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Research Article

Research on the System Dynamics-based Tripartite Evolution Game Models for Environmental Regulation in Food Producing Enterprise

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Abstract: This study, based on the relationships and the evolutionary game theories among Food processing Enterprise, enterprises and the integrated social benefit, builds two system dynamics-based tripartite evolutionary game models for Food processing enterprise environmental regulation-static punishment model and dynamic punishment model. By imposing varied policy strategies on the two models, including adjusting "Budget of pollution inspection", adjusting “Reward for no pollution discharge”, adjusting “Enterprise production gain”, adjusting “Punishment coefficient” and combine the adjustment schemes, this study observes the changes in the action and the value in the two models. Finally, the author compares and analyzes the operation of the two models under the same policy strategy. The result shows that the loss of the integrated social benefit and the type of punishment mechanism will have a significant impact on the selection of the environmental regulation strategies. However, compared with the single strategy, the combination of policy strategies can make greater efforts in promoting the environmental regulatory model to achieve the "ideal state".

Keywords: Environmental regulation, evolutionary game, food processing enterprise, policy strategy, system dynamics

INTRODUCTION

As an important concept in evolutionary game theory, evolutionary equilibrium strategy is defined as: a strategy is evolutionarily stable if, relative to its population, it performs better than any new and invading strategy. However, the evolutionary strategy is not necessary for the evolution game. In some evolution games, there is no evolutionary equilibrium strategy and there will be dynamic circulating oscillations among different strategies during the evolution games. Therefore, this study focused on the dynamic oscillations of same participants under the different policy strategies and the dynamic impact of different policy strategies on participants in their choice of strategies.

In the issue of Food processing Enterprise regulation of environmental policy and business, when selecting their strategy, Food processing Enterprise and enterprises show the following two characteristics (Chen and Chang, 2014): Interactive feedback and Applicability. Due to these characteristics, this study uses system dynamics as the research tool. As system dynamics concerns the system structure, it can better reflect the relationships between stakeholders inside and outside the system and can also simulate and evaluate the impact of different policies in different circumstances. In recent years, many research people, by using the dynamic, long-term, feedback, adaptability and situational characteristics of the system of system dynamics, have applied system dynamics in many research areas (Dutta *et al*., 2014; Kim and Park, 2010; Kim and Kim, 1997). Similarly, these characteristics of the system dynamics can make great contribution to the modeling and analysis of the strategies of the stakeholders in the evolutionary game. Therefore, researchers should also try to combine the system dynamics and game theory, especially the evolutionary game theory (Li and Duan, 2013; Shih and Tseng, 2014; Sice *et al*., 2000; Tian *et al*., 2014; Wang *et al*., 2011).

And Wang’s model has been developed by introducing the whole society as a third party in the model of the game system of the Food processing Enterprise and corporate environmental policy. And he also made policy simulation for the developed model and therefore revealed that under the two punishment mechanisms, namely, the static punishment mechanism and the dynamic punishment mechanism, the responses of Food processing Enterprise, enterprises and the integrated society and therefore analyzed the feasibility of different strategies under different punishment mechanisms.

Models: This study uses Vensim DSS 6.1c to establish system dynamics static punishment model and dynamic

