EXIT: An Alternative Approach for Structural Cross-Impact Modeling and Analysis

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Highlights

- EXIT is a novel approach for cross-impact modeling and analysis
- EXIT models are based on expert-sourced data of the direct interactions in a system
- EXIT can be used for structural analysis of many socio-techno-economic systems
- The output is information about the higher-order interactions in the system
- EXIT offers new analytical capabilities compared to existing approaches

Abstract

Cross-impact methods are planning, foresight and decision support tools often used in conjunction with the scenario technique. They enable systems modeling in a theory-driven way, grounded in expert judgment and understanding. This article presents the EXIT approach, a novel modeling technique and a computational method for structural cross-impact analysis. EXIT extracts insights from an expert-sourced cross-impact model, which describes the structure of direct interactions within a system. The EXIT transformation produces a relative quantification of the emergent, systemic relationships between model components, effectuating over the complex web of interactions in the system. Compared to the more established matrix multiplication approach, EXIT produces novel and more detailed analytical

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outputs on the basis of similar input, and offers new analytical possibilities in structural cross-impact analysis. A software implementing the EXIT transformation is freely available.

Keywords: Cross-impact analysis, Interaction analysis, Structural analysis, Systems analysis, Systems modeling, Expert methods

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Acknowledgements

This article is based on the research work supported by the Strategic Research Council (SRC) at the Academy of Finland under the project "Transition to a resource efficient and climate neutral electricity system" **(EL-TRAN) (decision number 293437)**.

1. Introduction

Cross-impact methods are planning, foresight and decision support tools often used in conjunction with the scenario technique (Gordon, 1994; Godet et al., 1991, 1994). They enable systems modeling in a theory-driven way, grounded in expert judgment and understanding. Cross-impact methods as modeling and analysis approaches fall in between empirical data-driven computational models and argumentative systems analysis, and they exhibit a high degree of disciplinary heterogeneity and focus on expert-sourced soft system knowledge (Weimer-Jehle, 2006).

The utility of cross-impact analysis is to provide deep insights into the operating logic of a system with complex interactions between its elements. A decision support-oriented utility for cross-impact models is to use them in examining the impacts of strategic choices, policy interventions or changes in the system. They are normally based on expert-sourced data on the interactions between system components, and thus enable modeling of systems that do not have ample empirical data that is required in use of traditional data-driven modeling techniques. Cross-impact analysis has become a popular technique for systems and decision analysis and well established in the fields of foresight and futures studies (Gordon, 1994; Godet et al., 1994; Cagnin et al., 2016).

The cross-impact approach has a long history in systems analysis and various foresight applications (Gordon and Hayward, 1968; Gordon, 1969; Turoff, 1971; Dalkey, 1971; Kane, 1972; Blackman, 1973; Jackson and Lawton, 1976; Mitroff and Turoff, 1976; Godet, 1976; Bloom, 1977; Martino and Chen, 1978; Nováky and Lóránt, 1978; Kaya et al., 1979; Burns and

Marcy, 1979; Ishikawa et al., 1980; Brauers and Weber, 1988; Godet et al., 1991, 1994; Gordon, 1994; Jeong and Kim, 1997; Weimer-Jehle, 2006; Choi et al., 2007; Pagani, 2009; Thorleuchter et al., 2010; Agami et al., 2010; Bañuls and Turoff, 2011; Bañuls et al., 2013; Lee and Geum, 2017; Ceric, 2016; Thorleuchter and den Poel, 2014; Mamdouh et al., 2015). The original impetus for the development was to complement the Delphi method by introducing analysis of interaction between elements of a given system (Gordon and Hayward, 1968; Gordon, 1969, 1994; Godet et al., 1994). However, recent research has focused mainly on application of cross-impact analysis (Chander et al., 2013; Alizadeh et al., 2016; Blanning and Reinig, 1999; Choi et al., 2007; Gorane and Kant, 2013) and methodological development has dwindled in recent years. In spite of the methodological discussion and development efforts on cross-impact modeling and analysis, many approaches are somewhat opaque in their documentation and lack software tools and implementations, presenting barriers for easy utilization of the cross-impact approach in modeling and research.

This article presents the EXIT (**E**xpress **Cross-I**mpact **T**echnique) method for cross-impact modeling and analysis. EXIT is a structure-oriented cross-impact modeling and analysis method for extracting insights from expert-sourced system model that describes the direct interactions of the said system. The EXIT transformation aims to reveal the emergent, indirect impact network structure of the modeled system and to relate this emergent structure to the direct impact structure described by the input. The analytical objective is an improved understanding of the true relationships between the modeled system parts, forces and events. The proposed approach for structural cross-impact analysis has several advantages compared to existing approaches processing a similar input model. The EXIT approach is compared to the matrix multiplication approach, which is a well established and simple approach for structural cross-impact analysis of very similar input data.

The process of information extraction from a cross-impact matrix used in EXIT is previously unutilized. The process results in more detailed output on the basis of equal input information and extends the analytical possibilities of structural cross-impact analysis. An efficient computation strategy, which allows for processing large cross-impact models, is presented. The contribution of this paper is to present this new, analytically more valuable way of processing cross-impact data. It documents transparently the method for which a freely available software implementation exists. The paper adheres to design science approach, delivering an artefact in the form of EXIT method and a descriptive evaluation (Siau and Rossi, 2011; Hevner et al., 2004; Prat et al., 2015; Cash et al., 2016).

2. Literature review

2.1. Overview to cross-impact analysis

Many quite different analytical techniques are called cross-impact analysis. The format of the inputs for the analysis, the computational process of transforming the inputs into some higher-order information, the nature of the outputs, and the details of the analysis of those outputs vary in the different techniques and their implementations. The development of the original cross-impact technique is attributed to Theodore Gordon and Olaf Helmer (Gordon, 1994; Matic and Berry, 2013), and this technique has largely inspired the other, more recent approaches. An important motivation for experimenting with the early cross-impact techniques was to find out "whether forecasting could be based on perceptions about how future events may interact" and enable analysis of interactions between events, which is not present in the Delphi method (Gordon, 1994; Godet et al., 1994, 139).

In general terms, cross-impact analysis could be described as an analytical technique for studying a system, and particularly interaction within it, consisting of several components, states, events and forces that are partially dependent on each other and therefore have influence on each other. The mentioned objects of the system are modeled as system descriptors. These system descriptors are referred to by different terms by authors of different cross-impact techniques. Gordon (1994) uses the term *event*, Godet et al. (1994) use the word *hypothesis*, and Honton et al. (1984) use the term *descriptor*. The influence the objects of the system have on each other are given a representation in the system model. The influence can be expressed in the model as conditional probabilities (see e.g. Gordon, 1994; Godet et al., 1994, 142–149), references to probability-adjusting functions (Honton et al., 1984; Luukkanen, 1994; Panula-Ontto, 2016), impact indices (Kane, 1972; Godet et al., 1994, 90–101), or in some cases simply a boolean indicator of interaction of some kind (Godet et al., 1994, 83).

The aim of cross-impact analysis is to extract information about the indirect and total interactions between the components of the modeled system on the basis of the input information about the direct interactions. In a system with a high number of components, the chains of impacts can be long and the indirect interactions can effectuate over a complex web of mediating components. Exploring these long impact chains and interaction webs can bring forward surprising and counter-intuitive results. Cross-impact analysis can reveal that a system component that is seemingly unrelated to another component of interest is actually of central importance and conversely that the effect of some other seemingly important component might be cancelled or reversed by the system's web of interactions. It can be used to investigate the effects of changes in the system and identification of effective policy actions and interventions, and their effects in the system, with the aim of discovering policy-relevant insights.

The cross-impact analysis inputs include the system descriptors, their direct interactions and the valuations of the different properties of the descriptors and interactions. Typically, this input data is provided by people with expertise considered relevant for the modeled system or topic. Having one person to supply all the necessary input data, regardless of the method, is technically enough to build the cross-impact model. Normally, however, there are several experts, perhaps a large number of them (Godet et al., 1991, 49). It is possible to have the experts work as a group that interacts during the process of providing the inputs; it is possible to have the experts provide the inputs via a questionnaire; or it is possible to combine these approaches in some way. An example of combining the approaches would be having the experts vote about the inputs anonymously using an online questionnaire and discuss about the results directly, then taking the vote again (observing a Delphi-like process). As the focus of this paper is not the process or facilitation of using experts in building a cross-impact model, but rather the description of a new cross-impact modeling language and the analysis of system models built with it, the questions of expert selection, model building, facilitating expert group work in model valuation and other processual intricacies are not examined in more detail. For further discussion of the use of experts in providing inputs for cross-impact modeling and analysis, see Enzer (1971); Linstone and Turoff (1977); Godet et al. (1991, 1994); Blanning and Reinig (1999); Seker (2015); Alizadeh et al. (2016).

