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MANAGEMENT SYSTEM STRUCTURE VS. BEHAVIOR – A SUPPLY CHAIN SIMULATION ANALYSIS

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Purpose: The purpose of this article is to present a research report on a system dynamics simulation modeling and experimenting of bullwhip effect (BWE) to examine effectiveness of some selected inventory control policies with down- and upstream information flow in a *Beer Distribution Game* (BDG) of a supply chain structure.
Design/methodology/approach: The impact of systems' structures and decision making policies in supply chains or logistics systems are measured and analyzed by an application of systems thinking paradigms and approaches. Particularly, the continuous simulation modeling approach with systems thinking *Iceberg model* metaphor, allowing to focus on strategic aspects of management with some recommendation to design better structures and decision making policies are taken. For the bullwhip effect analysis of a supply chain example (based on BDG model), a *System Dynamics* (SD) continuous simulation modeling method with some proposals in order to analyze feedback loop dominance are undertaken to explain supply chain behaviors and to make some sensitivity analysis for decision making (inventory control) policies.
Findings: The research findings outline the impact of cause – effect relations, feedback loops polarities, and decision making policies to particular behaviors of the BDG supply chain.
Research limitations/implications: Because of complexity of heuristic methods for feedback loop dominance analysis only simple approach was applied (LPD), and some selected scenario for simulation experiments were undertaken resulting in limited conclusions.
Practical implications: The conclusions of the research draw some practical recommendations for a design of information sharing system and an effectiveness of some inventory control policies to be applied in supply chains.
Social implications: One of the systems thinking elements in practical management is an influence to mental models of managers and decision makers. Managers in supply chain systems particularly need some recommendations to avoid bullwhip effect negative impacts. Additionally, managers and also scholars still call for more research to investigate the design and decision making in supply chains, therefore systems thinking simulation research can bridge the gap between traditional operations research and management with other approaches to provide insight into supply-chain dynamics and deliver impactful suggestions to managers.
Originality/value: The paper gives a concept of supply chain dynamic analysis by an application of *Iceberg model* systems thinking metaphor, feedback loop dominance analysis, and a measurement of some selected inventory control policies effectiveness.

Keywords: supply chain, bullwhip effect, inventory control, simulation modeling.

Category of the paper: research paper and a methodological review.

1. Introduction

The emergence of the simulation modeling (SM), as an important field of management systems modeling support, creates a new need and interest for management research community in the ways in which the SM method or technique can assist the process of modeling and analyzing macro-scope management systems, processes, functions and structures. However, despite the existing successful application examples, SM in dynamic management systems modeling has not to date received the methodological support to establish it as a separate research area in management theories' building. Also a micro-scope method of modeling, usually as stochastic discrete modeling, is another form of simulation to be applied rather at an operational level of management.

One of the major research problems in dynamic systems' SM is the identification of relationships between the structure of a dynamic system and the behavior it generates. It is obvious, that cause and effect relations, feedbacks, delays and amplifications, as basic structural features of systems and applied (implemented) decision making policies and rules in system's management or control on dynamic properties of systems, have a significant impact on the system. Complex systems (e.g. economic and management systems), behave in a way that is hard to identify and determine unambiguously (a paradigm of anti-intuitive and counter-intuitive behavior). The main reason for this is the coexistence of many nonlinear structures and higher order feedbacks. There are also '*shadow/phantom*' structures, resulting in the same types of behavior, difficult to identify in terms of feedback dominance. And although in such systems many so called '*system's effects*' are also created (synergy effects), understanding the nature of a single feedback and decision (control) making policies implemented within, is highly critical to a design process of appropriate structures and decision-making policies.

There is a substantial and still growing bibliography on the one of the most fundamental phenomena in supply chain management – a 'bullwhip effect' (BWE), and its impact on supply chain performance (Akkermans et al., 2005; Croson et al., 2005; Liang et al., 2006; Jakšič et al., 2008; Ouyang et al., 2010; Duc et al., 2010; Bhattacharya et al., 2011; Dass et al., 2011; Ding et al., 2011; Dobos, 2011; Sodhi et al., 2011; Zhang et al., 2011; Kristianto et al., 2012; Mesjasz, 2012; Sterman et al., 2015; Gonçalves et al., 2021). This effect is an amplification of order oscillations (fluctuations) and time phases lags moving up the supply chain (in an upstream direction) – away from the supply chain final point – a final customer. Given the impact of BWE on supply chains, scholars have called for more research to investigate the behavior of actors within a supply chain (Bolton, Katok, 2008; Narayanan, Moritz, 2015). Behavioral operations research (OR) and SM can bridge the gap between traditional management heuristics and other behavioral sciences such as psychology, neuroscience, and organizational science to provide insight into supply-chain dynamics and deliver impactful suggestions to managers.

The principles, structure and mechanics of BDG[1] game are well documented. Its successful history began with J.W. Forrester first business oriented research, being used basically as a supply chain model experimental setting and treatments in a board or computer controllable forms, however there is still a need to provide more profound research regarding its information system design, and inventory control policies impacts to supply chain performance. The game consists of four actors as players (4-echelon structure) and one actor as an external source of demand (customer or arbiter). Players take the role of inventory managers at one of these four echelons within an integrated supply chain: retailer, wholesaler, distributor, and manufacturer. Within each role, manager as a decision maker is responsible for placing orders to direct upstream supplier and filling orders placed by direct downstream customers. The decisions must be made repeatedly over series of periods, and within each period events occur in the following sequence: a) shipments arrive from direct upstream supplier, b) new orders arrive from direct downstream customer, c) new orders are filled and shipped from inventory, however when order quantity than available inventory (inventory on hand), unfilled order is placed in backlog and filled once the inventory becomes available in a future (in next periods), and d) each supply chain actor places an order to a direct upstream supplier.

The purpose of this paper is to present a research report on a system dynamics simulation modeling and experimenting of bullwhip effect (BWE) to examine effectiveness of some selected inventory control policies with down- and upstream information flow in a *Beer Distribution Game* (BDG) – a model to represent a 4-echelon supply chain structure. The paper addresses also to a methodological gap by investigating the suitability of macro SM in the context of management-oriented organizational analysis and design, and also tries to answer the question how management dynamics of systems are dependent on systems' structures. In fact, the management quality improvement is primarily a design problem and encourage a use of SM models with team/group communications to identify design/redesign requirements.

[1] A business game called BDG (*Beer Distribution Game*) was developed at the Sloan School of Management, Massachusetts Institute of Technology (MIT) in the 1960s as a version of the earlier (1958) *Refrigerator Game*. Demonstrated during the *System Dynamics Conference* (SDC) in Chestnut Hill - Boston by John D. Sterman (Sterman, 1989), it gained worldwide recognition and popularity among management theoreticians and practitioners. It has also an interactive Internet version (Machuca et al., 1997). In Poland, it was presented for the first time during a session of the *Economic Systems Simulation School* in Węgierska Górka in 1990 by Bogusław Wąsik (AE Kraków) and described in (Wąsik, 1992).

