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Chapter

Leveraging Integrated Model-Based Approaches to Unlock Bioenergy Potentials in Enhancing Green Energy and Environment

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Abstract

In the quest for a green economy, bioenergy has become a central component due to its ability to minimize depletion of natural energy resources and enhance environmental sustainability. However, the integration of bioenergy for a green economy has often led to policy resistance, the tendency for solutions to cause disastrous side effects on other aspects of the system that were not envisaged. The use of integrated model-based approaches for selection, design, and analysis of technological alternatives for bioenergy production would significantly enhance the systems' sustainability by optimizing design and operation, improving growth and profitability, and enabling a more synergistic interaction between the engineering and the macroeconomic aspects of bioenergy production systems. This chapter is designed to develop model-based methodological frameworks that will support sustainable decision making by all stakeholders involved in the design, operation, and commercialization of bioenergy production systems. Practical case studies are presented for bioethanol, biomethane, and synthetic gas production.

Keywords: system thinking, model identification and analysis, bioreactor synthesis, performance targeting, and economics

1. Introduction

1.1 Bioenergy as a source of sustainable energy

Increasing concerns about depletion of natural resources, precarious nature of waste management and sanitation challenges, as well as environmental deterioration and climate change, have led to a growing interest by many countries to switch to renewable energy technologies. Consequently, the last two decades have seen a rapid implementation of new renewable energy systems, followed by integration of renewable energy into plants where fossil fuels exist. Amongst the existing renewable energy technologies, bioenergy systems are of special significance, because in addition to

being able to generate renewable energy, these systems also breakdown pollutants as well as recycle valuable nutrients found in organic waste [1]. Recent studies have confirmed that the bioenergy technology is robust and offers a great potential not only to reduce energy poverty through the provision of green energy but also enhance a green environment by reducing emissions associated with poor waste management [2–4]. According to one estimate on a bioenergy system, the anaerobic digestion technology, co-digestion of wastewater in a decentralized treatment plant with food wastes could allow the generation of 0.9 kWh electricity per person per day, leaving the nutrients as part of organic matter intact for agricultural use [5]. The recognition of the advantages of bioenergy systems in complying with the progressively more restrictive environmental requirements has led to an increased development and use of new bioenergy technologies, some of which include: sugar fermentation for bioethanol production, anaerobic digestion for biogas generation, pyrolysis for bio-oil production, microbial fuels cells for electricity generation, transesterification for bio-diesel production, gasification for syngas production, etc. [6, 7].

Special challenges arise when attempting to implement a bioenergy technology for renewable energy generation in a given community. Firstly, assessing and selecting the optimal technological alternatives that meet social, economic, and environmental sustainability standards is a challenging task. This is because the successful operation of bioenergy systems depends on the availability of a sustainable supply of feedstock, requiring tradeoffs to be made, on whether to use feedstocks and other utilities for bioenergy generation or to channel these inputs to other industrial sectors requiring the same feedstocks and utility. In addition, bioenergy systems have specific characteristics, making them more adapted to specific feedstocks than others. Secondly, after knowing the technology to implement, challenges often arise from deciding on an optimal spatio-temporal strategy to implement the technology. A long-term perspective is needed to account for the spatio-temporal impact of the bioenergy system on the community to ensure that the system does not result in disastrous side-effects. Some systems might be reliable over the short term or in a given location but pose significant negative effects in the long-term or other locations. It is highly important to use systematic model-based techniques to understand the possible impacts of a given bioenergy system over time horizons that span from months to years, and determine the optimal implementation strategies, which maximize the positive effects and minimize the unwanted side-effects. Thirdly, wouldn't it be surprising if the authors state that getting the right technology and the right implementation strategy doesn't guarantee successful operation? Optimal operation of bioenergy systems requires optimal process configurations that ensure process stability, as well as maximize yield and productivity to ensure economic sustainability of the plant. Systematic mathematical and computational techniques are required for process modelling and simulation aimed at synthesizing optimal plant configurations well adapted to the specific feedstock characteristics of interest. Finally, after obtaining optimal process configurations, it is important to now shift the focus away from the technological solution and placing the focus on the practical considerations required for construction and installation of the technology vis-à-vis the required performance or need. This is highly important because the right technology, with optimal implementation strategy and optimal process configurations, can fail because of wrong equipment characteristics. For the same bioenergy technology, the choice of equipment components required for a rural community in a developing country would not be the same as that required in an urban setting. In addition, choice of equipment characteristics plays a significant role in the cost of installation, and there have been cases where projects have failed to get to completion due to high cost required for implementation. Systematic model-based techniques are again required to

understand how every specific component of the bioenergy system provides the value with regards to meeting the overall needs of the community. The objective here is to improve the economic value of the product by examining each component to determine how many functions that component performs, and the cost contributions of those functions. Systems components with high cost-function ratios are identified as opportunities for further investigation and improvement. The authors will like to mention here that a green economy cannot be achieved without changing the way we design and implement our solutions. However, international discussions on sustainable development have always focused on new technologies that can guarantee sustainability and ignored strategies or tools that can be used to design and implement technological solutions optimally. This chapter is therefore designed to fill this gap and provide a series of model-inspired tools, which can be used to enhance the successful implementation of bioenergy technologies.

1.2 Model-based techniques for sustainable bioenergy systems

When confronted by any complex system, with things about it that you're dissatisfied with (environmental pollution and climate change) and anxious to fix (such as using bioenergy to enhance a green economy), you cannot just step in and set about fixing with much hope of helping. This realization is one of the sore discouragements of our century. You cannot meddle with one part of a complex system from the outside without the almost certain risk of setting off disastrous events that you hadn't counted on in other, remote parts. If you want to fix something, you are first obliged to understand the underlying dynamics of the whole system. Intervening is a way of causing trouble. This is because positively intended solutions to real problems have often led to policy resistance, the tendency for interventions to be delayed, diluted, or defeated by the response of the system to the intervention itself. Considering the complex nature of the economy, model-based techniques, which simultaneously considers all degrees of freedom (the efficiency of the solution as well as the quantitative social economic and environmental impact both in time and space) by employing mathematical models becomes undoubtedly the strategy of choice. To understand the problems better and make good decisions, appropriate analysis tools are required. Previous analysis has tended to use 'soft' approaches, which do not require a knowledge of mathematical or computational techniques. These approaches can often be complementary to the techniques presented here. However, the use of mathematical and computational methods can be advantageous, due to the complexity and interactive nature of many of the problems involved and can, for instance, support decision making and making trade-offs in complex problems. However, many researchers are unfamiliar with the range of analytical, mathematical, and computational methods that could be applied in this area. Therefore, they are not able to take advantage of the full range of available methods in their research or analysis. This book chapter aims to fill this gap by providing both a basic introduction and advanced technical details of some of the available mathematical and computing methods, as well as illustrating their use through case studies and examples.

The methods presented here are aimed specifically at sustainable deployment of bioenergy technologies into production, and the case studies and examples are all in this area, but they have a wide range of other application areas, including in economics, medicine, and control systems. The techniques presented include:

- Systems theory and methodologies for structuring complex sustainable development problems to make it easier to obtain a solution to them.

- Optimization and decision-making techniques to support policy formulation and other decision applications.
- Attainable region technique for performance targeting, synthesis as well as analysis of process configurations required to operate bioenergy systems
- Functional analysis system technique, use to ensure that the engineering systems are designed and constructed with minimal cost, and strongly align the needs of the community using the system.

2. Theoretical background

2.1 Conceptual framework of an integrated model-based approach

The conceptual model-based framework that can be used for the implementation of a given bioenergy technology in a community is illustrated in **Figure 1**, consisting of five major stages. Stage one involves deciding on the type of bioenergy to install. This decision making in energy supply is influenced by factors such as social, economic, environmental, political, and technical impact, making it helpful in developing a sustainable solution to the local community. Due to the difficulty in complex interactions between the aforementioned factors, the Multicriteria Decision Method (MCDM) is employed. This provides an approach that eliminates the challenges by developing evaluation criteria and methods that reliably measure sustainability, leading to the selection of an appropriate bioenergy system for the community. The next stage involves the use of system dynamic modelling to devise an implementation strategy for the proposed bioenergy technology from stage one. This stage involves the development of linear and non-linear mathematical models for the underlying mechanism of the system and evaluating the dynamic behaviors to identify policy resistance and any human decisions that can exacerbate perturbations. The strength of the technique is that it helps to minimize unforeseen side effects and generate a forecast to determine future side effects, aiding in the

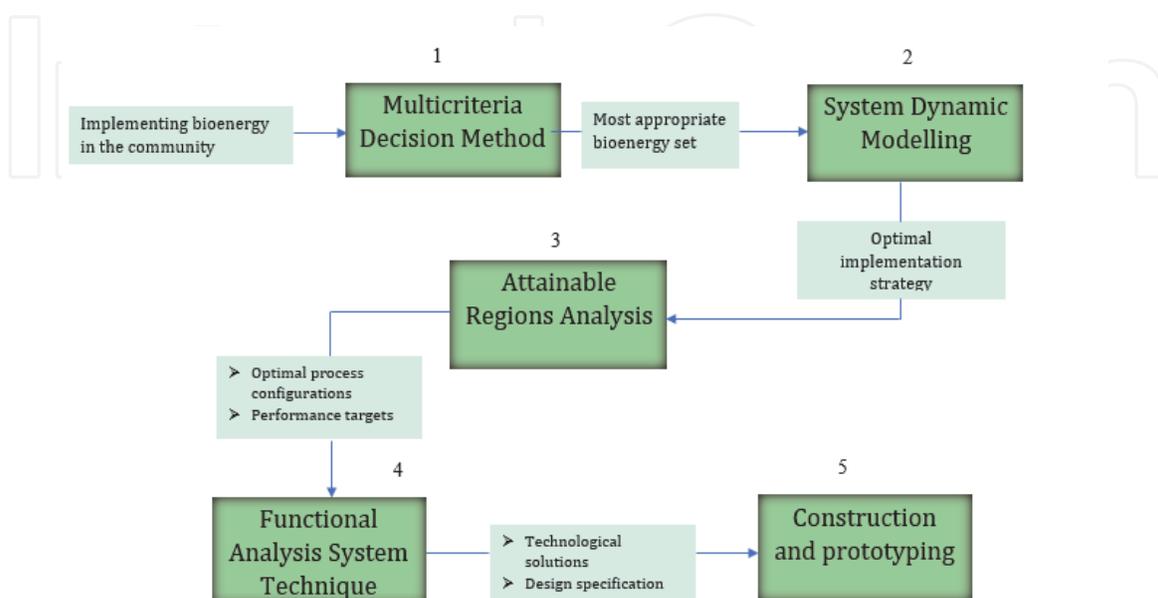


Figure 1. Model-based framework for bioenergy systems implementation in rural communities.

selection of an optimal implementation strategy for the system. In stage three, the concept of attainable regions is used for the design of optimal process configurations. The AR technique is a systematic approach to process synthesis, which integrates elements of geometry and mathematical optimization to understand how systems can be designed and improve. The power of the AR technique is that all possible states, for all possible bioreactor configurations, are first determined [8–10]. The AR can be constructed after specifying the geometric space, kinetic models, and the feed conditions; then, the appropriate objective functions can be overlaid on the AR boundary to identify the optimal operating points and associated process configurations [8]. Once the optimal process configuration has been identified, the next stage is to analyze the design process adequately. This is achieved by employing the functional analysis method, a technique that provides technological solutions and design specifications which permit the satisfaction of the principal and constraint function. Interesting, the technique provides an effective method in improving the quality and performance as well as minimizing the cost of the proposed solution [11]. Finally, the proposed solution can be constructed. It is worth noting that it is not the intention of the authors to discuss the construction phase, although it is mentioned.

