Evaluating Conceptual Modeling Languages

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Abstract

An important assumption for many KA researchers is *structure preservation* ; i.e. conceptual models can be converted in a straight forward manner into a design for an implementation. This assumption may not always hold. Seemingly trivial variants in a qualitative conceptual models can block pragmatically desirable properties such as KB-testability and KB-maintainability. KB-testability and KB-maintainability are an important property: we must not build knowledge bases that are untestable or unmaintainable. Hence, we argue against using these features within conceptual models. The tools used for identifying these features (instance generators, graph theory, studying KB-testability and KB-maintainability) are quite general and could be used to find restrictions to other conceptual modeling languages.

1 Introduction

Pragmatics must take precedence over elegance, for Nature cannot be impressed. Coggin's Law (from [Booch, 1994])

This paper is about pragmatic limits to conceptual modeling. We disagree with the conventional wisdom in the knowledge acquisition field (KA) (e.g [Wielinga *et al.*, 1992, Shadbolt & O'Hara, 1997, van Harmelen & Aben, 1996]) that:

- The conceptual modeling language should be expressive enough to capture all the expert's knowledge.

- Starting with a conceptual model of the required expertise, various *structure preserving* transformations can be applied to produce a working system. Such structure preserving transforms are straightforward conversions of the high-level structures in the conceptual model into the design model.

Experience with the QCM qualitative modeling language suggests that not all conceptual models can be structurally preserved. QCM is used in the earliest stages of KA. For our experts, it represents their ideas in a similar manner to how they first express those ideas. It can represent under-specified ideas and tolerate inconsistencies in an evolving specification. Further, QCM has a built-in validation engine which can help experts to review and improve their current specification. Hence, we say that QCM is a conceptual modeling language [Feldman *et al.*, 1989a, Menzies, 1995, Menzies, 1996a, Menzies & Compton, 1997, Waugh *et al.*, 1997]. We will use the criteria of KB-testability and KB-maintainability (defined below), to demonstrate the need for certain restrictions to QCM conceptual models. Roughly speaking, KB-testability means checking if a theory of X can reproduce known behaviour of X; and KB-maintainability means checking if we can tell if some change is an improvement to a theory. Seemingly trivial variants in the conceptual modeling language will be shown to have a large impact on KB-testability and KB-maintainability. We will propose below restrictions on size, connectivity, the use of conjunctions, and the types of temporal causal connections. In these restrictions are obeyed, then we have a necessary, but not sufficient proof, that a theory will be testable and maintainable. We only claim that if a system does not satisfy our criteria then it will not support KB-testability and KB-maintainability (and leave the converse statement to future work).

Our restrictions apply to any knowledge base (KB) which can be represented as a cyclic dependency and-or graph of literals. Many such representations exist including propositional rule bases used in a match-select-act loop, recursive ground horn clauses, or qualitative theories used for simulations. Further, the methods used here (instance generators, graph theory, analysis of KB-testability and KB-maintainability) are quite general and could be used to find restrictions to other conceptual modeling languages. We have argued elsewhere [Menzies, 1997] that the KE field urgently needs such general evaluation methodologies.

Our conclusions come from a theoretical and empirical analysis of a KB-testability and KB-maintainability algorithm. We take care to distinguish this work from the *worst-case* time complexity research of the knowledge representation (KR) community. Restrictions motivated by potentially exponential runtimes do not convince pragmatic knowledge engineers (KEs) since many successful expert systems have been built for theoretically intractable NP-hard problems. In this paper we motivate conceptual modeling restrictions using *pragmatic criteria* such as KB-testability and KB-maintainability. If such pragmatic criteria are ignored then, in the *usual case* if certain restrictions are not enforced then something important will stop working.

2 Preliminary Notes

2.1 Defining Evaluation Criteria

An expert system passes through many stages in its life cycle. This section argues that evaluation criteria for early-stage expert systems can be defined via a consideration of late-stage functionality.

When we review the the life cycle of an expert system [Gaschnig *et al.*, 1983], we see that empirical evaluations are not possible for all points in the life cycle. Gashing et.al. describes those stages are:

1. Top-level design and definition of long-range goals.
2. Prototype implementation to show feasibility.
3. System refinement including running some informal tests to generate feedback.
4. Structured evaluation of performance.
5. Field testing with representative users.
6. Follow-up studies to address issues found in field testing.
7. Changes arising from the follow-up studies.
8. General release.

Researchers often stop at steps 1 or 2. Examples of reports from 3 are not uncommon (e.g. [Schreiber & Birmingham, 1996, Menzies *et al.*, 1992]). Stage 4 reports are much less common (e.g. [Corbridge *et al.*, 1995]) since this stage requires the earlier work. There are very few examples of stage 5 reports (exceptions include [Hori & Yoshida, 1997]) or higher, but some exist (e.g. [McDermott, 1993]). As we progress through these stages, it gets harder to isolate conflating effects. For example, [Hori & Yoshida, 1997] reports benefits from using two techniques: problem solving methods and an object-oriented reuse technique called *design patterns* [Menzies, 1998]. It is hard to evaluate which of these contributed to the reported benefits.

One useful technique when evaluating at stage 4 is to define experiments using knowledge of how the system will be used in the latter stages. Suppose we can build a detailed model of some functionality desired at stage 8. Then, at stage 4, design variants can be assessed by how they impact on the desired stage 8 functions. In this article, we develop succinct computational models for two stage 8 activities: testing and maintenance.

2.2 Should Conceptual Modeling be Restricted?

This paper has two audiences. KR researchers may be unfamiliar with model-based KA. KA audiences may be unfamiliar with the expressibility vs tractability research in KR. This section discusses conceptual modeling in KA. The next section discusses tractability research in KR.

Conventional KA wisdom (e.g. [Wielinga *et al.*, 1992, Shadbolt & O'Hara, 1997]) advocates a separation between conceptual and design models. A conceptual model stores all requirements without being contorted due to implementation considerations. Only in the design model, says the conventional wisdom, are programmers permitted to make any pragmatic compromises required to create a practical implementation. This view assumes that there are no serious impediments to converting the conceptual model to the design model; i.e. structure preservation is possible. Structure preservation permits simpler knowledge base (KB) validation since an expert can see the connection of a KB back to their original conceptualisation [van Harmelen & Aben, 1996].

