

Understand the influence of Cap-&-Trade program through system dynamics models

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Keywords

System dynamics, Simulation modeling, Cap and Trade program

Abstract

Operating under Cap and Trade program conditions has brought significant challenges to industrial organizations pursuing green sustainable development by imposing more constraints on resource/energy acquisition and disposition in order to reduce green-house-gas (GHG) emission. New factors due to the conditions interact with each other and system's production/service functions, causing complicated dynamic relationship that collectively influence the overall performance of the enterprises. Decision makers now have to balance between production economy and green improvement. This research introduces a proactive approach based on system dynamics modeling to represent such complex systems and analyze the relationship to explore underline logic that drives system behavior under the conditions; and provides managerial insight for decision or policy makers to pursue environmentally friendly and economically sound production. Simulation experiments were designed to validate models and compare different strategies to analyze their impact on system's overall performance; such as long term over-emission, continuous green investment on emission reduction, and cost for purchasing emission allowance or paying penalty over-emission tax.

1. Introduction

Green production (GP) has been recognized globally as a key strategy for sustainable development of industrial enterprises. GP incorporates the principles of environmental protection and energy conservation into production and service operations to reduce waste, save energy/resource, and minimize pollution, while accomplishing production economy. Green sustainable development has become a critical issue for fast growing countries such as China and India, where rapid economic and technological development have been witnessed in past decades, accompanied with significant damage made to the environment and over-consumption of natural resource (Zhang, 2011). Although the efforts for establishing related standards or legislation are being made by governments and industries of different nations to improve the situation, great challenge remains for the research and effective implementation at enterprise level.

Green sustainable development projects are usually characterized by high initial investment, slow return, and higher risk; and significantly affected by government regulations and competitors' behavior (Montalvo, 2008). Enterprise decision makers have to make important trade-off between green improvement and economic performance with limited resource, bearing expectations from different stakeholders (Johansson and Winroth, 2010). For instance, expanding production/service capacity increases CO₂-equivalent (CO₂E in short) emission and energy consumption. On the other hand the improvement on green performance may affect

entire production and distribution process, including design, process planning, material supply, production planning, manufacturing, distribution, and post-sale technical support (Azzone and Noci, 1998). Further more government regulation (e.g. via emission tax or over-emission penalty) not only affects enterprises' economic performance (e.g. cost and profit), but also stimulates firms to invest more on improving their green capability. So does the "social responsibility" that becomes increasingly important from consumers' perspective (Jenkins, 2006).

An extensive review of related literatures has been conducted by the authors. Most of the studies have been devoted to green manufacturing strategies. To facilitate decision support for manufacturing enterprises to plan and implement GP projects, UNDSO (2003) proposed Environment Management Accounting (EMA) that combined enterprise cost accounting data to help manufacturer improve energy conservation and reduce environmental pollution and risk. Jasch and Stasiskiene (2005) improved EMA by adding a social cost item, and discussed how enterprises may evaluate their sustainability based on financial/accounting data. Laurinkeviciute and Stasiskiene (2010) developed a decision model based on benchmarking and activity cost for small and medium enterprises in Lithuania. Georgopolou et al (2008) developed a similar system that compares different green technologies based on implementation cost and green yield. Zhou et al. (2013) described the integration of multi-objective programming, genetic algorithm search and simulation to optimize green production strategies. A great deal of studies was put in the design of various criteria/indices for hierarchical evaluation based approach such as analytic hierarchy process (Tahir and Darton, 2010). While the literature seems abundant, there is still a significant lack of understanding about the nature of system dynamics that is critical in helping both researchers and practitioners better define and propose effective models to identify and assess related factors that interact with each other and influence overall system behavior, and the mechanisms that transmit the interactions and drive the critical trade-off between different system (sub-systems) configurations under dynamic and uncertain conditions. More recently, *Cap and Trade programs* (European Union, 2012; US-EPA, 2012) have been established in some developed countries (e.g. US and Europe) and developing countries (e.g. China).

