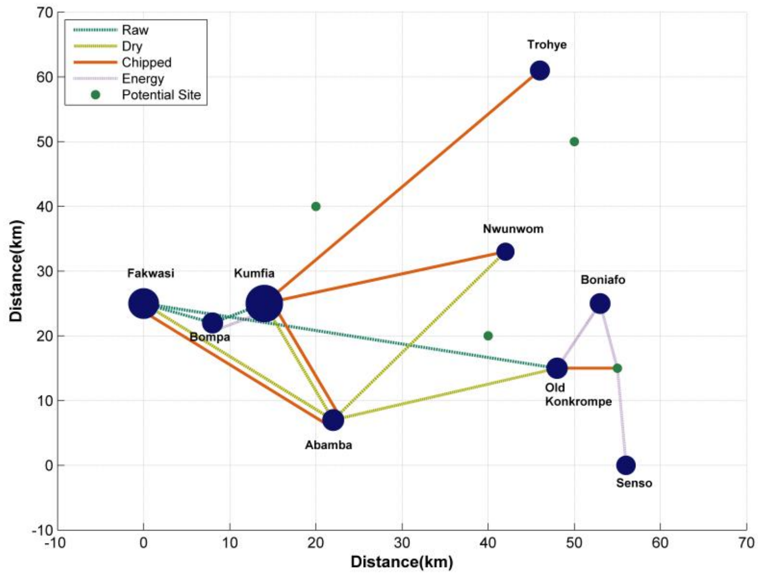

Fig. 9. Optimum network configuration selected using ELECTRE-IV method. Axes are in km. Each line represents the material/energy distribution among communities. Green dotted lines represent the raw material, golden dotted lines represents dry material, while orange lines represents the chipped material and finally purple lines represents the energy distribution.

It is important to highlight that this design highly depend on the definition of the thresholds for each criteria, therefore, another global overall solution can be found using different thresholds. From Fig. 9 it can be noticed that the final network is slightly different to that one associated to the best economic performance by reducing the amount of material distributed (Raw and chipped) at the expenses of treating that material at each particular site. Even with this small reduction in the final profit the use of this approach reduces the subjectivity in the selection procedure, since the solution comparison is carried out under fair and equal conditions.

4.2. Second case. Stochastic solution approach.

In this section, Model P is solved via the SAA algorithm described in sections 3.1 and 3.2. More precisely, for this model 50 scenarios were defined to model the MC, LHV and availability uncertainties. Hence, 50 different SC´s designs were obtained. The economic performance was expressed through its associated expected value ($ENPV$), while the environmental performance was represented as the worst environmental scenario, and social objective as the sum of the binary variables regarding unit installation.

The 50 solutions obtained after applying the proposed approach were evaluated through the ELECTRE-IV method in order to compare all the solutions with each other. As in the first case, ELECTRE-IV method provides a ranking for the 50 possible solutions as a function of the thresholds parameters defined by the decision maker (See Table 6).

Table 6. Ranked solutions according to its dominance for this case study

Ranking	Solution
1	9
2	18
3	4
4	12, 37
5	29
6	1-3, 5-11, 13-17, 19-28, 30-36, 38-50

The following Fig. 10 shows the scheme associated to best overall solution obtained after applying the proposed solution selection strategy.

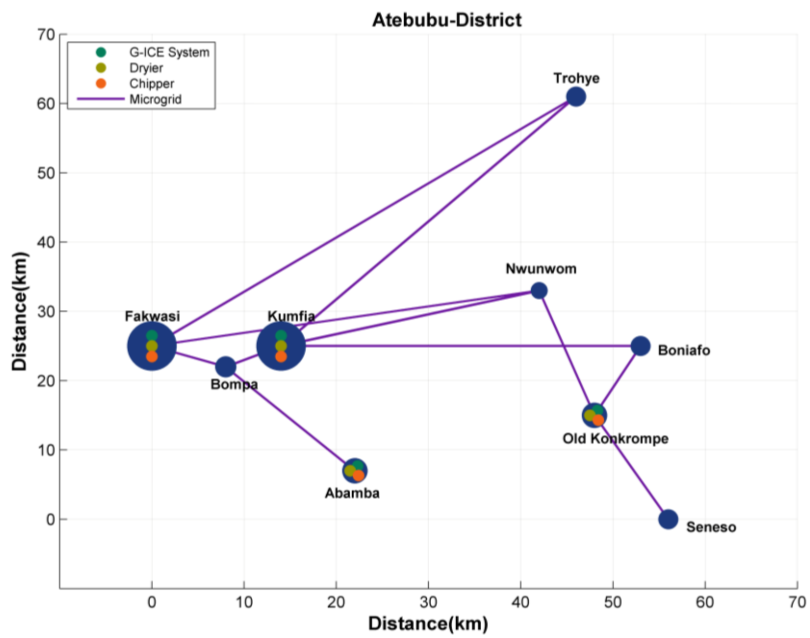

Fig. 10. Resulting robust network. A golden and orange dot represents the dryer and chipper pretreatments units, respectively. Similarly, green point represents the energy production system, while a purple line represents the micro-grid in order to allow the energy exchange among communities.