Cross-impact approach enables the modeling of systems that do not have a lot of statistical or empirical data available about them. As *expertise*, relevant to the modeled system or problem, is used as the source material in building the cross-impact models, many non-quantified or weakly quantified phenomena might be modeled with the approach. The expert-oriented modeling approach can be viable also in cases where lack of data makes employment of traditional modeling and simulation methods unfeasible. The cross-impact approach can be also seen as a way to process expert views and opinions in a systematic and formalized way. The collection, processing and synthesis of expert views are central methodological challenges in foresight and futures studies; cross-impact methods are tools to process and synthesize the expert-sourced data in a structured way.

2.2. Structural cross-impact analysis

The documented cross-impact methods can be divided into two categories by whether they explicitly compute probability values associated to the system descriptors or not. The methods computing probability values require more inputs and the cross-impact model construction is more time-consuming. They enable more analytical possibilities. These methods can be called *probability-focused*. The methods that do not compute probability values require less and simpler inputs and the model construction is faster. The analytical possibilities are reduced compared to methods that do compute probability values. These methods can be called *structure-focused*. The existing documented structure-focused cross-impact analysis techniques, such as MICMAC (Godet et al., 1994, 83) and its derivatives, and the ADVIAN approach by Linss and Fried (2010), are based on matrix multiplication method. EXIT falls in the category of structure-focused cross-impact methods as well, but while the inputs are similar to the inputs required by the approaches based on matrix multiplication method, the computational approach is very different. EXIT can be meaningfully compared against other structure-focused cross-impact approaches, of which MICMAC appears to be the most widely used.

The structure-focused methods deliver their analytical contribution by revealing the indirect impact chains and higher-order interactions of the cross-impact model directly from the description of the direct impacts. They do not compute probability changes for the cross-impact model. Methods in this category include the MICMAC method (Godet et al., 1994, 84), the ADVIAN method (Linss and Fried, 2010), and the EXIT method presented in this paper. The structure-focused methods reveal the importance of system components to each other and in the overall system. The structural cross-impact modeling and analysis can be used to discover the higher-order interactions, to give an understanding of the pivotal system components, and to identify effective intervention points for strategic action and policy on the basis of that information.

The motivation for using the structure-focused methods instead of the probability-focused methods is the clearly lower cost of modeling, especially model valuation, in time and effort. The trade-off is the reduction in analytical possibilities. The cross-impact model valuation is the process of defining the necessary values of model components and their properties for analysis. This, as explained, is usually done by expert valuators in the cross-impact approach. In probability-focused methods, initial or a priori probabilities for system descriptors are required. The interactions need also be described in terms of probability changes. Defining conditional probabilities in approaches such as Gordon's method Gordon (1994) or SMIC is extremely challenging and time-consuming. The description of interactions is easier for model valuators if the probability adjustment function approach is used (see Honton et al., 1984; Luukkanen, 1994; Panula-Ontto, 2016), but the level of complexity in valuation is still high compared to the structural cross-impact modeling approach. Valuation of a cross-impact model suitable for probability-focused approach requires, in practice, a committed team of experts for a considerable period of time. In comparison, experiments with the EXIT approach have shown that the valuation of a model suitable for structure-focused approach is possible to be completed in a single-day workshop, easing the requirement of deep expert valuator commitment to the modeling effort.

The complexity and cost of constructing cross-impact models suitable for probability-focused methods make the structure-focused approach a viable alternative in many research and modeling cases. If the main research interest is to generally understand the target system better and identify the most important components from some specific perspective, the analytical possibilities of probability-focused approaches might not be necessary or worth their cost. As the expert resources available for a cross impact modeling effort are, in practice, often limited, the complexity and time requirement of valuation phase limit the level of detail of the cross-impact model. For this reason, using an approach in which the valuation phase is easier makes it possible to *a*) build and study more expansive cross-impact models with more components, *b*) use a wider base of expertise in the valuation by involving more experts, and *c*) discuss, analyze and revise the valuation choices more thoroughly. These points improve the quality of the cross-impact model and make the resulting analysis more valuable. On these grounds, the structure-focused cross-impact methods should be preferred over the probability-focused methods, if their analytical output is sufficient for the purposes of the research.

2.3. The matrix multiplication method and methodological improvements proposed by EXIT

The structure-focused cross-impact modeling and analysis approaches, comparable to the EXIT approach, are the techniques based on matrix multiplication method. The most widely used technique in the category is the MICMAC method developed by Godet et al. (1994). The MICMAC method is, apparent by its relatively wide use, the established method for structure-focused cross-impact analysis. Recent applications of the MICMAC approach in research include Alizadeh et al. (2016), Dubey and Ali (2014), and Gorane and Kant (2013). The MICMAC method is used as a part of a larger analytical framework Godet calls ”structural analysis”. According to Godet, structural analysis is used to study systems consisting of interrelated elements, highlighting the structure of the relationships. The system is described using a cross-impact matrix interconnecting all the system components. Structural analysis aims to “permit analysis of the relationships and identification of the main variables” (Godet et al., 1994, 83).

The key variables are identified in structural analysis by using the MICMAC method. MICMAC is described as “a classification matrix using cross multiplication factors” (Godet et al., 1991, 26). The MICMAC classification process takes a direct impact index matrix as input. This matrix can have impact valuations that indicate the strength and direction of the impact in the same vein as EXIT (the EXIT inputs are discussed in detail in Section 3.1). The impact matrix can also just have values 0 or 1, 0 indicating no impact from variable to another and 1 indicating an impact of some strength and direction. This simple binary presence-of-impact style is how impacts are modeled in the examples of MICMAC approach Godet et al. (1991, 1994).

The impacts variable i has on other variables are marked as elements of impact matrix on row i. This means that the impacts all other variables in the model have on variable i can be read from column i of the matrix. The customary impact markup logic is presented also in Table 2 on page 14. In a cross-impact matrix with the aforementioned properties, the sum of the impact values on a row expresses the degree of influence a variable has in the entire system. The sum of the impact values on a column tells the degree of dependence of a variable in the system. The variables can be ordered by their general influence or dependence. In the MICMAC technique, this ordering is the initial ordering. The initial ordering is based on the direct impacts expressed in the impact matrix and it does not account for any higher-order interactions.

The matrix multiplication approach to extracting information about the indirect impacts is based on squaring the direct impact matrix iteratively. When the cross-impact matrix describing the direct impacts is squared, the second-order indirect impacts are revealed (Godet et al., 1994, 93–97). In the new matrix obtained by squaring the original direct impact matrix, the variables can again be ordered according to the row or column sums like with the direct impacts. The ordering is likely to be different in the power matrix as compared to the original. This squaring of the matrix is performed n times to reveal the $(n+1)^{\text{th}}$-order indirect impacts and the variable ordering is produced by calculating the row or column sums for each iteration.

As enough iterations have taken place, the ordering becomes stable, and the iteration can be stopped. This stable ordering, which no longer changes as the matrix is squared, is the MICMAC ordering or the *a posteriori ordering*. Godet et al. (1991, 26) state that this stable ordering often emerges at iteration 4 or 5 and elsewhere an estimate is given that stability is reached at iteration 7 or 8 (Godet et al., 1994, 94). The number of required iterations, in general, is dependent on the number of variables and the number of interactions in the cross-impact matrix.

The described matrix multiplication approach in structural cross-impact analysis produces an *a posteriori* importance (or dependence) ordering for the variables. This a posteriori ranking is based on the indirect impacts between the variables. The initial ordering of the variables is compared against the a posteriori ordering to highlight the change in the importance of variables. This method gives the prioritization of driving forces in the modeled system based on influence-dependence criteria, using the information about the indirect impacts acquired with the iterative matrix multiplication.

