A Vision Towards A Conceptual Basis for the Systematic Treatment of Uncertainty in Goal Modelling

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ABSTRACT

Goal modelling is one the most important early activities in requirements engineering. Here, we describe a vision for a conceptual basis for the systematic identification and treatment of uncertainty in goal modelling. We aim to characterize the wide variety of uncertainty in goal modelling and to provide a theoretical framework for systematic uncertainty analysis. We thus adopt Walker's taxonomy which distinguishes among three dimensions of uncertainty: location, level, and nature. In addition, we propose to adapt Walker's uncertainty matrix as a heuristic tool to categorize various dimensions of uncertainty in goal modelling to serve as a conceptual framework for improving comprehension and communication of uncertainty between modellers and stakeholders and among modellers themselves. Understanding the various dimensions of uncertainty is a vital step towards the sufficient recognition and treatment of uncertainty in goal modelling activities. This in turn will help identify and prioritize critical uncertainties, which affect the goal modelling process in its entirety. We thus propose a long-term research agenda and urge community contributions in this research direction.

CCS CONCEPTS

Software Engineering • Requirements analysis

KEYWORDS

Goal modelling, Uncertainty, Taxonomy

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1 Introduction and Motivation

Goal models are a way to capture and refine stakeholders' intentions to generate functional and non-functional requirements [1]. Goal modelling had proven its efficacy in identifying variability at the early stages of requirements engineering (RE) [2], where variability is expressed in goal models through capturing alternative ways by which stakeholders achieve their goals [3]. However, goal models are mainly useful for expressing information that is known (referred to as *intentional variability* [1]), but do not support representing information that a modeller does not know (whether they are known unknown or unknown unknown) at any phase in the software development process. This unknown variability is referred to in the literature as the *non-intentional variability*, which is a variability that is not a result of the stakeholders' intentions, such as variability due to context (e.g., time, weather, location), stakeholders' capabilities and characteristics, entities in the environment, etc. Considering non-intentional variability is a crucial factor in goal modelling as it shapes and constrains intentional variability in a significant way [3]. Non-intentional variability, along with other factors such as disagreements among stakeholders, unresolved decisions about their needs, gaps in domain knowledge, or incomplete understanding of model details, can all produce *uncertainty*. During the process of creating goal models, modellers try to uncover as much uncertainty as possible, related mainly to the contents and/or the structure of models, through continuous monitoring and further elicitation of requirements [4]. However, not all aspects of uncertainty can be resolved in goal models. This is due to the lack of an explicit characterization and identification of other potential sources or dimensions of uncertainty.

Uncertainty is of course a concern that affects any modelling language; we focus on goal models. Various approaches have been developed for addressing one or more sources of uncertainty in goal modelling [1], [3], [7]. However, to the best of our knowledge, existing approaches do not consider the impact of multiple dimensions of uncertainty (i.e., other than uncertainty in the content or structure of models) on the requirements to be fulfilled for a system-to-be. We envision a research agenda for a comprehensive and coherent process for exploring uncertainty and for modelling and analyzing its effects on goal models. We aim to provide a conceptual framework for the systematic management of uncertainty in goal modelling to improve the early stages of requirements elicitation and modelling.

To achieve this, we propose to adapt the taxonomy proposed by Walker et al. [5], which distinguishes among three dimensions of uncertainty, namely its *location*, *level* and *nature*. Specifically,

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we plan to adopt Walker's uncertainty matrix as a heuristic tool to classify and report the various dimensions of uncertainty in goal modelling, which provides a conceptual framework for better communication between modellers and stakeholders [5]. Understanding the various dimensions helps identify, capture, and highlight critical uncertainties. This is a crucial step to treat uncertainty more adequately in goal modelling in the early stages of RE.To motivate our work, we use the example of a meeting scheduler (Figure 1), adapted from [4] and originally published in [6]. The figure shows an i* goal model created to determine the requirements for an automated meeting scheduler, where the actor "*Meeting Initiator*" should organize meetings and identify their dates and ways of organization. The "*Meeting Scheduler*" actor's goal is to schedule meetings; the "*Meeting Participant*" should attend and participate in meetings and agree on meeting dates.