From Fig. 10, it can be noticed how all the pretreatment activities are performed at strategic locations. Those activities are highlighted in a color scheme. Additionally, Table 7 shows the capacities installed at each equipment unit to provide a robust structure for the complete uncertain solution space. This solution centralizes the treatment/pre-treatment units in just 4 sites. More precisely, Chipper units are installed near to its lower capacity (0.1 t/h), while Dryer ones shows a larger capacity in three cases. On the other hand, the G-

ICE systems capacity installed vary according to its localization. For example, gasifiers with low capacity are installed near the smallest communities, while the two gasifiers with highest capacity are located close to the largest communities in order to property satisfy the energy demand and minimize at the same time the transportation tasks. It is important to remember that the material flows highly depend on the conditions of each scenario.

Table 7. Equipment capacity for the robust networks configuration.

	Dryer (t/h)	Chipper (t/h)	G-ICE (kW_e)
Senso			
Old Konkrompe	0.17	0.1	168.98
Fakwasi	0.24	0.1	241.74
Kumfia	0.31	0.12	316.93
Trohye			
Bompa			
Nwunwom			
Boniafo			
Abamba	0.1	0.1	97.48
Extrasite1			
Extrasite2			
Extrasite3			
Extrasite4			

The above superstructure has an expected profit of \$ 1.54×10^5, while the remaining objectives achieve a value of 0.73 and 12, which represents a deterioration of 10%, 1% and 25% for the economic, environmental and social objectives, respectively, if compared with the solution with the best overall performance seen in the first case (i.e. Deterministic solution obtained using the ELECTRE-IV method). Note that this direct comparison might not be very insightful, as both designs are evaluated under different conditions. Hence, a more sophisticate comparison is described in the next section.

4.3. *Deterministic and Stochastic design comparison.*

A value of information analysis (VIA) was performed to quantify the performance reduction associated with a particular decision [35]. Let us consider the expected performance resulting from the solution for the second case (i.e. stochastic solution) and the solution for the first case (i.e. deterministic solution). Then, the difference between the stochastic and deterministic objectives represents the impact associated to neglecting uncertainties.

In order to properly apply the VIA, the designs obtained under deterministic and stochastic conditions in the first and second case studies must be fixed. Then, the problem has to be solved for their counterpart conditions (i.e. deterministic design under uncertain conditions and vice versa). The optimal values for each objective are shown in Table 8.

From Table 8, it can be seen how the deterministic design under stochastic conditions reach a deterioration of 8.57% and 4.16% for the economic and environmental performance. This means that the deterministic design is efficient only for specific and known parameters, however, when the situation change this network performs under suboptimal conditions (reducing the net revenues). On the contrary, the stochastic design evaluated under deterministic conditions reach a reduction of 52% and 36% for economic and environmental performance. This reduction seems important, however, it means that the stochastic design reduces the potential benefits under certain unfavorable conditions of uncertainty, but entails an increase in its average performance for the entire uncertain space. Therefore, this analysis demonstrated the utility of explicit and uncertain formulation when some of the required parameters are unknown.

Table 8. Equipment capacity for the robust networks configuration.

	Deterministic Design				Stochastic Design		
	$NPV(\$)$	$Impact_{overall}^{2002}$	SoC		$NPV(\$)$	$Impact_{overall}^{2002}$	SoC
Deterministic conditions	171,007	0.72	16	Deterministic conditions	101,729	1.15	12
Stochastic conditions	156,341	0.75	16	Stochastic conditions	154,836	0.73	12
Value of Information*	8.57	-4.16	0		-52.48	36.52	0

- This value is expressed in %

5. Conclusions

In this work, a systematic method to support the supply chain optimal design under uncertain raw material conditions has been proposed. This strategy allows optimizing a stochastic multi-criteria problem considering the quality of different streams. Our method consists of a STN formulation combined with a decomposition strategy to produce a flexible formulation while reducing the computational effort required to solve the problem. Additionally, the ELECTRE IV method was presented as a tool to take a final decision in a quick and systematic way, thus facilitating decision-making tasks and avoiding subjectivity in the selection of the final solution.

The capabilities of this approach have been successfully proved using as a test bed a multi-scenario multi-objective design and planning of a bio-based supply chain problem. It has been found that this method allows managing different material flows with different properties in a sustainable way, thus ensuring an energy supply and reducing operational costs.

