SYSTEM DYNAMICS: SYSTEMIC FEEDBACK MODELING FOR POLICY ANALYSIS

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Contents

"Que sais-je?" ("What do I know?") (Montaigne)

To the memory of my father who somehow taught me to be a student for life...

Summary

The world is facing a wide range of increasingly complex, dynamic problems in the public and private arenas alike. System dynamics discipline is an attempt to address such dynamic, long-term policy problems. Applications cover a very wide spectrum, including national economic problems, supply chains, project management, educational problems, energy systems, sustainable development, politics, psychology, medical sciences, health care, and many other areas. This article provides a comprehensive overview of system dynamics methodology, including its conceptual/philosophical framework, as well as the technical aspects of modeling and analysis. The article frequently refers to other articles in the same Theme as appropriate. Today, interest in system dynamics and related systemic disciplines is growing very fast. System dynamics can address the fundamental structural causes of the long-term dynamic contemporary socio-economic problems. Its "systems" perspective challenges the barriers that separate disciplines. The interdisciplinary and systemic approach of system

dynamics could be critical in dealing with the increasingly complex problems of our modern world in this new century.

1. Introduction

At the start of the new century, the world is facing a wide range of increasingly complex, dynamic problems in the public and private arenas alike: nations desire economic growth, yet growth also results in environmental and ecological—sometimes irreversible—destruction. Chronic high inflation, budget deficits, and simultaneous high unemployment together constitute a persistent problem for many developing countries. There is a widening gap between the so-called "north" and "south" nations and also a widening gap between the poor and the rich in a given nation. Markets—both commodities and financial—generate all sorts of short, medium, and long-term cycles, the uncertainty of which has been a major problem for private and public decision-makers for decades. Thousands of small companies are initiated each year, many enjoying a fast—yet unbalanced—growth, only to be followed by bankruptcy in a few years. Globalization is posing new challenges in the social, economic, and corporate domains. With the unprecedented speed of international communication, the "new" economy means that companies will soon find themselves in a complex network of relationships and only those that can understand its dynamics will be able to compete. We are already experiencing the first worldwide recession of the "new" economy—of the new millennium. In the socio-economic domain, there is a tension between the interests of the nation-states and those of international conglomerates, between increasing international interaction and increasing micro-nationalism. Many nations worldwide face the dilemma between full democracy/human rights and the special measures often needed against terrorism.

The examples listed above have some common defining characteristics: they are all dynamic, long-term policy problems. "Dynamic" means, "changing over time." Dynamic problems necessitate dynamic, continuous managerial action. Optimum oil well location problem may be a very difficult problem, but it is nevertheless a "static" decision problem. The decision is made once, and it is not periodically monitored and adjusted depending on the results. The dynamic problems mentioned above, however, must be continuously managed and monitored. Thus, in the specific context of management and policy making, dynamic problems are the ones that are of persistent, chronic, and recurring nature. We take managerial actions, observe the results, evaluate them and take new actions, yielding new results, observations, further actions, and so on, which constitutes a "closed loop." In other words, most dynamic management problems are "feedback" problems. Feedback loops exist not only between the control action and the system, but also in between the various components within the system. Therefore, it is also said that such dynamic feedback problems are "systemic" in nature, that is, they originate as a result of the complicated interactions between the system variables. Finally, since dynamic management necessitates a stream of dynamic decisions, the research focus should not be the individual decisions, but the rules by which these decisions are made, that is, the "policies." The individual decisions are the outcomes of the application of the adopted policies.

System dynamics discipline emerged in the late 1950s, as an attempt to address such dynamic, long-term policy issues, both in the public and corporate domain. Under the leadership of Jay W. Forrester, a group of researchers at M.I.T. initiated a new field then named Industrial Dynamics. (see "*On the history, the present, and the future of system dynamics*"). The first application area of the methodology was the strategic management of industrial problems. The main output of this research was the publication of *Industrial Dynamics*, the seminal book that introduced and illustrated the new methodology in the context of some classical industrial/business problems. The next major project was *Urban Dynamics*, presenting a dynamic theory of how the construction of housing and businesses determine the growth and stagnation in an urban area. With this application, "industrial dynamics" method moved to the larger domain of socio-economic problems and was eventually renamed "system dynamics." The second application in the larger socio-economic domain was *World Dynamics* (and *Limits to Growth*). These models show how population growth and economic development policies can interact to yield overshoot and collapse dynamics, when crowding and overindustrialization exceed the finite capacity of the environment. In a short period of time since the late 1970s, applications have expanded to a very wide spectrum, including national economic modeling, supply chains, project management, educational problems, energy systems, sustainable development, politics, psychology, medical sciences, health care, and many other areas. In 1983, the International System Dynamics Society was formed. The current membership of the Society is over 1,000. The number of worldwide practitioners is probably much higher than this number.

The purpose of the Theme articles (see *Related Chapters*) is to present a thorough exposition of the major aspects of system dynamics method, including its philosophical and historical roots, its technical components, selected exemplary applications, and specific illustrations of its potential in sustainability discourse. The Theme articles, written by experts in respective domains, are grouped under some natural "topics." We start with "*System dynamics in action*," a small collection of exemplary applications to give the reader an idea of how the methodology is applied, illustrating the breadth, as well as the depth. The second topic consists of articles discussing the historical, conceptual and philosophical foundations of the field. The third topic of the Theme covers some fundamental concepts and tools of the system dynamics methodology. We next focus on selected technical/mathematical issues in modeling, numerical problems in simulation and other software considerations. The fifth topic is about policy improvement and implementation issues, covering public policy as well as business strategy, plus some general concepts and procedures of implementation. Finally, the last topic consists of six different applications of system dynamics approach and methodology in areas closely related to sustainable development.

The goal of this particular Theme-level article is to provide a comprehensive overview of system dynamics methodology, including its conceptual/philosophical framework, as well as the technical aspects of model construction, analysis and policy design.

2. Dynamic Problems and Systemic Feedback Perspective

2.1. Dynamic Feedback Problems

The term "dynamic," in its general sense, means "in motion" or "changing over time." Dynamic problems are characterized by variables that undergo significant changes in time. Inventory and production managers must deal with inventories and orders that fluctuate; city administrations face increasing levels of solid waste, air and water pollution; wildlife managers are concerned about declining species diversity worldwide; citizens raise their voices against escalating arms race; at a personal level, we are concerned when our blood pressure or our heartbeat is unstable, or when our temperature goes up; national leaders are worried about increasing unemployment and inflation levels; the small company is in danger when a few years of fast growth is followed by a sharp decline in the market share. In each one of these cases, there are one or more patterns of dynamic behavior that must be managed (controlled, altered or even reversed). Figure 1 illustrates some typical dynamic patterns observed in real life: explosively growing world population, oscillating commodity (pulp) prices, exponentially declining cocaine prices, and growth-then-collapse in revenues (of Atari, Inc). Yet the defining property of a dynamic problem in our sense (in *systemic, feedback* sense) is not merely the variables being dynamic. More critically, in a systemic dynamic problem, the dynamics of the variables must be closely associated with the operation of the *internal structure* of some identifiable system. It is said that the dynamics is essentially caused by the internal feedback structure of the system. (*endogenous* perspective). Thus, oscillating inventories is a systemic, feedback problem because oscillations are typically generated by the interaction of ordering and production policies of managers. It would not be a systemic problem, if the oscillations were determined by an external force like fluctuating weather conditions: although it would still be a dynamic problem in its technical sense. In this latter case, there is not much the inventory managers can do to eliminate or reduce the oscillations. If, as allowed by a new deregulation, a multinational chain colonizes the grocery market, which in turn causes an unavoidable decline in small grocery store sales, this would not be a systemic feedback problem. There is not much "management" the small grocery store owner can do in order to reverse the deregulation or influence the policies of the multinational chain. The importance of the distinction is that if/when the dynamics are dictated by forces external to the system; there is not much space or possibility for managerial control and improvement. Systemic feedback problems on the other hand, necessitate dynamic, continuous managerial action.

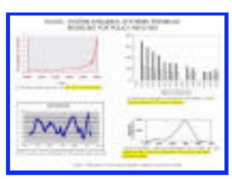


Figure 1. Illustrations of some typical dynamic patterns observed in real data.

