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GREEN PRODUCTION -- STRATEGIES AND DYNAMICS: A SIMULATION BASED STUDY

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ABSTRACT

There are a number of issues for enterprises to implement green production. From operations perspective, selecting green improvement strategy is critical but difficult due to the fact that it affects not only green performance, but also production economy. Important trade-off exists between different objectives and decisions are subjected to dynamic and uncertain conditions. From system dynamics perspective, there exist multiple factors interacting with one another to drive system's behavior and the trade-offs. Decision makers need to evaluate different scenarios to find appropriate balance between strategies. We report studies addressing both issues through an integrated approach emphasizing the use of simulation. First it focused on the optimization of green improvement strategies. A simulation model was developed to capture operations flow and decision logic. A multi-objective genetic algorithm, combined with improving heuristics, was developed to search for best solutions. Secondly, system dynamic models were developed to characterize the dynamic behavior of production systems under Cap and Trade conditions. Simulation experiments were run to analyze the relationship between system states and among the factors that cause the state transitions that influence the overall system behavior.

1 INTRODUCTION

Green production (GP) has become an important strategy for sustainable development and a niche for competition for manufacturing enterprises. It applies the principles of environmental protection and energy conservation to production activities to reduce industrial waste, save energy and resource, and minimize pollution, while accomplishing desired production economy. During the past several decades, great economic development and technological advancement have been witnessed in the regions where new economic powers grow rapidly, such as China and India. Unfortunately the remarkable achievements were accompanied with significant damages to natural environment and over-consumption/waste of natural resources (Zhang 2011). Efforts for establishing related standards or legislation are being made by governments and industries of different nations to improve the situation. However, great challenges remain for enterprises to deal with the issues.

GP improvement includes two steps. First, one or multiple production activities are identified (e.g., a sub-process in design, manufacturing, packaging or distribution); and the goals for improvement defined (e.g., reducing CO2 emission or saving energy). Cost-benefit analysis is usually performed based on estimated data. A post-improvement evaluation is conducted to assess the results of the improvement. Important characteristics are observed: (1) GP improvement affects production/distribution processes, such as design, process planning, material supply, production planning, manufacturing, or distribution (Azzone and Noci 1998). Likewise decisions made in production or distribution process directly affect the green performance of a production system. This interaction needs to be balanced properly (Johansson and Wiroth 2010). For instance, changing design requirement or processing method may bring significant reduction on energy consumption or pollution. But the same change can also negatively affect the economic performance of production, such as cost or customer service. Unfortunately this interaction is usually uncertain and dynamic, and makes related decisions difficult. (2) Improvement for green usually conflicts with economic goals of production, e.g., higher investment in GP projects may directly increase the cost and risk of production. There exist critical trade-off between green improvement and production economy (Zhou et al. 2012). Most GP projects are multi-objective optimization problems (MOOP) in which decision-makers try to optimize their decisions in terms of a set of conflicting goals by identifying the best tradeoff between the economy of production and benefit of green improvement. In reality most GP projects are characterized by high initial investment, slow return, high risk and technical difficulty (Montalvo 2008). Therefore one must adopt a systematic approach to evaluate various GP strategies and their associated risk, and identify the best decision alternative that optimizes the trade-off between conflicting goals. Unfortunately most manufacturers today are still using an *ad-hoc* approach in this critical process due to the lack of guidance and effective tools. A review of related literature revealed the fact that while the research on green production strategies seems abundant (Laurinkeviciute and Stasiskiene 2010; Georgopolou et al. 2008; Srivastara 2007; Tan 2002; Tahir and Darton 2010; Du et al. 2007), there is still a need to address the difficulties of optimizing decisions at enterprise's level through an integrated approach capable of assessing multiple tradeoffs under dynamic and uncertain conditions, and searching best solutions under multiple conflicting goals.