2.2 Modeling concepts

2.2.1 Multicriteria decision making

The implementation of successful sustainable energy solutions in local communities consist of a balance of social, economic, technical, and environmental aspects [12]. In that, the energy generated should: (1) be within an environmental tolerance limit, (2) generate employment opportunities for the locals, thereby improving their income and contribute to the regional or national economy, (3) meet the energy demand using available feedstock in the local community [13, 14]. These factors cannot be achieved without a systematic methodological framework that simultaneously considers all the degrees of freedom associated with the bioenergy system. This is because complex interactions exist between these factors, making the decision on the type of bioenergy system difficult. Therefore, sustainable decision making should integrate MCDM tool for successful bioenergy installation as this would guarantee the potentials for an increased standard of living as well as social and economic stability. The technique requires deciding on the type of decision model to employ and developing an evaluation criterion that reliably selects the best bioenergy alternative based on the aforementioned factors. **Table 1** illustrates the different categories of classifying MCDM and their respective methodologies.

2.2.2 System dynamics modeling

A system is a set of interrelated elements, where any change in any element affects the set as a whole. Only elements directly or indirectly related to the problem form the system under study. To study a system, we must know the elements that make it up and the relationships between them. A strong focus must be geared towards understanding the characteristics of its constituents and the nature of the relationship that exists between them. This is necessitated because, more often than not, positively intended solutions to real-life problems have often led to unwanted side effects that were not envisaged [16]. Therefore considering the complex nature of systems, a system thinking approach that simultaneously considers all degrees of freedom of the problem is undoubtedly the strategy of choice. System thinking, also known as system dynamics modelling is a scientific framework for addressing

Categories	Methodology
Multi-attribute utility and value theory	AHP/ANP
Multi-objective mathematical programming	<ul style="list-style-type: none"> • Constrain programming • Linear programming • Goal programming
Non-classical method	Fuzzy set methodology
Elementary aggregation method	<ul style="list-style-type: none"> • Weighted sum method • Weighted product method
Complex aggregation method	ASPID
Distance-to-target approach	<ul style="list-style-type: none"> • TOPSIS • Grey Relational Analysis • Data Enveloping Analysis
Direct ranking (high dependence on decision-maker)	<ul style="list-style-type: none"> • Stepwise expert judgment • Delphi • Scoring method
Outranking method	<ul style="list-style-type: none"> • ELECTRE I, IS, II, III • PROMETHEE I, II

Compiled from Refs. [13–15].

Table 1.
Categories for classifying MCDM methodologies.

complex, nonlinear feedback systems [17]. The strength of this technique is that it provides an opportunity to understand the dynamic behavior of the system under study and generate useful information that affects policy evaluations.

2.2.3 Attainable regions (performance targeting and equipment design)

Attainable region (AR) is an approach to graphical/geometric optimization of bioreactor network synthesis. The technique originated from the work of Horn, who defined the AR as the set of all possible values of the outlet stream variables, which can be reached by any possible (physically realizable) steady-state reactor system from a given feed stream using only the processes of reaction and mixing. The technique has been used in the synthesis of isothermal reactor networks [18], synthesis and design of biogas digester structures [19–22], classical variations and dynamic problem synthesis, optimal batch distillation for reduced energy consumption [23, 24], and in analysis to optimize particle breakage in ball mills [25]. Interestingly, in recent publications by Abunde et al., the concept of AR has been extended to include Self-optimizing attainable regions for the design of anaerobic digesters [21]. This is the first of its kind and sought to address the design of anaerobic digesters in situations where reliable kinetic coefficients are unavailable. The technique offers exciting possibilities for process synthesis seeing the countless opportunities it holds to address reactor network synthesis problems. More importantly, there are speculations of an extension of the concept to the design of dryers and distillation columns. Other future studies could look at how self-optimizing AR for design could be integrated with self-optimizing controllers to achieve optimality in processes. The strength of the AR approach is that it simultaneously considers all possible outputs for all possible process configurations, by interpreting the process as a geometric object that defines the limits of achievability without having to enumerate all reactor configurations explicitly [8].

2.2.4 Functional analysis (need analysis and technological features, design specification)

Function analysis, a vital component of value analysis, is a technique employed during the design and construction stage to assess a product's function to eliminate components that neither contribute to the quality nor improve the efficiency product. This technique provides an assessment of the proposed technology from different perspectives to adequately identify possible rooms of improvement [11]. The advantage of the technique is that it allows a transition from a focus on the expected solution to a problem to the appropriate and desired performance needs of the product.

3. Workflow of concepts and integrated model-based methodology

3.1 Workflow of methodology

This section discusses in detail, a step by step approach to how the techniques presented in the conceptual framework are deployed.

3.2 Overview of MCDM methodology

There are several MCDM tools to deploy in selecting an appropriate bioenergy technology. The decision on the tool to employ at this stage is vital and requires selecting the best alternative, which is a difficult decision since there exists characteristics that are peculiar to each technology.

It is expedient for readers to note that not all MCDM methods presented in Section 2.2.1 are same. This is because some methods incorporate more features than others that are rather limited from different perspective [26]. Moreover, the choice of method is usually dependent on the decision makers' knowledge of the techniques and the availability of software that support the method ([14, 27]). In this regard, most multicriteria decision problems are adjusted to suite a particular method. However, subjective and objective MCDM tools such as Analytical Hierarchy Process (AHP) and Technique for order preference by similarity to ideal solution (TOPSIS), respectively, are often used in sustainable energy decisions. AHP provides a very simple and flexible model for a problem and is useful in achieving a consensus in cases where there are multiple conflicting criteria. However, its inability to capture uncertainties and determine alternative ratings in decision making is complimented by TOPSIS, making the use of an integrated AHP-TOPSIS technique a more robust approach to decision making.

It is interesting to note that there exist frameworks that aid the selection of a decision-making tool as presented by Watróbski et al [27], that links a decision-making situation to the most suitable multicriteria decision method. However, this presents an inexhaustive, detailed and nearly impossible approach that takes into consideration all decision dimension, not to mention the extensive number and variety of methods available (in the reported presented by Watróbski et al, over 56 decision making tools exist). For this reason the authors focused on AHP and TOPSIS which has been successfully deployed by Akash et al., for the successful selection of an electric power plant [28] and Mohsen et al., in evaluation of an electric heating system [29]. It is also worth noting that it is not the intention of the authors to describe how to select a tool but rather to demonstrate how model-based techniques can be used to select an optimal bioenergy for a community. Interested readers can resort to the referenced material in this section.

AHP is a multi-level structured technique that presents a comprehensive framework for determining the different alternative solutions for a certain problem [30]. The technique was first introduced by Saaty in 1980 and is described in the following:

- The first step involves developing a hierarchy structure that describes the goal, alternatives, criteria, and sub-criteria for evaluation.
- Pair-wise comparison for the criteria and alternatives with respect to the goal (objective) is established to extract the decision matrices using a nine-point scale. Comparing an attribute to itself is assigned a value of 1 so that if an n given criteria matrix is constructed at any given level, the diagonal entries will all be 1. The value 1 also signifies, equal relevance of attributes. The numbers 3, 5, 7, and 9 correspond to “moderate importance,” “strong importance,” “very strong importance,” and “absolute importance”, respectively. It is important to note that the length of the pair-wise matrix is equivalent to the number of attributes.
- The pair-wise comparison procedure is repeated for each criterion, and then the priority of alternatives is acquired by accumulating the weights. Statistical techniques such as arithmetic mean method, characteristic root method, and least square method can be employed to accumulate the weights. Adopting an arithmetic sum approach, a vector $W = [W_1, W_2, \dots, W_N]$ is constructed to represent the weight of each criterion in a pair-wise comparison matrix A . Each element in column j of matrix A is divided by the sum of entries in the j column. This step generates a new matrix called the normalized matrix (A_{norm}).
- The final step involves making a decision based on the priorities set, but before that, the normalized matrix is subjected to a consistency check to evaluate whether the comparison made was sound. The check involves determining the maximum Eigen values and consistency index using Eqs. (1) and (2), respectively. One advantage of the consistency ratio is that it eliminates the problem of disagreements in individual judgments.

$$\lambda_{max} = 1/n \sum_{i=1}^n \frac{i^{th} \text{ entry in } AW^T}{i^{th} \text{ entry in } W^T} \quad (1)$$

where λ_{max} , maximum Eigen value; n , number of attributes; A , pairwise comparison matrix; W , the estimate of the decision-maker's weight.

Nevertheless, the consistency is checked by comparing the consistency Index (CI) to the Random Index (RI) for the appropriate value of n , used in decision-making [30]. If $(CI/RI) < 0.10$, the degree of consistency is satisfactory, but if $(CI/RI) > 0.10$, serious inconsistencies may exist, and the results produced by AHP may not be meaningful.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (2)$$

where the variables have their usual meaning.

TOPSIS selects the best alternative based on their geometric distance from the positive or negative ideal solution. According to the technique, the best alternative from the positive ideal solution has the shortest geometric distance, while the negative ideal solution has the longest geometric distance. Assuming for the bioenergy system understudy, we have m alternatives, n number of attributes, and

the score of each alternative with respect to each criterion is known, the following steps could be followed in order to rank each alternative.