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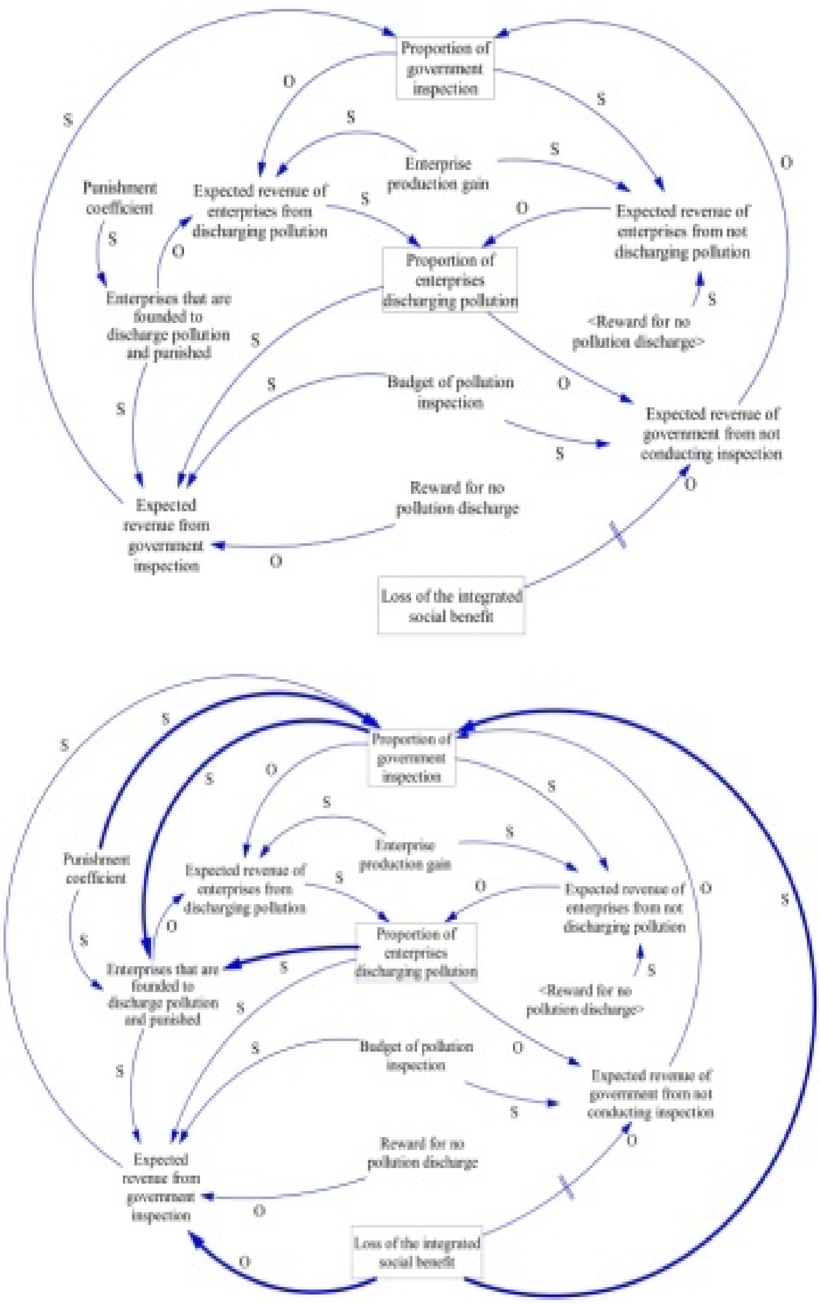

Fig. 1: Casual feedback diagram for the models

punishment model of Food processing Enterprise-enterprise-social environment problem evolutionary game, respectively. Figure 1 are the casual feedback diagrams of the static punishment model and dynamic punishment model, respectively.

We can find the two models are mainly different in the following aspects:

- Whether the change in "Loss of the Integrated Social Benefit" (LISB) will exert a direct impact on the "Proportion of Food Processing Enterprise Inspection" (PGI). If there is a direct impact, it is dynamic punishment; otherwise it is static punishment.
- Whether the variable "Enterprises that are Founded to Discharge Pollution and Punished" (EFDPP) is a fixed value. If this variable is a fixed value, it is static punishment; otherwise it is dynamic punishment.