In the case where a conceptual model is not be used directly for computational purposes, we have no issue with the *laissez faire* view of conventional KA. For example, in the KADS methodology [Wielinga *et al.*, 1992], only the expertise conceptual model is directly implemented. Tansley and Hayball [Tansley & Hayball, 1993] list over two dozen such expertise models including systematic diagnosis (localisation and causal tracing), mixed mode diagnosis, verification, correlation, assessment, monitoring, simple classification, heuristic classification, systematic refinement, prediction, prediction of behaviour and values, design (hierarchical and incremental), configuration(simple and incremental) planning, and scheduling. Other KADS conceptual models which are not directly implemented include the organisation model describing how workers will be effected by the expert system, or the application model which describes the project scope and external constraints.

However, if operational characteristics of the working program are ever used to revise the conceptual model, then computational issues associated with that model become relevant. For example:

- If any conceptual model is searched for conflicts (e.g. during the integration of multiple viewpoints from different experts), then computational issues associated with that model become relevant. A case could be made for restrictions to the conceptual model in order to permit effective conflict detection during requirements analysis. Conceptual models appropriate for conflict detection are discussed in [Mylopoulos *et al.*, 1992, Chung & Nixon, 1995].

- Many real-world complex domains can only be understood via an exploratory methodology. For example:

  - Menzies and Compton note that all the expert systems they have ever studied in detail are poorly understood; e.g. process control, farm management, economic modeling, biochemical interpretation, consumer lending, and model-based diagnosis [Menzies & Compton, 1997].
  - Software solutions to many standard business require extensive iterative development (e.g. [Jacobson *et al.*, 1992]);

  In exploratory approaches, experience with the running program informs revisions to this conceptual model. Limitations to testing and then changing (maintaining) the running program can hence effect the nature of those revisions.

A counter-argument to our case against *laissez faire* conceptual modeling is as follows: *if a domain really demands certain conceptualisations, then the conceptual model must really contain them.* Our reply to this counter argument is that it critically depends on a demonstration of a domain *really needing* those conceptualisations. Such a demonstration would require (i) the construction of systems with and without certain conceptualisations; (ii) an assessment of those systems using some objective success measure. Note that such a demonstration at least implies a test measure; i.e. this test of conceptual modeling may be only practical if the conceptual model do not violate our limits to KB-testability.

2.3 Worst-Case Time Complexity Analysis

This section argues that theoretical worst-case behaviour is not a sufficient reason to restrict the modeling process. Practical KEs prefer *pragmatic criteria*: i.e. a demonstration that in the *usual case*, something important will stop working (e.g. we lose KB-testability and KB-maintainability) unless we impose restrictions. This section discusses analogous results from the knowledge representation (KR) community. Some of these results are based on a *worst-case* analysis. Others use *instance generators* to create a large number of representative problems. We argue that such *worst-case* analyses are poor motivation for KB restrictions. Hence, we prefer pragmatic criteria such as KB-testability and KB-maintainability which reflect usual case behaviour. However, we apply the technique of instance generators in subsequent sections.

Expressibility vs tractability trade offs are discussed extensively in the KR literature (e.g. [Levesque & Brachman, 1985]). Solutions to a class of problems (the NP-hard problems) are known to have an exponential upper-bound on their runtimes; i.e. may be intractable. Much of the KR literature is concerned with finding restrictive cases in which a representation can be shown to tractable; i.e. worst-case runtimes are polynomial. For example:

- Tambe, Newell, and Rosenbloom [Tambe *et al.*, 1990, Tambe & Rosenbloom, 1994] discuss *multiple attributes* in production rule conditions. Given an attribute test of an object, if one a query to one attribute of that object can result in multiple matches, then the time bound on matching a single rule can be exponential. Multiple attributes can be detected using a simple local syntactic test.

- Brachman and Levesque [Brachman & Levesque, 1984] discuss a seemingly minor variation to a frame-based language FL. FL contains the RESTR construct which places restrictions on valid slot values. At first glance, RESTR seems to reduce the search space associated with processing that frame. However, Brachman and Levesque prove that the exact opposite is true. A language without RESTR (FL^{-}) can test if some frame subsumes another frame in, at most, polynomial time. However, the same test in FL has an upper bound of exponential time; i.e. it may be too slow to be practical.

Opponents of worst-case complexity analysis argue that potentially intractable runtimes are not sufficient reason to restrict our KR languages:

- A recent workshop on comparing different terminological logics highlighted two schools of thought [D. Fensel, 1997]. In the one camp were proponents of some restrictions to terminological logics to *description logics* which have well-understood runtimes. In the opposing camp were proponents of *frame logics* which maximise expressive power in order to capture ontological features that are inexpressible in description logics.

- It is sometimes possible to transform a KB such that the complexity is reduced. For example, for time-critical processing (e.g. real time expert systems) it could be argued that possibly exponential runtimes must be avoided. Tambe et.al. have shown that production rule conditions that only use *unique attribute* matching have a linear time bound on the matching process for a single production (in single attribute conditions, a query to one attribute of that object can result in only a single match). However, in practice, this may not be an expressibility limit since it is possible to convert conditions to unique attributes. Tambe et.al. report that a manual translation of 450 production rules for R1-SOAR from multiple to single attribute conditions took only two days. Tambe et.al. also speculate that tools could be built to fully automate the process. However, note that KB transformation is not a general method for removing NP-hard problems. For example, we cannot transform of FL to FL^- while preserving the semantics of RESTR.

If a problem is NP-hard, this does not necessarily imply that real-world examples of that problem cannot execute. Many expert systems tasks, while theoretically intractable, have proven to be practical for many real-world situation. For example, in we describe below an empirical demonstration that an NP-hard problem is practical for a range of real-world theories.

Further, it may be that only a narrow range within some space of theoretically hard problems are actually slow in practice. For example consider the instance generator studies of binary constraint satisfaction problems:

- A binary constraint satisfaction problem (2CSP) is to search for a set of state assignments to variables which do not violate constraints [Gent *et al.*, 1995, Smith, 1996].
- A 2CSP problem can be characterised by the parameters *(n,m,p1,p2)* where *n* is the number of variables; *m* is the number of states per variable; *p1* is the probability of a constraint existing between variable *n.i* and variable *n.j* and *p2* is the probability that, given *p1*, that some pair of state assignments is illegal.
- A 2CSP *instance generator* can build any number of examples problems from the parameters *(n,m,p1,p2)*.
- If *n,m,p1* are held constant, then there is a small range of *p2* in which the number of possible solution falls to zero. In this *phase transition* area, the cost of performing a 2CSP task spikes to very high values, before falling away to very low values in the no-solutions zone. For example, for *(8,10,1.0,p2)* problems where *p2* is between 0 and 0.4, the median cost of a 2CSP task is roughly constant. However, as *p2* moves from 0.4 to 0.5, the median cost rises rapidly by an order of magnitude before decaying exponentially [Smith, 1996].