The review of the literature also unveiled a significant lack of understanding about the system dynamics that is critical in helping decision-makers better define and propose effective models to identify and assess the related factors that interact to influence system behavior, and the mechanisms that transmit such interaction to drive critical trade-off between different system behaviors under dynamic and uncertain conditions. More recently, Cap and Trade programs (European Union 2012) have been established in many developed countries and developing countries. It is a policy tool that generates benefits (in terms of production economy and environmental protection) with a mandatory cap on emissions while providing sources flexibility in how they comply, e.g., allocating emission quotas to enterprises and allowing the quotas to be traded through market transactions. It is evident that production systems behave significantly different under these conditions or constraints (Zhou et al. 2013). In addition to regular production resource, manufacturers now have to consider the acquisition and disposition of environmental resources, e.g., commercialized right for emission of certain pollutant, and balance between production economy and green improvement. This requires a deeper understanding on the factors that interact with one another to drive system's behavior and constitute important tradeoffs, such as production capacity, resource consumption, CO2E emission, EQ transaction, and green investment. Enterprise decision makers need a tool to evaluate different scenarios to find appropriate balance for making rational decisions. In-depth analyses are also need to characterize the law of state transitions of eco-economic systems at micro or enterprise level, and help policy makers evaluate and improve the impact of government intervention policies.

System dynamics (SD) theory is a powerful tool for modeling and analysis of complex systems that are composed of interacting subsystems or factors working together to influence overall system behavior via dynamic cause-effect relationships. It models a system with multiple states (e.g., 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). SD has been widely used to evaluate policies/strategies for improving system performance via simulation experiments (Wang 1994). In terms of green sustainability, plentiful studies have been conducted on urban or regional sustainable development. A few employed SD to analyze the dynamic interaction among the factors that drive systems' behavior (Song et al. 2004). However, the projects reported were implemented from the perspective of governmental policy-makers, rather than enterprise management (Chen 2005). One objective of this study is to develop SD simulation models to characterize the dynamic behavior of production systems under Cap and Trade conditions and conduct simulation experiments to analyze the relationship between the factors that cause the state transitions that influence overall system behavior, and to help researchers and enterprise decision-makers develop a deeper and more comprehensive understanding and insight about similar systems and related issues in green sustainable development.

This paper reports the studies aimed at addressing the issues presented above. It first focuses on the work about the selection of GP strategies from a multi-objective perspective. Then describes system dynamic models (SD) developed to characterize the dynamic behavior of production systems under Cap and Trade conditions.

2 MODELS FOR STRATEGY SELECTION

The selection of GP strategy is considered as an integrated optimization problem that needs iterative evaluation of solutions under real world conditions and effective search for the best ones. The decision variables are conceived as a set of green improvement options $\boldsymbol{x} = \{x_1, \ldots, x_k\}$(e.g., changes of design or process parameters) that have significant impact on system performance measures which are functions of $\boldsymbol{x}$, i.e. $f_i(\boldsymbol{x}), i=1, \ldots, m$. The goal is to identify the best combination of $\boldsymbol{x}$ element values to optimize multiple objectives simultaneously, e.g., minimizing total cost and maximizing total green yield or energy saving. It is a multi-objective optimization problem (MOOP). The solution structure (i.e. decision space that impacts optimization search) is combinatorial and nonlinear. It is very difficult, if not impossible, to solve real-world problems of this kind via *classic* mathematical programming models (Deb 2009, Karlsson and Wolf 2008). This study proposed an integrated approach consisting of two interactive parts: (1) a simulation model to capture problem characteristics and mimic the dynamic and uncertain behavior of the affected objects; and (2) a robust search algorithm integrated the simulation to simultaneously identify Pareto-optimal solutions under multiple goals. The modules work independently but interact with each other. Production flow and decision logic for making GP improvements are captured through a discrete event simulation model. The solutions, i.e. decisions for GP improvement, are generated by an optimization module and fed into the simulation as a set of inputs. The simulation then evaluates system performance in terms of economic and green performance measures. The output from simulation is then transformed into a set of objective function values to feed the optimization module. With the "gradient" information provided by the simulation, the optimization module modifies the search according to some randomized (and heuristic) adjustment to find *better* solutions. The system iterates as solutions continue to improve until either optimization goal is achieved or some stopping rule satisfied (Zhou et al. 2012).