Furthermore, this approach can be used in different engineering problems in which material flows quality must be considered explicitly. In the future, the combination of this method with alternative decomposition strategies and scenarios reduction methods will be explored. Besides, additional works involving energy supply issues will be further investigated to increase the robustness of the final solution in real life energy supply chains.

Nomenclature

Abbreviations	
MO	Multi-objective
SC	Supply chain
MOO	Multi-objective optimization
MILP	Mixed integer linear programming
PSE	Process system engineering
SAA	Sample average approximation
STN	State Task Network
LCA	Life Cycle Assessment
LCI	Life Cycle inventory
IS	Industrial Symbiosis
G-ICE	Gasifier internal combustion engine
LV	Low voltage
MV	Medium voltage
LHV	Lower heating value
MC	Moisture content
O&M	Operation and maintenance
MILP	Mixed integer linear programming
VI	Value of information
MFP	Micronized food products
ANN	Artificial Neuronal Network
Indices	
s	Material State
j	Technology (Treatment/Pre-treatment equipment's)
i	Task
f	Origin sites
f'	Destination sites
t	Time period
c	Scenarios
k	Interval for Piecewise approximation (Economies of scale)
e	Supplier site
m	Market site
a	Midpoint environmental category
g	Endpoint damage category
Sets	
T_s	Task that produce material *s*
$\bar{T}_s$	Task that consume material *s*
C	Set of scenarios
E_{rm}	Suppliers *e* that provide raw materials
$\hat{E}_{prod}$	Suppliers *e* that provide production services
$\bar{E}_{tr}$	Suppliers *e* that provide transportation services
FP	Materials *s* that are final products
$\bar{I}$	Task *i* with variable input

I_j	Tasks *i* that can be performed in technology *j*
$\bar{J}_e$	Technology *j* that is available at supplier *e*
$\bar{J}_f$	Technology that can be installed at location *f*
J_i	Technology that can perform task *i*
J_{Stor}	Technologies to perform storage activities
Mkt	Market locations
Ntr	Not transport tasks
RM	Materials *s* that are raw materials
Sup	Supplier locations
Tr	Distribution tasks
RS	Raw set of solutions
$\bar{x}^*$	Optimal set of solutions for scenario c
ϕ	Space of uncertain parameters
KO_1	Ascending pre-ordered set of solutions
KO_2	Descending pre-ordered set of solutions
Parameters	
A_{sftc}	Maximum availability of raw material *s* in period *t* in location *f* and for scenario *c*
Dem_{sft}	Demand of product *s* at market *f* in period *t*
$Distance_{ff'}$	Distance from location *f* to location *f'*
$FCFJ_{jft}$	Fixed cost per unit of technology *j* capacity at location *f* in period *t*
FE_{jfk}^{limit}	Increment of capacity equal to the upper limit in interval *k* for technology *j* in facility *f*
$rate$	Discount rate
$Invest^{MV}$	Investment required for medium voltage
M	Big positive number
$NormF_g$	Normalizing factor of damage category *g*
$Price_{sft}$	Price of product *s* at market *f* in period *t*
$Price_{jfk}^{limit}$	Investment required for an increment of capacity equal to the upper limit of interval *k* for technology *j* in facility *f*
$Tortuosity$	Tortuosity factor
$Water_{sc}$	Moisture for material *s* and scenario *c*
$Water_{ij}^{max}$	Maximum moisture for task *i* performed in equipment *j*
α_{sij}	Mass fraction of task *i* for production of material *s* in equipment *j*
$\bar{\alpha}_{sij}$	Mass fraction of task *i* for consumption of material *s* in equipment *j*
β_{jf}	Minimum utilization rate of technology *j* capacity that is allowed at location *j*
ζ_{ag}	*g* endpoint damage characterization factor for environmental intervention *a*
$\theta_{ijff'}$	Capacity utilization rate of technology *j* by task *i* whose origin is location *f* and destination location *f'*
$\rho_{eff't}^{tr}$	Unitary transportation costs from location *f* to location *f'* during period *t*
τ_{sfet}^{ut1}	Unitary cost associated with task *i* performed in equipment *j* from location *f* and payable to external supplier *e* during period *t*
τ_{sfet}^{ut2}	Unitary cost associated with handling the inventory of material *s* in location *f* and payable to external supplier *e* during period *t*
χ_{est}	Unitary cost of raw material *s* offered by external supplier *e* in period *t*
$\psi_{ijff'a}$	Environmental category impact CF for task *i* performed using technology *j* receiving materials from node *f* and delivering it at node *f'*
ψ_{ija}^{T}	Environmental category impact CF for the transportation of a mass unit of material over a length unit
λ_c	Uncertain parameters vale
q	Indifference threshold
p	Preference thresholds
v	Veto thresholds
$Prob_c$	Probability of occurrence of scenario *c*
Variables	
$DamC_{\mathrm{gftc}}$	Normalized endpoint damage *g* for location *f* in period *t* and scenario *c*
$DamC_{gc}^{SC}$	Normalized endpoint damage *g* along the whole SC for scenario *c*
$EPurch_{etc}$	Economic value of sales executed in period *t* during scenario *c*
$ESales_{tc}$	Economic value of sales executed in period *t* and scenario *c*
$FAsset_{tc}$	Investment on fixed assets in period *t* and scenario *c*

