To TREND or not to: Comments on the representation of expectation formation processes in system dynamics

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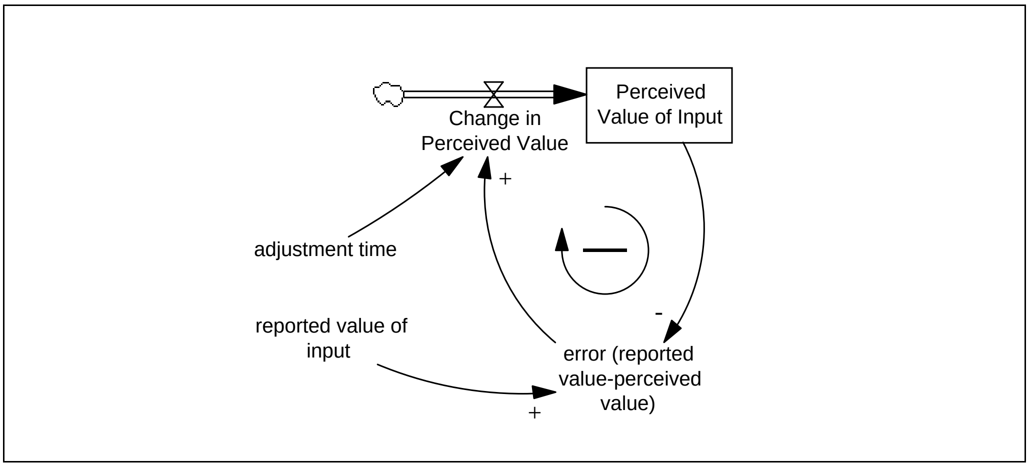
Abstract.
The paper discusses the representation of expectation formation processes in system dynamics. After a brief overview of current behavioural research on expectation formation, it analyses the implicit assumptions that arise from a representation with exponential smoothing and the TREND function. It addresses the limitations of univariate autoregressive algorithms and illustrates their difficulties in representing the causal reasoning processes that may underlie expectation formation. It is argued that exponential smoothing and TREND actually neglect the importance of causal and systemic reasoning and thus are not in line with the paradigm of systems thinking. Finally, three alternative approaches to modelling expectation formation are outlined.

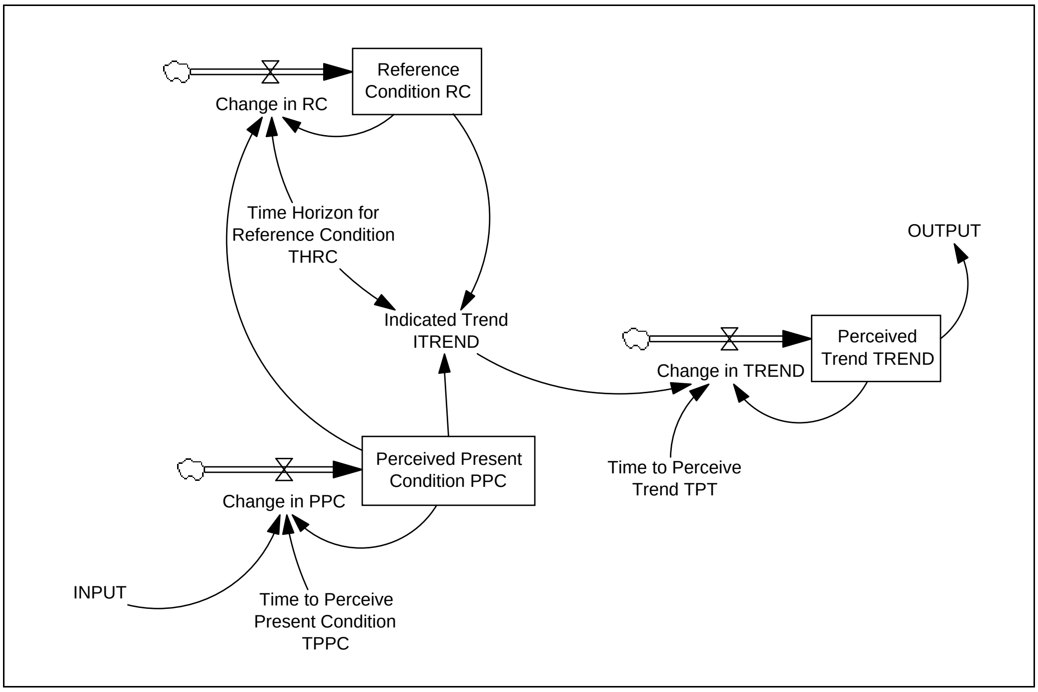
Keywords.
Methodology, expectations, TREND function, behavioural theory, reasoning, forecasting.

