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Measuring and Understanding Complex Phenomena

Indicators and their Analysis in Different Scientific Fields

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Preface

The international conference in Neuchatel, Switzerland, 2018, about partial order and its applications motivated to edit a new book representing the state of the art in the development and applications of partial order methodology. The very idea is to analyse multi-indicator systems. Part of the lectures presented in Neuchatel are now part of this book. However, due to many other actual contributions, this book is not a proceeding of the conference of 2018, but a monograph with a focus on indicators and their analysis.

Consequently, in this book (beside an introductory text) the reader will find

- Five chapters specifically concerned with indicators
- Six chapters where the methodological aspect of applied partial order is the main topic
- Three chapters with a sociological background
- Two chapters with an environmental background
- Finally, two chapters where software aspects are in the foreground

An introductory chapter may be helpful for interested scientists to understand how partial order in combination with multi-indicator systems can be applied. Furthermore, a brief overview about all 18 chapters is given.

For the future it is hoped that more scientists will be interested in the exciting field of applied partial order.

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Indicators and Partial Orders – An Introduction

Role of Indicators

Our world will increasingly be more and more complex. Hence, evaluation of the state (in order to find decisions for management in the future) will be correspondingly difficult. In many cases deterministic mathematical models can be sufficiently sophisticated to support decisions. In the evaluation of chemicals, such as EUSES (Heidorn et. al. 1997) or the former E4CHEM (Bruggemann and Drescher-Kaden 2003) are suitable examples. Even agent-based models, cannot encompass all eventualities of our daily life. (Agent based modelling within a general context is described in Wikipedia, 2020; within geographical simulations in Castle and Crooks, 2006 and within an ecological context in Hüning et al. 2016.) Hence, one can find everywhere indicators, e.g., Fragile State Index (FSI) 2019, (Carlsen and Bruggemann 2013, 2014, 2017) or the Human Environment Interface Index (HEI), Environment Performance Index (EPI) (for both within the Partial order context, see (Bruggemann and Patil 2011), World happiness Index (Helliwell et al. 2019), Human development Index (Human Development Report 2019), Gender equality Index (Gender Equality Index 2019), Bruggemann and Carlsen 2020, Sustainable Cities Index (Sustainable Cities Index 2018), Sustainable Society Index (Europe Sustainable Development Report 2019), Food Sustainable Index (Barilla 2019) or indicator helping to measure the quality of life in cities (El Din et al. 2013), just to mention some typical indicators. The general problem is, how to quantify these indicators (examples are mentioned above). Often sub-indicators (we will call them “preliminary indicators”) are defined which can be measured, or estimated by mathematical models or for which an ordinal scale is obvious. In the next step, this series of indicators typically is condensed to form a single quantity, sometimes called ‘the index’, or more precisely the composite indicator. In fact, this procedure, defining subsystems of indicators, leads to hierarchies of indicator systems, for example, that applied for the definition of the food index (Barilla 2019)).

The mathematical problem is how to carry out this condensation, or aggregation step, in the most sensible way possible. Bruggemann and Patil (2011) denoted the series of preliminary indicators a multi-indicator system (MIS). The information within a certain MIS is often important within a holistic point of view (see for instance Maggino and Zumbo 2012). The aggregation, independent of which method is applied, must be more or less considered as an averaging. Thus, it seems to be appropriate to evaluate the MIS as an interim aspect by mathematical methods, which are able to analyse multiple indicators with respect to the objective under which the MIS was constructed. The mathematical method of partial order theory is very helpful in this aspect, and, therefore, indicators and partial order are closely interrelated when an evaluation by ranking is wanted. Clearly, the partial order methodology is not the only possibility for studying an MIS (see, e.g., (Brans and Vincke 1985; Figueira et al. 2005; Colorni et al. 2001; Munda 2008; Munda and Nardo 2009; Roy 1972; Roy and Vanderpooten 1996; Maggino 2017)).

Here, however, the interplay of MIS and partial order is the main topic.

Partial Order Methodology

When one takes a closer look at the mathematics of partial ordering, it is closely, although not exclusively related to the regime of indicators. Partial ordering is a theory of binary relations and is as such especially well-suited for those indicators, which are ordinal in nature. The reason is that partial order is mathematically deeply intertwined with

- Graph theory
- Combinatorics
- Algebra

but not with numerical evaluation in the field of real numbers, see, for instance, (Trotter 1992). In the following, the three items are described in more detail.

