From Loop Dominance Analysis to System Behaviors

Ya-tsai Tseng
Department of Business Administration,
Tunghai University, Taichung, 407, Taiwan, R.O.C.
886-4-23590121 ext 3506
yttseng@mail.thu.edu.tw

Yi-ming Tu
Department of Management Information System,
National Sun Yat Sen University, Kaohsiung, 804, Taiwan, R.O.C.
886-7-5252000 ext. 4717
ymtu@mis.nsysu.edu.tw

Abstract

Causal links is the most fundamental building block complex and nonlinear systems. Instead of loops and pathways used often in most loop dominance research, this paper develops a causal-link based analysis approach to identify dominant structures. In the technique aspect, the rationality is to avoid the problem of linearization. And in the practical concern, the purpose of the causal link analysis is to design an analysis logic and procedure that is easy for practitioners to understand and follow. The analysis procedure can be applied to all kinds of model variables and simple spreadsheet software is enough for analysis. The proposed analysis approach is validated in this paper to examine the explanation power of behaviors and capability of facilitating policy designs. Although the causal link-based analysis is new to loop dominance analysis, this paper still represents an integrated work of previous research in the development and validation process of the proposed approach. Further research directions are proposed at the end of the paper.

Motivations

Loop dominance analysis is central to system dynamics study and practice. The term dominant loop is widely accepted as "some subset of the stock-and-flow/feedback structure of a model that is principally responsible for a particular pattern of model behavior" (Richardson, 1986). Loop dominance analysis explores the relationship between model structures and behaviors. Ultimately, the purpose of the loop dominance analysis is to facilitate people's understanding of the modeled system and illuminate directions for policy designs. However, This study assumes that people are willing to believe in a loop dominance analysis result and follow the proposed policy redesign suggestions only if they have a certain degree of confidence of the analysis approach. For practitioners and managers with few system dynamics knowledge or few mathematic computation skills, how to develop a loop dominance analysis approach that is friendly to its users but also offers excellent loop dominance analysis results is a practical problem to system dynamics research.

To enhance people's understanding and confidence in the model structure and simulated behaviors, a loop dominance analysis approach should satisfy several requirements. First, the logic of the analysis approach should be easy enough to be understood. That means an approach with too complex computation processes or in too abstract mathematic representation forms is not so appropriate for people to apply. Several loop analysis approaches employ the techniques of eigenvalue analysis and transform model structures to matrices of coefficients (N. Forrester, 1982; 1983; Eberlein, 1984). The advantage is the techniques used are distinct and well developed in classic control theory. However, to represent model structures as matrices of coefficients and model behaviors in a pure mathematic form may lose some physical meanings. And it may be rather unfamiliar and difficult for system stakeholders to understand. In turn, it may influence practitioners' or even modelers' confidence on the analysis.

The second feature of an applicable analysis approach is the analysis process should be easy to be manipulated and followed. There are several ways to satisfy this requirement. Ford (1999) escapes the maze of gain computation tasks common in loop dominance analysis by developing a behavioral analysis approach. The behavioral approach identifies dominant loops by activating and deactivating subsets of feedback structures. The logic of the Ford's behavioral approach is quite simple and easy to follow up. However, in large and complex models, to manipulate feedback structures iteratively may be a burdensome work. One important way to simplify the manipulation of an analysis approach is to automate it. As Richardson (1986) mentions, "…. Thus, the first necessary step is the creation and dissemination of simulation software….". Automation software would be quite convenient for people to analyze their models. *Digest* is software designed to execute the computation of pathway participation matrix developed by Mojtahedzadeh (1999). Because of the simpler logic than previous control theory based approached and the automation of computation process in *Digest*, Mojtahedzadeh's pathway participation technique is a quite nice analysis approach in considering practicability.

Although the pathway participation technique is good for its simple logic and easy operating procedures, the critical step of linearization in the pathway participation analysis has a serious potential problem with it. As Mojtahedzadeh says, "the computation of pathway participation metric requires linearizing the system at every time interval, dt, and identify feedback loops and pathways that are involved in generating the behavior of the variable of interest. The proposed method for computing pathway participation metrics is rather time consuming for computers. As a result the search for a better algorithm to identify related feedback loops and pathways and to calculate pathway participation metrics is essential." (Mojtahedzadeh, 1999). This is not only the problem of the pathway participation technique but also a matter bothering all eigenvalue-based approaches. Richardson mentions that: "…Mathematical approaches to determining dominant structure apparently have promise in linear model. Nonetheless, using linear approaches in nonlinear models raises a number of problems and unanswered questions…Can linearization be performed about successive operating points quickly enough to make eigenvalue or frequency response methods feasible in large models… Under what conditions would such linear techniques in a nonlinear model be seriously misleading…Under what conditions can the formal linear techniques be trusted in nonlinear systems?" (Richardson, 1986) To answer the above questions directly may take a great effort. But there is another way to dissolve the problems arising from linearization. That is, to analyze dominant structures without linearization! How to identify dominant structures in avoidance of linearization yet retain the advantage of simple analysis logic and procedure is the objective of this paper.

To solve the linearization problem, causal links, instead of pathways or loops, is to be the unit of analysis in the loop dominance analysis approach proposed in this paper. The reason for this paper to use causal links as the unit of analysis is rather straightforward. The nonlinearity of system dynamics models comes from the interactions of causal links between variables. Because loops and pathways are the products of causal link interactions, to employ loops or pathways as the unit of analysis must have to face the nonlinearity accompanying with loops and pathways. Hence, the simplest way to resolve this problem is not to use loops and pathways to be the unit of analysis. Skeptics may doubt the applicability of use causal links as the building block of a loop dominance analysis, for there may be a huge number of casual links in a model. To compute each causal link's impact on the variable of interest and make a complete comparison of those impacts could be a more labor-extensive work than linearization. Indeed, at the first glance, it seems to most people that to analyze pathways or loops may be more efficient than to analyze causal links. After all, the number of causal links in a model is definitely larger than the number of pathways or loops.

However, to analyze greater numbers of causal links does not necessarily imply more time consuming or labor extensive computations, especially in complex models. Highly complex mathematic computations are needed to linearize high order nonlinearity. Errors and biases may exist unavoidably. Because causal links are the relationships between any two variables, the comparison of the strengths of each links regarding the variable of interest can be done directly. Besides, other than the original model structure information, no further information is needed in causal link-based analysis. That's because information about the strengths of causal links regarding to the variable of interest can be derived directly from the values of causal variables and the effect variable. Hence, common system dynamics simulation engines plus spreadsheet software are enough to start a causal link-based analysis. Simple computation procedures and easy access of computer software make the proposed causal link-based analysis neither difficult nor time-consuming at all. Besides, unlike loops or pathways analysis, it clearly points out the most influential links and thus the sensitive parameters regarding to the variable of interest. For model builders, the identification of sensitive parameters not only makes validation about sensitivity testing easier but also facilitates parametric-level high leverage designs. What is more important is the causal link-based analysis is much easier for practitioners to understand because of the removal of linearization process. The easily understood logic is quite important in facilitating people to trust in the analysis results.

The rest of this paper is organized as followed: the next section describes the analysis logic and procedure of the analysis approach developed in this paper. Some examples are used to illustrate the analysis procedures and some validations are also done in later sections. Brief discussions and conclusions are at the last section.