Dynamic management problems in real life are typically feedback problems: we take managerial actions, observe the results, evaluate them and take new actions, yielding new results, observations, further actions, and so on, which constitutes a "feedback loop." Feedback loops exist not only between the managerial action and the system, but also in between the various elements within the system. That is, most dynamic management problems are also "systemic" in nature. The main purpose of system dynamics methodology is to understand the causes of undesirable dynamics and design new policies to ameliorate/eliminate them. Managerial understanding, action and control are at the heart of the method. System dynamics thus focuses on dynamic problems of systemic, feedback nature.

2.2. Systems, Problems, and Models

The term *system* refers to "reality" or some aspects of reality. A system may be defined as a "collection of interrelated elements, forming a meaningful whole." So, it is common to talk about a financial system, a social system, a political system, a production system, a distribution system, an educational system, or a biological system. Each of these systems consists of many elements interacting in a meaningful way, so that the system can presumably serve its "purpose." But it is not trivial for a system to serve its purpose effectively: the global socio-economic system is still facing millions literally starving to death—certainly not an intended result; on the other hand our economic development generates solid waste, air and water pollution levels that threaten the sustainability of life on earth; commodity and financial systems alike generate highly unstable fluctuations worldwide; national economies are often unable to control the simultaneous problems of budget deficit, inflation, and unemployment; small companies typically enjoy a fast growth initially, only to be followed by a sudden collapse—an inevitable result of the unbalanced growth itself; as individuals, we must often deal with health problems such as high blood pressure or cholesterol that our very life style creates, and so on. In short, systems at all levels, scale and scope, while solving one set of problems, simultaneously "produce" other complex challenges.

A common scientific tool used in investigating problems and solutions is *modeling*. A *model* can be defined as "a representation of selected aspects of a real system with respect to some specific problem(s)." Thus, we do not build "models of systems," but build models of selected aspects of systems to study specific problems. The crucial motivation, purpose that triggers modeling is a problem. The problem can be practical (such as increasing levels of unemployment, declining species population, or collapsing stock prices) or theoretical (such as analyzing a cognitive theory of how knowledge is acquired, or testing the validity of Marx's theory of class struggle, or whether long-term ecological/environmental sustainability is possible in a capitalist system). In any case, without a problem-purpose, "modeling a system" is meaningless. One does not build a model of a national economy, or a species population, or stock market. One builds a model of some selected elements and relations in a national economy that are likely to have caused a recent upward trend in unemployment; or a model of selected factors believed to play a strong role in an unstoppable decline in the population of a species of concern; or a model that selectively focuses on those factors that are likely to explain a crash in a specific stock market in a specific time period. In the theoretical domain, the principle is the same: one builds a model to study a specific problem/theory so as to contribute to the debate in the relevant community.

Models can be of many types: *Physical* models consist of physical objects (such as scaled models of airplanes, submarines, architectural models, models of molecules). *Symbolic* models consist of abstract symbols (such as verbal descriptions, diagrams, graphs, mathematical equations). System dynamics models are symbolic models consisting of a combination of diagrams, graphs and equations. In another dimension, models can be *static*, representing static balances between variables, assumed to be constant in a time period (such as an architectural model or a mathematical equation representing the relation between price, supply and demand at a point in time). Or they can be *dynamic*, representing how the variables change over time (such as an aircraft simulator to train pilots, Newton's laws of motion, or a mathematical model of price fluctuations in commodity markets). Another typical classification of models is: *descriptiv*e versus *prescriptive*. Descriptive models describe how variables interact and how the problems are generated "as is," they do not state how the system "should" function in order to eliminate the problems. Prescriptive (often optimization) models however assume certain "objective functions" and seek to derive the "optimum" decisions that maximize the assumed objective functions. Nonlinear dynamic feedback problems are typically mathematically impossible to be represented and solved by optimization models. System dynamics models are thus descriptive models. The policy recommendations are derived not by the model, but by the modeler, as a result of a series of simulation experiments. Finally, dynamic models can be *continuous* or *discrete* in time. In time-continuous models, change can occur at any instant in time (such as air temperature, humidity, or population of a city), whereas in time-discrete models, change can only occur at pre-defined discrete points in time (such as salaries changing in multiples of months, or student grade point average changing each semester). Real dynamic systems consist of both types of dynamics. So a system dynamics model can be continuous, discrete or even hybrid. In practice, if the discrete time steps associated with the discrete variables is small enough compared to the time horizon of interest (such as a model involving salary dynamics, simulated for decades) one can safely do the time-continuity assumption. The rationale behind this approximation is that continuous-discrete hybrid models can be very cumbersome to build, analyze, and communicate. Continuous system dynamics models are mathematically equivalent to *differential* (or *integral*) equations, whereas discrete models are *difference* equations. In sum, typical system dynamics models are descriptive, continuous or discrete dynamics models, focusing on policy problems involving feedback structures.

2.3. Structure and Behavior

The *structure* of a system can be defined as "the totality of the relationships that exist between system variables." In a production system, the structure would include the material and information flows related to production, where and how the various stocks are stored and shipped, how the ordering and production decisions are made, and so on. The structure of the system operates over time so as to produce the *dynamic behavior patterns* of the system variables. It is said, "the structure creates the behavior." The structure of the production department operates over time and generates production rate dynamics, raw material orders, oscillating inventories, and depending on system boundary, dynamics of product quality and sales. Dynamic behaviors of a few variables observed in different real systems were already illustrated in Figure 1. Figure 2 presents a generic template of most dynamic behavior patterns typically encountered in dynamic feedback problems. As seen in the template, the common dynamic behavior categories are: constant, growth, decline, growth-then-decline, decline-then-growth, and oscillatory. In each category there are different variants of the representative category, as seen in the figure. Furthermore, in reality these basic dynamic patterns can combine in various ways, such as oscillations followed by collapse or growth followed by decline-then-growth. Examples of such dynamic behavior patterns will be seen throughout this Theme.

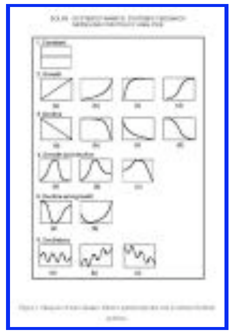


Figure 2. Categories of basic dynamic behaviour patterns typically seen in systemic feedback problems.

The structure of a real system can naturally be extremely complicated, hence not exactly or completely known. But we do know that there is a structure that operates to produce the dynamics of system variables. The *structure* of the model is a representation of those aspects of the real structure that we believe (or hypothesize) to be important, with respect to the specific problems of concern. In the production example, the problem may be large oscillations in inventories or a persistent decline in product quality. These two different problem-orientations would yield different model structures. The structure of the model comprises only those parts of the real structure that play a primary role in creating the problematic behavior patterns. The structure of a production model to study the problem of oscillating inventories must include all variables, factors and relations responsible for inventory oscillations

The structure of a system dynamics model consists of the set of relations between model variables, mathematically represented in the form of equations. That is, the structure of a system dynamics model is a set of differential and/or difference equations. The analytical (mathematical) solution of a dynamic model, if obtainable, would give the exact formula for the dynamic behaviors of variables. So, one way of obtaining the dynamic behavior of a model is solving it analytically. This is often possible in linear cases, but very rarely possible in non-linear ones. In such cases, the dynamic behavior of the model is obtained by *simulation*. Simulation is essentially a step-by-step operation of the model structure over compressed time. Much like the operation of the real structure over real time, the model structure operates over simulated time, so that the dynamics of model variables gradually unfold. A crucial notion in system dynamics method is that the term "model" refers strictly to the structure, to the set of equations describing it. The dynamic behavior of the model, whether represented in equations or plotted graphically, is not a "model" in system dynamics sense. The dynamic behavior is the output or the result of a model, very different conceptually from the model itself. In some disciplines such as forecasting, an equation representing a dynamic behavior would be legitimately called a model; but the structure-behavior distinction is crucial in system dynamics method.

Example 2.1: Consider a simple population dynamics of a single species on a large, isolated island. The structure of this system in real life would consist of males and females mating and reproducing, growing up, getting old, and eventually dying. Assuming that there is plenty of food, no competition, no epidemic, and a large island, if we start with a small number of animals (males and females), the operation of this structure over time would create an exponential growth in the population.

Assume that our purpose is to study this growth in population, its doubling time and its sensitivity to different birth and death rates. In the real system, there would be many details like some members being weak and unable to find food or mate, territorial fights, different categories of death (old age, fights, disease) geographical distribution of the population, weather conditions, seasonal changes in habitat, and so on. But for the simple purpose stated above, these details can perhaps be omitted and a simple model would be:

$$\frac{dx}{dt} = births - deaths,$$

which states that the rate of change of population is (*births* – *deaths*), where $x(t)$ denotes the population of the species at time t, and *births* and *deaths* must be specified.