Graph Theory

One of the most important visualization techniques of partial orders is the Hasse diagram. The Hasse diagram is a transitively reduced, acyclic digraph. This characterization may be enough for mathematicians, but not for scientists interested in applications. Thus, a few more details are given here.

Partial order is a binary relation among elements x_i and x_j of a set X which can be interpreted as 'better than', e.g., $x_i > x_j$. This relation obeys three axioms:

- Reflexivity, i.e., an element can be compared with itself.
- Antisymmetry, i.e., if an element x is 'better' than an element y, then y cannot be better than x, unless x and y are identical.

- Transitivity, i.e., if x is 'better' than y, and y is 'better' than z, then x is 'better' than z. A classical counterexample is the tournament. One may define 'better than' as team x beats team y. However, although team y may beat team z, it cannot be excluded that team z beats team x, which is a violation of the transitivity. On the other hand, when the order relation is associated with numerical, ordinal indicator values, the order relation between two elements is governed by the numerical relation between the indicator values. Thus, the elements can be ordered, i.e., fulfilling the axiom of transitivity.

If two elements of a set X have an order relation, one can define two vertices for the elements and connect them. Because the relation is oriented, the orientation for the two elements is indicated by an arrow and the relation can be described by our usual symbol '<'. When this recipe is performed for all elements of a set, a directed graph is obtained. When the order relation is based on only one single indicator, then a complete – linear – order is developed and each of the two elements of X are connected by an arrow. When there are three elements x, y, z and it is found $x < y$ and $y < x$, then transitivity demands that $x < z$. Hence, for most applications the arrow for $x < z$ can be omitted, as this relation follows due to the transitivity. The process of eliminating arrows is called a transitive reduction. Furthermore, a sequence of arrows such as $x_0 < x_1$, $x_1 < x_2$, ..., $x_{n-1} < x_n$, but $x_n < x_0$ is obviously not possible as it would be a violation of the transitivity as the transitive reduction would cause a cyclic graph. Eventually, the arrows can be replaced by simple lines, when the orientation is governed by the vertical position in the drawing plane. The resulting graph is called a Hasse diagram. Hasse diagrams or comparability graphs (graphs of the order relation, however without an orientation) can be analysed theoretically. Note that a sequence of lines which can be followed strictly upwards or downwards may be called an order theoretical connection, the set of objects within an order theoretical connection is called a chain.

An analysis can, e.g., investigate whether or not subsets of X dominate others, or whether subsets of X are strikingly not connected or only weakly connected with other parts of the graph. It is clear that 'weakly' needs a definition. Here it is used in the sense of 'only few connections'. As an example of a Hasse diagram, we can look at the development in Germany (2008–2015) in switching to more sustainable energy according to the UN Sustainable Development Goal No. 7, using three indicators (Table 1); for details see (Europe Sustainable Development Report 2019).

Instead of observing three line graphs for each indicator, the Hasse diagram shows at once some essential facts:

(1) All three indicators are not decreasing in their values for the time evolution: 2008-2009-2011-2012-2015. Other time series can be found, where the indicator values are simultaneously non-decreasing. One can see that for these special set of years, the pattern of indicator values is co-monotone with the time. Such subsets of objects, mutually comparable are called chains.
(2) 2010, 2011 and 2013 cannot be compared, because of a counter current development of indicator values. They are connected (in a general graph theoretical

Table 1 The three indicators

Indicator	Short	Description	Direction
sdg7_warm	sdg7_w	Population unable to keep homes adequately warm (%)	Low better
sdg7_eurenew	sdg7_e	Share of renewable energy in gross final energy consumption (%)	High better
sdg7_co2twh	sdg7_co2	CO_2 emissions from fuel combustion per electricity output (MtCO2/TWh)	Low better

context, but not order theoretically). These three objects are members of a so-called antichain.

(3) The group {2010, 2012} has no order theoretical connections with {2013}. The identification of the reasons in terms of indicator values is one main task in the applications of Hasse diagrams.

Combinatorics

Combinatorics comes mainly into play when directed graphs of the order relations are extended to form graphs with more connections maintaining the already given ones. This enrichment process can be continued until a complete order is obtained. However, when the Hasse diagram has elements of X that are not in an order relation, then the enrichment process delivers a set of complete orders, i.e., the set of linear extensions. However, the generation of linear extensions from a given Hasse diagram is computationally extremely difficult. Here combinatorics helps to find algorithms or even to find closed formulas. These, e.g., play an important role in an approximation, known as a local partial order model. An example would be the Hasse diagram (Fig. 1). It is possible to extend the graph to a linear order, where the sequence of years follows its natural order.