Analysis Logic and Procedures

Identifying the most influential causal links

The basic logic of the causal link-based analysis approach proposed is to measure and compare the strengths of each causal link that coming into the variable of interest. That is, compute each casual variable's influence on the variable of interest to identify the variable with relative higher impact during a specific period of time. Notify that the term "casual variable" is restricted to variables with direct links to the variable of interest. Variables with indirect impacts have to impact the variable of interest via other links and they are not causal variables defined here. The measurement of the strength of a causal link is the product of the absolute value of the partial derivative of the effect variable with respect to the causal variable multiplies the causal variable's change during a specific time period. For example, x and y are the effect variable and causal variable respectively. XRate is the change of variable x. The impact of y over x is computed as the following equation.

$$abs(\frac{\partial XRate}{\partial y})*(\frac{dy}{dt}) \tag{1}$$

The use of the function abs () is to acquire the absolute value of the parameter inside the parenthesis. The first part of equation (1) measures the contribution of variable y to the change of variable x. With the function abs(), the information acquired is pure information about the intensity of the impact, excluding the direction of the impact. The second part of the equation measures y's change during a small period of time, dt. The complete equation measure x's total change caused by y's change during time period, dt. To identify the strongest links and the most influential variables, one needs just to apply equation (1) to each causal variable that has direct link to the variable of interest. The variable that causes the greatest change of the variable of interest is the most influential variables.

According to the analytic logic discussed above, the operational procedure developed in this paper is not a standard mathematic computation aimed to derive analytic solutions. Rather, the way to acquire the information about the impact of causal links to the variable of interest is a stepwise procedure. The impacts of causal variables at are calculated for every simulation time point. The operational computation of equation (1) is the calculation of the difference between the values of the effect variable with and without the change of the causal variable during time t and time t+dt. The difference calculated is then used to disclosures the amount of impact of the causal variable's change during time period, dt, on the effect variable. The partial derivative in the equation (1) is capsulated in the calculation of the difference of the value of the effect variable and the first order derivative of the causal variable with respect to time is implied in the change of the value of the causal variable in the time period of time t and time t+dt.

To facilitate reader's understanding of the analytic logic, a simple model with two causal variables, Y and Z, and one effect variable XRate is used to an example for illustration. Figure 1 is the model structure and Table 1 is basic information about variables. Computations to identify the most influential link are as below.

Table 1 Value of variables in Figure 1

	Time 0	Time 1
Variable Y	100	90
Variable Z	120	110
Variable XRate (3*Y-2*Z)	60	50

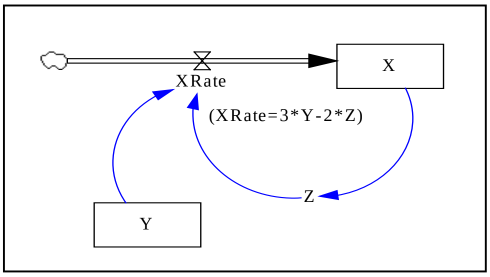

Figure 1 A simple example

XRate 1=3*Y(t+dt)-2*Z(t)=3*90-2*120=30 (2)

XRate 2=3*Y(t)-2*Z(t+dt)=3*100-2*110=80 (3)

abs((XRate 1-XRate(t))=abs(30-60)=abs(-30)=30 (4)

abs((Xrate 2-XRate(t))=abs(80-60)=abs(20)=20 (5)

For abs((XRate 1-XRate(t))=30 > abs((Xrate 2-XRate(t))=20, thus we can conclude that variable Y has greater impact over variable XRate than variable Z during the period between time 0 and time 1.

The above descriptions discuss the identification of the most influential links to the variable of interest. However, to identify the most influential causal links is not the ultimate purpose of loop dominance analysis. The purpose of a loop dominance analysis is to find out the feedback structures that have the greatest impact in generating system behaviors. Based on the causal link analysis procedures discussed, the analytic logic to identify dominant feedback structures is developed further.

Identifying dominant structures

With the causal link analysis procedures discussed above, one can identify the most influential casual variable and its link to the variable of interest. If the causal variable identified is not an exogenous variable or a constant variable, it must be influenced by other variable(s) while impacting the variable of interest. Identify the most influential causal variable for the influential identified can constitute a cascading series of influential links. Then the cascading influential links is the dominant structure. This paper employs a backward chaining policy to identify the influential cascading series of links. Start from the variable of interest and trace back to analyze causal variables with direct links to the variable of interest, rather than start from the causal variables and trace forward to the effect variable. The advantage of the backward chaining is the number of links that needs to be analyzed and compared can be reduced dramatically. There's no need to calculate the impact of every causal variable of the variable of interest. Only the strongest link(s) needs to be considered to be part of the dominant structure. In fact, in some circumstances, the variable under analysis may be influenced by one single causal variable. Under such a circumstance, one can bypass the variable under analysis directly and continue the analysis to the causal variable to trace backward.

