A Framework for Analysis and Evaluation of Renewable Energy Policies

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Abstract

The formulation and evaluation of renewable energy policies is a burning subject matter all over the globe. Policy makers seek to cautiously perceive information from the renewable energy market place so as to determine the dynamic factors, variables and policy parameters that influence the design of renewable energy policies. The perceived information is often imprecise or fuzzy, which makes policy formulation difficult. This paper presents a framework for evaluating renewable energy policies based on a fuzzy system dynamics (FSD) paradigm. First, we describe the renewable energy policy problem, with a case study example. Second, we present a framework for FSD modeling. Third, we propose a high-level causal loop analysis to capture the complex dynamic interactions among various energy demand and supply factors, from a fuzzy system dynamics perspective. Fourth, and finally, we propose an FSD model for renewable energy policy formulation and evaluation.

Keywords
Renewable energy policy, energy planning, policy evaluation, system dynamics

1. Introduction
Practical renewable energy policy analysis and evaluation is crucial at island, country, regional and global levels. Industrial growth has increased the demand for fossil fuels such as coal, petroleum, and natural gas. Due to high potential social and environmental repercussions of global warming and the consequential climate change, the international community has emphasized the need to conserve energy and to mitigate carbon emissions. The Intergovernmental Panel on Climate Change (IPCC) estimated that about 90% of global temperature rise is likely to be caused by greenhouse gas emissions, and the earth's average temperature will rise from 1.4 to 5.8°C in this century (IPCC, 2001). A number of international conventions held worldwide, such as Kyoto Protocol of United Nations Framework Convention on Climate Change, have called for a determined reduction of the emissions of greenhouse gases so as to mitigate climate change (UNFCCC, 1998). Several countries have since participated in the global actions targeted at reducing carbon dioxide (CO2) emissions by putting in place a set of greenhouse gas control strategies (Peters, G.P. 2008; Chang et al., 2010). Consequently, the concepts of low carbon economies, low carbon islands, low carbon regions, and low carbon cities and societies have increasingly become central issues aimed at building economies that consider the 3Es dimensions, that is, energy, economic development, and the environment (Qudrat-Ullah and Seong, 2010; Trappey et al., 2012). Increasingly, renewable energy technology (RET) policies and strategies are expected to steer the economy in the most sustainable direction.

Several countries have engaged themselves into developing low carbon islands in an attempt to establish RETs and to reduce CO2 emissions to an acceptable level. For instance, a number of interesting low carbon island projects exist in the literature, including empirical studies in Turkey (Demiroren and Yilmaz, 2010; Demiroren and Yilmaz, 2010), Kinmen Island in Taiwan (Liu and Wu, 2010), Taiwan (Trappey et al., 2012), Yakushima island in Japan (Uemura, 2002), Penghu island administrative region in Taiwan (Trappey et al., 2012), and in other countries such as Pakistan (Qudrat-Ullah and Davidsen, 2001), United States (Vicki and Tomas, 2008; Ernest and Matthew, 2009; GPO, 2009; China John et al., 1998; Han and Hayashi, 2008; Huang, 2009), India (Huang, 2009), Columbia (Dyner et al., 1995), among others. Among the several empirical studies, the central conclusion is that governments and stakeholders need to actively increase renewable energy adoption and promote effective policy incentives and policy controls so as to reduce the CO2 emissions prevalent in their countries and regions. Possible policies in this regard include, promoting solar energy industry (photovoltaic and solar thermal sectors), promoting solar energy adoption, promoting wind energy adoption, as well as promoting the adoption of other renewable energy sources such rain, tides, waves and geothermal heat. Subsidies, price cuts, campaigns, promotions and other control policies have a potential to contribute significantly to the popularity and adoption of RETs. It is anticipated that this endeavor will ultimately reduce CO2 emissions in the medium to long term.