Step 1: Construct the normalized decision matrix

In this step, the different attributes dimensions are transformed into non-dimensional attribute, to allow comparison across the attributes. Using the method represented in Eq. (3), the matrix $(x_{ij})_{m \times n}$ is normalized to $R = (r_{ij})_{m \times n}$ which takes the form shown below:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^m x_{ij}^2}} \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

$$R = \begin{pmatrix} r_{11} & \dots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \dots & r_{mn} \end{pmatrix} \quad (3)$$

Step 2: Construct the weighted normalized decision matrix

With the normalized decision matrix (R) computed from the previous step, the weighted matrix W from the AHP method is integrated into the R. This results in a matrix that is computed by multiplying each column of R with its associated weighted matrix W as represented in Eq. (4).

$$V_{ij} = w_j \times r_{ij} \text{ where } i = 1, 2, \dots, n \quad (4)$$

This computation results in a new matrix V, which is represented below

$$V = \begin{bmatrix} v_{11} & \dots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \dots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & \dots & w_n r_{1n} \\ \vdots & \ddots & \vdots \\ w_1 r_{m1} & \dots & w_n r_{mn} \end{bmatrix}$$

Step 3: Determine the ideal and negative ideal solutions

In this process, two artificial alternatives A^* (the ideal alternative) and A^- (the negative ideal alternative) are defined as:

$$A^* = \{v_1^*, v_2^*, \dots, v_n^*\} = \{(\max_j v_{ij} | i \in I'), (\min_j v_{ij} | i \in I'')\}, i = 1, 2, \dots, m; j = 1, 2, \dots, n.$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\} = \{(\min_j v_{ij} | i \in I'), (\max_j v_{ij} | i \in I'')\}, i = 1, 2, \dots, m; j = 1, 2, \dots, n.$$

where I' is related to benefit attributes and I'' is related to cost attributes

Step 4: Achieve the remoteness of all choices from A^+ and A^-

In the process, the separation measurement is done by calculating the distance between each alternative in V and the ideal vector A^* using the Euclidean distant which is given as Eqs. (5) and (6)

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad i = 1, 2, \dots, m \quad (5)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad i = 1, 2, \dots, m \quad (6)$$

where D_i^+ and D_i^- are the Euclidean distance from the ideal best and ideal worst, respectively.

At the end of this, two quantities namely D_i and S_j for each alternative has been counted, representing the distance between each alternative and both (the ideal and the negative ideal).

Step 5: Determine the relative closeness to the ideal solution using Eq. (7).

$$CC_i^* = \frac{D_i^-}{D_i^- + D_i^+} \quad i = 1, 2, \dots, m \quad (7)$$

where CC_i^* is the performance score.

Step 6: Rank the alternatives according to relative closeness to ideal solution
The set of the alternative A_i can now be ranked according to the descending order of CC_i^* , the highest value, the better performance. **Figure 2** represents an integrated AHP-TOPSIS for multicriteria decision making.

From **Figure 2**, the AHP is used to determine the weight of each criterion, while the TOPSIS is applied to achieve the final ranking of the alternative bioenergy technology closest to the ideal solution.

3.3 Overview of system dynamics modeling methodology

System dynamics deals with feedback and delays that affect system behavior over time. The power of the technique to capture the underlying dynamics of the essential components of the systems allows it to generate links and interactions that lead to a more accurate conclusion and a better understanding of a system. **Figure 3** illustrates a schematic diagram for the different theoretical and quantitative steps involved in system dynamic modelling.

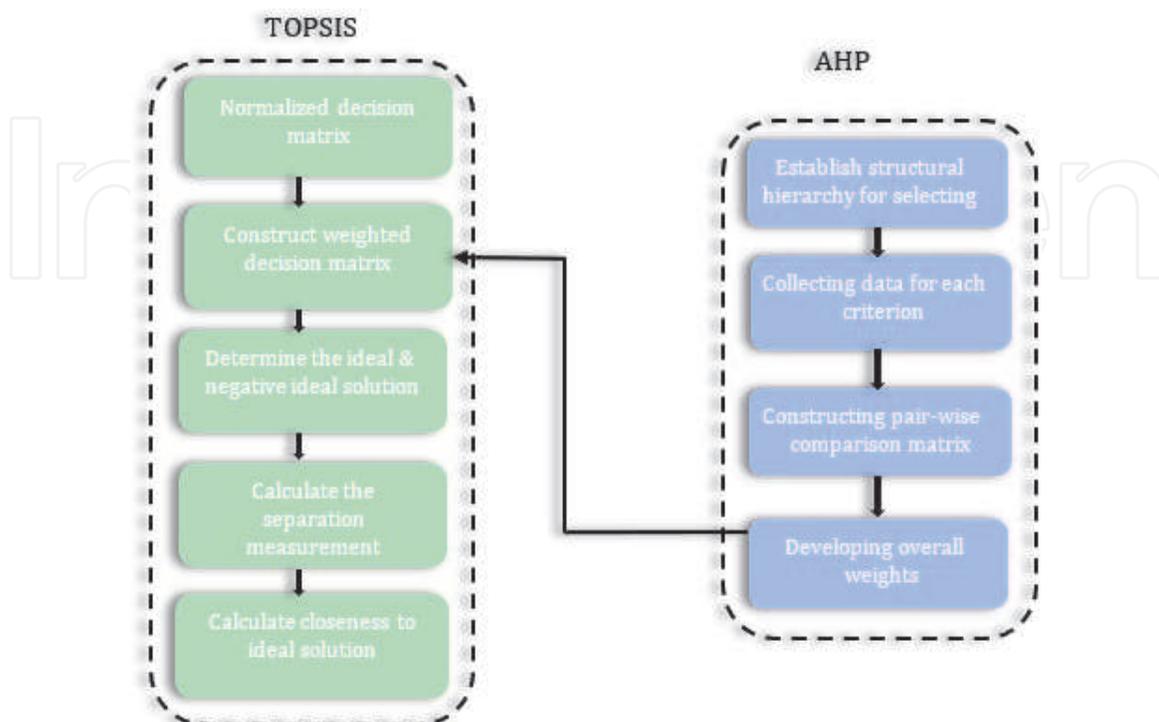


Figure 2. presents an integrated AHP-TOPSIS for multicriteria decision making.

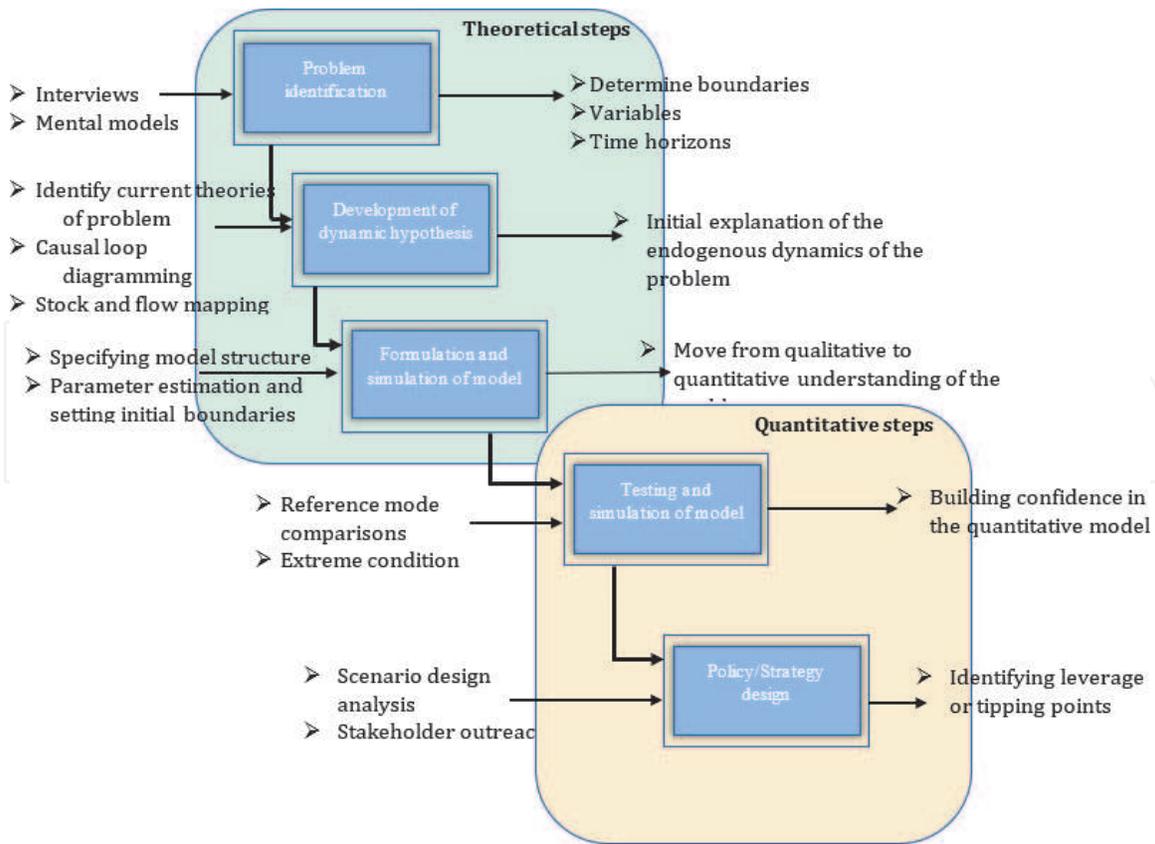


Figure 3.
 Schematic diagram showing the steps involved in system dynamic modeling.

3.4 Overview of AR methodology

The AR is generated using two fundamental reactor types (CSTR and PFR) and mixing. The AR construction involves four major steps which include:

- i. Generating the PFR trajectory from the feed point.

The PFR Eq. (8) was solved using *MATLAB ode45*, the yield of each extract was plotted as a function of PFR residence time τ using feed concentrations of $C_f = [X_f, P_f, S_f]$ for each extract.

$$\frac{dC}{d\tau} = r(C) \quad (8)$$

$$r(C) = \begin{bmatrix} r_{yE} \\ \tau \end{bmatrix} = \begin{bmatrix} f(t, z) \\ 1 \end{bmatrix} \quad (9)$$

where

$$f(t, z) = \begin{bmatrix} \mu X \\ Y_{PX} \mu X \\ -\frac{1}{Y_{XS}} r_X - \frac{1}{Y_{PX}} r_P - M_s X \end{bmatrix}$$

$$z = (X, P, S)$$

- ii. Plot the CSTR locus from the feed point.

The CSTR locus from the feed point C_f is found by solving the non-linear CSTR equation using MATLAB *fsolve* over a range of residence time, and plotting the yield in the $(y_E - \tau)$ space. The data from the CSTR solution are presented as a collection of points and not a line because each residence time corresponds to a different operating scenario. The CSTR relation is represented in the relation below

$$C_f + \tau_1 r(C) - C = 0 \tag{10}$$

iii. Extend the AR boundary by running a series of PFR from each CSTR locus.

