Chapter 2
Pedigree of Model Technologies

To successfully conduct the low carbon development for a region, excellent research should integrate the background review, a systemic problem description, a system modelling, and an effective solution method with an empirical research. However, there are many challenges have to face in practical operations, such as, how do we draw up the total flow path of the research? How can we reasonably construct the problem framework and model system? How can we scientifically describe the relationship of problem and model system, and integrate the functions of proposed models. How can we design an efficient algorithm to solve a particular problem? Finally how can we apply this integrated method to engineering fields?

To conquer these difficulties, we have to innovate the model technologies from a systems perspective, that is to say, a pedigree of model technologies have to be established. In this chapter, we will construct a systematic pedigree of model technologies from the steps, including total flow path, problem framework, model system, meta model, and general equilibrium.

2.1 Total Flow Path

Generally speaking, low carbon economic development is a new pattern of regional development aiming at reducing CO_2 emissions and achieving the sustainable development of the environment, economy, and society. According to the UK White Paper "Our Energy Future: Create Low-carbon Economy" in 2003:

> Low-carbon economy is through the less of natural resource consuming and less of the environmental pollution, to get more economic output, ... Low-carbon economy is an approach and chance to create a higher standard of living and better quality of life, and also creates opportunities for the development, application and output of advanced technology, at the same time, it also can create new business opportunities and more employment opportunities (UK Department of Trade and Industry 2003).

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Climate Change Management, DOI: 10.1007/978-3-642-45429-5_2,

The essence of regional low carbon economic development (RLCED) is the revolution in technological paradigm, the practice of which is a typical system engineering with economy, technology, ecology, environment and society as a whole.

2.1.1 Regional Low Carbon System Model

Regional low carbon economy is a macro-system with openness and complexity, since climate change is the most significant global public goods. Low carbon development is not a simple region internal problems, but the complicated problems between global public interests and the interests of the state, and the problems among the national interests. Low carbon economy refers to a new economic form with the goal of enforcing economic growth, improving social progress, and holding the ecological balance by the means of exploiting renewable energies and reducing CO_2 emissions. Its ultimate goal is to slow climate change, promote the sustainable development of human beings, and realize harmonious development between human and nature. As to RLCED, there are at least nine subsystems, including greenhouse gas control, ecological capacity evaluation, regional economic prediction, energy structure optimization, land resource utilization, industrial structure adjustment, low carbon industrial chains, low carbon transportation, and low carbon tourism. The subsystems interact to jointly promote the development goals of RLCED. The framework structure of regional low carbon economy system is shown in Fig. 2.1.

A system model is required to describe and represent all the multiple views of a complex system, such as planning, analysis, design, implementation, deployment, structure, behavior, input data, and output data. Actually, there has been a long history using the system models in the field of climate change (Schneider 1992). Climate models use quantitative methods to simulate the interactions of the atmosphere, oceans, land surface, and ice. They are used for a variety of purposes from study of the dynamics of the climate system to projections of future climate. Climate system modelling addresses all aspects of the climate system: the atmosphere and the oceans, the cryosphere, terrestrial ecosystems and the biosphere, land surface processes and global biogeochemical cycles (Trenberth and Blumberg 1994). The Community Climate System Model (CCSM) has recently been developed and released to the climate community (Blackmon et al. 2001). CCSM is a coupled Global Climate Model developed by the University Corporation for Atmospheric Research (UCAR) with funding from the National Science Foundation, Department of Energy, and NASA. The coupled components include an atmospheric model (Community Atmosphere Model), a land-surface model (Community Land Model), an ocean model (Parallel Ocean Program), and a sea ice model (Community Sea Ice Model) (Drake et al. 2005). CCSM is designed to produce realistic simulations over a wide range of spatial resolutions, enabling inexpensive simulations lasting several millennia or detailed studies of continental-scale dynamics, variability, and climate change (Boville and Gent 1998; Kiehl and Gent 2004; Collins et al. 2006). To provide support of policies formulation to address global climate change, Prinn et al. (1999) have developed

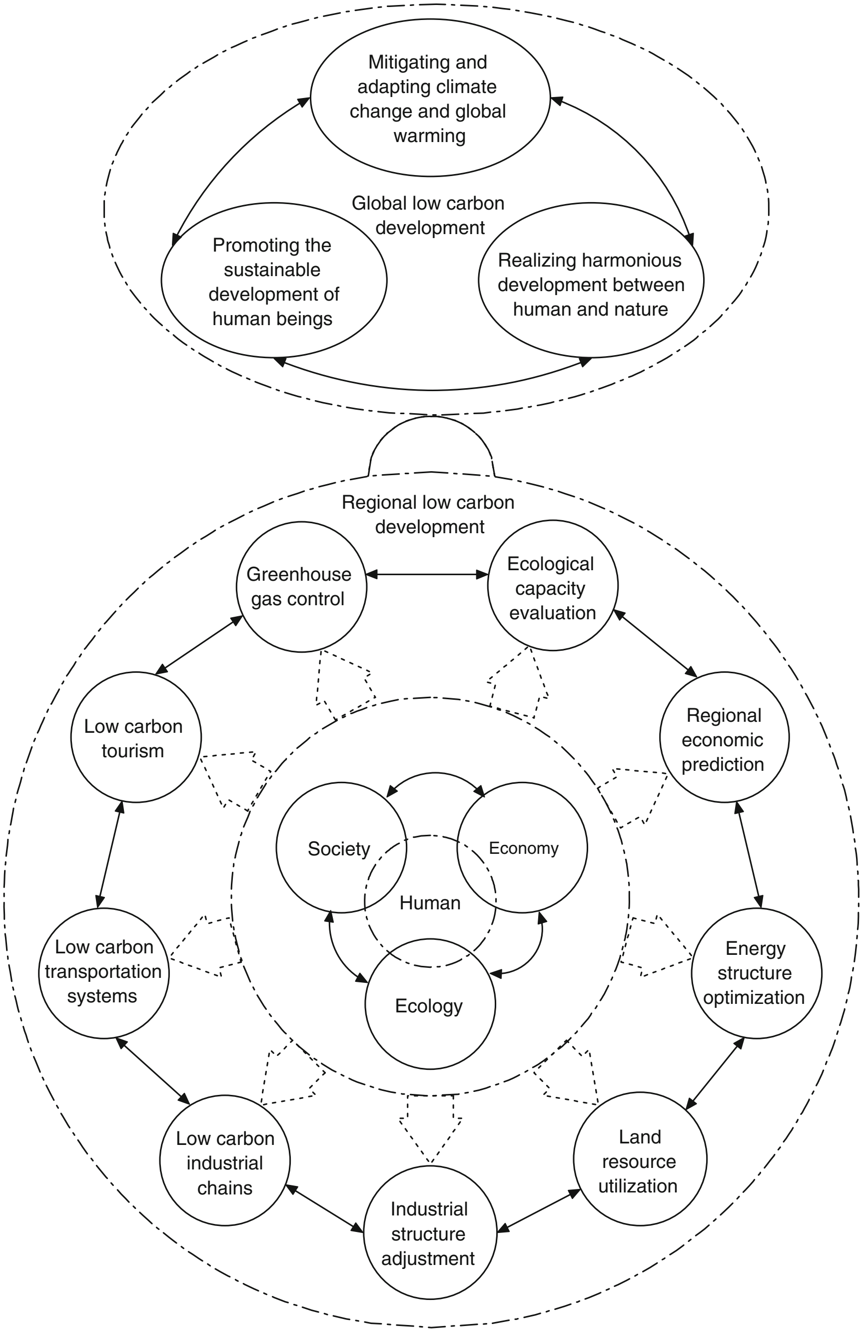


Fig. 2.1 The framework structure of RLCED system

an integrated global system model for climate policy assessment, which consists of coupled sub-models of economic growth and associated emissions, natural fluxes, atmospheric chemistry, climate, and natural terrestrial ecosystems. A computationally efficient climate model—ICLIPS climate model (ICM)—has been developed by Bruckner et al. (2003) that can be included in any kinds of integrated assessment models for global climate change.

However, there are few studies relative to system models for low carbon economy, which is significant for the RLCED. With this regard, we establish a low carbon system model (LCSM). The LCSM is a special application of the 6RMP methodology. The research ideal of 6RMP expresses the initial relationship between the Research, the Model and the Problem. R stands for the research system that includes research specifics, research background, research foundation, research realization, research framework, and applied research; M refers to the model system that includes concept model, physical model, physical and mathematical model, mathematical and physical model, designed model for algorithms, and describing the specific model. P represents a problem system that includes particular problem, class of problems, abstract problem, restored problem, solvable problem, and numerical problem (Xu and Zhou 2010; Xu and Yao 2011; Xu and Tao 2011). The framework of 6RMP methodology is shown in Fig. 2.2.

As can be seen in Fig. 2.2, there are six steps in each subsystem (i.e. Problem System, Research System, Model System), and each problem maps to a kind of research and a class of model. Of these, problem is the promotion of research and the elicitation of model; research is the identification of problem and the guidance of model; model is the modelling of problem and the restoring of research. The steps of LCSM can be depicted as follows:

(1) When research is started, we usually proceed to study a particular problem, which has research value and can be described as a concept model. This is the specifics of the research.
(2) After studying a particular problem and a problem with the same essence of the particular problem, then we can obtain a class of problem which has universality and can be abstracted to a physical model. This is the background to research.
(3) We generalize the typical problem ulteriorly to an abstract problem which can be abstracted to a mathematical problem with physical meaning, then we can propose the physical and mathematical model. This is the foundation of the research.
(4) Next we restore the physical sense of the problem, and set up the mathematical and physical model which can be solved by special algorithm. This is the realization of the research.
(5) Then we design the algorithm and obtain the model for the procedure of the solvable problem. This is the framework of the research.
(6) Finally we should apply the above models to a practical problem and establish a specific model for the numerical problem, and employ an algorithm to illustrate the problem solution and research completion.

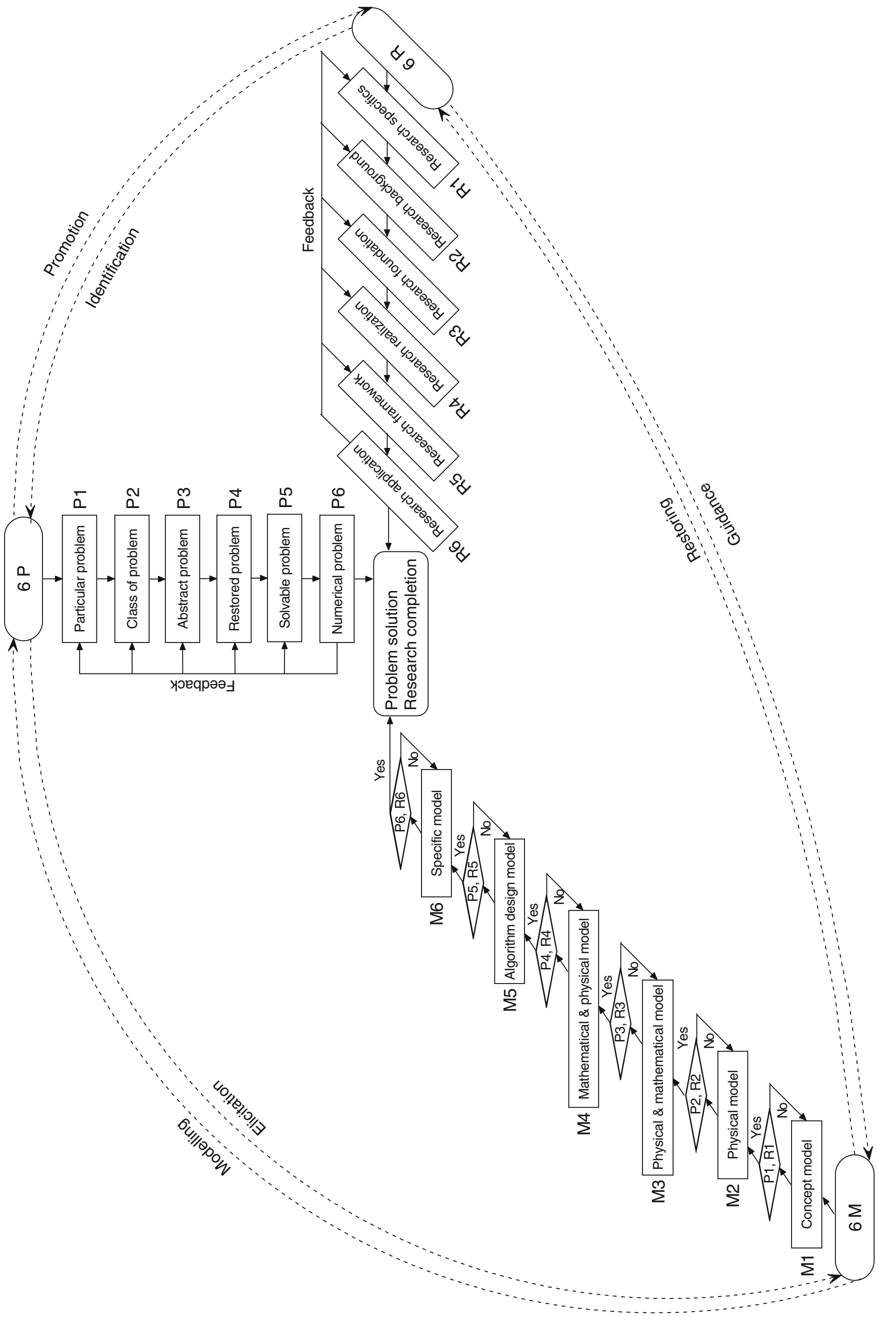


Fig. 2.2 The framework of 6RMP methodology

In a LCSM, Model System is the core, combining Problem System and Research System, and finally resolving the problem. The designed models have to reflect the essence of problems and significance of research.

Regional low carbon economic development is a complicated problem need to be systematically researched by integrated models. Following the idea of 6RMP, we summarize the research ideas and the framework of LCSM, see Fig. 2.3.

2.1.2 Flow Chart of LCSM

Development of low carbon economy is a social systems engineering with multi-disciplinary, multi-organizational, multi-level, multi-objective and multi-attribute. Therefore, we adopt the methodology and ideology of "hall for workshop on meta-synthetic engineering" (HWMSE) (Gu and Tang 2005; Tang 2007) to develop and manage the LCSM. According to the goals and tasks of regional low carbon economic development, there are seven jobs have to take in the LCSM management, as follows:

(1) overall design of LCSM management processes;
(2) general design of LCSM pedigree;
(3) dynamic monitoring of LCSM throughout the life cycle;
(4) management of experts, knowledge and machines systems;
(5) integration of system model, model group and model element;
(6) management of supporting information systems and database;
(7) integrated management of multiple viewpoints.

Overall design of flow chart is the primary task of LCSM management. According to the preliminary concept of RLCED set by the regional government, the research team has to conduct in-depth analyses and repeated discussions on the problem framework, model system, spectrum mapping and met-model function, and develop the flow chart of LCSM, as shown in Fig. 2.4.

2.2 Problem Framework

The low-carbon growth mode is the best way for regional future sustainable economic development under the climate change and global warming context. RLCED involves all the aspects of regional economic, social, ecological, demographic systems. There are many types of problems may emerge during the progress of low carbon innovation and development. To achieve the goal of RLCED, we have to discover, identify, and classify the related problems, and construct the systemic problem framework, and based on which to establish the model system.