$FCost_{ftc}$	Fixed cost in facility *f* for period *t* and scenario *c*
F_{jftc}	Total capacity technology *j* during period *t* at location *f* and scenario *c*
FE_{jftc}	Capacity increment of technology *j* at location *f* during period *t* and scenario *c*
HV_{sc}	Lower heating value for material *s* during scenario *c*
IC_{aftc}	Mid-point *a* environmental impact associated to site *f* which rises from activities in period *t* and scenario *c*
$Impact_{fc}^{2002}$	Total environmental impact for site *f* and scenario *c*
$Impact_{overa}^{2002}$	Total environmental impact for the whole SC
NPV_c	Economic metric for a deterministic case (just one scenario *c*)
$P_{ijff'tc}$	Specific activity of task *i*, by using technology *j* during period *t*, whose origin is location *f* and destination is location *f'* and scenario *c*
$Profit_{ftc}$	Profit achieved in period for each facility *f* at time period *t* and scenario *c*
Pv_{sijftc}	Input/output material of material *s* for activity of task *i* with variable input/output, by using technology *j* during period *t* in location *f* and scenario *c*
$Purch_{et}^{pr}$	Amount of money payable to supplier *e* in period *t* associated with production activities
$Purch_{et}^{rm}$	Amount of money payable to supplier *e* in period *t* associated with consumption of raw materials
$Purch_{et}^{tr}$	Amount of money payable to supplier *e* in period *t* associated with consumption of transport services
$Sales_{sff'tc}$	Amount of product *s* sold from location *f* in market *f'* in period *t* and scenario *c*
S_{sftc}	Amount of stock material *s* at location *f* in period *t* and scenario *c*
SoC_c	Surrogate social metric at each scenario *c*
x	First stage decision variables
y_c	Second stage decision variables
Sol_a	Solution 1 performance to compare in ELECTRE-IV
Sol_b	Solution 2 performance to compare in ELECTRE-IV
$ENPV$	Expected net present value
$ESoC$	Expected social performance
Binary Variables	
V_{jftc}	Technology installed at location *f* in period *t* and scenario *c*
$Z_{ff'c}$	Facilities *f* and *f'* interconnected by a medium voltage line during scenario *c*
SOS2 variable	
ξ_{jfkt}	Variable to model the economies of scale technology *j* in facility *f* at period *t* as a piecewise linear function

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Appendix A

Technologies characteristics

The gasifier requires that the inlet material strictly satisfies a physical homogeneity (chipped) and a MC lower than 20% (dried). It is assumed that chipper and dryer work an average of 8 h/d while the gasifier works in average 16 h/d. The project has a lifespan of 10 years which is a typical length in this type of SC`s [36]. On-field storage is allowed only before chipping and gasification. This kind of storage represents an economic and simple option providing assurance of biomass availability against seasonality, as well as aims to reducing pre-treatment/treatment capacities. It is important to notice that this kind of storages is only applicable for primary waste and if secondary waste is considered other type of storage may be required.

The capacities of chipper and dryer are assumed to have the same range than those capacities employed while processing maize in micronized food products (MFP) during one day. Those capacity ranges, the investment and operation and management (O&M) costs are taken from the literature. The required parameters and physical limitations used to model the activities in the mathematical formulation are described below.

1. Biomass generation. The cassava is harvested and subjected to different treatments in Food Industries which produce a cassava waste with unpredicted properties.
2. Drying. A rotatory drum is the equipment used to decrease the inlet MC to the desire value of 20%w/w. This unit has an energy efficiency of 99% and use diesel as utility. The diesel price is defined as $1133.31/t and the available capacities for rotatory drums are assumed in the range of 0.1-5 t/h [39]. In this task biomass changes its MC and LHV values proportionally to the water removed.
3. Chipping. Chipping task is mandatory, placed after drying one. It consumes electricity which is directly taken from the G-ICE system. Chippers have 96% energy efficiency and, similarly to dryer units, their available capacities range from 0.1 to 5 t/h [37].
4. G-ICE system. As has been commented, in this model the key parameter to control is the MC, since complementarily with the amount of inlet air highly influence the producer gas composition/performance. The gasification production capacity range between 5-100 kWe. The main parameters and outputs associated to this equipment are shown in Table A.1. Here, the equipment efficiency represents the main parameter and will impact in the amount of Biomass required [38].