2.1 Analytic Models

Without losing generality, we consider a serial production system consisting of m stages. A decision variable $x_j \in \boldsymbol{x}$ corresponds to a green improvement decision made on a design or process parameter at stage j and assumes a value in [0, 1], i.e. representing a percentage change on the parameter. Generally we could decide production quantity q and green improvement $\boldsymbol{x}$ simultaneously, subjecting to the requirement $q \geq d$ for the planning period. Possible objectives form a set $\{f_1(\boldsymbol{x}, q), f_2(\boldsymbol{x}, q), \ldots, f_k(\boldsymbol{x}, q)\}$ where each $f_i(\boldsymbol{x}, q)$ corresponds to a system performance measure, such as total cost or total green yield. Let $g(\boldsymbol{x}, q)$ represent a service characteristic depending on $\boldsymbol{x}$ and q (e.g., total production time), and T_s the required level of the service characteristic. We formulate a conceptual MOOP model as follows:

$$\begin{gathered}\text{Min. } \{f_1(\boldsymbol{x}, q), f_2(\boldsymbol{x}, q), \ldots\ldots f_k(\boldsymbol{x}, q)\} \\ \text{Subject to:} \\ q \geq d, \qquad \text{Demand constraint;} \\ g(\boldsymbol{x}, q) \geq T_s, \ \text{Service level constraint.}\end{gathered}$$

In realty it is very hard to declare the exact form (parametric structure) of the objective and constraint functions (i.e. $f_1(\boldsymbol{x}, q)$, …, $f_k(\boldsymbol{x}, q)$, and $g(\boldsymbol{x}, q)$) due to the lack of empirical data and knowledge. In this study, we focus on a subclass of this MOOP problem: where production quantity q is given (e.g., estimated based on demand forecast), and decision maker's goal is to determine the best GP improvement $\boldsymbol{x}$ so that the total cost is minimized and total green yield maximized, subjected to some service level constraints. We also assumed that the stages of a serial production flow are independent, therefore the total cost is simply the sum of stage costs; and so is the total green yield. Detailed mathematical form of the model is omitted here due to the limit of space (Zhou et al. 2013).

2.2 Simulation Models

To demonstrate the concepts and methods proposed in above, we constructed an experimental system as a test-bed which adequately represents the problem (e.g., a generic production system flow embedded with GP improvement activities); and allows us to apply and test optimization procedures. The system mimics the production flow of a multi-stage discrete manufacturing system and captures the decision-making logic for typical GP improvement strategies, shown in Figure 1. Customer orders enter the system randomly and are assigned a set of attributes to define their logical or quantitative characteristics relevant to simulation objective, e.g., order size and arrival time. The orders then flow through three stages where required manufacturing operations are performed. The operations' characteristics (e.g., processing time or energy consumption) are affected by various GP improvement decisions embedded at each stage.

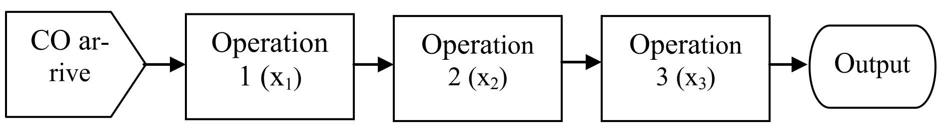

Figure 1: An experimental system designed for GP improvement processes.

