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Exploring the future with anticipatory networks

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Abstract. This paper presents a theory of anticipatory networks that originates from anticipatory models of consequences in multicriteria decision problems. When making a decision, the decision maker takes into account the anticipated outcomes of each future decision problem linked by the causal relations with the present one. In a network of linked decision problems, the causal relations are defined between time-ordered nodes. The scenarios of future consequences of each decision are modeled by multiple vertices starting from an appropriate node. The network is supplemented by one or more relations of anticipation, or future feedback, which describe a situation where decision makers take into account the anticipated results of some future optimization problems while making their choice. So arises a multigraph of decision problems linked causally and by one or more anticipation relation, termed here the anticipatory network. We will present the properties of anticipatory networks and propose a method of reducing, transforming and using them to solve current decision problems. Furthermore, it will be shown that most anticipatory networks can be regarded as superanticipatory systems, i.e. systems that are anticipatory in the Rosen sense and contain a future model of at least one other anticipatory system. The anticipatory networks can also be applied to filter the set of future scenarios in a foresight exercise.

Keywords: anticipatory networks; superanticipatory systems; causal fields; scenarios; foresight.
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INTRODUCTION

This paper introduces the reader to the theory of anticipatory networks, which generalizes the ideas related to anticipatory models of consequences in multicriteria optimization problems presented in [1,2,3]. We assume that when making a decision, the decision maker takes into account the anticipated outcomes of each future decision problem linked by the causal relations with the present one. In a network of linked decision problems, the causal relations can be defined between the time-ordered nodes only. The future scenarios of the causal consequences of each decision are modeled by multiple edges starting from an appropriate node. This network is supplemented by one or more relations of anticipation, or *anticipatory feedback*, which models the situation where decision makers take into account the anticipated results of some future decisions modeled by optimization problems while making their choice. They then explore the causal dependences of future constraints and preferences on the choice just made so that future decision outcomes fulfill the conditions specified as the anticipatory feedback relations.

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Both types of relations as well as forecasts and scenarios regarding the future model parameters form an information model, which is called the *anticipatory network*. We will present the basic properties of anticipatory networks and the methods of using them to computing the solutions to current decision problems.

The theory outlined above resulted from the need to create an alternative approach to selecting a solution to multicriteria optimization problems that takes into account direct multi-stage models of future consequences of the decision made [1]. The anticipatory behavior of decision makers corresponds to the definition of anticipatory systems proposed by Rosen [4] and developed further in [5,6]. Namely, a system is called *anticipatory* if it makes its decisions taking into account anticipated future states of its outer environment and of itself. A bibliographic survey of these ideas can be found in [7]. The ability to create a model of the future that characterizes an anticipatory system is also a prerequisite for an anticipatory network, where each node models an anticipatory system and they are able to influence each other according to causal order. Here, we restrict the study of anticipatory networks to model decisions made in networked optimization or gaming problems. If each decision node models an optimization problem, then a network of optimizers arises − a class of information processing systems studied in [2]. In a similar way, one can construct networks with nodes modeling Nash equilibria, set choice problems, random or irrational decision makers, or hybrid networks containing nodes of all types [3].

The study of anticipatory networks starts from its simplest form – the chains of anticipatory units, after which anticipatory trees and general networks will be analyzed. One can note that anticipatory networks with loops correspond to strong anticipatory systems in the Dubois sense [5], while the acyclic networks correspond to weak ones. Then, motivated by the properties of the anticipatory networks, we will present the basic properties of superanticipatory systems. By definition, a *superanticipatory system* is anticipatory in the sense of Rosen [4] or Dubois [5] (weak or strong) and contains a future model of at least one other anticipatory system whose outcomes may influence its current decisions when taking into account anticipatory feedback relations. This notion is idempotent, i.e. the inclusion of other superanticipatory systems into the model of the future of a superanticipatory system does not yield an extended class of systems. Moreover, they can be classified according to a grade that counts the number of nested superanticipation. Most anticipatory networks can be regarded as superanticipatory systems because future decisions can be based on similar anticipatory principles with respect to the subsequent nodes in the network.

Among real-life applications of anticipatory networks, we can include the selection of compromise solutions to multicriteria strategic planning problems applying scenarios of anticipated consequences provided by foresight exercises. Specifically, the models presented in [2] and in this paper have been applied to solve scenario filtering problems that occurred in an IT foresight research project. Reducing the number of plausible scenarios is made possible due to the elimination of scenarios that correspond to irrational or contradictory future decisions. Another relevant class of applications is the coordinated cooperation of autonomous robots that are capable of mutually anticipating team members' actions and planning their own operations taking into account a collective performance criterion.