Solving the CSTR non-linear equation results in a series of points known as the CSTR locus. These points for each residence time are used as initial feed conditions to generate the PFR trajectory.

iv. Construct the convex hull. In broad reactor network synthesis terms, convex hull can be defined as the smallest subset of a set of points that encloses the original set of points [8]. The convex hull operation was carried out using MATLAB *convhull*. Identifying the convex hull for the set of points helps to identify unique points that can be used for mixing in order to extend the limit of achievability for the system.

3.5 Overview of functional analysis

Figure 4 presents a graphical representation of FAST technique, showing the different phases that will be used in the analysis.

Some of the terms employed in functional analysis are described below

Function: this defines the effect of the produced a product or one of its components to satisfy a need.

Service function: it is the function realized by a product in response to the need of a given user.

Technical function: an internal action of the product defined by the designer within the framework of a solution to assure the service function;

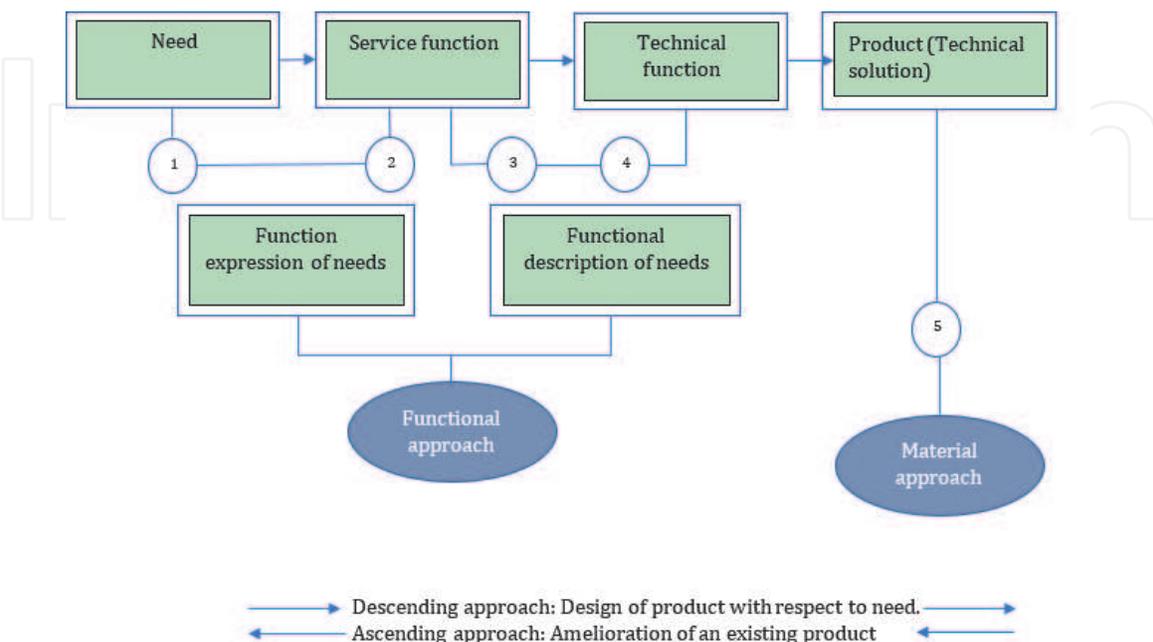


Figure 4.
The different phases of the functional analysis method.

Need: something that is necessary or desired by the customer

The different considerations concerning the functions of the bioenergy technology were obtained by applying the tools of the functional analysis technique.

4. Application case studies

This section deals with how the conceptual framework present in Section 2.1 is applied to a real-time bioenergy project. It's based on the implementation of bioenergy system in Kumasi, Ghana, a Sub-Saharan country in West Africa.

4.1 Deciding on the type of bioenergy system

This stage consists of using MCDM (AHP-TOPSIS) to decide on the type of bioenergy system to install considering the environmental, social, technical, and economic factors of the location.

Table 2 presents the Alternatives Bioenergy Technologies (ABT), which are utilized as potential candidates for installation. The list presented in **Table 2** is not exhaustive but only used to illustrate how the framework can be applied.

The alternative strategies can be evaluated based on multiple attributes, which can be benefit or cost, as shown in **Table 3**. To adhere to the objectives of affordable and clean energy called for by the United Nations Sustainable Development Goal 7, the criteria considered are those that are dominant in determining sustainability of the energy system.

Figure 5 presents a hierarchical decomposition of the decision-making problem summarizing the overall objective, the alternatives, as well as the criteria and sub-criteria used to evaluate the alternatives. This is structured in a well-organized manner such that it shows how each level depends on the upper level.

It is important to note that an initial assumption of equal weights for the major criteria was made, that is economic, environmental, technical, and social factors.

Figure 6 represents the weights of relative importance of each criterion obtained using the AHP method (see steps presented in Section 3.2).

The weights presented in **Figure 6**, implies that safety of the bioenergy technology is more relevant compared to the other criteria. Moreover, the different weights directly reflect the relative importance of environmental impact and safety criteria in the decision making of an alternative energy system.

The next step requires inputting the weights obtained from the AHP into the TOPSIS approach; this results in a ranking of the alternative source of bioenergy.

Symbol	Alternative strategy	Type of process
ABT1	Sugar fermentation to produce bioethanol	Biochemical
ABT2	Anaerobic digestion to produce biogas	Biochemical
ABT3	Transesterification of oils to produce biodiesel	Chemical
ABT4	Biomass gasification to produce syngas	Thermochemical
ABT5	Biomass carbonation to produce biochar	Thermochemical
ABT6	Biomass compression to Briquette	Thermochemical
ABT7	Using microbial fuel cells to generate electricity	Bio-electrochemical

Table 2.
 Matrix of bioenergy alternative.

Symbol	Name of criteria	Objective	Description
C1	Efficiency	Maximize	This measured quantity of bioenergy generated per quantity of feed for the different technologies
C2	Safety	Maximized	This measure the treat the technology possess on the employees and environment
C3	Investment cost	Minimize	This measure the capital required to establish the bioenergy technology
C4	Service life	Maximize	This defines how long the technology can sustainable run
C5	Environmental impact (CO ₂ emissions)	Minimize	This measures the environmental friendliness of each technology
C6	Land use	Minimize	This describes the land space required to construct each equipment
C7	Job creation	Maximize	This describes the degree of job opportunities generated by each technology
C8	Cost of feedstock	Minimize	This measures the quantity of readily available feedstock and their cost.
C9	Climate dependency	Maximize	Is the strategy optimal for different climatic and/or geographical conditions?

Table 3.
Set of decision criteria to appropriate bioenergy technology selection.

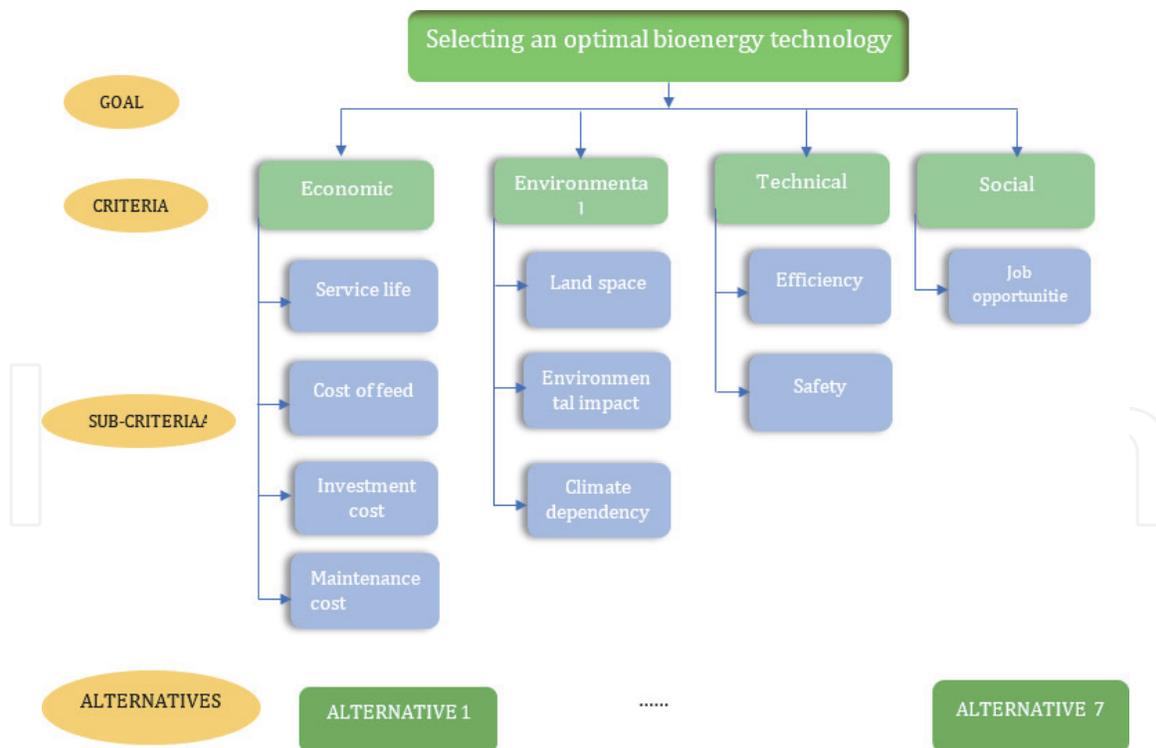


Figure 5.
Hierarchical breakdown of selecting the bioenergy system problem.

Based on the indicators used, lower-ranking of alternatives are more desirable and demonstrate favorability towards sustainability.