Operation 1 has a decision element x_1 that uses substitute materials/parts (measured in the percentage of substitution) for the operation. Using substitute materials reduces scarce resource consumption and generates a material saving, but causes additional processing cost that decreases as the amount of substitution x_1 increases. Original unit cost for Operation 1 is C_{10} (when $x_1 = 0$). When x_1 is increased, it reduces material cost per unit; but also causes an additional processing cost per unit. The more improvement, i.e. more substitute materials used, the lower the material cost per unit of production (e.g., using less expensive materials). But additional processing cost per unit may increase as x_1 increases since more substitution may require additional processing effort (e.g., in some design-for-disassembly applications). This interaction due to different cost drivers can be captured through following unit cost structure:

$$C_1 = \begin{cases} C_{10}, & \text{if} \quad x_1 = 0; \\ C_{10}e^{-\theta_{11}x_1} + \theta_{12}C_{10}x_1^m, & 0 < x_1 \le 1. \end{cases}$$

The first term reflects a gradual reduction of material cost per unit as x_1 increases, where θ_{11} is a coefficient initially set at θ_{11} =1. The second term represents the increase of a unit additional processing cost as x_1 increases, proportional to $\theta_{12}C_{10}$, initially θ_{12} = 0.2. Operation 2 at stage 2 involves a decision x_2= percent change of a process parameter that reduces the operation's energy consumption, but it also causes additional processing delay which in turn increases time-based operational cost, and elongates production cycle time (thus delivery time). Therefore adjusting x_2 reduces energy consumption, which leads to a unit energy saving; but also causes additional delay of the operation, which in turn increases the time-based processing cost at the station. This relationship is captured through following structure:

$$C_2 = C_{20} + \theta_{21}C_{20}x_2 - \theta_{22}C_{20}x_2^{1/n}, \quad n > 1.$$

Where the additional cost due to the additional delay is represented by the second term in the equation; and the energy saving per unit is captured in the third term that increases with a reducing rate, i.e. the increase of energy saving becomes slow as x_2 increases. Note that the additional cost and energy saving term are assumed proportional to C_{20} via coefficient θ_{21} and θ_{22} respectively. The decision x_3 at stage 3 selects a processing method to reduce pollutant emission, with three options: 0 = retain current method; 1= select improved method 1; and 2 = select improved method 2. We assume that the setup and operational cost for three methods are the same. New method 1 and 2 both reduces emission. But due to technical instability, method 1 and 2 have higher defective rate than the current method, leading to a higher defective disposition cost. While the two new methods do improve green performance, they cause higher defective rates due to the instability of new technology based on. In reality many green technologies are suffering from such instability (Li et al. 2010). We define p_0, p_1, and p_2 as the defective rates corresponding to method 0, 1 and 2 respectively; and assume $p_0 > p_1 > p_2$. We further label the unit processing cost for three methods as C_{30}, C_{31} and C_{32}, and assume $C_{31} < C_{30} < C_{32}$. The total cost by an order i of size $O_s(i)$ at station 3 is then given by: $O_s(i)C_{3j} + O_s(i)\,p_j\beta_3C_{3j} = O_s(i)C_{3j}(1+\beta_3p_j)$, for $j = 0, 1, 2$; β_3 is a defective cost coefficient. The total cost by an order of size $O_s(i)$, accumulated over all the three stages, is given by the following formula: $TC(i) = O_s(i)(C_1(i)+C_2(i)+C_3(i))$.