Such phase transition zones have been observed in numerous problems that, theoretically, have a exponential worst-case time complexity [Cheeseman *et al.*, 1991]. Cheeseman et.al. have argued that this phase transition marks the zone of truly slow tasks within the NP-hard problems. If the Cheeseman speculation is correct, then we can ignore worst-case time complexity results if we could somehow guarantee that our expert system tasks occur outside of the really hard zones within theoretically hard problems.

Given the current state-of-the-art, such guarantee can only be offered in terms of problem size and only in specific cases. For example, while KB-testability and KB-maintainability is NP-hard (shown later), we show below that we can define precise boundaries within which it is practical. Further, in a result analogous to the above results from the satisfiability community, seemingly trivial variants in the modeling language can make KB-testability and KB-maintainability impractical.

3 Topological Restrictions

This section argues that KB-testability is one such pragmatic criteria. KB-testability is then used to identify two topological limits: a size limit and a connectivity limit. In later sections, KB-maintainability will be used to identify limits to temporal modeling languages.

3.1 KB-testability

3.1.1 Motivation

This section explains why we view KB-testability as a necessary pragmatic criteria. Modern KA theorists view KB creation as the construction of inaccurate surrogates models of reality [Davis *et al.*, 1993, Wielinga *et al.*, 1992]. Agnew, Ford and Hayes [Agnew *et al.*, 1993] comment that *expert-knowledge is comprised of context-dependent, personally constructed, highly functional but fallible abstractions.* Practioners confirm just how inaccurate KBs can be. Silverman [Silverman, 1992] cautions that systematic biases in expert preferences may result in incorrect/incomplete KBs. Compton [Compton *et al.*, 1989] reports expert systems in which thernoe was always one further important addition, one more significant and essential change. Working systems can contain multiple undetected errors. Preece and Shinghal [Preece & Shinghal, 1992] document five fielded expert systems that contain numerous logical anomalies. Myers [Myers, 1977] reports that 51 experienced programmers could only ever find 5 of the 15 errors in a simple 63 line program, even given unlimited time and access to the source code and the executable.

Potentially inaccurate and evolving theories must be validated, lest they generate inappropriate output for certain circumstances. Testing can only demonstrate the presence of bugs (never their absence) and so must be repeated whenever new data is available or a program has changed. That is, testing is an essential, on-going process through-out the lifetime of a KB. If expressibility blocks testability, then expressibility should be restricted.

3.1.2 Definition

Arguments such as the above motivated Feldman and Compton [Feldman *et al.*, 1989b], followed by Menzies and Compton [Menzies, 1995, Menzies & Compton, 1997], to develop a general test framework called QMOD/HT4. This section describes KB-testability, a simplified version of that framework.

A KB can be characterised as domain facts and a set of problem solving methods. If we partially evaluate the problem solving methods over the domain facts, we arrive at the search space which could be traversed at runtime. This search space can be characterised as the tuple (E,V,O,S) where E is a set of directed edges connecting the vertices V of types *and*-vertex, *or*-vertex. *Or*-vertices represent literals and are generated from objects O with S mutually exclusive states (one vertex is generated for each state of each object). This characterisation fits qualitative theories such as QCM (where *S=3*: up, down, steady); propositional rule bases (where *S=2*: true,false) and any first-order theory that can be unfolded in a finite number of steps to a ground horn-clause theory (where *S=2*: true,false). *F* denotes the fanout of the graph formed by *(E, V)* (fanout is the number of edges touching a vertex and is the ratio of edges to vertices).

KB-testability can be characterised as the construction of pathways across *E* from output vertices back to known input vertices. Pathways must satisfy four criteria. (1) Pathways across an *or*-vertex must include at least one parent of that *or*. (2) Pathways across an *and*-vertex must include all the parents of that *and*. Pathways must (3) not contain loops and must (4) not contain mutually exclusive states. If an output vertex can be so connected to an input vertex, it is called an *explicable* output.

Pathway criteria number 4 makes this an NP-hard problem. Gabow et.al. [Gabow *et al.*, 1976] showed that finding a directed path across a directed graph that has at most one of a set of forbidden pairs is NP-hard. Such forbidden pairs are present in the above definition of KB-testability; i.e. two mutually exclusive states *S.i, S.j* of some object *O*. When implemented, KB-testability has been observed to exhibit exponential runtimes [Menzies, 1995], as one would expect for an NP-hard problem.

3.2 Topological Limit Number 1: Size

This section applies the KB-testability criteria to identify a size restriction to the topology of a KB search space.

Despite being NP-hard, KB-testability is still a practical validation algorithm for a sample of fielded expert systems and published theories of neuroendocrinology (the study of nerves and glands). To demonstrate this, a KB-testability instance generator was constructed by Menzies [Menzies, 1996b] as follows:

- Let *graph.0* be an and-or graph from a real-world theory with *baseline* parameters *E.b, V.b, O.b, S.b.*
- Let *AV(IN)* and *AV(OUT)* be the average number of vertices denoted as inputs and outputs respectively used when generating proofs over *graph.0.*
- Starting from the baseline, use a *mutator* to introduce an increment into one of the parameters and generate *graph.i.*
- Execute *graph.i* as follows. Randomly select up to *AV(IN)* vertices to be inputs and up to *AV(OUT)* different vertices to be outputs. Call KB-testability with those inputs and outputs.

For these experiments:

- *Graph.0* was the and-or graph of the Smythe'89 qualitative theory of human glucose regulation [Smythe, 1989] (described in detail in [Menzies & Compton, 1997]). In *graph.0*, *AV(IN)* was varied from 1 to 4 and *AV(OUT)* was varied from 1 to 10 and

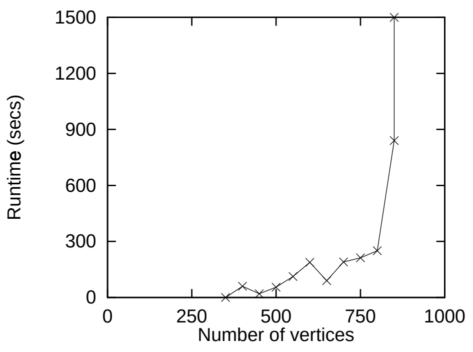


Figure 1: KB-testability runtimes.