2. Research method

2.1. Systems thinking paradigm and SD modeling method

For the ambitious research, a challenge of dynamic system structure influence to system behavior analysis is considered particularly with an application of System Dynamics (SD) method. This method, originated by J.W. Forrester (Forrester, 1961; Forrester, 1972), belongs to systems thinking and macroscopic continuous simulation modeling methodologies. The SD method relies extensively on system's structure (particularly feedback loops and delays) in order to analyze and explain how system structure drives behavior and leads to particular patterns of behavior. Even some formal methods are being developed for an analysis of "structure-behavior" relations (e.g. loop polarity dominance, behavioral analysis for loop dominance, pathway participation metrics, graph theory measurements), still practical analysis by simulation modeling and one- and multi-factor experimenting have largely been restricted to laboratory simple examples as guides to intuition. In social complex systems' SD modeling and analysis practice, large-scale models with many loops are still analyzed in a largely informal way, using trial-and-error simulation. Although this is not a weakness, any formal tool that might help identify important structures in the model as they affect a particular mode of behavior could be of enormous utility, particularly in large models trying to map complexity relations in social systems. According to control system theory, behavior of a system must be considered in a complex – as *input/system/output* framework. System dynamics particularly is analyzed in the context of input and system structure influences on system responses, as outputs. The most important dynamic system properties to be analyzed in feedback control systems are: stability, robustness, time and frequency response, and equilibrium state (Kampmann et al., 2008). System dynamics stability issues are an important part of feedback control system theory and practice.

Systems approach is a creative and epistemological approach, which focuses on systems and structure relations. In that sense it corresponds closely with structuralism - a philosophical school dealing with basic assumptions on ways of perceiving the world by the cognitive subject. The most important assumption is relativism, reducing cognitive forms of seeing entities (objects, subjects, elements) only to relations between entities (cognition in the structural context). It also corresponds to nativism which assumes genetic and biological skills of people to make some order and collect experiences in structural forms. The history of system sciences is an evolution of three branches: systems philosophy, systems theory and systems methodology. The systems philosophy, neglecting reductionism, determinism and linearity of cause-effect descriptions - tends towards interactive holistic thinking with perceiving final goals of systems. The systems theory describes systems of various domains in universal categorization - it implies some ambitious efforts to find *general theory of systems*. The systems methodology, with some philosophical and theoretical elements, is a theory of systems science developing system concepts, strategies to investigate, analyze and design systems. The systems approach in research implies accepting basic principles of "systems thinking". That is why both terms are also treated as synonyms. The dynamic simulation modeling in economic and social sciences is more difficult than in physical sciences (Kampmann et al., 2014). Cognitive subject and observer is also a part of a system - an active element of research object - and it is not a problem of an observer relativism and his/her measurement instruments. In one of the modern philosophy concepts - hermeneutics - experience and ways of world descriptions in models are proposed in no-foundation and no-atomic introspective analysis. It means that the "atomization" is treated as an epistemological deformation.

The macro-scope SD modeling method in social system is adopting also a systems thinking concept and approach. A model that is helpful for understanding "global" (holistic and systemic) issues in system SD modeling, is the *Iceberg Model* (Figure 1), often used in systems thinking and problem resolving or solving.

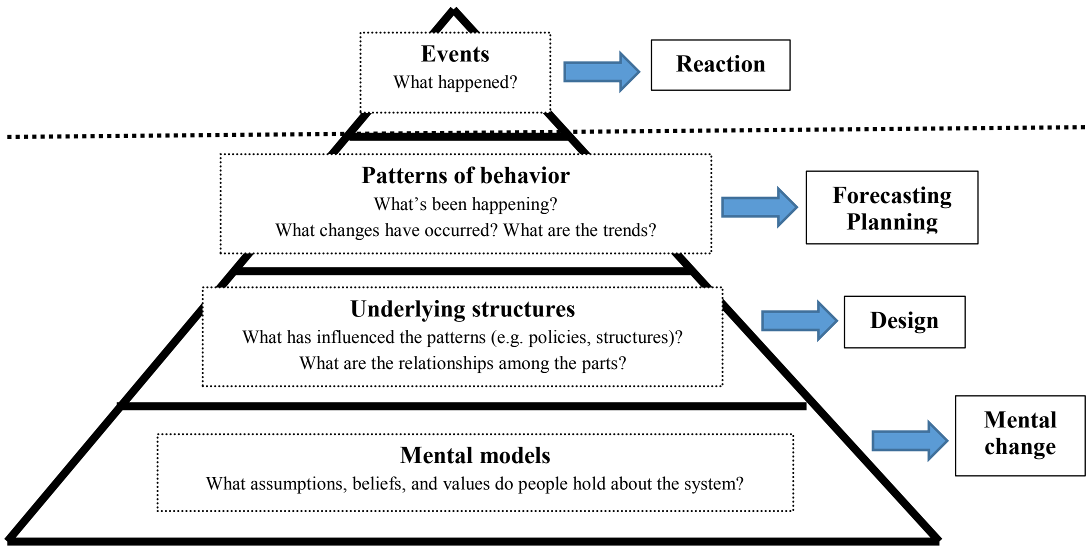

Figure 1. The systems thinking with *Iceberg Model* and SD modeling paradigms in system's analysis, forecasting, planning and design.

Source: own work based on http://www.systemsthinking.com.

In SD modeling life-cycle stages, global issues can be looked at in some research and analytical layers, allowing successful system and process restructures and improvements. The *Iceberg Model* is the systems thinking tool designed to help an individual or group discover the patterns of behavior, supporting structures, and mental models that underlie a particular system event. If we apply this model to SD modeling procedure, we could say by an iceberg metaphor, that at the tip above the water, are *events*, or thing that we see or hear about happening in the whole system. If we look just below the water line, we often start to see *patterns*, or the recurrence of events. Finally, at the very base of the iceberg are the assumptions and worldviews that have created or sustained the structures that are in place. The important thing to understand is that in problems' solving, the greatest leverage is in changing the structure.

Like the different levels of an iceberg, deep beneath the patterns are the *underlying structures* or root causes that create or drive those patterns. SD method in system modeling allows to analyze a managed system so as to: model the ways in which its information, action and consequences components interact to generate dynamic behavior; diagnose the causes of faulty behavior; tune its feedback loops to get better behavior.

The first stage in SD application to system modeling is to recognize the problem and to find out which people care about it, and why. Secondly, and the first stage in SD as such, comes the description of the system by means of an influence diagram, sometimes referred to as a “causal loop diagram” (CLD) or “cause-effect diagram”. This is a diagram of the forces at work in the system, which appear to be connected to the phenomena underlying people's concerns about it. Influence diagrams are constructed following well-established techniques – basically “least-extension” technique. Having developed an initial diagram, attention moves to the third stage - 'qualitative analysis' - looking closely at the influence diagram in the hope of understanding the problem better. This is, in practical SD, a most important stage, which often leads to significant results (sometimes it is the end of modeling project). If qualitative analysis does not produce enough insight to solve the problem, work proceeds to fourth stage, the construction of a simulation model with operationalizing “stock and flow diagram” (SFD). The next stage (the fifth one) is where results based on quantitative analysis start to emerge. Initially, use is made of the bright ideas insights and pet theories from qualitative analysis. This stage represents exploratory modeling of the system's characteristic patterns of behavior by experimenting with the aim of enhancing understanding and designing new polices and rules for system.