The matrix multiplication approach for structural cross-impact analysis is similar enough to the EXIT method in terms of the inputs and the ultimate aims of the analysis for making direct comparisons between the approaches. Both approaches start with an impact matrix describing the direct impacts in the cross-impact model. Both perform a transformation on the direct impact matrix to reveal the indirect impacts and consider the hidden or unobvious importance of the matrix variables from the perspective of these indirect impacts. However, the matrix multiplication approach has shortcomings on which the EXIT approach proposes improvements. The contribution of the EXIT method to the state of the art is highlighted by the following list contrasting the issues related to matrix multiplication approach against the methodological improvements proposed in EXIT.

1. Information about the directed pairwise influence of system components (or model variables) is not available. The rankings based on matrix multiplication approach provide information only about the overall influence or dependence of the variables in the system. The information on the relationship between individual variables is lost and only a general systemic ranking is made available. EXIT outputs information on the systemic relationship between individual variables.

A system-level quantification of the influence of an EXIT hypothesis can also be made available, as Table 9 shows.

2. The matrix multiplication method only produces an ordering or ranking by importance or weight of the variables. There is no measure of how much the importance of variables might differ. A single variable or small set of variables could dominate the system and the others might be relatively insignificant, but these characteristics of the system cannot be clearly observed from the mere ranking of the variables. The EXIT transformation yields a relative quantification of the total impact of all individual system components on all other individual components, instead of a simple ordering of the components based on general system-level influence or dependence.

3. The matrix multiplication method based approaches do not consider the direction of the influence. This is a significant drawback, as strong influences pulling to different directions can cancel each other out, and only examining the magnitudes of the influences instead of their direction in terms of probability change or more abstract support or antagonism might give a very inaccurate picture of the real relationships of the variables. EXIT is able to consider the directions of the impacts and is able to reveal possible conflicting influences in the system.

4. The rankings based on matrix multiplication approach are ultimately rankings of the variables considering the indirect effects specifically. It might well be, however, that the direct impacts are the most significant for majority of variables and the indirect impacts are of great importance only for some variables. A better approach would be to somehow quantify and sum the direct and indirect impacts instead of presenting the indirect impacts specifically as the highest-order understanding that can be extracted from the cross-impact model. EXIT considers both direct and indirect impacts, instead of an alternative ranking based on indirect impacts specifically to be compared with the obvious ranking based on direct impacts. As both direct and indirect impacts are important, the cross-impact analysis technique should be able to look at both under equal terms.

This paper presents in detail the novel EXIT method for cross-impact modeling and analysis. EXIT is compared to the matrix multiplication approach, the dominant technique used in structure-focused cross-impact analysis. The matrix multiplication approach is used to answer questions about indirect interactions and the importance of different system components, in a system modeled as cross-impacts, using direct impact indices to describe the impacts. Compared to the matrix multiplication approach, EXIT operates on similar input data but provides more detailed analytical output that is less ambiguous to interpret.

This paper focuses on presenting the modeling language of EXIT and the computational transformation of the novel EXIT method clearly, and the contribution is methodological. The computation process and the analytical outputs are illustrated with a small example model. The EXIT method is implemented as a Java program. It is available at `https://github.com/jmpaon/EXIT`, with source code and documentation. The current version features a simple command line interface. The implementation efficiently performs the EXIT transformation, detailed in Section 3.3, using a combination of full computation of impacts and a stratified sampling approach, discussed in Section 3.5.

3. The EXIT approach

3.1. The EXIT model

An EXIT model is a high-level description of a system, using the EXIT modeling primitives for definition of the system characteristics. An EXIT cross-impact model consists of *(a)* a set of hypotheses, *(b)* valuations for the *direct impacts* between the hypotheses, and *(c)* a value for the *maximum impact*. Hypotheses represent system components, states, events and driving forces. Direct impacts are unmediated influences of causal nature, of an *impactor* hypothesis on an *impacted* hypothesis. The maximum impact gives a scale or interpretation to the *valuations* of the direct impacts. These three modeling primitives make up the EXIT modeling language.

3.1.1. Hypotheses

The **hypotheses** are verbalised, and ideally precise, descriptions of states of the modeled system, its components or driving forces, or events in it. The following examples of EXIT hypotheses are from an energy system model:

- New nuclear plants will be constructed by year 2030
- Average electricity price will increase 25% from current level by 2030
- Electricity consumption in 2030 will be increased from current level

A hypothesis in the model has an unknown boolean truth value, which is "revealed as the future unfolds". The hypotheses should be formulated in an unambiguous way. In the examples provided, the assumed context of the cross-impact modeling exercise provides the necessary additional details to make the hypotheses unambiguous. The verbal formulation of the hypotheses should also be such that domain experts would be able, at least in theory, to assign a probability value for them. In EXIT, probabilities for the hypotheses are not assigned, as the object of the analysis is the impact network structure. The hypotheses should nevertheless ideally be formulated in such a way that assigning probabilities is possible. The aim of such formulation of the EXIT hypotheses is to make the expert-elicited impact valuations less ambiguous. When a hypothesis is formulated in a way specific enough to be able to assign a probability, it is possible to try to valuate its probability-changing impacts on other such hypotheses. If, however, the hypotheses are formulated so that assigning a probability is very difficult due to the vagueness of the hypothesis formulation, estimating how it might influence the probabilities of other hypothesis is equally difficult. These strict requirements for hypothesis formulation can, however, be applied more loosely if it makes sense in the context or for the purpose of the analysis.

3.1.2. Direct impacts

Direct impacts are directed and non-symmetrical relationships between hypotheses. In this relationship, one hypothesis is an *impactor* hypothesis and another is an *impacted* hypothesis. In a less formal way, the direct impacts can be understood as factors of *causal* support or opposition the hypotheses have on each other. The *value* of the impact describes the direction (support or opposition) and the strength of the effect. Usually impact values are integers, but any real numbers can be used. A positive value for impact of hypothesis A (H_a) on hypothesis B (H_b) means that H_a strengthens or supports H_b. A negative value for impact of H_a on H_b means that H_a weakens or is in opposition to H_b. In EXIT, a direct impact models an assumed direct causal relationship of the impactor on the impacted hypothesis: The impactor causes the effect on the impacted. Non-causal association or dependence is not intended to be modeled in the EXIT approach with direct impacts. The direct impact of hypothesis H_a on hypothesis H_b can be written as $H_a \to H_b$.

More formally, a direct impact $H_a \to H_b$ describes a probability-changing influence of a direct causal nature of H_a on H_b. This influence is expressed as an impact value, that conveys the direction of probability change and the strength or “size” of the influence. Therefore, a direct impact can be expressed as a 3-tuple, where the first element is the impactor hypothesis, the second one is the impacted hypothesis and the third one is the impact value. The direct impact of hypothesis H_a on hypothesis H_b with a value of i can be written as $H_a \xrightarrow{i} H_b$.

The impact value is interpreted so that if an impactor hypothesis is known to be true, probability of impacted hypothesis changes according to the impact index value: Increases, if impact value is positive, decreases, if impact value is negative, at a rate determined by the impact strength. Conversely, if the impactor hypothesis is known to be false, the probability of the impacted hypothesis decreases if the impact value is positive, and increases if the impact value is negative. Impact value can be interpreted in a yet more general way: if the probability of the impactor hypothesis changes, the probability of the impacted hypothesis changes according to the impact index value. In a case of a positive impact index value, the probability of the impacted hypothesis changes to the same direction as the probability of the impactor hypothesis. In a case of a negative impact index value, a decrease in the probability of the impactor hypothesis causes the probability of the impacted hypothesis to increase. This interpretation of impact values in terms of probability changes of impactor and impacted hypotheses is shown in Table 1.

$\Delta P(H_a)$	$H_a \xrightarrow{+} H_b$	$H_a \xrightarrow{-} H_b$
$P(H_a)$ increases	$P(H_b)$ increases	$P(H_b)$ decreases
$P(H_a)$ decreases	$P(H_b)$ decreases	$P(H_b)$ increases

Table 1: Direct impacts and their interpretation in terms of probability change of the impacted hypothesis

While the interpretation of the direct impacts is related to probability change, the impact values do not correspond to a specific amount of probability change. The impact values simply relate the impact “sizes” or strengths to each other. The impact $H_a \xrightarrow{2i} H_b$ is twice as strong as impact $H_b \xrightarrow{i} H_c$ and has half of the strength of impact $H_c \xrightarrow{4i} H_d$. Similarly, $H_d \xrightarrow{i} H_e$ is equal in strength to $H_e \xrightarrow{-i} H_f$, but the direction of the impact is opposite. Relating the impacts to each other in terms of strength is sufficient for extracting structural information about the cross-impact system.