Modeling renewable energy policies is a crucial undertaking that calls for system-wide analysis capabilities so as to obtain an in-depth understanding of the complex renewable energy systems. Understanding the complex interactions between the variables, the possible alternative decisions, and the likely consequences of the actions taken is crucial. A number of factors related to environment, economy, and the community have to be considered from a systems engineering point of view. This implies that the population, ground forest, industrial activities, commercial activities, transportation, daily domestic energy usage, and CO2 generation are among the several factors that need to be taken into consideration when designing and evaluating renewable energy policies. All these and other factors form a complex dynamic system with complex causal relationships as far as energy consumption and carbon emissions are concerned.

Systems dynamics (SD) has been applied to a number of problem instances in energy policy analysis (Qudrat-Ullah and Davidsen, 2001; Qudrat-Ullah and Seong, 2010; Trappey et al., 2012) and assessment of environmental impact (Li and Wu, 2010; Ford, 1997; Jan and Hsiao, 2004). Developing robust long term policies is non-trivial due to complex dynamics prevalent in those energy policy systems. However, no attempts have been made to consider capturing the fuzzy imprecise variables in renewable energy policy design. It is known that energy-low carbon economies are humanistic systems that are characterized with linguistic variables that are difficult to interpret and model using conventional systems simulation models. Clearly, the presence of fuzzy variables makes policy design and evaluation a complex responsibility for the policy maker who has to base his decisions on imprecise variables from the trends in the renewable energy marketplace. For instance, the policy maker may need to cautiously formulate investment decisions aimed at positively impacting renewable energy adoption which then leads to low carbon economy. The task is to utilize the fuzzy information at hand to formulate effective energy-low carbon policies in anticipation of long-term improvements in the economy, the environment, and the energy system. Thus, systems approaches that address both the complex dynamic features and fuzzy characteristics of renewable energy systems are imperative.

Motivated by the above issues, the purpose of this study is to present a framework for evaluating renewable energy policies based on a fuzzy system dynamics paradigm. First, we present a high-level causal loop analysis that captures the complex dynamic interactions between various energy demand and supply factors, from a fuzzy system dynamics perspective. Second, we present a framework for fuzzy system dynamics modeling. Third and finally, we propose a fuzzy system dynamics model for renewable energy policy evaluation.

The rest of the paper is organized as follows: The next section presents a background to fuzzy system dynamics. Section 3 gives a description of the proposed FSD framework for renewable energy policy design and evaluation. Section 4 presents policy scenarios for a simulation study, based on a case study example, together with relevant discussions. Finally, we provide conclusions and further research prospects.

2. Fuzzy System Dynamics

Tessem and Davidsen (1994) emphasized the need to include a qualitative approach to the simulation and analysis of complex dynamics systems, based on the theory of fuzzy sets and fuzzy numbers. Fuzzy system dynamics (FSD) is a systems simulation tool that incorporates fuzzy variables into system dynamics models so as to cater for system whose structures, state or behavior cannot be described with exact numerical precision (Tessem and Davidsen, 1994; Mutingi and Matope, 2013). System dynamics and fuzzy logic are powerful and viable tools in this regard.

2.1 System Dynamics

System dynamics (SD) is a system modeling tools introduced by Jay Forester in the 1960s (Forrester, 1961). The SD methodology follows through a basic simulation procedure (Coyle, 1996; Sterman, 2004). SD utilizes various control factors of the system under study and observes how the system behaves in response to time-based trends in the variables. Thus, SD can be used to assist in policy design especially when systems are complex and dynamic. SD simulation procedure essentially involves problem understanding and system description, qualitative analysis, simulation model development, and policy design and testing. Of particular interest is the development of the causal loop diagram which maps the system to show the main causal relationship between the main causal interactions between system variables. Consultations with the experts within the domain are essential in the construction and revision of the causal loop diagram. Another interesting stage in system dynamics is the model construction in terms of stocks and flows of information and or materials. Stocks represent the accumulation of the net inflows of the information or material, while flows represent the increase or decrease in the flows of the stocks. Mathematically, system dynamics flows can be represented thus;

$$\frac{\mathrm{d}}{\mathrm{dt}}(S) = inflow(t) - outflow(t) \tag{1}$$

where, S is the stock at time *t*; inflow(t) and outflow(t) represent the inflows and outflows at time t, respectively.