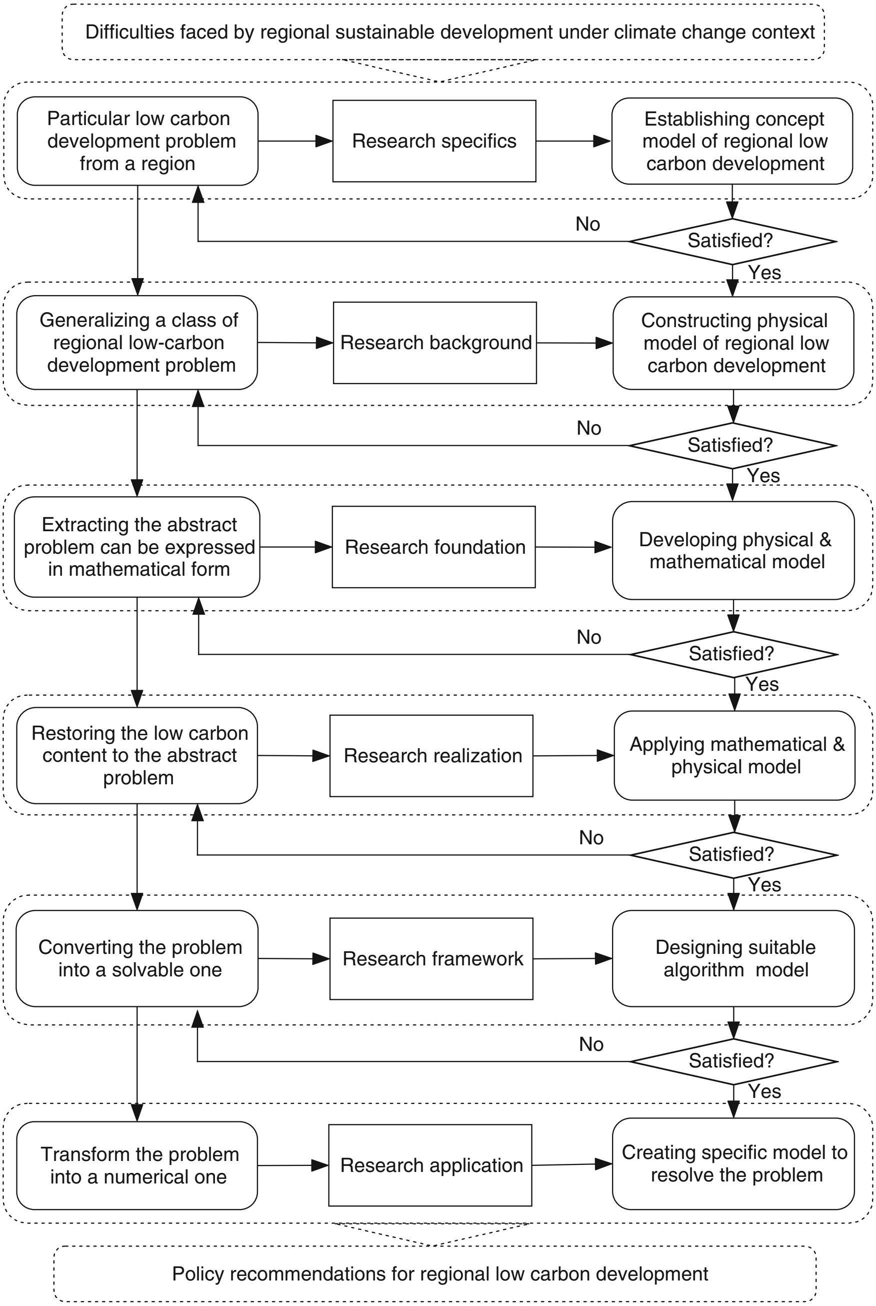


Fig. 2.3 The framework of LCSM

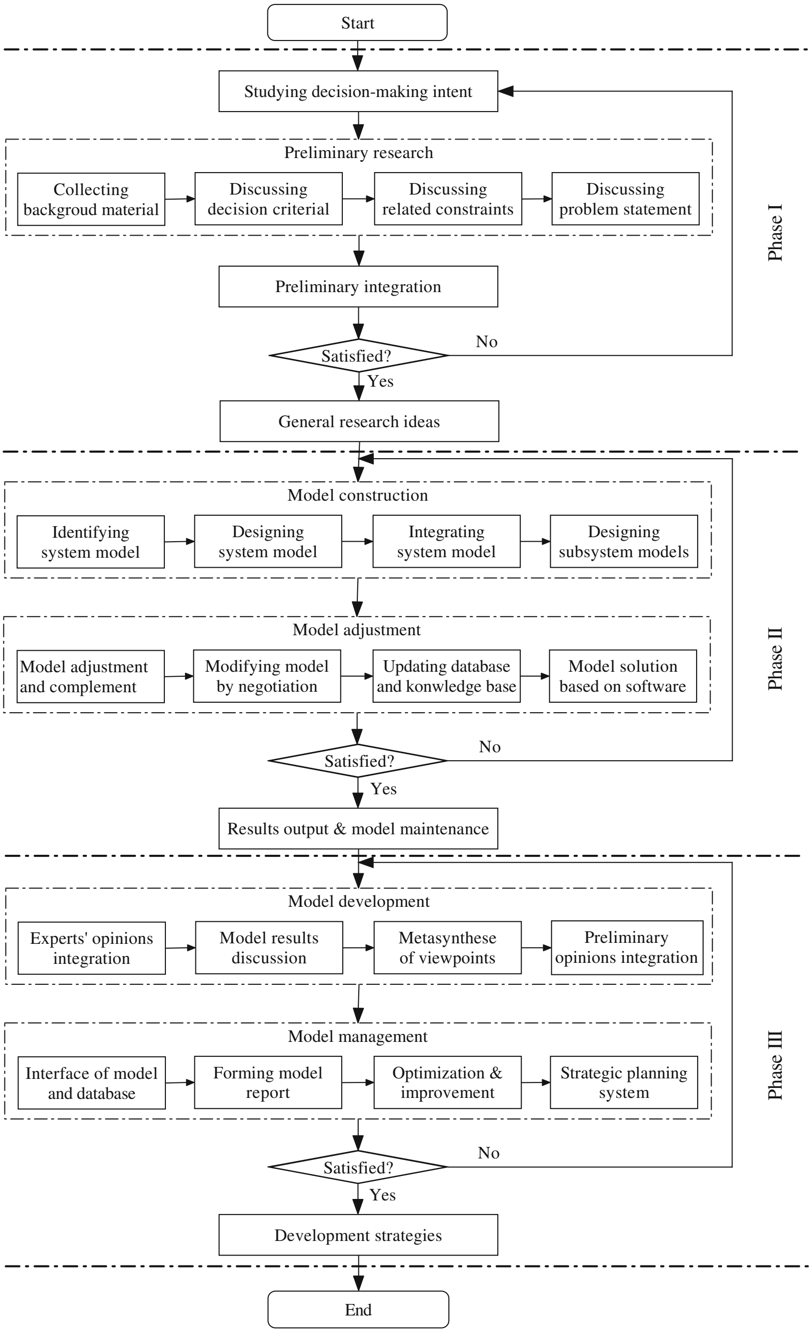


Fig. 2.4 The flow chart of LCSM

2.2.1 Problem Categories

As concluded in Chap. 1, there are mainly 9 key issues faced in the RLCED, including greenhouse gas control, ecological capacity evaluation, regional economic prediction, energy structure optimization, land resource utilization, industrial structure adjustment, low carbon industrial chains, low carbon transportation systems, and low carbon tourism. Though problem system relates to most aspects of regional economic development and seems very complicated, we can group them into three different levels of problem pedigree.

(1) Category I : fundamental problems. Greenhouse gas control, ecological capacity evaluation and regional economic prediction belong to this class of problems. Reasonable GHGs control, sufficient ecological carrying capacity, and appropriate economic development target are the foundation of the RLCED.
(2) Category II : significant problems. Energy structure optimization, land resource utilization and industrial structure adjustment belong to this class of problems. Energy, land and industries are the carriers of regional economic development. Low carbonized energy, land use and industrial structure are significant for the RLCED.
(3) Category III : crucial problems. Low carbon industrial chains, low carbon transportation systems and low carbon tourism belong to this class of problems. Industrial chains, transportation and tourism are normally the important GHGs emission sources. Develop low carbon industrial chains, transportation and tourism are crucial for the RLCED.

Indeed, each problem has its key issues and main goals in the process of the RLCED, as shown in Table 2.1.

2.2.2 Problem System

Based on the comprehensive analysis of categories, key issues and contents of the 9 important problems during the RLCED, we can construct the problem framework of the RLCED, see Fig. 2.5.

2.3 Model System

Corresponding to the 9 key problems, we develop 9 model groups to solve the problems.

(1) Energy structure optimization. Fuzzy multi-objective programming model, maximin method, particle swarm optimization algorithm, and system dynamics model are applied to research the problem.

Table 2.1 Categories of the RLCED problems

Category	Problem	Key issues	Problem content
I	Greenhouse gas control	Industrial GHGs emissions People's daily lives emissions Emission environmental costs	Calculating the economic loss caused by GHGs emissions from industrial products and daily lives to amend GDP
	Ecological capacity evaluation	Ecological carrying capacity Ecological footprint Ecological deficit	Indicating the sustaining function of regional ecological supporting system on regional low carbon development
	Regional economic prediction	Population, resource, social and industry subsystems Regional economic plan	Conducting the regional economic plan and management to promote coordinated development of regional economic system
II	Energy structure optimization	Energy consumption reduction Energy efficiency promotion Energy structure adjustment	Optimizing regional energy structure by predicting energy consumption and CO_2 emissions in a region
	Land resource utilization	Land utilization planning Low carbonized adjustment of land structures	Developing low carbonized land structures by analyzing the relationship between land resources and ecologic environment
	Industrial structure adjustment	Industrial system description Industrial structural evolution Low carbon industries development	Accelerating regional industrial structure upgrading and transformation to high-value and low-carbon industries by effective measures
III	Low carbon industrial chains	Energy efficiency Network design GHGs emissions	Implementing green and circular industrial chains management by optimizing energy efficiency, network design and GHGs emissions
	Low carbon transportation systems	Urban space Population Vehicles	Constructing low carbon transporttation system by calculating and simulating the optimal proportion of different transport means
	Low carbon tourism	Tourism Facilities Environment and energy Economic changes	Acquiring more tourism economic, social and environmental benefits under the pursuit of less carbon emissions

(2) Ecological capacity evaluation. Ecological footprint and system dynamics model are applied to research the problem.
(3) Regional economic prediction. Econometric model and system dynamics model are applied to research the problem.
(4) Energy structure optimization. Fuzzy multi-objective programming model, maximin method, particle swarm optimization algorithm, and system dynamics model are applied to research the problem.

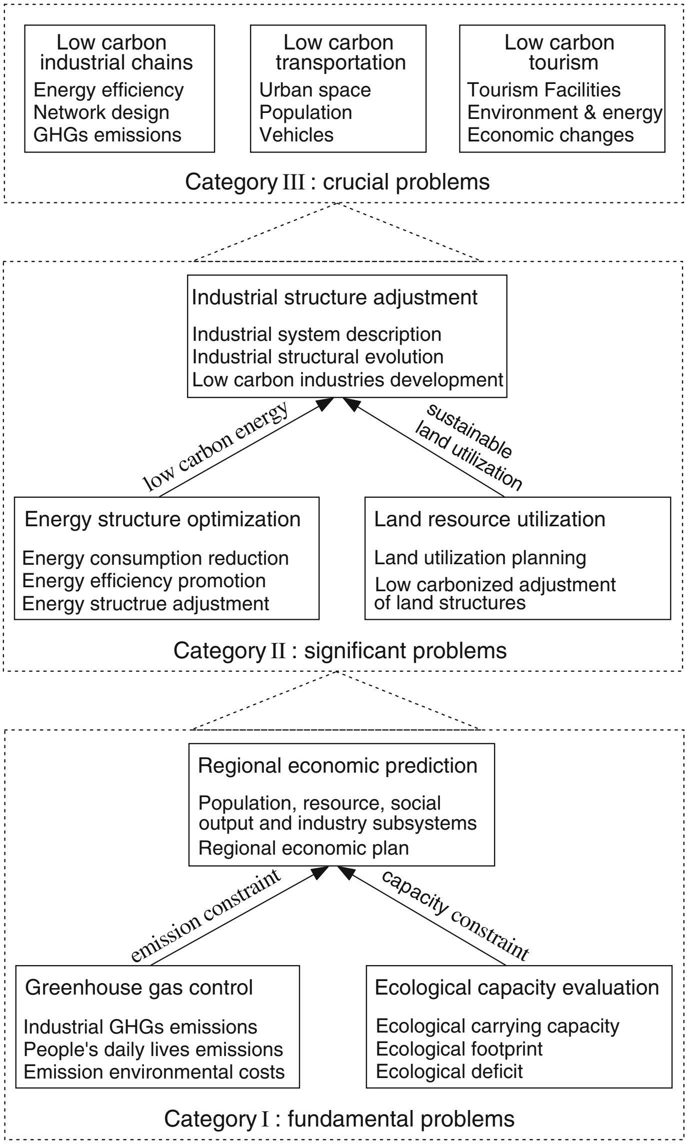


Fig. 2.5 Problem framework of the RLCED

(5) Land resource utilization. Fuzzy expected value model, ideal point method, genetic algorithm, and system dynamics model are applied to research the problem.

(6) Industrial structure adjustment. Fuzzy random multi-objective model, lexicographic method, genetic algorithm, and system dynamics model are applied to research the problem.
(7) Low carbon industrial chains. According to the three representatives of low carbon industrial chains, polysilicon industrial chain, textile industrial chain and pig industrial chain, three model groups have been applied to research the relative problems. Group one, fuzzy possibility multi-objective model, weight sum method, genetic algorithm, and system dynamics model are applied to research polysilicon industrial chain; group two, random multi-objective programming model and system dynamics model are applied to research textile industrial chain; group three, random chance constrained model, goal programming method, and system dynamics model are applied to research pig industrial chain.
(8) Low carbon transportation systems. Random expected value model, fuzzy programming method, tabu search algorithm, and system dynamics model are applied to research the problem.
(9) Low carbon tourism. Differential dynamic system model and simultaneous equations are applied to research the problem.

2.3.1 Model Categories

According to the functions of the models, we divide them into three categories: operation models, solution models, and simulation models, see Table 2.2.

(1) Category I: operation models. Operation models are applied to calculate the optimal objective and basic parameters of the RLCED, including multi-objective programming model, ecological footprint, econometric model, and differential dynamic system model. According to the different properties of problem parameters, the multi-objective programming model has many different transformations, such as random expected value model, fuzzy expected value model, random chance constrained model, fuzzy multi-objective programming model, fuzzy possibility multi-objective model, random multi-objective programming model, fuzzy random multi-objective model.
(2) Category II: solution models. Solution models specifically refer to methods and algorithms solving multi-objective programming problems. There are two kinds of solution models in our model system: traditional solution methods and hybrid intelligent algorithms. The former includes weight sum method, maximin method, ideal point method, lexicographic method, goal programming method, and fuzzy programming method; the latter includes simulated annealing algorithm, particle swarm optimization algorithm, genetic algorithm, and tabu search algorithm.
(3) Category III: simulation models. Simulation models are the premier tools used by researchers to analyze complex and dynamic systems, supplying the overall system analysis and the dynamical quantitative analysis. The main simulation

Table 2.2 Functions of the models

Category	Model	Model function
I	Ecological footprint	Tracking regional energy and resource consumption to turn them into production of biological land area
	Econometric model	Specifying the statistical relationship between various economic variables in regional economic systems
	Multi-objective programming model	Simultaneously optimizing two or more conflicting objective functions under a set of constraints
	Differential dynamic system model	Using applied mathematics to describe the behavior of complex dynamical systems by employing differential equations or difference equations
II	Weight sum method	Evaluating a number of alternatives in terms of a number of decision criteria
	Maximin method	A strategy to maximize the minimum possible payback
	Ideal point method	Constructing the ideal solution of evaluation objects, and make the degree of close to the ideal solution as classification criterion
	Lexicographic method	Ranking the objective function by its importance to decision makers and then resolve the next objective function after resolving the above one
	Goal programming method	Extension of linear programming to handle multiple, normally conflicting objective measures
	Fuzzy programming method	Using the fuzzy concept to study the fuzziness in the decision making process
	Simulated annealing algorithm	A generic probabilistic metaheuristic for locating a good approximation to the global optimum of a given function in a large search space
	Particle swarm optimization algorithm	A computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality
	Genetic algorithm	A search heuristic that mimics the process of natural evolution to generate useful solutions to optimization and search problems
	Tabu search algorithm	A metaheuristic local search algorithm that can be used for solving combinatorial optimization problems
III	System dynamics model	Simulating the behavior of complex systems over time by dealing with internal feedback loops and time delays
	Simultaneous equations	A particular specification of the values of all variables that simultaneously satisfies all of the equations

model applied in this book is system dynamics model. Simultaneous equations is also applied in low carbon tourism simulation.

Based on the above analysis, we can establish the model systems for the RLCED, as shown in Fig. 2.6.