A. Introduction

Expectations are an important prerequisite of reflected decision making (Eisenführ and Weber 1999; Miller 2003) and are often considered to be a keystone of management science (Weber 2003). The system dynamics literature suggests to model the cognitive processes underlying the formation of expectations with an adaptive algorithm like exponential smoothing or with the specifically configured TREND function (Sterman 1987, 2000). As system dynamicists strive for "a descriptive rather than normative representation of human behavior" (Sterman 1987: 190), the structures used for modelling expectation formation in fact "represent […] a behavioral theory of how people form expectations", as Sterman (2000: 634) states in his description of TREND. Figures 1 and 2 illustrate the level-rate structures of exponential smoothing and TREND, respectively. Exponential smoothing represents the adaptive formation of expectations about a variable's unknown, actual value, whereas TREND models a cognitive process of forming expectations about a variable's growth rate by comparing its current with a past value.



- - Figure 1: Structure of exponential smoothing (adapted from Sterman 2000: 428) - -



- - Figure 2: Structure of TREND (adapted from Sterman 2000: 635) - -

Both exponential smoothing and TREND have experienced a widespread application in the system community and have been implemented in software packages such as

Vensim or Powersim as a convenient way of representing expectation formation in system dynamics modelling.

Overview of current findings on behavioural modes of expectation formation

Current research on human expectation formation effectively describes two basic cognitive modes of expectation formation: Simple algorithms used to extrapolate the past into the future on the one hand, and causal reasoning processes on the other hand (Miller 2003).

The ‘algorithmic mode’ basically describes the projection of the known into the unknown: A variable’s historical development is transformed into a picture of the future (Wolter 1996; Miller 2003). The main characteristic of algorithms is the exclusive use of historical data for the generation of expectations. Therefore, this mode can also be named an ‘autoregressive’ way of expectation formation (Wolter 1996). Autoregressive algorithmic expectation formation can be used to develop assumptions about a variable’s future niveau, but also about its absolute future growth or its future growth rate, i.e. a trend (Wolter 1996). It serves as the conceptual and methodical basis of many formal forecasting procedures. Examples of such formal autoregressive methods are trend extrapolations and the more sophisticated ARIMA (autoregressive integrated moving average) and Box-Jenkins methods (Box and Jenkins 1970; Porter et al. 1991; Makridakis, Wheelwright, and Hyndman 1998). In addition to their use in mathematical models, several studies have shown that autoregressive approaches can also be identified in the intuitive generation of human, judgmental forecasts.

In an alternative track, researchers portray expectation formation as an either im- or explicitly performed reasoning process that draws on a mental model of heuristically gained causal relationships between independent (causal) and dependent variables (Wilhelm 2000; Selten 2001; Miller 2003). The literature describes two variations of this ‘reasoning mode’, differing in the complexity of the employed mental model: In a simple form, agents use direct bivariate causal reasoning to derive insights about the future of dependent variables. Expectations are deduced from a perception of changes in independent variables which are considered to have a direct effect on the focal variable to be forecasted. This way of expectation formation is especially popular if an agent wants to identify possible levers to influence a particular variable’s future development: “Most of us, especially if we are engaged in the process of planning, focus on the effect we want to create and then look for the most immediate cause to create that effect.” (De Geus 1988: 74)

Reasoning can also be based on the consideration of a more complex set of causal relationships (Miller 2003). Such ‘systemic reasoning’ describes that an agent uses a multivariate, complex causal model rather than a bivariate one. It accounts for the combined influences of multiple causal variables and allows for feedback between the considered variables. This more sophisticated version of causal reasoning basically represents the ideas of systems thinking (Leonard and Beer 1994; Senge 1994). By employing more complex heuristics and causal models in the reasoning process, the holistic reasoning that underlies systematically formed expectations is considered to allow a more differentiated expectation formation. This feature is of particular interest in strategic settings, as those are often perceived to be approached inadequately with the 'simpler' way of reasoning, leading to myopic argumentations, expectations, and decisions caused by the limited scope of its bivariate causal relationships (Ackoff 1981; Stacey 1993; Leonard and Beer 1994).