Algebra

It seems to be plausible to try to understand empirical partial orders as being composed of simpler graph structures. Any two partially ordered sets (posets) can be combined by following strict composition rules. These composition rules, such as addition, multiplication and disjoint union, have only little to do with the operations known for numbers. Nevertheless, this kind of composition is an important guideline to understand empirical posets. A remarkably richer algebra is obtained, when the order relations obeys additional requirements. The crucial concept is the uniqueness. Within an empirical poset, two elements of a set X can be in order relation to several others. However, when the additional requirement is uniqueness, then any

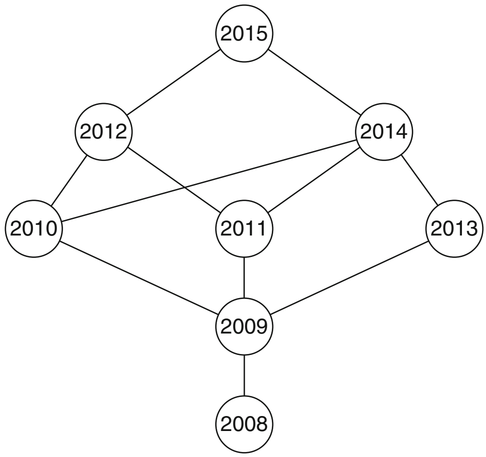

Fig. 1 Hasse diagram of Germany, years 2008–2015. Details in a publication, submitted

two elements are downwards and upwards, respectively, related to only one other graph theoretical neighbored element. Such posets are called lattices and a special realization is the formal concept analysis, deeply studied by the school of Wille (Ganter and Wille 1986; Ganter 1987; Ganter and Wille 1996) and Kerber (2017). The resulting lattices, formal concept lattices, are powerful tools in the analysis of multi-indicator systems, especially when the indicators can only take discrete numbers. The extension of the so-called formal concept analysis to indicators, having continuous data in concept, bears additional theoretical difficulties; see, e.g., (Kerber 2017).

When data are metric data, the obvious question is, how to deal which such data and what is the role of order relations compared to powerful statistical methods, such as correlation or regression analyses, principal component and cluster analyses, just to mention a few tools most often used in (multivariate) statistics.

When data are measured, then automatically data uncertainty comes into play. By comparing partial order and (conventional) statistical tools it should initially be made clear that partial order as a method to analyse data clearly belongs to statistics. So why is a discussion needed? The reason is that multivariate statistics is commonly associated with tools, which are already exemplified above. The aspect of evaluation, especially evaluation in multi-indicator systems makes partial order an important tool in this respect. Whereas applying conventional tools, a ‘good’ or ‘bad’ within a data set is not known, and partial ordering is specifically adapted to that. Applied partial order methodology, together with the analysis of the graph theoretical structure could be a relevant tool in decision making, operation research and, to some degree optimization.

The role of uncertainty in data analysis by partial ordering goes back to papers of Sørensen et al. (1998, 2000). Data, continuous in concept, cannot be considered as ideally suitable items for partial ordering. There are two main reasons: (i) The aforementioned role of uncertainty which often arises when data are measured. (ii) The information due to distances is lost. Both aspects can be methodologically handled within the framework of partial ordering, however at the price of its elegance. Furthermore, if the weights in linear sums of uncertain indicator values are not sharp, application of partial ordering, as we know it today, comes to its limits. Studies in this direction are for now just landmarks on a long way.

For readers interested in the mathematical aspect of partial order, we recommend (Maggino 2017; Trotter 1992; Neggers and Kim 1998; Schröder 2003; Davey and Priestley 2002).

This book, *Indicators and their Analysis in different Scientific Fields* reports recent developments in the field of partial order applications. Some chapters are based on presentations at the International Conference on Partial Orders in Applied Sciences in Neuchatel, October 2018. This conference series was initialized 1998 (cf. Table 2) and is a forum for the scientific community with special interests in the theory and application of indicators.

In the 18 chapters, a variety of new developments within the area of partial ordering can be found.

Indicators and Theoretical Developments

As mentioned above, indicators play an increasing role in characterizing complex systems and in decision problems. Indicators are necessary to understand system behaviour. Hence, several chapters focus on the various aspects of indicators, addressing subjects like scaling level, relevance and the role of the inherent characteristic of partial orders, i.e., the incomparability (See J. Wittmann, p. 3, F. Maggino et al., p. 17). Further chapters discuss the functionality of indicators, the workflow for building indicators, the structure of complex indicators and the sensitivity of indicator values, as well as assessment of inhomogeneous indicator-based typologies through the reverse clustering approach (See J. Owsinski et al., p. 31), using a typology of spatial units of Polish municipalities as an illustrative example.