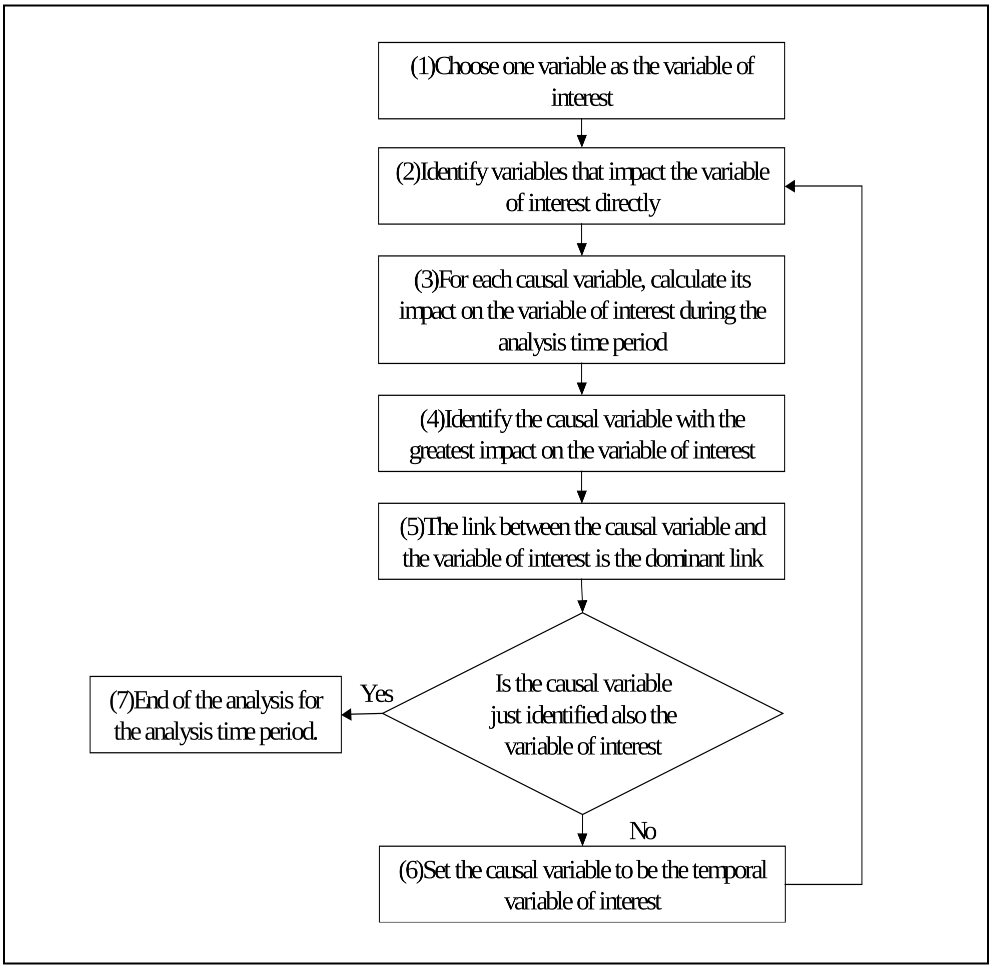

Figure 2 Causal link-based loop dominance analysis procedures

Figure 2 illustrates the casual link-based procedure to identify dominant structures. The procedures start from the location of the variable of interest. Identify the variable with the greatest direct impact on the variable of interest is. The causal link that connect the causal variable identified and the variable of interest is part of the dominant structure that contribute most to the pattern of the variable of interest. Then, set the causal variable to be the temporal variable of interest in the purpose of tracing back the dominant structure. Follow the previous analysis steps to find out the most influential causal variable and links with direct impacts on the temporal variable of interest. Repeat the above procedures iteratively until the analysis procedure meets the original variable of interest again. Notify that the analysis is to identify the dominant structure for a specific variable during a specific period of time. Hence, the above analysis procedures have to be executed for every time unit.

The causal link-based loop dominance analysis procedures can be applied to all kinds of variables, including level variables, rate variables, and auxiliary variables. Although links from level variables to rate variables are different from the links from rate variables to level variables, the analysis procedures can be applied to variables that may be influenced directly or indirectly by both kinds of the two links. For example, to analyze the dominant structure for a level variable, one just needs to identify which rate variable has greater impact on the level variable and then find out the link that impacts the rate variable most. For illustration, the simple urban model is analyzed. Different from the original model, the critical factor/variable Area that limits the model's pattern of growth is reformulated to change from the original value of 5000 arcs to 3000 arcs in year 50. The dramatic reduction of area shows a more severe environment for the model's growth.

A simple urban model

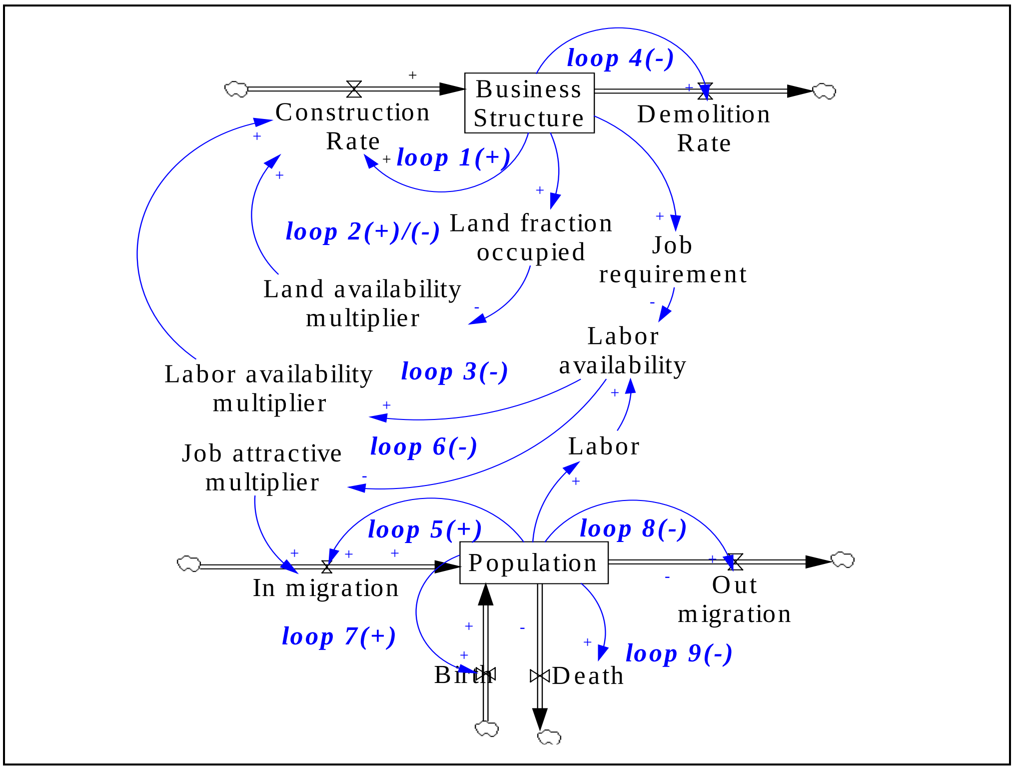

Figure 3 Model structure of the simple urban

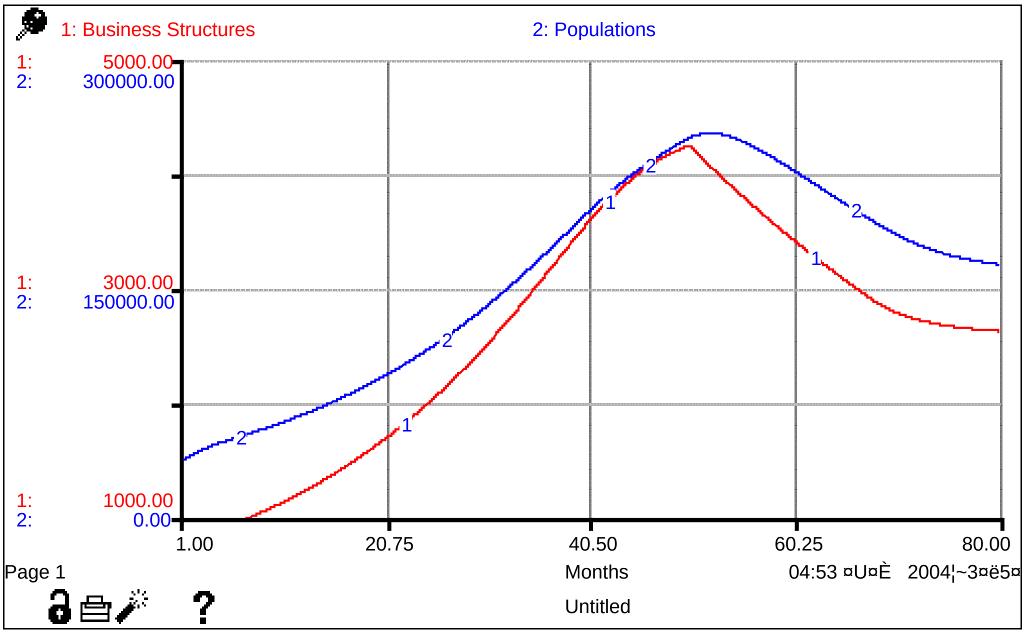

Figure 4 Simulated behavior of the simple urban model

Figure 3 shows the model structure and loops are identified and numbered. There are two level variables in the model: Business Structure and Populations. The total simulation period ranges from year 1 to year 80. DT is set to be 1 year. Simulated behaviors of the two level variables are plotted in Figure 4. The causal link-based analysis approach is applied at each time unit to identify which loops have the greatest impact on variable Business Structure and variable Populations respectively.

