Fuzzy System Dynamics: A Framework for Modeling Renewable Energy Policies

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Introduction

Renewable energy policy formulation and evaluation is an important subject matter at island, country, regional, and global levels. Industrial development 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. In addition, IPCC reported that the earth's average temperature is likely to rise by about 1.1–6.4 °C by the end of the twenty-first century (IPCC 2007), which is broadly consistent with earlier estimates (IPCC 2001). The Kyoto Protocol of United Nations Framework Convention on Climate Change called for a determined reduction of the emissions of greenhouse gases so as to mitigate climate change (United Nations 1998). Several countries have since participated in the global actions targeted at reducing carbon dioxide (CO_2) emissions by putting in place a set of greenhouse gas control strategies (Peters 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 2005; Trappey et al. 2012a).

Several countries have engaged themselves into developing low-carbon island policies by establishing renewable energy sources in an attempt to reduce CO_2 emissions to an acceptable level (Trappey et al. 2011; Chen et al. 2007). For instance, a number of interesting low-carbon island projects exist in the literature, including empirical studies in Gökçeada in Turkey (Demiroren and Yilmaz 2010),

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H. Qudrat-Ullah (ed.), *Energy Policy Modeling in the 21st Century,*
Understanding Complex Systems, DOI 10.1007/978-1-4614-8606-0_3,

Kinmen Island in Taiwan (Liu and Wu 2010), Taiwan (Trappey et al. 2012a), Yakushima Island in Japan (Uemura et al. 2003), Dodecanese Islands in Greece (Oikonomou et al. 2009), Penghu Island administrative region in Taiwan (Trappey et al. 2012a), and in other countries such as Pakistan (Qudrat-Ullah and Davidsen 2001), the United States (Vicki and Tomas 2008; Ernest and Matthew 2009; GPO 2009), China (John et al. 1998; Han and Hayashi 2008; Li et al. 2009; Huang 2009), India (Huang 2009; Peter 2010; Chandrasekara and Tara 2007), Columbia (Dyner et al. 1995), among others (Krushna and Leif 2008). 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 CO_2 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 as 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 renewable energy technologies (RETs). It is anticipated that this endeavor will ultimately reduce CO_2 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 highly imperative. 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 CO_2 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 problems concerned with formulation of energy policies (Naill 1992; Qudrat-Ullah and Davidsen 2001; Raja et al. 2006; Qudrat-Ullah and Seong 2010; Trappey et al. 2012a) and assessment of environmental impact (Ford 1997; Jan and Hsiao 2004; Trappey et al. 2011; Mutingi and Matope 2013). Developing robust long-term policies is nontrivial due to complex dynamics prevalent in those energy systems. However, no attempts have been made to consider capturing the fuzzy imprecise variables in renewable energy policy design. It is known that low-carbon energy economies are human systems 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 by observing 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 eventually leads to a low-carbon economy. The task is to utilize the fuzzy information at hand to formulate effective renewable energy policies in anticipation of long-term improvements in the economy–environment–energy system. Therefore, it is important to develop a systems simulation methodology that can address the complex dynamic features and the fuzzy characteristics inherent in renewable energy systems.

Motivated by the above energy and environmental issues, the purpose of this chapter is to present a framework for evaluating renewable energy policies based on a fuzzy system dynamics (FSD) paradigm. In this connection, the objectives of this chapter are as follows:

1. To present a causal loop analysis for the complex dynamic interactions between various energy-related factors
2. To present the proposed FSD framework incorporating system dynamics and fuzzy logic concepts
3. To present an application of the FSD framework to a case example in renewable energy policy evaluation

The rest of the chapter is organized as follows: The next section provides a background to FSD. The section "Fuzzy System Dynamics Framework" gives a description of the proposed FSD framework for renewable energy policy design and evaluation. The section "Case Example: South Africa" 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 in the section "Concluding Remarks and Further Research".

Fuzzy System Dynamics: A Background

System dynamics (SD) (Forester 1961; Morecroft 2007) and fuzzy logic (Zadeh 1965, 1978) are powerful and viable tools for modeling complex systems. Tessem and Davidsen (1994) emphasized the need to include a qualitative approach to simulation and analysis of complex dynamics systems, based on the theory of fuzzy sets and fuzzy numbers. FSD is a systems simulation tool that incorporates fuzzy variables into system dynamics models so as to cater for systems whose structures, state, or behavior cannot be described with exact numerical precision (Levary 1990; Tessem and Davidsen 1994; Mutingi and Mbohwa 2012). The FSD paradigm utilizes the strengths of the widely applied system dynamics and fuzzy logic methodologies.