During the construction of this model, modellers may face several uncertain or unknown situations. Examples of such uncertainties (captured in the figure using text annotations) include: (1) disagreements between stakeholders (e.g., two modellers may disagree about ways of organizing meetings), (2) gaps in the domain knowledge of the modellers (e.g., are there other alternative ways to organize meetings?), (3) uncertainties about the structure and content of the model itself (e.g., unknown if more content is needed to be added to the model, or if a particular element is really needed in the model), and other uncertainties that the modeller is either aware of (i.e., known unknowns), or not aware of their existence (i.e., unknown unknowns). A more detailed characterization of the potential uncertainties that may be encountered in goal models is provided in Sect. 3.

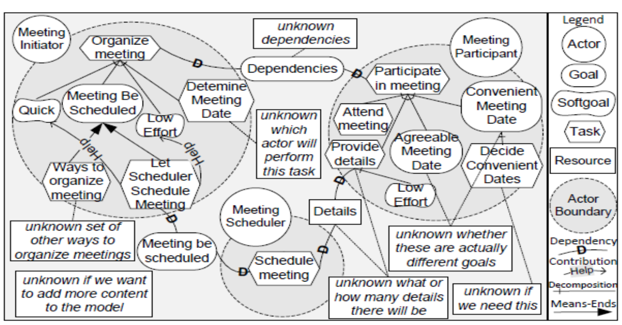

Figure 1: Meeting Scheduler Example [4][6].

2 Related Work

Many researchers investigated one or more types or sources of uncertainty which result from non-intentional variability. Mylopoulos et al. discussed the concept of *background variability*, which they defined as "the facts about the domain of discourse that unintentionally vary in the context where the fulfillment of a goal is attempted" [3]. Similarly, Lapouchnian et al. [1] discussed the modelling of *domain/context* variability, the specification of their effects on goal models, and the analysis of goal models with contextual variability. In addition, *requirements variability* has been discussed in [7] and [8] and was considered as a cornerstone in fulfilling the demands for software systems. Salay et al. [4] proposed an approach to manage requirements variability, which they referred to as *requirements uncertainty*. They focused on the problems of specifying uncertainty within requirements models, reasoning with models containing uncertainty and refining a model as uncertainty is resolved.

Ingolfo et al. [9] distinguished between two types of uncertainty in goal modelling and analysis: uncertainty in analysis results and uncertainty over the structure of the model. Uncertainty in analysis results refers to uncertainty about the satisfaction or applicability of a model element, while uncertainty of the model structure refers to uncertainty about the presence, uniqueness, or number of model elements and links. In that work, the authors only considered uncertainty in contribution links. Salay et al. [10] extended Ingolfo's work by considering uncertainty that may occur in any relationship or element. In particular, the authors proposed the formal MAVO partiality framework to capture uncertainty in a more general and expressive form. Famelis et al. [11] developed a general approach for defining partial models and applied it to modelling and reasoning about models with design-time uncertainty.

Besides, several researchers proposed approaches to identify uncertainties in the modelling of self-adaptive systems, for example, the works of Palacin and Mirandola [12], Ramirez et al. [13], Whittle et al. [14], and Zhang et al. 0. In all these works, the authors attempt to consider and address the inherent uncertainty in self-adaptive systems, which are known for their capability to autonomously modify their behaviour at run-time in response to changes in their environment. The above uncertainty-aware approaches focus only on one dimension of uncertainty, such as context/domain, content, requirements, or design-time uncertainty. To the best of our knowledge, none of these approaches investigated other dimensions of uncertainty, such as level or nature, which we believe also need to be considered for better managing and resolving uncertainty.

3 Goal Model Uncertainty: Taxonomy

We provide a taxonomy for uncertainty in goal modelling, based on a general definition of uncertainty in modelling given by Walker et al. as: "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system" [5]. Such deviations can lead to an overall "lack of confidence" in the obtained results based on a judgment that might be "incomplete, blurred, inaccurate, unreliable, inconclusive, or potentially false" [12] [15]. We present our taxonomy based on the dimensions suggested by Walker: *location*, *level,* and *nature*. We explain each dimension in the following.