The direct impacts between hypotheses can be presented in a cross-impact matrix. Table 2 presents the impact markup logic in a cross-impact

Table 2: Impact markup logic in EXIT cross-impact matrix

	H_a	H_b	H_c	H_d
H_a	$\varnothing$	$H_a \rightarrow H_b$	$H_a \rightarrow H_c$	$H_a \rightarrow H_d$
H_b	$H_b \rightarrow H_a$	$\varnothing$	$H_b \rightarrow H_c$	$H_b \rightarrow H_d$
H_c	$H_c \rightarrow H_a$	$H_c \rightarrow H_b$	$\varnothing$	$H_c \rightarrow H_d$
H_d	$H_d \rightarrow H_a$	$H_d \rightarrow H_b$	$H_d \rightarrow H_c$	$\varnothing$

matrix displaying the direct impacts in an EXIT model. The direct impact of H_a on H_b (or $H_a \rightarrow H_b$) is read from matrix entry (1,2) (row 1, column 2); The direct impact of H_d on H_c ($H_d \rightarrow H_c$) is read from matrix entry (4,3) (row 4, column 3). Table 3 in Section 3.2 presents a cross-impact matrix of an EXIT model complete with hypotheses.

It is required from a direct impact $H_a \rightarrow H_b$ that in the cross-impact model there are no intermediary hypotheses between impactor hypothesis H_a and impacted hypothesis H_b. In the real system the cross-impact model represents, there can be some intermediary mechanism or component that mediates the impact of H_a on H_b, even if this component would not be present in the model. If such intermediary system components are identified, however, it warrants consideration of modeling these components in the cross-impact model as additional hypotheses.

3.1.3. Maximum impact value

In the EXIT transformation, the indirect impacts extant in the model are related to the direct impacts. To this end, *relative impact values* are computed for both direct and indirect impacts. This process is discussed in detail in Section 3.3. A **maximum impact value** is defined for an EXIT model for computation of relative impacts. As explained in Section 3.1.2, the impact index value is the "size" or strength of the impact, interpreted relative to the other impact values. The *maximum impact value* is the greatest absolute value that the direct impacts can be valued at and the direct impact matrix is allowed to contain.

Normally the maximum impact value is a positive integer, but the maximum impact value can be any real greater than zero. As the impacts can also be negative, the opposite number of maximum impact value is the smallest impact index value allowed. It expresses the greatest possible probability-decreasing influence a hypothesis can have on another.

The EXIT approach does not force a particular interpretation of the maximum impact value. It is possible to think of an impact value equal to the maximum impact value as a fully determinate influence a hypothesis might have on another hypothesis. If this is the interpretation taken, the sum of impacts of impactors on any hypothesis in the model should not exceed the maximum impact value. This interpretation also dictates that the impacts are present only as positive values, without information about the direction of the impact: they only represent the strength of the impact. In this form, the analysis cannot consider the direction of the impact at all. In a standard case where the maximum impact value is not interpreted as a fully determinate impact, but simply as the greatest absolute impact value available for describing the impacts, this requirement does not hold. Disregarding the direction of the impacts might be useful in some applications of the cross-impact approach, but generally the direction of the impact is a very important aspect of an EXIT cross-impact model. Direct and systemic impacts can pull to different directions and cancel each other out. It is possible that the systemic impacts, when accounted for, negate the direct or obvious impact a system component has on another component. This is why consideration of the direction of the impact is generally of central importance.

3.2. Example model

Table 3: Direct impact matrix of an energy system model

		A	B	C	D	E	F	G
Electricity price will increase	A	∅	+2.5	+1.7	+2.0	+1.6	+1.2	-1.6
Wind and solar power production will increase	B	-0.1	∅	+2.6	+2.3	-2.1	+1.1	-0.2
Electricity storage will increase	C	-0.2	+2.2	∅	0	-0.5	-1.0	+0.1
Market based elasticity of electricity consumption will increase	D	-1.9	+1.1	+0.1	∅	0	-0.6	-0.1
New nuclear power plants will be constructed	E	-0.3	-1.6	-0.4	-0.4	∅	+0.9	-0.8
Electricity transmission capacity from neighbouring countries will increase	F	-1.2	+0.1	-1.5	-0.8	0	∅	+0.1
Subsidies for solar and wind power will increase	G	+0.2	+3.9	+1.5	+1.4	-1.0	+1.0	∅

The EXIT approach is illustrated with a small EXIT cross-impact model representing the Finnish energy system. The model hypotheses and the direct impact valuations are presented in Table 3. The example model has seven hypotheses, which are a subset of the hypotheses of a larger EXIT model, created in a foresight-oriented energy system modeling exercise in the EL-TRAN project. The hypotheses describe the state of, and possible developments in, the Finnish energy system with a timeframe of 2017–2030. The first column of Table 3 presents the hypotheses. the impact valuations of hypotheses on other hypotheses are read row-wise; the impacts of other hypotheses on a particular hypothesis are read column-wise (see Table 2). For example, the impact of hypothesis A ("Electricity price will increase") on hypothesis E ("New nuclear plants will be constructed"), valued at +1.6, is read from matrix row 1, column 5.

The cross-impact model is expert-sourced both in its *design* (selection and formulation of included hypotheses) and *valuation* (assignment of impact values for the direct impacts). The hypotheses of the original model were selected and formulated during several expert workshops, where the central driving forces and upcoming developments were mapped from the perspective of the EL-TRAN project premises. The participants were high-level experts in electricity technology, energy economics, energy policy and other fields related to the technological, economic and political aspects of the Finnish energy system.

The valuation of the direct impacts was individually performed by 16 expert participants, each of whom supplied a cross-impact matrix via e-mail. The matrix presented in Table 3 was obtained by averaging the impact valuations of the 16 expert-sourced cross-impact matrices. This way, if the valuating experts disagreed about the direction of the impact, the mean of valuations would be close to zero and the unclear impact would be mostly eliminated from the model. Another approach would have been to bring the disagreed-upon valuations up for further discussion in an attempt to find consensus on the valuations.

The values of the direct impact matrix (Table 3) relate the direct impacts of the included hypotheses to each other. The defined maximum impact value for the model is 4. The direct impacts are thought to be unmediated in the system model: the influence of the impactor hypotheses on impacted hypotheses do not effectuate through any other modeled system component. For instance, increasing electricity price (hypothesis A) directly incentivizes (with a direct impact valued at +2.5) to increase production of electricity with solar and wind (hypothesis B) and nuclear power (E, +1.6). Increasing electricity price will also directly support increase in electricity storage capacity quite strongly (+1.7). The experts also saw that the rising price of electricity makes the increase of subsidies for solar and wind power (hypothesis G) less likely, the impact valued at −1.6. On the other hand, construction of new nuclear capacity (hypothesis E) is modeled by the experts to be a rather uninfluential factor in the energy system *directly*. Its direct impacts on electricity price, storage, or consumption elasticity have relatively low impact values. The strongest direct impact new nuclear capacity is modeled to have is on the increase of wind and solar power production (-1.6), as the increased nuclear-sourced power supply to some extent eliminates the need for increased wind and solar power production.

With the system's direct impacts modeled and their valuations presented in the direct impact matrix, the question is how to account for the numerous possible *indirect impacts* possible in the system. For instance, the strong influence of increasing electricity price (hypothesis A) on increasing wind and solar power production (hypothesis B) can be thought to *indirectly* influence the increase in electricity storage capacity (hypothesis C) through hypothesis B, as B has a strong direct impact on C. The EXIT transformation detailed in Section 3.3 describes how these indirect impacts are accounted for and related to each other in the EXIT approach.

3.3. The EXIT transformation

The basic motivation for any type of simulation and modeling is to reveal the emergent or systemic characteristics of the modeled system. In structural cross-impact modeling, this means specifically revealing the systemic role of modeled components in the system, or the systemic relationship between system parts. This is done on the basis of input data about direct impacts, by consideration of indirect impacts in the system. The EXIT approach for revealing the systemic impacts is based on *relative quantification* of all the possible impacts in the system model, direct and indirect. The sum of relative quantifications of the direct impact and all indirect impacts of H_a on H_b is the *summed impact* of H_a on H_b.