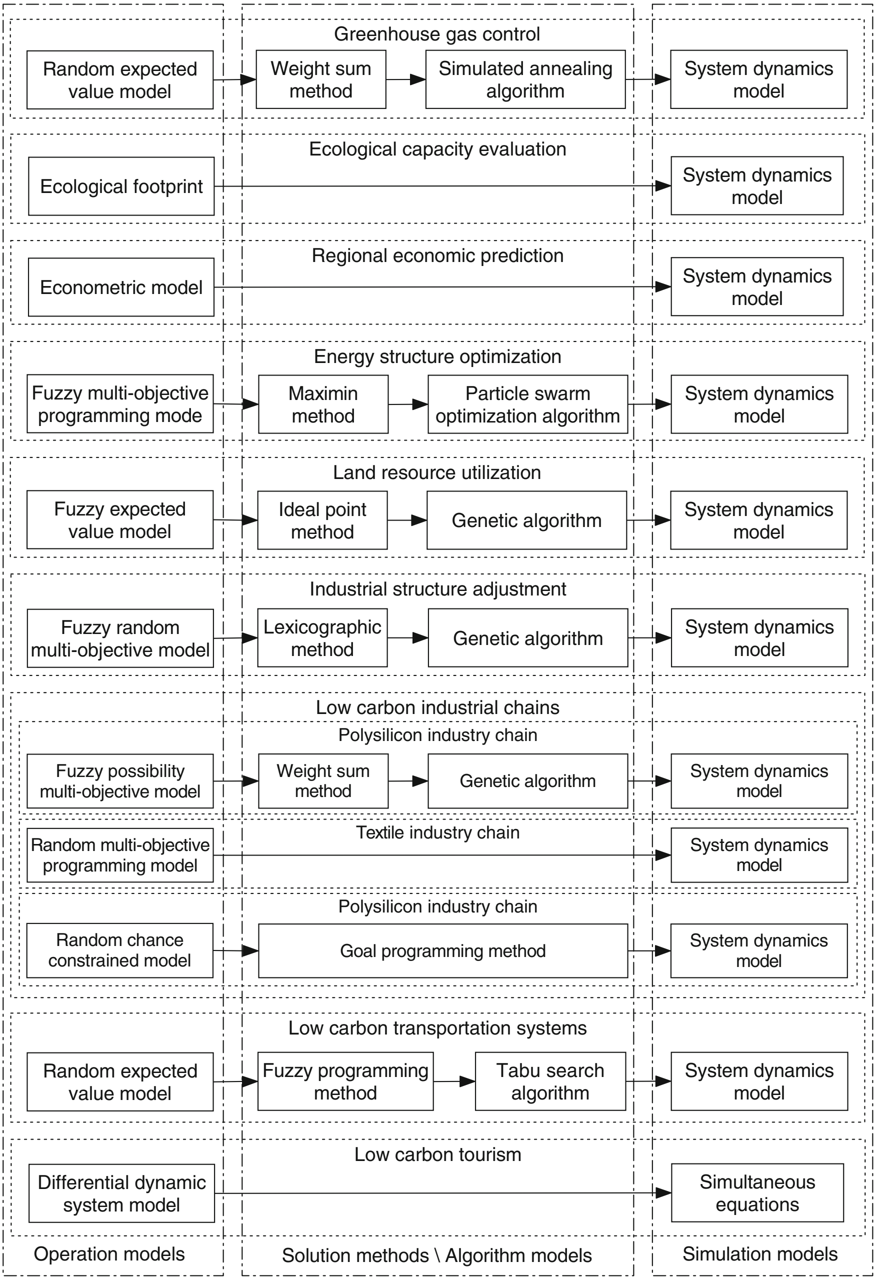


Fig. 2.6 Model system for the RLCED

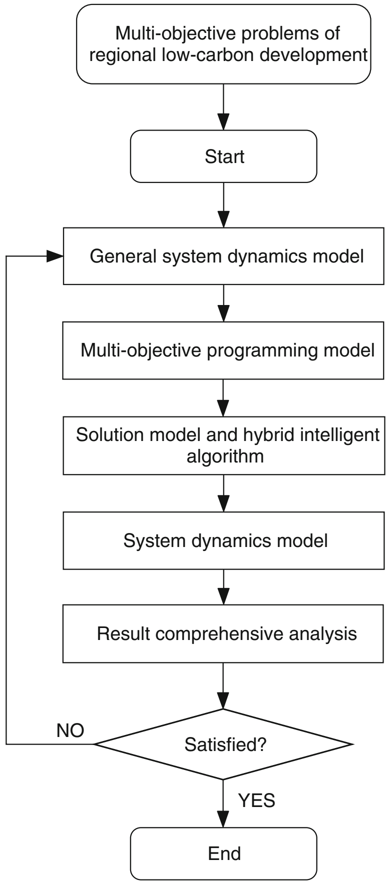


Fig. 2.7 Models flowchart of multi-objective problems

2.3.2 Model Flowchart

Focusing on different types of problems faced in the RLCED, we divide them into two categories according to decision process: multi-objective problems and forecasting problems. Corresponding to two types of problems, there are two kinds of model flowcharts, see Figs. 2.7 and 2.8.

Figure 2.7 illustrates the models flowchart of multi-objective problems of the RLCED. The multi-objective problems contain greenhouse gas control, energy structure optimization, energy structure optimization, land resource utilization, industrial structure adjustment and land resource utilization. For instance, the maximal total GDP and the minimal GHGs emissions is two objectives of the GHGs control problem; the maximal economic benefit, the minimal energy consumption and total GHGs emissions is three objectives of the energy structure optimization. In a decision process for the multi-objective problems of the RLCED, a general system dynamics

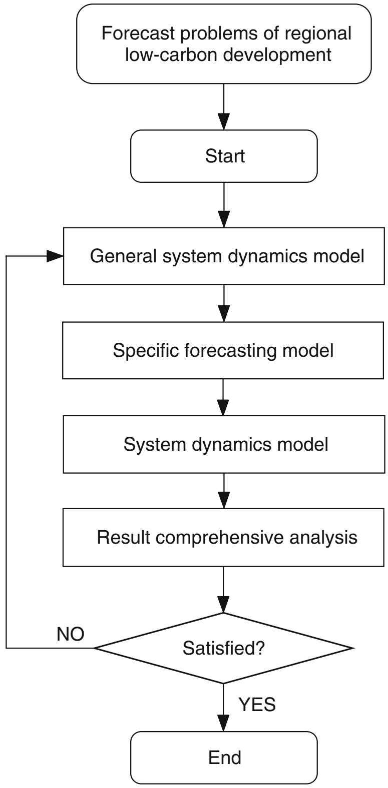


Fig. 2.8 Models flowchart of forecasting problems

model is primarily constructed to analyze the system structure and the correlation between subsystems. In this step, a set of experts and government officers provide their insights on the given problem, and the causal loop diagram and detailed flow diagram are established. By sensitive analysis, the key parameters which exert a great influence on the output are screened out. Multi-objective programming method is used to determine the best parameters. To deals with the uncertainties and optimize some parameters in a given system, random/fuzzy expected value model, random chance constrained model, random/fuzzy multi-objective programming model, and fuzzy random multi-objective model are applied to optimize and select parameters. Several traditional solution model and hybrid intelligent algorithm are used to solve the multi-objective programming problems. The system dynamics model again be used to simulate the dynamic system and forecast the system development. Based on results of the integrated approach, different policy experiments are compared to choose the best route. If the decision makers are satisfied with the recommendation of the system, then the decision process is end, otherwise another round decision process will be carried out.

Figure 2.8 illustrates the models flowchart of forecasting problems of the RLCED. The forecasting problems include ecological capacity evaluation and regional economic prediction. The main goal of ecological capacity evaluation and regional economic prediction is to forecast the ecological carrying capacity and regional socioeconomic situation, and guide the RLCED strategy in the future. In a decision process for the forecasting problems of the RLCED, we first construct a general system dynamics model to systematically describe the regional natural resources and economic structure. The second step is to establish specific forecasting model, such as ecological footprint method (measuring the gap between ecological footprint and ecological carrying capacity) and econometrics method (calculating the relationship between regional economic variables). Then, a system dynamics model based on the actual and predicted situation of the region is established. The system dynamics model can simulate the different scenarios of the RLCED. The experts then collectively analyze and discuss the forecasting and simulation results. The satisfied results provides scientific basis for the RLCED.

2.4 Meta Model

As have been discussed above, the LCSM is a integrated model system under the special spectrum mapping between RLCED problems and models. A meta unit of the LCSM is an integration of the mathematical model and the behavioral model. Of these, the mathematical models including the operation models, solution models and simulation models, which are the core models for planning optimization and path selection of the RLCED; the behavioral model then reflects the managers' and researchers' feedback and comments on the operating results of mathematical models. Each meta model is designed to resolve specific issues in the RLCED, thus it carries the maximum amount and the most frequently interactions of the LCSM. Therefore, the expression form and operation process of meta model should be regulated.

2.4.1 Model Pedigree

In the LCSM, there are several key meta models, such as system dynamics, multi-objective programming, ecological footprint, econometric model, and differential dynamic system. Each meta model is composed of a series of basic models. The model pedigree is as shown in Fig. 2.9.

2.4.1.1 System Archetypes of System Dynamics

System dynamics is an approach to understand the behavior of complex systems. A system dynamic model is usually extended by some system archetypes. A system archetype is usually illustrated by a circle of causation. Systems expressed by circles

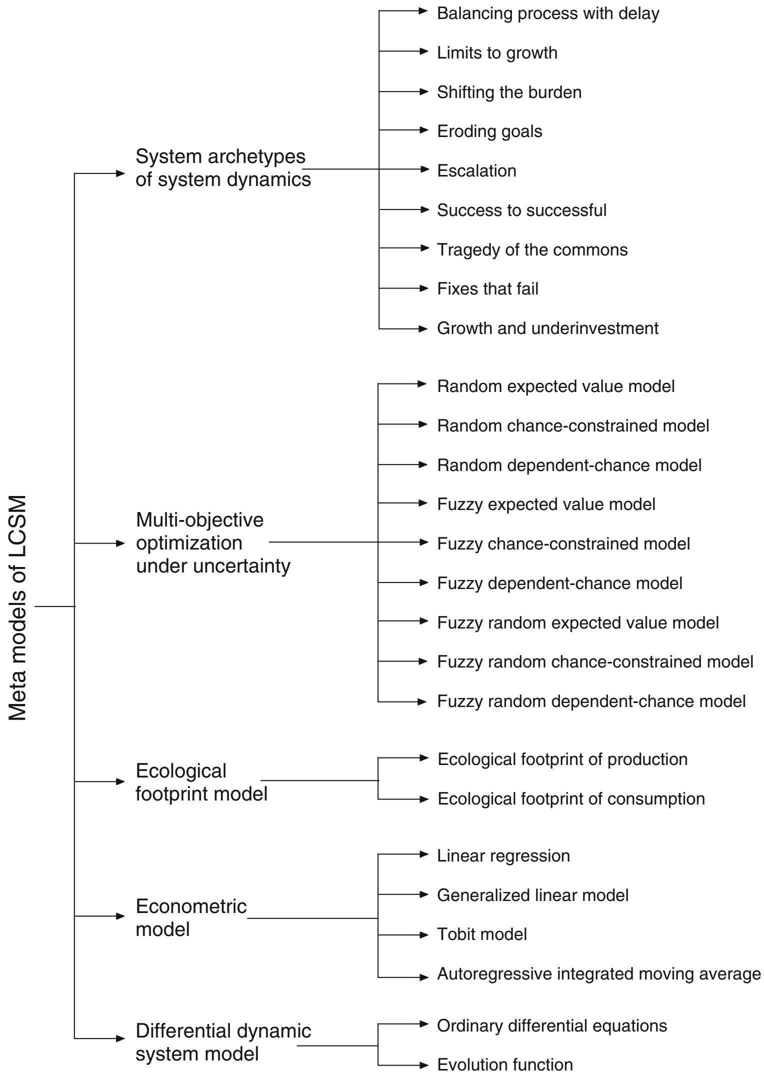


Fig. 2.9 Model pedigree of the LCSM

of causality have therefore similar structure. Identifying a system archetype and finding the leverage enables efficient changes in a system. There are usually 8 kinds of system archetypes as shown in Table 2.3.

Table 2.3 Eight kinds of system archetypes (Wikipedia 2013d)

System archetype	Description
Balancing process with delay	If the agents do not perceive the delayed feedback, they might overshoot or underestimate the requisite action in order to reach their goals (see Fig. 2.10)
Limits to growth	The unprecedented growth is produced by a reinforcing feedback process until the system reaches its peak (see Fig. 2.11)
Shifting the burden	The primary source of the problem is overlooked, because its remedy is demanding and has no immediate outcome (see Fig. 2.12)
Eroding goals	As current problems need to be handled immediately, the long-term goals continuously decline (see Fig. 2.13)
Escalation	This archetype could be seen as a non-cooperative game where both players suppose that just one of them can win (see Fig. 2.14)
Success to successful	Two people or activities need the same limited resources As one of them becomes more successful, more resources are assigned to him/it. The second one becomes less and less successful due to lacking resources, and prove the right decision to support the first one (see Fig. 2.15)
Tragedy of the commons	Agents use common limited resource to profit individually As the use of the resource is not controlled, the agents would like to continuously raise their benefits The resource is therefore used more and more and the revenues of the agents are decreasing. The agents are intensifying their exploitation until the resource is completely used up or seriously damaged (see Fig. 2.16)
Fixes that fail	In the fixes that fail archetype, the problem is solved by some fix (a specific solution) with immediate positive effect. Nonetheless, the “side effects” of this solution turn out in the future (see Fig. 2.17)

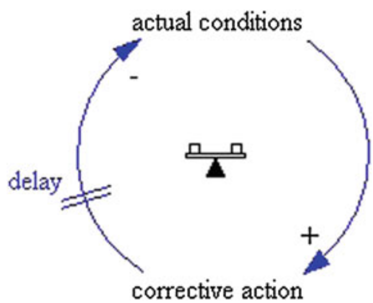


Fig. 2.10 Balancing process with delay

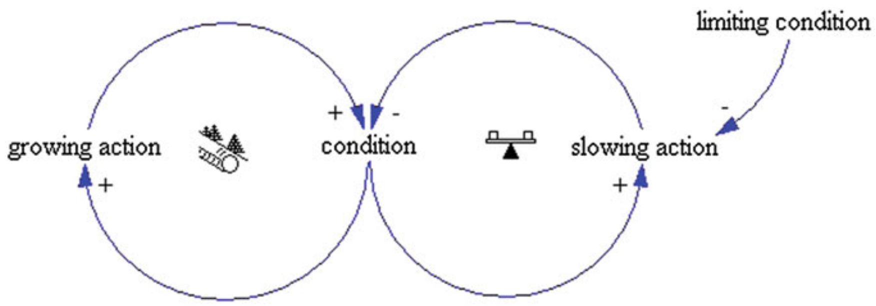


Fig. 2.11 Limits to growth

Fig. 2.12 Shifting the burden

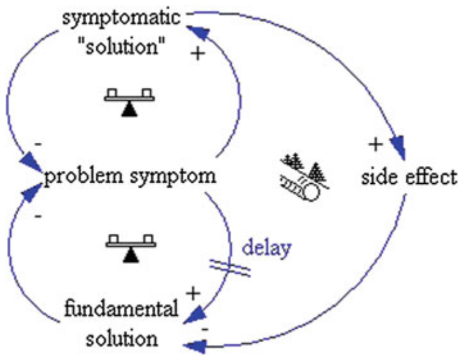
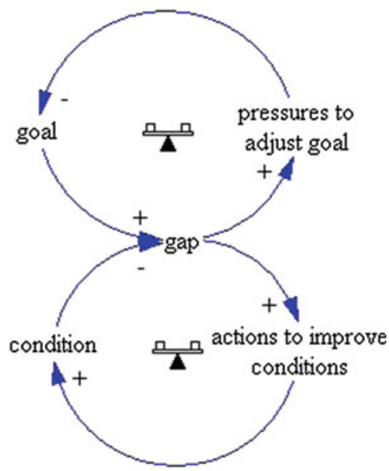


Fig. 2.13 Eroding goals



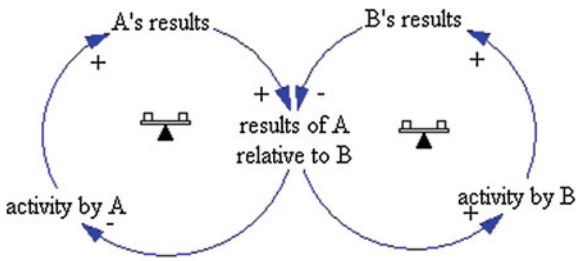


Fig. 2.14 Escalation

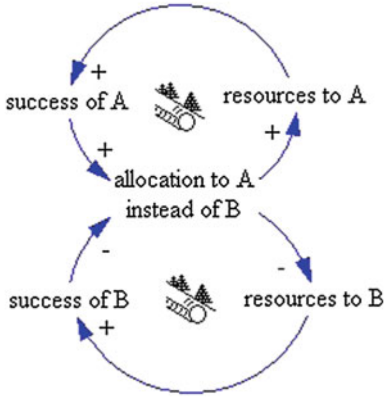


Fig. 2.15 Success to successful

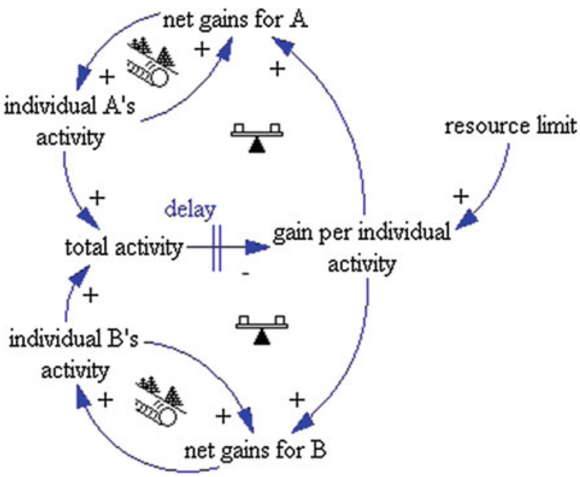
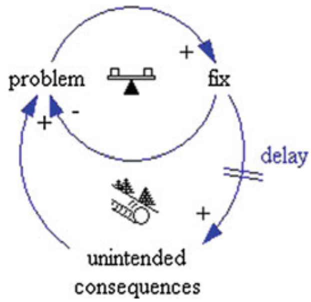


Fig. 2.16 Tragedy of the commons

Fig. 2.17 Fixes that fail



2.4.1.2 Ecological Footprint Model

The ecological footprint is a measure of human demand on the Earth's ecosystems. It is a standardized measure of demand for natural capital that may be contrasted with the planet's ecological capacity to regenerate (WWF et al. 2004). It represents the amount of biologically productive land and sea area necessary to supply the resources a human population consumes, and to assimilate associated waste. Using this assessment, it is possible to estimate how much of the Earth (or how many planet Earths) it would take to support humanity if everybody followed a given lifestyle (Wikipedia 2013b).

The ecological footprint uses yields of primary products (from cropland, forest, grazing land and fisheries) to calculate the area necessary to support a given activity. Biocapacity is measured by calculating the amount of biologically productive land and sea area available to provide the resources a population consumes and to absorb its wastes, given current technology and management practices. Countries differ in the productivity of their ecosystems, and this is reflected in the accounts (Network 2013). The Ecological Footprint of production,

$$EF_P = \frac{P}{Y_N} \cdot YF \cdot EQF \tag{2.1}$$

where P is the amount of a product harvested or carbon dioxide emitted, Y_N is the national average yield for P (or its carbon uptake capacity), and YF and EQF are the yield factor and equivalence factor, respectively, for the land use type in question. Yield factors capture the difference between local and world average productivity for usable products within a given land use type.