To variable Business Structure, there are two causal variables. One is Construction Rate and the other is Demolition. We start the analysis from time 2 to observe if there's any difference between the impacts of Construction Rate and Demolition when each variable changes from year 1 to year 2. Related computations are briefly listed below:

*Business Structures(t)=Business Structures(t-dt)+(Construction Rate-Demolition)*dt*
INIT Business_Structures = 1000 (6)

Impact of Construction Rate from year 1 to year 2 is:

ABS((BusinessStructures(1)+ConstructionRate(2)-Demolition(1))-(BusinessStructures(1)+Construction Rate(1)-Demolition(1)) (7)

Impact of Demolition Rate from year 1 to year 2 is:

ABS((BusinessStructures(1)+ConstructionRate(1)-Demolition(2))-(BusinessStructures(1)+Construction Rate(1)-Demolition(1)) (8)

For the value derived from equation (7) is greater than the value derived from equation (8), Construction Rate has greater impact on the variable of interest Business Structure and thus the causal link from Construction Rate to Business Structure is the dominant link during year 1 to year 2. Then, Construction Rate is set to be the temporal variable of interest to be analyzed. All other causal links and other variables with direct impacts on Business Structure can be skipped in the analysis process. Repeat the same procedures iteratively until the temporal variable of interest is set back to the Business Structure. The analysis result is shown in Figure 5.

Note that during time period of year 1 to year 3, Labor Availability Multiplier becomes the temporal variable of interest. Theoretically, one has to calculate the impacts of all causal variables on variable Labor Availability Multiplier. However, only Labor has direct impact on the temporal variable of interest. The computation and analysis tasks for Labor Availability Multiplier can be bypassed. Figure 6 represents dominance analysis result for the level variable Populations. The analysis procedures are all the same as for Business Structure. Table 2 summarizes the analysis results of the two level variables in the simple urban model.