MODEL RUNNING RESULTS

Result of static punishment model:

Running results of raw values: After the model runs, the changes of the variables "Proportion of Enterprises

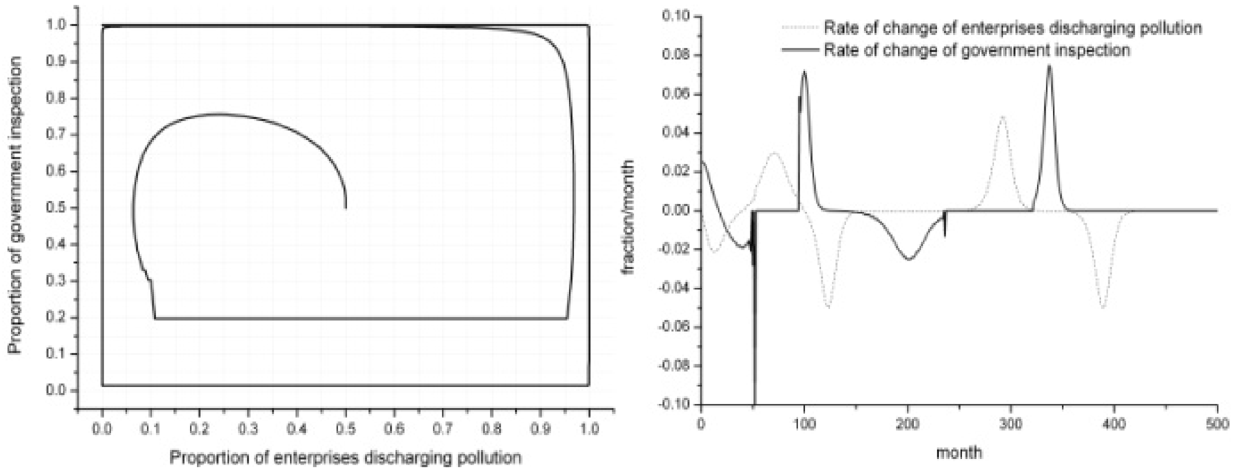

Fig. 2: Changes of raw values in the static punishment model

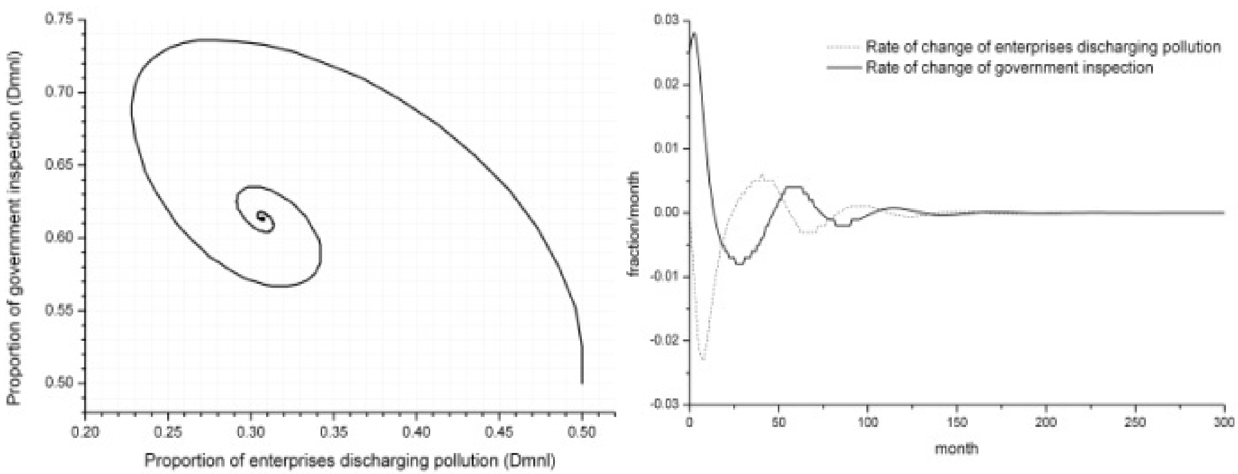

Fig. 3: Changes of raw value in the dynamic punishment model

Discharging Pollution"(PEDP), "Proportion of Food Processing Enterprise Inspection"(PGI), "Rate of Change of Enterprises Discharging Pollution"(RCEDP) and "Rate of Change of Food processing Enterprise Inspection"(RCGI) during the simulation are shown in Fig. 2. The change amplitudes of RCEDP and RCGI after the 500th simulation are both approximately 0, so Fig. 2 just shows the result of the first 500 simulations.