The set of possible impacts in the system are represented by the set of *impact chains* possible in the system model. Impact chains are directed sets of model hypotheses. An impact chain can also be defined as an ordered set of direct impacts, where each hypothesis included in the chain is present only once. The direct impacts are impact chains of length 2, as they consist of two hypotheses, the impactor hypothesis and the impacted hypothesis. The indirect impacts are impact chains of length $l \mid l > 2, l \leq n$, where n is the number of hypotheses in the model. The indirect impacts have, in addition to the impactor hypothesis and impacted hypothesis, one or more mediating hypotheses, which convey the impact of the impactor on the impacted hypothesis. An impact chain representing an indirect impact of H_a on H_b with y mediating hypotheses can be written as $H_a \rightarrow H_{x_1} \rightarrow H_{x_2} \rightarrow \cdots \rightarrow H_{x_y} \rightarrow H_b$, where $H_{x_1} \ldots H_{x_y}$ are the mediating hypotheses in the impact chain. Figure 1 presents the possible impact chains from impactor hypothesis H_a to impacted hypothesis H_b in an EXIT model consisting of 5 hypotheses.

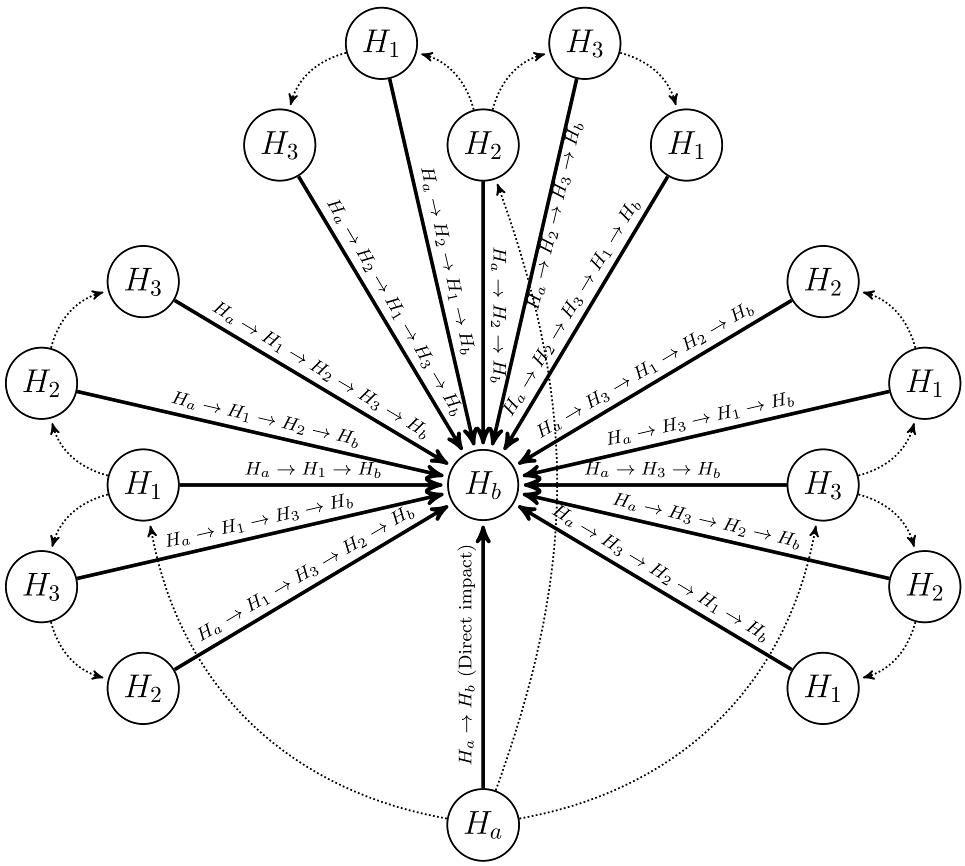

Figure 1: A directed acyclic graph of the impact of hypothesis H_a on hypothesis H_b in a system of 5 hypotheses. The nodes are model hypotheses. All edges are direct impacts, which can also be links in impact chains representing indirect impacts of H_a on H_b. Dotted edges are links in impact chains mediating the impact of H_a on H_b through H_1, H_2 and H_3 indirectly. Solid edges are the direct impacts on H_b, ultimately effectuating the impact of H_a on H_b.

The EXIT transformation does not compute the influence of *cyclic* impacts. In the matrix multiplication based approaches, cyclic impacts do have an effect on the results. This characteristic of EXIT is a logical consequence of the formal definitions of the EXIT modeling primitives, the *hypothesis* and the *direct impact*. An example of cyclic interaction would be, in the case of the system of Fig. 1, say, H_a influencing H_1 and H_1 in turn influencing H_a back. Allowing such cyclic interaction would mean that H_a would have indirect influence on itself through H_1. This would be against the definition of hypotheses as postulates or possible facts about the system state. The EXIT direct impact, in turn, is the probability-changing influence of the 'cause' hypothesis on the 'effect' hypothesis, conditional to the 'cause' hypothesis being true. This being the definition, cyclic interaction would not be logical in an EXIT model: A hypothesis being true cannot increase its own probability of being true. In EXIT, the definitions of hypothesis and direct impact are quite specific and formal, perhaps more so than in the matrix multiplication based approaches, and the definition precludes cyclic interaction. A technical or computational reason for not computing cyclic interaction is the lack of any kind of terminating condition for computing indirect impacts in a structural cross-impact model, if the cyclic interaction would be allowed: If a hypothesis could occur multiple times in an impact chains, there would be an infinite number of possible impact chains.

The relative quantification r of a direct impact $a \xrightarrow{i} b$ is computed as $\frac{i}{m}$, the ratio of the direct impact valuation i and the maximum impact value m. The relative quantification of an indirect impact $H_a \xrightarrow{i_1} H_{x_1} \xrightarrow{i_2} H_{x_2} \xrightarrow{i_3} \dots \xrightarrow{i_{y-1}} H_{x_y} \xrightarrow{i_y} H_b$ is computed as $\frac{i_1}{m} \times \frac{i_2}{m} \times \cdots \times \frac{i_y}{m}$, the product of the relative quantifications of the direct impacts involved in the impact chain. Table 4 shows a subset of the impact chains of the example model presented in Table 3, and the computation of their relative quantifications.

Table 4: Computing the relative quantification (r) of impact chain

	Impact chain	Computation	r
(1)	$A \xrightarrow{+2.5} B$	$\frac{+2.5}{4}$	+0.625
(2)	$A \xrightarrow{+1.7} C \xrightarrow{+2.2} B$	$\frac{+1.7}{4} \times \frac{+2.2}{4} = \frac{+3.74}{4^2}$	+0.234
(3)	$A \xrightarrow{+2.0} D \xrightarrow{+0.1} C \xrightarrow{+2.2} B$	$\frac{+2.0}{4} \times \frac{+0.1}{4} \times \frac{+2.2}{4} = \frac{+0.44}{4^3}$	+0.007
(4)	$A \xrightarrow{+1.6} E \xrightarrow{-1.6} B$	$\frac{+1.6}{4} \times \frac{-1.6}{4} = \frac{-2.56}{4^2}$	−0.160
(5)	$A \xrightarrow{-1.6} G \xrightarrow{-1.0} E \xrightarrow{+3.9} B$	$\frac{-1.6}{4} \times \frac{-1.0}{4} \times \frac{+3.9}{4} = \frac{+6.24}{4^3}$	+0.098

In Table 4, the relative quantification of chain 3 is close to zero, as the direct impact $D \xrightarrow{+0.1} C$ included in the chain largely nullifies the impact of the chain on C. In chain 4, the negative direct impact $E \xrightarrow{-1.6} B$ reverses the direction of impact of the chain: Hypothesis A causes the probability of hypothesis E to increase, which causes the probability of B to decrease, so the indirect impact of A on B through E turns out negative. In chain 5, the negative impact $A \xrightarrow{-1.6} G$ is reversed by the negative $G \xrightarrow{-1.0} E$, making the relative quantification of A's impact on B through G and E positive, as the positive direct impact of E on B does not again reverse the direction of the impact.