5. Transportation. Solid biomass should be distributed from its origin point to a storage place or to pre-treatment/treatment sites by tractors. The capacity of this equipment (Tractors) was set at 10 t, which represents the upper level of tractor capacity. The price of transport task depends on the amount of material transported and the distance among sites. Lineal distances among nodes expressed in km are corrected through a tortuosity factor of 1.8 [39].
6. Distribution grids. This task represent another type of transportation, but this time is energy transportation and not material. LV and MV are considered as "equipment". The LV distribution line has 6% losses in energy terms while MV distribution line losses are proportional to the power demand, as indicated in [40].

Table A.1. Principal output values and specification for the - G-ICE system.

Parameters	Values
Tgasif(°C)	702
Flowrate (kg/h)	35.33
LHV(MJ/kg)	6.32
CGE(%)	68
Power(kW_e)	15.8
η(%)	17

It is considered that the electricity demand should be partially or totally satisfied. The demand has been estimated for each community considering a direct relationship with its population density. Particularly, the highest gross demand is set to be 448.65 kWh/d, while the lowest is 21.17 kWh/d, as shown in Table A.2.

Table A.2. Energy demand and population distribution in Atebubu-Amantin district.

Community	Population (2010)	Net demand (kWh/d)	Gross demand LV (kWh/d)	Gross demand MV (kWh/d)
Senso	296	42.43	45	61.63
Old Konkrompe	566	88.6	93.96	119.48
Fakwasi	1881	333.2	353.35	393.67
Kunfia	2834	423.05	448.64	501.92
Trohye	376	58.65	62.2	78.84
Bompa	512	69.88	74.11	114.43
Nwunwom	122	19.97	21.17	31.57
Boniafo	489	84.86	89.99	115.51
Abamba	653	91.1	96.61	122.13

Appendix B

In order to ease the understanding of the model, the variables and constraints are classified in four groups. The first one describes process constraints, which provides the topology of the SC. The second one deals with the economic metric applied, while the third refers to the environmental model used. Finally the fourth group describes the objective function for this formulation.

5.1. Process model

As commented before, this model is an adaptation of the model presented by Pérez-Fortes et al. [20].which use an extended STN model representation adapted to the design and planning SC problem. The basis of this formulation is that a node is defined for each activity (transportation, pretreatment and treatment) collecting all the information through a single variable set. Therefore the key variable in this formulation is $P_{ijff'tc}$, which represents the specific activity of task i performed using technology j receiving input materials from site f and delivering output materials to site f' at time t and for scenario c. Treatment and pre-treatment activities are modeled considering that facility f and f' are the same since those activities must receive and deliver material within the same site (P_{ijfftc}). Otherwise, for distribution activity, facilities f and f' must be different. This feature eases the economic and environmental metrics formulation and also facilitates the control of inputs and outputs materials for all the activities. Notwithstanding, multiple meaningless variables are produced increasing the required computational effort.

The SC material balances were modelled by a single equation set for all materials and echelons as stated in the STN formulation. Those balances must be satisfied at each node of the network. The expression that balances each material s consumed at each potential facility f in every time period t and every scenario c is given in Eq. (B.1). Parameter α_{sij} is defined as the mass fraction of material s that is produced by task i performed using technology j; T_s set refers to those tasks that have material s as output, while $\bar{\alpha}_{sij}$ and $\bar{T}_s$ set refer to a task consuming s material.

$$\begin{aligned} S_{sftc} - S_{sft-1c} = & \sum_{f'} \sum_{i \in T_s} \sum_{j \in (j_i \cap \bar{J}_{f'})} \alpha_{sij} P_{ijf'ftc} \\ & - \sum_{f'} \sum_{i \in \bar{T}_s} \sum_{j \in (j_i \cap \bar{J}_f)} \bar{\alpha}_{sij} P_{ijff'tc} \end{aligned} \qquad \forall s, f, t, c \qquad (B.1)$$

Notice that the material coefficients (consumption/production factors) for a given activity are fixed and represented by the α_{sij} , $\bar{\alpha}_{sij}$ parameters; however, there are activities for which the model should define an inputs mixture in order to achieve a given value for a specific biomass property (i.e., moisture content). In order to account for those activities the mass balance must be modified as shown in Eq. (B.2).

$$S_{sftc} - S_{sft-1c} = \sum_{f'} \sum_{i \in T_s} \sum_{j \in (j_i \cap \bar{J}_{f'})} \alpha_{sij} P_{ijf'ftc} - \sum_{f'} \sum_{i \in \bar{T}_s} \sum_{j \in (j_i \cap \bar{J}_f)} \bar{\alpha}_{sij} P_{ijff'tc} + \sum_{i \in (T_s \cap \bar{I})} \sum_{j \in (j_i \cap \bar{J}_{f'})} Pv_{sijftc} - \sum_{i \in (\bar{T}_s \cap \bar{I})} \sum_{j \in (j_i \cap \bar{J}_{f'})} Pv_{sijftc} \qquad \forall s, f, t, c \quad (B.2)$$