The simplest formulation for *births* and *deaths* is the assumption that they are proportional to the population: *births=bx* and *deaths=fx,* where b is the birth fraction per year and f is the death fraction per year. Thus:

$$\frac{dx}{dt} = bx - fx$$

The above model is a differential equation. Alternatively, the same equation can be represented in integral form:

$$x(t) = x(0) + \int_0^t (bx - fx)dt,$$

which states that the population at time t is given by its value at time 0 plus the sum of all births minus all deaths between time 0 and time t. Population at time 0 is assumed to be known as $x(0)$.

In order to be able to solve this model, we must make one final assumption about the parameters b and f. In the simplest case, these fractions are assumed to be constant. Then, the simple differential equation model for population growth becomes:

$$\frac{dx}{dt} = (b - f)x = kx,$$

where we let $k = (b - f)$, also a constant.

To solve, use separation of variables and integrate:

$$\int(\frac{1}{x})dx = \int k dt,$$

which yields:

$\ln x + C1 = kt + C2$, where $C1$ and $C2$ are arbitrary constants of integration. Combining:

$\ln x = kt + C3$, where $C3$ is another constant. Taking exponential of both sides:

$x = e^{kt+C_3} = e^{C_3}e^{kt} = Ce^{kt}$, where C is yet another constant. To evaluate it, use $x(0)$:

$x(0) = Ce^0$, or $C = x(0)$. Thus, the complete solution is:

$x(t) = x(0)e^{kt}$.

We can plot this solution for possible values of k and obtain the dynamic behaviors shown in Figure 3(a). Note that the dynamic behavior of the model depends on the value of $k = b - f$. If $b > f$, then the behavior is an exponential growth, if $b < f$, then the behavior is a negative exponential decline and if $b = f$, then the population stays constant.

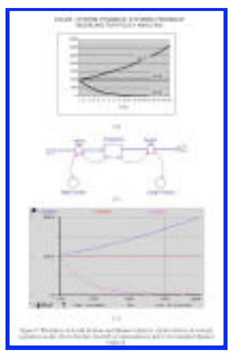


Figure 3. Illustration of model structure and dynamic behavior

The *structure* of this system is represented by the differential (or integral) equation given above. Its *dynamic behavior* is described by the solution equation ($x(t) = x(0)e^{kt}$). Alternatively, we typically represent the structure by a *stock-flow diagram* (and associated simulation equations). The dynamic behavior is then obtained by simulation and presented graphically. The stock-flow structure of the simple population model built in STELLA software and the simulated dynamic behavior are shown in Figure 3 (b) and (c).

2.4. Principles of "Systemic Feedback" Approach

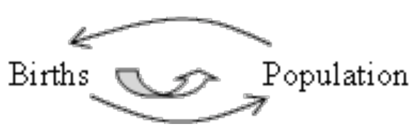
System dynamics discipline deals with dynamic policy problems of systemic, feedback nature. As discussed above, such problems arise from the interactions between system variables and from the feedbacks between the managerial actions and the system's reactions. The purpose of a system dynamics study is to understand the causes of a dynamic problem, and then search for policies that alleviate/eliminate them. This specific purpose necessitates the adoption of a particular philosophy of modeling, analysis and design. This philosophy can be called "systemic feedback" philosophy (or approach or thinking or perspective). Systemic feedback thinking has important historical links with various disciplines and philosophies, namely General Systems Theory (Ludwig von Bertalanffy), Systems Theory and Sciences (i.e. Kenneth Boulding and Herbert Simon), Systems Approach (i.e. West Churchman), Cybernetics (Norbert Wiener) and Feedback Control Theory (Gordon Brown). (see "*The role of system dynamics within the 'Systems' movement*") In a sense, systemic feedback philosophy integrates systems theory with cybernetics and feedback control theories. It is thus a unique systems theory, placing critical emphasis on the dynamic and feedback (closed-loop) nature of policy problems. From this perspective, it is possible to identify some principles that are absolutely essential to systemic feedback approach:

Principle 1: Importance of causal relations (as opposed to mere correlations).The purpose of a system dynamics study ("understanding and improving the dynamics") is very different from short-term prediction (forecasting) of future values of variables. The very purpose of system dynamics study requires that the model consist of causal relations, not mere statistical correlations. It is possible to generate excellent short-term forecasts by non-causal correlational models, but impossible to understand and control dynamic problems. For instance, swimsuit sales and ice cream sales are highly positively correlated (both going up in spring-summer season). If we have data on swimsuit sales (x), we can construct a correlational model $y = f(x)$ that would provide excellent forecasts for ice cream demand. For this narrow forecasting problem, the above model is very functional. On the other hand, assume that a company is faced with a consistent decline in ice cream sales after several years of growth and our objective is to understand (and reverse) this problematic dynamics. In this case, the correlational model $y = f(x)$ would be of no use, since this model gives no clue as to what "causes" the dynamics of ice cream sales. The input variable (swimsuit sales) has no causal influence on ice cream sales (y) whatsoever. Ice cream sales did not go down *because* swimsuit sales went down and they will certainly not improve by improving swimsuit sales (which is most likely not even part of our business)! Similarly, one can show that rainfall and skin cancer incidences are negatively correlated. (In cloudy regions, rainfall goes up and skin cancer goes down due to reduced sunrays). But rainfall does *not cause* skin cancer incidence to go down. If we confuse this negative correlation with negative causation, we would start marketing bottled rainfall for people to rub on their skins three times a day!

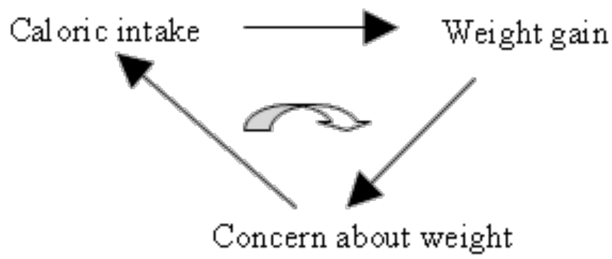
A causal relation $y=f(x)$ means that the input variable (x) has some *causal influence* on the output variable (y). Statements like "an increase in caloric intake causes weight gain" / "increased death rate causes the population to decline" / "increased pesticide application causes an increase in bird deaths" or "an increase in price causes the demand for a given commodity to go down" all reflect simple cause-effect relations. In each of these examples, if the cause variable is changed, one expects "some degree of change" in the effect variable. The term "expects" is important in the definition of "causality" in systemic feedback modeling. Whether the expected change actually occurs or what kind of change is observed (in the model or in reality) depends on many other factors. Each causal relation in a system dynamics model is a "*ceteris paribus*" argument: "other things being equal" the causality is expected to yield the stated effect. Since there are many other varying factors in a dynamic feedback model (and in reality), ceteris paribus condition would not/should not typically hold. Thus, an increase in price may not actually result in a decline in demand, because the price of the competitor product may have increased even more or the quality of the product may have simultaneously gone up. So the notation *X* ® *Y* reads "other things being equal, a change in *X* causes a change in *Y*."

From a philosophical perspective, causality is a very difficult and debatable notion. There is no universally accepted, non-problematic definition of causation in philosophy. Yet the notion of causality needed for system dynamics modeling is an operational, practical one: non-controversial cause-effect relations, well established either by direct real-life experience or by scientific evidence in the literature. In adopting this definition, the main idea is to avoid using mere statistical correlations in lieu of causation. Once this is understood, in this operational, practical sense, there is normally no disagreement on what is "causal" and what is merely "correlational." (The correlational and causal examples given in the above paragraph should make the point clear. More examples will be seen later in section 3).