In order to keep track of both the direct and indirect biocapacity needed to support people's consumption patterns, the Ecological Footprint methodology uses a consumer-based approach; for each land use type, the Ecological Footprint of consumption (EF_C) is thus calculated as

$$EF_C = EF_P + EF_I - EF_E \tag{2.2}$$

where EF_P is the Ecological Footprint of production and EF_I and EF_E are the Footprints embodied in imported and exported commodity flows, respectively (Ewing et al. 2010). The National Footprint Accounts calculate the Footprint of apparent consumption, as data on stock changes for various commodities are generally not available. One of the advantages of calculating Ecological Footprints at the national level is that this is the level of aggregation at which detailed and consistent production and trade data are most readily available. Such information is essential in properly allocating the Footprints of traded goods to their final consumers.

2.4.1.3 Econometric Model

Econometric models are statistical models used in econometrics (Wikipedia 2013c). An econometric model specifies the statistical relationship that is believed to hold between the various economic quantities pertaining to a particular economic phenomenon under study. An econometric model can be derived from a deterministic economic model by allowing for uncertainty, or from an economic model which itself is stochastic. However, it is also possible to use econometric models that are not tied to any specific economic theory (Sims 1980).

The most common econometric models are structural, in that they convey causal and counterfactual information (Pearl 2000), and are used for policy evaluation. For example, an equation modeling consumption spending based on income could be used to see what consumption would be contingent on any of various hypothetical levels of income, only one of which (depending on the choice of a fiscal policy) will end up actually occurring.

Linear regression. In statistics, linear regression is an approach to modeling the relationship between a scalar variable y and one or more explanatory variables denoted X. The case of one explanatory variable is called simple regression. More than one explanatory variable is multiple regression.

Generalized linear model. In statistics, the generalized linear model (GLM) is a flexible generalization of ordinary linear regression. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value.

Tobit model. The Tobit model is a statistical model proposed by James Tobin to describe the relationship between a non-negative dependent variable y_i and an independent variable (or vector) x_i (Tobin 1958).

Autoregressive integrated moving average. In statistics and econometrics, and in particular in time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). They are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to remove the non-stationarity.

2.4.1.4 Differential Dynamic System Model

Dynamical systems theory is an area of applied mathematics used to describe the behavior of complex dynamical systems, usually by employing differential equations or difference equations. When differential equations are employed, the theory is called continuous dynamical systems. When difference equations are employed, the theory is called discrete dynamical systems. When the time variable runs over a set which is discrete over some intervals and continuous over other intervals or is any arbitrary time-set such as a cantor set then one gets dynamic equations on time scales. Some situations may also be modelled by mixed operators such as differential-difference equations (Wikipedia 2013a).

In the most general sense, a dynamic system is a tuple (T, M, Φ), where T is a monoid, written additively, M is a set and Φ is a function

$$\Phi : U \subset T \times M \rightarrow M \tag{2.3}$$

with $I(x) = \{t \in T : (t, x) \in U\}$, $\Phi(0, x) = x$, and $\Phi(t_2, \Phi(t_1, x)) = \Phi(t_1+t_2, x)$, for $t_1, t_2, t_1 + t_2 \in I(x)$. The function $\Phi(t, x)$ is called the evolution function of the dynamic system: it associates to every point in the set M a unique image, depending on the variable t, called the evolution parameter. M is called phase space or state space, while the variable x represents an initial state of the system. We often write

$$\Phi_x(t) := \Phi(t, x), \quad \Phi^t(x) := \Phi(t, x)$$

if we take one of the variables as constant.

$$\Phi_x \ : \ I(x) \rightarrow M \tag{2.4}$$

is called flow through x and its graph trajectory through x. The set

$$\gamma_x \ := \{\Phi(t, x) : t \in I(x)\} \tag{2.5}$$

is called orbit through x. A subset S of the state space M is called Φ-invariant if for all x in S and all t in T, $\Phi(t, x) \in S$. In particular, for S to be Φ-invariant, we require that $I(x) = T$ for all x in S. That is, the flow through x should be defined for all time for every element of S.

2.4.1.5 Multi-Objective Optimization Under Uncertainty

Multi-objective optimization (or multi-objective programming), also known as multi-criteria or multi-attribute optimization, is the process of simultaneously optimizing two or more conflicting objectives subject to certain constraints. However, some incomplete information will result in so much difficulty for decision makers (Abbr. DMs). For example, the random phenomena and fuzzy environment are two obvious uncertainty. Then the uncertain multi-objective programming will be considered in the low carbon economic development.

Random expected value model. For those problems with random phenomena, the expected value operator is usually used to obtain the average value of the random coefficients and random expected value model (Abbr. REVM) is developed to help DMs to obtain the optimal strategies. The general model is described as follows,

$$\begin{cases} \max[E[f_1(\boldsymbol{x},\boldsymbol{\xi})], E[f_2(\boldsymbol{x},\boldsymbol{\xi})], \cdots, E[f_m(\boldsymbol{x},\boldsymbol{\xi})]] \\ \text{s.t.} \begin{cases} E[g_j(\boldsymbol{x},\boldsymbol{\xi})] \leq 0, \ \ j=1,2,\cdots,p \\ \boldsymbol{x} \in X \end{cases} \end{cases} \tag{2.6}$$

where $f_i(\boldsymbol{x},\boldsymbol{\xi})$ are return functions for $i = 1, 2, \cdots, m$. $\boldsymbol{\xi} = (\xi_1, \xi_2, \cdots, \xi_n)$ is a random vector on the probability space (Xu and Yao 2011). Sometimes, the interrelationship between the random coefficients is linear, then we get the linear random expected value model as follows,

$$\begin{cases} \max \left[E[\bar{c}_1^T \boldsymbol{x}], E[\bar{c}_2^T \boldsymbol{x}], \cdots, E[\bar{c}_m^T \boldsymbol{x}]\right] \\ \text{s.t.} \begin{cases} E[\bar{e}_r^T \boldsymbol{x}] \leq E[\bar{b}_r], \ \ r=1,2,\cdots,p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.7}$$

where $\boldsymbol{x} \in X \subset \mathbf{R}^n$, $\bar{c}_i = (\bar{c}_{i1}, \bar{c}_{i2}, \cdots, \bar{c}_{in})^T$, $\bar{e}_r = (\bar{e}_{r1}, \bar{e}_{r2}, \cdots, \bar{e}_{rn})^T$ are random vectors, and $\bar{b}_r$ are random variables, $i = 1, 2, \cdots, m$, $r = 1, 2, \cdots, p$. The symbol E means the expected value operator. For the model (2.7), it is easy to get the crisp equivalent model if all the random coefficients have the frequently-used distribution. For example, if $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$ in the model (2.7) are normally distributed, it follows that the model (2.7) is equivalent to

$$\begin{cases} \max \left[\mu_1^{cT} \boldsymbol{x}, \mu_2^{cT} \boldsymbol{x}, \cdots, \mu_m^{cT} \boldsymbol{x}\right] \\ \text{s.t.} \begin{cases} \mu_r^{eT} \boldsymbol{x} \leq \mu_r^b, \ r=1,2,\cdots,p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.8}$$

where $\mu_i^c = (\mu_{i1}^c, \mu_{i2}^c, \cdots, \mu_{in}^c)^T$, μ_r^e and μ_r^b are expected value vectors of $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$, respectively. If $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$ in the model (2.7) are exponentially distributed, it follows that the model (2.7) is equivalent to

$$\begin{cases} \max \left[\lambda_1^{cT} \boldsymbol{x}, \lambda_2^{cT} \boldsymbol{x}, \cdots, \lambda_m^{cT} \boldsymbol{x}\right] \\ \text{s.t.} \begin{cases} \lambda_r^{eT} \boldsymbol{x} \leq \frac{1}{\lambda_r^b}, r=1,2,\cdots,p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.9}$$

where $\lambda_i^c = (\frac{1}{\lambda_{i1}^c}, \frac{1}{\lambda_{i2}^c}, \cdots, \frac{1}{\lambda_{in}^c})^T$ and $\lambda_i^e = (\frac{1}{\lambda_{r1}^e}, \frac{1}{\lambda_{r2}^e}, \cdots, \frac{1}{\lambda_{rn}^e})^T$; λ_{ij}^c, μ_{rj}^e and μ_r^b are expected values of $\bar{c}_{ij}$, $\bar{e}_{rj}$ and $\bar{b}_r$, respectively.

Random chance-constrained model. For those problems with random phenomena, DMs usually wants to maximize the objective value on the condition of probability α, where α is predetermined confidence level and then the random chance-constrained model (Abbr. RCCM) is developed to help DMs to obtain the optimal strategies. The general model is described as follows,

$$\begin{cases} \max[\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_m] \\ \text{s.t.} \begin{cases} Pr\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \beta_i, \ i = 1, 2, \cdots, m \\ Pr\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \alpha_r, \ \ j = 1, 2, \cdots, p \\ \boldsymbol{x} \in X \end{cases} \end{cases} \tag{2.10}$$

where β_i and α_r are the predetermined confidence levels, $\bar{f}_i$ are critical values which need to be determined. Sometimes, the interrelationship between the random coefficients is linear, then we get the linear random chance-constrained model as follows,

$$\begin{cases} \max[\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_m] \\ \text{s.t.} \begin{cases} Pr\{\bar{c}_i^T \boldsymbol{x} \geq \bar{f}_i\} \geq \beta_i, \quad i = 1, 2, \cdots, m \\ Pr\{\bar{e}_r^T \boldsymbol{x} \leq \bar{b}_r\} \geq \alpha_r, \quad r = 1, 2, \cdots, p \\ \boldsymbol{x} \geq 0, 0 \leq \alpha_r, \beta_i \leq 1 \end{cases} \end{cases} \tag{2.11}$$

where α_r and β_i are predetermined confidence levels DMs give. For the model (2.11), it is easy to get the crisp equivalent model if all the random coefficients have the frequently-used distribution. For example, if $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$ are normally distributed, it follows that the model (2.11) is equivalent to

$$\begin{cases} \max[H_1(\boldsymbol{x}), H_2(\boldsymbol{x}), \cdots, H_m(\boldsymbol{x})] \\ \text{s.t.} \begin{cases} g_r(\boldsymbol{x}) \leq 0, r = 1, 2, \cdots, p \\ \boldsymbol{x} \geq 0, 0 \leq \alpha_r, \beta_i \leq 1 \end{cases} \end{cases} \tag{2.12}$$

where $H_i(\boldsymbol{x}) = \Phi^{-1}(1-\beta_i)\sqrt{\boldsymbol{x}^T V_i^c \boldsymbol{x}} + \mu_i^{cT}\boldsymbol{x}$, $g_r(\boldsymbol{x}) = \Phi^{-1}(\alpha_r)\sqrt{\boldsymbol{x}^T V_r^e \boldsymbol{x} + (\sigma_r^b)^2}$ $+ \mu_r^{eT}\boldsymbol{x} - \mu_r^b$ and Φ is the standardized normal distribution; $\mu_i^c = (\mu_{i1}^c, \mu_{i2}^c, \cdots, \mu_{in}^c)^T$, μ_r^e and μ_r^b are expected value vectors of $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$, respectively. V_i^c, V_i^e are covariance matrixes and $(\sigma_r^b)^2$ are variances of $\bar{b}_r$.

Random dependent-chance model. For those problems with random phenomena, DMs sometimes want to maximize the chance functions subject to an uncertain environment and then the random dependent-chance model (Abbr. RDCM) is developed to help DMs to obtain the optimal strategies. The general model is described as follows,

$$\begin{cases} \max \begin{bmatrix} Pr\{f_1(\boldsymbol{x}, \boldsymbol{\xi}) \leq \bar{f}_1\} \\ Pr\{f_2(\boldsymbol{x}, \boldsymbol{\xi}) \leq \bar{f}_2\} \\ \cdots \\ Pr\{f_m(\boldsymbol{x}, \boldsymbol{\xi}) \leq \bar{f}_m\} \end{bmatrix} \\ \text{s.t.} \quad Pr\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \beta_r, r = 1, 2, \cdots, p \end{cases} \tag{2.13}$$

where $f_i(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0$ are represent events ε_i for $i = 1, 2, \cdots, m$, respectively. $\bar{f}_i$ are predetermined objective values. Sometimes, the interrelationship between the random coefficients is linear, then we get the linear random dependent-chance model as follows,

$$\begin{cases} \max \left[Pr\{\bar{c}_1^T \boldsymbol{x} \geq f_1\}, Pr\{\bar{c}_2^T \boldsymbol{x} \geq f_2\}, \cdots, Pr\{\bar{c}_m^T \boldsymbol{x} \geq f_m\} \right] \\ \text{s.t.} \begin{cases} Pr\{\bar{e}_r^T \boldsymbol{x} \leq \bar{b}_r\} \geq \beta_r, \ r = 1, 2, \cdots, p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.14}$$

where f_i is predetermined objective value and β_r is the predetermined level value. For the model (2.14), it is easy to get the crisp equivalent model if all the random coefficients have the frequently-used distribution. For example, if $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$ are normally distributed, it follows that the model (2.14) is equivalent to

$$\begin{cases} \max \left[1 - \Phi\left(\frac{f_i - \mu_i^{cT} \boldsymbol{x}}{\sqrt{\boldsymbol{x}^T V_i^c \boldsymbol{x}}} \right), i = 1, 2, \cdots, m \right] \\ \text{s.t.} \begin{cases} \Phi^{-1}(\beta_r)\sqrt{\boldsymbol{x}^T V_r^e \boldsymbol{x} + (\sigma_r^b)^2} + \mu_r^{eT} \boldsymbol{x} - \mu_r^b \leq 0 \\ \boldsymbol{x} \geq 0, r = 1, 2, \cdots, p \end{cases} \end{cases} \tag{2.15}$$

where $\mu_i^c = (\mu_{i1}^c, \mu_{i2}^c, \cdots, \mu_{in}^c)^T$, μ_r^e and μ_r^b are expected value vectors of $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$, respectively. V_i^c, V_i^e are covariance matrixes and $(\sigma_r^b)^2$ are variances of $\bar{b}_r$.

Fuzzy expected value model. Sometimes, DMs have to face another uncertainty, that is fuzzy environment. It means that DMs have to make the decision under the fuzzy environment in which there is no enough historical data. For this uncertainty, the expected value operator is usually used to obtain the average value of the fuzzy coefficients and fuzzy expected value model (Abbr. FEVM) is developed to help DMs to obtain the optimal strategies. The general model is described as follows,

$$\begin{cases} \max[E[f_1(\boldsymbol{x}, \boldsymbol{\xi})], E[f_2(\boldsymbol{x}, \boldsymbol{\xi})], \cdots, E[f_m(\boldsymbol{x}, \boldsymbol{\xi})]] \\ \text{s.t.} \begin{cases} E[g_j(\boldsymbol{x}, \boldsymbol{\xi})] \leq 0, \ j = 1, 2, \cdots, p \\ \boldsymbol{x} \in X \end{cases} \end{cases} \tag{2.16}$$

where $f_i(\boldsymbol{x}, \boldsymbol{\xi})$ are return functions for $i = 1, 2, \cdots, m$. $\boldsymbol{\xi} = (\xi_1, \xi_2, \cdots, \xi_n)$ is a fuzzy vector on the possibility space (Xu and Zhou 2010). Sometimes, the interrelationship between the fuzzy coefficients is linear, then we get the linear fuzzy expected value model as follows,

$$\begin{cases} \max \ E\left[\sum_{j=1}^{n} \tilde{c}_{ij} x_j, i = 1, 2, \cdots, m \right] \\ \text{s.t.} \ \begin{cases} E[\tilde{a}_{rj} x_j] \geq E[\tilde{b}_r], \ r = 1, 2, \cdots, p \\ x_j \geq 0, \ j = 1, 2, \cdots, n \end{cases} \end{cases} \tag{2.17}$$

where $\boldsymbol{x} \in X \subset \mathbf{R}^n$, $\bar{c}_i = (\bar{c}_{i1}, \bar{c}_{i2}, \cdots, \bar{c}_{in})^T$, $\bar{e}_r = (\bar{e}_{r1}, \bar{e}_{r2}, \cdots, \bar{e}_{rn})^T$ are fuzzy vectors, and $\bar{b}_r$ are fuzzy variables, $i = 1, 2, \cdots, m$, $r = 1, 2, \cdots, p$. The symbol

E means the expected value operator. For the model (2.17), it is easy to get the crisp equivalent model if all the fuzzy coefficients have the frequently-used membership functions. For example, if $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$ in the model (2.17) are trapezoidal fuzzy numbers, it follows that the model (2.17) is equivalent to

$$\begin{cases} \max \left[\sum_{j=1}^{n} \frac{(c_{1j}^1+c_{1j}^2+c_{1j}^3+c_{1j}^4)}{4} x_j, \cdots, \sum_{j=1}^{n} \frac{(c_{mj}^1+c_{mj}^2+c_{mj}^3+c_{mj}^4)}{4} x_j \right] \\ \text{s.t.} \begin{cases} (a_{rj}^1+a_{rj}^2+a_{rj}^3+a_{rj}^4)x_j \geq b_{rj}^1+b_{rj}^2+b_{rj}^3+b_{rj}^4, \ r=1,2,\cdots,p \\ x_j \geq 0, \ j=1,2,\cdots,n \end{cases} \end{cases} \tag{2.18}$$

