ABSTRACT

Many testing and benchmarking scenarios in software and systems engineering depend on the systematic generation of graph models. For instance, tool qualification necessitated by safety standards would require a large set of consistent (well-formed or malformed) instance models specific to a domain. However, automatically generating consistent graph models which comply with a metamodel and satisfy all well-formedness constraints of industrial domains is a significant challenge. Existing solutions which map graph models into first-order logic specification to use back-end logic solvers (like Alloy or Z3) have severe scalability issues. In the paper, we propose a graph solver framework for the automated generation of consistent domain-specific instance models which operate directly over graphs by combining advanced techniques such as refinement of partial models, shape analysis, incremental graph query evaluation, and rule-based design space exploration to provide a more efficient guidance. Our initial performance evaluation carried out in four domains demonstrates that our approach is able to generate models which are 1-2 orders of magnitude larger (with 500 to 6000 objects!) compared to mapping-based approaches natively using Alloy.

ACKNOWLEDGMENTS

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metamodel (graph schema), (2) a set of well-formedness (WF) constraints expressed in first-order graph logic with transitive closure and optionally (3) an initial model fragment. Existing approaches like [14–20] map the instance generation problem of consistent graph models into logic solvers such as Alloy [21, 22], SMT-solvers [23], SAT-solvers or constraint solvers when the efficiency of graph model generation depends on the scalability and performance of back-end logic solvers, which primarily excel in finding inconsistencies in complex specifications. However, the generation models as a side-effect of the proof construction is much less efficient.

In fact, these solvers guarantee neither scalability [24] nor diversity [25] when they need to generate well-formed graph instances of a specification – regardless of how smart the mapping is from a high-level graph model to the underlying logic solver. From a practical perspective, while the specification of complex industrial modeling tools may contain hundreds of classes (in their metamodel) and WF constraints, no existing model generation technique could derive a consistent graph that contains at least one object from each class.

**Contribution.** We propose a novel automatic generation technique to derive consistent domain-specific graph models for specifications by exploiting and innovatively combining a multitude of advanced graph-based and core SAT-solving techniques.

1. We formulate model generation as a refinement of partial models [26, 27] where initial abstract model fragments are gradually refined and concretized during exploration.
2. We provide partial model refinement rules as decision and unit propagation steps by following core SAT-solving techniques.
3. We use incremental graph query evaluation of the VIATRA engine [28] to efficiently evaluate violations of constraints over partial models during model generation [27].
4. We integrate shape analysis as state encoding [29–31] for graphs to efficiently detect if two partial models should be treated as equivalent during exploration.
5. We exploit rule-based design space exploration [32] to drive the generation process directly over graph shapes using an objective function approximating the distance from a solution.
6. We evaluate the scalability of our approach using 6 tests sets of four domains (including industrial DSLs) and compare its performance with the well-known Alloy Analyzer [21].

**Added Value.** To our best knowledge, our framework is one of the first attempts to automatically generate consistent models by operating natively over (typed and attributed) graphs. Moreover, according to our scalability experiments, it is capable of generating consistent graph models of 1-2 orders of magnitude larger (with 500-6000 nodes) compared to models derived by Alloy and the generated model suite is also more diverse [24]. As such, our graph solver can serve as a back-end where Alloy was used previously for model generation purposes in testing and benchmarking scenarios.

## 2 MODELING PRELIMINARIES

Our model generation technique will be illustrated by automatically generating test inputs for Yakindu Statecharts Tools [33], which is an industrial integrated modeling framework for developing reactive, event-driven systems. First, we give a brief introduction to the formal definition of partial models using a three-valued logic, which will drive the automated generation of consistent models.

### 2.1 Metamodels

A domain-specific (modeling) language (DSL) is typically defined by a metamodel and a set of well-formedness constraints. A metamodel defines the main concepts and relations in a domain, and specifies the basic graph structure of the models, and WF constraints further restrict valid models of the language by defining additional design rules. In this paper, the Eclipse Modeling Framework (EMF) [34] is used for domain modeling, which is a de facto industrial standard.

![Figure 1: Metamodel of Yakindu statecharts](image)

**Example 2.1.** A metamodel extracted from Yakindu is illustrated in Figure 1. A Statechart consists of Regions, which in turn contain Vertices and Transitions. An abstract state Vertex is further refined into RegularStates (like State) and PseudoStates like Entry and Synchronization states. The source and target states of a transition are identified by the source and target references.

To reason about the consistency of DSLs, a formal algebraic specification is frequently created [19, 27, 35–38]. We briefly revisit the notion of [27] to provide a precise background for our model generation approach (but for space consideration, we omit the detailed handling of attributes, which could be introduced accordingly).