A superficial first glance at the findings of behavioural research may suggest the necessity of a differentiated representation of autoregressive expectation formation and reasoning, respectively. The structures of both exponential smoothing and TREND quite obviously represent only the first of the two basic modes: Expectations are generated as results of an algorithmic transformation of the focal variable's perceived historical behaviour. The question remains, to what extent the two structures are able to mimic the actual expectation forming behaviour of a causally reasoning agent.

Discussion of the assumptions implied by the formulation of exponential smoothing and TREND

Exponential smoothing and TREND share two major characteristics which shall serve as a starting point for the development of an answer: Firstly, both structures effectively use only one source of information for the formation of expectations, namely *the focal variable's* time series, cf. Figures 1 and 2, respectively. Other inputs, such as the parameters which are used to account for delays in the information retrieval about the focal variable's actual present value, as well as those used to describe the extrapolation's time horizon in TREND, simply are parameters to specify the transformational algorithm in greater detail. They do not represent information an agent would retrieve and process in order to obtain expectations. Thus, only one source of data effectively serves as an informational input to both exponential smoothing and TREND. Therefore, both approaches shall be denominated *univariate* algorithms. Secondly, the two modelling approaches share a limitation to *historical* data as exclusive data input. Thus, as has already been mentioned earlier, they are *autoregressive* in nature. These two conceptual characteristics and their implications shall be investigated in the following.

In a first step we examine if regressive expectation formation necessarily has to be univariate as well. Regarding the algorithms proposed in the forecasting literature (Makridakis, Wheelwright, and Hyndman 1998) and popular methodologies used in corporate foresight like scenario planning (Wack 1985a, b; Godet 1987; Gausemeier, Fink, and Schlake 1996; Schoemaker 2004; Bradfield et al. 2005), this assumption seems to be questionable. Empirical studies report that many organizations actually use a number of multivariate methods for expectation formation, ranging from large-scale econometric models over scenarios and multidimensional expert assessments (Al-Laham 1997; Burmeister et al. 2002; Kreibich, Schlaffer, and Trapp 2002; Jain 2004). Thus, at least for organizational expectation formation the assumption of univariance has to be considered to be an inappropriate simplification, even if large forecasting models still may draw on past data exclusively. Regressive expectation formation needs not necessarily to be univariate.

Now, Sterman argues that a representation of complicated, multivariate procedures is rarely needed for an effective and realistic representation of expectation formation processes, since individual, less comprehensively formed expectations may effectively dominate organisational decision processes: “There are cases where simulation models do incorporate the other models used by the organization. In practice, however, such complexity is rarely needed. […] An organization may use a large econometric model with hundreds of variables to forecast the economic environment, but if senior managers ignore the model’s output and go with their gut feelings, then your model of the forecasting process can’t assume the sophistication of the large-scale model.” (Sterman 2000: 632) This argumentation makes it necessary to examine if individual expectation formation can be described reliably with a univariate, autoregressive approach. We assess a logically derived set of assumptions that are implied by a representation with TREND or exponential smoothing: Univariate, autoregressive expectation formation may be used if one of the three following situations exists: (a) The agent has no other information than past data about the focal variable. Or, (b) the agent does possess other, but only irrelevant (i.e. no better) information. (c) Or, the agent has other, relevant (better) information, but she does not use it for some reason, e.g. due to cognitive constraints. If one of these three cases is true, the simplification of real expectation formation procedures to a univariate, autoregressive algorithm may be justified and possible without distorting and misrepresenting the actual process.