In the EXIT transformation, the relative quantification is computed for all possible impact chains for all possible impactor-impacted pairs. The summation of the relative quantifications yields a new matrix, the *summed impact matrix*: The relative quantifications of impact chains where the impactor hypothesis is H_a and impacted hypothesis is H_b are summed as the value of entry (H_a, H_b) of the summed impact matrix. The values of the summed impact matrix reflect the total impacts of all system parts on each other, when all the systemic interactions have been accounted for; its values relate the *total* impacts of hypotheses on each other, taking into consideration, in addition to the direct impacts, the higher-order interactions in the system. Table 5 presents the summed impact matrix that the EXIT transformation yields from the example model of Table 3.

Table 5: Summed impact matrix resulting from the EXIT transformation

		A	B	C	D	E	F	G
Electricity price will increase	A	Ø	+0,11	+0,16	+0,31	+0,22	+0,17	-0,40
Wind and solar power production will increase	B	-0,29	Ø	+0,68	+0,67	-0,74	-0,20	+0,20
Electricity storage will increase	C	-0,19	+0,66	Ø	+0,47	-0,51	-0,28	+0,14
Market based elasticity of electricity consumption will increase	D	-0,43	+0,27	+0,19	Ø	-0,30	-0,28	+0,17
New nuclear power plants will be constructed	E	+0,19	-0,80	-0,59	-0,65	Ø	+0,26	-0,20
Electricity transmission capacity from neighbouring countries will increase	F	-0,13	-0,28	-0,43	-0,44	+0,14	Ø	+0,05
Subsidies for solar and wind power will increase	G	-0,49	+1,31	+1,00	+1,17	-1,13	-0,26	Ø

The values of summed impact matrix are not directly comparable with the values of the direct impact matrix, as the two matrices are not in the same scale. The summed impact matrix values can only be meaningfully compared, without any further transformations, to other values in the summed impact matrix. To enable comparison between corresponding entries of the direct and summed impact matrices, both should be transformed to have the same scale.

The summed impact matrix does not have a defined maximum impact value, like the direct impact matrix has. A theoretical maximum impact

Table 6: Normalized direct and summed impact matrices

		Normalized direct impacts								*Normalized summed impacts*						
		A	**B**	**C**	**D**	**E**	**F**	**G**		**A**	**B**	**C**	**D**	**E**	**F**	**G**
Electricity price will increase	**A**	Ø	+2.8	+1.9	+2.2	+1.8	+1.3	-1.8	**A**	Ø	+0.3	+0.5	+0.9	+0.6	+0.5	-1.1
Wind and solar power production will increase	**B**	-0.1	Ø	+2.9	+2.6	-2.3	+1.2	-0.2	**B**	-0.8	Ø	+1.9	+1.9	-2.1	-0.6	+0.6
Electricity storage will increase	**C**	-0.2	+2.5	Ø	0	-0.6	-1.1	+0.1	**C**	-0.5	+1.8	Ø	+1.3	-1.4	-0.8	+0.4
Market based elasticity of electricity consumption will increase	**D**	-2.1	+1.2	+0.1	Ø	0	-0.7	-0.1	**D**	-1.2	+0.8	+0.5	Ø	-0.8	-0.8	+0.5
New nuclear power plants will be constructed	**E**	-0.3	-1.8	-0.5	-0.5	Ø	+1.0	-0.9	**E**	+0.5	-2.2	-1.6	-1.8	Ø	+0.7	-0.6
Electricity transmission capacity from neighbouring countries will increase	**F**	-1.3	+0.1	-1.7	-0.9	0	Ø	+0.1	**F**	-0.4	-0.8	-1.2	-1.2	+0.4	Ø	+0.1
Subsidies for solar and wind power will increase	**G**	+0.2	+4.4	+1.7	+1.6	-1.1	+1.1	Ø	**G**	-1.4	+3.7	+2.8	+3.3	-3.2	-0.7	Ø

value for the summed impact matrix exists, and is dependent on the maximum impact value of the direct impact matrix and the number of hypotheses in the model. This theoretical maximum impact value is, however, not well suited to be used as the assumed maximum impact value of the summed impact matrix, as it is, in all practical cases, bound to be very high in comparison to the summed impact values. A sensible approach to making the matrices comparable is to normalize both matrices. This could be done in different ways, but the recommendation of the authors is to divide the matrix entry values by the mean of the absolute values of all matrix entries (or the average distance of values from zero). After this normalization, the 'unit' of the cross-impact matrix is the *cross-impact unit*, the average impact of an average impactor on an average impacted hypothesis in the system. When both direct and summed impact matrices are normalized, their values can be directly compared between matrices. The effects of the systemic and emergent interactions can be observed from the difference between the normalized summed impacts and the normalized direct impacts.

The summed impact matrix values reflect a more 'real' valuation of the interaction between the system components, as the systemic effects are appraised alongside the obvious direct impacts. Comparing the summed impact valuations to the direct impact valuations can reveal surprising systemic properties, such as *a*) relationships that are seemingly important but whose effects are cancelled out by other systemic effects, *b*) relationships that are hidden and revealed only through mapping of the indirect impacts, or *c*) relationships that are reversed as the indirect impacts are considered: the total impact of a hypothesis on another might be opposite to the obvious logic of the direct interaction.

Table 6 presents the normalized direct and summed impact matrices. The consideration of indirect impacts in the system changes the picture of the interactions considerably: 14 (33%) of the 42 directed pairwise impacts change more than one cross-impact unit either positively or negatively. For instance, while the direct impacts of hypothesis A ("Electricity price will increase") are substantial on all other hypotheses, the indirect impacts significantly curtail the direct impacts. The strong positive direct impact of price increase on growing solar and wind power production is almost completely neutralized by the impacts A has B through the other system components. While the impacts of A do not change their direction after computation of indirect impacts (A still supports hypotheses B–F and restrains G), the impacts are greatly weakened. On the basis of the direct impacts only, the increasing electricity price appears to be a strong driver in the system, but in the systemic perspective, its influence is quite limited. The impact of A on G ("Subsidies for solar and wind power will increase") is the only total impact that exceeds one cross-impact unit (with a value of -1.1).

On the other hand, the summed impact values of hypothesis G ("Subsidies for solar and wind power will increase") on other hypotheses are considerably higher than the direct impact valuations. While the subsidies on solar and wind do appear to be a quite strong driver in the energy system directly, their influence on several developments such as increase of electricity storage, market-based elasticity of electricity consumption, and construction of new nuclear capacity, is further amplified by the indirect impacts. In the light of the example model of the energy system, increasing solar and wind subsidies restrains the electricity price increase, but this effect is enacted indirectly, as the direct impact is close to neutral.

Some relationships change in their nature altogether, going from supporting to restraining or vice versa, when the higher-order interactions are computed. Increased wind and solar power production (hypothesis B) and increased subsidies on solar and wind power (hypothesis G) are modeled to directly support the increase of electricity transmission capacity from neighboring countries (hypothesis F), but their systemic impacts change the total impact into negative. Section 3.4 presents further transformations which can be used in facilitating analysis of the EXIT output.

3.4. Facilitation of interpretation and analysis

The difference of the summed impacts and direct impacts for each directed hypothesis pair equals the indirect impacts of each directed hypothesis pair. Table 7 presents a difference matrix, where the direct impact matrix has been subtracted from the summed impact matrix. The difference matrix can be useful in observing for which interactions the higher-order, systemic interactions change the relationship considerably. In the example model, the relative quantification of all indirect impacts is less than the relative quantification of the direct impact for 23 (55%) of the modeled relationships and less than 50% of the direct impact in 16 (38%) of the relationships, so for the majority of cases, the direct influence is still dominant even after consideration of the emergent, systemic interactions. On the other hand, 19 (45%) of the relationships are such that the sum of the indirect impacts is greater than the direct impact. Three relationships, namely (C,D), (D,E), and (F,E) only effectuate indirectly through the system's impact network, as there is no direct impact in these relationships. From analytical standpoint, the relationships that have substantial indirect impacts might often be interesting for further analysis.