From **Figure 7**, sugar fermentation to produce bioethanol is the most appropriate technology for installation in the location of interest. So far, this section has focused on how MCDM tool can be used in selecting an appropriate bioenergy

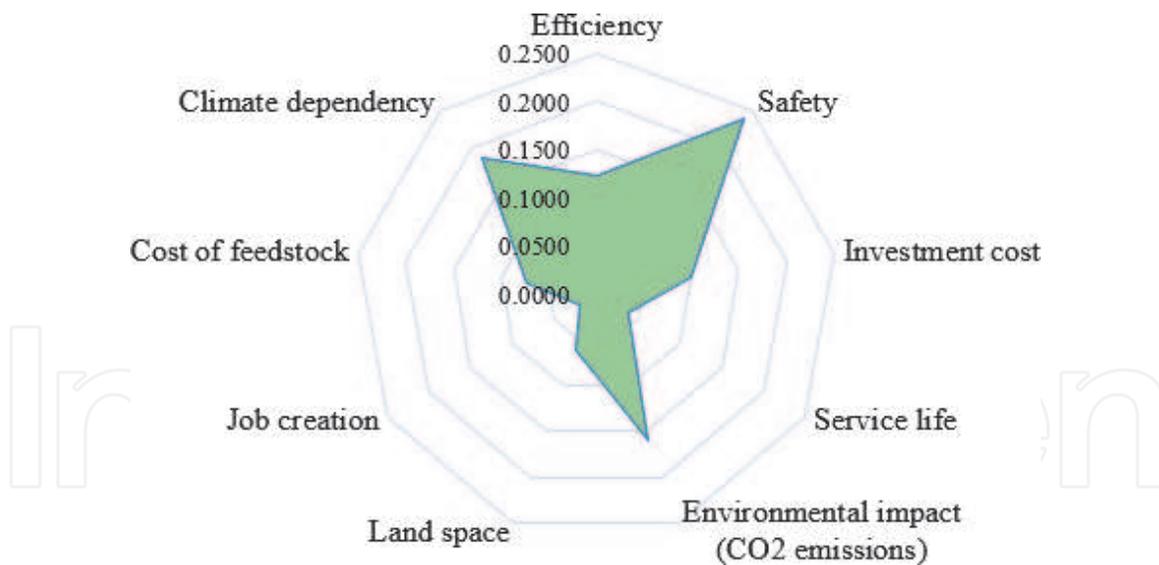


Figure 6.
 A spider web diagram that describes the weight of each criterion.

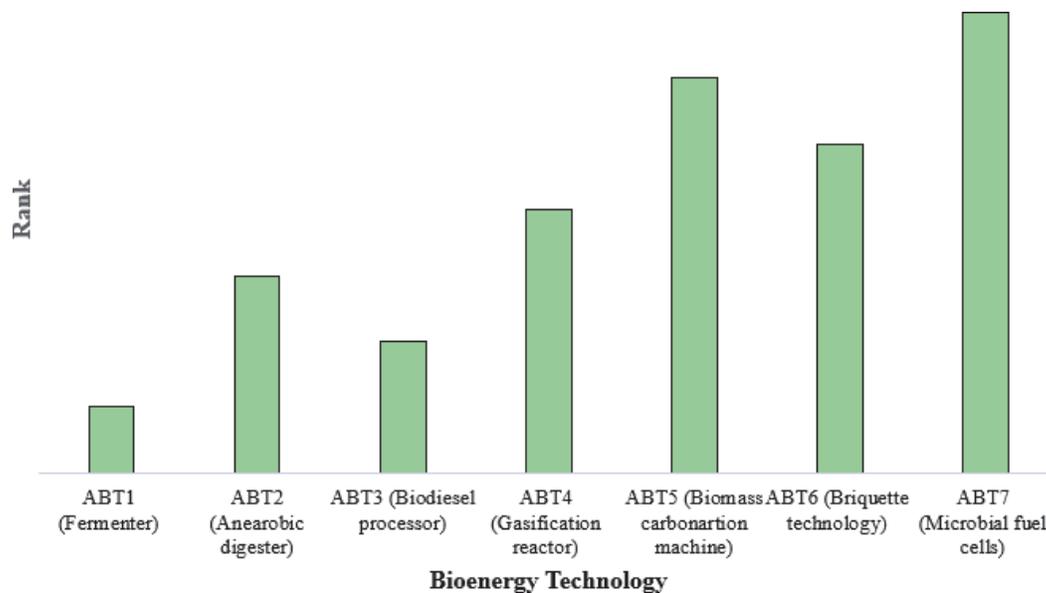


Figure 7.
 Presents the ranking of alternative bioenergy technologies after an integrated AHP-TOPSIS approach.

technology. However, before proceeding to the installation of the technology, the next section will discuss how an optimal implementation strategy could be identified using system dynamic modelling.

4.2 Designing an optimal implementation strategy

With the appropriate technology selected, the next step involves the selection of an optimal implementation strategy that requires the development of dynamic models. It is relevant to note that the outcome of the proposed models from the methodology can be used to identify places of management potential (bioenergy policies) and future tipping points that can alleviate potential economic, environmental, and social challenges. The description of the dynamic behavior for bioethanol production was based on the underlying feedbacks and interactions between selected indicators is illustrated through the integrated causal loop diagram in **Figure 1**. The key relevant factors are investment, environmental impact,

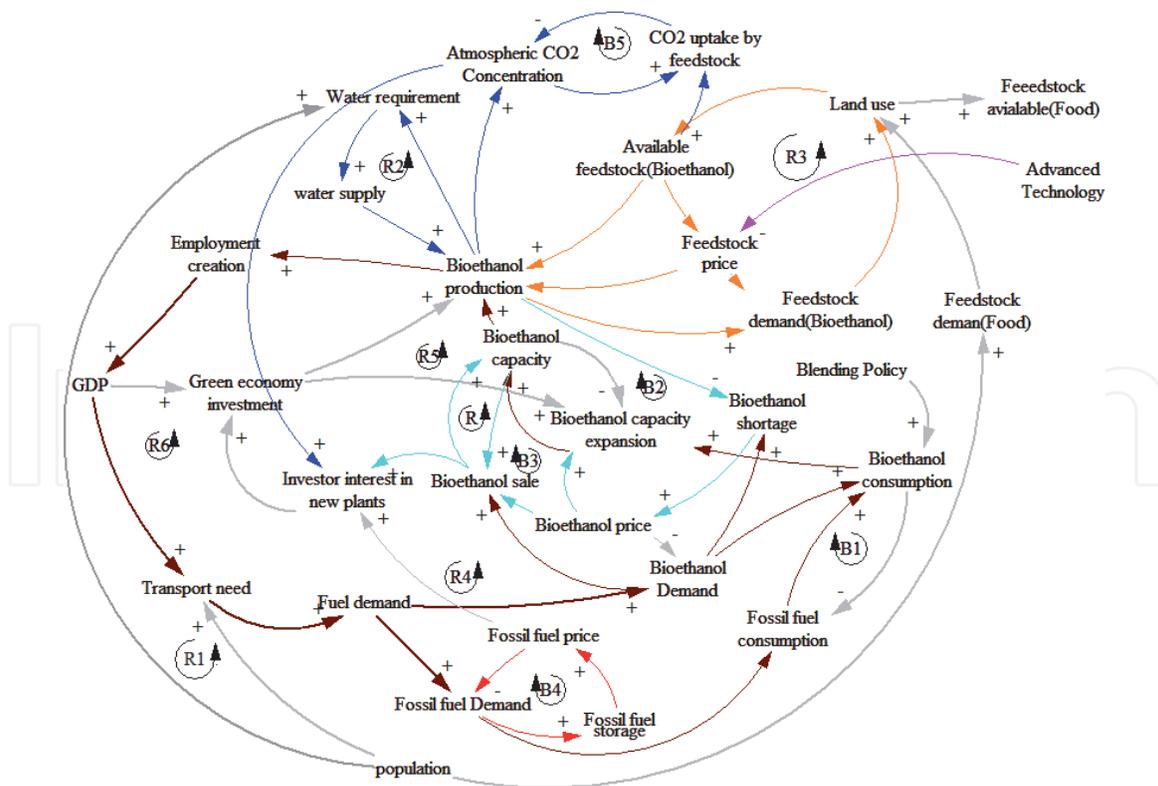


Figure 8.
Casual loop diagram (CLD) for bioethanol production.

employment creation, cost of feedstock, and land space. The causal loop diagrams (CLDs) presented in **Figure 8** are flexible and useful tools for diagramming the feedback structure of systems in any domain [16].

From **Figure 8**, interesting observations can be made considering the reinforcement loop (R) and the balancing loop (B).

1. An increase in population leads to a greater demand for transport (private, commercial, or public), increasing in fuel demand (bioethanol demand) (R1). This will indirectly lead to an increase in fossil fuel and bioethanol demand and consumption. This has the propensity to lead to a shortage in bioethanol, which leads to an increase in prices, but an expansion of bioethanol capacity will lead to an increase in bioethanol production, which in turn will lead to a decrease in bioethanol shortage and price as well. Similarly, an increase in fossil fuel demand will lead to shortage due to production and imports. This can lead to an increase in price and the loop is closed by a decrease in demand due to high prices (loop B4).
2. An increase in bioethanol production leads to an increase in feedstock, which leads to an increase in the land space required (loop (R3)). More importantly, it also leads to the creation of employment. With greater land space being used for feedstock production, price of feedstock will reduce. It is interesting also to notice how an increase in advance method of feedstock production can lead to the use of fewer resources, which directly reduces price of feedstock.
3. An increase in biofuel production leads to an increase in employment and GDP, which again increases the transport need, fuel demand, and biofuels demand and consumption. This loop reverts to increase biofuel production (loop R6). Moreover, an increase in GDP leads to capital available for

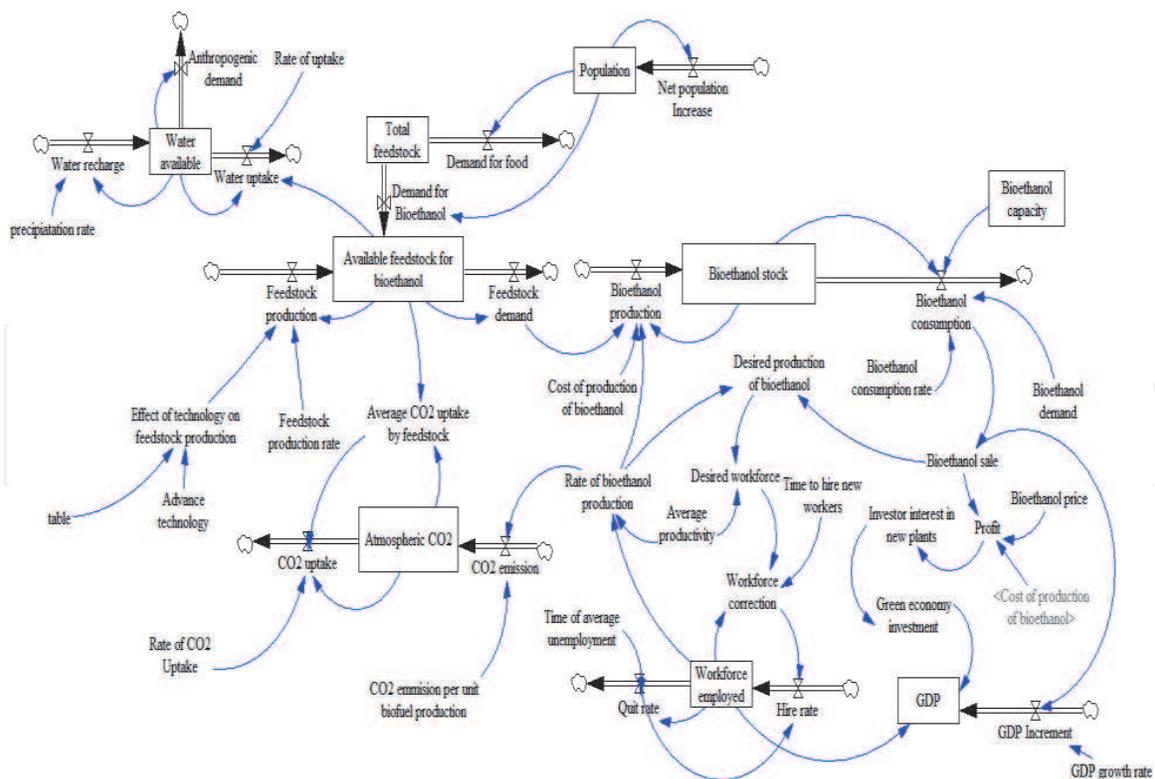


Figure 9.
 Stock flow diagram for bioethanol production.

investment into a green economy. This has a direct positive influence on the capacity of bioethanol plants.