Indicator values often are considered as continuous in concept, thus the evaluation and exploration is of some fuzzy character. This aspect is considered in two chapters (see pp. 83–101) where a strict generalization is given central importance. Evaluations using parameters can usually be considered as sets over lattices. These two chapters (See A. Kerber and R. Bruggemann, p. 83, and R. Bruggemann and Kerber, p. 91) are devoted to this approach, whereby the theoretical concept is exemplified in a study of heavy metals and sulphur pollution along the southern part of river Rhine.

Very often a strict linear order is wanted, which in the case of multiple indicators typically is obtained as a result of aggregation of indicators, e.g., leading to a weighted sum. Although attractive due to its simplicity, the disadvantages are, e.g., that potential conflicts expressed by the values of single indicators are suppressed. A chapter is devoted to the idea of combining the advantages of linearly weighted sums and partial order theory in order to relax the requirements for a strict linear

Table 2 List of international conferences concerning applied partial order theory

Year	Organisers, site of conference	Main ideas	Remarks	Reference
1998	Bruggemann, Simon, Grell, Berlin, Germany	Hasse diagrams and their use in different fields Basics of POT	Initialization Workshop in honour of E. Halfon, who was a guest scientist in the Leibniz Institute of Freshwater Ecology and Inland Fishery	1
1999	Sørensen, Carlsen, Roskilde, Denmark	Role of uncertainty		2
2000	Bruggemann, Pudenz, Lühr, Berlin, Germany	Analyses of larger sets Decision systems		3
2001	Voigt, Welzl, Iffeldof, Germany	Statistics meet Partial order		4
2002	Sørensen, Carlsen, Lerche, Roskilde, Denmark	Needs of decision makers Integrative approach	Decision to continue every two years	5
2004	Frank, Bruggemann, Bayreuth, Germany	Concept of Local Partial Order Bringing general chemistry		6
2006	Todeschini, Pavan, Verbania, Italy	Towards a tool for decision making	The first time, where there was a need for a historical overview about this kind of international conference	7
2008	Owsinski, Bruggemann, Warsaw, Poland	Probabilistic concepts Combinatorial and algebraic concepts Multicriteria ranking		8
2010	De Baets, De Meyer	Combinatorial aspects, new topics coming from social sciences		9
2012	Bruggemann, Wittmann, Berlin, Germany	Posetic coordinates	Decision to continue every three years	10

(continued)

Table 2 (continued)

Year	Organisers, site of conference	Main ideas	Remarks	Reference
2015	Fattore, Maggino, Florence, Italy	Ordinal data vs. metric data Social science		11
2018	Beycan, Suter, Neuchatel, Switzerland	Development and application of indicators	The activity around partial order is now a part of the more general topic of indicators	12

The table clearly shows the trend from partial order theory to the more general theory of indicators.

References of Table 2

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2:1999 Sørensen, PB, Carlsen, L, Mogensen, BB, Bruggemann, R, Luther, B, Pudenz, S, Simon, U, Halfon, E, Bittner, T, Voigt, K, Welzl, G and Rediske, F, eds. Order Theoretical Tools in Environmental Sciences - Proceedings of the Second Workshop , October 21st, 1999 in Roskilde, Denmark. National Environmental Research Institute, Roskilde.

3:2000: Pudenz, S, Bruggemann, R, Lühr, H-P, eds. Order theoretical tools in Environmental Science and Decision Systems. Proceedings of the third Workshop, November 6th-7th, 2000, in berlin, Germany, Leibniz Institute of freshwater Ecology and Inland Fisheries, Heft 14 , Sonderheft IV

4:2001: Voigt, K and Welzl, G, eds. Order Theoretical Tools in Environmental Sciences - Order Theory (Hasse diagram technique) Meets Multivariate Statistics-. Shaker - Verlag, Aachen.

5:2002: Sørensen, PB, Bruggemann, R, Lerche, DB, Voigt, K, Welzl, G, Simon, U, Abs, M, Erfmann, M, Carlsen, L, Gyldenkaerne, S, Thomsen, M, Fauser, P, Mogensen, BB, Pudenz, S and Kronvang, B, eds. Order Theory in Environmental Sciences - Integrative approaches, Proceedings of the 5th workshop held at NERI, 2002. NERI, Ministry of the Environment, Denmark, Roskilde.