Principle 2: Importance of circular causality (feedback causation) over time. Identification of one-way causal relations described above is only the first step in dynamic feedback model conceptualization. The next crucial phase is the identification of dynamic, circular causalities (feedback loops) over time. One-way causality is in a sense "static" causality at a point (or small interval) in time. The relation births ® population states that births are a cause and population is an effect. But when examined dynamically over time, it is also true that population causally affects births. (The more people, the more births there will be). Thus we have:



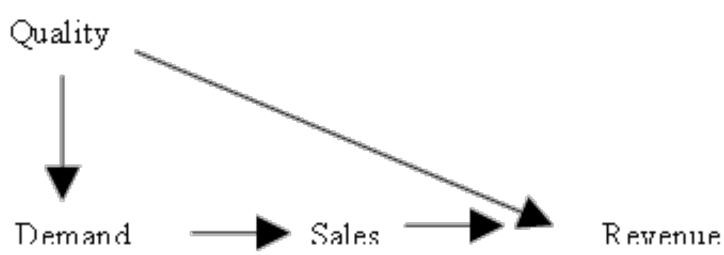
The above picture says that over time, births determine population and population determines births. Such a circular causality is only possible dynamically; it requires passage of time, because at a fixed instant in time it would be impossible for births to determine population *and* be determined by it. But over time, cause and effect (births and population) continuously trade places. More births mean higher population, which causes even more births, causing even higher population, and so on. The operation of this loop over time would create exponentially growing population. The feedback loop is in this sense the "engine" of change. (As will be seen later, interaction of multiple loops would constitute a much more sophisticated engine, creating much more sophisticated dynamics). In general, for a feedback loop to form between two variables, one or more variables would intervene. For instance, using the very first causality example above:



The above picture states that the more calories I take, the more weight I gain and as I realize my weight gain, I become concerned about it, which leads me to cut down on my caloric intake. In the original example, caloric intake was cause and weight gain was the effect. In this dynamic version, we observe that weight can be in time an indirect *cause* of caloric intake, via the new variable "concern about weight." Notice also that the dynamic behavior of this loop would be very different from the births-population loop; it would keep the caloric intake under control. The behavior of this loop would be a convergent one, rather than a divergent one. A more technical discussion of these two types of loops will be given later in the following section.

The above 3–variable loop illustrates another important sub-principle: A cause-effect arrow in a model must represent a "direct causality" between two variables, given the other variables in the model. In the above example, it would be wrong to draw a link from weight to caloric intake directly (caloric intake ¬ weight), since the effect must really go through the intervening variable "concern about weight." As a more typical example, consider Quality of a product, Demand, Sales and Revenues. A simple causal diagram would be:

The diagram says: higher quality causes an increase in demand, meaning higher sales, hence higher Revenues, (assuming fixed price). In daily talk, one often summarizes the above diagram by "quality causes increased revenues." An erroneous causal diagram would be obtained, if one were to implement this simplification in the above diagram:



(a) Wrong inclusion of "indirect" causality.

(b) "Correct" in the context of given variables.

The conceptualization in (a) is clearly wrong, as it is "double counting" the effect of quality on revenues. Quality has no known direct influence on Revenues, other than influencing it via Demand. Also note that the diagram would still be wrong, even if one eliminated the arrow from Quality to Demand (to avoid double counting). Given that the model already has the variables Demand and Sales, it would be illogical for the Quality to affect the Revenues directly. However, the diagram in part (b) would be a correct simplification, given the assumption that Demand and Revenues are not needed in the model. In this case, the "indirect" causal arrow from Quality to Revenues is an acceptable simplification. Thus the principle of "direct causality" is important in system dynamics, but it is also relative: "direct causality in the context of other variables in the model."

Principle 3: Dynamic behavior pattern orientation (rather than event-orientation. It is crucial to reiterate that the purpose of a system dynamics study is to understand the causes of a dynamic problem, and search for policies that alleviate/eliminate them. Dynamic problems are characterized by undesirable performance patterns, not by one or more isolated "events." In ordinary daily life, we all react to events: a sudden drop in the stock prices, a jump in the interest rates, resignation of a cabinet, or the September 11 attack on the World Trade Center are dramatic examples. Dynamic feedback approach argues that such events can not be analyzed or understood in isolation from their past dynamics. When isolated by their past histories, and by the dynamics of related variables, events seem random, unavoidable, and externally caused. But dynamic systems approach argues that most important events occur as a result of some accumulations (often hidden) reaching threshold levels over time. Short-term event orientation makes it impossible to understand the real historical and structural causes of events. Hence, analysis and understanding requires that we move away from the common event-orientation and focus on historical behavior patterns associated with potential events. With the proper behavior-pattern orientation, the goal is to construct a hypothesis (a model structure) that explains why and how the dynamic patterns of concern are generated. (Typical dynamic behavior patterns were illustrated in Figures 1 and 2).

Principle 4: Internal structure as the main cause of dynamic behavior (Endogenous perspective). The structure of a system was already defined as "the totality of the relationships that exist between system variables." One way of representing the structure of a system is diagramming the causal links and (especially) loops that exist between the variables. As stated above, the interaction of the feedback loops in a system is the main engine of change for the system. That is why it is said: "the structure causes the behavior of the system." This principle is critical in a system dynamics study, because the purpose is to understand the causes of an undesirable behavior and try to improve it. The principle can be better illustrated by an example.

Example 2.2: Consider the dynamics of the population of a modern city—perhaps a strong early growth followed by stagnation. A static and exogenous model for population would be:

Population = f(Job availability, Salaries, Expenses, House prices, House availability, Crime rate, School quality, Air/water quality...)

A pictorial representation of this model is shown in Figure 4(a). This model basically says that it is possible to determine population level, once the values of the input variables (eight of them) are given.

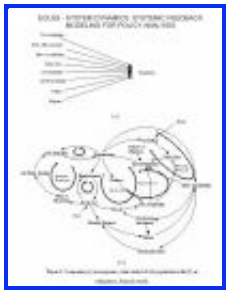


Figure 4. Comparing a) an exogenous, static model of city population with b) an endogenous, dynamic model.

This model has some very strong assumptions. It assumes that the input variables are strictly *independent* variables. That is, they are not influenced at all by Population, or by any of the other seven input variables. (These external inputs are called "forcing" functions in engineering and their existence makes the system "forced" or "non-autonomous"). The model in Figure 4 (a) is of course an extremely unrealistic situation. In reality, Population would strongly affect some of these "independent" variables and some of them would strongly influence others as well. Such a model therefore is not a causal model of population dynamics, and as such cannot give any information on why the population behaves the way it does. On the other hand, this model could produce very reliable predictions of the population levels, for given values of input variables. Thus, such an exogenous model can be useful for short-term population forecasting, but cannot be used at all for policy analysis and design purposes.

Contrast the above model with the one shown in Figure 4(b). This second one is a dynamic and endogenous account of the dynamics of city population. Note that in this diagram there is no obvious distinction of "input" and "output." All major factors in the city influence one another and ultimately their own dynamics, around many feedback loops. This example is designed deliberately such that most variables in the two models are common, so that the two can be easily compared. For instance, Job availability in the second model is given by the ratio Jobs/Workers, not an input variable. Jobs depend on Businesses and Workers are a fraction of the population. Businesses are initiated by entrepreneurs, which depend on Population as well as Businesses. (A fraction of Population yields potential entrepreneurs, but how active they actually are depends also on existing businesses). Finally, Job availability influences the in/out migration, which in turn creates an increase or a decrease in Population. Thus, a feedback loop emerges: Population ® Entrepreneurs ® Businesses ® Jobs ® In/out migration ® Population. This loop says that more people, more entrepreneurs, more businesses, more jobs, a more in-migration. This is probably one of the major loops that create typical early booms in newly industrialized cities. But this growth is not without opposition; there are other loops. For instance, more Businesses, more Waste/Emissions, lower Air/water quality and lower net birth rate. Thus, Population ® Entrepreneurs ® Businesses ® Waste/Emissions ® Air/Water Quality ® Net birth rate ® Population loop suppresses the indefinite population growth suggested by the previous loop. In a similar fashion, one can trace several other growth loops and balancing loops in the diagram. In the end, the dynamics of the population is determined as a result of complex interactions between these loops. The dynamics could be growth, collapse, growth-and-stagnation, growth-and-collapse, and so on. A technical discussion would require building of a complete model with equations, beyond the scope of this section. (For a discussion of the structure of a classical urban dynamics model and the resulting growth-stagnation dynamics, see "*Urban dynamics*"). The point of this example is to illustrate the principle of "internal structure as main cause of dynamic behavior." The example demonstrates that it is the internal structure (the nature and interaction of the loops, their relative strengths, and so on) that determines the dynamic behavior. This model is an endogenous theory about the dynamics of city population, because the dynamics is not merely imposed by external forces, it is internally determined. On such a model, it is possible to study the causes of, say growth-then-collapse of the population of a modern city and explore alternative policies. By contrast, the previous static and exogenous model is not a theory about population dynamics; it can be used for forecasting purposes only.