Running results of policy and strategy:

Adjust the "Budget of Pollution Inspection" (BPI): After the value of BPI is adjusted, the model can reach equilibrium point after different times of simulations, but the values of equilibrium points are different. Besides, after the value of the variable BPI is adjusted, the value of the variable LISB will form a great prominence during the game simulation and its peak is very huge. It is important to notice that after the value of BPI increases to 0.6, the equilibrium point of game simulation will reach (1, 1) and then, the times of game simulations needed to reach equilibrium point reduces to 449.

Adjust the "Reward for No Pollution Discharge" (RNPD): Increase or decrease the value of variable RNPD from 0.2 with a step size of 0.1. When the value of RNPD decreases to 0, the value of the variable LISB will become very huge, which will cause that the value calculated by the system exceeds the number range of the variable the software defines. When the value of RNPD decreases to 0.2, the model reaches equilibrium point, but the equilibrium point is not ideal and the value of the variable LISB will experience a very huge peak. When the value of RNPD is 0.6 or above, the model can reach equilibrium point (1, 0) after different times of game simulations. At that time, the peak value of LISB is relatively low.

Adjust the "Enterprise Production Gain" (EPG): When the value of EPG is gradually decreased to 0.0, the behavior and value of the model does not change significantly. When the value of EPG is gradually increased to 1.0, the model can reach equilibrium point (0, 1) and in the gaming process of reaching equilibrium point, the value of the variable LISB will experience a very huge peak. And there is another interesting phenomenon that when the value of EPG increases to 0.61 from 0.6, the times of evolutionary game stimulations needed to reach equilibrium point greatly changes: when the value of EPG is 0.6, the model only needs around 433 game simulations to reach equilibrium point, but when the value increases to 0.61, about 944 game simulations are needed for the model to reach equilibrium point.

Adjust the "Punishment Coefficient" (PC): After the value of PC is adjusted, compared to the raw value, the model behavior does not change significantly and only the relevant values change.

Combine the adjustment schemes: With the optimization function of Vensim DSS, define the optimization objective as the minimum value of PEDP and LISB and the adjusted variables are RNPD, EPG and PC. After the optimal calculation simulation, the following optimization adjustment scheme is obtained: increase the value of the variable RNPD to 0.4 and that of the variable PC to 2. After the model values are adjusted according to the above optimization scheme, the model reaches equilibrium point (0, 1) after 653 game simulations and the peak value of the variable LISB is only around 75. Compared to the raw value and the results after the adjustments of other variables, this result is relatively ideal.

Results of dynamic punishment model:

Results of original numerical value operation: After the operation of the model, the changes in PEDP, PGI, RCEDP and RCGI during the simulation period are showed in Fig. 3.

Results of policy and strategy operation:

Adjustment of BPI: In the dynamic punishment model, after the adjustment of the numerical value of BPI, the comparison between the changes in PEDP, PGI, RCEDP, RCGI and LISB and the results of the