SD method is originally based on feedback control theory which includes both hard (quantitative) and soft (qualitative) approaches in analyzing dynamic behaviors of the development and changes of a system. SD approach assists to improve decision making process and policy formation through its characteristics of incorporating all relevant cause-effect relationships as well as feedback loops in dynamic behavior modes of systems. By developing a mathematical model as a set of differential equations solved by numerical integration (e.g. by Euler method) and in a computer simulation environment, SD is capable to resolve any dynamic, inter-dependent, counter-intuitive and complex problem, such as problem of investigating the impact of social (management and economic) factors on system outcomes.

2.2. Methods of analytical and simulation based loop dominance analysis

The dominant feedback loop in a multi-feedback system determines the behavior of the system. The concept of dominance is a temporal one, depending on the operating conditions of the system - different feedback loops can be activated and deactivated, causing a change in the feedback loop dominance (Richardson, 1995; Kampmann et al., 2006; Kampmann et al., 2006; Güneralp, 2006; Rahmandad et al., 2009; Kampmann, 2012; Abdelbari et al., 2017; Naumov et al., 2018).

The concept of feedback loop polarity, particularly important in a mathematical method of feedback loop polarity dominance (LPD), is a concept that allows to read loop dominance in a certain way. The feedback in the system contains (should contain) at least one state variable as an integration variable (SD method stock $x(t)$ at time t). Let us consider feedback loop with a stock (resource) x and the flow variable described by the differential equation:

$$\dot{x} = dx / dt\,, \tag{1}$$

The polarity of the feedback loop containing the resource variable x and its derivate (dx/dt), representing a dynamic of the resource, is calculated as:

$$sign(d\dot{x} / dx) = sign((dx / dt) / dx)\,. \tag{2}$$

Determination of any feedback loop polarity and dominant feedback loop polarity in more complex systems (with number of feedback loops $n > 2$), as well as polarity turning points becomes analytically more difficult. In practice of any system's SD method modeling there is also a need to introduce many types of variables, as levels (stocks), rates (flows) and auxiliaries (converters), which in turn depend on the other system's variables belonging to particular feedback loops. For the case, where in a given feedback loop there are: state variable x, its rate $\dot{x} = dx / dt$ variable, and auxiliary a_1, a_2, …, a_n variables, the sequence of cause – effect relations is $x \rightarrow a_1 \rightarrow a_2 \rightarrow \ldots \rightarrow a_n \rightarrow \dot{x} \rightarrow x$. Polarity in such a feedback loop is therefore referred to as a complex function:

$$sign(\partial\dot{x} / \partial x) = sign((\partial a_1 / \partial x) \cdot (\partial a_2 / \partial a_1) \cdot (\partial a_3 / \partial a_2) \cdot \ldots \cdot (\partial a_n / \partial a_{n-1}) \cdot (\partial\dot{x} / \partial a_n))\,. \tag{3}$$

The LPD method is a part of a set of eigenvalue elasticity analysis (EEA) methods to analyze and evaluate the effect of structure on behavior in dynamic systems' models.

The other proposal as a method for the identification and behavioral analysis of feedback loop dominance (BAFLD) consists of an iterative 8-step heuristic procedure (Ford, 1999):

1. Identification and selection of a model variable of interest to the analyst from the point of view of feedback loop dominance, for which a preliminary simulation is performed and a trajectory of time behavior is determined.
2. Identification of time periods in which the selected model variable behaves in an elementary way. Reference patterns of behavior are linear, exponential and logarithmic. The conditions for obtaining elementary standards are determined by the system structure and model parameters.
3. Identification of the model feedback loops affecting the tested model variable and selection of one feedback loop as the dominant loop to be found, starting from the feedback loop containing the tested variable inside.
4. Identification or creation of a control variable in the tested feedback loop, which is not a variable belonging to other model feedback loops at the same time. This variable should influence the polarity of the test feedback loop and is used to activate or deactivate the test feedback loop.

5. Simulation of behavior of the tested variable in time intervals with the tested feedback loop in the deactivation state and identification of an elementary pattern(s) of behavior of the tested variable in time intervals.
6. Identification of time periods in which the observed variable behaves in an elementary pattern. If the elementary behavior in the time interval determined in the previous step is different from the behavior initially determined (in step 2), the feedback loop under test is dominant for the behavior of the model variable under test under system conditions. If the behavior is the same, two situations are possible: a) the tested feedback loop is not a dominant loop, b) the tested feedback loop is a dominant loop, but it also has a “parallel" feedback loop, a “shadow" type loop. In order to identify the shadow loop, repeat steps 4-6 with the tested feedback loop deactivated, which will allow to unambiguously identify the parallel loops. After the identification of a shadow loop, it should be deactivated and then the dominance tests for the tested loop should be repeated. If there is no change in the model variable being tested, it is to conclude that there is no dominance of the feedback loop for the model variable being tested.
7. Repeat steps 3-6 with the active test feedback loop to identify possible multiple dominant feedback loops in the test intervals.
8. Repeat steps 1-7 for different time periods to identify changes in feedback loop dominance and loop dominance for other model variables.

Unfortunately, in the BAFLD heuristic approach there is an emerging computational and experimental challenge to test all the possible structure paths and to identify possible “parallel” (shadow) feedback loops and to identify time intervals for patterns of behavior comparisons.

The next heuristic method as a feedback loop pathway participation metrics analysis (PPMA) is based on the use of feedback loop participation metrics in the overall behavior of the dynamic system (Mojtahedzadeh et al., 2004). Since the influences of different feedback loops may be crossing in the model variable under test, the analysis of the model is based on the identification of the most significant feedback loops by evaluating the effects of single paths. The basic intuitive assumption of the PPMA method is also based (similarly to the BAFLD method) on the identification of elementary patterns of behavior. The analysis is based on the following 7 elementary patterns of behavior: linear growth, linear decline, reinforcing growth, reinforcing decline, balancing growth, balancing decline, equilibrium. The results of the SD model simulation for selected model variables are analyzed in relation to the model variables and the simulation time intervals. The mathematical algorithm (Mojtahedzadeh et al., 2004; Mojtahedzadeh, 2011) identifies variables with the same polarity by calculating the first and second derivative on time. The non-linear dynamic system under consideration has a form:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{p}), \tag{4}$$

where:

x is a vector of *n* state variables,

$\dot{\mathbf{x}}$ is a derivative of the **x** vector in time,

p is a vector of model parameters.