Formally, a metamodel defines a vocabulary $\Sigma = (C_1, \ldots, C_n, \text{exist}, R_1, \ldots, R_m, \sim)$ with unary predicate symbols $C_i$ ($1 \leq i \leq n$) defined for each $EClass$, and binary predicate symbols $R_j$ ($1 \leq j \leq m$) for each $EReference$. To represent abstract (partial) models, a unary exist predicate is introduced to denote the existence of an object in a given model, while $\sim$ denotes an equivalence relation over objects.

### 2.2 Partial Models

Partial models (PM) were introduced in [35, 38] to represent uncertain (possible) elements in instance models where one partial model represents a range of possible instance models. In this paper, 3-valued logic [39] is used to explicitly represent unspecified or unknown properties of models with a third $\{1/2\}$ truth value (besides 1 and 0 which stand for true and false) in accordance with [11, 27, 31]. A partial model is represented as a 3-valued logic structure $P = (\text{Obj}_P, I_P)$ of $\Sigma$, where $\text{Obj}_P$ is the finite set of individuals in the model (i.e. the objects), and $I_P$ provides a 3-valued interpretation for all constants in $\text{Id}$ and predicate symbols in $\Sigma$.

**Type Predicates.** $I_P$ is a 3-valued interpretation of each class symbol $C_i$ in $\Sigma$: $I_P(C_i) : \text{Obj}_P \rightarrow \{1, 0, 1/2\}$: 1, 0 and $1/2$ means that it is true, false or unspecified if an object is an instance of a class $C_i$.

**Reference Predicates.** $I_P$ gives a 3-valued interpretation to each reference symbol $R_j$ in $\Sigma$: $I_P(R_j) : \text{Obj}_P \times \text{Obj}_P \rightarrow \{1, 0, 1/2\}$, where
1, 0 and \(1/2\) means that it is true, false or unspecified if there is a reference \(R_j\) between two objects.

**Existence Predicate.** \(I_P\) gives a 3-valued interpretation for the existence predicate \(I_P(\text{exist}) : \text{Obj}_P \rightarrow \{1, 0, 1/2\}\), where 1 values represent an object that must be, \(1/2\) value represents objects that may exist or they might be removed later from the model. Node \(P\) may represent any type of objects. In a refinement step, properties with refinements may exist or they might be removed later from the model. Node \(P\) gives a 3-valued interpretation to the ordering relation between the objects \(P\).

**Equivalence Predicate.** \(I_P\) gives a 3-valued interpretation to the \(\sim\) relation between the objects \(I_P(\sim) : \text{Obj}_P \times \text{Obj}_P \rightarrow \{1, 0, 1/2\}\). An uncertain \(1/2\) value relation between two objects means that those object may be equal and can potentially be merged. On the other hand, uncertain equivalence of a single object (itself) implies that it may represent multiple separate objects.

Example 2.2. Four partial models are illustrated in Figure 2. As a notation guide, (1) the truth value of a type predicate is denoted by labels on nodes, where missing labels are treated as 0 values, while (2) reference predicate values 1 and \(1/2\) are represented by edges with solid and dashed lines (respectively), while missing edges between two objects represent 0 values for a predicate, (3) existence predicate values 1 and \(1/2\) are represented by nodes with solid and dashed borders, respectively, while objects with 0 existence values are simply not depicted. Finally, (4) uncertain \(1/2\) equivalences are marked by dashed line with an \(\sim\) symbol. Otherwise, each node represents a single, unique object (i.e. for all object \(o: [0 \sim 0] = 1\) and for all different objects \(o_1\) and \(o_2: [o_1 \sim o_2] = 0\)).

In \(P_0\) (on the left side of Figure 2), object \(r\) is of type \textbf{Region} but not of type \textbf{State}: \([\text{Region}(r)]^{P_0} = 1\) and \([\text{State}(r)]^{P_0} = 0\). In case of object \textbf{new}, all type predicates are \(1/2\), which means that the object may represent any type of objects. In \(P_0\) there is a certain \textbf{vertices} reference between \(r\) and \(s\) and \(r\) and \(e\), and a possible reference between \(r\) and \textbf{new} or as a self-loop of \textbf{new}. Nodes \(r, r, e\) and \(s\) represent objects that must exist, and \textbf{new} represent possible objects which may exist or they might be removed later from the model. Node \textbf{new} may also represent multiple objects (note the self-loop edge \(\sim\)), which can later be refined into multiple distinct model elements.

**2.3 Refinement and Concretization of PMs**

During model generation, the level of uncertainty will gradually be reduced by refinements deriving partial models that represent more concrete instance models. In a refinement step, properties with \(1/2\) values can be refined to either 0 or 1 which imposes an information ordering relation \(X \sqsubseteq Y\) where either \(X = 1/2\) and \(Y\) is refined to 1 or 0, or values of \(X\) and \(Y\) remain equal: \(X \sqsubseteq Y := (X = 1/2) \lor (X = Y)\).