6:2004: Bruggemann, R, Frank, H and Kerber, A,. Proceedings of the Conference “Partial Orders in Environmental Sciences and Chemistry” (Bayreuth, 15-16 April 2004). MATCH Commun.Math.Comput.Chem. 54 (2005) 487-690.

7: 2006: No proceedings. However, an impression may be obtained, visiting**:** Bruggemann, R and Carlsen, L, eds. Partial order in environmental sciences and chemistry, Springer, Berlin, 2006

8: 2008: Owsinski, J. and Bruggemann, R, eds. Multicriteria Ordering and Ranking: Partial Orders, Ambiguities and Applied Issues. Systems Research Institute Polish Academy of Sciences, Warsaw.

9: 2010: Bruggemann, R., Partial Order in Applied Sciences, Statistica Applicazioni, Special issue 2011

10: 2012: Bruggemann, R, Carlsen, L and Wittmann, J, eds. Multi-indicator Systems and Modelling in Partial Order. Springer, New York, 2014

11: 2015: Fattore, M, Bruggemann, R, Partial Order Concepts in Applied Sciences. Springer, Cham, Switzerland, 2017

12: 2018: Bruggemann, R and Carlsen, L, eds. Indicators and Partial Orders, Springer, This book

order (See R. Bruggemann and L. Carlsen, p. 63). A further study along these lines is reported in a separate chapter (See R. Bruggemann et al., p. 63) focusing on the possible generation of a weak order from a partially ordered set without the need for subjectively defining parameters beyond the data matrix.

Indicators for Special Purposes

Two chapters (see N. Pankow et al., p. 105 and G. Al-Sharrah and H.M.S. Lababidi, p. 119) focus on the selection of indicators for specific purposes. One chapter focuses on the development, assessment for their applicability and relevance of indicators for sustainability assessment in the procurement of civil engineering services, whereas a second chapter reports on dependent indicators for environmental evaluation of desalination plants with a special focus on which types of correlations between environmental indicators may affect decision-making when it is done by ranking.

One chapter presents some efficient sampling designs based on partial order sets and (sampled) linear extensions as a more flexible process than other designs and is executable with acceptable initial sample size, the new design in general being more efficient than its rival designs (See B. Panahbehagh and R. Bruggemann, p. 135).

It is often seen that potentially harmful substances are actually in their own sense beneficial for their specific purposes, but, e.g., harmful to the environment. As an exemplary case, partial order methodology has been applied for the search for suitable alternatives to lead split shots (See L. Carlsen, p. 153).

A chapter with elements from both the environmental and social area puts forward the question: who is paying for our happiness? The well-defined index for happiness, the World Happiness Index, was used for ranking 157 countries based on 7 indicators, the result being compared to a similar ranking of the countries applying the Happy Planet Index focusing on the exploitation of our planet's resources (See L. Carlsen, p. 205).

Activated carbon is used for many purposes, e.g., for wastewater treatment as a strong sorbent. It has a long history and has been prepared from a variety of material using methods involving physical and/or chemical activation. One of the latest attempts has been based on *Miscanthus* straw. One chapter is devoted to a study that compares 21 different methods for obtaining activated carbon from various materials (See L. Carlsen and K. Abit, p. 165).

Organisms such as bacteria, fungi or algae have the ability to trap and immobilize Uran, U; however, bioremediation does not reduce widespread U contamination. One chapter is dedicated to investigating the ability to concentrate U in bio-organisms. Partial order methodology discloses which organisms are the optimal U trappers (See N.Y. Quintero, p. 181).

Indicators in Social Sciences

The area of social science is the subject of two chapters, where one chapter focuses on the main motivations (see M. Fattore and A. Arcagni, p. 219) for applying partial order theory in the statistical analysis of socio-economic data, whereas the second chapter demonstrates the use of partial order methodology to an analysis of subjective well-being data from a European harmonized official statistical survey based on indicators for life satisfaction, meaning of life and emotional status (See L.S. Alaimo and P. Conigliaro, p. 243).

Software

One of the most popular software packages for studying partial ordering is the PyHasse. The package contains today more than 100 specialized modules, many of which are developed for specific purposes. However, it has been argued that PyHasse constitutes as a tool for 'connoisseurs'. Hence, web-based versions of PyHasse were developed (See R. Bruggemann et al., p. 291). However, they include only a limited number of modules.

However, other approaches to ranking are available, e.g., the Deep Ranking Analysis by Power Eigenvectors (DRAPE), which is illustrated in a chapter by a study of the sustainability of 154 countries based on 21 human, environmental and economic well-being criteria (See C. Valsecchi and R. Todeschini, p. 267).