For the *k-th* state variable, the model equation has a form:

$$\dot{x}_k = f(x_1, x_2, \dots, x_n, \mathbf{p}). \tag{5}$$

Differentiating the changes occurring in the feedback loop for the tested *k-th* state variable for $x_k \neq 0$ from the same variable we get:

$$\frac{d\dot{x}_k}{dx_k} = \sum_{i=1}^{n} \frac{\partial f_k}{\partial x_i} \cdot \frac{x_i}{x_k}. \tag{6}$$

In the equation above, feedback loops and their possible paths, beginning on *i-th* state variable and ending on *k-th* state variable being a subject of analysis, are represented. The decomposition of each feedback loop and its paths with x_k state variable influences is done by a calculation:

$$\frac{d\dot{x}_k}{dx_k} = \sum_{i=1}^{n} \sum_{j=1}^{m(i)} \frac{\partial f_k^j}{\partial x_i} \cdot \frac{x_i}{x_k}. \tag{7}$$

where *m*(*i*) is the number of loops and paths that start with the *i-th* state variable and end with *k-th* state variable, $\partial f_k^j / \partial x_i$ is a polarity of a path or feedback loop. The x_i/x_k expresses the relative changes of *i*-th state variable and the relative changes of the *k*-th state variable. The influence of each feedback path can be normalized in such a way, that it can be expressed between -1 and 1. Therefore, for each path leading to a state variable under study, a metrics can be used to measure the influence of that path (or irrelevant feedback loops) on the behavior of the variable under study. The Path Participation Metrics (*PPM*) is defined as:

$$PPM(i, j) = \frac{\dfrac{\partial f_k^j}{\partial x_i} \cdot \dfrac{x_i}{x_k}}{\displaystyle\sum_{i=1}^{n} \sum_{j=1}^{m(i)} \left| \frac{\partial f_k^j}{\partial x_i} \cdot \frac{x_i}{x_k} \right|}. \tag{8}$$

For the dominant path or feedback loop, the participation metrics (PPM) is the largest one and it has the same sign (polarity) as the expression 7. If the model variable being tested is not a state variable, the relative changes for the selected variable should be determined, and the same procedure should be followed. Let us consider a dynamic system model in which a is a vector of model variables that are not state variables and are associated with state variables by *g* function, while *p* is a vector of parameters:

$$\mathbf{a} = \mathbf{g}(\mathbf{x}, \mathbf{p}), \tag{9}$$

If the variable under consideration is a_k, the relative changes of this variable in time *dt* (numerical integration step) are expressed as:

$$\dot{a}_k = \sum_{i=1}^{n} \frac{\partial g_k}{\partial x_i} \cdot x_i \ . \tag{10}$$

When calculating a derivative of the change, we get it as:

$$\frac{d\dot{a}_k}{da_k} = \sum_{i=1}^{n} \left(\frac{\partial^2 g_k}{\partial x_i \cdot \partial a_k} \cdot x_i + \frac{\partial g_k}{\partial x_i} \cdot \frac{dx_i}{da_k} \right), \tag{11}$$

and after transformation it means:

$$\frac{d\dot{a}_k}{da_k} = \sum_{i=1}^{n} \left(\sum_{j=1}^{n} \left(\frac{\partial^2 g_k}{\partial x_i \cdot \partial a_k} \cdot \frac{x_i}{a_k} \right) \cdot x_i + \frac{\partial g_k}{\partial x_i} \cdot \frac{dx_j}{dx_i} \cdot \frac{x_i}{a_k} \right). \tag{12}$$

The procedure of the PPMA method consists of the following stages:

1. Identification and selection of a model variable of interest to the analyst from the point of view of feedback loop dominance, for which a preliminary simulation is performed and a trajectory of time behavior is determined.
2. Division (decomposition) of the trajectory of the tested model variable into phases corresponding to one of the 7 elementary patterns of system behavior (identification of elementary phases).
3. Looking for fragments of structures responsible for elementary patterns of system behavior identified at the step of decomposition in appropriate feedback loops, i.e. being a significant reason for the observed behavior of a variable. In the appropriate mathematical procedure for a given model variable (*x*) the influence of the change of this variable (*dx*/*dt*) on the calculated variable $d\dot{x}/dx = (dx/dt)/dx$, which is a measure of a given path participation in the Total Pathway Participation Metrics, is determined. This metrics shall contain information about the derivatives (1st and 2nd) for the model variable being tested.
4. Identification of the feedback loop path that has a significant influence on the behavior using the calculated participation metrics. The dominant feedback loop path is identified as the one for which the calculated metrics is the largest and has the same polarity as the total changes.

An automated calibration (AC) approach - to systems dynamics modeling, a new interesting concept for classical 'structure – behavior' problem solving with an application of graph theory and its tools was also created (Oliva, 2004). This approach aims at formalizing the heuristics for model partitions and a sequencing strategy for the calibration/testing process in modeling. Even it tends only towards incremental improvements of a SD model confidence (validity) in the model design process, it can be helpful to identify and assess particular system structure elements in the context of their influence to overall system behavior. Given an available set of data (model variables and input parameters for which historical data are available), it is possible to iteratively identify the set of equations (for variables and parameters) that are directly involved in the outcome variable calculations. Therefore, it is possible to identify the minimum equation set that can be used for estimations. The minimum equation set will guarantee that all parameters used in the estimation are involved in the generation of the selected model outcomes and, hence, that the best use of the input data is made. Confidence in a dynamic system hypothesis is usually built by step-by-step procedure to integrate more complex and strongly connected system's components into simple and observable parts of structure.

The dynamic system independent loop set (ILS) consists of feedback loops with at least one edge not included in the previous accepted loops. Then, after an application of graph theory optimization it is possible to find the shortest independent loop set (SILS) and because of reflexive property of reachability matrix (non-zero values of elements on main diagonal), it is possible to find distance matrix, that shows in each cell the length of the shortest path (a sequence of non-repeating connected vertices and edges) between two vertices, as a walk, a sequence of connected vertices and edges, with non-repeating vertices (Huang et al., 2012).

The GTA method (Oliva, 2004) for the identification and behavioral analysis of feedback loop dominance, and model parameters calibration consists of an iterative 5 step heuristic procedure with some graph theory optimizations:

1. Identification of dynamic system model relations between quantities (variables and parameters) and setting relational matrixes – adjacency matrix (AM) and reachability matrix (RM) in graph theory formalisms to visualize and analyze model structure.
2. Identification of data-availability partitions according to empirical set of data.
3. Structural partitions for SD model levels. Identification of level partitions in AM by blocking (i.e. block consists of only one model level) – the algorithm generates an array with the list of vertices that correspond to each level in each cell. If the adjacency matrix (AM) is reordered according to level structure, the resulting matrix is a lower block triangular with each block representing a level.
4. Structural partitions for SD model feedback loop cycles. Identification of cycle partition as a set of strongly connected elements that contain *all* the feedback complexity of a dynamic system model structure. By an application of RM, it is possible then to calculate the distance matrix (DM) that shows in each cell the length of the shortest path (a sequence of non-repeating connected vertices and edges) between two vertices. A path is a walk, a sequence of connected vertices and edges, with non-repeating vertices.
5. Identification of minimal structures by calculation of geodetic cycle lists and model graph parameters.

Unfortunately, the GTA method algorithm only identifies "geodetic circuits" and does not detect all the feedback loops in the cycle partition. Moreover, simple logical tests can ensure that only cycles, circuits with non-repeating nodes are included in the list. The geodetic cycle list generated by this algorithm is *unique* if the cycle partition has no shortest paths of equal length between any two vertices in the cycle set. While the algorithm has no explicit way of selecting among alternative shortest paths of equal length (if they exist), it does guarantee that, if it exists, a shortest cycle linking every vertex-pair is included in the list. While the number of geodetic cycles is still large, the algorithm is more efficient than an exhaustive loop search. And also by adopting the GTA representation of a SD model, we can focus on structural complexity feedback loops components rather than the dynamic complexity that arises from linear or nonlinear relations with delays and amplifications.