SD has been used to assess environmental issues and CO2 emissions (Vizayakumar and Mohapatra, 1993; Anand et al., 2005; Qudrat-Ullah and Davidsen, 2001). A dynamic ecological footprint forecasting model for policy modeling of urban sustainability was proposed in Jin et al. (2009). Han and Hayashi (2008) developed an SD model to assess CO2 mitigation policy for inter-city passenger transport in China. Furthermore, in Trappey et al. (2011), SD was used to model life cycle dynamics to control mass customization carbon footprints. Related applications also exist in the literature (Trappey et al., 2012). Though the SD paradigm can be applied effectively in system modeling of complex dynamic systems, there is need to add to the approach, a method of capturing fuzzy linguistic variables that often exist in real world systems. Fuzzy variables can be captured effectively by the use of fuzzy logic. Formal fuzzy logic tools have a useful way of incorporating linguistic values into policy design and evaluation models.

2.2 Fuzzy Logic System

A fuzzy logic system is a logic-based system that uses fuzzy theory. Fuzzy set theory relates to classes of objects that have non-crisp boundaries to which membership is a matter of degree (Zadeh, 1978). The most important component of every fuzzy logic system is a set of fuzzy rules that converts inputs to outputs (Kosko, 1995). In practice, fuzzy approximation theorem is used (FAT) (Kosko, 1992). In practice, the inputs to a fuzzy logic system are the information that relates to the state of the system, and the output is a specification of the action to be taken. As such, fuzzy logic incorporates a rule-base that contains a set of “if then” rules of the form:

$$\text{IF } x \text{ is } A \text{ THEN } y \text{ is } B \tag{2}$$

where, *A* and *B* are linguistic values defined by fuzzy sets on the ranges *X* and *Y*, respectively.

According to fuzzy logic concepts, “*x* is *A*” is the antecedent, while “*y* is *B*” is the consequent. This provides strong constructs for fuzzy inference, a process of formulating the mapping from a given input to an output based on some fuzzy logic set of rules (Sugeno, 1985; Mamdani, 1975). The mapping provides a basis from which decisions can be made based on a set of linguistic control rules obtained from experienced decision makers. The process of fuzzy inference involves the following constructs: membership functions, logical operations, and if-then rules. The fuzzy inference process involves crisp (non-fuzzy) inputs, linguistic (fuzzy) rules, and defuzzifier and the crisp output.

Fuzzy logic builds on the experience of experts who understand the system under study. It is built on the structures of qualitative description used in everyday natural language, which makes it easy to use. This is because, oftentimes, systems do not have enough precise data to allow statistical analysis which normally demand data collection over a long time. Fuzzy logic, being tolerant of imprecise data, builds this understanding into the process rather than tacking it onto the end. Moreover, fuzzy logic can model nonlinear functions of arbitrary complexity. A fuzzy logic system can be described in three steps: fuzzification, fuzzy rules, and defuzzification (Labibi et al., 1998).

3. FSD Modeling Framework

Fuzzy system dynamics inherits its concepts from system dynamics and fuzzy theory. Figure 2 shows a set of steps to guide a systems analyst in a thorough and sound dynamic simulation study in a fuzzy environment. The FSD simulation methodology generally follows through 6 phases: (1) identification of problem situation, (2) causal loop analysis, (3) model formulation and development, (4) verification and validation, (5) policy analysis and improvement, and (6) implementation. Descriptions of each phase are presented, following the framework structure.