A refinement is defined as a function \(\text{ref} : \text{Obj}_P \rightarrow \{0, \text{Obj}_Q\}\) which maps each object of a partial model \(P\) to a set of objects in the refined partial model \(Q\). A refinement respects the information ordering of type, reference, equivalence and existence predicates for each \(p_1, p_2 \in \text{Obj}_P\) and \(q_1, q_2 \in \text{ref}(p_1), q_2 \in \text{ref}(p_2)\):

- For each class \(C_i\) \(\exists! C_i(p_1) \subseteq \exists! C_i(q_1)\).
- For each reference \(R_j\) \(\exists! R_j(p_1, p_2) \subseteq \exists! R_j(q_1, q_2)\).
- \([p_1 \sim p_2]^{P_1} \subseteq [q_1 \sim q_2]^{Q}\).
- \(\exists\text{exist}(p_1)^P \subseteq \exists\text{exist}(q_1)^Q\), and if \(\exists\text{exist}(p)^P = 1\) then \(\text{ref}(p)\) is not empty.

Refinement from partial model \(P\) to \(Q\) is denoted by \(P \sqsubseteq Q\).

If a 3-valued partial model \(P\) only contains 1 and 0 values, and there are no \(\sim\) relations between different objects (i.e. all equivalent nodes are merged), then \(P\) represents a traditional \textit{instance model}. A \textit{concretization} defines a trivial refinement to a 2-valued fully defined concrete model by rewriting all \(1/2\) type, reference and exist predicates values to 0, and rewriting all \(1/2\) equivalence predicate to 0 between different objects, and to 1 on the same object.

Example 2.3. Figure 2 illustrates two refinement steps from \(P_0\) to \(P_2\). In \(P_0\) object \textbf{new} is split into two different objects: \textbf{new} and \(t\) of \(P_1\), where \(\exists\text{new} \sim \exists\text{new}^{P_0} = 1/2\) is refined to \(\exists\text{new} \sim \exists\text{new}^{P_1} = 0\), \(\exists\text{new} \sim \exists\text{new}^{P_2} = 1/2\). Additionally, \(\exists\text{new}^{P_0} = 1/2\) is refined to \(\exists\text{exist}(t)^P = 1\), and \(\exists\text{Transition}(\text{new})^{P_0} = 1/2\) is refined to \(\exists\text{Transition}(\text{new})^{P_2} = 1\), thus creating a new \textit{Transition} object \(t\), while all other \(1/2\) type predicates are refined to 0. Finally, \textbf{source} predicates are refined to 1 with \(e\) as target, and to 0 with all other objects as target.

In step \(P_1\) to \(P_2\), possible \textbf{target} predicates are refined to 1 with \(s\) as target object, and to 0 with \(e\) and \textbf{new} as target objects. Note that refinement step \(P_1 \sqsubseteq P_2\) will illustrate the decision rule while \(P_2 \sqsubseteq P_3\) will illustrate the unit propagation rule later in section 3.1. \(P_3\) is a concretization of \(P_2\), which is also a refinement \(P_2 \sqsubseteq P_3\).

**2.4 Defining constraints over PMs**

In many industrial modeling tools, domain-specific WF constraints are captured either by standard OCL constraints [40] or by graph patterns (GP) [28, 41]. A graph pattern captures complex structural conditions over an instance model. In order to have a unified and
where variable binding $\phi$ value of lel references of opposite direction always occur in pairs. Finally types, (3) $R$ include (1) representation. In case of EMF metamodels, such constraints in-
tructionsWF constraints and validation rules \cite{19}. Since a formalization of these structural restrictions as WF constraints is provided in \cite{19}, the graph predicate language of Figure 3 can uniformly be used for both kinds of structural constraints.

Example 2.4. The Yakindu documentation states several con-
straints for statecharts that can be formalized as graph predicates 
\cite{24}. For instance, constraint noOutgoing($e$) in Figure 4 (depicted as a graph pattern and a graph predicate) detects an entry state $e$ without an outgoing transition. The explicit use of equality constraints $e \sim e_1$ and $t_1 \sim t_2$ is responsible for performing a natural join operation over the edges as predicates. As a result, the same formula can be evaluated with both 2-valued and 3-valued interpretation.

2.5 Approximating constraints over PMs

While WF constraints can be directly evaluated on concrete instance models in EMF are expected to be arranged into a (6) Contain-
ment (CON) hierarchy, which is a directed tree along relations marked in the metamodel as containment (e.g. regions or vertices). Since a formalization of these structural restrictions as WF constraints is provided in \cite{19}, the graph predicate language of Figure 3 can uniformly be used for both kinds of structural constraints.