Principle 5: Systems perspective. For the system dynamics methodology to be applicable to a problem, the dynamics of the variables must be closely associated with the operation of the internal structure of a system. But what if the dynamics in the real problem are dictated by external variables? There are two possibilities: Rarely, it may be indeed true that by its very nature, the real system may be too vulnerable to external influences. We already mentioned such an example: If a multinational grocery chain opens a super-store next to a small grocery store, which in turn causes an unavoidable decline in small store sales, this would not be a systemic feedback problem. There is not much "management" the small grocery store owner can do in order to influence the policies of the multinational chain, economies of scale, regulations, and so on. Such extreme cases are simply "ill-chosen" system dynamics problems and there is not much the methodology can do. The problem itself is "too open" by definition. But more often, the argument that the dynamics of the system are caused by external forces is a result of narrow system conceptualization, not a property of the real problem. For instance, in the population example above, the first model was static and exogenous whereas the second one was dynamic and endogenous. But assume now that, lacking systems perspective, the second model omitted Businesses and related variables. In this case, Jobs availability, Water/air quality and Housing availability would all become external input variables. The dynamics of Population would then be determined essentially by these external input variables in the second model as well. In general, the modeler faces the challenge of adopting proper systemic perspective such that the major forces and interactions are included in the internal structure. This is the critical "model boundary" determination issue in system dynamics method. From systems perspective, the model boundary must be wide enough so as to have an internal structure rich enough to provide an endogenous account of the dynamics of concern.

The importance of the endogenous/exogenous distinction is that, if external forces dictate the dynamics, there is not much possibility for managerial control and improvement. In real life, perhaps as a self-defense mechanism, we tend to give much more weight to external forces compared to the internal factors. At a personal level, when I am behind in my research, I put all the blame on the university bureaucracy, too much unnecessary committee work, inefficient assistants, and even bad luck, all of which means that I have no fault. The failing manager blames the unfavorable macro economic conditions, vicious/unethical competitors, unprofessional suppliers and yes, bad luck too. The prime minister blames the opposition parties, the chamber of commerce, worker unions, the president (if from another party), hostile foreign governments, extraordinary weather conditions, and so on. "The enemy is out there." The major problem with this attitude is that it frees the management of the system (whether private life or a professional organization) from responsibility, which means no critical self-evaluation and no prospect for improvement. One of the challenges for a system dynamics study is to convince people that this type of defensive attitude is unproductive. From a systemic perspective, the dynamic problem is caused neither by the "external" enemy nor by the manager. There is no single person or entity to blame. The cause of the dynamic problem lies in a system structure that cannot cope with unfavorable external conditions. (The famous mass-spring system oscillates, when pushed by an external force. It does not oscillate *because* it is pushed. It oscillates because it has a spring, a structure ready to oscillate when touched). The cause is not the external enemy, but the way our system relates to/deals with the "external enemy." The internal structure of the model must include not only the relationships between the internal elements of a system, but also how the system relates/reacts to its environment, to the external forces. That is why "model boundary" determination is a subtle and critical task, quite dependent on the perspective and skills of the modeler. The model boundary is not automatically dictated by some natural "system boundary;" the modeler determines it.

2.5. Complexity of Dynamic Systems and Necessity of Modeling and Simulation

It is often said that dynamic systems are "complex." This is especially true for non-linear feedback systems involving human actors—typical subject matter of system dynamics studies. Here are some of the main reasons why such problems are complex:

Dynamics: Dynamic problems are naturally harder than static problems. Variables change over time as they interact. The changes are not straightforward to predict. There are time delays involved between causes and effects and between actions and reactions. Dynamics of systems may be hard to predict by intuition even with only a few variables.

Feedback: The problem is further complicated when dynamics are created by operation of feedback loops. It means that which way the system will move is not easily predictable; the evolution path unfolds gradually and continuously determines its own path into the future. (Path-dependent dynamics). Feedback dynamics are harder to predict by intuition, because they require mental simulation of interactions of several loops simultaneously.

Non-linearity: Most system dynamics problems are non-linear. This means that the cause-effect relations between variables are not proportional. Non-linear effects are subtle, because a certain effect observed in one range may not be valid at all in another range. Non-linearity furthermore often means that there are "interaction effects" between variables. That is, doubling the advertising may increase the demand by 20 percent when the price is around US$100, but the same effect may be only 5 percent when the price is around US$125. Non-linearity is very hard to analyze not only intuitively, but also mathematically, especially when embedded in a dynamic feedback context.

Scale: As the number of variables increases, the complexity of the problem increases nonlinearly. With only three or four variables, even a non-linear feedback problem can be analyzed in most cases mathematically and perhaps intuitively. But even "small size" policy problems involve tens of variables. At this scale, a non-linear feedback problem immediately becomes impossibly hard to track—mathematically and intuitively.

Human dimension: Typical system dynamics problems involve human actors. So we must model not only the physics of the system (including information flows), but also how people react to situations, make decisions, set goals, make plans, and so on. This "human dimension" adds yet another layer of complexity. Human elements are much harder to model than the mechanical/physical aspects. There are no established, tested laws of how people behave, react, or make decisions. Quite often, the modeler must create his/her own theory of how the human actors would behave in the specific context of a given task and environment. Human dimension makes the study harder not only in modeling, but also in testing and analysis phases.

Cause and effect separated in time and space: The result of the above facts is that in a non-linear dynamic feedback model with several variables, the cause-effect relations become detached in time and space. When an action is applied at point A in the model with an expected immediate result at point B, this result may never be obtained and furthermore, some unintended effect may be observed at a distant point C, after some significant time delay. We make a change in our marketing activity to boost sales, but nothing substantial happens at first and then, after many months, we may observe some unintended consequences in our production department.

Intuitive inadequacy: We human beings are not naturally equipped to deal with this type of detached cause-effect relation. A baby touches the stove with his/her index finger, and the index finger burns, and it burns now. The child learns immediately that touching the stove burns the hand; the causality is easy to extract, because the cause and effect are close in time and space. Like all animals, we can immediately learn this type of cause-effect relation. Our very survival depends on this intuitive skill. Now assume a strange hypothetical world where when a baby touches the stove, nothing happens to his hand, but weeks later his nose starts bleeding. It would be close to impossible for the baby to be able to link the effect to its cause in this strange world, because cause and effect are detached in time and space. What is worse, the baby would probably link the effect to some wrong causes, as he surely did many other things involving his nose just a few days, hours, or minutes before the bleeding. Organizations, socio-economic systems, are unfortunately like this strange world. A new decision in one sector of the economy can have several unexpected effects in other sectors, after many months or even years. With our time and space-constrained intuition of causality, we are prone to make wrong causality inferences about effectiveness of critical managerial, public or personal decisions. Finally, our intuitive ability is further impeded by delays, errors, omissions, and bias in data/information that we observe in real life.

All of the above complexities lead to the following conclusion: Large scale, non-linear, dynamic feedback models are too complex to be even partially analyzed and understood by our natural intuition. So we need help. The help that we obtain is two-fold: first, *formal modeling*. We build a formal model in order to make our *mental model* explicit, rigorously analyzable and testable, making scientific improvement possible. Our mental models have some major drawbacks: they are vague, implicit, often biased, ambiguous, and non-testable. (see "*Mental models of dynamic systems*"). A formal model, in contrast is explicit, precise, less biased, unambiguous and testable. So, a well-constructed formal model can eliminate most of the weaknesses of mental models. But this is only half of the story. The other major issue is *analysis* of the formal model. The exact and most general scientific method is, of course, mathematical analysis. But the required mathematics is unfortunately almost always impossible for large, non-linear dynamic feedback models. Thus, the second major assistance we seek is *computer simulation*. Simulation is an *experimental* way of analyzing the problem, which is another standard method of analysis in science. But in simulation, instead of experimenting with the real system, we experiment with a model of the real problem. In simulation, the model structure operates over simulated time, just like the operation of the real structure over real time, so that the dynamics of the variables gradually unfold. Thus, a set of carefully designed experiments can be carried on the simulation model, yielding some results about the dynamic properties of the system, the causes of the problematic dynamics, and how they can be improved. The validity of the model is of course vitally important in this approach. In system dynamics studies, simulation experimentation is often the only feasible scientific method of analysis. The other two classical methods, mathematical analysis and experimenting in the real system are unfortunately too often impossible. The impossibility of real system experimentation comes from huge risks, costs, time delays and other practical impossibilities involved in experimenting with socio-economic systems. Simulation combines the cost and risk advantages of mathematical modeling/analysis, with the mathematically unconstrained power and flexibility of experimental analysis.

3. Modeling Methodology and Tools

3.1. Steps of the System Dynamics Method

A typical system dynamics study goes through some standard steps. Although there will be variations depending on the nature of the problem and style of the modeler, main steps can be nevertheless summarized as follows.