Fuzzy chance-constrained model. For those problems with fuzzy coefficients, DMs usually wants to maximize the objective value on the condition of possibility α, where α is predetermined confidence level and then the fuzzy chance-constrained model (Abbr. FCCM) is developed to help DMs to obtain the optimal strategies. The general model based on Pos measure is described as follows,

$$\begin{cases} \max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_m] \\ \text{s.t.} \begin{cases} Pos\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \delta_i, \ i=1,2,\cdots,m \\ Pos\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \theta_r, \ r=1,2,\cdots,p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.19}$$

where δ_i, θ_r are the predetermined confidence levels, $\bar{f}_i$ are critical values which need to be determined. The general model based on Nec measure is described as follows,

$$\begin{cases} \max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_m] \\ \text{s.t.} \begin{cases} Nec\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \delta_i, \ i=1,2,\cdots,m \\ Nec\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \theta_r, \ r=1,2,\cdots,p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.20}$$

where δ_i, θ_r are the predetermined confidence levels, $\bar{f}_i$ are critical values which need to be determined. The general model based on Cr measure is described as follows,

$$\begin{cases} \max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_m] \\ \text{s.t.} \begin{cases} Cr\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \delta_i, \ i=1,2,\cdots,m \\ Cr\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \theta_r, \ r=1,2,\cdots,p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.21}$$

where δ_i, θ_r are the predetermined confidence levels, $\bar{f}_i$ are critical values which need to be determined. Sometimes, the interrelationship between the fuzzy coefficients is linear, then we get the linear fuzzy chance-constrained model based on Pos measure as follows,

$$\begin{cases} \max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_m] \\ \text{s.t.} \begin{cases} Pos\{\sum\limits_{j=1}^{n} \tilde{c}_{ij} x_j \geq \bar{f}_i\} \geq \delta_i,\ i = 1, 2, \cdots, m \\ Pos\{\sum\limits_{j=1}^{n} \tilde{a}_{rj} x_j \leq \tilde{b}_r\} \geq \theta_r,\ r = 1, 2, \cdots, p \\ x_i \geq 0,\ i = 1, 2, \cdots, m \end{cases} \end{cases} \tag{2.22}$$

where max $\bar{f}_i$ is the δ_i-return defined as $\max\{\bar{f}_i | Pos\{\sum\limits_{j=1}^{n} \tilde{c}_{ij} x_j \geq \bar{f}_i\} \geq \delta_i\}$. The linear fuzzy chance-constrained model based on Nec measure is described as follows,

$$\begin{cases} \max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_m] \\ \text{s.t.} \begin{cases} Nec\{\sum\limits_{j=1}^{n} \tilde{c}_{ij} x_j \geq \bar{f}_i\} \geq \delta_i,\ i = 1, 2, \cdots, m \\ Nec\{\sum\limits_{j=1}^{n} \tilde{a}_{rj} x_j \leq \tilde{b}_r\} \geq \theta_r,\ r = 1, 2, \cdots, p \\ x_i \geq 0,\ i = 1, 2, \cdots, m \end{cases} \end{cases} \tag{2.23}$$

where max $\bar{f}_i$ is the δ_i-return defined as $\max\{\bar{f}_i | Nec\{\sum\limits_{j=1}^{n} \tilde{c}_{ij} x_j \geq \bar{f}_i\} \geq \delta_i\}$. For the model (2.22) and (2.23), it is easy to get the crisp equivalent model if all the fuzzy coefficients are the frequently-used fuzzy numbers. For example, if $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$ are L-R fuzzy numbers, it follows from the definition of the measure Pos that the model (2.22) is equivalent to

$$\begin{cases} \max\ \{f_1, f_2, \cdots, f_m\} \\ \text{s.t.} \begin{cases} f_i \leq c_i^T \boldsymbol{x} + R^{-1}(\delta_i)\beta_i^{c\mathrm{T}} \boldsymbol{x}, \quad i = 1, 2, \cdots, m \\ b_r + R^{-1}(\theta_r)\beta_r^b - a_r^{\mathrm{T}} \boldsymbol{x} + L^{-1}(\theta_r)\alpha_r^{a\mathrm{T}} \boldsymbol{x} \geq 0,\ r = 1, 2, \cdots, p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.24}$$

It follows from the definition of the measure Nec that the model (2.23) is equivalent to

$$\begin{cases} \max\ \{f_1, f_2, \cdots, f_m\} \\ \text{s.t.} \begin{cases} f_i \leq c_i^T \boldsymbol{x} - L^{-1}(1-\delta_i)\alpha_i^{c\mathrm{T}} \boldsymbol{x}, \quad i = 1, 2, \cdots, m \\ b_r - L^{-1}(1-\theta_r)\alpha_r^b - a_r^{\mathrm{T}} \boldsymbol{x} - R^{-1}(\theta_r)\beta_r^{a\mathrm{T}} \boldsymbol{x} \geq 0, \quad r = 1, 2, \cdots, p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.25}$$

Fuzzy dependent-chance model. For those problems with fuzzy coefficients, DMs sometimes want to maximize the chance functions subject to the fuzzy environment and then the fuzzy dependent-chance model (Abbr. FDCM) is developed to help DMs to obtain the optimal strategies. The general model based on the Pos measure is described as follows,

$$\begin{cases} \max\ [Pos\{f_1(\boldsymbol{x},\boldsymbol{\xi}) \le 0\}, Pos\{f_2(\boldsymbol{x},\boldsymbol{\xi}) \le 0\}, \cdots, Pos\{f_m(\boldsymbol{x},\boldsymbol{\xi}) \le 0\}] \\ \text{s.t.} \begin{cases} Pos\{g_r(\boldsymbol{x},\boldsymbol{\xi}) \le 0\} \ge \theta_r,\ r = 1, 2, \cdots, p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.26}$$

where $\theta_r \in [0, 1]$, $r = 1, 2, \cdots, p$ are the predetermined level value. The general model based on the Nec measure is described as follows,

$$\begin{cases} \max \left[Nec\{f_1(\boldsymbol{x},\boldsymbol{\xi}) \le 0\}, Nec\{f_2(\boldsymbol{x},\boldsymbol{\xi}) \le 0\}, \cdots, Nec\{f_m(\boldsymbol{x},\boldsymbol{\xi}) \le 0\}\right] \\ \text{s.t.} \begin{cases} Nec\{g_r(\boldsymbol{x},\boldsymbol{\xi}) \le 0\} \ge \theta_r,\ r = 1, 2, \cdots, p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.27}$$

where $\theta_r \in [0, 1]$, $r = 1, 2, \cdots, p$ are the predetermined level value. Sometimes, the interrelationship between the fuzzy coefficients is linear, then we get the linear fuzzy dependent-chance model based on the Pos measure as follows,

$$\begin{cases} \max\ \left[Pos\{\tilde{c}^T\boldsymbol{x} \ge \bar{f}_i, i = 1, 2, \cdots, m\}\right] \\ \text{s.t.} \begin{cases} Pos\{\tilde{a}_r^T\boldsymbol{x} \le \tilde{b}_r\} \ge \theta_r,\ r = 1, 2, \cdots, p \\ \boldsymbol{x} \ge 0 \end{cases} \end{cases} \tag{2.28}$$

where $\bar{f}_i$ is predetermined objective value and θ_r is the predetermined level value. The linear fuzzy dependent-chance model based on the Nec measure is described as follows,

$$\begin{cases} \max\ \left[Nec\{\tilde{c}^T\boldsymbol{x} \ge \bar{f}_i, i = 1, 2, \cdots, m\}\right] \\ \text{s.t.} \begin{cases} Nec\{\tilde{a}_r^T\boldsymbol{x} \le \tilde{b}_r\} \ge \theta_r,\ r = 1, 2, \cdots, p \\ \boldsymbol{x} \ge 0 \end{cases} \end{cases} \tag{2.29}$$

where $\bar{f}_i$ is predetermined objective value and θ_r is the predetermined level value. For the model (2.28) and (2.29), it is easy to get the crisp equivalent models if all the fuzzy coefficients are the frequently-used fuzzy numbers. For example, if $\bar{c}_i$, $\bar{e}_r$ and $\bar{b}_r$ are L-R fuzzy numbers, it follows that the model (2.28) is equivalent to

$$\begin{cases} \max\ \left\{\frac{c_i^T\boldsymbol{x}-f_i}{\beta_i^{c\mathrm{T}}\boldsymbol{x}},\ i = 1, 2, \cdots, m\right\} \\ \text{s.t.} \begin{cases} b_r + R^{-1}(\theta_r)\beta_r^b - a_r^{\mathrm{T}}\boldsymbol{x} + L^{-1}(\theta_r)\alpha_r^{a\mathrm{T}}\boldsymbol{x} \ge 0,\ r = 1, 2, \cdots, p \\ \boldsymbol{x} \ge 0 \end{cases} \end{cases} \tag{2.30}$$

It follows that the model (2.29) is equivalent to

$$\begin{cases} \max\ \left\{\frac{c_i^T\boldsymbol{x}-f_i}{\alpha_i^{c\mathrm{T}}\boldsymbol{x}},\ i = 1, 2, \cdots, m\right\} \\ \text{s.t.} \begin{cases} b_r + R^{-1}(\theta_r)\beta_r^b - a_r^{\mathrm{T}}\boldsymbol{x} + L^{-1}(\theta_r)\alpha_r^{a\mathrm{T}}\boldsymbol{x} \ge 0,\ r = 1, 2, \cdots, p \\ \boldsymbol{x} \ge 0 \end{cases} \end{cases} \tag{2.31}$$

Fuzzy random expected value model. Sometimes, DMs have to face another uncertainty, that is fuzzy random environment. It means that DMs have to make the decision under the mixed environment simultaneously including the randomness and fuzziness. For this uncertainty, the expected value operator is also usually used to obtain the average value of the fuzzy random coefficients and fuzzy random expected value model (Abbr. FREVM) is developed to help DMs to obtain the optimal strategies. The general model is described as follows,

$$\begin{cases} \max \left[E[f_1(\boldsymbol{x},\boldsymbol{\xi})], f_2(\boldsymbol{x},\boldsymbol{\xi}), \cdots, f_m(\boldsymbol{x},\boldsymbol{\xi})]\right] \\ \text{s.t.} \begin{cases} E[g_j(\boldsymbol{x},\boldsymbol{\xi})] \leq 0, j = 1,2,\cdots,p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.32}$$

where x is n-dimensional decision vector and $\boldsymbol{\xi}$ is n-dimensional fuzzy random vector. Sometimes, the interrelationship between the fuzzy coefficients is linear, then we get the linear fuzzy random expected value model as follows,

$$\begin{cases} \max \left[E[\tilde{\bar{c}}_1^T \boldsymbol{x}], E[\tilde{\bar{c}}_2^T \boldsymbol{x}], \cdots, E[\tilde{\bar{c}}_m^T \boldsymbol{x}]\right] \\ \text{s.t.} \begin{cases} E[\tilde{\bar{a}}_r^T \boldsymbol{x}] \leq E[\tilde{\bar{b}}_r], r = 1,2,\cdots,p \\ x_j \geq 0, j = 1,2,\cdots,n \end{cases} \end{cases} \tag{2.33}$$

where $\tilde{\bar{c}}_i = (\tilde{\bar{c}}_{i1}, \tilde{\bar{c}}_{i1}, \cdots, \tilde{\bar{c}}_{in})^T$, $\tilde{\bar{a}}_r = (\tilde{\bar{a}}_{r1}, \tilde{\bar{a}}_{r1}, \cdots, \tilde{\bar{a}}_{rn})^T$ are fuzzy random vectors, $\tilde{\bar{b}}_r$ are fuzzy random variables, $i = 1,2,\cdots,m$, $r = 1,2,\cdots,p$. For the model (2.33), it is easy to get the crisp equivalent model if these fuzzy random vectors, as well as fuzzy random variables have special forms. For example, if $\tilde{\bar{c}}_i$, $\tilde{\bar{a}}_r$ and $\tilde{\bar{b}}_r$ in the model (2.33) are trapezoidal fuzzy numbers with normal random parameters, it follows that the model (2.33) is equivalent to

$$\begin{cases} \max \left[\frac{1}{4}\sum_{t=1}^{4}\sum_{j=1}^{n} \mu_{1jt}x_j, \frac{1}{4}\sum_{t=1}^{4}\sum_{j=1}^{n} \mu_{2jt}x_j, \cdots, \frac{1}{4}\sum_{t=1}^{4}\sum_{j=1}^{n} \mu_{mjt}x_j\right] \\ \text{s.t.} \begin{cases} \sum_{t=1}^{4}\sum_{j=1}^{n} \mu_{rjt}x_j \leq \sum_{t=1}^{4} \mu_{rt}, r = 1,2,\cdots,p \\ x_j \geq 0, j = 1,2,\cdots,n \end{cases} \end{cases} \tag{2.34}$$

Fuzzy random chance-constrained model. For those problems with fuzzy random coefficients, DMs usually wants to maximize the objective value on the condition of possibility α and probability β, where α and β are predetermined confidence levels and then the fuzzy random chance-constrained model (Abbr. FRCCM) is developed to help DMs to obtain the optimal strategies. The general model is described as follows,

$$
\begin{cases}
\max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_n] \\
\text{s.t.} \begin{cases}
Ch\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\}(\gamma_i) \geq \delta_i,\ i = 1, 2, \cdots, n \\
Ch\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\}(\eta_r) \geq \theta_r,\ r = 1, 2, \cdots, p \\
x \in X
\end{cases}
\end{cases}
\tag{2.35}
$$

where Ch is the chace measure of the fuzzy random events, $\gamma_i, \delta_i, \eta_r, \theta_r$ are the predetermined confidence level, f_i and x_i are the decision variables, $i = 1, 2, \cdots, n$. As we know, the measure for fuzzy numbers includes two classes, that is Pos and Nec. General FRCCM based on $Pos - Pr$ measure is described as follows,

$$
\begin{cases}
\max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_n] \\
\text{s.t.} \begin{cases}
Pr\{\omega | Pos\{\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\
Pr\{\omega | Pos\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\
\boldsymbol{x} \in \boldsymbol{X}
\end{cases}
\end{cases}
\tag{2.36}
$$

where $\delta_i, \gamma_i, \theta_r, \eta_r \in [0, 1]$ are the predetermined confidence level, $Pos\{\cdot\}$ denotes the possibility of the fuzzy events in $\{\cdot\}$, and $Pr\{\cdot\}$ denotes the probability of the random events in $\{\cdot\}$. General FRCCM based on $Nec - Pr$ measure is described as follows,

$$
\begin{cases}
\max\ [\bar{f}_1, \bar{f}_2, \cdots, \bar{f}_n] \\
\text{s.t.} \begin{cases}
Pr\{\omega | Nec\{\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\
Pr\{\omega | Nec\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\
\boldsymbol{x} \in \boldsymbol{X}
\end{cases}
\end{cases}
\tag{2.37}
$$

where $Nec\{\cdot\}$ denotes the necessity of the fuzzy events in $\{\cdot\}$. Sometimes, the interrelationship between the fuzzy random coefficients is linear, then we get the linear fuzzy random chance-constrained model based on $Pos - Pr$ measure as follows,

$$
\begin{cases}
\max\ \{f_1, f_2, \cdots, f_m\} \\
\text{s.t.} \begin{cases}
Pr\{\omega | Pos\{\tilde{\bar{c}}_i(\omega)^{\mathrm{T}} \boldsymbol{x} \geq f_i\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\
Pr\{\omega | Pos\{\tilde{\bar{e}}_r(\omega)^{\mathrm{T}} \boldsymbol{x} \leq \tilde{\bar{b}}_r(\omega)\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\
\boldsymbol{x} \geq 0
\end{cases}
\end{cases}
\tag{2.38}
$$

wherein $\delta_i, \gamma_i, \theta_r, \eta_r \in [0, 1]$ are the predetermined confidence level, $Pos\{\cdot\}$ denotes the possibility of the fuzzy events in $\{\cdot\}$, and $Pr\{\cdot\}$ denotes the probability of the random events in $\{\cdot\}$. The linear fuzzy chance-constrained model based on $Nec - Pr$ measure is described as follows,

$$
\begin{cases}
\max\ [f_1, f_2, \cdots, f_m] \\
\text{s.t.} \begin{cases}
Pr\{\omega | Nec\{\tilde{\bar{c}}_i(\omega)^{\mathrm{T}} \boldsymbol{x} \geq f_i\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\
Pr\{\omega | Nec\{\tilde{\bar{e}}_r(\omega)^{\mathrm{T}} \boldsymbol{x} \leq \tilde{\bar{b}}_r(\omega)\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\
\boldsymbol{x} \geq 0
\end{cases}
\end{cases}
\tag{2.39}
$$

wherein $\delta_i, \gamma_i, \theta_r, \eta_r \in [0, 1]$ are the predetermined confidence level, $Nec\{\cdot\}$ denotes the necessity of the fuzzy events in $\{\cdot\}$, and $Pr\{\cdot\}$ denotes the probability of the random events in $\{\cdot\}$. For the model (2.38) and (2.39), it is easy to get the crisp equivalent model if all the fuzzy random coefficients are the frequently-used fuzzy numbers. For example, if $\tilde{\bar{c}}_i$, $\tilde{\bar{e}}_r$ and $\tilde{\bar{b}}_r$ are L-R fuzzy random numbers with normal random parameters, it follows that the model (2.38) is equivalent to

$$\begin{cases} \max\ \{H_1(\boldsymbol{x}), H_2(\boldsymbol{x}), \cdots, H_m(\boldsymbol{x})\} \\ \text{s.t. } \boldsymbol{x} \in X \end{cases} \tag{2.40}$$

where $H_i(\boldsymbol{x}) := R^{-1}(\delta_i)\beta_i^{c\mathrm{T}}\boldsymbol{x} + d_i^{c\mathrm{T}}\boldsymbol{x} + \Phi^{-1}(1-\gamma_i)\sqrt{\boldsymbol{x}^{\mathrm{T}}V_i^c\boldsymbol{x}}, \quad i = 1, 2, \cdots, m.$ It follows that the model (2.39) is equivalent to

$$\begin{cases} \max\ [G_1(\boldsymbol{x}), G_2(\boldsymbol{x}), \cdots, G_m(\boldsymbol{x})] \\ \text{s.t. } \ \boldsymbol{x} \in X' \end{cases} \tag{2.41}$$

where $G_i(\boldsymbol{x}) := d_i^{c\mathrm{T}}\boldsymbol{x} - L^{-1}(1-\delta_i)\alpha_i^{c\mathrm{T}}\boldsymbol{x} + \Phi^{-1}(1-\gamma_i)\sqrt{\boldsymbol{x}^{\mathrm{T}}V_i^c\boldsymbol{x}}, i = 1, 2, \cdots, m.$