It is a policy tool that generates benefits (both economy and environmental protection) with a mandatory cap on emissions while providing sources flexibility in how they comply, e.g. allocating emission allowance or quotes to enterprises and allowing the quotes to be traded through market transactions. It is evident that production systems behave significantly different under the conditions of Cap and Trade program (Du et al., 2009). In addition to regular production resource, firms now have to consider the acquisition and disposition of environmental resources (e.g. emission allowance or emission quote (EQ), i.e. commercialized right for emission of CO₂E), and balance between production economy and green requirements. This needs a more comprehensive and deeper understanding on the factors that interact with one another to drive system's behavior and constitute the important trade-offs, such as production capacity, resource consumption, CO₂E emission, emission quote transaction, and green investment. Enterprise decision makers need a tool to evaluate different scenarios (e.g. sequences of interactions of different factors) to find appropriate balance for rational decisions. Policy makers need models to evaluate the impact of government intervention to help design or improve the policies. Researchers also need in-depth analyzes to uncover and characterize the state transitions of eco-economic systems at a micro- or enterprise level.

System dynamics (SD) is an effective tool for modeling and analyzing complex systems composed of interacting subsystems or factors that work together to influence overall system behavior via dynamic cause-effect relationships. It models a system with multiple states, i.e. aspects of performance, that interact with each other and transit dynamically, and characterizes the interaction or changes (relational transitions) between the system states via analytic or empirical functions (Forrester, 1961). This modeling approach has been widely used to evaluate different policies or strategies for improving system performance via simulation experiments (Wang, 1994). Plentiful studies have been conducted on urban or regional sustainable development. Most studies focused on the design and development of multi-criteria and comprehensive indices systems for evaluation (Tahir and Darton, 2010; Zhou et al., 2012). Some employed methods of SD to analyze the dynamic interaction between the factors that drive systems' behavior (Song et al., 2004). However, most of these reported projects were implemented from the perspective of governmental policy-makers, rather than enterprise management (Chen, 2005). Only a few focused on the dynamics of production systems subjected to green sustainability related conditions. For instance, Yang et al (2012) used a system dynamic model to the impact of different "emission policies" on supply chains, focused on the change of CO₂ emission at production and inventory stage (connecting producer and retailer), and compared supply chain performance under Cap-&-Trade and emission tax policies. In Shenzhen, one of the most developed areas in China, most of the enterprises chosen to participate in a government-lead experimental Cap-&-Trade program are totally uncertain (or lack of knowledge) about what would happen to their business performance under the new conditions (Shenzhen Emission Exchange, 2012). The purpose of this study is to develop a descriptive model, via SD simulation, to illustrate and characterize the dynamic behavior of production/service systems under Cap-&-Trade conditions; and conduct simulation experiments to analyze the relationship between system states and between the factors that cause the state transitions that influence overall system behavior, and develop a comprehensive and scientific understanding about the complex system behavior based on the experiments to provide enterprise decision-makers (as well as government policy-makers and researchers) with useful insights to help improve their decisions or strategies under the pressure of green sustainable development. In the following sections, we briefly introduce the ongoing research conducted by the authors. Note that due to the page limitation only part of the research work is presented in this paper.

2. Conceptual model design

From a system engineering (SE) point of view, an industrial enterprise is conceived as a dynamic system interfaced with market demand and consisting of production, service, and sustainable development functions. The system functions may contain many structural factors that change along with time and interact with one another to derive required services and influence system's overall behavior. One of the very important system characteristics is the causal relationship between the factors, i.e. the change of one factor causes the change of another. Combining such cause-effect relationship among the factors, one can form so called feedback loops (Forrester, 1961) that represent the significant dynamic behavior of overall system. This helps enterprise managers find out how a production system change when system conditions (internal or external) change dynamically at a lower (factor) or local level, and provide useful insight for decision making or policy design. A production/service system under Cap-&-Trade conditions is conceptualized via a graphical model, displayed in Figure 1. It