System Dynamics Applications

The strengths of SD can be seen from its wide application in related studies. SD has been utilized to assess environmental issues and CO_2 emissions (Vizayakumar and Mohapatra 1993; Anand et al. 2005; Qudrat-Ullah and Davidsen 2001). Jin et al. (2009) proposed a dynamic ecological footprint forecasting model for policy modeling of urban sustainability. In the same vein, Han and Hayashi (2008) investigated inter-city passenger transport in China using an SD model to assess CO_2 mitigation policy. Furthermore, Trappey et al. (2011) used SD to model life cycle dynamics to control mass customization carbon footprints. Related applications also exist in the literature (Trappey et al. 2012b, c). However, none of these SD applications considered the presence of fuzzy variables. Though the SD paradigm can be used 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 that take linguistic values can be captured effectively by the use of fuzzy set theoretic applications such as fuzzy logic. Formal fuzzy logic tools can provide a useful way of accommodating linguistic values into policy design and evaluation models.

Fuzzy Logic System

A fuzzy logic system is a logical system that utilizes the theory of fuzzy sets. Fuzzy set theory relates to classes of objects that have non-crisp boundaries to which membership is a matter of degree (Zadeh 1965, 1978). The most important component of every fuzzy logic system is a set of rules that converts inputs to outputs based on the theory of fuzzy sets (Kosko 1992a, 1994, 1995). In practice, it is implemented using the fuzzy approximation theorem (FAT) (Kosko 1992b). Usually, 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:

$$\mathrm{IF} x \mathrm{is} A \mathrm{THEN} y \text{ is } B \tag{1}$$

where, A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively.

According to the fuzzy logic concepts, "x is A" is called the antecedent, while "y is B" is known as the consequent. This provides strong constructs for fuzzy inference. Fuzzy inference is the 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, as well as "if-then" rules. The fuzzy inference process involves crisp (non-fuzzy) inputs, linguistic (fuzzy) rules, a defuzzifier, and the crisp output.

Fuzzy logic is built on top of the experience of experts who already understand the system under study. It is built on the structures of qualitative description used in the 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 demands 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. In general, a fuzzy logic system can be defined in three steps: fuzzification, fuzzy rules, and defuzzification (Labibi et al. 1998).

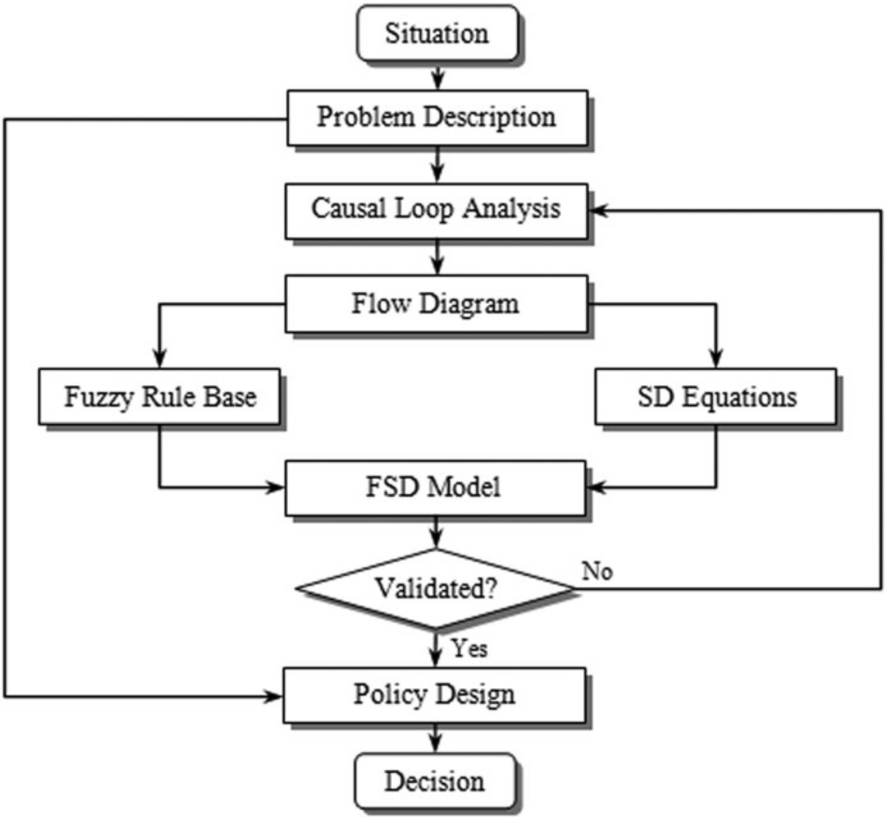

Fig. 1 Steps in an fuzzy system dynamics (FSD) study

Fuzzy System Dynamics Framework

FSD inherits its concepts from system dynamics and fuzzy set theory. Figure 1 shows a set of steps to guide a systems analyst in a thorough and sound dynamic simulation study in a fuzzy environment. The steps are categorized into six phases as follows:

Fuzzy System Dynamics Phases

The proposed FSD simulation methodology generally follows through six 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 structure shown in Fig. 1.

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 investigated. It is important for the modeler to make any necessary observations on the behavior of the actual system. Variables relating to the problem are filtered out while investigating their possible impact on the behavior of the actual system. This leads to system conceptualization stage in the next phase, known as causal loop analysis.

Phase 2: Causal Feedback Loop Analysis This stage involves system conceptualization, which is concerned with identification of the causal linkages and interactions between the main variables of the problem, based on the principles of cybernetics and feedback analysis. The main variables are those that are expected to have significant influences on the overall behavior of the actual system in the context of the observed 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 indicates that the tail and the head variables change in the opposite direction.

Phase 3: Model Formulation and Development The end product of model formulation and development is the FSD model. First, a stock flow diagram is developed using a suitable simulation tool such as Simulink to represent input and output flows. The block diagram should include the fuzzy logic block diagrams that model the fuzzy variables and relationships. Second, the modeling process branches into two parallel activities to produce the FSD model: (1) the development of the fuzzy rule base using suitable fuzzy logic tools, (2) the development of the SD equations.

The fuzzy rule base is constructed from expert knowledge and experience based on fuzzy logic. A set of "if-then" rules are constructed to emulate the expert in the subject area. Parallel to the construction of the fuzzy rule base, SD equations are built into the block diagram (flow diagram). The two activities yield the FSD model obtained by linking the fuzzy rule base with the SD model blocks that contain the SD equations.

Phase 4: Verification and Validation In this stage, the FSD model is verified to check for any errors 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 FSD model, an appreciable set of verification and validation methods is commonly adopted with success (Forrester and Senge 1980; Sterman 2004; Barlas 1996; Saysel and Barlas 2006; Qudrat-Ullah and Seong 2010). Table 1 lists the methods that are generally accepted for validation.

Table 1 Structural validity testing methods

Number	Validation method	Brief description
1	Structural validity test	This method tests whether the model structure is consistent with relevant descriptive knowledge of the system being modeled
2	Indirect structural validity test	The indirect structure validity test method distils essential structures of the model, simplifying the model to tell the fundamental dynamics of a large-scale model
3	Extreme conditions	This method tests whether the model exhibits a logical behavior when selected parameters are assigned extreme values
4	Parameter verification of the system	This approach tests whether the parameters in the model are consistent with relevant descriptive and numerical knowledge
5	Dimensional consistency	This approach tests whether each equation in the model dimensionally corresponds to the real system
6	Boundary adequacy	This method tests whether the important concepts and structures for addressing the policy issues are endogenous to the model

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.

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.

Central to the FSD paradigm, is the development of the fuzzy logic system that can address the fuzzy variables of the system under study. The method incorporates fuzzy modeling concepts, fuzzy logic, and fuzzy logic rule base to improve realism in the modeling process. This can be implemented using system dynamics software tools such as Simulink® on a Matlab® platform and Vensim®. In this chapter, illustrations are based on Simulink applications. The next section provides an explanation of the causal loop analysis upon which the FSD model is built.

Fuzzy System Dynamics Modeling

The process of FSD modeling can be divided into two broad parts: 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