Table 7: Difference matrix of summed and direct impact matrices

		A	B	C	D	E	F	G
Electricity price will increase	A	Ø	-2.5	-1.5	-1.4	-1.2	-0.9	+0.7
Wind and solar power production will increase	B	-0.7	Ø	-1.0	-0.7	+0.3	-1.8	+0.8
Electricity storage will increase	C	-0.3	-0.6	Ø	+1.3	-0.9	+0.3	+0.3
Market based elasticity of electricity consumption will increase	D	+0.9	-0.5	+0.4	Ø	-0.8	-0.1	+0.6
New nuclear power plants will be constructed	E	+0.9	-0.4	-1.2	-1.4	Ø	-0.3	+0.3
Electricity transmission capacity from neighbouring countries will increase	F	+1.0	-0.9	+0.5	-0.3	+0.4	Ø	0
Subsidies for solar and wind power will increase	G	-1.6	-0.7	+1.1	+1.7	-2.0	-1.9	Ø

Information about the differences between the direct and summed impact matrices can also be summarized with a matrix, where the nature of the effect of the indirect impacts and emergent relationships between the hypotheses is represented with an appropriate symbol. The utility of such matrix is to highlight how the higher-order interactions change the relationship of system components. Table 8 presents a summary matrix with the differences between direct and summed impacts are classified into seven categories, listed in the table legend.

As the compared matrices have been normalized to cross-impact unit scale, a threshold of $\frac{1}{3}$ cross-impact units can be used to define what amount of change is deemed significant and what range of impact values is considered to be a small or insignificant impact. The threshold and the way the

Table 8: Summary matrix on the nature of the emergent relationships

		A	B	C	D	E	F	G
Electricity price will increase	A	Ø	↳	↘	↘	↘	↘	↘
Wind and solar power production will increase	B	↧	Ø	↘	↘		↺	↥
Electricity storage will increase	C		↘	Ø	↥	↗		
Market based elasticity of electricity consumption will increase	D	↘	↘	↥	Ø	↧		↥
New nuclear power plants will be constructed	E	↥	↗	↗	↗	Ø		↘
Electricity transmission capacity from neighbouring countries will increase	F	↘	↧	↘		↥	Ø	
Subsidies for solar and wind power will increase	G	↧	↘	↗	↗	↗	↺	Ø

Absolute difference smaller than ⅓ CIU (cross-impact unit)	No significant change	(empty)
Significant direct impact, total impact close to 0	Systemic neutralization	↳
Direct impact close to 0, total impact negative	Negative activation	↧
Direct impact close to 0, total impact positive	Positive activation	↥
Impacts have same sign, total impact smaller than direct	Systemic curtailment	↘
Impacts have same sign, total impact greater than direct	Systemic boost	↗
Impact sign changes when indirect impacts are computed	Systemic negation	↺

understanding of the impact of a hypothesis on another changes as the indirect impacts are discovered are used in classifying the relationships. In the summary matrix of Table 8, *a*) cases where absolute differences between direct and summed impacts are smaller than the threshold are classified in the ”no significant change” class, *b*) cases where the impact changes from positive or negative to neutral are classified as ”systemic neutralization”, as the systemic effects largely cancel out the direct impacts, *c*) cases where the impact changes from neutral to negative are classified as ”negative activation”, as the directly neutral relationship becomes negative through the impact network, *d*) cases where the impact changes from neutral to positive are classified as ”positive activation”, *e*) relationships that retain the direction of their influence after discovery of indirect impacts, but where the influence is weakened by systemic effects, are classified in the ”systemic curtailment” class, *f*) relationships that retain the direction of their influence but where the influence is strengthened by systemic effects, are classified in the ”systemic boost” class, and *g*) relationships for which the systemic effects overpower the direct impact, switching the direction of the influence, from positive to negative or from negative to positive, are classified as ”systemic negation”.

For 8 (19%) relationships in the model, there is no significant change when the indirect impacts are accounted for. One relationship (impact of electricity price increase on increase of wind and solar power production) is systemically neutralized. 10 (24%) of the relationships are neutral in the light of direct impacts, but are systemically activated to have either positive or negative impact. 21 (50%) of the relationships remain supporting or restraining as the direct impacts indicate, but are boosted or curtailed more than the threshold of $\frac{1}{3}$ cross-impact unit. Two relationships (impacts of increasing wind and solar production (B) and increasing subsidies for solar and wind power (G) on (F) electricity transmission capacity) are reversed by the systemic effects: both directly support the increase of electricity transmission capacity from neighboring countries but systemically restrain the development.

Table 9: Systemic influence and dependence in the energy system model.

		Influence		Dependence	
		Direct	Summed	Direct	Summed
Electricity price will increase	**A**	11.8	3.9	4.3	4.8
Wind and solar power production will increase	**B**	9.4	7.8	12.7	9.6
Electricity storage will increase	**C**	4.5	6.3	8.7	8.5
Market based elasticity of electricity consumption will increase	**D**	4.2	4.5	7.7	10.4
New nuclear power plants will be constructed	**E**	4.9	7.5	5.8	8.5
Electricity transmission capacity from neighbouring countries will increase	**F**	4.1	4.1	6.5	4.1
Subsidies for solar and wind power will increase	**G**	10.0	15.0	3.2	3.2

The MICMAC approach for structural cross-impact analysis produces a ranking of the model descriptors based on systemwide influence or dependence, reflecting the overall 'impactingness' or 'impactedness' of the system components. This is done on the basis of direct impacts and also after the iterative matrix multiplication, with the idea of observing how the ordering of the descriptors changes. If a similar analytical output is required, it can be extracted from the EXIT model by summing the absolute values of rows or columns, for both direct and summed impact matrices. In EXIT, the sum of absolute row values can be understood to reflect the systemwide influence of each hypothesis. Similarly, the sum of absolute column values reflects the systemwide dependency. This information for the example energy system model is presented in Table 9.

The influence-dependence quantification shows the relative sidelining of the influence of electricity price in the systemic outlook. Also the intensification of the influence of subsidies can be easily observed from the figures of Table 9. Compared to the matrix multiplication approach, the information could be seen as of higher value as a quantification is provided of the influence and dependence, instead of mere ordering. However, important aspects of the information provided by the EXIT transformation is lost if the influence-dependence values of the hypotheses are used as the analytical focal point. The influence-dependence valuations only provide a summary of the general role of the components of the system, and the directed pairwise impact valuations offer far more insight into the relationships in the modeled system.

3.5. Estimation strategies for large EXIT models

The number of impact chains that can be formed from a cross-impact matrix is dependent on the number of hypotheses. The total number of possible impact chains in a cross-impact model with $n \mid n > 1$ hypotheses is $\sum_{k=0}^{n-2} \frac{n!}{k!}$, while the total number of impact chains longer than 2 hypotheses (the number of impact chains that represent indirect impacts) is $\sum_{k=0}^{n-3} \frac{n!}{k!}$. As the number of hypotheses in the cross-impact model grows, the number of possible impact chains grows exponentially.

For models with 10 or less hypotheses, full computation of indirect impacts is fast, but as the number of hypotheses grows, calculating the relative impacts of all possible impact chains quickly becomes unfeasible due to computational cost. An efficient strategy for accurate estimation of the summed impacts without full computation is needed to process big cross-impact models. The possibilities for estimation of summed impacts are the following:

1. **Cutting computation of indirect impacts at a specified chain length.** Computing impacts fully for all impact chains that are shorter than a given threshold is a straightforward approach and accounts for the most important indirect impacts if the chain length threshold is big enough (say, 7-8 hypotheses). Each individual uncomputed impact chain will most likely have a low relative impact value. For example, in a cross-impact system where 5 is the defined maximum impact value, a very strong 8-hypothesis impact chain consisting of direct impacts all

having absolute value of 4 ($H_1 \overset{\pm\frac{4}{5}}{\rightarrow} H_2 \overset{\pm\frac{4}{5}}{\rightarrow} H_3 \overset{\pm\frac{4}{5}}{\rightarrow} H_4 \overset{\pm\frac{4}{5}}{\rightarrow} H_5 \overset{\pm\frac{4}{5}}{\rightarrow} H_6 \overset{\pm\frac{4}{5}}{\rightarrow} H_7 \overset{\pm\frac{4}{5}}{\rightarrow} H_8$) would have an absolute relative impact of $(\frac{4}{5})^8 \approx 0.168$. While this is still a quite significant relative impact, impact chains as strong as this are highly improbable in normal cross-impact models. Most likely the relative impact of an average 8-hypothesis impact chain is close to zero. If the average direct impact value in a 8-hypothesis impact chain would be 3, a very high average impact, the relative impact of the impact chain would be only $(\frac{3}{5})^8 \approx 0.017$, and with an average direct impact of 2.5, the relative impact of such chain would be as low as $(\frac{2.5}{5})^8 \approx 0.004$. Hence, full computation of only shorter impact chains is sufficient for approximation of summed impacts in many cases.