The functions for generating green yield are also defined at different stages. For Operation 1, the green yield R_1 (equivalent CO2E reduction due to material saving) increases as x_1 increases, but in a decreasing rate, i.e. the increasing rate of R_1 is a decreasing function of x_1. This kind of relationship has been observed from a number of green manufacturing applications (Chen 1994; Gungor and Gupta 1999), indicating that the yield from GP improvement saturates beyond some point no matter how much more effort is made. A simple representation of this relationship models $R(\cdot)$ as a quadratic function of x, i.e. $R_1(x_1) = \alpha_1(\text{rate of change of } R_1)x_1 = \alpha_1(\beta_{11} - \beta_{12}x_1)x_1$; where α_1 is a proportion coefficient that transfers energy equivalent quantity (in the unit of *kWh*) into CO2E reduction (in the unit of *kg*) and the rate of change of R_1 is modeled through a linear function with a negative slope: $\beta_{11} - \beta_{12}x_1$, in which coefficient β_{11} and β_{12} transfer material saving into energy equivalent quantity (*kWh*). For Operation 2, R_2 is defined as an equivalent CO2E reduction due to energy saving. It increases initially as x_2 increases, but decreases after reaching a maximum due to the fact that the increase of x_2 also causes additional processing delay (therefore time-based cost), which eventually breaks even with the energy savings achieved. For simplicity the relation is modeled again with a quadratic function, $R_2(x_2) = \alpha_2(\text{rate of change of } R_2)x_2 = \alpha_2(\beta_{21} - \beta_{22}x_2)x_2$; where α_2 , β_{21}, β_{22}, and the rate of change of R_2 (e.g., $\beta_{21} - \beta_{22}x_2$.) are defined similarly as those for α_2 , β_{21}, and β_{22}. The yield for Operation 3 by an order of size O_s is defined as a constant proportional to the processing cost of a chosen method: $R_3(x_3)= \gamma_3(x_3)C_3(x_3,O_s)O_s$ for $x_3=0,1,2$; where $\gamma_3(x_3)$ = a coefficient that transforms the improvement effort into green yield.

2.3 Multi-objective Genetic Search Mode

Although it is possible to implement MOOP via designed simulation experiments, it is generally inefficient and less effective than random search procedures such as genetic algorithm. In this research the genetic algorithm adopted for implementing multi-objective optimization search is a type of NSGA-II (Deb 2009) due to its low computational requirements and parameter-less sharing approach. The chromosome structure was defined as a binary string with thirty genes to represent the three decision variables: the first fourteen genes express the value of x_1, the second fourteen are used for x_2, and last two for the choice of x_3. The fitness function includes two goals: total cost f_1 and total green yield f_2. Note that x_3 is ternary (it assumes only three values: 0, 1, 2) and independent of x_1 and x_2, i.e. the choice of x_3 does not affect the selection of x_1 or x_2 during the search. Therefore in the experiments we can fix the value of x_3 at 0, 1 and 2 respectively and run the search for x_1 and x_2 to obtain the result which would be the same as we run the search simultaneously on all three variables. To ensure the diversity of initial solution population and balance computational effort, we initialize the population through experimental trials and the population size thus decided is 80. A roulette selection was used to select chromosomes, a uniform crossover to perform crossover operation, and a random genes-reverse rule to perform mutation (Gen and Cheng 2000). The new individuals created are merged with parent individuals. A non-domination sorting procedure is used to sort individual solutions, i.e. grouping them into different non-domination Pareto fronts (Murata et al. 1996). The solutions from each front are then selected to join the new population according to a sorted order. Once a new solution is formed, it is decoded into a pair of x_1 and x_2 values, and fed into the simulation model to evaluate the fitness function f_1 and f_2 via an interface routine. The MOGA procedure was coded in C++. User-specified routines were designed to interface the MOGA search module with the simulation model which was implemented with ARENA©.

3 MODELS FOR ANALYZING SYSTEM DYNAMICS

From a system engineering (SE) point of view, an industrial enterprise can be considered as a dynamic system that is interfaced with market demand and consists of production, service, and sustainable development functions. The system functions contain many structural factors that change with time and interact with each other to derive required services and influence overall system behavior. One of the very important system characteristics is the causal relationship between the interacting factors, i.e. the change of one factor causes the change of another. Combining such cause-effect relationship among the factors, we can form so called feedback loops that represent the significant dynamic behavior of overall system. This helps us find out how a production system change when conditions (internal or external) change dynamically at deeper level, and provide useful insight for decision making or policy design.