  - *O.b*=80
  - *S.b*=3
  - 554 verticies (*V.b*). Note that the number of vertices is greater than *(O.b*S.b)*. In a qualitative theory, a conjunction of two competing upstream influences can cancel each other out; i.e. *up* and *down* can lead to a *steady*. 314 conjunctions were used in *graph.0* to handle steadies.
  - 1246 edges (*E.b*) so the fanout was 2.25.

- The instance generator *mutator.1* was built which generated 257 graphs with a constant fanout and with 400 to 850 vertices. These were executed 1991 times. For that study, some *give up* time had to be built into the system to recognise non-terminating runs. We used a *give up* time of 14 minutes (840 seconds).
- Many of the sample sizes used in this study are not simple whole numbers. For example, 257 is not 200, 250, or 300. The results reported here were generated from thousands of runs generated from prototype mutators, some of which crashed for random reasons. When we discarded the data from the crashed runs, we were left with the sample sizes described here.
- Figure 1 shows the observed runtimes.

Note that an approximately linear increase in runtimes was noted up to 800 vertices. However, KB-testability did not terminate for theories with more than 850 vertices in under the *give up* time (the vertical line in the results). We conclude that the *knee* in the exponential runtime curve kicks-in at around 800 vertices.

The claim the NP-hard process called KB-testability is valid for a range of real-world theories relies on the observation that a sample of real-world expert systems have less than 850 verticies. This observation comes from the verification community which collects the size of the dependency graph between literals in fielded propositional expert systems [Preece & Shinghal, 1992] (see Table 1).

These results suggests that a practical KB-testability must work at least for between 55 to 510 verticies and a fanout of 2 to 7. That is, KB-testability is practical for real-world expert systems, despite being NP-hard.

Application	vertices	fanout
displan	55	2
mmu	65	7
tape	80	4
neuron	155	4
DMS-1	510	6

Table 1: Figures from a sample of fielded expert systems. From [Preece & Shinghal, 1992].

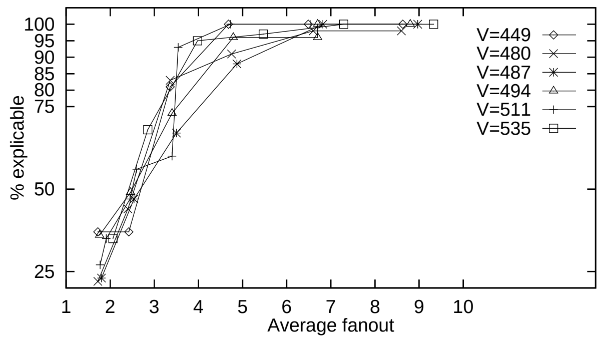


Figure 2: KB-testability explicables. From [Menzies, 1996b].

In other demonstrations of its practicality, KB-testability has been used to detect faults in theories of neuroendocrinology published in international refereed journals (neuroendocrinology is the study of nerves and glands). Feldman and Compton [Feldman *et al.*, 1989a], followed by Menzies and Compton [Menzies & Compton, 1997], have shown that KB-testability could detect previously unseen errors in theories in neuroendocrinology published in international refereed journals. Interestingly, these faults were found using the data published to support those theories.

3.3 Topological Limit Number 2: Connectivity

This section applies the KB-testability criteria to identify a connectivity restriction to the topology of a KB search space.

In other studies with QCM, another instance generator (*mutator.2*) was built for the Smythe '89 theory which kept the number of vertices (roughly) constant but added edges at random to produce new graphs of larger fanouts. Six graphs were generated with *(449, 480, 487, 494, 511, 535)* vertices. Figure 2 shows the results.

At low fanouts, many behaviours were inexplicable. However, after a fanout of 4.4, most behaviours were explicable. Further, after a fanout of 6.8, nearly all the behaviours were explicable [Menzies, 1996b]. Hence, another KB-testability limit is that, after a certain level of inter-connectivity, a theory is able to reproduce any input/output pairs; i.e. it is not adequately *restrictive*. An unrestrctive inference procedure that condones any behaviour at all from a theory is not a useful inference procedure. After the point where the percent explicable approaches 100 percent, KB-testability becomes a useless evaluation tool.

4 Expressibility or Topological Limits?

The previous section can be summarised as a pragmatic recommendation of restricting KB topology to medium-sized theories which are not highly connected. A drawback with applying these limits is the *forbidden fruit* problem (the forbidden fruit is always the sweetest and hence the most desirable). Suppose a KE has invested considerable effort into certain assertions; e.g. they have developed them over a long period of time or have successfully defended them from all critics. If we tell such a KE that some of these assertions are forbidden due to their undesirable properties (e.g. possible exponential runtimes, phase transition problems, limits-to-test problems), then the KE may still object to their deletion.

More formally, Silverman notes that agents which criticise a KB can be divided into *influencers* which block errors occurring and *debiasers* which fix errors after they occur [Silverman & Wenig, 1993]. Silverman has experimental results suggesting negative feedback (i.e. the use of a debiasers) is almost always unsuitable, if only used without positive feedback (influencers). The limits of the previous section would be classed as debiasers since they can only act after the KE has created a problematic KB.

A representation language in which it is impossible to make pragmatically problematic assertions would act as a very strong influencer to a KE. If a KE can't assert X, then they'll never have a running example which is hindered after X is removed. The rest of this article searches for any such pragmatic expressibility restrictions within QCM.

Expressibility restrictions for KB-testability relate to the steady nodes in QCM and *asymmetrical causal connections.* Asymmetric causal connections do not comment on the connection of all upstream states to all downstream state. Steady nodes are implemented via *and*-vertices that combine the influence of two competing upstream parents down to a steady vertex. It will be found that if we intend to use QCM for very long simulation runs, then we need to forbid both these constructs.

Expressibility restrictions for KB-maintainability relate to temporal causal connections. In a qualitative language, if we say that (e.g.) X encourages Y (denoted $X{+}{+}Y$), it is under-specified how long it takes for the X influence to effect Y. It will be found that different interpretations of this time delay have a significant effect on maintainability.