highlights the factors (internal or external) that are grouped together to perform the system's functions of interest and exhibit a cause-and-effect relationship between them, especially those characteristics and activities of the system under the conditions of a Cap-&- Trade program. For instance, market demand influences positively the production capacity (i.e. the increase of market demand stimulates the increase or expansion of production capacity). Production capacity positively influences resource/energy consumption. The more resource/energy is consumed, the more CO₂E emission generated; which in turn causes higher transaction cost (to purchase extra emission quote) or regulation cost (to pay higher tax for over-emission). The higher the transaction/regulation cost can harm enterprise's social or public image and pushes product price going up, which negatively affects the market demand; but stimulates a higher investment on green improvement. Higher GP investment improves system's green capability (a positive influence), which causes a reduction of CO₂E emission (a negative influence). The graph was drawn according to standard SD flow diagram convention (i.e. all the graphical objects, boxes, arrows, and signs were standard notation). Rectangular boxes stand for state or level variables; arrows between boxes represent causal relationship between them; and the signs by the arrows define the nature of an influence or relationship, either positive (+) or negative (-). The arrows drawn in solid lines imply strong relations, while those in dashed lines represent weak or uncertain relations. Note that some variables are continuous accumulating variables (e.g. CO₂E emission, GP investment), while others are used to represent factors (e.g. product price, production capacity, energy consumption, GP capability). To simplify the task of modeling and implementation, we actually decomposed the overall system into two sub-systems during the initial phase of the research, which is not discussed here due to the limited space.

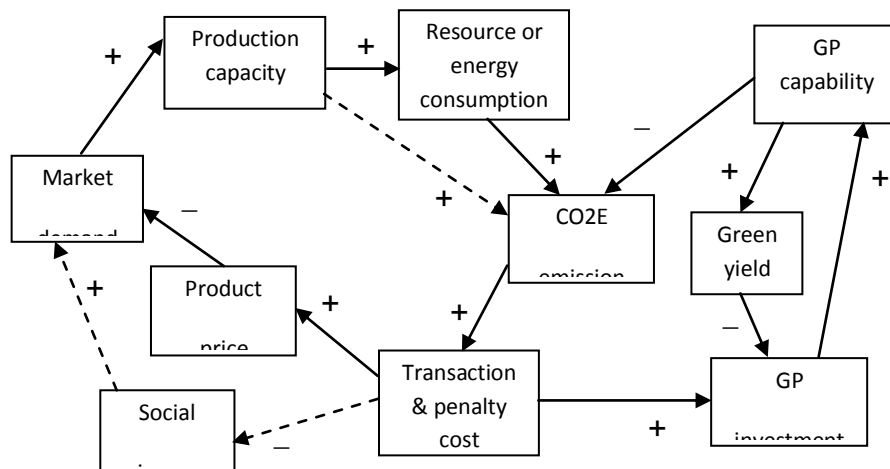


Figure1. Conceptual model for overall system (cause-effect diagram)

3. Modeling for system dynamics simulation

While the conceptual model proposed in Figure 1 provides a robust structure that can fit almost any type of production enterprise, we have to realize and test the conceptual framework by constructing a system dynamic model for simulation experiments. It is therefore necessary to define variables and mechanisms that implement system functions based on the conceptual framework, and meet the purpose of the simulation and SD modeling requirement through

quantitative specifications. The system dynamic model is specified as a virtual manufacturing system operating under Cap-&-Trade program and used as an experimental platform for simulation analysis. In the context of SD modeling, we have to convert the conceptual framework into a structural model to formalize the logical relationship between system functions or factors, and specify the attributes of the factors in terms of state or flow variables, rate variables and auxiliary variables, and define the relations that connect the variables logically (Wang, 1994). According to the system dynamic modeling theory (Wang, 1994), a flow variable accumulates a quantity that changes on a continuous scale and is influenced by other variables and/or system parameters via input and output rates that characterize the velocity of the flow variable accumulation.