While casual loop diagram emphasizes the feedbacks structures within the bioenergy system, stocks and flows diagram amplifies the underlying physical structures of the system. **Figure 9** presents a stock-flow diagram for bioethanol production.

Stocks for this case study include water, bioethanol, feedstock, atmosphere CO₂, populations, workforce, and GDP. These characterize the state of the bioenergy system and generate useful information for policy development. For example, the availability of feedstock for bioethanol has influenced the flow of CO₂ uptake, feedstock production rate, and bioethanol demand. Simulation of these factors was conducted overtime period of 100 months. This indicated a strong correlation between the aforementioned factors and bioethanol production.

Summarily, a hybrid system that works with the national grid is most preferable. This is because such a system will: (1) reduce environmental impact, (2) reduce pressure of land space for feedstock plantation and bioethanol plants, (3) ensure available water for human consumption and (4) most importantly ensure that there is a balance in the quantity of feedstock converted to fuel and consumed as food by the population. Readers need to note that not all the elements of the system were captured, rather key elements that significantly affect the behavior of the system.

4.3 AR construction

Once the optimal implementation strategy had been achieved, the next step is obtaining an optimal fermenter configuration for engineering design and specifications. The technique employed, attainable regions analysis, which is based on the interpretation of the fermentation process as a geometric object by defining a region of achievability that can be attained by the fundamental processes occurring in the

fermenter: mixing and bioreaction. The approach captures all possible bioreactor structures and finds the bounds on the performance of the system.

Eqs. (12)–(14) describes the kinetic models that characterize the fermentation of cassava supplemented by malt using *Saccharomyces carlsbergensis*. Cassava extract was selected due to its relative abundance compared to other crops within the region under study. Also, the monod model adopted to capture the substrate, limiting bioreaction taking place, incorporates two-dimensional substrate-product inhibition patterns.

$$\frac{dX}{dt} = r_X = \mu X \quad (11)$$

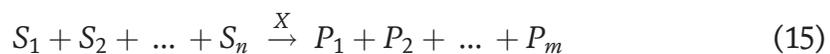
$$\frac{dP}{dt} = r_P = Y_{PX}\mu X \quad (12)$$

$$\frac{dS}{dt} = r_S = -\frac{1}{Y_{XS}}r_X - \frac{1}{Y_{PX}}r_P - M_s X \quad (13)$$

$$\mu(S, P) = \left(1 - \frac{S}{K_{is}}\right) \frac{\mu_{max} S}{K_{sx} + S} \left(1 - \frac{P}{K_{iP}}\right) \quad (14)$$

Eq. (15) is substituted into the dynamic relations (Eqs. (12)–(14)).

Before constructing the AR, it is expedient to determine the dimension in which the AR will reside. The dimensions of the AR depend on the number of independent reactions taking place. From Eq. (5), only one independent reaction involving three components (X–S–P) is taking place; hence the AR constructed must reside in a one-dimensional subspace of \mathbb{R}^3 for all achievable set of points.



Since the dimension of the AR is one, we, therefore, need to select a variable which contains the effect of all three states for which case the bioethanol yield (y_p) has been selected. To enable graphical visualization of the AR, another variable, residence time (τ_p) will be added to the system such that it can be plotted in a two-dimensional space. A major consideration when selecting variables for plotting attainable regions is that the variables must follow the linear mixing law. It has been reported in literature by Mings et al. and Abunde et al., how the residence time and yield follow the linear mixing law [8, 20, 22]. This is represented by Eqs. (17) and (18).

$$\tau^* = \lambda \tau_1 + (1 - \lambda) \tau_2 \quad (16)$$

$$y_E^* = \lambda y_E^1 + (1 - \lambda) y_E^2 \quad (17)$$

Where τ_1 and τ_2 are the residence time in two reactors and τ^* is the residence time upon mixing. y_E^1 and y_E^2 are the yields of reactor 1 and reactor 2, respectively, and y_E^* is the yield upon mixing.

With the kinetic model and initial conditions now known, we begin constructing the AR by generating the PFR trajectory and then the CSTR locus, then generating PFR trajectories using the CSTR locus, as illustrated in **Figure 10**.

From **Figure 10**, the boundary of the candidate AR can be defined by two main reactor configurations: (1) A CSTR followed by a PFR and (2) A CSTR followed by a PFR with a bypass from the feed to the effluent stream. This implies that all the ethanol yield contained within the defined region can be achieved by the above reactor types, with differences coming at the level of the residence time. Furthermore, the operating limits of the system (defined by the area of the convex hull) are

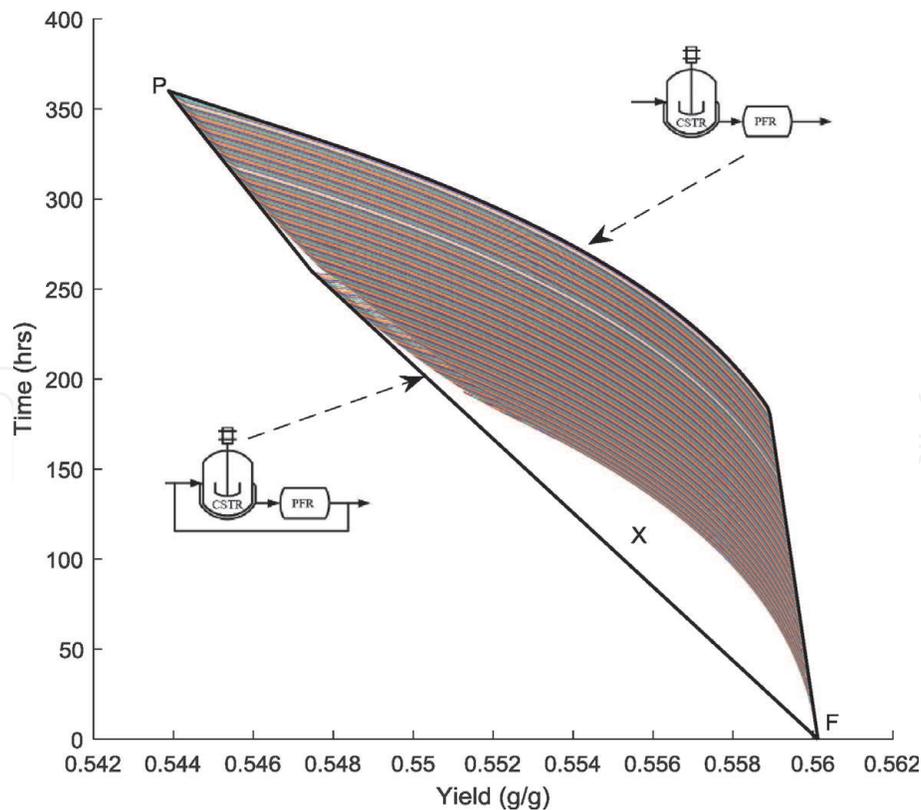


Figure 10.
Two-dimensional candidate attainable regions for Cassava extract using two-dimensional sudden stop substrate and product inhibition patterns.

1.762 (g/g hrs), which provides a geometric representation of all possible yields that can be achieved by the aforementioned reactor structures. It can also be inferred from the figure that using a fermenter structure (A CSTR followed by a PFR with a bypass) as opposed to a single fermenter reduces the overall residence time of the fermentation process. More interestingly, yields within the region of X, which were initially not achievable, are now achievable by using a fermenter structure.

Once the candidate AR has been constructed for a given kinetic and feed concentration, the limits of achievability of the system are defined. The candidate AR generated can, therefore, be used to answer design questions and determine performance targets by developing appropriate objective functions, which can be overlaid as contours on the AR boundaries. For illustration, an economic index such as Payback period, which is key to investors, is considered. Economic models were then developed, incorporating the dimension of the AR and overlaid as contours on the candidate AR.

Figure 11 illustrates the payback periods overlaid on the Candidate AR to obtain optimal operating points and corresponding reactor structures by identifying the points of intersection of the objective function on the AR boundary.

Interestingly, two major observations can be made from **Figure 10**: (1) The range of payback periods considered intersect the AR at many points in the region, indicating that there are multiple operating points (multiple optima) for this system. Therefore the actual operating points to be selected vehemently depend on other auxiliary factors such as the investor's available capital. (2) Shorter PBP are achievable for higher yields at lower reactor volumes. This is interesting because an investment that involves smaller reactor volumes (lower investment cost) and higher operating yields (higher annual benefits) should require a shorter to recover investment. (3) Another interesting observation is that, as the payback period increase, the influence of running cost (reactor volume) on the PBP decreases.