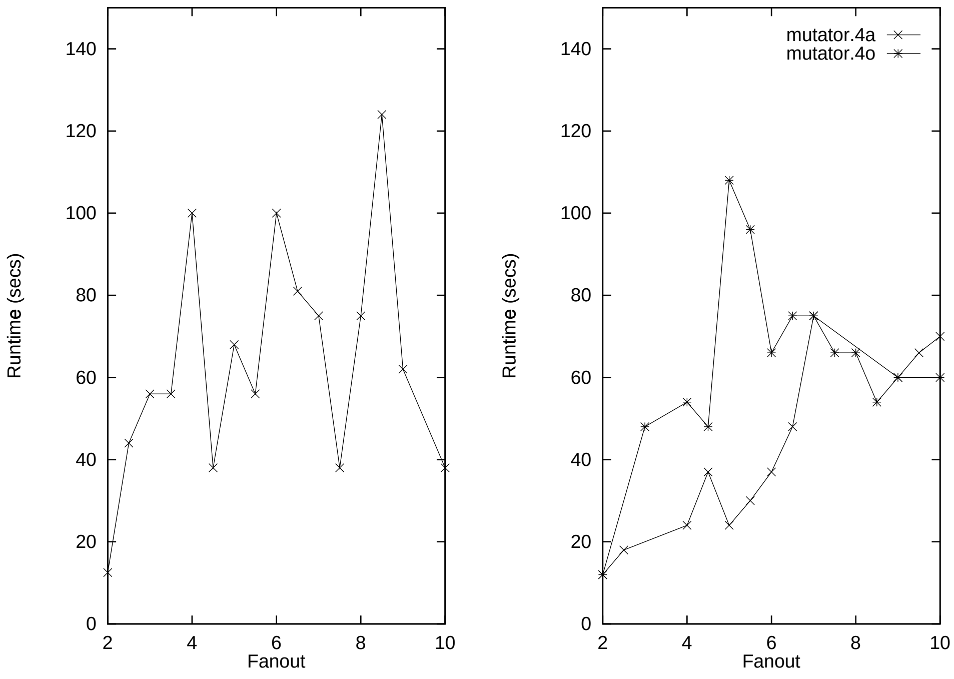
4.1 KB-testability: Studies With Basic Conjunction

One observation made in the above changing fanout study was that runtimes varied widely as the fanout was increased. To explore this further, we built new instance generators (*mutator.3, mutator.4a, mutator.4o*) which kept the number of vertices, *AV(IN)* and *AV(OUT)* constant while varying the fanout. In all, 155 graphs were generated and executed 2513 times (see Table 2).

Mutator.3 worked as follows. Starting with the and-or graph from Smythe '89, edges were added at random till some desired fanout was reached. The runtimes of *mutator.3* seemeded independent of fanout. It was hypothesised that the observations of *mutator.3* was displaying more than one effect. Hence, two more studies were performed where (i) edges were only added upstream to *and*-vertices (*mutator.4a*); (ii) edges were only added upstream to *or*-vertices

	Generated graphs	Number of runs
mutator$_3$: basic changing fanout study	76	1597
mutator$_{4a}$: changing fanout, `and`s only	42	483
mutator$_{4o}$: changing fanout, `or`s only	37	433
Totals	155	2513

Table 2: Number of experiments with mutating fanout.



A. *Mutator.3* runtimes

B. *Mutator.4a* and *mutator.4o* runtimes.

Figure 3: KB-testability runtimes.

(*mutator.4o*). Note that in both *mutator.4a* and *mutator.4o*, the number of vertices, *AV(IN)* and *AV(OUT)* were kept constant. The runtimes of *mutator.4a* were observed to always be less than or equal to *mutator.4o* (see Figure 3).

We hypothesis that adding edges upstream of an *and* vertex increases the constraints on proof generation over that vertex (i.e. more pre-conditions need to be satisfied). Roughly speaking, adding *and*s adds constraints making it more likely that proof generation will terminate earlier.

We conclude that for KB-testability, conjunction adds constraints which restricts inferencing and decreases the associated runtimes. Hence, for the purposes of KB-testability, the creation of theories with numerous conjunctions should be encouraged.

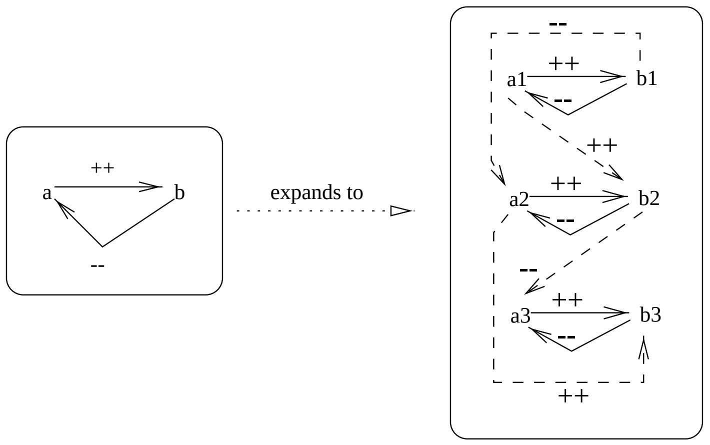


Figure 4: A theory (left) renamed over 3 time intervals and connected using IEDGE (time edges shown as dashed edges).

4.2 KB-testability: Studies With Conjunction and Long Simulations

The study in the previous section assumed the basic KB-testability constraint; i.e. no object can be assigned more than one state. In several commonly used KBS representations, this assumption is not valid since objects can be assigned several states of the lifetime of a simulation:

- Rule-bases that are processed via a standard match-select-act loop may assert and retract facts many times during its processing;
- As the inference executes over loops in qualitative theories or topoi graphs (topoi graphs depict statements of gradual knowledge such as *the more this, the less that* [Dieng *et al.*, 1995]), literals may be assigned different belief values at different times.

We use the term KB-time-testability to denote the KB-testability variant in which the belief values of literals can change during a simulation. The rest of this section explores limits to KB-time-testability.

One approach to KB-time-testability would be to create one copy of the search space for each time interval in the simulation. For example, consider the theory *A encourages B* but *B discourages A*. In QCM, this is denoted *A++B* and *B–A* where *++* and – are QCM causal connections. *X++Y* means that *Y* being *up* or *down* could be explained by *X* being *up* or *down* respectively. *X–Y* means that *Y* being *up* or *down* could be explained by *X* being *down* or *up* respectively. If we executed *A++B* and *B–A* over three time ticks, we could search the space shown in Figure 4.

Here we are connecting objects at different time intervals by an *implicit time edge linking* or IEDGE policy: when i.e. *X++Y* implies that *X* at time *T=i* also connects to *Y* at *T=i+1* (see the dashed lines). Alternatives to IEDGE are discussed later in the discussion on KB-maintainability.