3.1 Conceptual or Logical Model

A production system under Cap and Trade condition is conceptualized via a graphical model, shown in Figure 2. It highlights the factors which are grouped together to perform the system's functions of interest and exhibit the cause-and-effect relationship under the conditions of a Cap and Trade. For instance, market demand influences positively the production capacity, which in turn influences resource/energy consumption. The more resource consumed, the more CO2E emission generated; which causes higher transaction cost (to purchase extra emission quota) or regulation cost (higher tax for over-emission). The higher transaction/regulation cost harms enterprise's public image and push product price going up, which negatively affects the market demand; but stimulates a higher investment in green improvement. Higher GP investment improves system's green capability, which causes a reduction of CO2E emission. The graph was drawn according to standard SD flow diagram convention (Wang 1994). Rectangular boxes stand for state/level variables; arrows between boxes represent causal relationship between them; and the signs by the arrows define the nature of relationship (positive + or negative -). The arrows drawn in solid lines imply strong relations, while those in dashed lines represent weak or uncertain relations. 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).

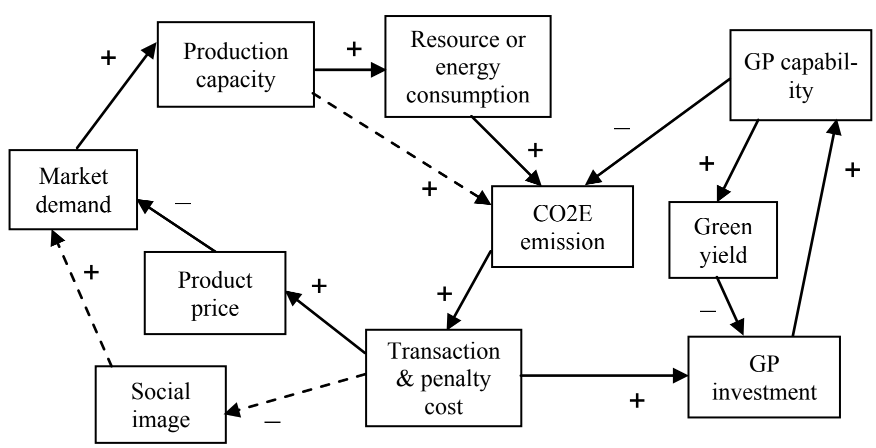

Figure 2: Conceptual model for overall system (cause-effect diagram).

3.2 Simulation Model Development

In the context of SD modeling, we need to convert the conceptual model 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 (Zhong et al. 2009). 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: $S_1(t) = S_1(t\text{-}1)+\Delta t(R_{1I}(t)\text{-}R_{1O}(t))$; Where $R_{1I}(t)$ and $R_{1O}(t)$ are input and output rate functions for flow variable $S(t)$ respectively. $R_{1I}(t)$ defines the rate of increase and $R_{1O}(t)$ defines the rate of decrease of $S_1(t)$. In this problem, $R_{1I}(t)$ is a function of energy or resource consumption (which in turn is a function of production capacity). $R_{1O}(t)$ 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 (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: $S_2(t) = S_2(t\text{-}1)+\Delta t(\alpha f_{21}(t)+(1\text{-}\alpha)f_{22}(t))$; 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 ($1\text{-}\alpha$); and vice versa.

The third flow variable is $S_3(t)$ = Green investment, defined as: $S_3(t) = S_3(t\text{-}1)+\Delta t(f_{31}(t)+f_{32}(t))$; 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 investment of green improvement. 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 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 "*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*) can bring 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.

3.3 Model Implementation

The system dynamic model designed previously was implemented using VENSIM© to validate proposed concepts and structures, and for sensitivity analysis of model parameters. The experimental model simulates a manufacturing system that conforms to the design and structure described in Figure 2 (e.g., a production system with finite capacity, subjected to resource constraints and Cap and Trade conditions, interfaced with market demand, and influenced by green performance and improvement. While several other modeling languages are available, we choose VENSIM© for implementation due to its easy of use and popularity among academia and industry users. The experiments 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 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 deal with over-emission, and *Z* = Production capacity is low (*L*), meaning to adopt a fixed capacity strategy.

4 EXPERIMENTAL RESULTS

In this section, we present the experimental results separately for GP strategy optimization problem (Section 2) and system dynamic modeling and simulation (Section 3). Due to the space limitation, we can only present a small part of the experimental results for each study, and encourage the readers of interest to go in more details through the references (Zhou et al. 2012, Zhou et al. 2013).