ANTICIPATORY NETWORKS: BASIC IDEAS

The original idea behind introducing anticipatory networks as consequence models can be formulated [1,2] as follows "*To use anticipated future consequences of a solution selected in a decision problem as additional preference information*". The exploration of anticipatory feedback in multicriteria decision making is possible owing to the following assumptions:

- There exist estimates (forecasts or foresight scenarios) of future decision problem formulations, their solution rules and preference structures.
- The decision making unit responsible for solving any decision problem included in the network knows whether and how the parameters of future problems are influenced by the solutions to preceding problems. This allows us to model and control the consequences of a decision to be made in any problem modeled by the network.
- The assessment of the anticipated outcomes of some future problems can be merged with the preference structures of the causally preceding problems.

Thus an anticipatory network is a synthetic structure that incorporates decision-making units that can be living intelligent beings, groups or organizations of them, as well as artificial intelligent agents and even animals. The question as to whether the anticipatory mechanisms occur at a neural level [8] is the subject of neurophysiological research. The nature of such mechanisms could be based on learning causal sequences that may activate the anticipatory neural response if there is an associated consequence in the internal memory in response to an input signal. Similar mechanisms can even be exhibited by non-specialized cells [9]. However, it is not clear how anticipatory reactions at the cellular level can explain the informed anticipation and model building at human intelligence level, and whether it is possible at all. To address this question, in [10] a formal anticipatory neuron and a model of an artificial anticipatory neural network has been proposed. The internal memory makes this neuron capable of forming artificial anticipatory neural networks that can simulate reinforcement learning and exhibit interesting properties, but the future model building capability remains unexplained.

An even more intriguing issue related to anticipatory systems and networks is the physical realization of anticipation beyond causal model building. Recently, quantum entanglement across time has been investigated a. o. in [11,12] showing a way to constructing strong anticipatory systems [5], i.e. systems, where anticipation is based on a direct functional influence of the future on the present rather than on a modeled (predicted) future. However, in this paper we will not apply a feedback with future events: the anticipatory feedback defined further in this section uses the predicted model of the future to influence the present assuming that that the three assumptions above and the causality principle hold. This complies with the definition of weak anticipatory systems [5].

Anticipatory networks model causally-linked decision problems and their environment. According to a slightly more general definition given in [2], a decision maker A acts as an optimizer on a set of feasible decisions U and on the preference structure P and selects a subset $X \subset U$ according to P and to the fixed set of optimization criteria F that are characteristic for this decision problem.

We will assume that the decision units at each node of the network solve the multicriteria optimization [13] problems of the form

$$(F{:}U\rightarrow E)\rightarrow min(P), \tag{1}$$

where P is an arbitrary preference structure, i.e. $P{:=}\{\pi(u)\subset U{:}\ u\in U\}$ such that if $v\in \pi(u)$ and $w\in \pi(v)$ then $w\in \pi(u)$. Usually E is a vector space with a partial order introduced by a convex cone θ, and

$$\pi(u){:=}\ \pi(u,\theta)=\{v\in U{:}\ F(v)\leq_\theta F(u)\}.$$

A *free decision maker* A [14] may select any solution u_0 from U that is *nondominated* with respect to P and F in (1), i.e. if u_0 belongs to the set

$$\Pi(U,F,P){:=}\{u\in U{:}\ [\ \forall v\in U{:}\ F(v)\leq_\theta F(u)\Rightarrow v=u]\} \tag{2}$$

A is then uniquely characterized by U, F, and P and may be denoted as a 3-tuple $A{:=}(U,F,P)$. If the admissible solution set for A may be different from $\Pi(U,F,P)$ and equal to $X\subset \Pi(U,F,P)$, we will denote it as $A{:=}(U,F,P,X)$. X will be interpreted as the set of those solutions to the problem (1) which are capable of being actually selected.

Besides their optimizing capabilities, the solutions made by any decision maker may influence the parameters of some future decision problems, thus forming networks with some new properties compared to the theory of multi-level multicriteria problems [15]. In particular, in feed-forward anticipatory networks of multicriteria decision problems, constraints and preference structures in some problems are causally linked to the results of solving other problems and may depend on their preference structures. Thus, in a network of multicriteria decision problems the parameters of the actual instances of problems to be solved vary depending on the solutions of other problems in the network.