3.1 Location

Location of uncertainty refers to the place where the uncertainty manifests itself within the whole model complex [5]. Uncertainty can be located in the following parts of a model:

- *Context uncertainty* is an identification of the boundaries of the model; that is uncertainty about the information to be modelled. This uncertainty concerns the portions of the real world that are inside the system, the portions that are outside, and the completeness of its representation. The identification of the model context is usually determined at the problem framing stage and it is a vital step as it clarifies the issues to be addressed and the expected outcomes to be delivered by the model. In Figure 1, elements annotated with "*unknown if we want to add more content to the model*" is an example of such type of uncertainty.

- *Model structural uncertainty* is the uncertainty about the form of the model itself. This uncertainty refers to how accurately the structure of the model (i.e., its entities and their relationships) represents the subset of the real world that must be modelled. Following the example in Figure 1, elements of the model annotated with "*unknown if we need this*" represents this kind of uncertainty.
- *Input uncertainty* is associated with the model inputs, the actual values of variables given as inputs as well as with the methods used to calibrate the model parameters. In Figure 1, elements annotated with *"unknown what or how many details there will be*" and also the actual values of model elements (e.g., importance of goals and weights of contribution links) are examples of input uncertainty.
- *Model outcome uncertainty* is the accumulated uncertainty associated with model outcomes of interest, which is strongly influenced by context, structural and input uncertainty. E.g., uncertainty about the implementation of the algorithm used to analyze the model and produce the output results.

3.2 Level

The level of uncertainty is where the uncertainty manifests itself along the spectrum between *deterministic* knowledge and *total ignorance*. To distinguish between the various levels of uncertainty, we adapt the terminology used in [5] as follows:

- *Determinism* is the ideal situation in which we know everything precisely. It is not attainable but acts as a limiting characteristic at one end of the spectrum.
- *Statistical uncertainty* is any uncertainty that can be described adequately in statistical terms. Statistical uncertainty can apply to any location in the model, if the deviation from the true value can be characterized statistically. An example of statistical uncertainty in Figure 1 is the *measurement uncertainty* associated with all input data.
- *Scenario uncertainty* is the uncertainty related to the external, usually future, environment of a system and its effects on the system. Unlike statistical uncertainty (where a statistical expression of the uncertainty present can be formulated), scenario uncertainty implies that there is a range of possible outcomes, but the mechanisms leading to these outcomes are not well understood. In the example illustrated in Figure 1, scenario uncertainty can manifest itself in various ways. For instance, as a range in the analysis outcomes due to different underlying assumptions, or as uncertainty about which changes in the model will impact outcomes of interest.
- *Recognized ignorance* where we know neither the functional relationships nor the statistical properties of the model. In addition, the scientific basis for developing scenarios is weak. Recognized ignorance can happen at any place in the model in Figure 1.
- *Total ignorance* implies a deep level of uncertainty: we do not even know that we do not know. This is the other extreme from determinism on the scale of uncertainty.

We argue that this characterization, as a scale of graduation from determinism to total ignorance, provides a complete structure of the level of uncertainty required for uncertainty analysis. The goal of a modeller is to reduce the level of uncertainty along this spectrum from indeterminacy towards determinism.

3.3 Nature

We follow the classification of Walker et al. [5] for the nature of uncertainty as follows:

- *Epistemic uncertainty* is the uncertainty due to the lack of enough data to build reliable knowledge, imperfection in the process of building the knowledge from the data, or imperfection of the acquired data itself. This kind of uncertainty could be reduced by more empirical studies and research.
- *Variability/Aleatory uncertainty* due to inherent variability of the system to be modelled, which is especially pertinent in human, economic and natural systems.