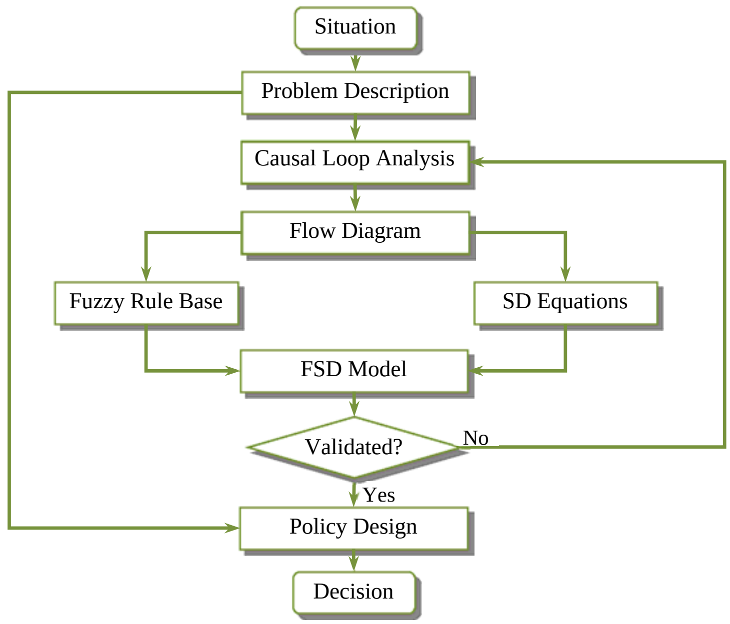

Figure 2: Steps in a fuzzy system dynamics study

Phase 1. Identification of problem situation: This phase is concerned with the identification and understanding of the problem situation, which leads to a clear problem statement. Trends in the key variables relating to the identified problem are identified and investigated. Based on the principles of cybernetics, variables relating to the problem situation are filtered out and related to find out the causal linkages between them and the feedbacks in the system. This leads to system conceptualization stage in the next phase, which is known as causal loop analysis.

Phase 2. Causal feedback loop analysis: This stage involves system conceptualization, which is concerned with identification of the linkages and interactions between the main variables of the problem. Main variables are those that have significant influences on the overall behavior of the system, in the context of the identified problem. A causal link is indicated by an arrow that connects the causal variable at the tails of the arrow, to the effect variable at the head of the arrow. A "+" sign close to the arrowhead indicates that both the causal and the effect variables change in the same direction, while a "-" sign indicate that the tail-head variables change in the opposite direction.

Phase 3. Model formulation and development: The end product of model formulation is the FSD model. Two activities are involved in coming up with an FSD model, that is: (i) identify fuzzy variables and their fuzzy relationships, and develop a suitable fuzzy rule base, using suitable fuzzy logic tools, (ii) develop a stock flow diagram and build the relevant SD equations. The final FSD model is then obtained by linking the fuzzy rule base with the stock flow model. Central to the fuzzy system dynamics paradigm, is the development of the fuzzy logic system that can address the fuzzy variables of the system under study. This can be implemented using system dynamics software tools such as Simulink® on a Matlab® platform, and Vensim®.

Phase 4. Verification and validation: In this stage, the fuzzy system dynamics model is verified to check for any bugs in the logical flow of the model. This is followed by model validation which determines whether or not the model is an accurate representation of the real system. Validation is usually achieved through an iterative comparison of the model with the actual response of the system under study. Any discrepancies between the two are used to improve the system model. The availability of data is crucial for the success of this stage. In practice, when developing the fuzzy system dynamics model, an appreciable set of validity test methods are commonly adopted with success (Sterman, 2004; Qudrat-Ullah and Seong, 2010). Table 1 lists the methods that are generally accepted for validation.

Phase 5. Policy analysis and improvement: In this phase, alternative scenarios are designed for simulation analysis in line with decisions that need to be considered. For each scenario, decisions need to be made in regards to the length of simulation runs, the run step, as well as the warm-up period. Simulation runs and their subsequent analysis are then used to estimate the performance indicators for the alternative system designs or alternative policy designs.

Table 1: Structural validity testing methods

No.	Validation method	Brief Description
1.	Structural verification	This method tests whether the model structure is consistent with relevant descriptive knowledge of the system being modeled
2.	Extreme conditions	This method tests whether the model exhibits a logical behavior when selected parameters are assigned extreme values.
3.	Parameter verification of the system	This approach tests whether the parameters in the model are consistent with relevant descriptive and numerical knowledge
4.	Dimensional consistency	This approach tests whether each equation in the model dimensionally corresponds to the real system.
5.	Boundary adequacy	This method tests whether the important concepts and structures for addressing the policy issues are endogenous to the model.