The algorithmic detection of archetypal structures (ADAS) method (Yucel et al., 2011; Shoenenberger et al., 2015) is an approach to test dynamic hypotheses about archetypal structures belonging to the four generic system's archetypes (i.e.: the underachievement, relative achievement, relative control, and out-of-control) as a result of intended and unintended consequences of system's feedback loops. This approach is based on classical (analytical) feedback loops and cycles' partitions, and it takes also graph theory analysis (GTA) method as an assumption. However, for the detection of generic structure archetypes, it requires not only vertices and edges but also other dynamic parameters as input data – polarities, magnitudes and delays. A qualitative, algorithmic procedure of ADAS method consists of the following stages:

1. Identification of archetype reference behavior of a variable of interest.
2. Formulation of a hypothesis (SFD model) to explain particular system's behavior.
3. Conversion of SFD model into directed graph in adjacency matrices (AM) for polarities and delays.
4. Setting the variable of interest (from stage 1) as the outcome (observable) variable in the algorithm.
5. Algorithmic checking for the variable of interest the other archetype structures with a presence of this variable.
6. Identification of plausible archetypal structures that cause the problematic behavior of the variable of interest, and then reinterpreting the archetypes in stage 5 in the context of SFD model in stage 2.
7. Introducing policies as classical SD solutions.
8. Simulation of the model and reviewing the behaviors for the variable of interest.

The ADAS approach (as a practical application of GTA) to feedback loop analysis, is based on an assumption that the dynamic system structure represented in a model can be relevant to and accurately described as a directed graph. It implies that model variables and relations must be translated into vertices and edges, respectively, and to analyze complex and large scale dynamic systems with complex feedback loops to return to many types of archetypal structures. This problem can be effectively solved by reduction of structure partitions with feedback loops (e.g. by SILS algorithm or by identification of minimal feedback loop structures).

2.3. Comparison of analytical and heuristic methods of loop dominance analysis

To compare structure and behavior analysis methods we must have some assumptions regarding relevant classification criteria and measuring metrics to be identified. Particularly, feedback loop impact as the most important structure issue is taken first into consideration. However, the presented above an arbitrary selection of feedback loop dominance analysis methods, which are presented in most of research applications and published SD journals and reports, form different level of maturity. Some approaches are rather only theoretical concepts without serious practical implementations, some other approaches are practical algorithms to solve particular research problem (e.g. calibration of model parameters). The methods and algorithms for feedback loop dominance identification and analysis, as described above, have many common features. However, there are also some fundamental differences in the proposed approaches (Table 1).

Table 1.
A comparison of feedback loop dominance analysis methods

Criterion	Method				
	LPDA	BAFLD	PPMA	GTA	ADAS
Method type	Mathematics	Heuristics	Mathematics/ heuristics	Heuristics	Heuristics
Method aim	Identification of dominant feedback loop polarity	Identification of dominant feedback loop polarity	Identification of dominant feedback loop polarity	Calibration of the model parameters	Identification of intended and unintended archetypes
Problem solving	Differential calculus	Iterative	Iterative	Graph optimization	Iterative
Behavioral patterns	No	Linear, exponential, logarithmic	Linear growth, linear decline, reinforcing growth, reinforcing decline, balancing growth, balancing decline, equilibrium	No	Underachievement, relative achievement, relative control, out-of-control
Metrics	Relative change	No	Path participation	Distance	Edge weights
Model variable	All types	All types	All types	Levels	All types
Shadow feedback identification	No	Yes (no dominance analysis)	No	No	No
Model simplification	No	Yes (versions)	No	Yes (minimization)	Yes (minimization)
Software	No	No	Yes (*Digest* prototype)	Yes (*SILS* algorithm)	No

The 5 methods being analyzed (LPDA, BAFLD, PPMA, GTA, ADAS) are a result of an attempt to implement a sound postulate expressed by many systems' analysts (particularly simulation –oriented modelers of SD community) – to develop tools for feedback loop analysis with the use of formal dynamic system representation.

According to the above overview of some loop polarity detection methods, there are some prospects to have in a near future some effective software tools to support an analytical process of management systems' behavior identification. However, we also cannot give any hope for a *unified theory of systems analysis*, that is able to automatically provide modelers with any guideline to identify directly *dominant structures*. But this is also not to say that formal (or even heuristic) methods should not be developed. In practice, by the implementation of many SD modeling simulation projects and customer-oriented modeling techniques (customer knowledge and experience, needs and expectations), the issue of dominant feedback loop identification and analysis can be solved/resolved by an intuitive, heuristic, and subjective experimental procedure. Properly designed simulation experiment allows to recognize those parts of the model (paths and feedback loops, delays) which determine model behavior.

3. Supply chain dynamics – BDG analysis

3.1. Generic supply chain models – basic analysis

For example, in a dynamic generic supply chain system structure (Figure 2) with two feedback loops of the 1st order and dynamic equation given as:

$$\dot{x} = a \cdot x - b \cdot x = (a - b) \cdot x, \tag{13}$$

where x is an inventory level, a and b are constant parameters describing dynamic rates for supply inflow (a) and supply outflow (b). According to this definition, polarity of the system with the two feedback loops is equal to $sign(a\text{-}b)$. It means, that when $a > 0$ and $b > 0$, the polarity as $sign(a - b) > 0$ if $a > b$, and polarity as $sign(a - b) < 0$ if $a < b$ (Table 2).

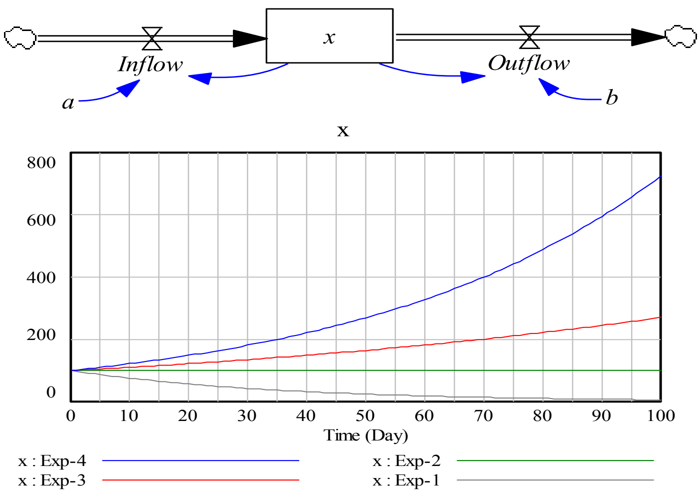

Figure 2. Dynamics of 1-echelon generic supply chain system example with 2 feedback loops and some canonical (exponential increase/decrease) behaviors by the change of a parameter $\{a$=0.002, 0.03, 0.04, 0.05$\}$, and $x(0)$=100, b=0.03.