3.4 Uncertainty Matrix

The three-dimensional taxonomy (Sect. 3.1-3.3) is illustrated in Figure 2 as an *uncertainty matrix,* which we also adapted from Walker et al. [5]. In this matrix, the *Location* dimension is placed as the first column, and the *Level* and *Nature* dimensions are placed as the first row in the matrix. Each cell represents the intersection between the three dimensions. For each such cell, we show examples or sources of uncertainty as discussed above. For example, the value in the intersection between "Scenario" in the *Level* dimension and "Input" in the *Location* represents uncertainty due to having a range of values of inputs. The "Model outcomes" row reflects the aggregated effects of the different uncertainties on the results of the model analysis. In other words, the uncertainty of model outcomes is directly associated with the uncertainties of the information represented in the model (i.e., context, structure and input that are of different levels and natures), and how they are handled during analysis.

Location	**Level**			**Nature**	
	Statistical	Scenario	Recognized Ignorance	Epistemic	Variab-ility
Context	deviation from true values	External/ future environment	Possible at any location	Possible at any location	Possible at any location
Model Structure	deviation from true values	different assumptions about structure			
Input	measurement uncertainty	Range of values			
Model Outcome	accumulated uncertainty which results from uncertainty in location× level× nature				

Figure 2: Our proposed uncertainty matrix

4 Research Agenda

We structure the presentation of our research agenda on the DETUM uncertainty lifecycle model, introduced in [16]. Even though the DETUM model was conceived for design-time uncertainty, we find it useful here to talk about its three phases: (a) *Articulation*: when modellers express uncertainty in a model, (b) *Deferral*: when they work in the presence of uncertainty, and (c) *Resolution*: when modellers remove uncertainty from their model. Each of the phases has different concerns.

Articulation Phase: The main concern during this phase is the identification of *sources* of uncertainty and the accurate representation of uncertainty in a goal model. In our future work, we plan to classify sources of uncertainty according to the taxonomy presented in Sect. 3. This will help in the selection of general approaches that can deal with multiple uncertainties concurrently, rather than using one approach at a time for each one. Besides, having the sources of uncertainty articulated according to a taxonomy will make easier the comparison between their effect on the overall outcomes of model analysis.

For example, if we consider "future parameters value" as a source of uncertainty in the model in Figure 1, then the *location* dimension of this uncertainty can be classified as "input uncertainty" and the *nature* dimension is "epistemic uncertainty". Regarding the *level* dimension, we believe that the source of uncertainty can be of any level depending on the implemented capabilities in the system that should deal with the uncertainty.

Deferral Phase: The main concern during this phase is to work in the presence of uncertainty. This also entails maintaining traceability information about uncertainty and managing models that contain it. The works of on the one hand Salay et al. [4] and on the other hand Alwidian and Amyot [17] represent examples of approaches that articulate uncertainty and variability and work in their presence using the respective modelling artifacts: partial models and union models.

As in the case of the articulation phase, we plan to classify the approaches used for the deferral phase according to the taxonomy of uncertainty dimensions provided in Sect. 3. Our next step is also to propose new approaches for deferral of uncertainty according to the latter's sources and dimensions.

Resolution Phase: The main concern during this phase is the systematic elimination of uncertainty by incorporating new information to the model.

For this phase, we plan to survey existing approaches currently used to reduce or eliminate uncertainty in general. The purpose of this survey will be to discover opportunities of adapting such approaches for the context of goal modelling, and also to provide guidelines for proposing new resolution approaches tailored to particular sources of uncertainty (identified in the articulation phase) of different dimensions (i.e., location, nature, and level).

5 Conclusion

We presented our research agenda for setting a conceptual basis for the systematic identification and treatment of uncertainty in goal modelling. We adapted Walker's three-dimensional taxonomy of uncertainty and the uncertainty matrix as a heuristic tool to categorize various dimensions of uncertainty in goal models for the purpose of providing a better communication of uncertainty between modellers and stakeholders. Understanding the dimensions of uncertainty is crucial for its recognition and treatment in goal modelling activities, which in turn, helps in identifying and prioritizing critical uncertainties, which affect the process of goal modelling as a whole.

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