Phase 6. Decision support and policy implementation: Being the last step of the simulation study, the success of the implementation phase is much dependent on how well the previous phases have been performed. The system analysis should ideally involve all the ultimate model users. The success of the implementation stage also depends on the underlying assumptions that were used in building the model.

4. FSD Model Development

FSD modeling can be divided into two broad parts, that is, causal feedback loop analysis and FSD model construction. A causal feedback loop analysis diagram shows the major causal linkages between the main variables of the system under investigation. Identification of the major causal feedback loops of the system is crucial, together with the system inputs and outputs. Causal loops are used to estimate the causal linkages between related variables, directions of variable influences, and the system boundaries of the system. Our focus is on renewable energy policy formulation and evaluation in a fuzzy environment. Figure 3 shows the causal feedback loops, describing the relationship between renewable energy policies and the associated carbon emissions. The inputs to the FSD system include the information on a particular RET to be implemented, while the outputs of the system are the reduction of carbon emissions, the RET dynamic policy, and the associated cost of policy implementation. In a typical community, carbon emissions are produced indirectly from industrial and domestic electricity consumption, and directly from industry, transportation, and domestic usage. The main variables in the causal feedback loops are briefly described as shown in Table 2.

Following the causal loop analysis described above, the FSD model is constructed in order to simulate and evaluate alternative RET policy scenarios. The model was developed based on a control-theoretic approach using Fuzzy logic tools and Simulink in Matlab, consisting of three stocks, namely: the RET capacity, transport, and the population. Through fuzzy system dynamics simulation expert knowledge is built into a fuzzy rule base and simulated to see the related effects of alternative dynamic fuzzy rules on the amount of carbon emission. To capture the fuzzy variables, the perceived carbon reduction gap is converted to a fuzzy set, called preferred error. The error is defined as a function of the difference between the maximum acceptable carbon reduction gap and the perceived reduction gap. In essence, the perceived gap should be as close as possible to the maximum acceptable gap, which directly implies that the error should be as close to zero as possible. Therefore, perceived error is;

$$error = \frac{perceived\_gap}{perceived\_gap_m} - 1 \tag{3}$$

Here, *perceived_gap* is the maximum acceptable perceived *gap*, and *perceived_gap* is the observed gap. Since *perceived_gap* and $perceived\_gap_m$ are supposed to be as close as possible, preferred error values close to zero are most preferable, and the level of preference diminishes fast as the error magnitude increases. Apart from error, we define perceived trend as a function of the observed carbon emissions;

$$trend = \frac{\mathrm{d}}{\mathrm{dt}}(CO_2\ emissions) \tag{4}$$

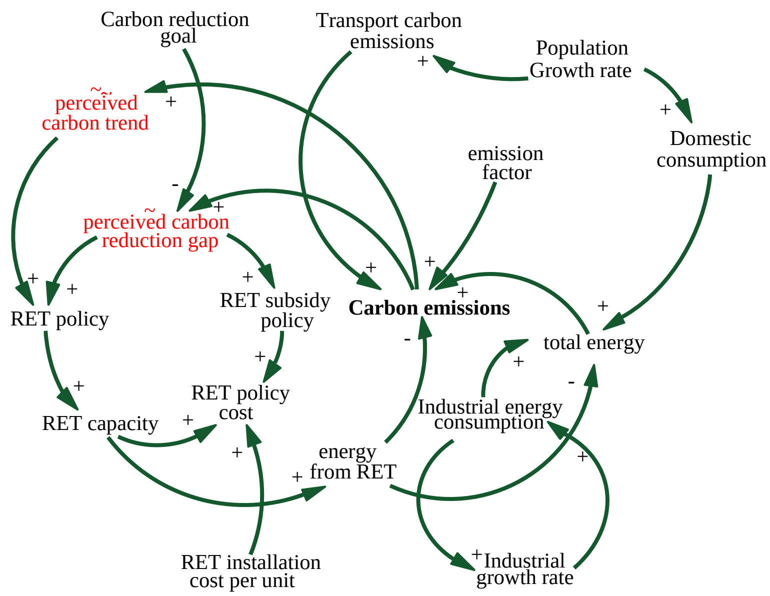

Figure 3: The causal feedback loops for renewable energy policy with fuzzy variables