The advantage of this approach is that we could use the QCM inference procedures (e.g. KB-testability) for testing time-based simulations. The dis-

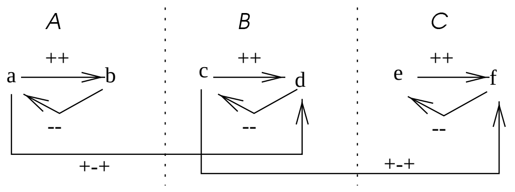


Figure 5: A theory with asymmetric edges from `a` to `d` and from `c` to `f`.

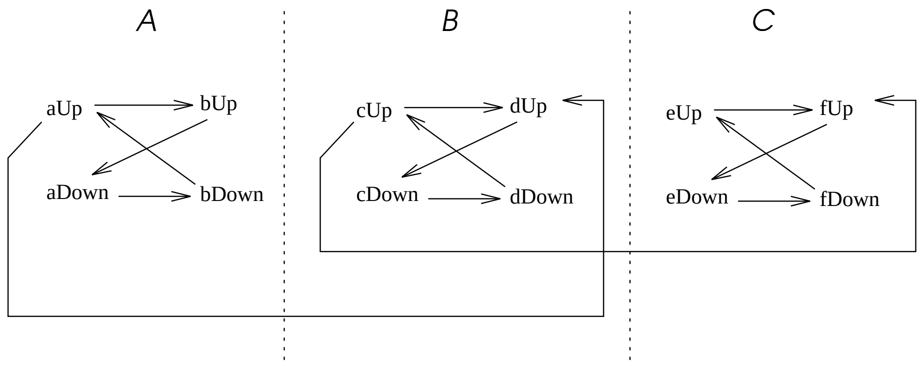


Figure 6: The graph within Figure 5.

advantage of this approach is that the graph size would increase linearly with the number of copies. Recall that, experimentally, KB-testability has been observed to exhibit the exponential runtimes. Hence, long simulation runs are not KB-time-testability in this manner.

Note that each time copy repeats some structure for the known time intervals in the simulation. A compelling intuition is that no explanation path can be found through *T+1* copies that can't be found in *T* copies. If this were true, then we could reduce the search space of KB-testability by not copying the structure at all. Menzies amd Cohen [Menzies & Cohen, 1997] show that this optimisation is not possible if we allow *asymmetric edges* in our theories. *X++Y* and *X–Y* are examples of *symmetric causal edges* in that they make some statement about every state of the downstream vertex *Y*. *X+-+Y* is an example of an asymmetric causal edge: *Y* being *up* could be explained by *X* being *up* but not visa versa.

For example, Figure 5 contains two asymmetric causal edges (*A+-+D*; *C+-+F*) which expands into the graph of Figure 6. This figure duplicates the topology of our above theory in the regions *A,B,C* with an extra link from the top-left vertex of one region to the top-right vertex of the next region. A path from *bUp* to *eUp* will take at 3 time intervals to cross from top-left to top-right in each of the regions *A,B,C*. By repeating *A,B,C* more times, we can generate dependency graphs which would require any number of intermediaries to traverse. This example suggests that between each measured time interval we may need many intermediary copies.

We have shown elsewhere [Menzies *et al.*, 1997] that for theories whose variables take only *S* states and which lack asymmetric edges and which are connected via IEDGE, then if we can't generate a proof in *S* copies, then we will never be able to generate a proof at all. Roughly speaking, if every edge offers

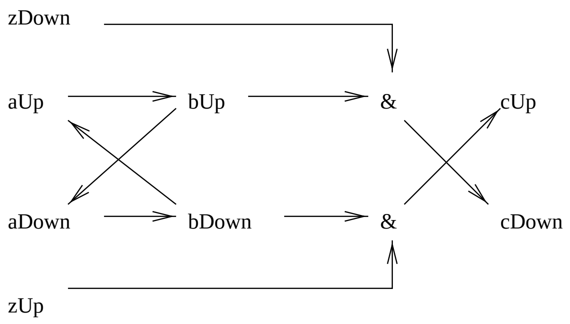


Figure 7: An example graph. A minimum of three time intervals are required to explain *cUp* in terms of set *(aUp, zUp)*

a comment on all the states of its downstream vertices (i.e. they are symmetric), then the state space rapidly *saturates* and we can reduce the granularity of the time axis to just under twice the granularity of the measurements of that theory. We can use this proof as an optimisation technique as follows. Suppose, for example, that:

- We had a *S=2*-state device with symmetric edges which has been running for a million time steps.
- We only collected measurements at three time points (say, 1 and 500,000 and 1,000,000.

If we had not proved saturation for our device, then the search for these proofs would have to explore 1,000,000 renamings. Given the exponential runtimes of KB-testability, this is clearly undesirable. However, since we have proved saturation, then we know that if a proof cannot be found in two renamings, then no such proof exists. Consider a proof from (e.g.) time 1 to time 500,000. If that proof cannot terminate in the space 1 and 500,000, then it will never terminate. That is, when building this proof, we could ignore the search space that used the renamings from 2 to 499,999. A similar argument could be made for proofs from 500,000 to 1,000,000. In practice, we would only need to search the space created for the three measured time points. That is, in this example, this optimisation lets us reduce the search space to three-millionths of the unoptimised version. More generally, if an *S* state device which supports saturation is run for *T1* time ticks, and if we only measure this theory at *T2* time intervals, then we can reduce the search space by a factor of *T2/T1*. In the case where *T2* is very much smaller than *T1*, then this is a significant reduction in the search space.

Recall that in QCM, conjunction is used to conceptualise explanations of steady values (a conjunction of two competing upstream influences can cancel each other out). We now demonstrate by counter-example that conjunction blocks saturation. That is, if we add conjunction to bi-state devices connected by symmetric edges, then we need an unbounded number of copies in order to perform KB-time-testability. Note that this rejection of conjunction implies that we can't execute steadies in a QCM theory.

Consider the graph in Figure 7. Three time intervals are required to explain *cUp* in terms of *(aUp,zUp)*. In the first time interval we explain *(aUp,bUp,zUp)*.

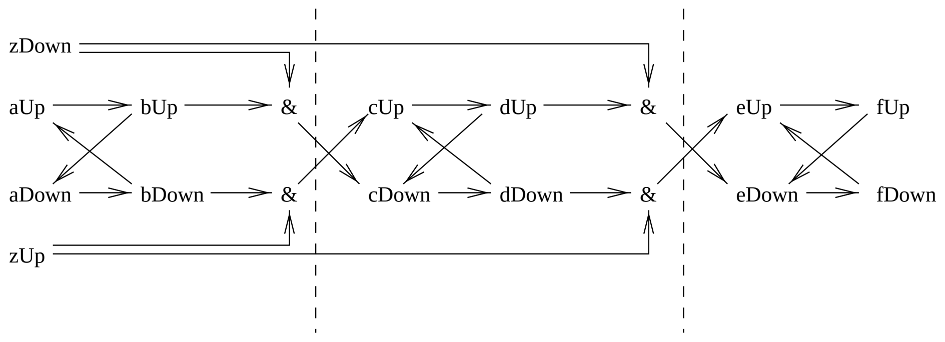


Figure 8: An example of the construction of our counter-example. In this case, a minimum of 7 time intervals is required to explain "fUp" in terms of "(aUp,zUp)".