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2.5 Approximating constraints over PMs

While WF constraints can be directly evaluated on concrete instance models, checking the correctness of a partial model is a challenging task, because one partial model may represent multiple concretiza-
tions. A constraint $\phi$ can be evaluated on a partial model $P$ using the 3-valued logic and open-world semantics by a constraint rewriting technique \cite{27} which over- and under-approximates the results:

- **Under-Approximation**: If $\|\phi\|^{P} = 1$ in a partial model $P$, then $\|\phi\|^{Q} = 1$ in any partial model $Q$ where $P \subseteq Q$.
- **Over-Approximation**: If $\|\phi\|^{Q} = 1$ in a partial model $Q$, then $\|\phi\|^{P} \geq 1/2$ in a partial model $P$ where $P \subseteq Q$.

Using these properties, we define a monotonous derivation se-
quence of valid partial models which (1) starts from the most ab-
tract partial model where all constraints are evaluated to $1/2$, which partial model (2) is gradually refined into more and more concrete partial models (with less number of predicates evaluating to $1/2$). Refinement steps are continued until a concretized graph model of a designated scope eventually satisfies all WF constraints with 2-valued interpretation. During these refinement steps, special care needs to be taken to handle two situations:

- **False negatives** are partial models $P$ which do not violate an under-approximated (must) constraint, i.e. $\|\phi\|^{P} \leq 1/2$, but they can never be concretized into a valid instance model with $\|\phi\|^{Q} = 0$ where $P \subseteq Q$. These sequences are dead ends, and ideally, they should be detected as early as possible.
- **False positives** are partial models $P$ which violate an over-
approximated (may) constraint, i.e. $\|\phi\|^{P} \geq 1/2$, but they can be further refined into partial model $\|\phi\|^{Q} = 0$ where $P \subseteq Q$. These sequences might be postponed during model generation, but they may eventually lead to a concrete model that satisfies all WF constraints, thus they should be kept.
3 AUTOMATED GRAPH GENERATION

In this paper, we propose a general and automated graph model generation approach which takes a domain specified by (i) a vocabulary \( \Sigma \) defined by a metamodel, and (ii) a theorem \( T \) defined by a set of well-formedness constraints \( \{ -\varphi_1^{WF}, \ldots, -\varphi_n^{WF} \} \), and (iii) a search scope (i.e. minimal and maximal number of nodes in a solution graph) and (i) generates a consistent (valid) concrete graph model \( G \models T \) as output.

The model generation framework gradually refines partial models by rule-based design space exploration (DSE) [32] into a well-formed instance model which complies to the metamodel and all WF constraints are satisfied, if such a concrete model exists within the given search scope. During exploration, our framework simultaneously operates on (concrete) instance models and WF constraints as well as (abstract) partial models and approximated WF constraints introduced in section 2 by applying refinement rules. Refinement rules are defined as graph transformation rules [27, 42] manipulating directly over partial models with 3-valued interpretations by concertizing a single atomic uncertain \( \frac{1}{3} \) value in each step.

Refinement rules are grouped into two categories: (1) Decision rules are derived from \( \Sigma \) to reduce the number of valid concretizations of a partial model (i.e. new information is added) while (2) Unit propagation rules are derived from \( T \) to propagate the consequences of previous decisions in order to simplify a solution candidate without excluding potential solutions.

Model generation is initiated from an initial partial model provided as input by an engineer, or from the most abstract partial model where all predicates are unknown, i.e. (1) there is a single (abstract) object \( Obj = \{ \text{new} \} \); (2) \( \exists \text{new} = \frac{1}{3} \) and \( new \sim new = \frac{1}{3} \) thus this object may represent multiple possible objects of the concrete models; (3) for all class predicate \( C_i \): \( C_i(\text{new}) = \frac{1}{3} \) and (4) for all reference predicates \( R_j \): \( R_j(\text{new}, new) = \frac{1}{3} \).

3.1 Decision Rules

Decision rules (see Figure 5) define various refinements to concretize information in partial models to construct possible solutions. They are derived from the vocabulary \( \Sigma \) of the metamodel, where each predicate symbol \( C_i \) and \( R_j \) represents a Class and Reference. In general, decision rules are responsible for (1) introducing new objects by splitting the abstract new object or (2) rewriting an \( \frac{1}{3} \) value to 1 as detailed by (the scheme of) four decision rule classes.