We briefly introduce the model construction by defining three flow (or “level”) variables. They represent system flows that characterize important quantity accumulations within the simulated production system. The first flow variable $S_1(t)$ = CO2E emission, measured in the units of “metric ton” and is defined by: $S_1(t) = S_1(t-1) + \Delta t(R_{11}(t) - R_{10}(t))$; Where $R_{11}(t)$ and $R_{10}(t)$ are input and output rate functions for flow variable $S_1(t)$ respectively. $R_{11}(t)$ defines the rate of increase and $R_{10}(t)$ defines the rate of decrease of $S_1(t)$. In this problem, $R_{11}(t)$ is a function of energy or resource consumption (which in turn is a function of production capacity). $R_{10}(t)$ is a function of saved energy (or reduced emission), which in turn is a function of “green improvement”. Note that “assistant variables” (Wang, 1994) are often needed to help define flow or rate variables. As emission level reduced (or energy saved) through green improvement, the accumulation of CO2E emission in each period (a simulation cycle) is reduced. The second flow/level variable is $S_2(t)$ = Transaction and regulation cost (“*T and R cost*” in short), and defined through: $S_2(t) = S_2(t-1) + \Delta t(\alpha f_{21}(t) + (1-\alpha)f_{22}(t))$; where $f_{21}(t)$ = transaction cost of purchasing emission quote (EQ) through an *EU-ETS* type of market (European Union 2012), and a function of over-emission and market price; $f_{22}(t)$ = cost of paying over-emission penalty, a function of over-emission and penalty rate. α is a parameter that adjusts decision preference between $f_{21}(t)$ and $f_{22}(t)$, and $0 \leq \alpha \leq 1$; i.e. α partitions the remedy for over-emission into two parts: one part is met by purchasing extra EQ from market, and the other met by paying penalty (e.g. over-emission tax). Consequently α assigns different weights to decision options: if the weight for *purchasing EQ* is α , then for *paying over-emission tax* is $(1-\alpha)$; and vice versa. The third flow variable is $S_3(t)$ = Green investment, defined as: $S_3(t) = S_3(t-1) + \Delta t(f_{31}(t) + f_{32}(t))$; where $f_{31}(t) = \beta S_2(t)$, i.e. it is a rate function of accumulated transaction/regulation cost $S_2(t)$, and β = a proportion coefficient that transform the effect of transaction/regulation cost on the green investment. Evidently higher transaction or regulation cost stimulates enterprise to invest more on green improvement effort. Rate function $f_{32}(t) = \gamma B$, where B = enterprise’s total product (in monetary value) and γ = an investment coefficient, $0 \leq \gamma \leq 1$.

Under the pressure of low-carbon production, many enterprises in China adopted a practice of investing a small portion of their total product (or sales revenue) into the effort of technological innovation or green improvement, varying from 0.1%~3% (Wang and Li, 2009). Other important assistant variables involved in the model include *Market demand* (for the enterprise’s product/service), *Production capacity*, *Product price* and *Social image* (Figure 2). *Market demand* is defined as a random variable following a uniform distribution, influenced both externally and internally. In the baseline model we define the *Production capacity* as linear function of *Market demand*. The *Product price* is a function of several factors, e.g. production quantity, operations cost, transaction and regulation cost, green improvement cost and a profit

mark-up. We introduced an assistant variable “Enterprise/Social image” to capture the fact that under increasing pressure of “social responsibility” (Jenkins, 2006), the enterprise must now consider how the operation decisions affect their public image from a broader society perspective (including customers and potential customers) in terms of social responsibility. For instance, higher *CO2 over-emission* (reflected through higher *T&R cost*) causes a negative impact on the enterprise public image, which may in turn causes a decrease on the market demand.

After all the flow variables, rate and assistant variables are defined, we assemble them into a complete sub-system model; then put all sub-system models together to form an overall system model. In this case, the two sub-system models are assembled together via *CO2 Emission* and *Transaction and Regulation Cost*, the two flow variables referenced in both sub-system models. A complete system flow diagram (drawn with VENSIM©) is presented in Figure 2.