In order to ensure the energy balance Eq. (B.3) is defined. Here, the heating value (HV_{sc}) for material s and scenario c changes in activity i if this task is a pretreatment one and explicitly modifies the biomass properties or if it is a task that just changes the shape of biomass but it is receiving different kinds of biomass as input.

$$\sum_{s \in T_s} HV_{sc} * Pv_{sijftc} = \sum_{s \in \bar{T}_s} HV_{sc} * Pv_{sijftc} \qquad \forall i \in \bar{I}, f, t, c \quad (B.3)$$

Notice that the heating value for the feedstock depends on the properties of the raw material, and specifically on their moisture content, therefore Eq. (B.4) must be satisfied. In this constraint $Water_{sc}$ and $Water_{ij}^{max}$ represents the moisture content for material s and scenario c and the maximum moisture content permitted for task i performed in equipment j, respectively.

$$\sum_{s \in S_i} Water_{sc} * Pv_{sijftc} \le Water_{ij}^{max} \sum_{s \in \bar{S}_i} Pv_{sijftc} \qquad \forall i \in \bar{I}, j, f, t, c \quad (B.4)$$

The combination of Eq. (B.3) and Eq. (B.4) allows reducing the energy required to dry the biomass allowing the mixture of different quality biomass feedstocks. Therefore both the design and retrofit of SCs will be affected by those mixtures. In this sense, Eq. (B.5) and Eq. (B.6) select the installation of the equipment technology in the potential locations as well as its temporal capacity increase. In order to skip a complex non-linear formulation while calculating the capacity expansion, a piecewise linear approximation in *k* different intervals was applied. This formulation uses the so-called SOS2 variable (ξ_{jfktc}), in which at most two consecutive variables are non-zero. The FE_{jfk}^{limit} represents the limit of capacity expansion for interval *k* while V_{jftc} is a binary variable indicating if the capacity of technology j is expanded at site f in period t and scenario c or not. Eq. (B.7) describes the total capacity F_{jftc} bookkeeping taking into account the amount increased during planning period t (FE_{jftc}).

$$\sum_{k} \xi_{jfktc} * FE_{jfk}^{limit} = FE_{jftc} \qquad \forall\, j \in \bar{J}_f, f, t, c \qquad (B.5)$$

$$\sum_{k} \xi_{jfktc} = V_{jftc} \qquad \forall\, j \in \tilde{J}_f, f, t, c \qquad (B.6)$$

$$F_{jftc} = F_{jft-1c} + FE_{jftc} \qquad \forall\, j \in \tilde{J}_f, f, t, c \qquad (B.7)$$

In order to ensure the total production rate at each plant, Eq. (B.8) defines the boundaries for the production rate being bigger than a minimum level (β_{jf}) and lower than the available capacity. This capacity is expressed as equipment j available time during one planning period, then $\theta_{ijff'}$ represents the time required to perform task i in equipment j per unit of produced material. Since operation times are determined, this parameter can be readily approximated beforehand.

$$\beta_{jf} F_{jft-1c} \leq \sum_{f'} \sum_{i \in I_j} \theta_{ijff'} * P_{ijff'tc} \leq F_{jft-1c} \qquad \forall\, j \in \tilde{J}_f, f, t, c \qquad (B.8)$$

Eq. (B.9) guarantees that the amount of biomass s purchased from site f at each time period t is lower than an upper bound given by physical availability A_{sftc} which is different at different scenarios (e.g., seasonality, crop/plantation yield in a specific region). Eq. (B.10) aims to stablish the electrical network (i.e. if locations f' and f are interconnected). The binary variable $Z_{f'fc}$ has a value equal to one if f' and f are interconnected at scenario c, and 0 otherwise; while M represents a big positive number. Additionally, the model assumes that part of the demand can be left unsatisfied because of limited production or supplier capacity. Thus, Eq. (B.11) forces the sales of product s carried out in market f during time period t to be less than or equal to maximum demand.

$$\sum_{f'} \sum_{i \in \bar{T}_s} \sum_{j \in \bar{J}_i} P_{ijff'tc} \leq A_{sftc} \qquad \forall\, s \in RM, f \in Sup, t, c \qquad (B.9)$$

$$P_{ijff'tc} \leq M * Z_{f'fc} \qquad \forall\, s \in FP, i \in Mkt, f' \notin Mkt, t, c \qquad (B.10)$$

$$\sum_{f'} \sum_{i \in T_s} \sum_{j \in \bar{J}_i} P_{ijf'ft,c} \leq Dem_{sft} \qquad \forall\, s \in FP, f \in Mkt, t, c \qquad (B.11)$$

For further model details the reader should refer to [20].