An influence relation r that describes how the decision maker A_1 affects the scope of admissible decisions in the subordinated decision problem A_2 may be defined as

$$A_1 {:=}(U_1,F_1,P_1,X_1)\ r\ A_2 {:=}(U_2,F_2,P_2,X_2) \Leftrightarrow \exists\varphi{:}X_1 \rightarrow 2^{U_2}{:}\ X_2=\varphi(X_1), \tag{3}$$

where φ is a multifunction that defines the restriction of the admissible decision scope at A_2, $U_1\subset E_1$, $U_2\subset E_2$. Influence relations linking preference structures may be defined analogously. If r is acyclic it will be termed a *causal relation*. From this point on, the term *causal network* will refer to the graph of a causal relation. In a causal network of decision problems, the function φ influences the constraints in A_i transforming the outputs from the problem preceding A_i into additional constraints. One can also consider influence relations with multifunctions φ capable of creating additional admissible solutions in E_2 beyond U_2.

To complete the definition of anticipatory networks, we will define the anticipatory feedback relation.

Definition 1. Suppose that G is a causal network consisting of decision problems and that a decision problem A_j in G precedes another one, A_i, in causal order r. Then the *anticipatory feedback* between A_i and A_j in G is an information flow concerning the anticipated output from A_i regarded as an input information to the decision to be made at the node A_j. ■

As in the case of causal relations, there may also exist multiple types of anticipatory information feedback in a network, each one related to the different way the anticipated future decisions, usually the optimization results, are considered at a decision node. Both relations, the causal influence and the anticipatory feedback, when considered jointly and expressed in a diagram, form an anticipatory network of decision problems.

Definition 2. An *anticipatory network* (of decision problems) is a causal network of decision problems with at least one additional anticipatory feedback relation. ■

In general, for given decision problems O_k, O_n and O_m, there may exist different ways of influencing O_m by O_n, so a causal diagram of an anticipatory network could be a multigraph. This is discussed further in the next sections, where we will also solve the anticipatory networks, according to the following definition.

Definition 3. An anticipatory network is termed *solvable* if the process of restricting the sets of admissible decisions at all problems represented in the network by considering the anticipatory feedbacks results in selecting a unique non-empty solution set at the starting problem. ■

A simple causal graph of decision problems that can be embedded in a straight line will be called a chain. The general underlying idea behind anticipatory network solution procedures is to analyze chains of decision problems linked by a causal influence relation, then to identify in a network of decision problems elementary cycles consisting of causal influence along chains and future information feedback relations, i.e. cycles which do not contain other cycles. For chains and trees of decision problems we have proposed numerical solution procedures [2] based on an analysis of the above-defined elementary cycles, starting from those most distant in the network. The procedures are also based on replacing a solved elementary cycle by a synthetic decision unit and updated links to the remaining elements of the network. The process is repeated iteratively until all cycles are solved. A general network can be decomposed into chains, which makes it possible to apply aggregated chain rules iteratively, gradually eliminating solved chains.

SOLVING ANTICIPATORY NETWORKS

We will refer to anticipatory networks of multicriteria optimizers (1)-(3) with the causal influence relation defined by linking multifunctions

$$Y_i{:}F_{i-1}(U_{i-1})\rightarrow 2^{U_i},\ \varphi(i):=Y_i\circ F_{i-1} \tag{4}$$

imposing additional constraints in sets U_i. The dependence of preference relations P_i on the outcomes of previous problems is defined by the functions

$$\psi{:}\ X(U_{i-1},F_{i-1},P_{i-1})\ni f\rightarrow P_i. \tag{5}$$

In [2] the anticipatory information feedback in causal networks of decision problems has been applied to selecting a solution to networked discrete choice problems with respect to multiple criteria. Specifically, while making a decision, the decision maker takes into account forecasts concerning the parameters of future decision problems, the anticipation concerning the behavior of future decision makers as well as the forecasted causal dependence relations linking the parameters of nodes in the network. Also taken into account are the anticipatory relations that point out relevant future outcomes to particular decisions to be made at nodes preceding them in the causal order.

A large class of anticipatory networks can be reduced to a subsequent analysis of all chains in a network. A formal background for solving the initial decision problem $A{:=}(U,F,P)$ in an anticipatory chain of decision problems A_i, $i=0,1,\dots,N$, with discrete admissible solution sets U_i, is given below.

Causal relations between decision problems are given in the form of restrictions in the scope of admissible decisions defined as multifunctions $\varphi(i)$ that depend on solutions of previous problems modeled by A_{i-1}, for $i=1,\dots,N$. Future information feedback is defined as information about anticipated fulfillment (or not) of certain conditions by the values of criteria in future optimization problems. The following definitions will be helpful for describing the solution procedure in a more rigid manner.