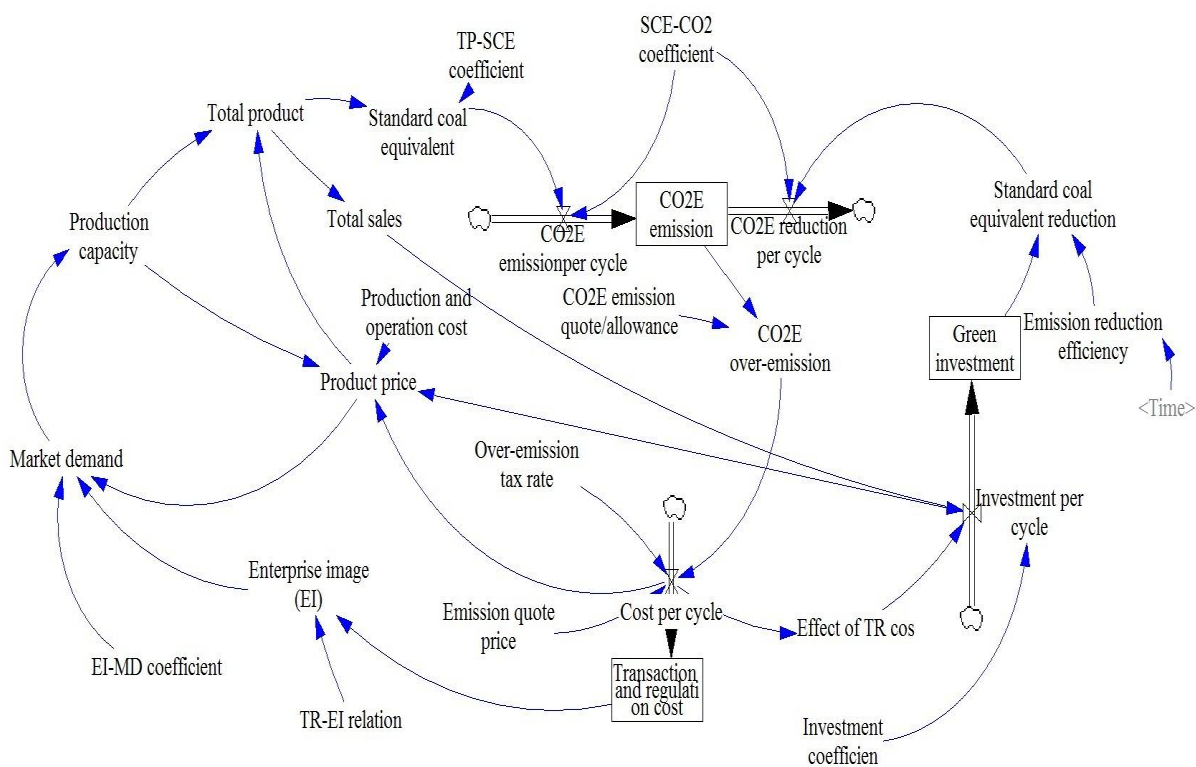


Figure 2: A system flow diagram constructed with VENSIM©

4. Model Implementation and Experiment Design

The system dynamic model designed previously was implemented through VENSIM© to validate proposed concepts and structures for analyzing system’s behavioral characteristics, i.e. the relationship between system inputs (and changes at factor level) and outputs (changes at system level), and for the sensitivity of the model parameters. The experimental model simulates a manufacturing system that conforms to the design and structure described in Figure 1 and 2 (e.g. a production system with finite capacity, subjected to resource constraints and Cap-&-Trade conditions, interfaced with market demand, and influenced by green improvement).

While several other modeling languages are available, we choose VENSIM© for implementation due to its easy of use and popularity among industrial and academic users.

The experiments are designed and conducted for the verification and validation test of basic system functions under a baseline configuration, i.e. to see if the model structures can perform the functions intended and render outputs consistent with observations from real systems under a “standard” baseline setting of parameters. Secondly experiments for sensitivity analysis of modeling parameters are needed. The experiments are also designed to compare the combinations of different planning or operational strategies. Three dimensions or type of strategy, X , Y and Z , were considered, where X = Green investment, Y = Purchase of emission quote (EQ), and Z = Production capacity. Each was set at two levels {Low, High} for experiments. This results in $2^3 = 8$ experimental treatments, and each is a combination of strategy options. For instance, a treatment of *LHL* represents that X = Green investment is low (L), Y = Purchase of EQ is high (H), i.e. relying on purchasing additional emission quote from market to satisfy over-emission, and Z = Production capacity is low (L), meaning to adopt a fixed capacity strategy. More detailed descriptions on the strategy design are provided in the reference (Zhou et al., 2013).