- Rule addRoot \((C)\) selects a non-abstract class \( C \) (see the precondition in the left hand side) if no other roots have been created (denoted by NEG) to ensure that the model has a single root (as required by EMF). Its effect (prescribed by the right hand side) is to split the initial new object by creating a new root as an instance of \( C \), which acts as a root element for the containment hierarchy and all self-loop references on new are extended to both objects.
- Rule addChild \((C_p, R_C, C_C)\) selects an existing parent object of type \( C_p \), the new object with a non-abstract type \( C_C \), and a containment reference \( R_C \) from parent to new. Upon execution, it splits new into a new object child of type \( C_C \) connected to parent via \( R_C \), thus unfolding a new object along the containment hierarchy. During the unfolding step, all outgoing \( R_i \) incoming \( R_j \) and loop \( R_k \) references of new are extended (copied) to child.
- Finally, two rules addType \((C)\) and addReference \((R)\) refine uncertain \( \frac{1}{3} \) classes and references in the partial model. In the latter case, the rule requires that the types of the endpoints are already fixed appropriately.

Example 3.1. The refinement step \( P_0 \subseteq P_1 \) in Figure 2 introduces a new object \( t \) by applying the decision rule addChild \((C)\) (of Figure 5), which changes \( \frac{1}{3} \) values of transition \((t)\) and source \((t, e)\) to 1.

3.2 Unit Propagation Rules

Unit propagation rules are responsible for refining unspecified elements in a partial model without excluding any valid solution to simplify the partial model propagating the consequences of previously applied decision rules. Unit propagation rules are applied repeatedly right after a decision rule is applied. They are derived from the structural constraints (1)-(6) introduced in section 2.4. In general, unit propagation rules rewrite \( \frac{1}{3} \) elements to 0 (or 1) if a 1 (or 0) value would contradict to a constraint. Figure 6 illustrates (the scheme of) unit propagation rules used in this paper.

- Type hierarchy \((TH)\) is maintained by two rules: propTH \((C, C_s)\) propagates a positive \( \frac{1}{3} \) type predicate of \( C \) to a supertype \( C_s \); propTH \((C', C)\) rewrites a \( \frac{1}{3} \) type predicate value to 0 for type \( C \) if the object already has an incompatible type \( C' \) where \( C \) and \( C' \) do not have a common subclass (all classes are considered to be subclasses of themselves).
- Type compliance \((TC)\) is checked by two rules: propTC \((C,R)\) and propTC \((R,C)\). Both rules remove possible references if the types of the reference end-points are incompatible.
- Rule propMUL \((C)\) checks the upper multiplicity \((MUL)\) of a reference, and removes all possible additional links if the upper limit is reached.
- The Inverse \((INV)\) structural constraint is checked by two rules: propINV \((R,R)\) and propINV \((R,R)\) which set a \( R \) predicate value to 1 or 0 if an inverse \( R \) value is already set.
- To ensure containment hierarchy \((CON)\), first decision rules enforce that each non-root object has a parent. Then, additional possible incoming containment references are removed by unit propagation rule propCON \((R,R)\). Finally, propCON \((R)\) removes possible reference predicates that would create a loop in the containment hierarchy.

Decision and unit propagation rules are in close analogy with the DLL62 algorithm of traditional SAT-solvers [43]: values of variables are graph elements in our case (instead of Boolean values), complex graph predicates are evaluated (instead of conjunctive normal formuale), and the state space of graphs needs to be continuously stored during exploration (instead of a search tree).
Example 3.2. Refinement step $P_1 \sqsubseteq P_2$ is a result of a decision rule
addChild to set the $1/2$ value of target$(t, s)$ to 1 followed by a unit propagation rule propMULUpper(target) which aims to prevent the partial model from violating an upper multiplicity constraint by setting $1/2$ values of target$(t, e)$ and target$(t, new)$ to 0 as a direct consequence of the previous decision rule.

As a preprocessing step, decision and propagation rules are derived. Moreover, under-approximated (must) predicates are synthesized from graph predicates in accordance with [27] to detect unsolvable WF constraints early in a partial solution.

3.3 Exploration

During exploration (see Figure 7), refinement rules are repeatedly applied driven by an objective function and a rule selection strategy. As such, the size of partial models is continuously growing up to the designated scope, while the number of uncertainties and constraint violations in these partial models are decreasing to ensure that the process converges to consistent instance models. Now we discuss the steps of the model generation process.

(1) After initializing the search with an initial partial model, an unexplored decision rule is selected and applied to derive a new (refined) partial model along a partial model refinement step (section 2.3). The role of these refinement rules is in direct analogy with the decision steps in SAT solvers.

(2) After executing a decision rule, our framework executes all possible unit propagation rules on the partial solution to propagate the consequence of the decision, thus further refining the partial model. This step is again in direct analogy with SAT solvers, but it is carried out by incremental, change-driven model transformation rules [44] to improve efficiency.

(3) To prevent traversing the same (graph) state twice, a state code is calculated and stored for the new partial model by using graph isomorphism checks over graph shapes [30]. Graph shapes abstract from node identities, but they efficiently identify if two graphs can be distinguished by the neighborhood (i.e. incoming and outgoing edges) of a node.