Problem identification and definition (purpose): A system dynamics project is done to study a dynamic problem (applied or theoretical). Selection and articulation of a meaningful dynamic feedback problem is critical for the success of the project. The problem must be not only dynamic, but also of feedback nature. Externally driven dynamic problems are not meaningful system dynamics topics. Dynamic problems are characterized by behavior patterns that may be observed in plotted data or they may be deduced from available qualitative information. In a theoretical study, the dynamics would be a hypothetical plot. Some of the sub-steps of problem identification are:

· Plot all the available dynamic data and examine the dynamic behaviors.

· Determine the time horizon (into the future and into the past) and basic time unit of the problem.

· Determine the *reference* dynamic behavior: What are the basic patterns of key variables? What is suggested by data and what is hypothesized if there is no data? What is expected in the future?

· Write down a specific, precise statement of what the dynamic problem is and how the study is expected to contribute to the analysis and solution of the problem. Keep in mind that this purpose statement will guide all the other steps that will follow.

Dynamic hypothesis and model conceptualization: The objective of this step is to develop a hypothesis, a theory that explains the causes behind the problematic dynamics. This must of course be an "endogenous" explanation. Later, this hypothesis will be converted to a formal simulation model and the validity of the hypothesis will be tested. Dynamic hypothesis can also be called a conceptual model; a model that describes our hypothesis, not yet in a formal, testable form. This step involves the following main activities:

· Examine the real problem and/or the relevant theoretical information in the literature.
· List all variables playing a potential role in the creation of the dynamics of concern.
· Identify the major causal effects and feedback loops between these variables.
· Construct an initial causal loop diagram and explore alternative hypotheses.
· Add and drop variables as necessary and fine-tune the causal loop diagram.
· Identify the main *stock* and *flow* variables.
· Use other conceptualization tools (like sector or policy diagrams) as suitable.
· Finalize a dynamic hypothesis as a concrete basis for formal model construction.

Formal model construction: In this step, the formal simulation model is built. This involves the following sub-steps:

· Construct the stock-flow diagram; the structure of the model
· Write down mathematical formulations that describe cause-effect relations for all variables
· Estimate the numerical values of parameters and initial values of stocks
· Test the consistency of the model internally and against the dynamic hypothesis (*verification*).

Model credibility (validity) testing: Is the model an adequate representation of the real problem with respect to the study purpose? Model credibility has two aspects: first, Structural: is the structure of the model a meaningful description of the real relations that exist in the problem of interest? And second, Behavioral: are the dynamic patterns generated by the model close enough to the real dynamic patterns of interest? (see "*Model testing and validity*"). Examples of structural tests are: having experts evaluate the model structures, dimensional consistency with realistic parameter definitions, and robustness of each equation under extreme conditions and extreme condition simulations. Behavior tests are designed to compare the major *pattern components* in the model behavior with the pattern components in the real behavior. Such pattern measures include slopes, maxima and minima, periods and amplitudes of oscillations (autocorrelation functions or spectral densities), inflection points, and so on. Two principles are critical: first, unless structural validity is established to begin with, behavior validity is meaningless in system dynamics, and second, behavior testing does not involve point-by-point comparison of model behavior with real behavior; it involves comparing of *patterns* involved in the two.

Analysis of the model: The purpose in this step is to understand the important dynamic properties of the model. This can be done very rarely (sometimes partially) by mathematical/analytical methods. Although it is impossible to find the solution equations of system dynamics models mathematically, we can sometimes find the constant equilibrium levels and determine their stability. (see "*Equilibrium and stability analysis*"). More typically, analysis is done by simulation experiments. A series of logically related simulation runs can provide quite reliable (although not exact) information about the properties of the model. These simulation runs are also called sensitivity tests, as they try to assess how much the output behavior changes as a result of changes in selected parameters, inputs, initial conditions, function shapes, or other structural changes. (see "*Sensitivity analysis*").

Design improvement: Once the model is fully tested and its properties understood, the final step is to test alternative new *policies* to see to what extent they can improve the dynamics of the model. A policy is a decision rule, a general way of making decisions. Thus, a production policy would be represented by a set of equations that describe how the productions decisions are being made in the company. (An outcome of these equations would be a production *decision*). In this last step, alternative policies are designed and then tested by simulation runs. Policy improvement is a complicated task: The recommended policy must be realistic, considering the environment in which it will be implemented; the policy must be *robust*, in the sense that it should work under different environmental conditions and scenarios; interactions (positive or negative) of policies must be considered; transition dynamics—the response of the system during the transition from old policy to the new one—must be explicitly analyzed by simulation experiments as well. (see "*Intellectual roots and philosophy of system dynamics*").

Implementation: This step is applicable if the system dynamics study is an applied one. Needless to say, it is a vitally important step, since the ultimate success of an applied system dynamics project means a demonstrable and sustainable system improvement. A successful implementation in some sense depends so much on project specifics that it cannot be prescribed general rules or procedures. On the other hand, there are some general aspects of implementation success that system dynamics researchers have attacked. (see "*Implementation issues*"). There are some important new developments that seek to enhance implementation success, such as group model building (see

"*Group model building*") and interactive learning environments (see "*Modeling for learning and interactive environments*").

3.2. Stock and Flow Variables

In system dynamics models, it is essential to distinguish between two types of variables: *Stocks* and *flows*.

Stocks: They represent results of accumulations over time. Their values are "levels" of the accumulations. They are also called "states" as they collectively represent the state of the system at time *t*. The standard symbolic shape for a stock is a rectangle.

Stock Examples:

· population
· cash balance
· inventory of goods
· weight
· anger level
· knowledge level
· temperature
· glucose in blood

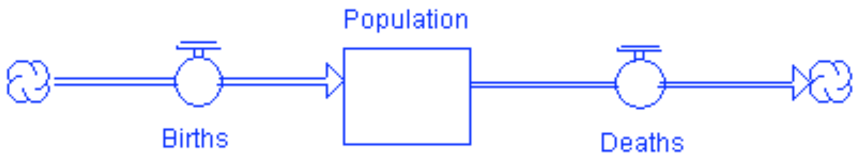
These examples show that stocks can be physical entities as well as information entities; they can be managerial control variables as well as natural/biological variables. Stocks are universal; they represent the critical accumulations on which the very existence of all sorts of life forms depend.

Flows: They directly flow in and out of the stocks, thus changing their values. They represent the "rate of change" of stocks. The symbol for a flow is an arrow (representing the direction of flow) and a valve (T or representing the fact that the flow quantity is being regulated).

Flow examples:

· births, deaths
· income, expenses
· production, sales
· caloric intake, calories burned
· increase and decrease in anger level
· learning and forgetting (or obsolescence rate)
· heat in, heat out
· glucose intake, glucose consumption

Note that the flow examples above are naturally paired with the stock examples above. For instance, Births are an *inflow* and Deaths an *outflow* for the Population stock. The symbolic representation:



Mathematically, the above diagram states:

$$\frac{dPop}{dt} = births - deaths$$,

in a continuous model. Or, to stress the accumulation nature of a stock:

$$Pop(t) = Pop(0) + \int_0^t (births - deaths)dt$$,

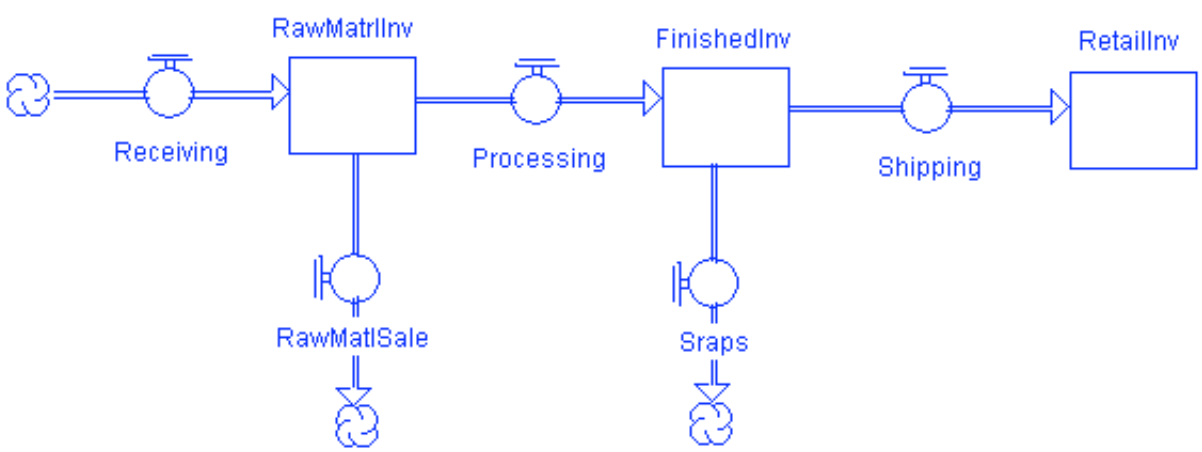
Pop(0) given. In numerical simulation, the same equation is approximately represented as:

$Pop(t) = Pop(t - dt) + ...$ for $t = dt, 2dt, 3dt...$

Finally, if the model described a discrete dynamic system, then:

$Pop(t) = Pop(t - 1) + (births - deaths)$, for t=1,2,3...