For sensitivity analysis, we analyzed system’s marginal behavior when the model parameters are sequentially changed. The set of parameters investigated include initial CO2E emission quote θ_1 , unit purchasing cost of emission quote θ_2 , over-emission tax rate (i.e. unit penalty cost) θ_3 , and green improvement efficiency θ_4 (also called CO2E reduction efficiency). Each parameter was varied at $\pm 10\%$, $\pm 20\%$ and $\pm 30\%$ respectively around its baseline value, and related experiments were run to observe the system’s outputs under the sequential change of the parameters, i.e. we changed the parameters one at a time, while keeping others fixed at a “baseline level”. For each level of change of a selected parameter, we replicate the simulation with the same length, observed and recorded system output (marginal performance relative to the parameter change).

5. Experimental results and discussions

The results for testing a baseline model are first presented. The model was built as a basis for verification, sensitivity analysis and experiments on strategy comparison. The values specified for model parameters were based on the related industrial or national or international standards, for instance, *TP-SCE coefficient* and *SCE-CO2 coefficient* (NBSC, 2011; Jiang, 2009). The values for *Market price of EQ* and *Unit over-emission penalty* were based on the recent studies of EU-ETS system (European Union, 2012; Wei et al. 2010). Using a value around 3% (0.03) for *Green investment coefficient* was based on a recent study on Chinese manufacturing enterprises (Wang and Li, 2009).

Finally, setting *Production cost*, *Initial CO2E emission*, *Allocated emission quote*, and *Market demand* were based on the assumptions of a middle-size industrial enterprise (i.e. annual CO2 emission around 3000 tons) in Shenzhen, subjected to the industrial enterprise classification code (by CO2 emission level) by the Shenzhen Municipal Government (Shenzhen Emission Exchange, 2012). The enterprise’s total product was estimated = Total production quantity \times product price. We then multiplied the total product with a transfer coefficient to obtain standard coal

equivalent (*SCE*); then multiplied *SCE* with another *SCE-CO2* coefficient to determine the related CO2 emission for each simulated period.

The exemplary results for the baseline model were presented through Figure 3 to Figure 6. The plots showed the change of different system performance indices over simulated time periods (cycles). Apparently there is a transit period during which system's total emission increases sharply (Figure 3), causing high over-emissions (Figure 3 right). However after cycle 9, the system settles down in which total emission (and over-emission) varies in a lower and relatively stable range.

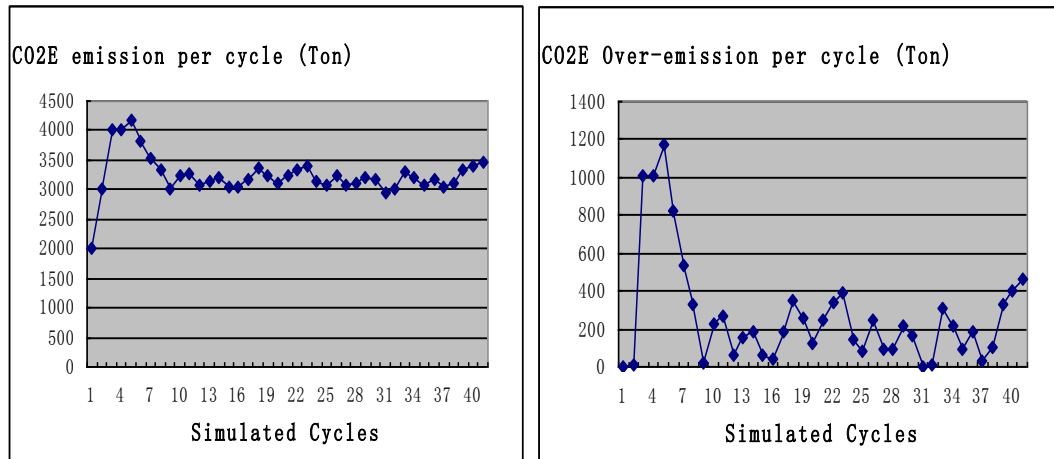


Figure 3: Changes of CO2E total emission and over-emission per cycle

Figure 4 (right) showed the change of transaction and regulation cost. Initially the cost increased sharply to a very high level, but decreased quickly as system's effort to reduce the emission increased quickly (e.g. green investment, Figure 4 left). It maintained a random variation after cycle 9 at a much lower level. Generally these observations are consistent with the model inputs and modelers' expectation and experience.