Table 2: Variables and their descriptions

Variable	Variable Description
Carbon emissions	This refers to total carbon emissions which vary in accordance with industrial, domestic, and transport energy usage.
Perceived carbon reduction gap	The perceived difference between the carbon reduction goal and the actual emissions; the variable may take values “low”, “ok”, and “high.”
Perceived carbon trend	The perceived trend, i.e., increase or decrease, of the current carbon emissions; the variable may take linguistic values “decreasing”, and “increasing.”
Energy from RET	This variable represents the surplus energy generation saved through the application of the RET such as solar water heater systems, photovoltaic systems, and wind energy systems.
RET policy	This variable is influenced by the perceived carbon reduction gap and the perceived carbon trend.
RET capacity	The capacity of renewable energy in use, which varies according to the RET policy, that is, policy incentives, promotion policy, and policy control.
RET policy cost	The cost of RET policy is influenced by the subsidy policy cost, the installation costs, and the capacity of the RET.
Total energy	This is the total energy in form of electricity generated by thermal production for industry consumption and domestic consumption.

The perceived trend, defines whether the quantity of carbon emissions is increasing or decreasing. It follows that if the trend is increasing, then the intensity of the corresponding energy policy initiatives should be increased. Conversely, if the trend is decreasing, then the desired policy efforts should be decreased. The set of these expert rules can form an effective platform for managing investment, promotional, and incentive policies that influence the adoption of renewable energy which ultimately leads to low carbon societies. Based on the fuzzy causal loop analysis explained earlier, a fuzzy rule base is constructed to represent the fuzzy policy design for the renewable energy market place. As an illustration, let the variable *policy_change* represent the desired policy adjustment. Then, a fuzzy rule base can be constructed as illustrated in Fig. 4.

R1: IF (error is ok) THEN (policy change is zero);
R2: IF (error is low) THEN (policy change is reduce fast);
R3: IF (error is high) THEN (policy change is increase fast);
R4: IF (error is ok) and (trend is positive) THEN (policy change is reduce slow);
R5: IF (error is ok) and (trend is negative) THEN (policy change is increase slowly);

Figure 4: Fuzzy rule base for renewable energy policy evaluation

According to rule R1, since the error is ok, the desired policy change is zero. With reference to rule R2, when the error is low, it follows that the desired policy change is to reduce the current policy fast since the perceived carbon reduction gap is much lower than acceptable. On other hand, if the preferred error is high, then the policy should be *increase fast*. In addition, if the error is ok, that is, in the neighborhood of zero, then the actual decision depends on whether the current trend (rate) of carbon emissions is increasing or decreasing. If the trend is positive then policy should ideally be reduced slowly. Conversely, if rate is decreasing, then policy should be increased slowly since the trend shows that carbon emissions are somewhat on the increase. The FSD model was tested and verified using the following methods:

- Extreme conditions: test whether the model exhibits a logical behavior when selected parameters are assigned extreme values (Qudrat-Ullah and Davidsen, 2001; Qudrat-Ullah and Seong, 2010)
- Structure verification: test whether the model structure is consistent with relevant descriptive knowledge of the system being modeled Sterman (2004).

We present experimental simulation approaches essential for further evaluation and analysis of renewable energy policies in a fuzzy environment, deriving useful managerial insights. A case example is provided for discussions.

4. Experimental Simulation Approaches

Further to the formal FSD framework outlined, this section selects a case example of South Africa (SA) as a base example for analysis and discussion.