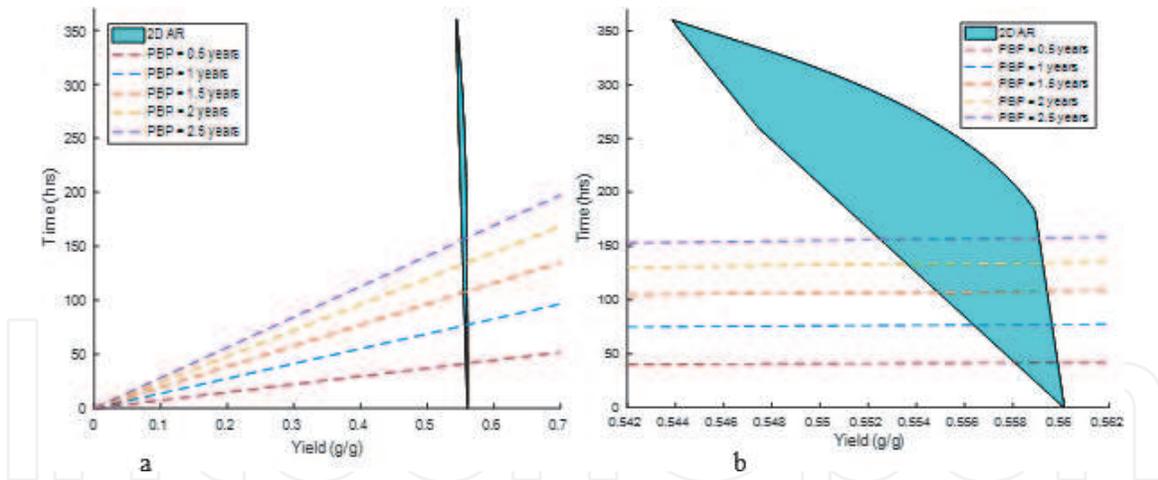


Figure 11. Different contours of payback period overlaid onto the AR for cassava extract to determine the optimal operational points ((b) is a closer zoom of (a), demonstrating how the contours of the PBP intersect the AR).

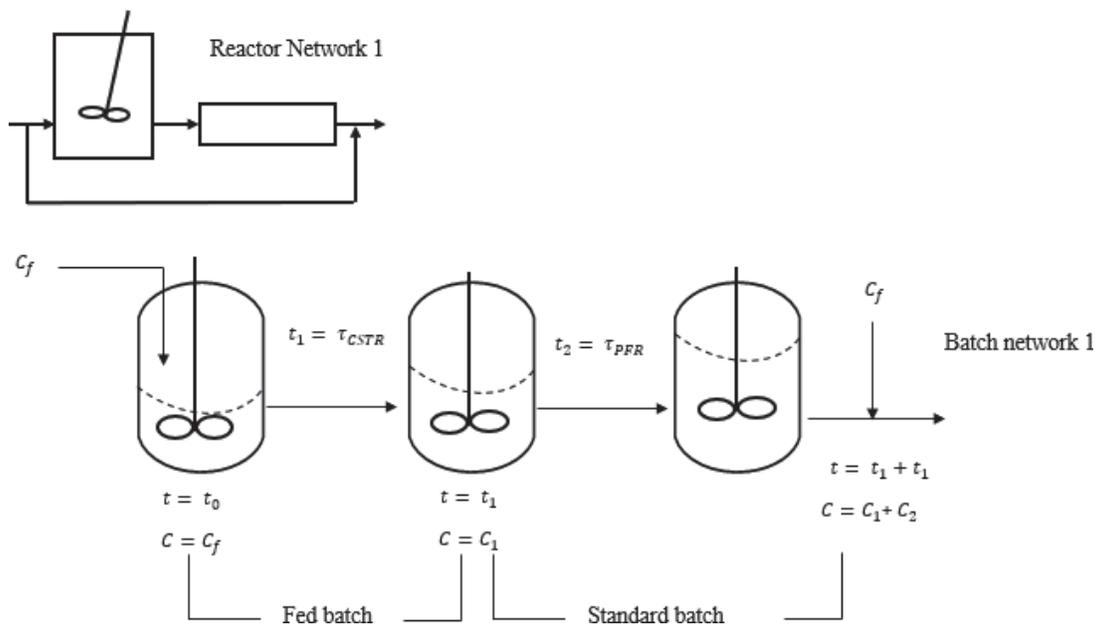


Figure 12. Optimal continuous fermenter structure and its corresponding batch fermenters.

This is observed from **Figure 11a** by the closeness of the contours from 1.5, 2, and 2.5 years. Therefore, it is sensible to construct a fermenter volume that is larger for payback periods between 1.5 and 2.5 years, since the cost influence is minimal, and that reactor volume can be used to achieve all desired payback periods.

In summary, the AR theory presents a geometric technique that can be used to identify optimal process configuration. Therefore **Figure 12** illustrates the optimal continuous reactor and its corresponding batch fermenter for bioethanol production.

5. FAST analysis

5.1 Functional analysis of need

The Horned Beast diagram, illustrated in **Figure 13**, provides a visual tool that seeks to answer three fundamental questions:

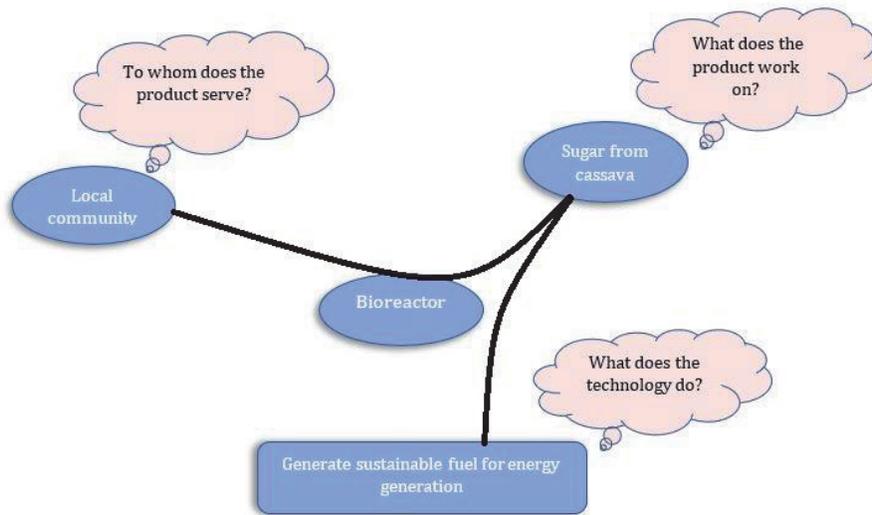


Figure 13.
 The horned beast diagram above is used to determine the needs to which the technology answers.

1. Who will the product serve?
2. What does the product interact with?
3. What does the product do?

5.2 The octopus diagram

Figure 14 presents an Octopus diagram that comprises the product in question to be designed and the different components of its external medium. The figure further describes the elements associated with the bioreactor and its environment.

The above functions involved in **Figure 14** are elucidated in **Table 4**. The advantage of the octopus diagram is that it helps to visualize and validate the elements of the technology.

Figure 15 shows a FAST diagram that presents the technological solutions which permit the satisfaction of the principal and constraint functions.

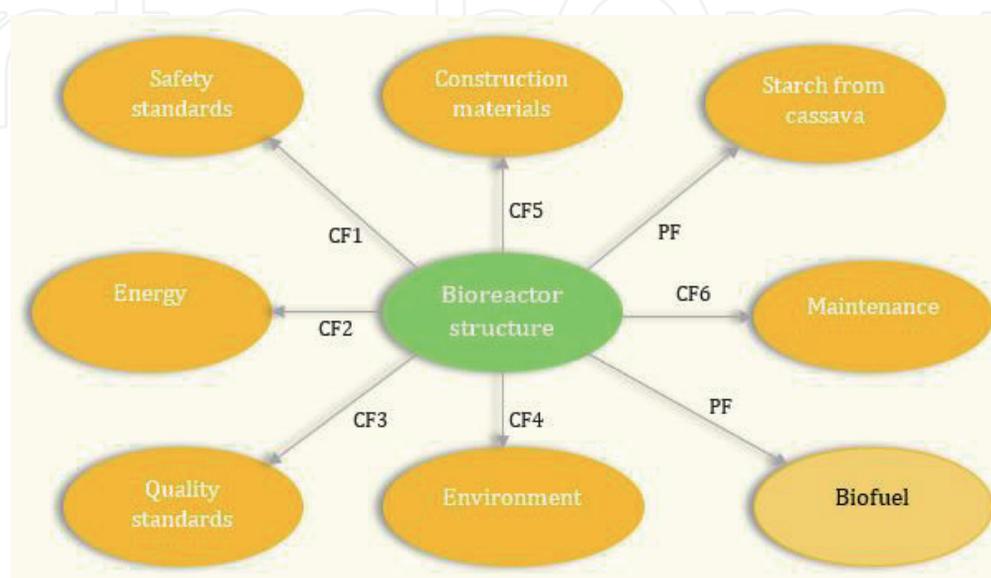


Figure 14.
 The octopus diagram showing the relationship between the bioenergy system and its environment.

Principal function	
PF	Conversion of starch to bioethanol in order to generate energy
Constraint functions	
CF1	The biofuel should meet all required safety standards and minimize losses from accident
CF2	The technology should use a renewable energy source
CF3	The biofuel produced should meet international standards for fuels
CF4	The technology should have a less environmental impact
CF5	Material of construction should be available and less expensive
CF6	Maintenance should be simple and easily carried out routinely

Table 4. Principal functions together with the constraints.