In the second time interval we explain *(aDown,bUp,zUp)*. In the third time interval we explain *(bDown,zUp)*, and by conjunction, *cUp*. We create our counter-example by connecting duplicates of this graph as demonstrated in Figure 8.

In this figure a minimum of 7 time intervals is required to explain *fDown* in terms of *(aUp,zUp)*. It is easy to show that in general, with *D* duplicates connected in this manner, the maximum number of time intervals to perform an explanation is at least *2D+1*, which is not a constant. This contradicts our previous result for the case of symmetric edges without conjunctions (i.e. 2 time intervals were enough for explanation).

We conclude that long simulation runs is not KB-time-testability if the theory includes conjunction. Note that short simulation runs of theories with conjunction is still be KB-testability if we (i) ignoring the symmetric edges optimisation; (ii) creating one copy for each time tick. However, for long simulation runs, we recommend using a QCM variant formed by removing conjunction (and hence steadies) and the asymmetric causal edges.

5 KB-maintainability

This section describe KB-maintainability, an extension to KB-testability.

Given we can test a theory, what kind of results assist in maintaining that theory? One requirement would be the ability to check if some variation of a theory is better than the original theory. We divide this requirement into two parts. Firstly, we need a quick first-pass test that can clearly identify obviously poor theories. Secondly, we need a more detailed view that can assess minor variants on a theory. Given a range of theories which degrade from *good* to *poor*, we like to see the *maintenance success* curve of Figure 9.

A good theory is *permissive*; i.e. it can explain known behaviour (the success curve rises high on the left-had-side). However, we also need to test that the permissiveness is not due to a poorly-constrained theory. A theory that condones any conclusion is a poor theory. Hence, a theory must also be *restrictive* (the success curve descents to a low value on the right-hand-side). Further, we want the second derivative of this graph to be non-negative; e.g. the ski-slope shape of success curve. With such a curve, we can quickly get feedback if some

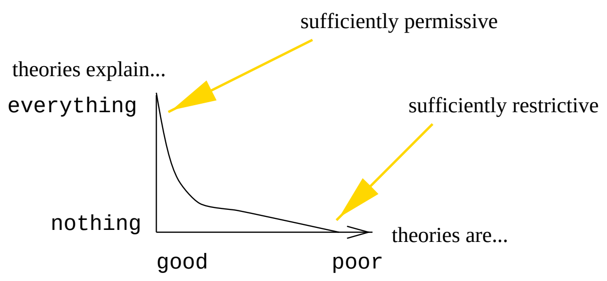


Figure 9: Visualising a maintainable representation language. The KB-testability curve of a good representation should be both *permissive* to all good theories (explains correct behaviour) and *restrictive* to all bad theories (prevent poor theories explaining any behaviour).

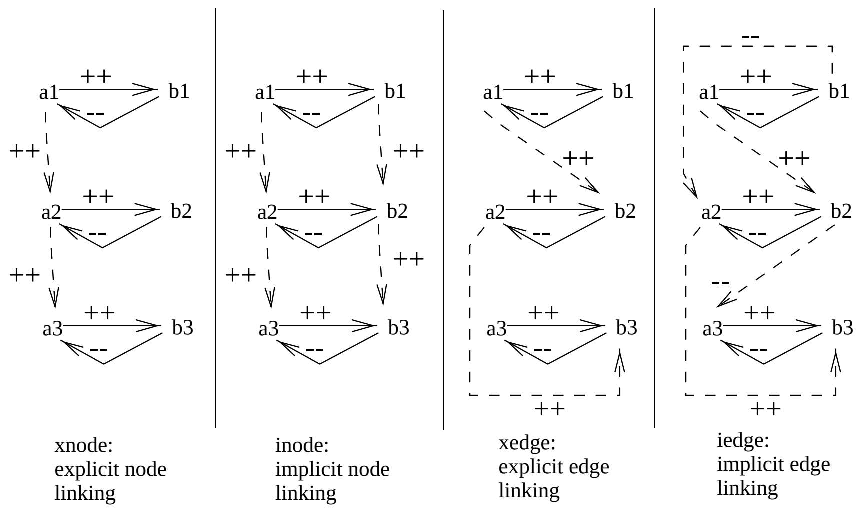


Figure 10: Figure 4 (left) renamed over 3 time intervals using different time linking methods. Dashed lines indicate time edges.

change improves or degrades a theory.

We say that a representation is KB-maintainability if its KB-testability curve for good to bad theories looks like the ski-slope of the success curve. We show below that only some representations of time in QCM satisfy this definition of KB-maintainability. Hence, in QCM, conceptual modeling should be restricted to these representations of time. Note that KB-maintainability uses KB-testability as a sub-routine; i.e. KB-maintainability is NP-hard since KB-testability is also NP-hard.

How can time be represented in QCM? We saw above the use of IEDGE: when X connects to Y, then we say that X at time $T{=}i$ also connects to Y at $T{=}i{+}1$. IEDGE is only one of a family of temporal QCM languages. Firstly, we can cross time over edges or over nodes. Secondly, we can cross time on all structures in the theory, or only on those explictedly mentioned by the user. Each combination of these alternatives defines a new temporal modeling language, illustrated in Figure 10. In this figure, in the *explicit node linking* language (or

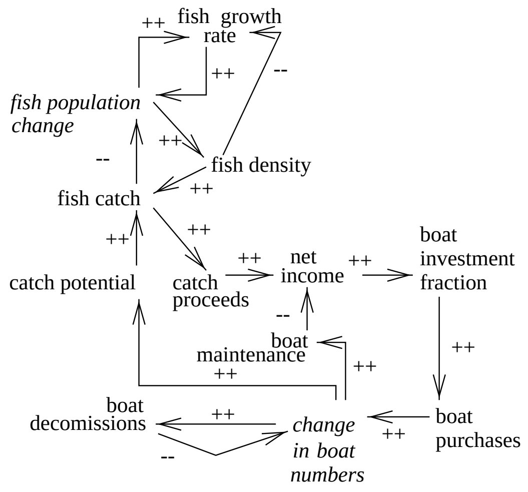


Figure 11: The fisheries model. Adapted from [Bossel, 1994] (pp135-141). Variables in italics were used in the XNODE study. Edges downstream of an XNODE were used as the explicit time edges in the XEDGE language.