Table 2.
Polarity in a system with 2 feedback loops of the 1st order

	Polarity					
	+	-	-	+	-	+
Conditions	a>0 b>0 a>b	a>0 b>0 a<b	a<0 b>0	a>0 b<0	a<0 b<0 |a|>|b|	a<0 b<0 |a|<|b|

For example of more complex, 2-echelon inventory supply chain example (Figure 3) with four feedback loops of the 1st and 2nd orders, dynamic equations are given as:

$$\dot{x} = a \cdot (n - y) + c \cdot y - b \cdot x, \tag{14}$$

$$\dot{y} = b \cdot x - c \cdot y, \tag{15}$$

where x and y are inventory levels, a, b, c, n, are constant parameters describing dynamics rates for supply inflows (a and b) and supply outflows (b and c), and n as a constant parameter describing desired (normative) level of y inventory (Figure 4). The four feedback loops (Figure 3) are as follows: (1) $x \to$ *Outflow-x* $\to y \to$ *Outflow* $\to$ *Inflow* $\to x$, (2) $x \to$ *Outflow-x* $\to y \to$ *Inflow* $\to x$, (3) $x \to$ *Outflow-x* $\to x$, (4) $y \to$ *Outflow* $\to y$.

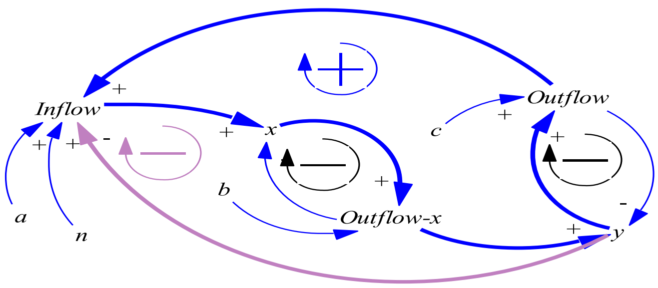

Figure 3. Influence diagram of the 2-echelon inventory supply chain model with 4 feedback loops.

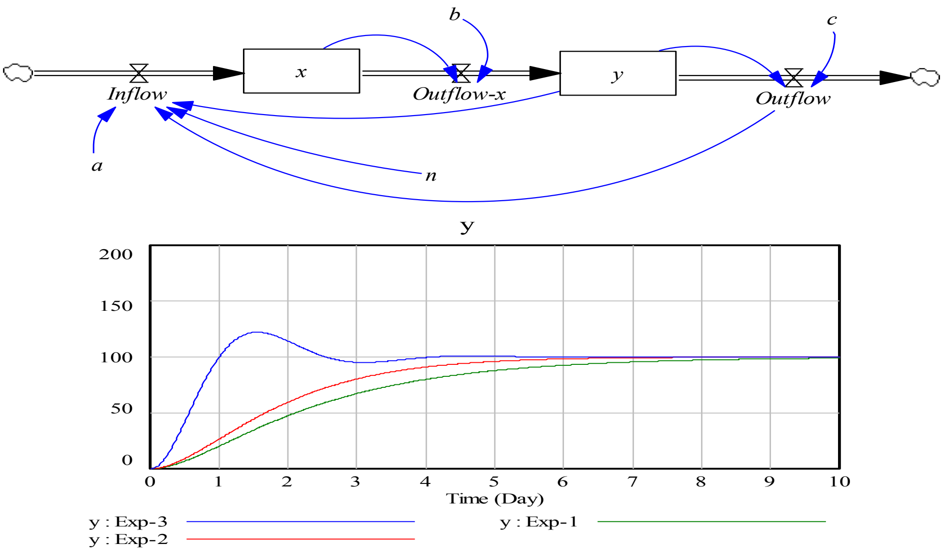

Figure 4. Dynamics of 2-echelon generic supply chain system example with 4 feedback loops and some canonical (goal seeking, S-shape, oscillation) behaviors by the change of a parameter {a=0.75, 1.00, 5.00}, and x(0)=0, y(0)=0, b=1, c=1, n=100.

According to the polarity definition, dominant polarity of the system with the four feedback loops possible to identify in this supply system above is more complex and must be determined by equation (3). In fact, due to a, b, c, and n parameters positive or negative values, we can expect rather combinations of elementary polarities. For positive values, we can identify a dominant negative polarity in order to get steady state behavior – very fundamental one in any inventory control system with temporal exponential growth, S-shaped, and oscillation patterns of dynamics behavior (Table 3).

Table 3.
Polarity in a system with 4 feedback loops of the 1st order

Conditions	Polarity
	+/-
Critically overdamped inventory control – Exp-1	$(b + c)^2 > 4 \cdot a \cdot b$
Critically damped inventory control – Exp-2	$(b + c)^2 = 4 \cdot a \cdot b$
Critically underdamped inventory control – Exp-3	$(b + c)^2 < 4 \cdot a \cdot b$

3.2. BDG supply chain – upstream vs. downstream information impact

Now let us consider a more complex 4-echelon supply chain model, possible to identify in a very famous supply chain business BDG game. This game is a commonly recognized game, as a most important tool to educate and train logistics managers, particularly to illustrate dynamics aspects of decision making in logistics management, and also a very negative impact of BWE phenomenon to supply chain performance. There are many analytical (e.g. operations research) and simulation oriented studies regarding decision making ordering principles and possible co-operations of game actors in order to increase effectiveness, efficiency, and also adaptability (e.g. resilience) of supply chain management. The model described below is a representation of BDG game in forms of *cause-effect* relationships (Figure 5) and *Vensim* simulator, developed with SD continuous simulation modeling approach (Figure 6).

The model consists of four independent organizations (4-echelon structure), as supply chain cooperating actors: retailer (*RetInv*), wholesaler (*WhoInv*), distributor (*DisInv*), manufacturer (*ManInv*) and one actor as a source of demand (*CustDem*). Within each organization, manager as a decision maker, is responsible for placing orders to direct upstream supplier and for filling orders placed by direct downstream customers (Figure 5). The decisions must be made repeatedly over periods, and within each period events occur in the following sequence: a) shipments arrive from direct upstream supplier, b) new orders arrive from direct downstream customer, c) new orders are filled and shipped from inventory (e.g. *RetOut*), however when order quantity than available inventory (inventory on hand), unfilled order is placed in backlog (e.g. *BlRetOrd*) and filled once the inventory becomes available in a future, and d) each supply chain actor places an order to a direct upstream supplier. In the SD model presented below, also some economic aspects of overall supply chain performance are included (*Total cost*).

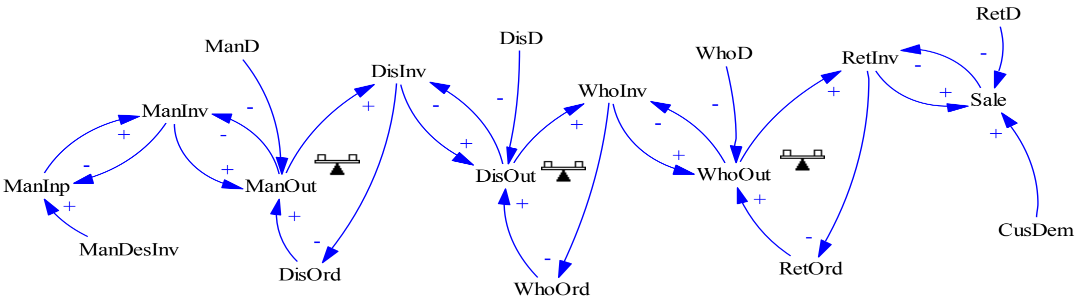

Figure 5. Influence diagram of the basic (no information sharing) BDG 4-echelon supply chain model.