4.1 Case study: South Africa

South Africa intends to lower its carbon emissions to 34 % below current expected levels by 2020 and to about 42% below current trends by 2025 (NER, 2006). Currently, the country is dependent on thermal power which accounts for 80 to 90 % of the total primary energy supply in the year 2010. SA's renewable sources include solar, wind, hydro, biomass, geothermal and ocean energy. This shows that the country need to put in place an active policy to pursue RETs and set up effective policies in order to reduce carbon emissions (Winkler, 2006). For instance, such policies should promote the development of solar energy industry and the utilization of solar energy products, which have an availability factor of 60% (NER, 2006). Thus, the SA government intends to promote her renewable energy policy by promoting the utilization of solar-energy products, including photovoltaic systems and solar water heating systems. Several households, clinics, and schools have photovoltaic systems. There is a steady increase of solar water heater installations in households, with more than 100,000 installations every month. In addition to solar energy, wind energy is also harvested and the installations are on the increase (Winkler, 2006). The government reports that at least 10,000 GWh per year of final energy demand should be met by renewable energy sources, including solar, wind, and small hydro (NER, 2006)

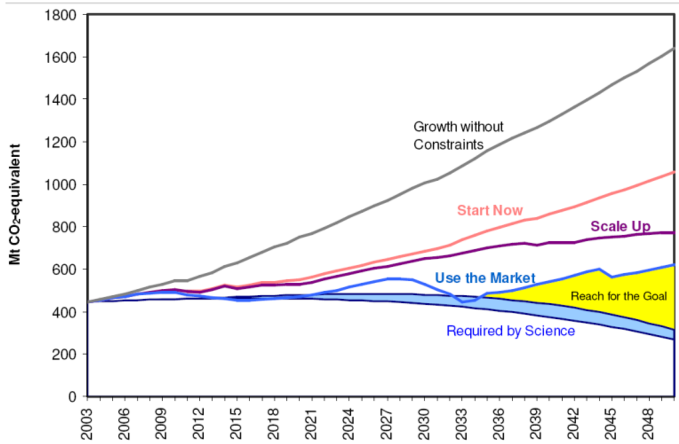

Figure 5: Carbon emission projections (Letete et al., 2009)

The National Integrated Energy Plan for South Africa (DEES, 2004) estimates that the economic growth of the country in terms of GDP is 2.8% per annum and the population growth rate is about 1.3% per annum. The energy demand growth is expected to grow by a margin of about 2 to 3% per annum (NER, 2006). Figure 5 shows carbon emission projections. The start now scenario refers to the use of basic mitigation actions such as energy efficiency and waste minimization strategies (Letete et al., 2009). The "scale up" scenario, extends the using basically extends all the extendable mitigation actions in the start now scenario, while the "use the market" scenario uses economic instruments such escalating CO2 tax on the energy sector to generate revenue for provision of incentives for renewable electricity, wind and solar water heating. To reach the goal, people-oriented or market-oriented measures may be useful, therefore need further investigations (Letete et al., 2009; SBT, 2007). This implies that a more dynamic approach based on market behavior is practical and effective in reaching the desired carbon reduction goal.

The SA energy policy has five objectives for the energy sector: (a) increased access to affordable energy services; (b) improving energy governance; (c) stimulating economic development, (d) managing energy related environmental impacts, and (e) securing diversity through diversity, which addresses the need to provide alternative renewable energy sources (NER, 2006). It recognizes the potential of RETs in securing supply through diversity.

4.2 Policy Scenarios for Simulation

SA endeavors to implement a renewable energy policy in form of wind and solar energy resources, with the aim of reducing carbon emissions from thermal production of electricity, industry and domestic use (MED-SA, 2003). In this connection, the policies can be matched into three possible scenarios. The first scenario, the base case, is aimed at benchmarking the carbon emissions without promoting any renewable energy policies. On the contrary, the second scenario observes the variation of carbon emissions when solar energy policies are implemented. It is important to note that policies can be deterministic, whereby the intensity of the promotion is constant or increasing periodically, or fuzzy dynamic, in which case the policies are adjusted according to the observed fuzzy trends in the 3Es system. In this frame of mind, this scenario is twofold: first, the simulation is carried out based on the assumption that a deterministic control policy is used without incorporating the fuzzy-based dynamic policy, and second, the simulation is run assuming that a fuzzy dynamic control policy is implemented based on the two fuzzy variables: perceived carbon trend and perceived carbon reduction gap. In a similar, the third scenario observes the variation of carbon emissions when wind-based RET polices are implemented. The scenario is twofold; first, with deterministic promotion policies without dynamic fuzzy feedback from the market trends. Table 2 provides a summary of the policy scenarios for simulation and evaluation. The next section presents concluding remarks, contributions, and further research.