Case (a): The agent has no other information than past data about the focal variable.

Three hypothetical situations have to be examined to decide whether this case may actually become effective: Firstly, a situation is possible where the agent has past data only, but about more variables than just the focal one. This situation can be assumed to be true for all agents involved in expectation formation processes. What remains is the question of the additional information’s relevance. This leads us directly to case (b).

Secondly, the agent may have information about other variables’ future development. Similar to the previous situation this is a quite common condition: We all frequently get information about a future change in one variable or another. For example, if a corporation publishes a plan to pay a dividend, or if a government announces to increase the VAT rate at the beginning of the next year, we know something about a future state of a variable.

And, thirdly, the agent might in fact have information only about the focal variable, but she may know something about its future. In this case, expectation formation obviously lacks reasonability: If I do already possess reliable information about a variable’s future, then cognitively engaging in the formation of expectations is obviously of no further use (Ackoff 1981). Certain knowledge dominates speculative expectations. Univariate expectation formation thus has to be autoregressive.

The actually quite common availability of information about other variables is a fact that lets us rule out case (a). In a next step we have to examine if such additional information is in fact useful for expectation formation.

Case (b): The agent possess information about other variables, but it is irrelevant.

For an evaluation of this possibility we have to determine in which case information about other variables may be of value to the expectation forming agent. Basically, valuable information needs to allow her to draw conclusions about the (unknown) future development of the focal variable var^e. That means that the agent has to assume some kind of relationship between the two variables, either a causal link or at least a strong correlation. The latter is of particular interest if the additional variable is a so-called leading indicator, a variable that shows a high correlation paired with a forward shift in its behaviour. Changes in the leading indicator are frequently trailed by the focal variable. If the lag between the indicator's movement and the variable's imitation of that change is larger than the agent's perception delay for changes in the indicator, then in fact knowledge of another variable's past behaviour represents valuable additional information.[1] The agent may use this additional, valuable information to form an expectation by linking the indicator *i* and var^e by the heuristically gained assumption of a predictive character of *i* concerning var^e. She may even assume a delayed causal link. Such a behaviour has earlier been called expectation formation by direct causal reasoning. Leading indicators are frequently used in practice, for example, in concepts like economic the leading indicator analysis (Baisch 2000; Horváth & Partner 2000) and Ansoff's weak signal analysis (Ansoff 1975) or strategic issue management (Ansoff 1980). If an agent applies such an approach in her individual expectation formation, a univariate, autoregressive term won't be able to represent it correctly.

Similarly, if an agent forms expectations through causal reasoning, also information about some variable *x*'s future development may be of particular value if the agent assumes a causal effect – delayed or not – of *x* on var^e. For example, to an agent interested in the further development of a stock price, the announcement of a dividend payment represents additional valuable information as dividend payments induce a decrease in the stock price on the day of the payment. Or, as a second example, for a forecast of a product's future retail price the fact that an increase in the VAT rate has just passed legislation is additional valuable information. If the agent knows or only assumes that *x* will change in future, she can reason that var^e will change as a direct consequence.

Thus, as information about other variables' behaviour may be valuable, the second case (b) does not hold as justification for a univariate modelling of expectation formation either. An agent using causal reasoning for expectation formation is not adequately represented by exponential smoothing or TREND in a situation characterised by the availability of additional, valuable information. This has two reasons: On the one hand, the agent does not form her expectations univariately due to the availability of valuable information. Causal reasoning is an at least bivariate approach. On the other hand, the actually formed expectation may differ significantly from an univariately (and thus, as we have concluded above, necessarily autoregressively) formed one. Therefore, logical considerations have revealed a setting in which exponential smoothing and TREND

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[1] I.e. $lag_{i-var}{}^e > TPPC$ for TREND or $lag_{i-var}{}^e > adjustment\ time$ for exponential smoothing, applying the denomination used in Figure 1 and Figure 2, respectively. It is important to recognize that the relationship between the indicator *i* and var^e need not be a direct causal relationship, but may as well be a distant, indirect effect $i \rightarrow var^e$.

obviously fail conceptually with respect to the process and the outcome of a human expectation formation process.