Fuzzy random dependent-chance model. For those problems with fuzzy random coefficients, DMs sometimes want to maximize the chance functions subject to the fuzzy random environment and then the fuzzy random dependent-chance model (Abbr. FRDCM) is developed to help DMs to obtain the optimal strategies. The general model based on the Pos measure is described as follows,

$$\begin{cases} \max\ [\delta_1, \delta_2, \cdots, \delta_m] \\ \text{s.t.} \begin{cases} Pr\{\omega | Pos\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\ Pr\{\omega | Pos\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.42}$$

The general model based on the Nec measure is described as follows,

$$\begin{cases} \max\ [\delta_1, \delta_2, \cdots, \delta_m] \\ \text{s.t.} \begin{cases} Pr\{\omega | Nec\{f_i(\boldsymbol{x}, \boldsymbol{\xi}) \geq \bar{f}_i\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\ Pr\{\omega | Nec\{g_r(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\ \boldsymbol{x} \in \boldsymbol{X} \end{cases} \end{cases} \tag{2.43}$$

Sometimes, the interrelationship between the fuzzy random coefficients is linear, then we get the linear fuzzy random dependent-chance model based on the Pos measure as follows,

$$\begin{cases} \max\ [\delta_1, \delta_2, \cdots, \delta_m] \\ \text{s.t.} \begin{cases} Pr\{\omega | Pos\{\tilde{\bar{\boldsymbol{c}}}_i^{\mathrm{T}}\boldsymbol{x} \geq \bar{f}_i\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\ Pr\{\omega | Pos\{\tilde{\bar{\boldsymbol{e}}}_r^{\mathrm{T}}\boldsymbol{x} \leq \tilde{\bar{\boldsymbol{b}}}_r\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.44}$$

where $\bar{f_i}$ is predetermined objective value. The linear fuzzy random dependent-chance model based on the Nec measure is described as follows,

$$\begin{cases} \max\ [\delta_1, \delta_2, \cdots, \delta_m] \\ \text{s.t.} \begin{cases} Pr\{\omega | Nec\{\tilde{\bar{\boldsymbol{c}}}_i^{\mathrm{T}} \boldsymbol{x} \geq \bar{f_i}\} \geq \delta_i\} \geq \gamma_i, & i = 1, 2, \cdots, m \\ Pr\{\omega | Nec\{\tilde{\bar{\boldsymbol{e}}}_r^{\mathrm{T}} \boldsymbol{x} \leq \tilde{\bar{\boldsymbol{b}}}_r\} \geq \theta_r\} \geq \eta_r, & r = 1, 2, \cdots, p \\ \boldsymbol{x} \geq 0 \end{cases} \end{cases} \tag{2.45}$$

where $\bar{f_i}$ is predetermined objective value. For the model (2.44) and (2.45), it is easy to get the crisp equivalent models if all the fuzzy coefficients are the frequently-used fuzzy numbers. For example, if $\tilde{\bar{c}}_i$, $\tilde{\bar{e}}_r$ and $\tilde{\bar{b}}_r$ are L-R fuzzy numbers, it follows that the model (2.44) is equivalent to

$$\begin{cases} \max \left[\frac{\Phi^{-1}(1-\gamma_i)\sqrt{\boldsymbol{x}^{\mathrm{T}} \boldsymbol{V}_i^c \boldsymbol{x}} + d_i^{c\mathrm{T}} x - \bar{f_i}}{\beta_i^{c\mathrm{T}} \boldsymbol{x}}, i = 1, 2, \cdots, m \right] \\ \text{s.t.} \begin{cases} R^{-1}(\theta_r)\beta_r^b + L^{-1}(\theta_r)\alpha_r^{e\mathrm{T}} \boldsymbol{x} - (d_r^{e\mathrm{T}} x - d_r^b) \\ \qquad - \Phi^{-1}(\eta_r)\sqrt{x^{\mathrm{T}} V_r^e x + (\sigma_r^b)^2} \geq 0, \quad r = 1, 2, \cdots, p \\ x \geq 0 \end{cases} \end{cases} \tag{2.46}$$

It follows that the model (2.45) is equivalent to

$$\begin{cases} \max \left[\frac{\Phi^{-1}(1-\gamma_i)\sqrt{x^{\mathrm{T}} V_i^c x} - \bar{f_i} + d_i^{c\mathrm{T}} x}{\alpha_i^{c\mathrm{T}} x}, i = 1, 2, \cdots, m \right] \\ \text{s.t.} \begin{cases} \Phi^{-1}(1-\eta_r)\sqrt{x^{\mathrm{T}} V_r^e x + (\sigma_r^b)^2} - L^{-1}(1-\theta_r)\alpha_r^b - R^{-1}(\theta_r)\beta_r^{e\mathrm{T}} x \\ \qquad + (d_r^b - d_r^{e\mathrm{T}} x) \geq 0, \quad r = 1, 2, \cdots, p \\ x \geq 0 \end{cases} \end{cases} \tag{2.47}$$

2.4.2 Expression Form

The general expression form of meta model in the LCSM is as follows:

$$opt\mathrm{MM}_i \begin{cases} \begin{cases} \mathrm{MMM}_i = \max_{k \in J_{i1}} f_i(f_{i1}(x_{ik}), f_{i2}(x_{ik}), \ldots, f_{im}(x_{ik})) \\ \mathrm{BMM}_i = opt\{x_{ik} | k \in J_{i2}\} \end{cases} \\ \text{s.t.} \begin{cases} J_{i2} = \emptyset, \mathrm{MM}_i = \mathrm{MMM}_i \\ J_{i1} = \emptyset, \mathrm{MM}_i = \mathrm{BMM}_i \\ J_{i1} \bigcup J_{i2} = N_i = \{1, 2, \ldots, n_i\}, J_{i1} \bigcap J_{i2} = \emptyset \\ x_i \in X_i = (\mathrm{OMM}_i \bigcup \mathrm{MMDB}_i) \bigcup \mathrm{BMDB}_i \end{cases} \end{cases}$$

where, MM_i represents the ith meta model of the LCSM; MMM_i and BMM_i represent the mathematical model and the behavioral model of the ith meta model separately; f_i is the objective function of the mathematical model; OMM_i, MMDB_i, BMDB_i are expressed by the information outputs from behind of support model MM_i, constraints produced by MM_i mapping problem environment and knowledge reasoning, empirical judgments to decision variable, parameter x_i of managers and experts; X_i is a decision-making set that is formed by the restricts of the three variables above.

It is noteworthy that the integration of meta models has its significant features. They are composed of several models with different forms and functions. In a general sense, $f_i(f_{i1}(x_{ik}), f_{i2}(x_{ik}), \ldots, f_{im}(x_{ik}))$ describes the combination or integration processes of meta models. Specially, there are two types of integration forms in the LCSM.

(1) The meta model is assembled by several smaller models units. For instance, the ecological footprint model integrates emergy analysis method, ecological footprint method and ecological carrying capacity method. The econometric model is a system of econometric methods of economic analysis in real resource allocation structure, production capacity and constraints of the structure of output.

(2) The meta model is combined of several functional models with similar modelling mechanism and the combination process can be completed simply. For instance, the traditional solution models (weight sum method, maximin method, ideal point method, lexicographic method, and fuzzy programming method) and hybrid intelligent algorithms (simulated annealing algorithm, particle swarm optimization algorithm, genetic algorithm, and tabu search algorithm) can freely combined to solve the multi-objective programming problems.

2.4.3 Operation Process

The solving process of meta model in the LCSM, according to the following steps:

(1) Generate a meta model.
(2) Order $J_2 = \emptyset$ or $J_1 = \emptyset$.
(3) Read the proprietary data database. The proprietary data of database are formed by other supporting model outputs and statistics. For the formation of $J_1 = \emptyset$, the proprietary data are generated by the behavioral model.
(4) Obtain results by using the solver.
(5) Interactions occur. Managers and experts judge the results if satisfied then stop; otherwise, point out J_2, update the proprietary data, repeat step (3); Or request to re-generate meta model, go back to step (1).
(6) Confirm the mathematical meta model expression and the results.

2.5 General Equilibrium Framework

In recent years, quantitative analysis of the effects of policies on economic outcomes has grown sharply. In the field of RLCED, the related policy synthesis is necessary and effective. Because climate change may affect various sectors of the economy directly or indirectly, interactions between different sectors must be studied to assess the impacts of climate change on regional economy. General equilibrium framework is well suited to depict interactions between all the sectors in the economy, and give a sense of the order of magnitude that a change in policy can mean for the RLCED. The main benefit of general equilibrium framework is that they offer a rigorous and theoretically consistent framework for analyzing climate change policy questions.

2.5.1 Regional General Equilibrium

Response to climate change need for a coordinated, effective, efficient, and equitable global response. The evidence presented so far indicates that climate change will impose significant costs on mankind and ecosystems. While there are many kinds of actions that provide significant co-benefits helping to mitigate or to adapt to climate change, in general, investments in mitigation and adaptation have some costs, which call for an integrated approach to making simultaneous decisions on optimal levels of effort on both fronts. But in a simplified framework, one can focus on the optimal level of mitigation efforts and assume that, given the resulting expected climate change impacts, adaptation expenditures will be decided optimally, by taking into account the corresponding costs and benefits of such actions. Both the marginal costs and the marginal benefits of mitigating climate change depend on the scale of the emission reductions to be undertaken. On one hand, the costs of additional mitigation efforts tend to increase with the level of emission reductions. Low levels of emission reductions can be attained at relatively low costs; as reduction targets become more ambitious, these cheap solutions are exhausted and more expensive investments are required. The marginal benefits of mitigating climate change, on the other hand, tend to fall with the scale of emission reduction efforts.

The optimal degree of effort to mitigate the consequences of climate change would be the point at which the marginal cost of reducing emissions by one more ton just balances the damages avoided by doing so: Q* with a socially efficient price of carbon of P* (see Fig. 2.18). In a world in which all costs and benefits were taken into account by the same decision makers with perfect information, this optimal solution might be reached.

General equilibrium (GE) theory is a formalization of the simple but fundamental observation that markets in real world economies are mutually interdependent. A regional general equilibrium (RGE) approach is ideal for analyzing the effects of regional effects for climate change mitigation and low carbon development. A GE analysis is able to account for all the linkages between sectors of an regional

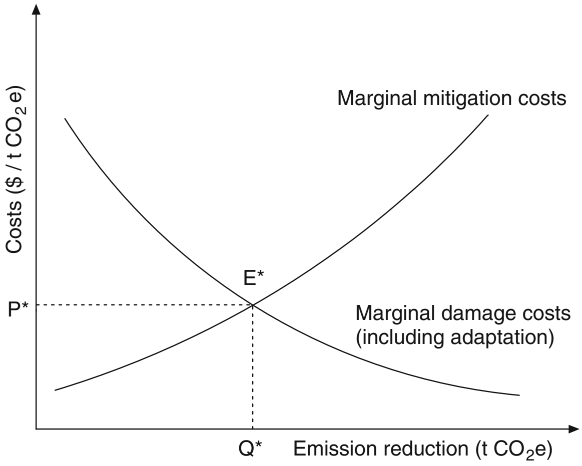


Fig. 2.18 The equilibrium of marginal mitigation and damage costs

economy. These could be linkages between industries, or linkages between household expenditures and incomes. Some of these economic linkages are captured by the circular flow picture of the regional economy's operation.

There are two important institutions involved in the circular flow: households, who are the consumers and the owners of factors of production such as land labor and capital, and firms. Households sell the services of factors of production to firms. So, there is a flow of these factor services from households to firms. In exchange, firms sell goods and other services to households. Hence, there is a reverse flow of products and other services going from firms to households.

In a closed economic system (e.g. regional economy), the value of these flows should be equivalent. This is reflected in accounting identities. Total expenditures on goods and services must equal total income received by owners of factors of production. If households save part of their income, this foregone consumption must be equal to investment which allows an economy to increase its productive potential over time. In the circular flow, the government is the core, intending to implement available policies to maintain the equilibrium of regional economic operation. A common GE framework for a regional economy is shown in Fig. 2.19.

GHGs emissions reduction is no doubt the primary task of regional low carbon economic development. Emissions of CO_2 are considered proportional in a fixed ratio to the energy content of the fuel used. This implies that they are linked to fossil fuel consumption in each economic sector and are calculated on a sector basis for each model time step. The introduction of a climate policy affects the cost of production and also the pattern of investment. This implies a change in the relative demand of factor inputs, particularly energy, and, thus, mitigation of CO_2 emissions. Non-CO_2 emissions, however, are not limited to fuel combustion. Therefore, emissions of

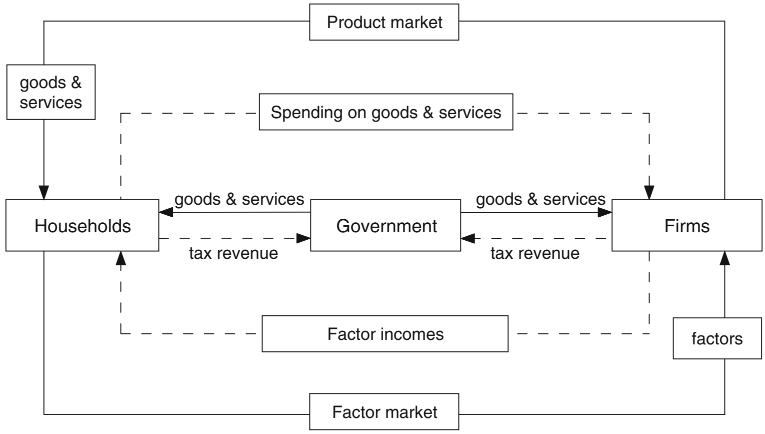


Fig. 2.19 A common GE framework for a regional economy

Table 2.4 GHGs emission sources

Gas	Source #	Emissions source
CO_2	1	Oil combustion
	2	Gas combustion
	3	Coal combustion
CH_4	4	Coal production
	5	Enteric fermentation
	6	Natural gas and oil systems
	7	Solid waste
N_2O	8	Agricultural soil
	9	Industrial processes
	10	Manure
	11	Fossil fuels
	12	Waste
	13	Solvent use and other product use
HFC_s	14	Ozone depleting substances substitutes
PFC_s	15	Aluminum
	16	Semiconductor
SF_6	17	Electricity distribution
	18	Magnesium

Adapted from Sands and Schumacher (2009)

non-CO_2 gases require a different tracking procedure. Table 2.4 shows the GHGs and their sources that are included in our GE analysis.

The nature of low carbon development is to realize the dynamic equilibrium of GHGs (particularly for CO_2) emission and absorbing in the production and consumption process. Regional general equilibrium analysis for low carbon polices (LC-RGE) is a special application of GE theory and a general framework of policy formulation for the RLCED. The LC-RGE framework presents a flexible tool for simulating

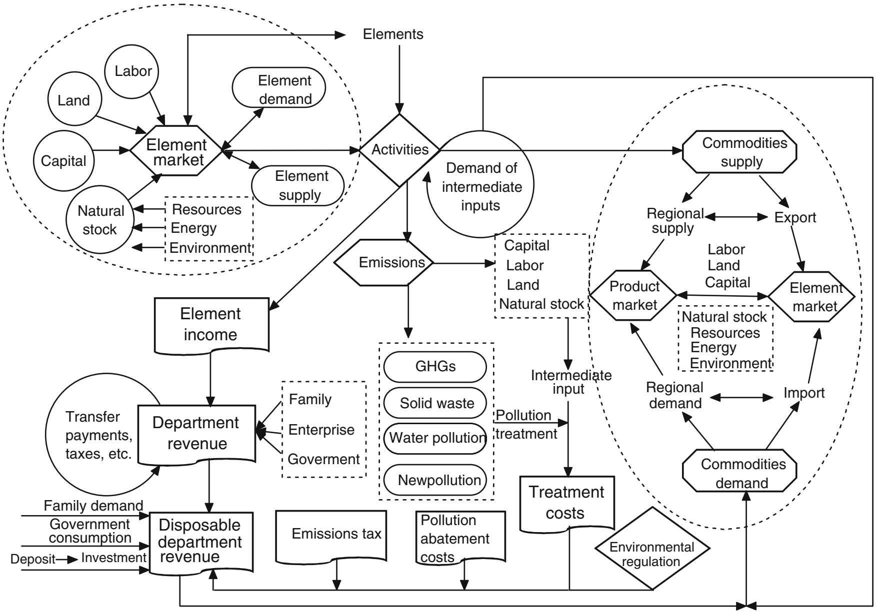


Fig. 2.20 The LC-RGE framework

GHGs emissions that can accommodate a wide variety of assumptions about electricity technologies, CO_2 prices, fuel prices, and baseline energy consumption. It aims to reduce influence of economic development on the carbon circulation in the global or regional ecosystem, and increase the carbon sequestration and resilience ecosystem. The LC-RGE framework is shown in Fig. 2.20.