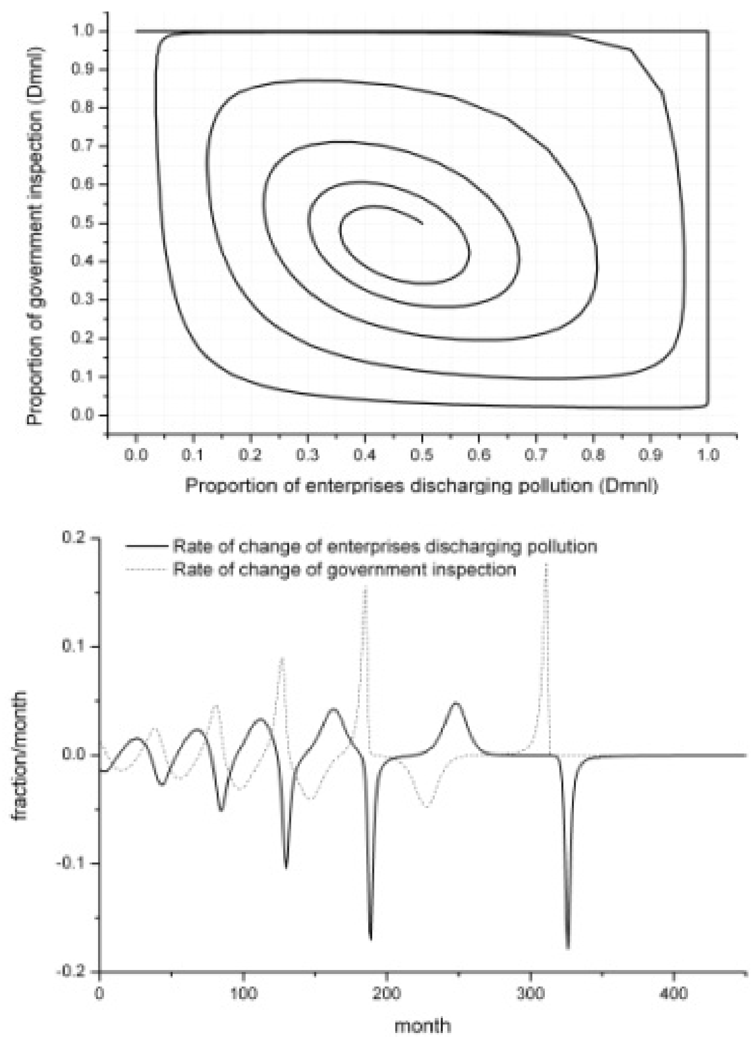

Fig. 4: Adjustment of RNPD in the dynamic punishment model

operation of original numerical value of dynamic punishment model concludes a relatively obscure change.

Adjustment of RNPD: In the dynamic punishment model, when the value of RNPD improves to 0.2, the changes in numerical value of PEDP, PGI, RCEDP, RCGI are listed in Fig. 4. When the numerical value of RNPD reaches 0.3, the value of LISB may have a sharp increase and outnumber the system calculation value to the range of variable value defined by the software.

Adjustment of EPG: Where the numerical value of EPG is increased, the comparison between the numerical value of other variables and the original numerical value of dynamic punishment model remains unchanged; where the numerical value is reduced, the final equilibrium point still remains unchanged; however, the numerical value of LISB declines from the initial point. Only the game simulation times required by the one reaching the game equilibrium point show a limited increase.

Adjustment of PC: If the PC is adjusted, the game equilibrium point begins to come closer to (0, 0) point along with the increase of the PC. When the numerical value of PC is 10, the game equilibrium point reaches (0.173, 0.346); and in the process of adjusting the numerical value of PC, the LISB declines from the initial point.

DISCUSSION

- Both of the raw value and different policy strategies, the static punishment model can not deal with the problem of the integrated social benefit which is huge losses, while the dynamic punishment model can lower the amount of loss of the integrated social benefit with both of the raw value and different policy strategies.
- Effected by the policy strategy of adjust BPI, adjust RNPD and adjust EPG, both of the static punishment model and the dynamic punishment model can not make the model achieve to the acceptable ideal status.
- The policy strategy of adjusting PC express great different between the static punishment model and dynamic punishment model. Sometimes it can improve the system and sometimes disaggregate the system. Consequently we should make sure the system's style and operational aspect when decide to use the policy strategy of adjusting PC.
- The combined policy strategy of raising RNPD and PC can impactfully improve the expression of the model under the static punishment model and dynamic punishment model and make it near to the ideal status. But the expression will be more demonstrable under the dynamic punishment model.

CONCLUSION

This study's correlation models which are building in system dynamics have expressed the related situation of the tripartite party benefits and reach the conclusion that tripartite part's benefits greatly effect the feasibility of the policy strategy. Therefore, the benefit of tripartite parties relevant information on the evolution of environmental protection issues should be pay attention to and reflected in the relevant model. Only by doing this, can you make the actual effect reach to the desired effect (Wang *et al*., 2008).

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