XNODE), we only cross time on the nodes explicitly denoted as time nodes by the user (in this example, A). In the *implicit node linking* language (or INODE), we cross time on all nodes. In the *explicit edge linking* language (or XEDGE), we only cross time on the edges explicitly denoted as time edges by the user (in this example, A to B). Lastly, in IEDGE, we cross time on all edges.

5.1 Testing KB-maintainability

To test KB-maintainability for these four temporal languages, we performed the following experiment. First, we implemented a quantitative *fisheries simulation model* using the equations from [Bossel, 1994] (pages 135-141). Secondly, we built a qualitative form of the fisheries model as shown in Figure 11. The quantitative model was used to generate numeric test data which was stored in the *measure* array. From each comparison of *measure(i)* with *measure(j)*, entries were written to an array of qualitative observations called *changes*. *Changes* was used to generate the input/output needed for for KB-testability. For example, if in comparison *change(37)*, the fish density *fdens* was increased and the fish catch *fcatch* was always seen to decrease at all time steps, then *change(37).in* is *(fdensUp)* and *change(37).out* is *(fcatch(t=1)Down, fcatch(t=2)Down, fcatch(t=3)Down, fcatch(t=4)Down, fcatch(t=5)Down)*

Next, we built *mutator.5* as follows: the sign on a random sample of the X statements in the qualitative theory were *corrupted*: i.e. flipped (*++* to – or visa versa). Given a model with E edges, then as we vary X from *0 to E*, we are moving from a *good* model to a *poor* model; i.e. the x-axis of our maintenance success curve. This corrupted model was then copied to create a set of time *copies*. These time copies were connected using one of our temporal languages: IEDGE, INODE, XEDGE, XNODE. *Change* inputs were mapped into *copy(0)*. *Change* outputs were mapped into some *copy(i)* (i greater than

```
T  := MaxTime;
M0 := fisheries;                      measure := run_quantitative_model(T,M0)
M1 := qualitativeVersionOf(M0);        change := comparisons(measure)
for policy ∈ (IEDGE, INODE, XNODE, XEDGE)  begin
   for corrupted:=0 to |E| begin
      for r:=1 to 20 begin
         M2 :=corruptSomeEdgesChoosenAtRandom(corrupted,M1)
         for t:=0 to T   copy(t):= M2
         for t:=0 to T-1 time_connect(copy(t),copy(t+1),policy)
         for i:=1 to |change| begin
            (In,Out(1..T)):= change(i)
            Xplained(1..T):= run_qualitative_model(copy,In,Out)
            Xplicable(policy,r,corrupted,i):=|Xplained(T)|*100/|Out(T)|
end end end end
```

Figure 12: Experimental design for assessing linking options

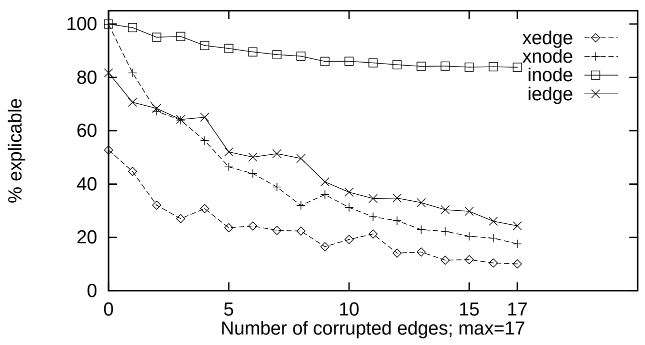


Figure 13: Graph of `Xplicable` from Figure 12.

zero). The success of each run was assessed by recording the percent of the *explicable outputs* i.e. those outputs that the model could connect back to inputs. The details of this experiment are shown in Figure 12.

5.2 Results

Figure 13 graphs the average values of *Xplicable* variable from the experimental design. INODE was not sufficiently restrictive. Even with all edges corrupted, INODE allowed theories to explain correct behaviour. Also, XEDGE was not sufficient permissive. Even on correct theories, XEDGE could only explain half the known behaviour. XNODE was the closest to the maintenance success curve, followed by IEDGE. However, IEDGE was not as permissive as XNODE. Hence, except in the case where we need to optimise long simulation runs, we recommend XNODE. Otherwise, we recommend IEDGE.

Note that for XNODE and IEDGE, after only a third of the theory being mutated, only half the outputs were inexplicable. This is a nice result: with these modeling languages, we can get a clear and early indication if we are stray from a good theory.

We conclude that, in terms of KB-maintainability, the four variants on the

QCM conceptual modeling language are ranked: XNODE (best for short to medium length simulation runs), then IEDGE (best for long simulation runs), then XEDGE (poor: no permissive enough) and INODE (poor: not restrictive enough).

6 Conclusion

If there are no blocks to structure preservation, then we our conceptual modeling need not be restricted. Unrestricted conceptual modeling requires that we can structurally preserve conceptual structures. If structure preservation is blocked by certain features of a conceptual modeling language, then if we use those features, our implementation may be compromised.

In order to identify such blocks to structure preservation, we need to first identify pragmatic success criteria for our KBs. Such pragmatic success criteria should reflect functionality that we will require, in the usual case. Worst-case time complexity analysis is not such a pragmatic criteria. However, KB-testability and KB-maintainability are pragmatic criteria since checking and revising a theory is so important when performing KA (construction inaccurate surrogates of reality). Topological restrictions were found via KB-testability:

- Size restrictions;
- Connectivity restrictions;

For none-time-based simulations, the use of conjunctions was observed to improve KB-tesability. In the case where the conceptual model will be used for time-based simulation runs, expressibility restrictions were found via KB-time-testability and KB-maintainability:

- No conjunctions;
- No steadies;
- No asymmetric causal connections;
- Avoid XEDGE or INODE temporal connections.

We have hence shown that there are cases where it is necessary to restrict a conceptual modeling language. That is, there exists conceptual knowledge that we just should not add to our KBs. This belief runs counter to the standard wisdom in the KA community; i.e. design and implementation considerations should not contort the high-level descriptions of an expert's conceptual knowledge. The techniques we used (KB-testability, KB-maintainability, instance generators, graph theory) represent a general evaluation methodology and could be applied to many other theories and representations.

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