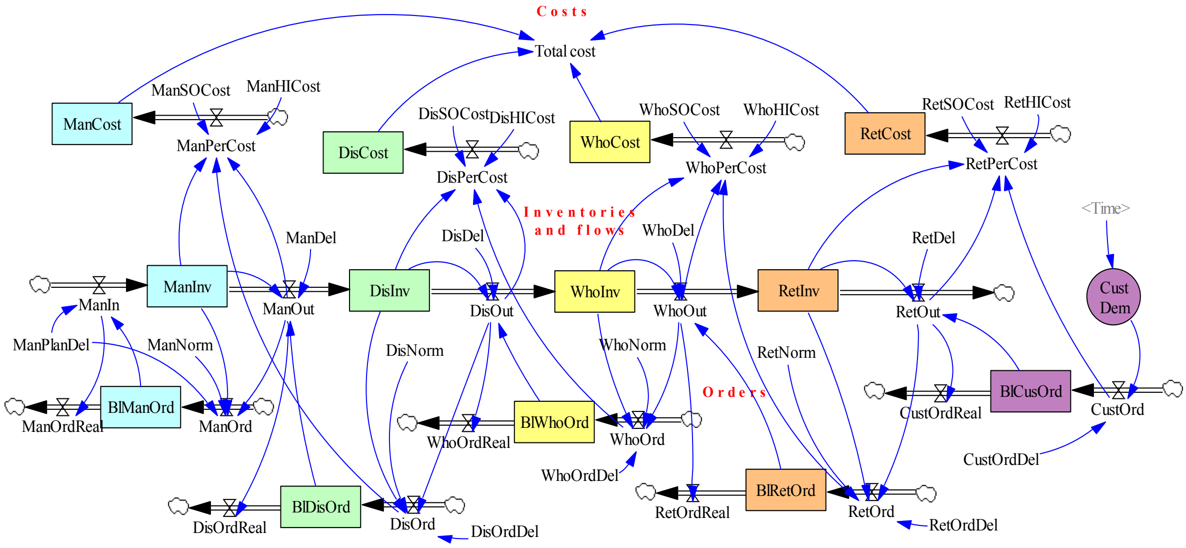

Figure 6. Stock and flow diagram (SFD) of the basic BDG 4-echelon supply chain model with inventory control by norms, and no information sharing.

In simulation experiments made on the model above, an impact of 3 customer demand functions to overall supply chain performance was tested: a sinusoidal function (Figure 7) *CustDem*=4+4·SIN((2·π/26)·*Time*), a step function (Figure 8) *CustDem*=4+STEP(4,·26), and random uniformly distributed function (Figure 9) *CustDem*=RANDOM(0,8,1).

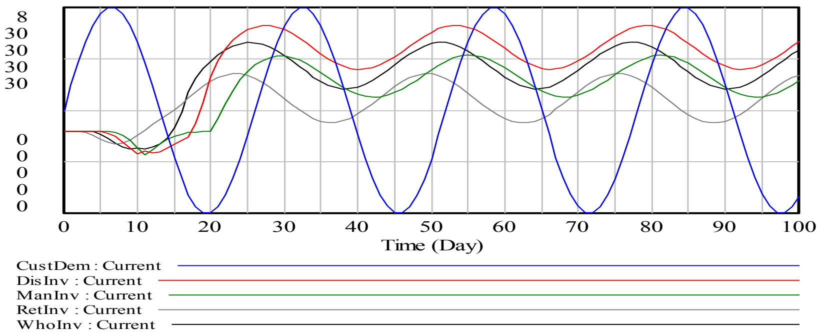

Figure 7. Dynamics of 4-echelon generic BDG supply chain system example with 4 feedback loops, with goal seeking behaviors, inventory control by norms, and no information sharing, as a response to customer demand sinusoidal function.

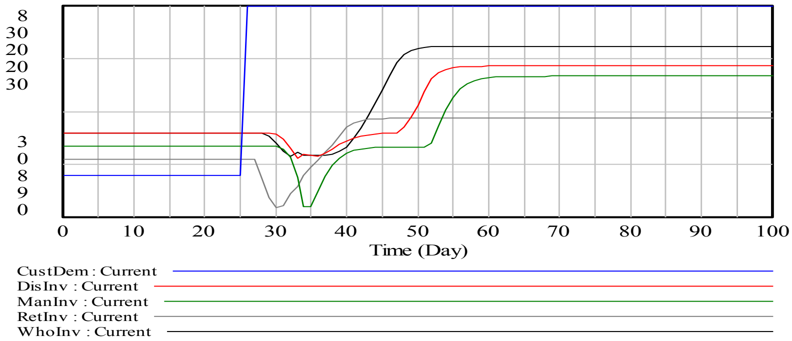

Figure 8. Dynamics of 4-echelon generic BDG supply chain system example with 4 feedback loops, goal seeking behaviors, inventory control by norms, and no information sharing, as a response to customer demand STEP function.

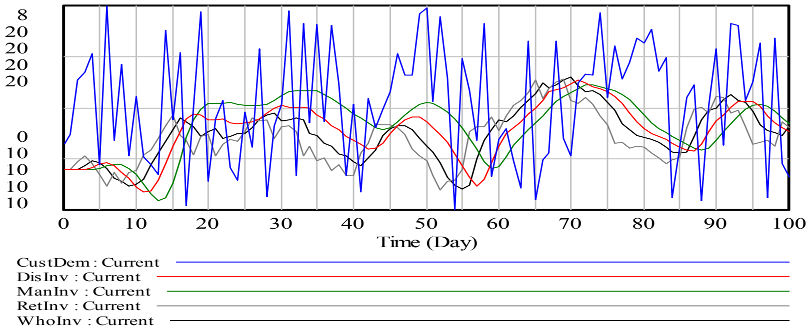

Figure 9. Dynamics of 4-echelon generic BDG supply chain system example with 4 feedback loops, goal seeking behaviors, inventory control by norms, and no information sharing, as a response to customer demand RANDOM function.

To compare no information sharing supply chain performance with information sharing supply chain performance, 2 versions of the model above were developed: a downstream information sharing model, where ordering decisions are made by exponential smoothing averages of direct downstream orders (Figure 10), and an upstream information sharing model, where ordering decisions are made by backlogs and an information on current inventory levels of direct upstream actors (Figure 11).