(4) Had the new state been already explored, the partial model is dropped and a new refinement rule is applied (1).
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Figure 7: Exploration strategy for automated model generation

(5) If a new partial model is reached, then our framework checks if it satisfies all under-approximated (must) constraints by partial evaluation of these constraints [27] using an incremental graph query engine [28]. If an under-approximated constraint is violated by the partial model then an inconsistency is detected, thus the partial model can never be refined into a well-formed instance model so it can be dropped (1).

(6) Next the partial model is concretized into an instance model by removing all uncertainties and all the original WF constraints are checked on this candidate model by the incremental graph query engine to detect inconsistencies. If no violations are found, then the entire model is stored as a solution, and the exploration may terminate (if designated model scope is reached) or continue to find other solutions (1). Note that checking the original WF constraints on a concretized model guarantees the correctness of our solver.

(7) Finally, our framework approximates the distance for a solution by an objective function, adds the current partial model to the exploration path and continues refinement from with new unexplored decision refinement. For each partial model, this objective function is calculated as the sum of constraint violations and the number of missing objects wrt. a designated size.

For selecting the next match where a decision rule is to be applied, we use a combined exploration strategy with best-first search heuristic, backtracking, backjumping and random restarts in an advanced design space exploration framework [32]. The search selects the best candidate wrt. the objective function, then it randomly fires (with uniform distribution) an enabled decision rule, subsequently, it fires all possible unit propagation rules. If no further decision rules can be applied, then it backtracks to continue along the previous partial model candidate. At each step, the exploration may backtrack to the best model candidate found so far during the exploration. Finally, the search is occasionally restarted from a randomly chosen intermediate model candidate. Such a random restart is a common technique in SAT-solvers to avoid local optima.

Our framework operates directly over graph models and the exploration itself is driven on such a high-level. Thus, it combines the advantages of multiple advanced graph-based techniques with core SAT-solving techniques to tackle the scalability problems of existing mapping-based approaches:

- The approximated and the original of WF constraints are efficiently evaluated over partial models (in (5) and (6, B)) using incremental graph query evaluation techniques [28].
- Refinement rules are divided into decision (1) and unit propagation rules (2) as facilitated by core SAT-solving algorithms.
- Isomorphic states are detected during exploration (3) by combining shape analysis techniques [30, 31].
- Our framework has full control over the graph generation process (1, 7) via rule-based DSE techniques [32].

3.4 Soundness and Completeness

Starting from the abstract initial model, our decision rules guarantee the completeness of graph model generation [11], i.e. any concrete graph can possibly be derived within a bounded scope: Rule addRoot can derive any root objects, addChild is responsible for deriving new elements along the containment tree, addType can assign any types to an object while addReference can build any graphs by adding edges. However, efficient strategies are needed to initiate the execution of decision rules in proper order.

The soundness of graph model generation is guaranteed by checking all WF constraints on each generated candidate graph instance. As such we obtain at least the same guarantee as provided by Alloy, namely, if a consistent graph model exists within a given scope then our approach will derive it.

If no well-formed models are found within a given scope then Alloy provides no further details (stating that the problem may be inconsistent). In contrast, if the search is terminated in our approach with no valid refinements (i.e. all branches of the state space are closed) then the specification is surely inconsistent. This is primarily ensured by the fact that if an under-approximated predicate \( \phi \) has a match in a partial solution it cannot be refined to a valid model. Furthermore, we guarantee that any well-formed model (of a larger scope) can only be derived by refining existing partial models at the edge of the search horizon, i.e. our approach can incrementally continue exploration for a larger scope.

3.5 Strengths and Limitations

Our approach operates on connected sparse graphs with edges as relations (i.e. no edge identities and no parallel edges of a type) as underlying data model, which is less expressive than full relational algebra in case of Alloy. As a current technical limitation, our graph generation approach is showcased for EMF metamodels and models, which are widely used in industrial modeling tools, but it could be easily adapted to other graph formalisms. The expressive power of graph predicates used for capturing WF constraints is equivalent to first order logic with transitive closure over binary predicates.

Our solver efficiently handles complex structural graph constraints defined in first order logic with transitive closure. However, it includes only enumerations as attribute values but excludes strings, integers, etc. Such attribute values could be handled in the future by calling external solvers (e.g. SMT-solvers) during the exploration or as a post-processing step.

While the decision procedure of our graph solver provides stronger completeness guarantees than Alloy within a bounded scope, it does not provide an unsatisfiable core (i.e. minimal contradictory set of formulae) to highlight contradiction between WF constraints, which is supported by many SAT and SMT-solvers.
4 EXPERIMENTAL EVALUATION
We carried out an experimental evaluation of generating consistent instance models to address the following research questions:

RQ1 How does our graph solver scale (in time and model size) when generating consistent models of increasing size?