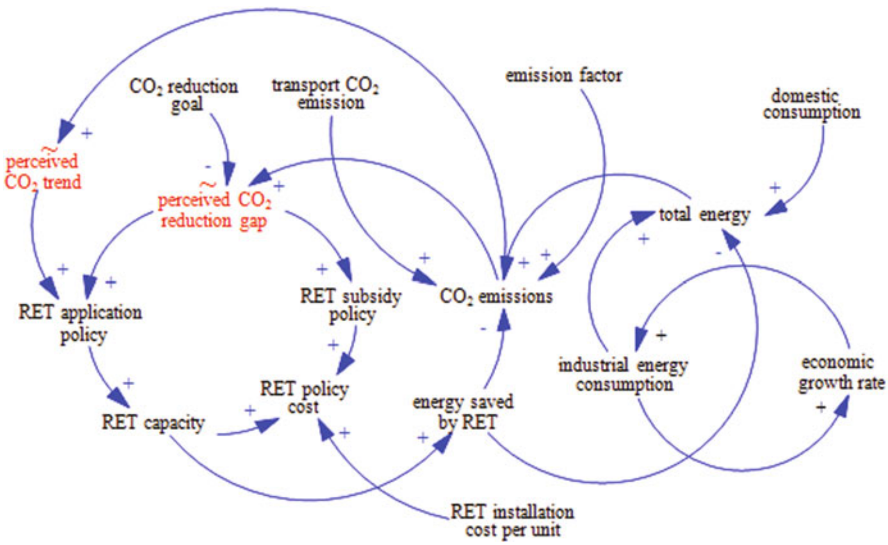

Fig. 2 The causal feedback loops for renewable energy policy with fuzzy variables

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 model the causal linkages between related variables, directions of variable influences, and the system boundaries of the system. The focus of this chapter is on renewable energy policy formulation and evaluation in a fuzzy environment.

Figure 2 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 the particular RET system 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 influenced indirectly by industrial and domestic consumption of electricity generated from thermal power, and directly by transportation and domestic usage of thermal power. The main variables in the causal feedback loops are briefly described as follows:

- Perceived carbon reduction gap: the perceived difference between the carbon reduction goal and the actual emissions; the variable may take linguistic 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”
- Carbon emissions: the total carbon emissions which vary in accordance with industrial, domestic, and transport energy usage
- Energy saved by 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 application 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 application 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

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, the transport, and the population. Through FSD 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 perceived 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, we define the perceived error, *error*, as follows:

$$error = \frac{perceived\_gap}{perceived\_gap_m} - 1 \tag{2}$$

Here, $perceived\_gap_m$ 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, the *error* values close to zero are most preferable, and the level of preference diminishes fast as the magnitude of the error values increases. Apart from *error*, we also define perceived trend, *trend*, as a function of the observed carbon emissions, as follows:

$$trend = \frac{\mathrm{d}}{\mathrm{dt}}(CO_2\ emissions) \tag{3}$$

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*

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 slowly);

R5: IF (error is ok) and (trend is negative) THEN (policy change is increase slowly);

Fig. 3 Fuzzy rule base for renewable energy policy

represent the desired policy adjustment. Then, a fuzzy rule base can be constructed as illustrated in Fig. 3.

According to rule R1, whenever the gap is ok, the desired policy change is "zero", meaning that the current policy remains unchanged. With reference to rule R2, whenever the error is low, it follows that the desired policy change is "reduce fast" meaning that the current policy efforts should be reduced at a faster rate since the perceived carbon reduction gap is much lower than the acceptable level. On the other hand, if the 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 increasing then the policy should ideally be "reduce slowly". Conversely, if the current is decreasing, then the policy should be "increase slowly" since the trend shows that carbon emissions are somewhat on the increase. The FSD model was tested and verified using the following validation methods:

- Extreme conditions: This method tests whether the model exhibits a logical behavior when selected parameters are assigned extreme values (Qudrat-Ullah and Davidsen 2001; Qudrat-Ullah and Seong 2010)
- Indirect structure validity test: The validity test method distils essential structures of the model, via simulation, to tell the fundamental dynamics of the model (Barlas 1996; Saysel and Barlas 2006)

Following the verification of our FSD model, we present experimental simulation approaches that are essential for further evaluation and analysis of renewable energy policies in a fuzzy environment, deriving useful managerial insights. A case example is provided for further analysis and discussion in the next section.

Experimental Approaches for Simulation

Further to the formal framework suggested and outlined above for simulation and evaluation of renewable energy policies in a fuzzy environment, this section selects a case example of South Africa (SA) as a base example for analysis and discussion.

Case Example: 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, subject to adequate financial support from the international community (BBC 2009). Currently, the country is dependent on thermal power which accounts for 80–90 % 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 2004). 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,GWh per year of final energy demand should be met by renewable energy sources, including solar, wind, and small hydro (NER 2004).

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 is expected to grow by a margin of about 2–3 % per annum, as shown in Fig. 4 (Winkler 2006).

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 sources of energy including renewable energy. It recognizes the potential of renewable energy in securing supply through diversity.