In any case, we see that the standard stock equation is a basic conservation equation over time. To represent the conservation more explicitly, the flow Births would flow out of some stock (Babies in conception) and Deaths would flow in some stock (dead people). In the above diagram, "clouds" represent the implicit stocks "Babies in conception" and "Dead people." The cloud symbol means that these two stocks are *outside the model boundary*, so we do not need to track them. ("Cloud" usage is standard in "information" stock-flows such as "knowledge increase," because an increase in my knowledge does not decrease somebody else’s knowledge: information flows typically are not conserved). More generally, in a stock-flow diagram there would be multiple stocks and flows, such as:



The above example says that there can be some sales directly from raw material inventory and some scraps from finished inventory. The computational stock equations in this case would be:

RawMatrlInv(t) = RawMatrlInv(t – dt) + dt * (Receiving – Processing – RawMatlSale)

FinishedInv(*t*) = *FinishedInv*(*t* – *dt*) + *dt* * (*Processing* – *Shipping* – *Sraps*)

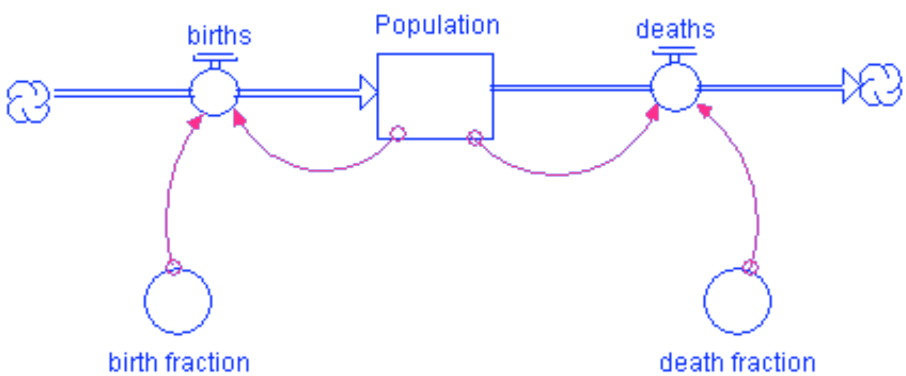
RetailInv(t) = RetailInv(t – dt) + dt * (Shipping)

In general, if a stock has j flows, the continuous stock equation is:

$$Stock(t) = Stock(0) + \int_0^t \left(\sum_j flows\right)dt$$

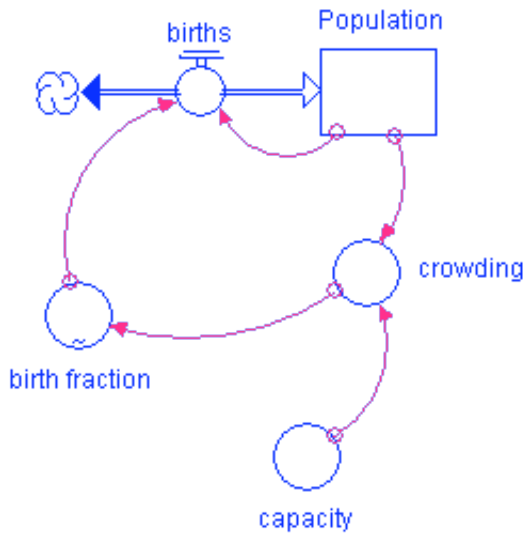
If a model has *n* stocks, it is said to be of *order n*. This is mathematically equivalent to a set of *n* 1^{st} order differential equations, or a single *n*th order differential equation (that is, highest derivative involved is of order *n*).

The above examples do not represent complete models. To be solvable (analytically or by simulation), the equations for flows must be specified. For example, in the simple population model, the simplest specification for births and deaths would be: *Births* = *b**Population* and *Deaths* = *d**Population*, where *b*: constant birth fraction and *d*: constant death fraction. The stock-flow diagram would then be:



The "effect" arrows in this diagram show that *Births* = *f* (*Population*, *Birth Fraction*) and *Deaths* = *f* (*Population*, *Death Fraction*).

Finally, in writing equations for flows, one often needs to define some intermediate variables, called *auxiliary* or *converter* variables. For examples, consider a situation where *Birth Fraction* is not constant, but depends on the "crowding level" of the population, defined as *Crowding* = *Population*/ *Capacity*. Birth Fraction would then be *f* (*Crowding*), where *f* (.) is typically a monotonically decreasing function. A stock-flow diagram including such an auxiliary variable (*Crowding*) is shown below:



In the above diagram, the flow is "net births" (*births – deaths*), represented as a "bi-flow" that flows in when its value is positive and flows out when it is negative. This formulation is obtained by defining the Birth Fraction function such that when *Crowding* < 1 it is positive (*births* > *deaths*) and when *Crowding* > 1 it is negative (*births* < *deaths*). (This model will be further studied below).

How to identify stocks and flows?: "Bathtub" is an excellent metaphor for stock variables. Water in the bathtub is the stock; water flowing in and flowing out are its flows. If a variable in the real problem fits this bathtub metaphor, it is a potential stock. Note that the stock examples listed above all fit the metaphor. A quick and effective test to identify the stocks is to "freeze" time and motion, and see which variables still persist. Since stocks are accumulated quantities, they are well defined, even if there is no time and motion. Population, inventory, cash balance, knowledge level... the stocks still persist; but their flows vanish: there can be no births, no deaths, no production, no sales, no expenditures, and no learning without passage of time. If a given stock were measured in certain units (say people, liras, items...) its flows would be in units/time period (people/year, liras/month, items/hour ...). That is why flows become undefined without passage of time, but stocks persist.

The above test is important and presents a necessary condition for a variable to be a stock, but the condition is not sufficient. Not all variables that pass the test would be modeled as a stock; many would be instead modeled as *auxiliary* variables. Identifying a variable as a stock means deciding to model its flow variables. This would not only make the modeling more complicated, but addition of stock-flow structures would also complicate testing, analysis, and design phases, because stock-flow structures add to the dynamic and scale complexity of the model. Thus, the second important principle is that stock variables identified in a problem are believed to be *especially important accumulations* that decisions in the real system try to control or depend on. In the simple example above, although the variable Crowding passes the "freeze" test, we did not model it as an accumulation, because it was not believed to be important enough to justify the added complexity of formulating its flows in and out. Similarly, many such variables are approximated by auxiliary variables. Stock variables are those accumulations that seem most important with respect to the dynamic problem definition. Finally, potential stocks that vary too slowly compared to the time horizon of the model are modeled as constants. Selections of stocks are therefore also relative to the time horizon and time units of the problem. In some cases, even the stock-flow distinction can be relative. Cars traveling from Ankara to Istanbul can be a stock variable in one problem definition (short-term, micro dynamics), but it would be a flow variable (cars traveling per day) in a longer term, macro problem.

Importance of stocks: Stocks play a central role in dynamic feedback management problems for several reasons. Their control is often the primary responsibility of managers, since the survival of the system is often critically dependent on them: water in reservoirs, grain stocks, cash in banks, food stock in our kitchen, glucose in blood, and pollutant level in air. We not only control these variables, but also use their values as basis for action in managing other variables. Yet, controlling stocks is subtle and dynamically complex by their very nature:

· Stocks can be changed only via their flows: If we want to change the value of an inventory, we cannot directly and immediately change it. It can only be changed by changing its inflow and/or its outflow (production rate and/or sales). We can directly manipulate our caloric intake by changing our eating (flow), but cannot directly manipulate our weight. If changing our eating habit is hard, changing our weight will be indirect, delayed and much harder.