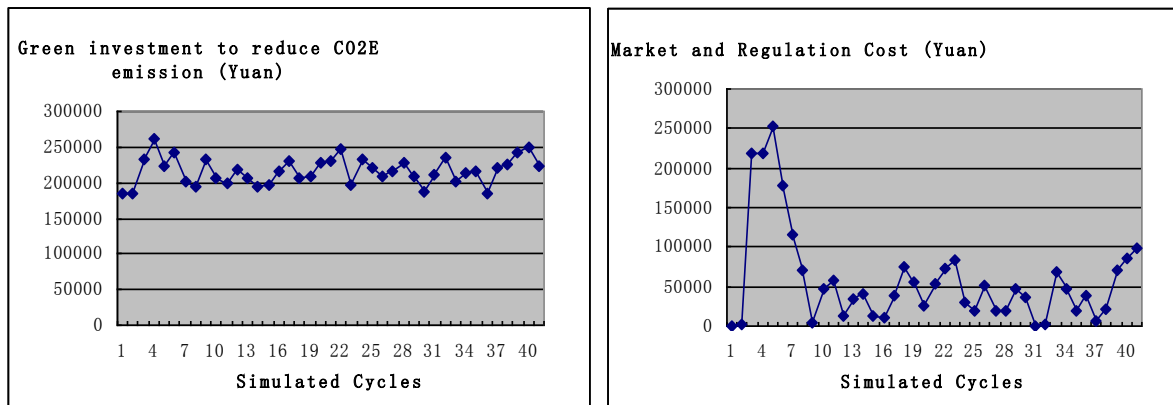


Figure 4: Changes of green investment, transaction and regulation cost

After the validation, we conducted sensitivity analysis to investigate how the changes on the model parameters affect the model behavior and outputs. As mentioned earlier, the parameters analyzed include initial CO2E emission quote θ_1 , purchase cost of emission quote θ_2 ,

over-emission tax rate (unit penalty cost) θ_3 , and green improvement efficiency θ_4 . Each parameter was varied at $\pm 10\%$, $\pm 20\%$ and $\pm 30\%$ respectively, and related experiments were run to observe the system's outputs under different changes. As an example, Table 1 showed the results on θ_1 , initial CO2E emission quote. The values filled in the cells of the table are the percent deviations of the parameter value from their baseline level. Key performance measures (KPI) include V_1 = CO2E emission per cycle; V_2 = CO2E over-emission per cycle; V_3 = Total green investment; and V_4 = Total transaction and regulation cost. It is clear that the change of θ_1 is sensitive on system performance V_1 , but not on V_3 .

Table 1: Change of system performance corresponding to the change of θ_1

| $\Delta\theta_1$ | -30% | -20% | -10% | +10% | +20% | +30% |
|------------------|----------|----------|---------|---------|----------|----------|
| KPI | | | | | | |
| V_1 | -28.401% | -18.929% | -9.46% | 9.4743% | 18.9499% | 28.4265% |
| V_2 | -2.871% | -1.827% | -0.84% | 1.0821% | 2.1859% | 3.306% |
| V_3 | -0.097% | -0.061% | -0.028% | 0.0383% | 0.0772% | 0.1165% |
| V_4 | -2.871% | -1.827% | -0.84% | 1.0821% | 2.1859% | 3.306% |

Figure 5 showed a plot of sensitivity analyses on initial emission quote θ_1 . The pattern matches with the results calculated in Table 1. Initially emission quote θ_1 affects system's overall emission significantly, but settles down quickly as the system picks up on green investment and emission trade actions, exhibiting a short-term effect during transit-period. The long-term sensitivity of θ_1 (on over-emission) was not significant under the baseline setting.