Case (c): The agent has other, relevant (better) information, but she does not use it for some reason, e.g. due to cognitive constraints.

Still, the existence of considerable cognitive constraints to the agent's information processing ability may actually destroy the validity of this logically derived result. The extensive body of research on the boundedly rational character of human decision making and the constraints of human information processing shows that such limitations take effect in cognitive processes such as reasoning (Simon 1976; Kahneman, Slovic, and Tversky 1982; Selten 2001). But, in turn, the findings do not promote a univariate conceptualization of expectation formation processes. Constraints do not mean that additional information is not used at all. Rather, a limited use of additional information in reasoning processes appears to be a realistic conceptualisation. In fact, research on the informational economics of financial markets underline the idea that agents use a lot of different pieces of information, but not all of the data available in total (Brealey and Myers 2003). Empirical studies on the validity of the rational expectation hypothesis, which normatively assumes that agents use all available information in expectation formation, come to a similar conclusion (Levine 1993; Blanchard 2000; Cogley 2001).

Therefore, none of the three examined settings justifies a strictly univariate conceptualization of expectation formation processes. Instead, they point out that univariate algorithms actually may result in an unrealistic and misleading representation of expectations in system dynamics, since their real counterparts formed in a reasoning process may not be mimicked adequately.

The discussion of the three theoretical cases which might have justified a reduction to a generally univariate approach has illustrated that a manager forming expectations by reasoning considers more than one informational input and may obtain expectations that systematically differ from univariately formed ones. Therefore, Sterman's suggestion to refrain from an explicit consideration of more complex algorithms seems acceptable for models dealing with aggregated, autoregressive expectations of a large group of agents, for which the modeller assumes that the differences in individual modelling compensate each other. This is the case for the examples Sterman uses in his argumentation (Sterman 2000). But if a model is supposed to describe a less abstract problem, e.g. the competition in a specific market rather than a macro-economic question, and the involved agents might use multivariate, systemic reasoning, then the simplification becomes a critical assumption. Exponential smoothing and TREND would presumably fail to represent actual expectation formation. Thus, the diversity of cognitive modes distinguished earlier can hardly be represented with the exclusive use of univariate algorithms.

After the univariate specifications of exponential smoothing and TREND have been discussed in length, also a brief reassessment of the autoregressive nature of the two structures appears necessary: As our argumentation has shown, future-related information about other variables than the focal one may increase the quality of expectations if they are accounted for by reasoning. The strictly autoregressive formulation does not hold as a generally valid approximation. Rather, the limitation to past data may result in discontenting and hardly realistic model behaviour: If a real-world agent has information about a substantial change in an independent variable and accounts for it in her expectation formation,[2] then her expectations about the focal variable's future will deviate considerably from an extrapolation of its past development.

Consistency with the systems thinking perspective

It has been shown that the structures proposed to model expectation formation processes actually neglect and distort important characteristics of human behaviour. They are not necessarily able to represent the reasoning processes used in expectation formation adequately, and need not generate comparable results either. As causality as well as reasoning are major components of systems thinking, we consider it useful to look at the particular compatibility of exponential smoothing and TREND with the systems perspective.

Systems thinking facilitates the identification and understanding of complex causal structures and of the resulting systems behaviour. It fosters the formation of reflected expectations about the future of the world we live in, and these expectations need not be comparable with their algorithmically formed counterparts. Actually, they won't be at all in many cases, and the results of systemic enquiries frequently challenge those expectations and perspectives on a system's future which are based on algorithmic expectation formation. The Limits to Growth (Meadows et al. 1972) is maybe the best known example of a system dynamics study that questioned widely-held expectations. The ability to generate different, initially unexpected (!) insights is one of the major advantages of system dynamics. As a model shows "behavior which is at odds with the initial expectations of the model builder or client" (Mass 1981: 2) and if this behaviour "withstands scrutiny [it] reveals previously unappreciated aspects of the system." (Mass 1981: 2) A model showing surprise behaviour may initiate a revision of an agent's expectations. It can thus serve as a means to trigger a discussion about the reasonability of widely held beliefs about the future.