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Part I
Indicators and Theoretical Developments

Some Basic Considerations on the Design and the Interpretation of Indicators in the Context of Modelling and Simulation

Jochen Wittmann

1 Indicators: In General, in Mathematics, in Modelling and Simulation

Indicators are necessary and widely used means to understand system behavior. An overview on the work concerning multi-indicator systems with focus on a ranking of the indicator quantities gives (Bruggemann et al. 2014).

This paper does not focus on a ranking of different indication aspects a system provides, but on aggregation these aspects to a single compressed value.

The definition of "indicator" bases on the fact, that the system (or model) quantity of interest is difficult to observe or completely hidden within the system. This kind of definition can be found e.g. in the field of economic sciences as "Measurable variable used as a representation of an associated (but non-measured or non-measurable) factor or quantity." (Businessdictionary 2017). The same reference gives the representative example for an indicator with the "consumer price index (CPI) [that] serves as an indicator of general cost of living which consists of many factors some of which are not included in computing CPI." (Businessdictionary 2017).

Beside economics, there is a wide range of other domains using indicators intensively: Biology knows indicator plants or organisms that are representatives for special types of ecosystems (see e.g. Haseloff 1982), but also indicators in the sense of summarizing measures for the state of the environment such as the index of biodiversity for example as a measure for the intactness of an ecosystem (Campbell and Reece 2003).

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Medicine as well knows indicators, e.g. the vital signs as a measure for the state of a patient especially in intensive medicine (for example the wide range of patient monitoring systems (Elliott and Coventry 2012). However, another interpretation gains in importance with respect on sending alarms if the situation becomes instable or dangerous. The Early-Warning-Score (HealthcareInstitute 2017; Helios-Kliniken 2017) provides an indicator for the over-all state of the patient and combines a list of vital signs to a single value. Thus, the indicator excerpts the information of the n vital signs and combines them to a single, highly aggregated measure.

So far, we know an indicator as an aggregating measure for at least partially hidden or inaccessible system quantities. In the context of system analysis, modelling, and simulation, however, an indicator is required quite in the sense of medical applications as a tool to sign whether the systems situation is normal, critical, or catastrophic. The intention is to aggregate the “control panel” of the system (or model) under observation with its lots of parameters (levels, tachometers, diagrams . . .) to one single value. The expression range of a traffic sign with its colors green, yellow, and red is the desired level of aggregation for the system manager.

At the end of this short introduction stands the observation, that indicators in modelling context loose the function of making hidden quantities visible and measurable because the model description is man-made and virtual and, therefore, transparent and accessible on every level. What remains is the aggregating and/or ranking function of indicators, which should be discussed more in detail in the following sections.

2 Functionality of Indicators

2.1 Typical Application Types for Indicators

Before we deal with the structure of indicators, a distinction should be made at the application level as to which functional tasks are to be solved by indicators or indicator systems. In the course of this paper it will be worked out that an exact specification of the expected function of an indicator is the decisive key for an effective and efficient use. Therefore, at this point, an (incomplete) list of possible fields of application for indicators.

2.1.1 Warnings

A relatively simple requirement is to interpret the indicator or the current indicator value as an indication of whether the current system status is within the normal range or is cause for concern. In this case, exceeding a previously set limit will result in a warning about the current system status.

This use is based on two basic ideas: firstly, the fact that the indicator value serves as an indicator for a more or less complex and less transparent system state, and secondly, that several influencing variables can be combined in such an indicator value, which, as an aggregated value, provide indications of the current behavior of the overall system.

Typical examples are warnings regarding the condition of complex industrial plants or in intensive care medicine to summarize the values from various vital parameters.

2.1.2 Decisions Between Alternatives

While in the first case the scale of the indicator together with an absolute threshold value comes to the fore and requires special design considerations, the second field of application requires an indicator design that evaluates different decision alternatives and thus allows a comparison of these alternatives. Typical examples are the classic advantage and disadvantage lists for previously given decision scenarios and a decision for the overall problem derived from the individual arguments collected in these lists. In this case, the focus is not so much on the state of the system itself, but much more on a relative evaluation, a ranking that relates the different scenarios of the decision problem to one another.

2.1.3 Optimization

A much more complex use of indicators is found in the solution of system optimization tasks. In this case it is assumed that the behavior of a system can be influenced by setting parameters (the so-called manipulated variables), whereupon the value of the target variable changes. Through targeted changes of the manipulated variables, an optimum of the target function value is to be achieved iteratively during optimization.