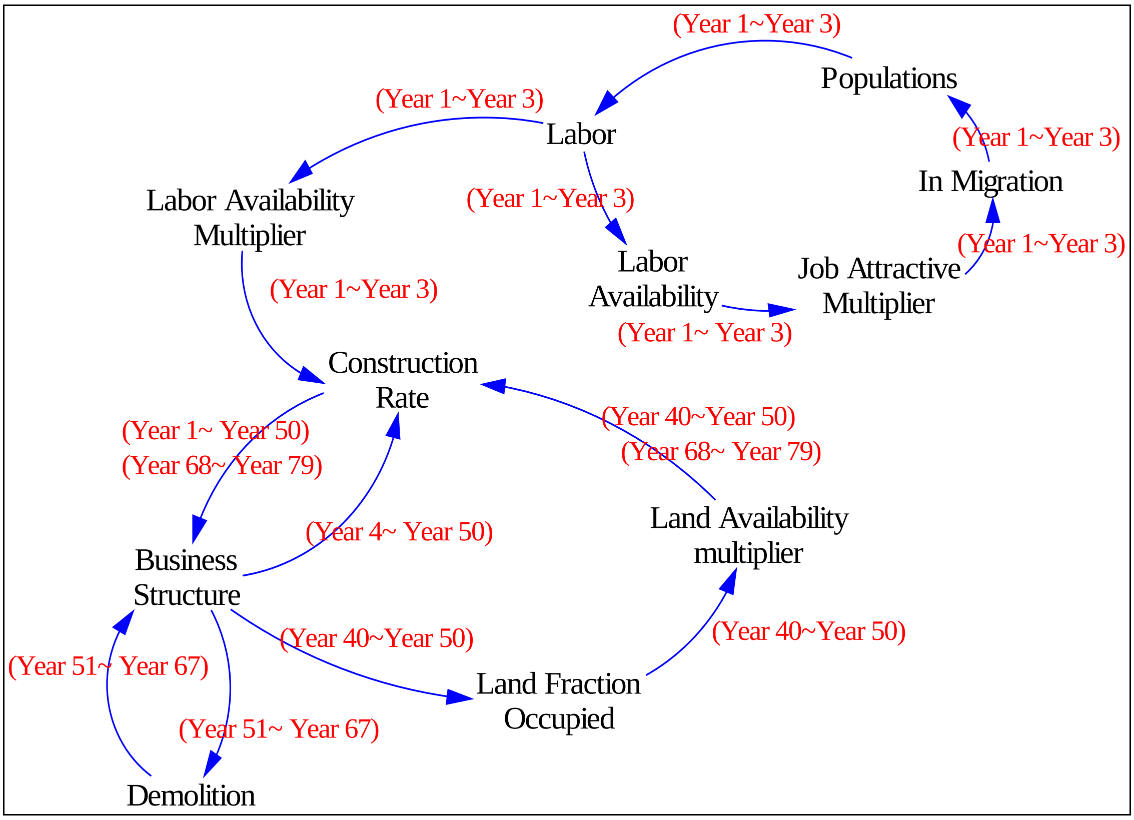

Figure 5 Dominant Structures of variable Business Structure

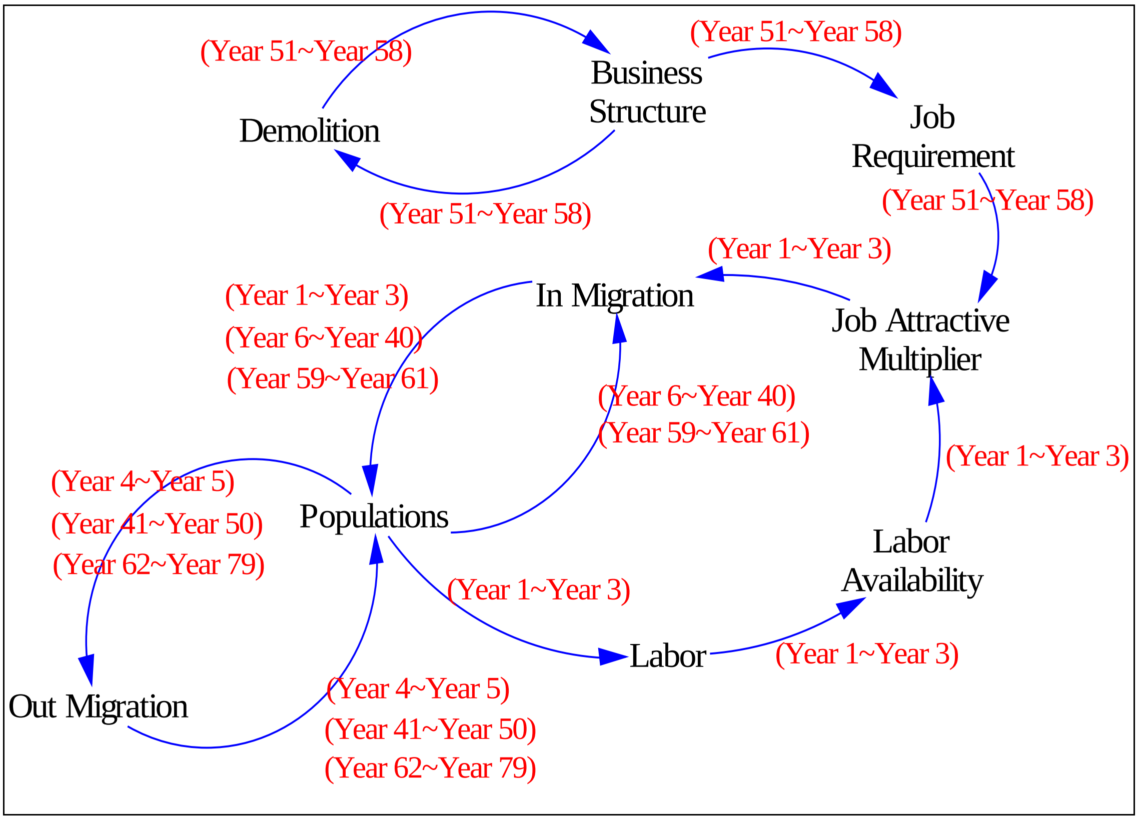

Figure 6 Dominant Structures of variable Populations

Table 2 Summary of analysis result

Variable of interest: Business structure		
Time	Dominant structure	Polarity
Year 1~Year 3	Loop 6	-
Year 4~Year 39	Loop 1	+
Year 40~Year 50	Loop 2	-
Year 51~Year 67	Loop 4	-
Year 68~Year 79	Loop 2	-
Variable of interest: Populations		
Time	Dominant structure	Polarity
Year 1~Year 3	Loop 6	-
Year 4~Year 5	Loop 8	-
Year 6~Year 40	Loop 5	+
Year 41~Year 50	Loop 8	-
Year 51~Year 58	Loop 4	-
Year 59~Year 61	Loop 5	+
Year 62~Year 79	Loop 8	-

Validations of the proposed analysis approach

As stated at the beginning of this paper, the ultimate purpose of a loop dominance analysis is to facilitate people's understanding of a modeled system and illuminate directions for policy designs. This section validates the analysis approach developed in terms of these two purposes. The validation is also accompanied by a comparison with another loop dominance analysis approach: the pathway participation technique developed by Mojtahedzadeh (1997). The pathway participation technique is selected for several reasons. First, both of the two approaches start the analysis by selecting the variable of interest where later analysis is focus on. Second, they use the same way toidentify dominant structures. That is, to compute the gains of the units of analysis (in spite of different units of analysis and computation algorithms), rather than identify dominant structure from a behavioral perspective like Ford (1999). Third, both approaches can be applied in all kinds of variables. And fourth, there is software, *Digest*, developed for the pathway participation analysis available that can facilitate the comparison. The validation and comparison works are completed in the simple urban model discussed in the previous section.

The explanation power of simulated behaviors

According to Mojtahedzadeh (1997) the first derivative of a variable determines whether it experiences a growth or a decline pattern and the second derivative of the variable with respect to time reveals the curvature of the variable at any point of time. There are six combinations of the information of slope (steepening, linear, or flattening) and curvature (growth or decline). Each combination characterizes a different time varying behavior. Mojtahedzadeh employs the derivative of the net changes in the level variables with respect to the level variables to acquire the information about the polarity of the feedback loops and to derive the information about the mode of the behavior of variables. The information about the mode of behavior of variables is implied in what Mojtahedzadeh calls "total participation measure (TPM)". The polarity of the dominant loop identified should be consistent with the sign of the total participation measure in the time interval under analysis. The consistence of the dominant loop's polarity with the sign of TPM is used in this paper to validate the identified dominant structure's ability to explain simulated behaviors. To validate the causal link-based approach's power to explanation behavior patterns, the first step is to examine the consistence between the polarity of the identified dominant loop and the sign of the TPM calculated by the software *Digest*. Then the second step is to examine whether the dominant loops identified by the causal link-based analysis and the pathway participation technique are the same. If there exists differences of identified dominant loops, further experiments will be arranged to identify which analysis approach accounts simulated behavior better by deactivating the dominant structure identified to observe the changes of time patterns due to the deactivations.

Analysis results for Business Structure by the two analysis approaches are shown in Table 4. It reveals that both of the two analysis approaches identify dominant loops that are consistent with the signs of the TPM during the whole analysis period. The proposed causal link-based analysis approach bypasses the first stag of the behavioral validation. Then, ignoring minor analysis variations that may due to computation biases, further examinations also reveals that in most of time, the two analysis approaches identify the same dominant structures except the time period from year 4 to year 35. About the time period from year 4 to year 35, a major analysis gap exists between the proposed approach and the pathway participation technique. The time pattern of Business Structure during this period is steepening growth. The growth engine identified by the causal link-based approach is a self-reinforcing loop driven mainly by Business Structure itself (loop 1). But by the pathway participation technique, the major driving force does not come only from Business Structure or Population. It is the cross-reinforcing loop constituted by both Business Structure and Populations dominating the exponential growth of Business Structure and Populations. That is the expanded loop composed of loop 3 and loop 6. To examine which loop identified has greater explanation power, the deactivations of loop 1 and loop 6 are experimented respectively below.

The experiments are based on the behavioral loop dominance analysis (Ford, 1999). The behavioral analysis uses changes in atomic behavior patterns to signal dominance. There are three atomic behavior patterns: linear behavior, exponential behavior, and logarithmic behaviors. If the atomic behavior of variable of interest changes in deactivating some specific loop, the deactivated loop is identified to be dominant in generating the behavior pattern of the variable of interest. Loop 1 and loop 6 are deactivated respectively to find out the loop with higher impact on variable Business Structure. The variable Construction Rate is reformulated for each experiment as below. Experiment results are shown in Figure 7.

Table 4 Analysis results for Business Structure of causal link- based analysis and pathway participation technique

Causal link-based Analysis				
Time	Dominant Loop no.	Variable sequences	Polarity	TPM
Year 1-3	Loop 6	Labors, Labor Availability, Job Attractive Multiplier, In Migration, Populations	-	-
Year 4-39[1]	***Loop 1***	***Business Structure, Construction Rate***	+	+
Year 40-50	Loop 2	Business Structure, Land Fraction Occupied, Land Availability Multiplier, Construction Rate	-	-
Year 51-67	Loop 4	Business Structure, Demolition	-	-
Year 68-79	Loop 2	Business Structure, Land Fraction Occupied, Land Availability Multiplier, Construction Rate	-	-
Pathway Participation Technique				
Time	Dominant Loop no.	Variable sequences	Polarity	TPM
Year 1-3	Loop 6	Labors, Labor Availability, Job Attractive Multiplier, In Migration, Populations	-	-
Year 4-35	***Loop 3*Loop 6***	***Business Structure, Job Requirement, Labor Availability, Populations, Labors, Labor Availability Multiplier, Construction Rate***	+	+
Year 36-40*	Loop 6	Labors, Labor Availability, Job Attractive Multiplier, In Migration, Populations	-	-
Year 41-51	Loop 2	Business Structure, Land Fraction Occupied, Land Availability Multiplier, Construction Rate	-	-
Year 52-70	Loop 4	Business Structure, Demolition	-	-
Year 71-80	Loop 2	Business Structure, Land Fraction Occupied, Land Availability Multiplier, Construction Rate	-	-

[1] The sign double *denotes the major difference between the two analysis. The sign of single * represents minor differences.