Over the last 50 years the ideas and concepts of systems thinking have experienced a rapid diffusion. Argumentations in line with systemic approaches find expression, e.g., in the perception and acceptance of natural or logical limits to growing phenomena, and are a widely shared and accepted basis for argumentation and analysis. The ability to allow a holistic and sustainable analysis is, to our understanding, the major advantage of the systems perspective that has led to its current importance. Therefore, the suggestion to represent expectation formation with structures that are incapable of modelling causal reasoning processes – neither simple ones nor complex, systemic ones – ignores the broad application of systems thinking. In fact, it promotes a contradiction to the systems thinking paradigm and disregards the practical experiences of systems thinkers. No matter how abstractly they are supposed to represent actual behaviour, with their univariate and autoregressive specification exponential smoothing and TREND

[2] In scenario thinking this is called a trend-breaking discontinuity. (Geschka 1999)

obviously are not capable of representing a systemically thinking agent expecting, for example, a particular non-linear behaviour mode like S-shaped growth. It is difficult to understand why system dynamicists virtually forbid the agents represented in a system dynamics model to employ the way of thinking they themselves propagate so enthusiastically. If a system dynamics model shall “capture the ways in which the managers’ intuitive judgments are formed, that is, how the information they consume and the way they digest it lead to that certain feeling in their gut” (Sterman 2000: 632), then a confident systems thinking community must not use modelling approaches that neglect the relevance of systems thinking in a behavioural theory.

Conclusion & further research: alternative approaches for modelling expectation formation

Our argumentation has shown several critical aspects of the modelling approaches proposed in the system dynamics literature. The actual application and practical relevance of causal and systemic thinking show that two of the most striking features of exponential smoothing and TREND – univariance and autoregression – are massive and not generally acceptable simplifications in the representation of human expectation formation. A much more faceted approach appears to be desirable. As criticism is of limited use if it does not set off the development of a solution to the identified problems, we propose four alternatives for modelling expectation formation processes. They allow a more specific representation of different cognitive modes and procedures, depending on the modeller’s individual assumption about the dominating mode of expectation formation applied in the system under investigation. For a start we briefly describe the alternatives. The actual formal structures are currently under development.

(1) If algorithmic, autoregressive expectation formation shall be incorporated into a model, exponential smoothing or TREND certainly represent actual human behaviour very well, especially for modelling expectation formation with a rather short time horizon, such as operative demand forecasts for the optimization of a production process, which are actually frequently obtained with the help of autoregressive methods (Jain 2004).

(2) To model the behaviour of a scenario thinker, a multivariate and multifaceted expectation formation process generating a funnel of possible futures needs to be covered by a handy structure. Scenario thinkers consider possible variance in independent, causal variables and try to infer a multifaceted picture of possibly resulting futures, acknowledging that univalent predictions are a fragile basis for strategic decision making as they might pretend a non-existent certainty about future developments and evoke a false sense of security (Godet 1994; Godet et al. 1999). Therefore, a range of possible expectation values needs to be generated that can be used for further calculation in the model without resulting in a fuzzy, hardly interpretable or even completely unspecific model behaviour.

(3) The most appropriate way to represent a systems thinker might be to follow Conant and Ashby’s idea of the systems regulator who is a model of that system (Conant and Ashby 1970). That means that the expectation forming behaviour of a systems thinker

can be represented by a small, generic structure that represents the dominating behaviour mode of the system as it is perceived by the agent in her expectation formation. Certainly such an approach calls for a careful reconsideration of the chosen and appropriate model boundary.

(4) Finally, if the boundedly rational character of expectation formation processes is considered to be characteristic for the system under consideration, a structure might be helpful which allows specifying the dominance of a particular bias. For example, different degrees of risk-averseness, of optimism or pessimism, or a more or less conscious information collection and processing should be accounted for in the expectation formation process (Kahneman and Lovallo 1993).

The formulation of adequate model structures to represent different modes of expectation formation properly will offer a solution to some of the current difficulties in the incorporation of expectations in system dynamics models. As handy structures or readily provided building blocks to be included in larger models, they will support a still easily applicable, but more accurate modelling.

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