The description of the optimization procedure clearly shows the use of indicators: The indicator fulfils the function of the so-called target function and thus summarizes the system state achieved by setting the manipulated variables on a single scale. On this scale, the mechanism of the optimization algorithm then takes effect and iteratively minimizes or maximizes the target function or indicator value.

2.1.4 Modelling Real Systems

Similar to the use for triggering warnings, several indicators can be recorded and observed simultaneously and their dynamic change in indicator values can be interpreted as an image of the underlying real system. Once again, the example from intensive care medicine is the most vivid: the measured vital parameters are not combined into one indicator variable, but their value progression is visualized as if in a control station. The expert observer interprets the dynamics of the different indicator values as an image of the real system and its dynamics and draws conclusions about the future behavior of the system. The measured values are therefore not interpreted in the actual sense as indicators, but as current values of system variables that determine dynamics.

A significant difference to system modelling must be noted at this point: The dynamic courses of the indicators are exclusively visualized and must be interpreted by the observer himself. Relationships between the individual variables are not explicitly specified in the sense of a model, but can only be assumed by attentive observation of the functional processes. However, the internal structure of the observed system always remains hidden. Findings about the structure as well as predictions about future system behavior remain pure hypotheses in the mind of the observers; they cannot be derived from the set of indicators. Here lies a substantial difference to the structural models (glass box), as they are set up in the system modelling for example by systems of differential equations.

2.2 *Structural Alternatives for Indicators*

Main confusing fact defining and using indicators seems the definition of the functionality of the indicator. Not only the reachability of a value seems to be of importance but also the aggregating and valuating character of an indicator. With the applications of Sect. 1 in mind and together with the differentiation of the application types from Sect. 2.1, there is a differentiation concerning the functions of an indicator easily possible that leads to the following three levels of functionality:

2.2.1 Level 1: Observation and Transmission

The intention is to observe a certain system or model quantity. If this quantity is not measurable directly, transmission becomes necessary. Transmission means taking the indicator value instead of the value of the hidden or less accessible model quantity.

A very simple example should illustrate the distinction between the different functional levels when using indicators: a box of muesli is given together with the question of how high the proportion of fruits and cereals is. The box is opaque, so that a direct answer to the question is not possible. An indirect measure must be found. In this case, the different specific gravity of the proportions is used to calculate the quotient between the weight of the box and its volume. This value serves as an “indicator” for the ratio of grain to fruit in the interior. The indicator value thus provides information about a system quantity that is inaccessible to the black box (Fig. 1).

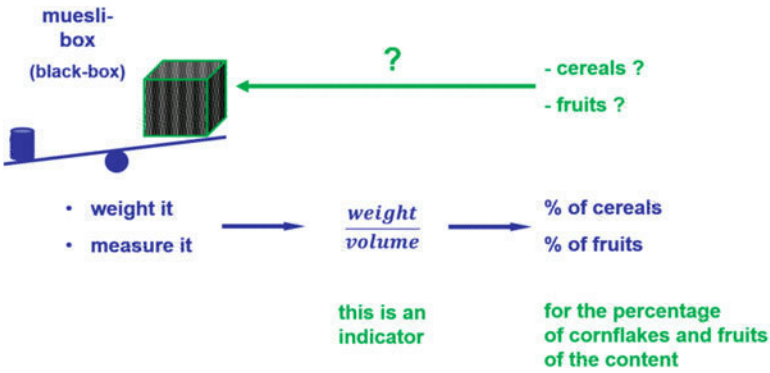

Fig. 1 Example muesli box I

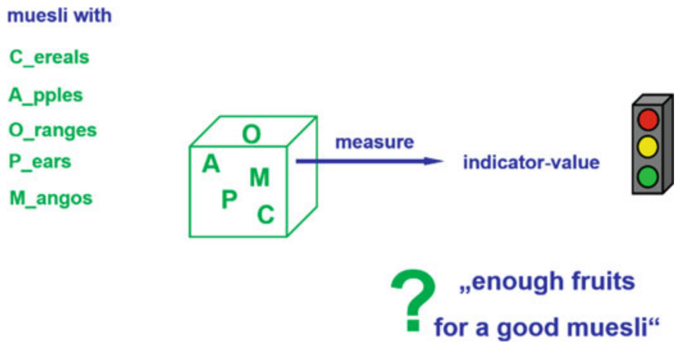

Fig. 2 Example muesli box II

2.2.2 Level 2: Judging

In the second step, the user is interested in a rating beyond the mere value of the indicator variable. In addition to the scale of the indicator, a decision must therefore be made as to whether the measured value is "good" or "bad" or how the indicator values should be ranked between alternatives when making a decision.