The LC-RGE synthesis process is shown in Fig. 2.21. As can be seen, there are four main steps in the processes of LC-RGE: structure study, operation practice, simulation application, and policy proposal.

2.5.2 LC-RGE Structure

To realize the functions of analyzing the effects of low carbon policies on regional economy, LC-RGE should have an integral structure. Figure 2.22 outlines the basic LC-RGE structure, which contains seven components, including Production, Households, Government, Market, Equilibrium, Dynamics, and Closure.

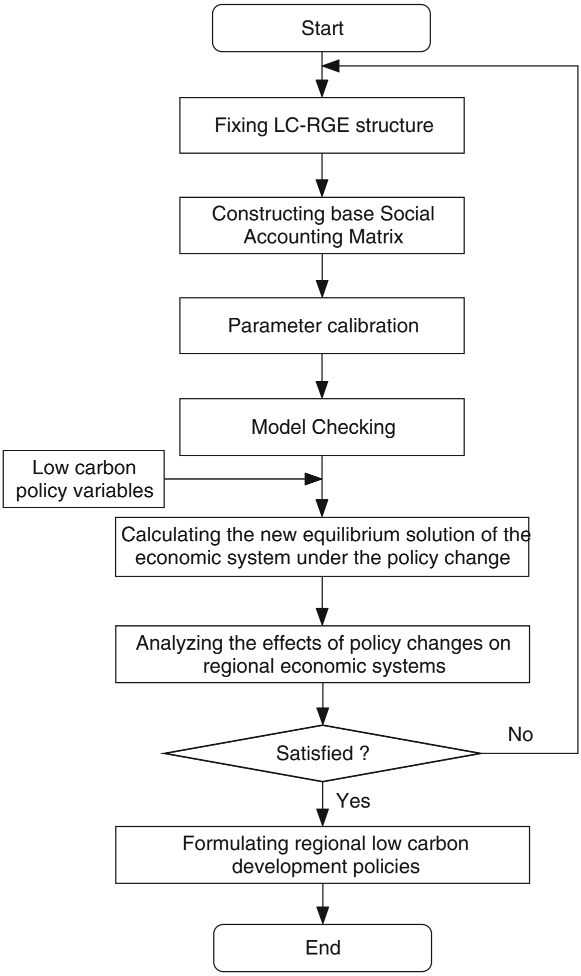


Fig. 2.21 The synthesis LC-RGE processes

2.5.2.1 Production

The Production Section of LC-RGE is represented by a set of goods and services, provided by the firms. Normally, the Production Section is the main source of GHGs emissions in a region. Primary factors (e.g. capital, land, labor and energy) are used as inputs to produce goods and services for households and government. Control over the Production Sector of the regional economy is exercised by profit-maximizing firms. Using prices of goods and the factors of production as market signals, they make their decisions on how much of each good to produce. They purchase primary factors from households and intermediate goods from other firms and use these to

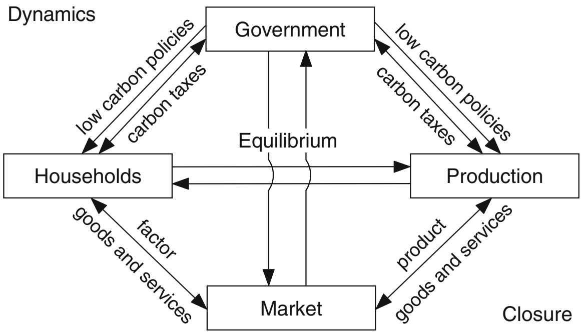


Fig. 2.22 The LC-RGE structure

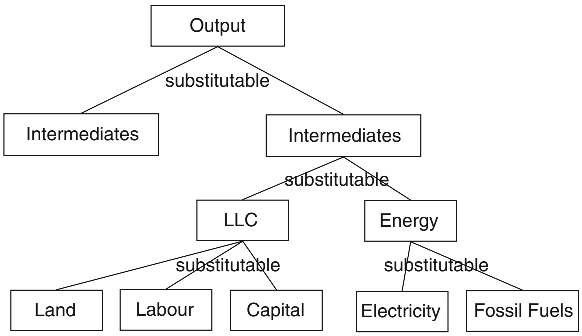


Fig. 2.23 Nesting structure of the production function

produce the goods which, in turn, are sold back to households. In this circular flow, the firms would not carefully consider the negative effects of GHGs emissions. The LC-RGE uses the nested constant elasticity of substitution (CES) function to model the production in each sector of the economy and assumes constant returns to scale. The LC-RGE intended to elucidate low carbon development policies need to have an elaborated treatment of the demand for fossil fuels, thus sectors that are affected by GHGs emissions are treated as separate production sectors, such as electricity, energy and transportation sector. Nesting structure of the production function is shown in Fig. 2.23.

The sectoral production functions basically define substitution possibilities between explicitly defined input factors. The production function of a representative Production Sector j in a typical GE model can be written

$$X_j = f_j(K_j, L_j, B_j, M_j, F_j, E_j) \tag{2.48}$$

where X_j is gross output, K_j capital, L_j land, B_j labor, M_j non-energy intermediate (denoted "materials") inputs, F_j fuels and E_j electricity. In most cases F_j is an aggregate of various fossil and non-fossil fuels. The Production Function $f_j(\cdot)$, or rather its dual cost function, is assumed to have a so called flexible form and the parameters are econometrically estimated.

In the general equilibrium analysis, it is important to distinguish not only between land, labor, capital, non-energy intermediate inputs and energy, but also between fossil and non-fossil energy. Often it is also convenient to distinguish between electricity and fossil fuels. Thus the production function of a representative Production Sector j in the LC-RGE can be written

$$X_j = f_j(L_j, B_j, M_j, Q_j(K_j, H_j(F_j(F_{j1}, F_{j2}, \ldots, F_{jn}), E_j))) \tag{2.49}$$

Thus fuels (F_j), which is an aggregate of n different types of fossil and non-fossil fuels, and electricity (E_j) are combined in a CES aggregate that defines a composite energy good (H_j). The composite energy input is combined with Capital in a CES aggregate of Capital-Energy. Then the composite Capital-Energy input Q_j is combined with labor (L_j) and materials (M_j).

2.5.2.2 Households

Households are the consumers as well as the owners of factors of production. As owners of land, labor and capital, they receive rent, wages and interest paid out by firms. This income is then spent on goods and services that households consume. Some of the income may be paid as taxes to government directly or indirectly. The utility maximization problem is often posed in terms of a representative household. With the objective of maximizing utility, it must decide on how much of its income to allocate to the goods and services that are available in the market. Particularly, the carbon taxes can be added to the goods and services, which are finally consumed by households. Where impacts on individual households are important, like in the case of the impact of a policy change on consumption, general equilibrium analysis can be complemented by region-specific case studies to establish the potential effect on different household groups within a region.

2.5.2.3 Government

In a region, governments function to collect taxes and tariffs, disburse subsidies and purchase goods and services. These activities are not necessarily assumed to satisfy some optimization goal, unlike the case of consumers and firms. However, changes to these policy instruments provide the exogenous shocks that lead to adjustments to the rest of the economy which the LC-RGE seeks to capture. It is then possible to conduct a welfare analysis of the policy changes (e.g. energy polices, carbon taxes) and to rank the available policy choices for promoting the RLCED.

2.5.2.4 Market

The product and factor markets are normally assumed perfectly competitive. This means households and firms make their decisions, regarding the purchase and sales of products and factors of production, taking the prices of these goods and factors as given. Perfect competition also means that in equilibrium firms do not make economic profits. In an general equilibrium analysis with product differentiation, policy changes for regional low carbon development affect an economy also through the impact on the number of varieties available to consumers. Since consumers love variety, the larger the range of products available in the market the greater their well-being. In a low carbon society, the goods and services with low carbon properties would be more popular and paid more attention.

2.5.2.5 Equilibrium

General equilibrium involves searching for the set of prices that produces market equilibrium. In equilibrium, demand for goods equals their supply. The demand for factors of production equals the available endowments. Consumers (households) have chosen the utility-maximizing basket of goods given their incomes while firms have chosen production levels that maximize their profits. In a LC-RGE framework, the utility maximization of households and firms should fit to the low carbon polices, such as carbon taxes and emission constraint. The LC-RGE equilibrium structure is shown in Fig. 2.24.

2.5.2.6 Dynamics

It is obvious that models in which forward looking behavior on the part of households and firms is assumed and stock accumulation relations are explicitly included should be denoted "dynamic" (Devarajan 1988). "Dynamic" is a prominent characteristic of LC-RGE, because RLCED is a dynamic growth process, and the effect of policy changes need take some time to reveal. In a dynamic LC-RGE model, households choose a consumption plan during the period under consideration which maximizes the discounted stream of their utilities. For their part, firms choose a production plan that maximizes their discounted stream of profits. The growth rate in a dynamic LC-RGE model is endogenously determined by the savings and investment behavior of households and firms.

2.5.2.7 Closure

When building a model to analyze the impact of a low carbon policy, analysts need to define the "model closure". The choice of the closure will be determined by the specific nature of the problem and by the variable the modeler intends to shock.

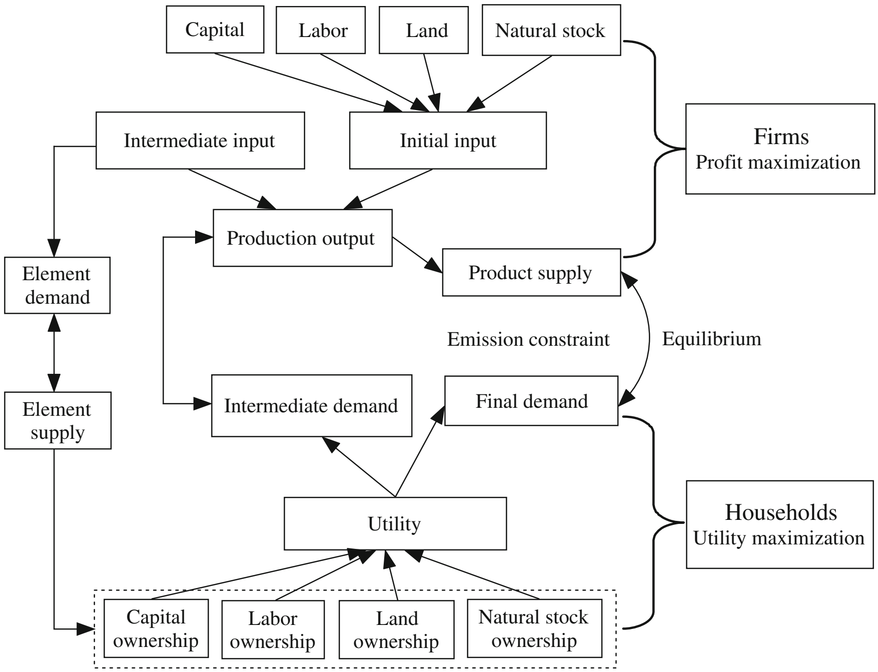


Fig. 2.24 The LC-RGE equilibrium structure

The case of a good produced in a regional economy and on which the government levies an import tariff. In a LC-RGE model, prices are exogenously fixed by the analyst, while quantities are endogenously determined by the model. The modeler can simulate the impact of a tariff cut, simply by solving the equations for the demand and supply for the new price.

2.5.3 LC-RGE Operation

To fully operationalize LC-RGE requires building the associated social accounting matrix (SAM) and obtaining estimates of important behavioral parameters governing consumer demands, and production technology. The final step involves calibrating the model.

2.5.3.1 Social Accounting Matrix

The first step to operationalize LC-RGE is to organize the data on the structure of the regional economy in a way that takes into account the fundamental relationships

Receipts	Expenditures							
	Activities	Commodities	Factors	Enterprises	Households	Government	Capital account	TOTAL
Activities		*Gross output*						*Total sales*
Commodities	*Intermediate goods demand*				*Household consumption*	*Government consumption*	*Investment*	*Aggregate demand*
Factors	*Vale added*							*Factor income*
Enterprises			*Gross profits*			*Transfers*		*Enterprise income*
Households			*Wages*	*Distributed profits*		*Transfers*		*Household income*
Government	*Indirect taxes*	*Tariffs*	*Factor taxes*	*Enterprise taxes*	*Direct taxes*			*Government revenues*
Capital Account				*Retained earnings*	*Household savings*	*Government savings*		*Savings*
TOTA L	*Total costs*	*Aggregate supply*	*Factor expenditure*	*Enterprise expenditure*	*Household expenditure*	*Government expenditure*	*Investment*	

Fig. 2.25 Example of a SAM for a regional economy

between all agents in the economy and across all sectors. The SAM is a tool that helps to take into account of all these interactions in a systematic way and without errors. The SAM builds on the circular flow conception of the economic system where each expenditure must be matched by a corresponding receipt or income. As its title suggests, the relationships between sectors in a SAM are represented in the form of a chart containing rows and columns. Figure 2.25 shows the example of a SAM for a regional economy. The rows correspond to the income or receipts while the columns correspond to the outlay or expenditures of a sector. Each sector of the economy will appear as a row (recipient of income) and as a column (as a source of expenditures) which means that the SAM is a square matrix. Given that income of a sector must equal its expenditure, the sum of the entries in the ith row must equal the sum of the entries in the ith column.

A SAM is constructed using several basic sources of regional economic information: the economy's input-output table, the macroeconomic accounts, government budgetary accounts, balance of payments and trade statistics. The input-output table provides information on the production sector of the regional economy, showing detailed inter-industry linkages and the contribution made by primary factors of production to each sector. Thus we know how much steel, rubber, plastics, goes into the car industry. The macroeconomic accounts provide a breakdown of aggregate demand according to consumption, investment, and government spending. The government budgetary accounts provide information on public expenditures and revenues. Integrated with the other accounts in the SAM, it is possible to obtain information on government spending on goods and to determine how much revenues are generated tariffs. It is important to note that an LC-RGE model should be built using value data. The general practice is to define quantity units as the amount that can be bought for one unit of currency (say one euro or one dollar) in the baseline dataset. This means that in most cases, baseline prices will all be set to unity.

2.5.3.2 Behavioral Parameters

After all information about the expenditures and revenues and the interactions of all agents have been included into a SAM, the modeler needs to provide the value of the called behavioral parameters that characterize the behavior of producers and consumers. These parameters measure the responsiveness of producers and consumers to relative price and income changes and therefore have an important bearing on the outcome of LC-RGE simulation. There are at least three types of behavioral parameters which are needed. First are the elasticities of substitution in value added which govern the substitutability of the primary factors of production. Second, are the Armington elasticities which determine the substitutability of the domestic versus the imported composite product. Third, are the demand and income elasticities of the households or consumers.

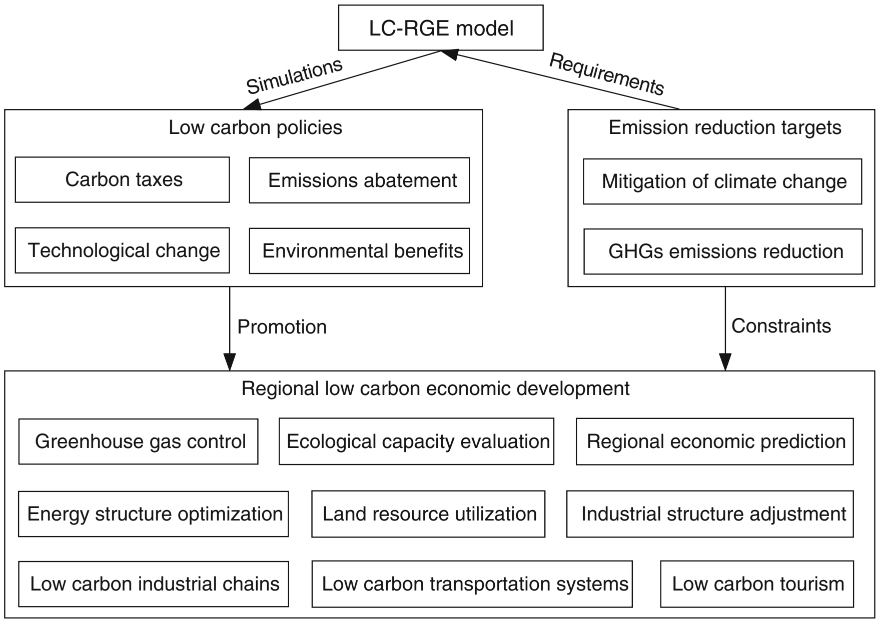


Fig. 2.26 The LC-RGE simulations

2.5.3.3 Calibrating a Model

The final stage for operationalizing LC-RGE consists in calibrating all the remaining unknown parameters. Calibration involves choosing the values of a subset of the parameters in such a way that together with the assembled SAM and the values of the behavioral parameters, the model is able to reproduce exactly the data of a reference year C the baseline. All simulations of LC-RGE will be based on a comparison with this baseline. Usually the parameters that are calibrated are share or scale parameters.