The deactivation of loop 1:

Construction Rate=If ((time >35) and (time<4))

then (Business Structure*Labor_Availability_Multiplier*

Land_Availability*Construction_Fraction)

else (Constant Business Structure*Labor_Availability_Multiplier*

Land_Availability*Construction_Fraction)

Constant Business Structure=500(buildings)

The deactivation of loop 3:

Construction Rate=If ((time >35) and (time<4))

then (Business Structure*Labor_Availability_Multiplier*

Land_Availability* Construction_Fraction)

else (Business Structure*Land_Availability*Construction_Fraction

*Constant Labor_Availability_Multiplier)

Constant Labor_Availability_Multiplier=1(dimensionless)

Atomic behavior= derivn(abs(derivn(Business_Structures,1)),1)

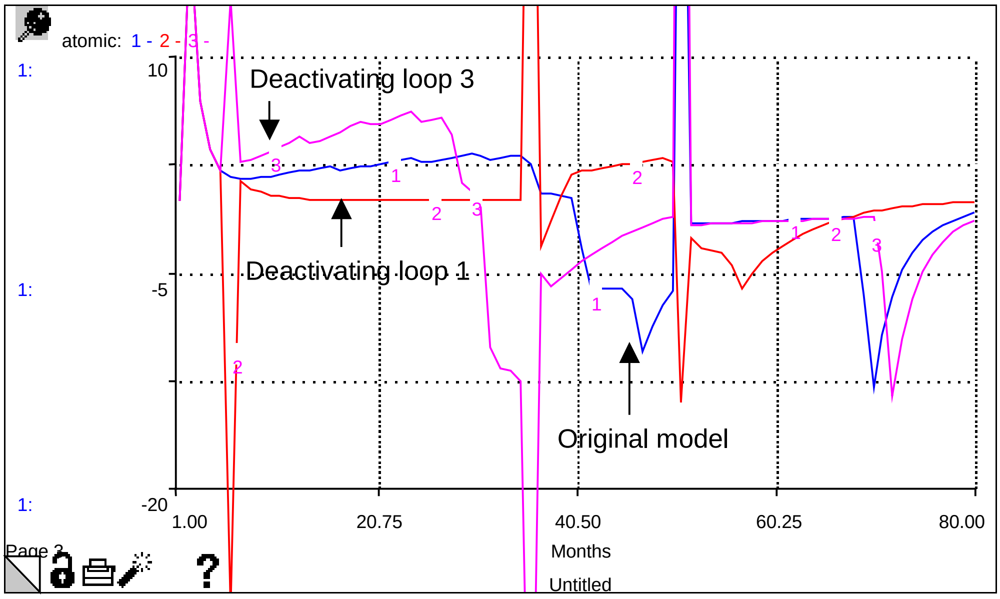

Figure 7 Experiment results of loop 1 and loop 3

As Figure 6 shown, deactivating loop 1 produces a more obvious change in the atomic behavior of variable Business Structure than deactivating loop 3 does. The behavior pattern of variable Business Structure when deactivating loop 3 is similar to the original model. That implies the steepening growth of Business Structure is not driven mainly by the cross-reinforcing loop composed of loop 3 and loop 6v, but by loop 1 that contains only one level variable Business Structure. Similar experiments are also done with variable Populations. The growth behavior of Populations is generated mainly by the loop traveling from Population to variable In Migration. With more experiments to analyze the declining pattern of the two level variables after year 41, the limits of growth for Business Structure and Populations are verified to be the land available and job requirement respectively. The two factors limit their corresponding level variable's growth behaviors and later shift the dominance to other negative loops. With the analysis and experiments discussed, it is concluded that the proposed analysis approach have a certain degree of explanation power of simulated behaviors.

The facilitation of policy design

According to Macedo (1989), current methods used to conceive the best policy of a system dynamics model can be classified into three families: the heuristic methods, the modal methods, and the optimization methods. Heuristic methods largely rely upon a sufficiently deep, intuitive understanding of the problem or by some simple principles and rules of thumb (Forrester, 1961; Graham, 1976). Thus, most heuristic methods do not offer formal mechanisms to develop new policies for its lack of theoretical basis. Relative to the heuristic methods, policy design methods of the modal and optimization categories possess formal analysis procedures to design high leverages. However, they are too difficult for managers and designers to understand and follow. In consistent with this paper's objective, to develop a practical loop dominance analysis approach, the causal link-based analysis approach facilitates the policy design stream of heuristic family.

Before starting the validation of the proposed analysis approach's ability to facilitate policy design, we have to admit that to apply loop dominance analysis in policy design is not an easy job. That's because dominant loops are the reductions of model structures. The identification of dominant structure highlights some parts of a model structure but also bring the rest parts of the structure into background. However, that does not mean those parts of the structure in the background have few impacts on the variable of interest. They are just not as influential as the dominant loops identified but they may still be rather influential to the variable of interest. Even each feedback loop in the background does not have great impact on the variable of interest individually, they may be important to generate system behaviors collectively. After all, the model system operates as a whole. Hence, the manipulation of model behaviors with dominant loops should not focus the dominant loop identified only, but focus on the redesign of the relationships between dominant loops and non-dominant loops. Loop dominance analysis is just a facilitation tool for policy design. But it cannot be the main body of the policy design process. The simple long wave model

(Sterman, 1985) is used to demonstrate how causal link-based analysis facilitates policy design process.

Simulation behaviors of the original model and the causal link-based analysis result are shown in Figure 8 and Figure 9. The variable of interest selected in the analysis is variable Capital. The purpose of policy design in this experiment is to change the variable's oscillation behavior to a stable time pattern. To redesign the system to be stable, the two different flows Capital flow and Backlog flow in the model should be balanced. However, the two flows are tightly coupled together. Any changes of one flow can cause the other flow to change. As shown in Figure 9, the frequent dominant loop shifts shows that those tightly coupling feedback loops in the central part in Figure 9 are almost equally influential. The variable Desired Orders is selected to demonstrate how causal link-based analysis result help to rearrange the power distribution between dominant links and non-dominant links. The variable is selected for three reasons. One reason is that Desired Orders is not part of the tightly coupling dominant structures. It impacts on the Capital flow and Backlog flow in the same directions. There is less possibility for Desired Orders to accelerate the oscillation behaviors. Another reason is Desired Orders has certain degree of impact in initiating the operations of variable Supply and variable Backlog in the periods of time 53 to 55, time 67, and time 105 to 106. Still another reason to select Desired Orders is it is composed of three decision elements: Depreciation, Capital Adjustment, and Supply Line Adjustment. Among the three elements, Capital Adjustment constantly has great impacts over Desired Orders than the other two variables to Desired Orders almost in