Let's extend the example of the muesli box by distinguishing the fruit content in apples, oranges, pears and mangoes and ask the evaluative question: Does the muesli contain enough fruit to make it taste good? It is obvious that a distinction between "good" and "not good" is necessary depending on a threshold value of the indicator.

Thus, judging means introducing a classification for the values of the indicator quantity and thus introducing classes of interpretation as well (Fig. 2).

2.2.3 Level 3: Aggregation

Aggregating is the usage mainly applied: not only one but several aspects of a system are

(a) measured (see level 1)
(b) classified (see level 2),
(c) weighted to each other, and
(d) functionally combined to one resulting single value.

As can already be seen from the example in 2.2.2, the task of judging is in most cases not a one-dimensional problem but a multidimensional one. In the context of indicators and system optimisation, it is better to speak of a multi-criteria problem. Different aspects should be considered when assessing the state of the system measured by the indicator. As in Level 1 and Level 2, a scale must be introduced for each of these individual aspects and an evaluation or definition of threshold values must be carried out.

At this point the problem arises that the evaluation of sub-criteria is contradictory and therefore no simple and unambiguous decision can be made. Ultimately, the Hasse diagrams, which are the subject of many contributions in this volume, represent an alternative solution to this decision problem by defining a partial order for the subcriteria.

The second fundamental alternative is to combine the individual criteria into an aggregated value. This can be done by arbitrary mathematical operations. Usually, the values of the subcriteria are added, but multiplication, exponentiation and any other connections are also conceivable. In order to compensate for imbalances with regard to the dimensions of the criteria but also to realize an application-specific weighting of the subcriteria, the values are usually weighted before they are subjected to the aggregation function. The aim of this aggregation is always to determine a one-dimensional indicator value with only one scale, on the basis of which a clear ranking or a clear decision can then be made.

In the muesli example, the quantity available for each type of fruit must be determined, a weighting factor must be assigned, and the individual values determined in this way must be aggregated (for example, by forming totals) to determine the final indicator value for the "quality" of the muesli. Obviously, the problem of the weighting of the individual aspects ("Can 2 slices of mango compensate for the lack of 20 pieces of apple?") and the decision for the aggregation operation (sum formation? product? ...) come to light. The advantage of this alternative, however, is that there is a single indicator value at the end and no incomparability has to be discussed, as occurs with the use of partial orders.

2.2.4 Hierarchy of the Levels

The hierarchy of the levels is obvious: level 1 describes the access to a quantity under observation, level 2 deals with the range of the values of the quantity observed, and at last, level 3 broadens the functionality by permitting n inputs of level-2-type mathematically combined to an aggregated level-3-indicator. Of special interest is the structure of the mathematical mapping calculating from n values one.

Two degrees of freedom offers this mapping to the user: First, the possibility to give the measured parameter values an additional weight before composition. Second, the kind of functional composition of the n input parameters itself.

These two degrees of freedom influence the design of a hierarchically aggregated indicator essentially. After the following, more procedural section concerning the workflow for building indicators, Sect. 4 will focus on the design of a complex, hierarchically structured indicator and will discuss weights and composition in some more detail.

2.3 Fitting Structural Alternatives to the Application Types

Before we dedicate ourselves to the workflow with the design of an indicator in the 3rd section, a short comparison between the levels just explained and the typical application fields from the previous section should be made at this point.

The selection of suitable criteria is always connected with the specification of a scale (level 1) and in the vast majority of cases additional classes are formed on this scale which correspond to level 2 (judging). Thus the application fields “Warnings” and “Decisions between alternatives” can be treated. For system optimization, it is necessary that the indicator value be designed in such a way that a new value assignment for the manipulated variables is constructively possible from the current value. In addition to judging, the indicator must also constructively allow the calculation of feedback on the input variables of the system. In the case of optimization, it is sufficient to consider this system as a black box under observation. This changes, if the claim of the investigation lies in the modelling of the real system. Then it is not sufficient to observe and visualize the current values of system variables as indicator values; rather, in the sense of a glass box, knowledge about the static and dynamic relationships between the observed variables is necessary. Consequently, a pure indicator system cannot replace a real model of a system.

3 The Workflow for Building Indicators

If the focus lies on how to get an indicator, it will be essential to bring the corresponding workflow to mind and reflect its steps in detail. The Fig. 3 shows the actions in green and the resulting objects in blue colour.

Step 1: scope and borders

The first step is the decision, which model quantities among the complete set (given by the system or the model) are of interest for the indicator objective. Thus,