Definition 4. For a chain of decision problems A_k $k=0,1,\dots,N$, let us define the (weak) *anticipatory feedback* condition at A_i, $0\leq i<N$, as a requirement that

$$\forall j \in J(i) \text{ for a given family of subsets } \{V_{ij}\}_{j\in J(i)}\ u_j \in V_{ij} \subset U_j \text{ or } u_j \text{ is closest to } V_{ij} \tag{6}$$

where the sets V_{ij} represent the most preferred decisions to be made at the j-th decision problem from the point of view of the decision maker that is responsible for the outcomes from the i-th decision problem and the satisfaction of this preference is measured by the proximity of the solutions of the j-th problem to V_{ij}. ■

The satisfaction of the anticipatory feedback condition (6) means that the decision maker at A_i strives to select the solution which guarantees that the results of future decision problems A_{ij} are as close as possible to the specified solution sets V_{ij}. The criteria values $F_j(V_{ij})$ are of special importance to the decision makers and can be defined as reference sets [16].

In an anticipatory network with the starting node (U,F,P) the following decision problem can be formulated:

Problem 1. For all chains in the network find all the sequences of decisions starting at an $u_0 \in U$ that additionally fulfil anticipatory feedback condition (6). ■

The solution approach for anticipatory chains can easily be generalized for the case where solutions of each decision problem can influence multiple decisions to be made in the future and that do not depend on each other. If such a situation occurs, it can be represented as a *causal tree*. An example of a simple causal tree is given in Fig. 1.

The reduction of the analysis of anticipatory trees to the subsequent analysis of anticipatory chains in the tree is possible due to the following property:

Theorem 1. Assume that the decision made at the decision making unit A_i influences two causally independent decision problems A_k and A_m in an anticipatory tree T and let A_t be the (unique) bifurcation decision problem for A_i,A_k and A_m. , i.e. such that no other problem that is causally influenced by A_t can influence both A_k and A_m. Furthermore, let C_k and C_m be the sets of admissible decision chains starting at A_i and ending at A_k and A_m, respectively, and let $C_k{}'$ and $C_m{}'$ contain the elements of C_k and

C_m, respectively, starting at A_i and truncated at the bifurcation problem A_t. Then the set of all admissible decision chains with respect to both A_k and A_m starting at A_i can be generated as extensions of the elements of the intersection of $C_k^{'}$ and $C_m^{'}$. More precisely, an extension of any such sequence of decisions starting at A_i and ending at A_t is to be concatenated with an arbitrary subsequence starting at A_t of an admissible decision chain that was truncated at prior to the intersection of $C_k^{'}$ and $C_m^{'}$. ■

Proof of the above theorem is given in [2] (Proposition 2).

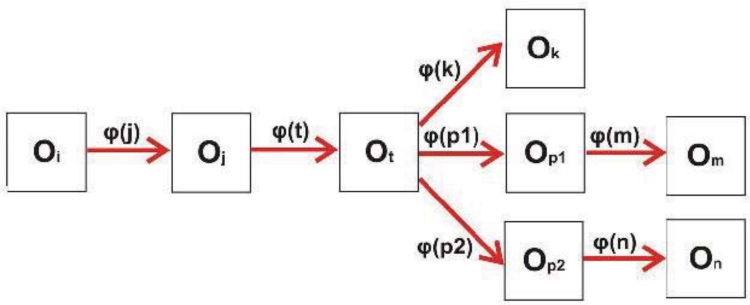

FIGURE. 1. An example of a causal tree, where O_t is the bifurcation problem (cf. Thm.1) for O_m, O_n. O_k, O_{p1} and O_{p2}. Causal relations are defined by the multifunctions $\varphi(i):=Y_i \circ F_{i-1}$. Anticipatory feedback relations can occur between any pair of causally linked decision problems (not shown in this figure).