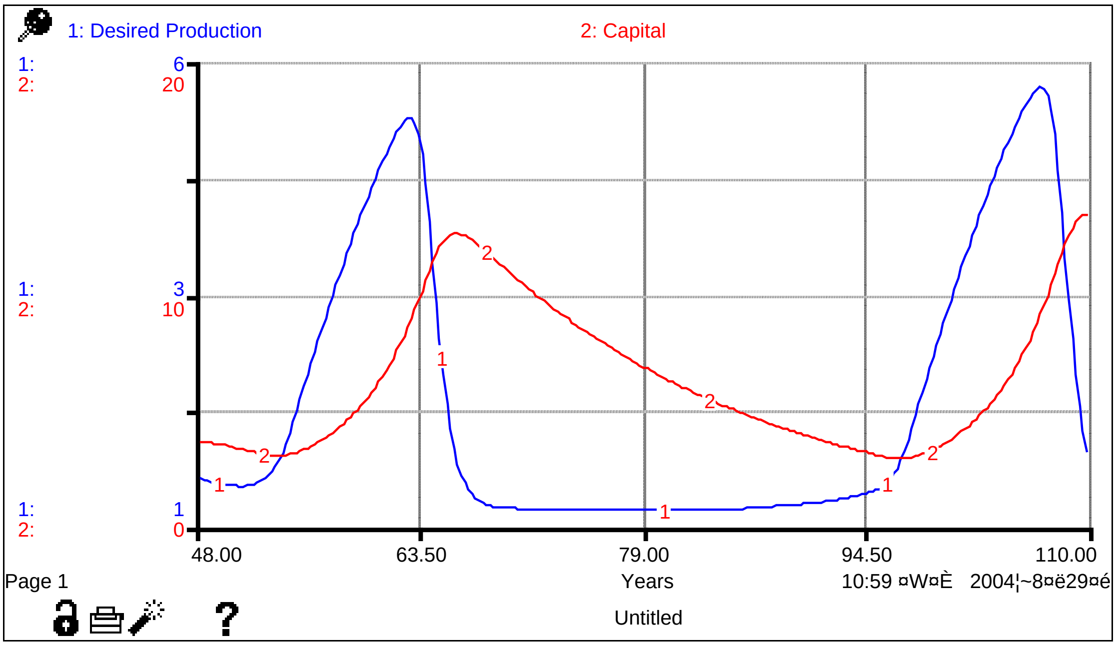

Figure 8 Simulation behaviors of the simple long wave model

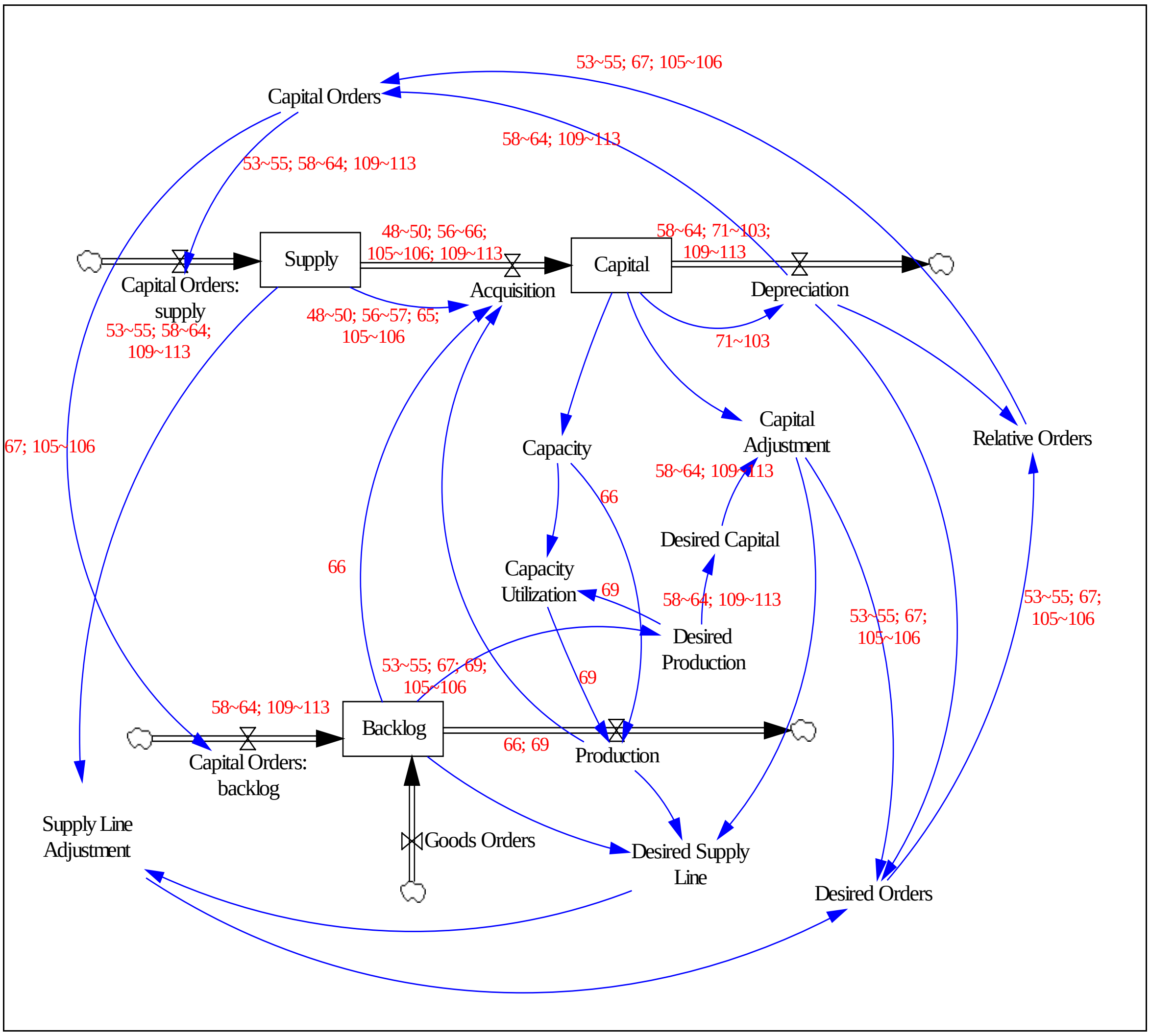

Figure 9 Causal link analysis results of the simple long wave model

the whole the analysis process. The improvement policy can be the rearrangement of the power distributions of Desired Capitals and other tightly coupling structures by manipulation the three causal variables of over Desired Orders.

The manipulation of Depreciation, Capital Adjustment, and Supply Line Adjustment aims to strengthen the impact of Desired Orders on Relative Orders. That is, to amplify the change of Desired Orders in each unit of time. According to the analysis result shown in Figure 9, it is suggested that Capital Adjustment is the most influential variable. It is rather intuitive that the impact of the shortening of Capital Adjustment Time should be greatest and Capital Adjustment Time is the suggested high leverage point. However, with deeper deliberations, one can observe that capital adjustment is a negative loop with two level variables. That means if the capital adjustment loop becomes dominant, it would generate an oscillation pattern which may initiate other loops to amplify the oscillation. Consider another variable Supply Line Adjustment Time. It controls the power of supply line adjustment loop. It is a first order negative loop that is supposed to bring the system to be stable. The shortening of Supply Line Adjustment Time is the suggested policy in this paper. How about the variable Depreciation? Depreciation is not suggested to be the leverage point for it is highly interrelated with Capital that would induce other unexpected changes via Capital. Figure 10 shows the experiment results. Curve 1 is the original pattern of Capital. Curve 2 and Curve 3 are Capital's new pattern with Supply Line Adjustment Time and Capital Adjustment Time reset from 1.5 to .3. The suggested policy (shortening the Supply Line Adjustment Time) improves the behavior of interest successfully!