2. **Pruning the search space using a threshold value for relative impact of chains.** Another solution for approximation of summed impacts, satisfactory in most cases, is to only compute the impact chains which are significant, having a impact value higher than a significance threshold value defined by the analyst. If only significant chains are considered, only a fraction of the set of possible impact chains need to be examined. The threshold value should be a real in the range $]0, 1[$. If threshold is 0, all chains that have a relative impact different from 0 are significant; if threshold is 1, no chains are seen as significant. In practice, a suitable threshold value is close to 0.

   Any impact chain in an EXIT model can be thought to have a (possibly empty) set of *immediate expansions*. The set of immediate expansions for an impact chain c includes the impact chains that are longer than c by one hypothesis, which is in the cross-impact model but not in the chain c. For instance, the chain $H_1 \overset{-2}{\rightarrow} H_4 \overset{-3}{\rightarrow} H_2$ formed from a cross-impact model of 5 hypotheses would have the immediate expansions $H_1 \overset{-2}{\rightarrow} H_4 \overset{-3}{\rightarrow} H_2 \overset{-3}{\rightarrow} H_3$ and $H_1 \overset{-2}{\rightarrow} H_4 \overset{-3}{\rightarrow} H_2 \overset{+1}{\rightarrow} H_5$. The immediate expansions of an impact chain have, in turn, their immediate expansions, which are also *non-immediate expansions* of the original chain. The immediate expansions of any impact chain can have, at most, the same relative impact as the impact chain they expand. This means that if the relative impact of an impact chain is lower than the threshold, all its expansions will also have relative impacts lower than the threshold.

   When calculating the summed relative impacts for a cross-impact model, it is possible to start with the direct impacts and compute a particular impact's immediate expansions only if the relative impact of the direct impact exceeds the threshold. The same principle is then applied recursively on the immediate expansions. This way only impact chains that can possibly have an impact greater than the threshold are considered. The impact chains that have a relative impact below the threshold are not examined in the computation, greatly reducing the computational cost. For big cross-impact models, the computation can still be very slow when a low threshold value is used.

3. **Using a sampling-based approach.** The estimation of summed impacts can also be based on sampling the population of possible impact chains. As the number of chains of a given length for a cross-impact system is known, this information can be used for sample stratification. The number of impact chains of length L between H_a (impactor) and H_b (impacted) is, in a system of n hypotheses, $\frac{(n-2)!}{((n-2)-L)!}$. The number of intermediary chains of any length from H_a to H_b in such system is $\sum_{L=2}^{n} \frac{(n-2)!}{((n-2)-L)!}$.

   In estimating the summed impact of H_a on H_b, a sample is drawn for each intermediary chain length that is possible in the system. This means that in a system of of n hypotheses, samples are drawn from the sets of chains between H_a and H_b with $1, 2, \ldots, n-2$ intermediary hypotheses (producing $n-2$ samples). For each sample, a sample mean is computed and it is multiplied by the number of possible impact chains of that length. For each impactor-impacted pair (H_a, H_b) the total relative impact of H_a on H_b is approximately $\sum_{L=2}^{n} \bar{x}_L \times \frac{n!}{(n-L)!}$, where $\bar{x}_L$ is the sample mean of relative impacts of chains of length L: the estimated summed impact between H_a and H_b is the sum of the weighted sample means and the relative direct impact.

In any cross-impact model, the overwhelming majority of possible impact chains will be long impact chains which involve more than half of the hypotheses in the model. For instance, in a cross-impact system of 15 hypotheses, more than 90% of the possible impact chains are longer than 10 hypotheses; in a system of 20 hypotheses, only (1.02×10^{-5}) % of possible impact chains will consist of 10 or less hypotheses. The relative impacts of these long chains will be very small in comparison to the relative impacts of shorter chains. However, as there are great numbers of these small impacts in the vast uncomputed set of possible impact chains, any possible structure in these high-order impacts might have noticeable impact on the results; if the positive and negative impacts of these long impact chains do not cancel each other out, the estimates of summed impacts derived by approaches 1 or 2 might be inaccurate. The sampling-based approach to estimation, when large samples ($n > 10^6$) are used, provides more than sufficiently accurate estimates even for big cross-impact models, considering the somewhat rough and approximate nature of the expert-sourced input data. The sampling-based approach is able to estimate the summed impacts in linear time, making it a feasible approach for estimation of summed impacts in large (15+ hypotheses) cross-impact models.

The EXIT approach to estimation is to fully compute short impact chains and estimate the impacts of longer impact chains based on the stratified sampling approach. In the EXIT implementation, the definition of a short chain is dependent on the user-defined sample size k. The sample size defines, in the estimation of the summed impact of hypothesis H_a on H_b, how many impact chains of each possible chain length are sampled. If the number of possible chains of length L is smaller or equal than the user-defined sample size k (and therefore it is faster to do the full computation instead of drawing the sample) the chain length L is short and the full computation is performed. Otherwise the impacts of impact chains between H_a on H_b of length L are estimated by computing a sample mean of the relative impacts of a sample of size k of such chains in the system. The user can also force a minimum full computation length.

4. Discussion

This paper presents the EXIT approach for cross-impact analysis. EXIT improves on the existing structure-focused cross-impact methods that process expert-sourced system models to extract insights about the emergent, higher-order and indirect interactions from the system of direct impacts described in the model. EXIT method is positioned among other cross-impact approaches and compared against the approaches based on multiplication method, which is discussed in Section 2.3. The improved analytical capabilities of the EXIT approach, as compared to the matrix multiplication approaches, and the additional information extracted from the cross-impact model input are explained in Section 2.3. The enhanced analytical power, the transparent documentation of the approach and the freely available software implementation make EXIT a strong candidate for structural cross-impact analysis where the main interest lies in the structure of the system and the role and importance of the system components in light of higher-order interactions. The previously unutilized way of the extraction of information and insights on the higher-order impacts in the cross-impact system is the main contribution and has been detailed in Section 3.

The broader framework of EXIT method includes several phases that are of critical importance to the cross-impact modeling and analysis. These include identifying the expertise relevant to the study, finding the experts with this expertise, securing their commitment to participate, organizing their work in both selecting the cross-impact model hypotheses and valuating the impacts between the hypotheses and ultimately analysis of the results. These challenges and the best practices concerning them are, however, discussed in existing literature (see e.g. Linstone and Turoff, 1977) and fall outside the scope and focus of this paper introducing the EXIT approach and detailing the EXIT modeling language and the process of information extraction from models built using the language.

In Section 3.2, the use of EXIT in systems modeling has been illustrated with a small example model, based on a larger modeling exercise of the Finnish energy system. For practical purposes of clear presentation of the EXIT approach and its methodological and computational details, the example model presents only a subset of the components of the original system model. The EXIT transformation, which quantifies the systemic and emergent impacts on the basis of description of the system's direct impacts, is of the greatest utility when the analysed models are relatively large, consisting of a big number of components. In a more extensive model, the impact chains are longer and the analysis of the impact network can bring forth results and insights which are difficult, if not impossible, to access without a systematic computational approach like EXIT. While increasing the number of components in the model obviously means more work for the experts providing the model valuations, the cognitive cost of describing the direct interactions in the simple modeling primitives used in EXIT remains comparatively low, especially when compared to probability-oriented cross-impact approaches. Design and valuation of extensive cross-impact models is, while certainly labour-intensive, completely feasible using the described approach.

Generally, the modeling approach of using experts as a principal information source in describing system characteristics has many interesting possibilities. It makes modeling of systems and problem domains that are characterized by lack of empirical data and difficulties of quantification more natural or possible in the first place. Especially foresight-oriented modeling about phenomena whose modeling cannot be based on yet-nonexistent empirical data will benefit from development of approaches and tools that enable modeling of these domains for which the traditional data-driven approaches are not well suited. It also makes incorporating less quantifiable aspects of systems easier, helping to avoid the omission of possibly essential system features and resulting limited strategic and policy scope, resulting from methodological limitations in modeling. In light of the challenges that occur in attempting to understand the uncertainty of impacts and interactions of driving forces in complex systems, structural cross-impact analysis and the EXIT approach have great potential to enhance the understanding of the importance of the systemic and higher order interactions that may significantly improve the foresight ability of futures techniques.

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