RQ2 How does our approach scale (in time and model size) compared to the widely used model finder Alloy [21]?

RQ3 How do the different steps of the exploration influence performance of the graph solver?

Selected DSLs for evaluation. As model generation for DSLs still lacks systematically constructed performance benchmarks, we evaluated our approach in the context of 6 test sets of four different domains. First (1) a small File System (FS) example was taken from the Alloy documentation [45]. Ecore, the meta-metamodeling language of EMF [34], has been used as a case study by different approaches [14, 16, 19, 24, 46, 47] using Alloy as a background solver for model generation purposes. Our measurements also cover two DSLs that were developed in industrial projects, namely, (3) Yakindu [33] and (4) Functional Architecture Model (FAM) developed for avionics [48]. Due to their complexity, domains (3) and (4) are split into two cases: we generate models first with only general metamodel constraints (w/o WF), and then in the presence of extra WF constraints (with WF). In addition to their direct practical relevance, these DSLs have already been used in the context of model generation in numerous papers [19, 24, 49] in the past.

Benchmarking setup. To measure scalability, we set up a time-out of 3 minutes for each model generation run with increasing model size. For each measurement point, model generation was executed 30 times and the median of the runs were taken. To account for warm-up effects and memory handling of the Java virtual machine, we added an extra 20 runs before the actual measurements and called the garbage collector explicitly between runs. As a baseline of comparison, Alloy Analyzer V4.2 (the latest stable version available at the Alloy download site) was used with two underlying SAT solver libraries: Sat4J (default in Alloy) and MiniSAT (recommended by Alloy). All measurements were executed on an average desktop computer with 12 GB heap size.

Experimental results. For RQ1 we evaluate the execution time of our approach for the four domains by increasing the target model size from 50 to 500 objects (with a step size of 50 new objects), and measuring (in Figure 8a–Figure 8d) the total execution time. As a key observation, our approach is able to generate consistent models with 500 elements for all four domains within 10 seconds for FAM version available at the Alloy download site) was used with two

open-sourced back-end SAT solver libraries: Sat4J and MiniSAT (recommended by Alloy). All measurements were executed on an average desktop computer with 12 GB heap size.

For RQ2, we compare model generation time of our Graph Solver with Alloy for small model sizes (from 5 to 50 objects, step size of 5 new objects) for the 6 test cases. As a baseline, we use a state-of-the-art EMF-to-Alloy mapping technique [16, 19, 24, 46, 47] and tool to obtain Alloy specifications for the Yakindu, FAM and Ecore domains, and the original Alloy specification is used for FS. According to the results (see Figure 8e–8j and Figure 8k), our approach scales much better as it generates models 1-2 orders of magnitude larger than Alloy could handle regardless of the back-end SAT solver which only had little impact on scalability. This is in line with previous measurements for Alloy in [19, 24]). Alloy dominantly ran out of memory when mapping input specification into a SAT problem which results in over 6 million variables and several million clauses when aiming to generate a model with 40-90 objects.

Note that the Alloy Analyzer is not primarily targeted to generate models but to check the consistency of a relational specification within a given scope and synthesize small counterexamples. In fact, Alloy had a smaller runtime for very small models, thus the warm-up cost of our graph solver is higher. However, our graph solver is able to generate much larger graph models even for all four domains with similar consistency guarantees as Alloy.

For RQ3, we also measured (in Figure 8a–Figure 8d) how much time is spent in different model generation by our graph solver (see Figure 7) such as initialization, partial model refinement, state encoding and exploration. The preprocessing phase (1.5 seconds for FS, 4 seconds for Ecore, 2 seconds for FAM and 4 seconds for Yakindu) is a one-time penalty which is proportional to the complexity of the metamodel and the WF constraints, thus we expect it to be negligible for model generation in case of other domains. Refinement is the dominant phase in the Yakindu and FS cases, while state encoding is dominant for Ecore. These results show that future research should primarily improve on refinement by providing a better transformation engine or refinement rules.

Quality of generated models. The quality of the generated models can be investigated from different aspects. To ensure correctness, all WF constraints were checked on each generated graph instance by using an external tool, the VIATRA graph query engine [50]. To assess diversity when a sequence of models are generated by the proposed graph solver (within similar scope), each model is guaranteed to be non-isomorphic by the state codes (Step (4) in Figure 7) or by a distance metric [51] in case of repeated calls to the solver, which offers increased diversity compared to Alloy [51]. Systematically assessing the realistic nature of models is a more complex task [13] which necessitates to obtain a large set of real models authored by engineers. Our graph solver ensures that only enumeration values can be isolated nodes in a graph otherwise all graphs are connected by default, i.e. all regular nodes are arranged into a containment hierarchy. In order to assure connectedness, Alloy requires an extra constraint to capture this concept, thus by default, our solution appears to be more realistic. In addition, [11, 13] contain an in-depth investigation of realistic models for the Yakindu domain. All generated models are available at [52].