Table 1. A summary of policy scenarios for simulation and evaluation

No.	Scenario	Description
1	Bases case	This scenario represents the as-is model aimed at benchmarking the carbon emissions of SA without any renewable energy promotion policies.
2	Promote solar RET with/without fuzzy policy control	The scenario observes the variation of carbon emissions when solar RET policies are enhanced, first without fuzzy control then with fuzzy control promotion.
3	Promote wind RET with/without fuzzy policy control	This scenario observes the variation of carbon emissions when wind RET policies are promoted; first with deterministic policies, then with fuzzy-based policies.

5. Conclusions

This paper provides a formal framework for realistic formulation and evaluation of renewable energy policies. Unlike previous simulation models and frameworks, the current framework considers that real world low-carbon energy, environment and economic systems are inundated with fuzzy variables which make the whole system complex. As such, policy makers rely on imprecise information from the renewable energy marketplace so as to formulate appropriate medium to long-term policies. With this realization, the framework identifies two major fuzzy variables: perceived CO2 reduction gap and perceived CO2 trend that are modeled as linguistic variables from a fuzzy causal loop perspective. Drawing from a fuzzy causal loop analysis, the framework provides a step-wise guide to building a fuzzy system dynamics model based on fuzzy logic tools and control theoretic simulation on a Matlab platform. Overall, this work contributes to the existing body of knowledge in policy formulation and evaluation for the 3Es concept of energy, economic development, and the environment aimed at building a low carbon society.

5.1 Contributions to Theory

The 3Es concept of energy, economy and environment is a complex system characterized with dynamic and fuzzy variables. No doubt, the policy formulation and evaluation for such as system demands the application of system modeling tools that address both dynamic and fuzzy features of the problem. This work points to the existence of these complexities in the 3Es concept, highlighting the imperative need for developing simulation approaches that can capture the complex features of the system. Therefore, the development of a fuzzy system dynamics model is an important contribution to the system dynamics community and to the practicing policy makers in governments and other stakeholders. In addition, this research work points out the need to build more realism into systems simulation models especially for humanistic models where essential variables involve human judgments and perceptions. Fuzzy set theory is a viable and important inclusion into SD models when information is imprecise.

5.2 Managerial Implications

Policy formulation and evaluation for a fuzzy 3Es system of energy, environment and economy is complex due to the presence of fuzzy and dynamic variables. As such, the policy maker needs to have in place an appropriate guide for renewable energy policy formulation. First, the policy maker needs to identify dynamic interacting variables in a causal loop form. This is followed by identification of fuzzy variables upon which the policies are anchored in order to make robust dynamic policies. The approach offers a number of advantages:

- The method provides key variables upon which dynamic renewable energy policies can be anchored, that is, perceived carbon reduction gap and perceived carbon trend;
- Dynamic policies can be formulated based on dynamic market trends, that is, energy policies are market-based, as opposed to static policies which do not adjust to dynamic changes in the marketplace;
- Fuzzy logic and control-theoretic tools are intelligent and fast, which makes FSD model building easy.
- The fuzzy system dynamics approach builds from the prior knowledge captured from experts in the field such that the users gain confidence and trust in the model as it is based on practical knowledge of experts.
- Expert knowledge can easily be built into the fuzzy rule base and updated with ease.

In light of the above mentioned managerial implications, the application of fuzzy system dynamics offers significant advantages to the policy maker concerned with renewable energy formulation and evaluation. Therefore, the suggested FSD framework is contributes to the practicing policy makers concerned with low carbon energy, economy and environments.

5.3 Further Research

The proposed FSD model presented in this study can be enhanced further. For instance, the fuzzy rule base can be optimized, e.g., using genetic algorithms. The rule base and the weights of the specific rules can be fine-tuned and optimized using soft computing tools in Matlab. This can further enhance policy formulation for renewable energy systems. Furthermore, we note that though FSD was applied on renewable energy policy formulation, its application can be extended to other complex systems in supply chains and healthcare.

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