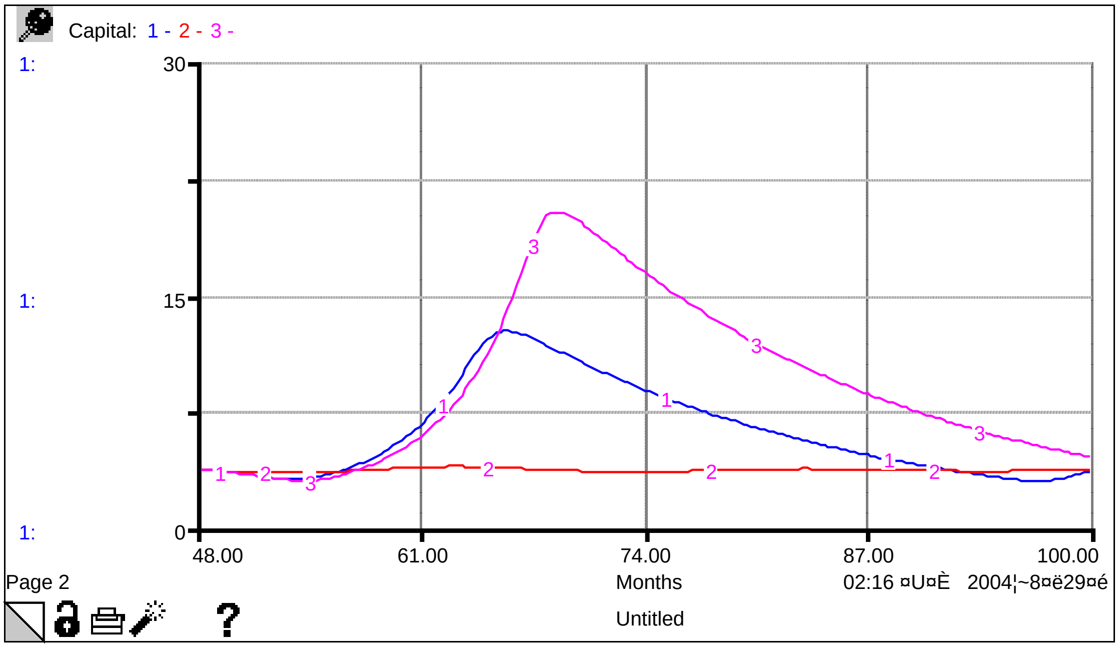

Figure 10 Experiment results of policy designs

Conclusions

Ford (1999) proposes three issues are essential in the loop dominance analysis: the location of dominance, gains, and the behavior patterns. The location of dominance means to select a variable to be the variable of interest to identify its corresponding dominant structures. The causal link-based analysis procedure starts at the selection of the variable of interest indeed and the variable of interest selected can be a level variable, rate variable, and auxiliary variable. The analysis procedures are all the same for each kind of variables. In terms of gains, this paper designs a stepwise procedure to calculate the strength of causal links. The computation logic of a causal link's gain is rather simple. No complex mathematic computation is needed. One has just to compute the value of the variable of interest in considering the presence of the change of the causal variable for each simulation unit time, dt. All the computation works can be completed by simple spreadsheet software, although more convenient computer software integrating simulation and analysis is still under development by the authors. This paper further employs the backward chaining policy to trace back the most influential variable(s) sequentially to identify cascading influential links that constitutes a dominant structure. The number of links to be analyzed can be dramatically reduced with backward chaining policy. Only the strongest links needs to be considered to be part of the dominant structure and the variables with multiple causal sources need to be analyzed where the greatest impact is from.

As to the behavior patterns issue proposed by Ford, this paper employs the definition by Mojtahedzadeh (1996) directly. The definition of behavior patterns is used in this paper for validating the proposed analysis approach. The comparison with alternative approach and the experiments of deactivating inconsistent loops identified by the two approaches proves that the causal link-based analysis approach identifies dominant loops with a certain degree of explanation power to behaviors. Furthermore, this paper also attempts to apply the proposed approach to facilitate policy designs. The result also supports the proposed approach’s capability in facilitating policy designs.

The development and validation process of the causal link-based analysis approach in this paper is not the whole new work in loop dominance research stream. Past research results by other researchers are extensively referenced and employed. For example, the definition of behavior patterns by Mojtahedzadeh, the behavioral perspective (to validate the dominant loop identified) and atomic behaviors proposed by Ford, and even the stepwise computation of the gains of causal links may be rooted in a long time ago from the paper by Kim (1995). This paper suggests a direction of integration works for loop dominance research. In additions, there is one critical problem to be solved. Is the “gain” of causal loops the only one or the most important criterion in identifying dominant loops? Are there any other factors also important to be considered in deciding the explanation power of feedback structures? For example, to new system thinking learners, the direct mapping of behavioral characteristics of simplified model structures to system behaviors may be more important than the strengths of a simplified model to system behaviors. Is behavioral-oriented or gain-oriented loop dominance analysis more important? Or for whom, which kind of analysis is more relevant? Finally, there still a big gap between dominant loop analysis and policy design. It is rather interesting to look for a way to combine the two research topics. Future research can work toward this research.

References

Ford, D.N. 1999. A behavioral approach to feedback loop dominance analysis, *System Dynamics Review*, 15(1): 3-36.

Forrester, J.W. 1961. *Industrial Dynamics.* Cambridge, MA: Productivity Press.

Forrester, J.W., 1968. *Principles of Systems.* Cambridge, MA: Wright-Allen Press.

Graham, A.K. 1977. Principles on the Relationship Between Structures and Behavior of Dynamic Systems. Ph.D. thesis. Massachusetts Institute of Technology, Cambridge, MA.

Kampmann, C.E. 1996a. Feedback loop gains and system behavior. *Proceedings of the 1996 International System Dynamics Conference*. Cambridge, MA: Systems Dynamics Society.

Kim, D.H. 1995. A new approach to finding dominant feedback loops: loop-by-loop simulations for tracking feedback loop gains. *System Dynamics, an International Journal of Policy Modeling* 7(2):1-15.

Macedo, J. 1989. A reference approach for policy optimization in system dynamics models. *System Dynamics Review*, 5(2):148-175.

Mojtahedzadeh, M.T. 1996. A Path Taken: Computer-Assisted heuristics for Understanding Dynamic Systems. State University of New York, Albany, NY.

Richardson, G. P. 1986. Dominant structure. *System Dynamics Review* 2(1): 68-75.

Richardson, G.P. 1995. Loop polarity, loop dominance, and the concept of dominant polarity(1984). *System Dynamics Review* 11(1):67-88.

Richardson, G.P. and A.L. Pugh III. 1981. *Introduction to System Dynamics with Dynamo.* Portland, or: productivity Press.

Sterman, j. D. 1985. A behavioral model of the economic long wave. *Journal of Economic Behavior and Organization* 6: 17-53.

Senge, P. M. 1990. *The Fifth Discipline*, *The Art and Practice of the Learning Organization.* New York: Doubleday.