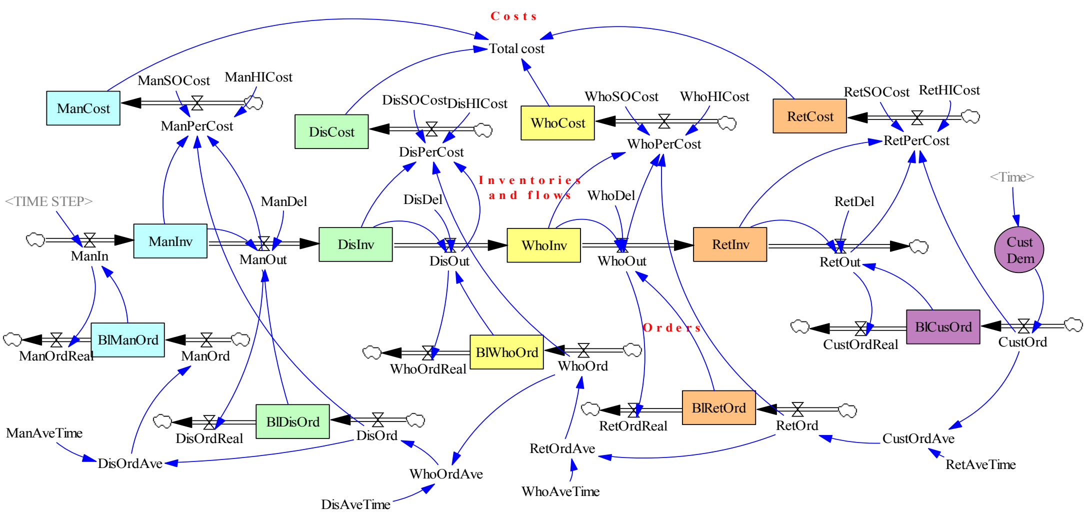

Figure 10. Stock and flow diagram (SFD) of the basic BDG 4-echelon supply chain model with inventory control by average demand with direct downstream information sharing.

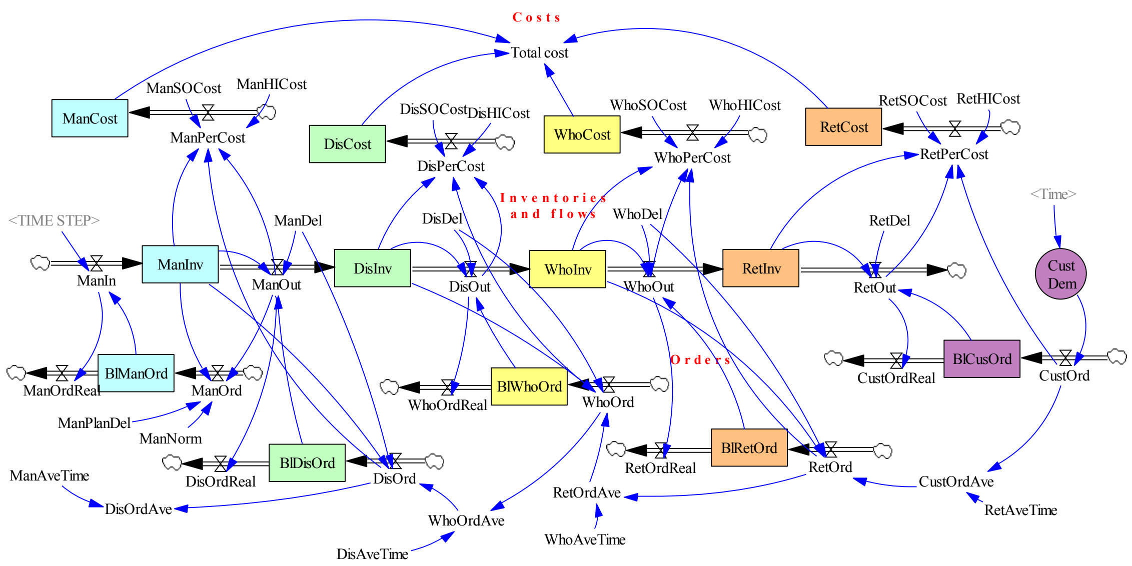

Figure 11. Stock and flow diagram (SFD) of the basic BDG 4-echelon supply chain model with inventory control by average demand by direct upstream inventory information sharing.

The simulation results of all these BDG model versions in the case of 3-type exogenous *CustDem* input functions (sinusoidal, step, and random) have proved better performance of upstream and downstream information sharing ordering policies in the supply chain (Table 3).

Table 3.
Total cost of supply chain in BDG model with 3 options to share information

Demand pattern	Information sharing		
	no information	direct downstream	direct upstream
Sinusoidal	3139.43	3173.24	2476.43
Step	3897.79	3073.89	2608.58
Random	2891.73	2413.65	2218.93

4. Summary and final remarks

The methodology of dynamic system analysis and understanding, e.g. the issue of supply chain system's structure influence to system's behavior, is still an important research challenge for theory and practice of systems science, systems' modeling and management. As presented above in a loop polarity detection methods comparison, we cannot give any hope for a *unified theory of systems analysis*, that is able to automatically provide modelers with any guideline to identify directly *dominant structures*. But this is also not to say that formal (or even heuristic) methods should not be worked out. Relatively well developed mathematical methods and techniques concern gradient systems as well as some classes of non-linear systems. In practice, in the implementation of many simulation projects with an application of SD modeling method and customer-oriented modeling techniques (customer knowledge and experience, needs and expectations), the issue of dominant feedback loop identification and analysis is solved (resolved) rather by an intuitive, heuristic, and subjective experimental procedure. The lack of an effective mathematical (or heuristic) methods to select structurally responsible systems' paths and feedback loops for systems' behavior is a limit to disseminate SD approach in systems' modeling. Existing solutions in the form of software tracking tools for feedback loops in SD models in some software packages (*Vensim*, *IThink*, *Stella*, *PowerSim*) are far to provide satisfactory results (Heyward et al, 2014).

Important challenges for the future SD modeling of social and economic systems aiming at dynamic systems' analysis, diagnosis, and design (redesign) for management purposes (e.g. in supply chains) still remain. It contains development of theory foundations, technological and model implementation environments, and education with training resources. In the theory context, the most important challenges are nonlinearity and complexity of dynamic systems, social and economic evolution processes, influence of mental models (e.g. individual models, group models, team models) on systems' comprehension and decision making policies design, identification of potential behavior of a dynamic system just from the structure, and some typical theory of modeling issues, i.e. aggregation (e.g. metamodeling) and disaggregation (e.g. agent-based modeling), relevance of models (e.g. validity, verification, certification). In the technological and implementation context, the future challenges are improvements in available modeling technologies and software tools, i.e. effective and efficient algorithms, functions and methodological integration, standardization, parameters' calibration, automated and interactive modeling stages with help and assistance, visualization of model runs, input and output data analysis, consensus development in soft systems (e.g. group model building approaches, communication in modeling). In the context of knowledge propagation (education and training), the future research issues are systems thinking and dynamic systems modeling knowledge-based systems' design (e.g. best modeling practice and guidance library collection), new (better) curricula and pedagogy for schools (primary, secondary, high), and universities.

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Footnotes

A business game called BDG (*Beer Distribution Game*) was developed at the Sloan School of Management, Massachusetts Institute of Technology (MIT) in the 1960s as a version of the earlier (1958) *Refrigerator Game*. Demonstrated during the *System Dynamics Conference* (SDC) in Chestnut Hill - Boston by John D. Sterman (Sterman, 1989), it gained worldwide recognition and popularity among management theoreticians and practitioners. It has also an interactive Internet version (Machuca et al., 1997). In Poland, it was presented for the first time during a session of the *Economic Systems Simulation School* in Węgierska Górka in 1990 by Bogusław Wąsik (AE Kraków) and described in (Wąsik, 1992).