5.2. Economic model.

The expression representing the operation costs, the total capital investment, and NPV are next described in detail. The total expected revenue obtained in any period t can be easily modelled as stated in Eq. (B.12).

$$ESales_{ftc} = \sum_{s \in FP} \sum_{f' \in Mkt} Sales_{sff'tc} * Price_{sf't} \qquad \forall\, f \notin (Mkt \cup Sup), t, c \qquad (B.12)$$

Overall operating cost can be computed by means of the estimation of indirect and direct costs. The total fixed operating cost for a given SC structure can be represented as Eq. (B.13), where $FCFJ_{jft}$ is the fixed unitary capacity cost of using technology j at site f.

$$FCost_{ftc} = \sum_{j \in J_f} FCFJ_{jft} * F_{jftc} \qquad \forall\, f \notin (Mkt\, \cup Sup), t, c \qquad (B.13)$$

The Eq. (B.14) describes the cost of purchases from supplier$e$, considering raw material purchases, transportation, and production resources at any scenario c.

$$EPurch_{etc} = Purch_{et}^{rm} + Purch_{et}^{tr} + Purch_{et}^{pr} \qquad \forall\, e, t, c \qquad (B.14)$$

The purchases of raw materials ($Purch_{etc}^{rm}$) made to supplier e are evaluated in Eq. (B.15). The variable X_{est} represents the cost associated with raw material s purchased to supplier e. Transportation and production variable costs are determined by Eq. (B.16) and Eq. (B.17), respectively. The provider unitary transportation cost from location f to location f' during period t is represented by $\rho_{eff't}^{tr}$. Similarly, τ_{ijfet}^{ut1} signifies the unitary production cost associated to perform task i using technology j, whereas τ_{ijfet}^{ut2} represents the unitary inventory costs of material s storage at site f. The parameter τ_{ijfet}^{ut1} and τ_{ijfet}^{ut2} entails similar assumptions to the ones considered with regard to α_{sij} and $\overline{\alpha}_{sij}$, since the amount of utilities and labor required by an activity are proportional to the amount of material processed.

$$Purch_{etc}^{rm} = \sum_{s \in RM} \sum_{f \in F_e} \sum_{i \in \overline{T}_s} \sum_{j \in J_i} P_{ijfftc} * X_{est} \qquad \forall\, f \in E_{rm}, t, c \qquad (B.15)$$

$$Purch_{etc}^{tr} = \sum_{i \in Tr} \sum_{j \in (J_i \cap \bar{J}_e)} \sum_{f} \sum_{f'} P_{ijfftc} * \rho_{eff't}^{tr} \qquad \forall\, e \in \bar{E}_{tr}, t, c \qquad (B.16)$$

$$\begin{aligned} Purch_{etc}^{pr} = & \sum_{f} \sum_{i \notin Tr} \sum_{i \in \overline{T}_s} \sum_{j \in (J_i \cap \bar{J}_e)} P_{ijfftc} * \tau_{ijfet}^{ut1} \\ & + \sum_{s} \sum_{f \notin (Sup\, \cup Mkt)} S_{sftc} * \tau_{ijfet}^{ut2} \end{aligned} \qquad \forall\, e \in \tilde{E}_{prod}, t, c \qquad (B.17)$$

The total capital investment is calculated by means of Eq. (B.18) and Eq. (B.19). Investment costs include those required to expand the technology's capacity j in facility site f in period t as well as to connect two different locations f and f' by using a medium voltage network ($Invest^{MV}$). Recall that an economy of scale for technologies capacity is considered in which $Price_{jft}^{limit}$ is the investment for a capacity expansion equal to the limit of interval k (FE_{jfk}^{limit}).

$$FAsset_{tc} = \sum_{j} \sum_{f} \sum_{k} Price_{jft}^{limit} * \xi_{jfktc} + \sum_{f} \sum_{f'} Invest^{MV} Distance_{ff'} Z_{ff'c} \quad \forall\, t = 0, c \qquad (B.18)$$

$$FAsset_{tc} = \sum_{j}\sum_{f}\sum_{k} Price_{jft}^{limit} * \xi_{jfktc} \qquad \forall\, t > 0, c \qquad (B.19)$$

The calculation of profit at each time period is represented at Eq. (B.20). Finally, the rate of return used in a discounted cash flow analysis to determine the *NPV* is computed by means of Eq. (B.21).

$$Profit_{ftc} = ESales_{ftc} - \left(FCost_{ftc} + \sum_{e} EPurch_{eftc} \right) * X_{est} \qquad \forall\, f, t, c \qquad (B.20)$$

$$NPV_c = \sum_{f}\sum_{t} \left(\frac{Profit_{ftc} - FAsset_{ftc}}{(1 + rate)^t} \right) \qquad (B.21)$$