· Stocks have inertia: Since they have historically accumulated values, they cannot be easily changed. We can suddenly increase the inflow into the bathtub by 100 percent, but if it was already half-full, it will be a long time before the stock in the batch tub increases by just 10 percent. If I have a negative opinion of a political party, it would take quite an effort (and time) to change it.

· Multiple flows make the control even harder: Stocks and their flows may move in opposite directions. We may have increasing revenues, but the cash stock will still go down, if the expenses (outflow) are greater than revenues. We may have decreasing births *and* increasing deaths, but the population will still increase if births are nevertheless greater than deaths. In general, controlling the dynamics of a stock requires taking into account all of its flows simultaneously, which is not a trivial task, theoretically and practically.

· Stocks are the source of endogenous dynamics: Stocks make it possible for the inflows and outflows to differ. The differences between the flows accumulate in the stock. There are several water reservoirs around the city of Istanbul. Water in these reservoirs is a stock, streams feeding into the reservoirs are the major inflow and the water consumption of the city is the major outflow. Without reservoirs, the consumption of the city would have to equal the stream flows at all times, which means the consumption would fluctuate the same as stream flows do. Such wild fluctuations in water availability would make life in the city impossible. The reservoirs allow smooth water consumption (outflow), by buffering against seasonal fluctuations in the stream flows. The stocks influence their own flows in various ways. Since stocks are of such critical importance we continuously monitor their values and take actions to keep their values in some desired band. Stocks also cause time delays in systems. In the raw material supply chain diagram shown above, the fact that there are two stocks between the receiving of raw material and the shipments of goods to the retailers introduces a time delay between "Receiving" and "Shipping" flows. Similarly, information (or perception) delays also involve stocks. In sum, stocks play a central role in the creation of the endogenous dynamics in a system.

Basic stock-flow dynamics: Stocks *integrate* the flows, modifying and complicating the dynamics involved. Figures 5, 6 and 7 illustrate some basic flow-stock dynamics. Since stock integrates it flows, observe in Figure 5 that when the inflow and the outflow are constant, stock is linearly increasing or decreasing (or constant when inflow = outflow).

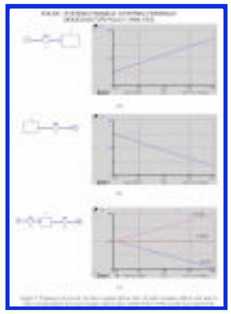


Figure 5. Dynamics of a stock

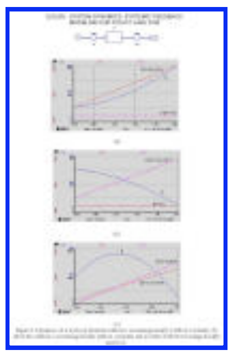


Figure 6. Dynamics of a stock (a) when the inflow is increasing linearly b) when the outflow is increasing linearly and c) when both flows change linearly and cross.

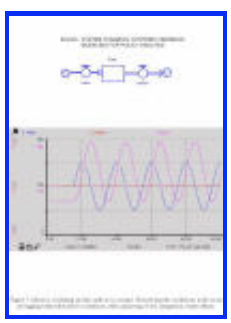


Figure 7. Inflow is oscillating and the outflow is constant.

In Figure 6, we see the dynamics of the stock when the inflow and/or the outflow are changing linearly. Note that the stock is increasing or decreasing non-linearly (quadratic), due to integration.

Finally in Figure 7, the inflow is oscillating and the outflow is constant. The purpose of this example is to illustrate how integration creates time delay. Note that the stock imitates the inflow, except that it lags behind the inflow with phase lag of p/2, since integral of cosine is sine and sin (ß) = cos (ß-p/2). Also observe that amplitude of the oscillations in stock is more than the amplitude of the inflow (amplification).

3.3. Positive and Negative Causal Effects and Feedback Loops

Positive and negative effects: We already mentioned that causal relation *x* ® *y* means the input variable (*x*) has some *causal influence* on the output variable (*y*). A *positive* influence means: "a change in *x*, ceteris paribus, causes *y* to change in the same direction." Examples are:

Population ——>$^+$ Housing Demand

Births ——>$^+$ Population

Pesticide ——>$^+$ Bird deaths

Motivation ——>$^+$ Productivity

The "+" symbol denotes positive causality. (Some authors use the symbol "s" denoting "same direction"). When population goes up, housing demand goes up, ceteris paribus. (The ceteris paribus condition will be true in all causal relations, but will be omitted from now on to avoid repetition). Conversely, when population goes down, housing demand goes down. The same reasoning is true for the Pesticide ® Bird deaths and Motivation ® Productivity examples. But the second example is somewhat different: when births go up, population either goes up or it *decreases less than it would otherwise have been* (this would be true if, in spite of increased births, deaths were still higher). This situation is possible when the cause-effect relation is a flow-stock relation. Thus, the term "in the same direction" is subtle when flow-stock relation is involved. It means, "an increase (decrease) in *x* causes *y* to increase (decrease) above (below) what it would otherwise have been."

A *negative* influence means: "a change in *x*, ceteris paribus, causes *y* to change in the opposite direction." Examples are:

Unemployment ——>$^-$ Immigration

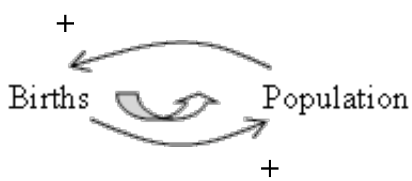
Deaths ——>$^-$ Population

Price ——>$^-$ Demand

Frustration ——>$^-$ Studying

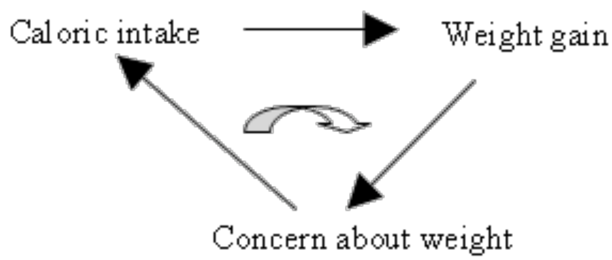
The "-" symbol denotes negative causality. (Some authors prefer the symbol "o" denoting "opposite direction"). When unemployment in a country goes up, immigration goes down, ceteris paribus. Conversely, when unemployment goes down, immigration goes up. The same reasoning is true for the Price® Demand and Frustration ® Studying examples. But the second example, being a flow-stock relation, is again somewhat different: when deaths go up, population either goes down or it *increases less than it would otherwise have been* (this would be true if, in spite of increased deaths, births were still higher). Thus, the term "in the opposite direction" in this case means, "an increase (decrease) in x causes y to decrease (increase) below (above) what it would otherwise have been."

Positive and negative feedback loops: As seen before, a feedback loop is a succession of cause-effect relations that start and end with the same variable. It constitutes a circular causality, only meaningful dynamically, over time. The *sign* (or *polarity*) of a loop is the algebraic product of all signs around the loop. If the resulting sign is +, the loop is "positive" or "compounding" or "reinforcing."

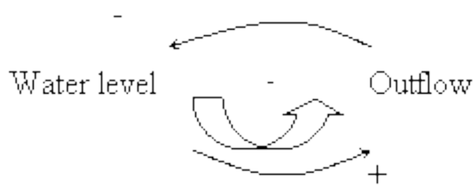


The above picture says that more births mean higher population, which causes even more births, causing even higher population, and so on. The operation of this loop over time would create exponentially growing population. This feedback loop reinforces or compounds an initial change. Not all positive loops create growth; some create *collapse* as will be seen later.

If the resulting sign of the loop is negative, then the loop is called "negative" or "balancing" or "goal-seeking." This type of feedback loop seeks a balance or a goal.



The above picture states that the more calories I take, the more weight I gain and as I realize my weight gain, I become concerned about it, which leads me to cut down on my caloric intake. This loop tries to keep the caloric intake (hence the weight) under control. The behavior of this loop would be a convergent one, rather than a divergent one. In this example, the person tries to control her weight around some "desired" ("goal") weight. In some other negative loops, there is no explicit or deliberate goal. For instance, consider a tank of water emptying itself out of a hole punched in the bottom. The outflow would be approximately proportional to the water level, so the diagram would be:



In the above example, there is no conscious goal seeking. The tank would empty itself out and it would "decay" gradually to zero level. (One could say that the "effective" or implicit "goal" of this system is to reach zero water levels).

Positive and negative feedback loops are basic building blocks of dynamic structures. In reality, many such loops interact together. The feedback loops in interaction are displayed together in *causal loop diagrams*. (See for instance Figure 4 (b)).

4. Dynamics of basic feedback structures