2.5.4 LC-RGE Simulation

Important efforts have gone into evaluating the effects of alternative policies on the RLCED. The LC-RGE accommodate several policies simultaneously, providing numerical estimates of efficiency and distribution effects, such as carbon taxes, emissions abatement, technological change, and environmental benefits. The relationship of low carbon policies simulated by the LC-RGE and the RLCED is shown in Fig. 2.26.

2.5.4.1 Carbon Taxes

The economy-wide character of the issue implies that elucidating the impacts of carbon taxes requires the kind of analysis for which LC-RGE is particularly well suited. The decision makers are concerned that any emission reduction strategy could have a negative impact on economic development. A carbon tax may reduce the growth rate of carbon emissions as well as impose constraints on sector-related and overall economic growth. Nonetheless, it has a progressive effect on welfare levels in all simulations, meaning that it benefits the groups with lower income levels. The analysis indicates that a double dividend, namely emission reductions and an increase in GDP, may be an achievable goal under a CO_2 emission reduction policy in the case of many economies (Boyd and Ibarraran 2002; Palatnik and Shechter 2010). A carbon tax is implemented in the model as a counter-factual scenario. Both firms and households have to pay this tax when purchasing energy if their use of the energy commodity causes CO_2 emission. The tax rate is differentiated according to the emission factor of each energy source, which depends on its carbon content. The carbon tax is technically implemented in the model as an ad valorem energy tax (Boyd et al. 1995).

2.5.4.2 Emissions Abatement

The emissions of GHGs (especially CO_2) generally are not measured directly, and in many cases direct measurement is difficult and costly. Instead the emissions are estimated on the assumption that they are proportional to the use of various types of fossil fuels. This assumption implies that emission reductions can be brought about only by reductions of the consumption of fossil fuels or by changes in the composition of fossil fuel consumption. In practice inter-fuel substitutions can lead to quite significant emission reductions. For instance, the combustion of natural gas gives rise to less emissions of CO_2 per unit of energy than coal. Thus substitution of natural gas for coal ceteris paribus reduces the emissions of CO_2 at give output levels.

However, the CO_2 emission can be reduced not only by output reduction, but also by fuel switching. There are also direct abatement possibilities. In order to capture abatement measures, the LC-RGE incorporates abatement cost functions, usually estimated on the basis of generic rather than site-specific engineering data. In the LC-RGE the abatement activity is assumed to depend on economic incentives so that abatement takes place whenever the marginal cost of abatement is less than or equal to the cost to the firm, or household, of marginal emissions. The marginal cost of emission, in turn, is determined by charges on emissions or by the price of emission permits (Hill and iStockholm 2001). From an institutional point of view it is assumed that specialized firms are supplying abatement services to industries obliged to comply with emission constraints.

2.5.4.3 Technological Change

In the short and medium term substitution between inputs is a key mechanism in the adjustment to various low carbon policy measures. However, the time horizon in environmental policy analyses often extends several decades or even a century into the future. Thus the development and implementation of new technologies might affect emissions and other impacts on the climate change much more than substitution between currently existing technologies. Expectations about future relative prices, taxes and regulations clearly have an impact on the speed and direction of technological development.

Technological change is an exogenous factor making the total factor productivity an increasing function of time. The LC-RGE intended for low carbon policy analysis can incorporate specific assumptions about "autonomous energy efficiency improvements" (AEEI) (Manne and Richels 1990). The AEEI-factor is assumed to be exogenously determined and to reflect all factors, except current price-induced substitutions, that make the input of energy in a given production sector grow slower than the output of that sector. The numerical value of the AEEI-factor is often assumed to be in the interval 0–2 % per annum. An AEEI-factor at the level of 1 % per annum or more has a very significant impact on energy use, and thus on emissions, in a 50–100 years time perspective. Thus the assumptions made about the numerical value of AEEI in key production sectors may have a very significant impact on the results of the whole modeling exercise. As the LC-RGE is supposed to elucidate the impact of changes in relative prices on the allocation of resources in the economy, it is of course somewhat disturbing to be forced to treat technological change as an exogenous factor.

2.5.4.4 Environmental Benefits

One way of using LC-RGE is to focus on the cost of specific low carbon policy measures, or on the cost of attaining a specific low carbon policy goal. However, if the model is to be used for evaluation of policies it should be capable of quantifying both the costs and the benefits of the policies in question. This means that the LC-RGE needs to have an "environmental module" in which the environmental benefits of carbon emissions reduction are quantified and expressed in monetary units.

What is needed in order to construct a "benefit function" can be divided into two sets of functional relationships. The first is a set of physical damage functions that convert emissions and other environmental effects of production and consumption into measures of physical environmental damage (such as the anthropogenic climate change) or improvements (such as the reduced emissions). The estimation of such functions is obviously outside the realm of economics, and it does not seem to be a prime concern for natural scientists. The second is a set of functions defining the value, in monetary units, of changes in the physical characteristics of the environment.

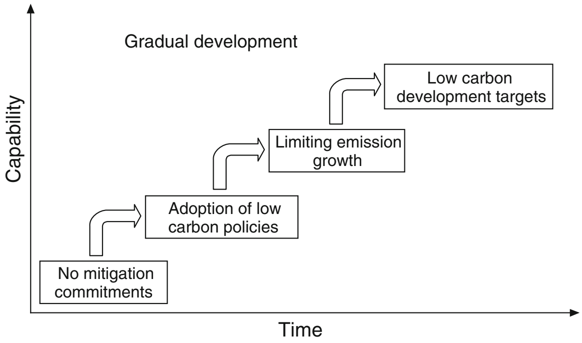


Fig. 2.27 Gradual development of low carbon policies

2.5.5 Low Carbon Policy System

How to alleviate the tradeoffs between economic development targets and climate change constraints would have some countries and regions start with a focus on "climate-friendly" development policies (i.e. low carbon development policies). In order to uphold the integrity of the RLCED, all mitigation efforts, whether based on low carbon policies or eventually on low carbon development targets, would have to be objectively measured and reported, and independently verified (Fig. 2.27).

Regional low carbon economic development involves institutional arrangement, incentives, planning, regulations, legislation, development path and instruments, complying with production level and regional development strategies. A RLCED system is consisted with numerous participators (including government, enterprizes, communities and non-government organizations) and multi-driving forces technology, project, trade and legislation. Based on different participators and driving forces, the RLCED system can be categorized as the following eight modules (see Fig. 2.28).

- **Government-led module.** Government plays primary roles in pushing the RLCED. Regional administrations can contribute to low carbon industrial production and enable low carbon technology innovation by creating incentives and support mechanisms for green industry start-ups, energy conservation, and through the creation of knowledge-sharing platforms.
- **Enterprize-pioneered module.** Enterprizes are major players in the regional economic development. Without their participation, low carbon economy cannot take roots in a certain region. The leading low-carbon enterprizes in economic development will lead to organizational evolution of industries, stimulate dissimilation of low-carbon technologies among enterprizes, and finally realize the overall development of low carbon economy.
- **Community-guide module.** The bad consumption habits of community residents also increase the generation of GHGs for electricity generation and the production of goods and services. Without undermining the quality of life of people, there is

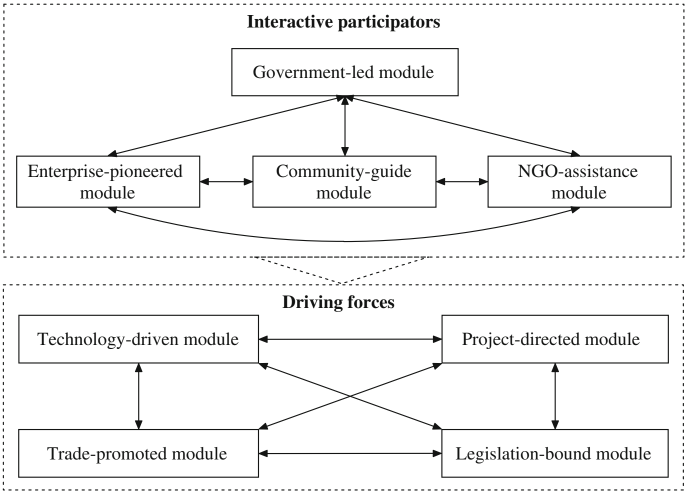


Fig. 2.28 Modules of the RLCED system

still huge potential of energy conservation and emission reduction for communities. Low carbon lifestyle is also crucial in the generation of a low carbon society.

- **NGO-assistance module.** Non-government organizations (NGOs) refer to social organizations that exist between governments and markets, representing interests of communities. They are playing more and more important roles in promoting low-carbon economy. Community-based initiatives and public education campaigns led by NGOs can influence individual behavioral choices for low carbon lifestyle.
- **Technology-driven module.** Energy conservation and emission reduction rely heavily on technological progress and innovation in industries. Technological innovation can lead to clean and efficient utilization of coal, enhancement of added-value of oil gas and coal bed gas, development of renewable and new energies, realization of CO_2 capture and storage, etc. Development of low carbon technologies can provide driving force to low-carbon economy.
- **Project-directed module.** Due to many factors including economic performance, switching costs and path dependence, and lock-in effect, low carbon economy is difficult to achieve large-scale development in a wide region in the short run. However, projects with particular objectives, timetable, inputs, outputs and outcomes can serve as platforms and carriers for RLCED.
- **Trade-promoted module.** Since exchange of commodities, according to the Coase Theorem, can be regarded as trade for property rights, the discharge right of GHGs can also be exchanged. Carbon trade is proved to be the most effective solution to pollution under the market framework. Therefore, the region aiming for low carbon development should actively participate in the construction of global carbon market.
- **Legislation-bound module.** Government may set minimum energy permission targets and discharge permission standards through legislation and law enforce-

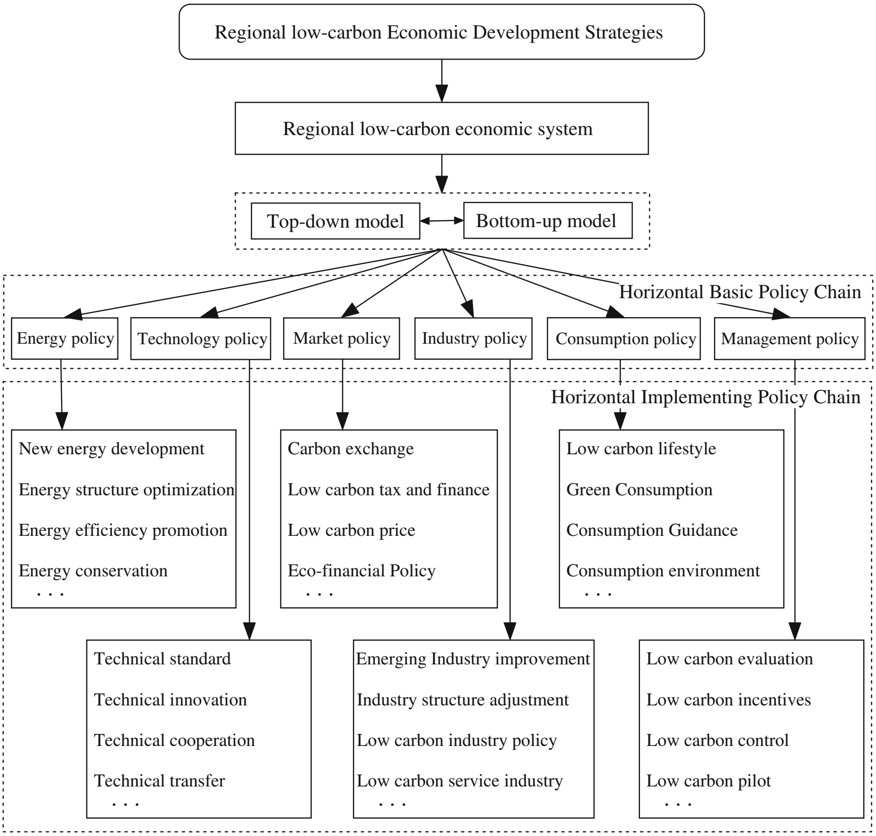


Fig. 2.29 Low carbon economic development policy system

ment to promote the development of low carbon economy. This module is featured by authoritative, open and stable practices.

Based on different leading participators, low-carbon economic development models can be categorized as top-down model and bottom-up model. The former is usually led by government and pushed forward by establishing institutions and mechanisms that could create favorable political, legal and market environment for the development of low carbon economy. Governments' leading role in the model can improve the public awareness and encourage low-carbon investment and consumption. This model features high efficiency and authoritative credits. But sometimes there is gap between model and regional development. Therefore, it suits the primary and developing stages of low carbon economy. The bottom-up model is usually led by NGOs, combining efforts of enterprizes, social communities and government. This model gives consideration of the leading role of market and public opinions on low-carbon and climate related issues. Compared with the top-down model, this type is less efficient. It requires NGOs that have good understanding of the low carbon economy and

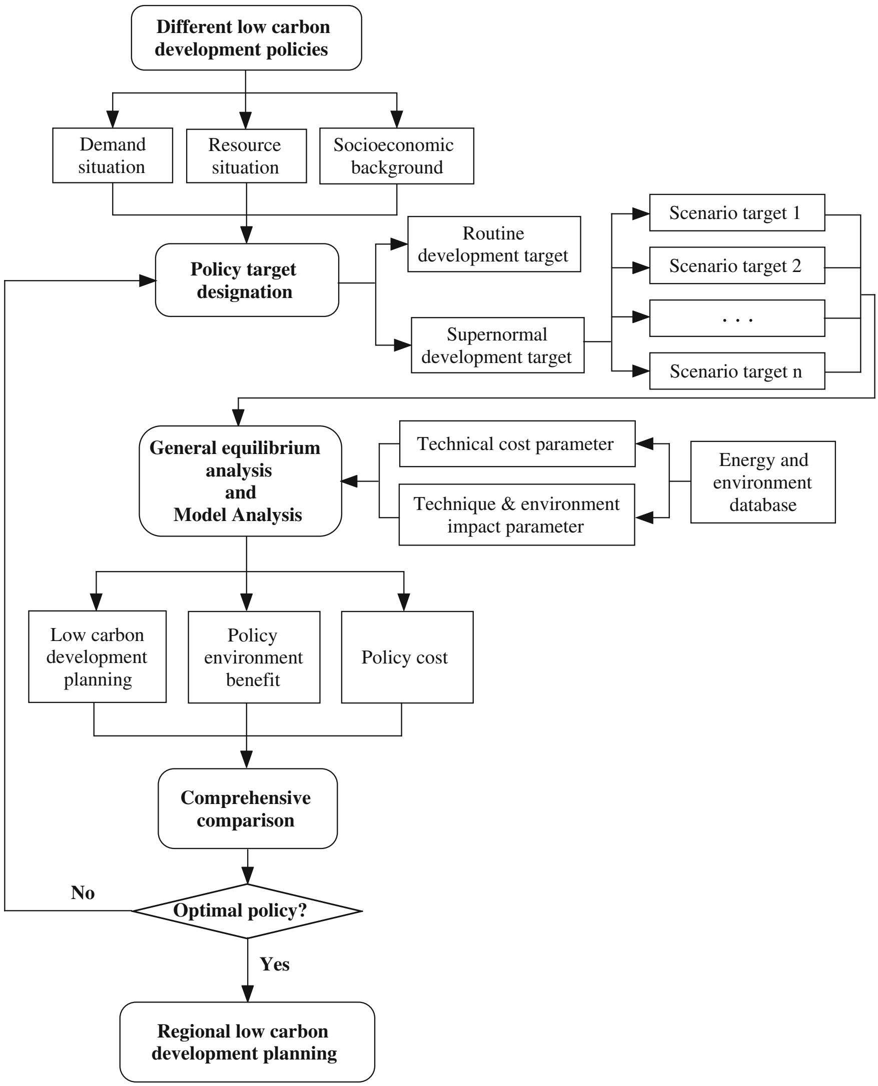


Fig. 2.30 Flow chart about low carbon policy formulation

can balance or even sacrifice their own interests for the regional long term interests. Normally, both of the two models are applied to conduct the RLCED.

Experience of some developed countries and regions has showed that through enforcing appropriate policies, low carbon economy can realize well development and yield apparent social and economic benefits. According to the module composition and model integration of the RLCED, the RLCED policies can be divided vertically into overall strategy, basic policies and implementing policies, as can be seen in Fig. 2.29.

Regional low carbon economic development strategy refers to the macro-level central plan and outlook for the low carbon economic development. It sets guiding principles for regional low carbon policy formulation. Basic policies refer to general policies within a particular sector. They give policy guidance within the sector and sustain the implementing policies. At the bottom, implementing policies are practical measures under the basic policy.

Relevant policies and intensify institutional innovation should be integrated and coordinated to amplify the function of low carbon policies. Low carbon economy is closely related to economy, society, energy and environment. So low carbon economic policy should be a comprehensive system to include all these factors and there should be rigorous laws and powerful policy measures to ensure its implementation. Firstly, in terms of government expenditure, low carbon policies should play more important roles in technical upgrading and innovation, energy-saving consumption and renewable energy development. Secondly, we should establish a sound government procurement system, giving considerations to energy saving and GHGs emissions reduction. The purchased products should get rigorous energy certification. Thirdly, we should set the agenda to establish a special carbon fund, and carbon tax should be collected as the major funding source once the opportunity is mature. This fund should be used to support the energy efficiency improvement, technical innovation, industry development, etc.

It is necessary for the policy makers to select the best policy which could achieve a rational balance between cost control and environment benefit by comparison analysis and scenario analysis. The comprehensive comparison between policy cost and environment benefit from the planning would achieve an optimal balance point. The steps for the above course are shown as Fig. 2.30.

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