4.1 Results on Strategy Selection Problem

Figure 3 showed a plot of the Pareto-optimal solutions obtained for the system described in Section 2 (under a baseline parameter setting), after running the integrated model on a PC for 50 iterations (about 3 hours). The solutions are well compromised with regard to the two optimization goals (f_1 = Total cost and f_2 = GP yield).

Sensitivity analyses for model parameters were performed. Each parameter was changed by ±5%, ±10%, and ±20% respectively around its baseline value, and observed how the changes on the parameter affected simulation outputs and solutions. Due to the limited space, only two plots of the sensitivity analyses were shown in Figure 4, the distribution of Pareto-optimal solutions for parameter C_{10} (left plot) and β_{11} (right plot) under ±5% and ±20% deviation from their baseline values. The pattern exhibited on these plots are consistent with the numerical results, i.e. the changes on C_{10} had no significant impact on f_2, but affected f_1 significantly, and the changes on had no significant influence on f_1, but affected f_2.

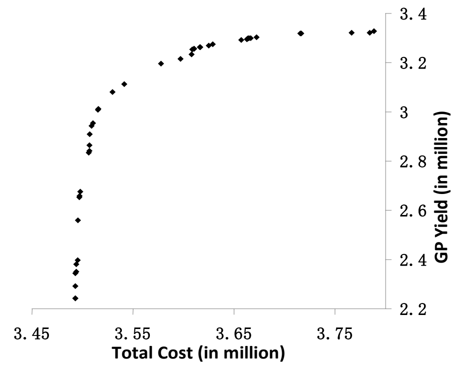

Figure 3: Plot of non-inferior or Pareto-optimal solutions.

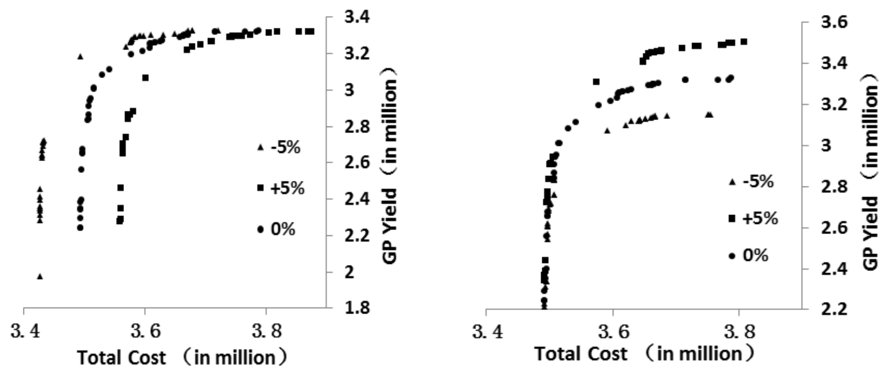

Figure 4: Sensitivity plots of cost parameters.

4.2 Results on System Dynamics Simulation

The simulation results of the baseline SD model were presented through Figure 5 to 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 5 left), causing high over-emissions (Figure 5 right). However after cycle 9, the system entered a period of steady-state in which system's total emission (and over-emission) varies in a relatively stable range.

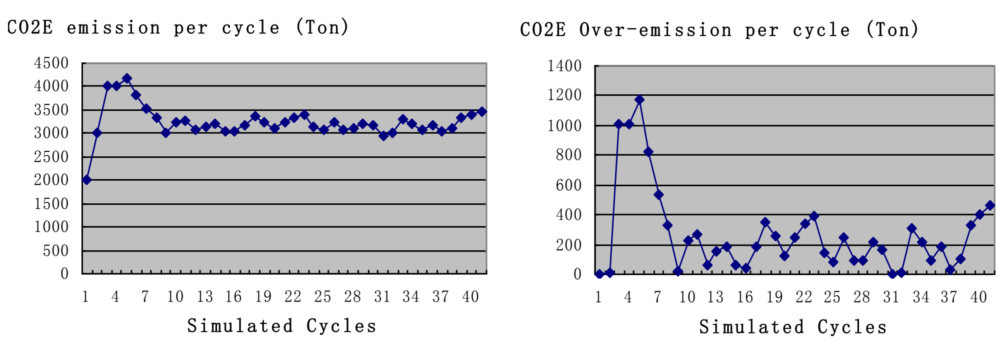

Figure 5: Changes of CO2E total emission and over-emission per cycle.