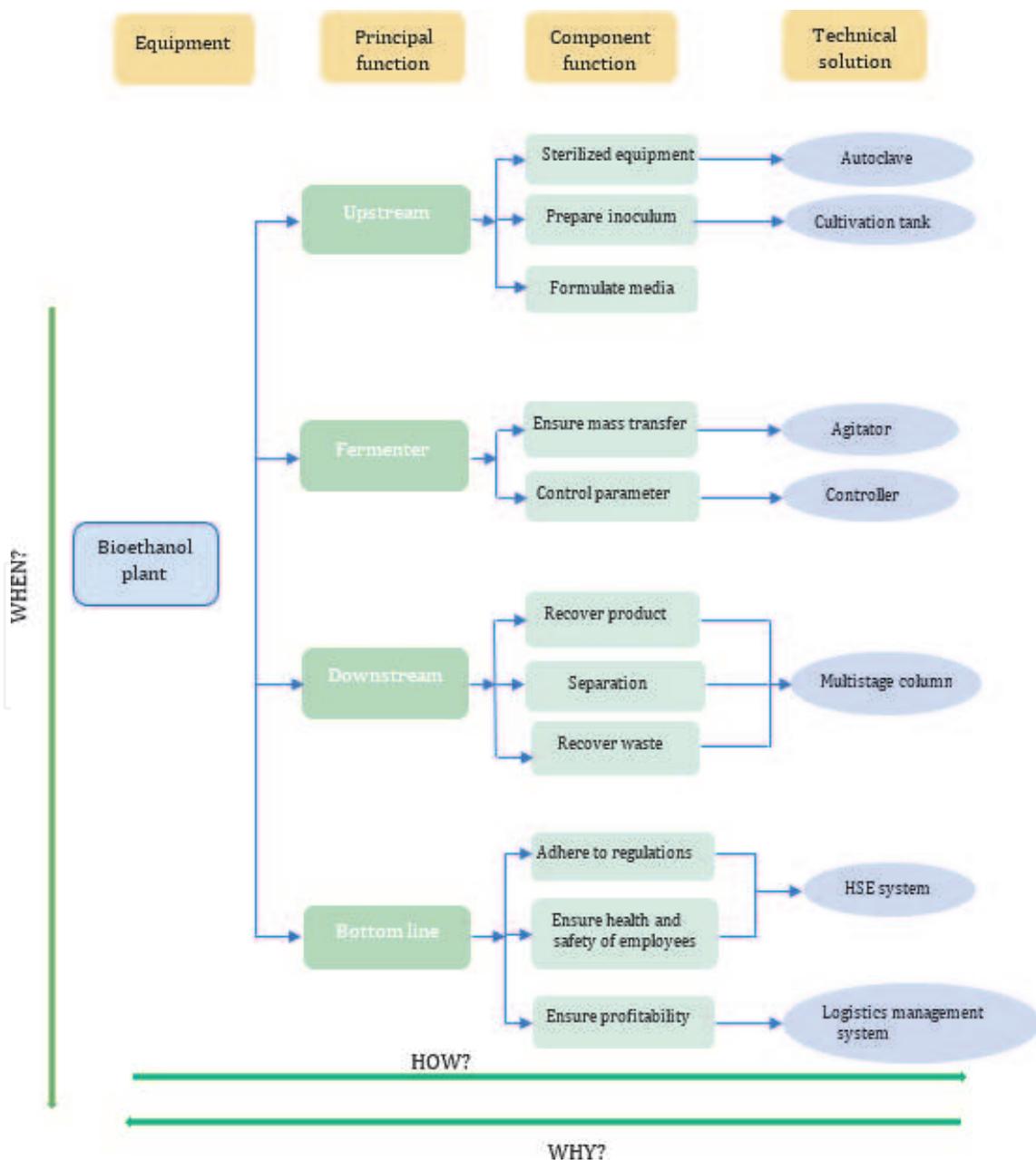


Figure 15. FAST diagram showing functions and their corresponding technical solutions.

Once the FAST diagram is constructed, the next step is to develop a Value Analysis Matrix that examines the component costs of the equipment in relation to the value perceived by the customer. Value Analysis Matrix, also known as Functional-Cost Matrix, was derived from the Quality Functional Deployment Methodology. The strength of this technique is that it associates the functions of a product back to the customer's needs. It can also develop mechanisms that relate to functions as either strongly, moderately, or weakly supporting the given function and can also be used to calculate each mechanism's relative weight in satisfying the designated functions. This enables management to check whether the money spent on function and component is worth it. For illustrations, the approach was not exhausted in this work. Once exhausted, management can move further into the equipment specification, then the installation of the equipment.

6. Conclusion

Returning to the challenges posed at the beginning of this chapter, it is now possible to state that (1) MCDM provides an appropriate technique for selecting and assessing an optimal bioenergy technology (bioethanol fermenter) that seeks to address the social, economic, technical and environmental factors for sustainable development. (2) A hybrid energy system that comprises of the bioethanol plant along with the national grid proved at optimal implementation strategy as it ensured a balance in the bioenergy system. It is quite interesting to notice how system dynamics modeling presents an efficient tool to model and simulate energy systems and their interaction with other systems, as demonstrated in this chapter. The tool was used to investigate the economic, environmental and social impact of bioethanol production in view of respecting sustainability criteria while striking a balance between the several subsystems involved (3) the optimal fermenter structure required for the fermentation of the different extracts includes a CSTR followed by a PFR as well as a CSTR followed by a PFR with bypass from feed. And finally, a value analysis was conducted to identify the components required for the technology to meet its functions. More importantly, the methodological framework presented an exciting and thrilling route to how sustainable technologies could be successfully installed. This chapter has gone some way towards enhancing our understanding of how model-based approaches relative to conventional implementation strategies ensure sustainable development. A model-based approach to delivering sustainable solutions is gradually becoming an exhilarating area for sustainable systems engineers. Readers should expect electrifying exploits from the authors as they seek to leverage on model-based techniques, Artificial Intelligence (AI), and digital technology to unlock Africa's potential in the food-water-energy-health nexus.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

$(r_{ij})_{m \times n}$	normalized matrix
λ_{max}	maximum Eigen value
n	number of attributes
A	pairwise comparison matrix
W	the estimate of the decision-makers weight
τ_1	residence time

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References

- [1] Chatterjee R, Gajjala S, Thirumdasu RK. Recycling of organic wastes for sustainable soil health and crop growth. *International Journal of Waste Resources*. 2017;**07**(03). DOI: 10.4172/2252-5211.1000296
- [2] Smith A, Brown K, Ogilvie S, Rushton K, Bates J. *Waste Management Options and Climate Change: Final Report to the European Commission*. DG Environment. 2001
- [3] Gingerich DB, Mauter MS. *Air Emission Reduction Benefits of Biogas Electricity Generation at Municipal Wastewater Treatment Plants*. 2018
- [4] Koch K, Helmreich B, Drewes JE. Co-digestion of food waste in municipal wastewater treatment plants: Effect of different mixtures on methane yield and hydrolysis rate constant. *Applied Energy*. 2015;**137**:250-255
- [5] PNUMA. *UN Environment Annual Report, Empowering People to Protect the Planet*. 2016, p. 20
- [6] Chel A, Kaushik G. Renewable energy technologies for sustainable development of energy efficient building. *Alexandria Engineering Journal*. 2018;**57**(2):655-669
- [7] Mustafa A et al. Renewable energy technologies and characterization. **1**(4) (TR-109496):102-116
- [8] Ming D, Glasser D, Hildebrandt D, Glasser B, Metzger M. *Attainable Region Theory: An Introduction to Choosing an Optimal Reactor*. Hoboken, New Jersey: John Wiley & Sons, Inc; 2016
- [9] Ming D, Glasser D, Hildebrandt D. Application of attainable region theory to batch reactors. *Chemical Engineering Science*. 2013;**99**:203-214
- [10] Hildebrandt D. *Synthesis of chemical reactor networks*. 1995
- [11] Snegirev DA, Valiev RT, Eroshenko SA, Khalyasmaa AI. Functional assessment system of solar power plant energy production. In: *Proc. 8th Int. Conf. Energy Environ. Energy Saved Today is Asset Futur. CIEM 2017*. 2017. pp. 349-353
- [12] Wüstenhagen R, Wolsink M, Bürer MJ. Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy*. 2007;**35**(5):2683-2691
- [13] Wang JJ, Jing YY, Zhang CF, Zhao JH. Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews*. 2009; **13**(9):2263-2278
- [14] Ibáñez-Forés V, Bovea MD, Pérez-Belis V. A holistic review of applied methodologies for assessing and selecting the optimal technological alternative from a sustainability perspective. *Journal of Cleaner Production*. 2014;**70**:259-281
- [15] Mardani A, Jusoh A, Nor KMD, Khalifah Z, Zakwan N, Valipour A. Multiple criteria decision-making techniques and their applications—A review of the literature from 2000 to 2014. *Economic Research-Ekonomska Istraživanja*. 2015;**28**(1):516-571
- [16] Sterman J. *Business dynamics: Systems thinking and modeling for a complex world*. Boston: Irwin/McGraw-Hill; 2000
- [17] Turner BL, Menendez HM, Gates R, Tedeschi LO, Atzori AS. *System dynamics modeling for agricultural and natural resource management issues: Review of some past cases and*

forecasting future roles. Resources. 2016;5(4)

[18] Asiedu N, Hildebrandt D, Glasser D. Experimental simulation of three-dimensional attainable region for the synthesis of exothermic reversible reaction: Ethyl acetate synthesis case study. *Industrial & Engineering Chemistry Research*. 2015;54(10): 2619-2626

[19] Abunde Neba F, Jiokap Nono Y. Modeling and simulated design: A novel model and software of a solar-biomass hybrid dryer. *Computers & Chemical Engineering*. 2017;104:128-140

[20] Neba FA, Asiedu NY, Addo A, Seidu R. Attainable regions and fuzzy multi-criteria decisions: Modeling a novel configuration of methane bioreactor using experimental limits of operation. *Bioresource Technology*. 2019:122273

[21] Neba FA, Tornyeviadzi HM, Østerhus SW, Seidu R. Self-optimizing attainable regions of the anaerobic treatment process: Modeling performance targets under kinetic uncertainty. *Water Research*. 2020: 115377

[22] Abunde Neba F, Asiedu NY, Addo A, Morken J, Østerhus SW, Seidu R. Simulation of two-dimensional attainable regions and its application to model digester structures for maximum stability of anaerobic treatment process. *Water Research*. 2019;163:114891

[23] Asiedu NY, Hildebrandt D, Glasser D. Batch distillation targets for minimum energy consumption. *Industrial & Engineering Chemistry Research*. 2014;53(7):2751-2757. DOI: 1021/ie402044y

[24] Asiedu N, Hildebrandt D, Glasser D. Experimental simulation of a two-dimensional attainable region and its application in the optimization of

production rate and process time of an adiabatic batch reactor. *Industrial & Engineering Chemistry Research*. 2014; 53(34):13308-13319

[25] Metzger MJ, Glasser D, Hausberger B, Hildebrandt D, Glasser BJ. Use of the attainable region analysis to optimize particle breakage in a ball mill. *Chemical Engineering Science*. 2009;64(17):3766-3777

[26] Mota P, Campos AR, Neves-Silva R. First look at MCDM: Choosing a decision method. *Adv. Smart Syst. Res*. 2013;3(2):25-30

[27] Wątróbski J, Jankowski J, Ziemia P, Karczmarczyk A, Ziolo M. Generalised framework for multi-criteria method selection. *Omega (United Kingdom)*. 2019;86:107-124

[28] Akash BA, Mamlook R, Mohsen MS. Multi-criteria selection of electric power plants using analytical hierarchy process. *Electric Power Systems Research*. 1999;52(1):29-35

[29] Jaber JO, Jaber QM, Sawalha SA, Mohsen MS. Evaluation of conventional and renewable energy sources for space heating in the household sector. 2008; 12:278-289

[30] Saaty RW. The analytic hierarchy process-what it is and how it is used. *Mathematical Modelling*. 1987;9(3-5): 161-176