Finally the expected NPV is defined as in Eq. (B.22), considering the probability of occurrence $prob_c$.

$$ENPV = \sum_{c} NPV_c * prob_c \qquad (B.22)$$

5.3. Environmental model.

In accordance with the LCA method, environmental interventions are translated into environmental impact through a characterization factors which are represented in Eq. (B.23). The environmental impact associated with site f, as a consequence of carrying out activities in period t under scenario c is calculated through the variable IC_{aftc}. Parameter $\psi_{ijff'a}$ represents a characterization factor for the environmental impact associated to a specific task i performed using technology j, receiving materials from node f and delivering them at node f' for each environmental category a.

$$IC_{aftc} = \sum_{j \in \tilde{J}_f}\sum_{i \in I_j}\sum_{f'} \psi_{ijff'a} * P_{ijff'tc} \qquad \forall\, a, f, t, c \qquad (B.23)$$

Since all environmental impacts are assumed linearly proportional to the activity performed ($P_{ijff'tc}$), parameter $\psi_{ijff'a}$ should be fixed and constant. The value of the environmental impact factor $\psi_{ijff'a}$ is associated with transport and therefore it is calculated for each pair of nodes as is formulated in Eq. (B.24). Here Parameter ψ_{ija}^{T} represents the a characterization factor of the environmental impact associated to the amount of material transported over a given distance. In order to correct the estimated distance between nodes, a $Tortuosity$ factor was defined. In this work the environmental impact in distribution activities is assigned to the origin node.

$$\psi_{ijff'a} = \psi_{ija}^{T} * distance_{ff'} * Tortuosity \qquad \forall\, i \in Tr, j \in J_i, a, f, f' \qquad (B.24)$$

Eq. (B.25) introduces $DamC_{gftc}$ variable, which is a weighted sum of all environmental interventions. They are combined using g endpoint damage factors ζ_{ag}, normalized with $NormF_g$ factors, as the LCA method indicates [41]. Moreover, Eq. (B.26) calculates g normalised endpoint damage along the SC ($DamC_{gc}^{SC}$).

$$DamC_{gftc} = \sum_{a \in A_g} NormF_g * \zeta_{ag} * IC_{aftc} \qquad \forall g, f, t, c \qquad (B.25)$$

$$DamC_{gc}^{SC} = \sum_{f} \sum_{t} DamC_{gftc} \qquad \forall g, c \qquad (B.26)$$

Eq. (B.27) sums the endpoint environmental damages for each site f while Eq. (B.28) calculates the expected environmental impact as a function of the probability of occurrence of scenario c.

$$Impact_{fc}^{2002} = \sum_{g} \sum_{t} DamC_{gftc} \qquad \forall f, c \qquad (B.27)$$

$$Impact_{overall}^{SC} = \sum_{f} \sum_{t} \sum_{g} \sum_{c} DamC_{gftc} * prob_c \qquad (B.28)$$

For further details about the operational and environmental formulation the interested reader is referred to [42].

5.4. *Objective function.*

Without loss of generality the social impact is associated to the amount of working places which promote the economic activation and will lead to an improvement in the lifestyle of the community around the industry. Therefore, social criterion is the number of sites that have a treatment or pre-treatment system installed as shown in Eq. (B.29). The binary variable V_{jftc} characterizes the number of units installed per site, this criterion assigns a value of 1 to each unit installed per site f.

$$SoC_c = \sum_{j} \sum_{f} \sum_{t} V_{jftc} \qquad \forall c \qquad (B.29)$$

It is very important to comment that in order to ease the formulation of the MO problem, Eq. (B.30) introduces the expected SoC impact as a function of the probability of occurrence $prob_c$.

$$ESoC = \sum_{c} SoC_c * prob_c \qquad (B.30)$$

It is important to highlight that the proposed social performance calculation is less efficient than other methods, such as social life cycle assessment. However, here the social performance is used as a crude assessment to illustrate its effect on the solution's selection in the proposed method. In this particular model $ESoC$ and $Impact_{overall}^{2002}$ will be optimized (maximized and minimized respectively) together with the economic criteria ($ENPV$). The overall optimization problem can be posed mathematically as follows:

$$\max_{\mathcal{X},\mathcal{Y}} \{ENPV, -Impact_{overall}^{2002}, ESoC\} \qquad (B.31)$$

Where, $\mathcal{X}$ denotes the binary variables set, while $\mathcal{Y}$ corresponds to the continuous variable set.

$$\mathcal{X} \in \{0,1\};\ \mathcal{Y} \in \mathbb{R}^{+} \qquad (B.32)$$