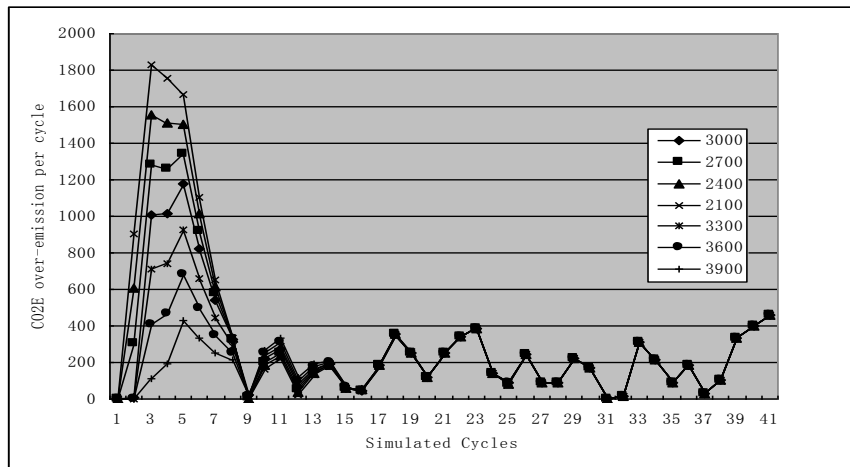


Figure 5: Sensitivity plot of initial emission quote

Table 2 showed another example that compared two operation strategies via simulation experiments: Strategy 1 with $X=LGI$, $Y=PEQ$, $Z=FLC$ (i.e. low green investment, purchase EQ, and flexible capacity); and strategy 2 with $X=HGI$, $Y=PEQ$, $Z=FLC$ (i.e. high green investment, purchase EQ, and flexible capacity). It can be seen that, under the given model parameters, Strategy-2 outperforms Strategy-1 in terms of accumulated total over-emission, average

transaction/regulation cost, and average total product; while the average green investment for Strategy-2 is about 11% higher than that of Strategy-1, as expected.

Table 2: comparison of Strategy 1 and Strategy 2

| | Strategy 1 | Strategy 2 |
|-------------------------------------------------------------------|------------|------------|
| Accumulated total over-emission (Metric ton) | 24861.4 | 3755.1 |
| Average green investment (in 10 ³ RMB or Yuan) | 208.035 | 230.551 |
| Average transaction and regulation cost (in 10 ³ Yuan) | 126.126 | 19.0502 |
| Average total product (in 10 ³ Yuan) | 13619.1 | 14254.3 |

6. Summary

This paper reported an on-going study that applied system dynamic theories to model and characterize the behavior of production systems subjected to the conditions of Cap-&-Trade program and green performance requirement, and interfaced with the uncertain changes of market demand. The model focused on the important interactions between the system components (factors) that collectively influence the dynamic behavior of the overall system. SD modeling functions accurately represented the factors (or variables) and the causal relationship between them, and connected the relations between factors to form closed feedback loops to simulate the complicated dynamic behavior of the system under various conditions. This improved effectively the study of such complex systems. Designed experiments were conducted to verify the concepts/functions proposed and validate model development, compare the effects of different operations and green improvement strategies, and analyze the sensitivity of the model parameters. While the results were limited, they adequately proved that a valid and properly built SD model can help enterprise decision-makers evaluate the effect of different factors (internal or external) due to the new challenges (e.g. Cap-&-Trade program), design and compare different strategies, and select the proper ones. The study also provided insight to government policy makers on designing regulation rules that can effectively control the damage to the environment but also encourage enterprises pursuing a health economic growth. To continue on fulfilling these tasks, we need to expand and enhance the current SD model in terms of functional structures, e.g. being able to represent new application aspects or deeper logic behind the dynamic interactions of the related functions. This is a promising direction for future research.

Acknowledgement: This project is funded by the Natural Science Foundation of China (Grant ID: 71172057 and 71272089) and Guangdong Provincial Commission of Science and Technology (ID: 2012B070300074) and Guangdong Provincial Natural Science Foundation (S2012010008868).

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