In general, in a network of decision problems there may exist units that are influenced causally by two or more predecessors. Such problems may emerge in practice when, for example, an input to a production function comes from two independent technological processes, which are both optimized with respect to quality and price. In order to deal with such a situation, observe first that the causal dependences in the form of constraints on the set of admissible decisions in a subsequent problem A_k that comes from two or more causally independent decision problems $A_i=(U_i,F_i,P_i)$ and $A_j=(U_j,F_j,P_j)$ as the multifunctions Y_i and Y_j, *respectively,* yield, in fact, just an intersection of constraints that can be represented as a new multifunction Y defined on the Cartesian product of $F(U_i)$ and $F(U_j)$ in the following way

$$Y(u_{ip},u_{jr}):= Y_i(u_{ip}) \cap Y_j(u_{jr}).$$

Based on this observation, in the case of arbitrary networks, the calculations can again be reduced to an analysis of chains and elementary loops in the network, i.e. loops which may consist of both causal relations and anticipatory feedbacks, and do not contain other loops. Analogously to surveying the bifurcation decision problems and ‘cutting the branches’ of an anticipatory tree, all decision problems which are causally influenced by two or more predecessors must be surveyed. If an elementary loop is detected, it can be replaced by a synthetic decision unit with a reduced set of admissible chains and updated links to the remaining elements of the network. The process can be repeated iteratively until the 0^{th} decision problem has been reached.

To solve Problem 1, information about future optimization problems and their mutual relations is required. If the time horizon of anticipatory planning is large compared to the time allotted to modeling and computing the decision, usually the changes in the modeled environment also proceed slowly enough allowing an analyst to rely on the information gathered prior to performing all computations. This is the case of foresight applications, where the time horizon is usually between 10 and 20 years, the analytic phase can be stretched over several months and the resources available allow us to explore the future to a sufficient extent.

Anticipatory Networks as Superanticipatory Systems

Let us observe that in the above presented approach to solving anticipatory networks we have assumed that anticipation is a universal principle governing the solution of decision problems at all stages. In particular, future decision makers modeled at the starting decision node A_0 can in the same way take into account the network of their relative future decision problems when making decisions. Thus, the model of the future of the decision maker at A_0 contains models of future agents including their respective future models. This has motivated us to introduce the notion of superanticipatory systems, which are direct generalizations of anticipatory systems in the sense of Rosen [4]:

Definition 5. *A superanticipatory system is an anticipatory system that contains at least one model of another future anticipatory system and both are linked either by a causal or by an anticipatory feedback relation.* ■

Since, by definition, every superanticipatory system is also anticipatory, the class of superanticipatory systems remains closed when an anticipatory system contains a model of a superanticipatory one. However, the notion of a superanticipatory system grade can be introduced, namely a superanticipatory system *is of grade n* if it contains a model of a superanticipatory system of grade *n-1*. By definition, an anticipatory system that does not contain any model of another such system is superanticipatory of grade *0*. It can be observed that an anticipatory network containing a chain on *n* decision problems, each one linked with A_0 and with all its causal predecessors by an anticipatory feedback, is an example of a superanticipatory system of grade *n*.

FINAL REMARKS

This paper presented the main ideas concerning anticipatory networks, the basic methods of solving them, and their extension, so-called superanticipatory systems.

Anticipatory networks may be applied to model and solve a broad range of problems, both real-life and theoretical. The above approach focuses on the problem of finding feasible foresight scenarios based on the identification of future decision-making processes and on anticipating their outcomes. Scenarios, such as those defined and used in foresight and strategic planning [17], can depend on the choice of a decision in one of the networked optimization problems as well as be external-event driven. When included in a causal network of decision problems, the anticipation of future decisions and alternative external events would allow us to generate alternative structures of decision problems in the network. Assuming that at each decision problem in the causal network the decision makers strive to select their decisions in a rational way and applying multicriteria optimization methods to find all potential variants of anticipated future problem outcomes, a set of potential elementary scenarios [18] of future trends and events modeled by the network can be found. In addition, considering the anticipatory feedbacks in the network that are defined in the next section, a filtering of plausible outcomes from each problem is made possible, as well as a reduction of the set of plausible elementary scenarios. This application can be very supportive when building foresight scenarios by clustering elementary scenarios. For further potential fields of application of anticipatory networks, the reader is referred to [2].

Anticipatory networks should be regarded as a new class of world models that can describe decision making processes in a clear formal way. The *forecasting* of events in causal systems can thus be complemented by *anticipation* of rational decisions. Furthermore, the ideas behind anticipatory networks naturally led us to introduce superanticipatory systems.

Future research on further extensions of the theory and potential applications of anticipatory networks will include relations to anticipatory neural mechanisms that would make it possible to build neural structures which fit forecasting and anticipation tasks in an optimal way. Moreover, observing that the anticipatory capabilities of an autonomous system go beyond the abilities attributed usually to artificial consciousness, further studies of superanticipatory systems should provide clues as regards the structure of artificial consciousness.

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