Proposed Policy Scenarios

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 either constant or changing periodically, or fuzzy dynamic, in which case the policies are adjusted according to the observed fuzzy trends in the system. In this framework, this

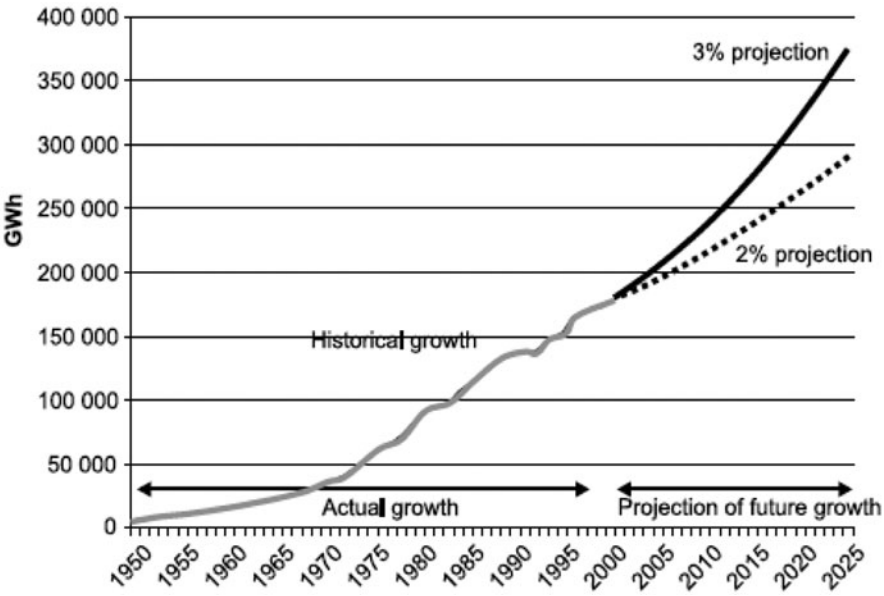

Fig. 4 Growth in electricity sales, actual and future projections. (NER 2000)

scenario is twofold: First, 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 manner, 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, and second, with dynamic fuzzy feedback from the market trends. Table 2 provides a summary of the policy scenarios for simulation and evaluation.

The next section presents a summary of this chapter, concluding remarks, contributions, and further research.

Concluding Remarks and Further Research

This chapter 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-term to long-term strategies. With this realization, the framework identifies two major fuzzy variables, namely, perceived CO_2 reduction gap and perceived CO_2 trend that are modeled as

Table 2 A summary of policy scenarios for simulation and evaluation

No.	Scenario	Description
1	Bases case—without RET policies	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 and without fuzzy-based policy control	This 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 and without fuzzy-based policy	This scenario observes the variation of carbon emissions when wind RET policies are promoted, first with deterministic policies, then with fuzzy-based policies

RET renewable energy technologies, *SA* South Africa

linguistic variables from a fuzzy causal loop perspective. Drawing from the fuzzy causal loop analysis, the framework provides a stepwise guide for building an FSD model based on fuzzy logic tools and control theoretic simulation on a Matlab platform. Overall, the chapter 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.

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 an FSD 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 behavioral models where essential variables involve human judgments and perceptions. Fuzzy set theory is a viable and important inclusion into system dynamics models when information is fuzzy or imprecise.

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 proposed approach in this chapter offers a number of advantages for the decision makers:

- FSD provides the modeler with the opportunity to model fuzzy variables upon which dynamic renewable energy policies can be anchored, that is, perceived carbon reduction gap and perceived carbon trend.
- FSD uses fuzzy logic and control-theoretic tools, that is, tools which make model building easy within a reasonable modeling time
- The FSD 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, rather than theoretical assumptions
- Expert knowledge can easily be built into the fuzzy rule base and updated on time with ease

In light of the above-mentioned managerial implications, the application of FSD offers significant advantages to the policy maker concerned with renewable energy formulation and evaluation. Therefore, the FSD framework suggested in this chapter is an important contribution to the practicing policy makers concerned with low-carbon economy societies, environments, and economies.

Further Research

Further research prospects are realized in this chapter. The FSD model presented in this study can be enhanced further. For instance, when building the fuzzy rule base, the construction can be such that the rules are optimized using an optimization tool such as genetic algorithms. Given enough sample data, the rule base and the weights of the specific rules can be fine tuned and optimized using soft computing tools such as genetic algorithms in Matlab. This can further enhance policy formulation for renewable energy systems.

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