Figure 6 (right) showed the changes 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 (e.g., green investment, Figure 6 left). It maintained a stable random variation after cycle 9 at a lower level.

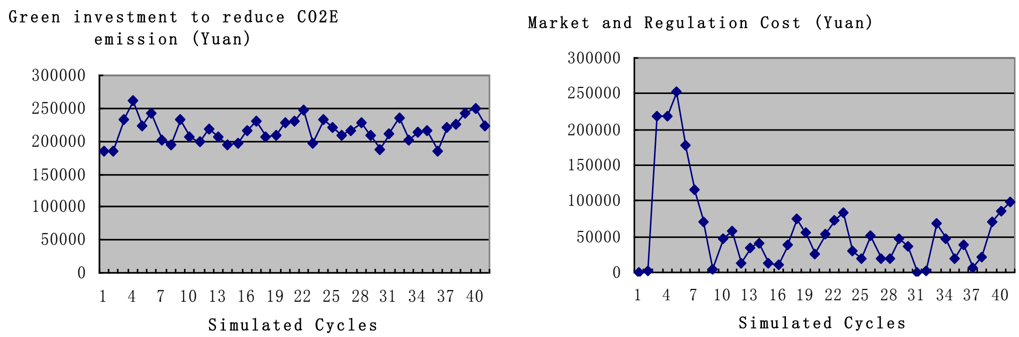

Figure 6: Changes of green investment, transaction and regulation cost.

5 CONCLUSIONS

This paper reported, in a very brief way, an ongoing study in two regards. First it addressed the difficulties in evaluating and optimizing green production strategies by formulating the problem as a multi-objective optimization involving dynamic and uncertain conditions; then proposing an integrated approach to analyze the complicated tradeoffs between production economy and green performance. The method combines simulation with the evolutionary computing to fulfill the task. Simulation models capture production system flow and decision-making logic for GP improvement, and evaluate system performance under prescribed strategies; while an optimization module, designed by incorporating heuristics into a multi-objective genetic algorithm (MOGA), is used to search for better solutions based on the evaluation of the simulation. Secondly the study focused on identification and assessment of the related factors that interact to influence system behavior and the mechanisms that connect and transmit such causal interactions to drive different system behaviors and tradeoffs under dynamic and uncertain conditions, especially under Cap and Trade programs, via system dynamic modeling.

The experimental results (only a small part was reported due to the page limits) provided useful insights to researcher and practitioners. For instance, when the problem is simple enough (e.g., static, single or fewer objectives, without the effect of uncertainties) and the data for parameterzing cost/yield functions available, one can solve the problem directly via a classic analytic method; When dynamic conditions and structural uncertainties associated with the problem and its solution process must be considered, an integrated approach based on simulation and evolutionary optimization can be used to effectively reduce modeling difficulty and improve solution quality and efficiency. At a more strategic level, system dynamic models can help enterprise decision-maker evaluate the effect of different factors caused by the new conditions, e.g., Cap-&-Trade program, design and evaluate different strategies. It also provided insight to government policy makers on designing or improving regulation rules to more effectively control the damage to the environment without discouraging enterprises to pursue a healthy economic growth. The methods and models proposed are robust and flexible, and can be extended to many applications where the differences primarily lie in system parameters or parameterization, which often poses serious difficulty for analytic methods. With growing maturity of simulation technology and evolutionary computing, the software implementation of the proposed integration should minimize the developmental effort on the functional modules (e.g., DES simulation model and MOGA model).

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