Threats to validity. In order to strengthen internal validity, our experiments include an extensive warm-up phase prior to the actual measurements to decrease the fluctuation of runtime results caused by the JVM (instead of the natural fluctuation of solver runtimes). We used default setups for running Alloy and our graph solver, i.e. no extra hints and performance optimizations were provided in the two approaches. Domain-specific fine tunings may improve scalability in some cases but it would simultaneously decrease the general-purpose nature of these solvers.

To address external validity, our measurements cover 6 test cases including 3 industrial domains (Ecore, Yakindu, FAM) with complex
structural WF constraints, thus our experimental scalability results for our graph solver are likely generalizable to other domains of similar size and complexity within the limitations of section 3.5. In case of simple WF constraints, the difference between the performance characteristics of Alloy and our graph solver may be smaller. Since the performance of Alloy depends on the backend SAT-solver, our measurements already included two state-of-the-art solvers (SAT4J and MiniSAT). Thus the large scalability difference in the size of generated models can likely be attributed to our graph solver.

**Summary.** Our graph solver provides a strong platform for generating consistent graph models which are 1-2 orders of magnitude larger (with similar or higher quality) than derived by mapping based approaches using Alloy with an underlying SAT-solver. Such a difference in scalability can only partly be dedicated to our conceptually different approach which combines several advanced graph techniques to improve performance instead of fine-tuning a mapping. However, it likely indicates fundamental shortcomings of existing mapping based approaches. Based on in-depth profiling we suspect that representing each potential edge between a pair of nodes as a separate Boolean variable blows up the state space for sparse graph with only linear number of edges. Moreover, SAT-solvers have major problems in evaluating complex predicates over larger graph models [11] where graph query evaluation was particularly efficient [28].

## 5 RELATED WORK

We compare our solution with existing model generation techniques with respect to the characteristics of inputs and output results in Table 1. As for inputs, the model generation can be (1) initiated from a partial snapshot. Additionally, an approach may support (2) local and (3) global constraints as WF constraints: a local constraint accesses only the attributes and the outgoing references of an object, while a global constraint specifies a complex structural pattern. Local constraints are frequently attached to objects (e.g. in UML class diagrams), while global constraints are widely used in DSLs. As outputs, the generated models may (i) be metamodel-compliant (ii) satisfy all well-formedness constraints of the language. We consider a technique (iv) scalable if there is no hard limit on the model size (as demonstrated in the respective papers). Finally, a model generation
approach may be (v) decidable which always terminates with a result. Our comparison excludes approaches like which do not guarantee metamodel-compliance of generated instance models.

Logic Solver Approaches. Several approaches map a model generation problem into a logic problem, which is solved by underlying SAT/SMT-solvers. Complete frameworks with standalone specification languages include Formula [35] (which uses Z3 SMT-solver [23]), Alloy [36] (which relies on SAT solvers like Sat4j[53]) and Clafer [20] (using backend reasoners like Alloy).

There are several approaches aiming to validate standardized engineering models enriched with OCL constraints [54] by relying upon different back-end logic-based approaches such as constraint logic programming [17, 37, 55], SAT-based model finders (like Alloy) [14, 16, 19, 24, 46, 47, 56], CSP solvers [49] first-order logic [57], constructive query containment [58], higher-order logic [59, 60], or rewriting logics [61]. Partial snapshots and WF constraints can be uniformly represented as constraints [19]. Growing models are supported in [15, 24] for a limited set of constraints.

Scalability of all these approaches is limited to small models/counter-examples. Furthermore, these approaches are either a priori bounded (where the search space needs to be restricted explicitly) or they have decidability issues. As our approach is independent from the actual mapping of constraints to logic formulae, it could potentially be integrated with most of the above techniques by complementing or replacing the back-end solvers.

Uncertain Models. Partial models are similar to uncertain models, which offer a rich specification language [38, 62] amenable to analysis. They are more user-friendly language compared to 3-valued interpretations, but without handling additional WF constraints. Potential concrete models compliant with an uncertain model can be synthesized by the Alloy Analyzer [63], or refined by graph transformation rules [26]. Each concrete model is derived in a single step, thus their approach is not iterative like ours. Scalability analysis is omitted from these papers, but refinement of uncertain models is always decidable, thus termination is guaranteed.

Approaches like [64] analyze possible matches and executions of model transformation rules on partial models by using a SAT-solver (MathSAT4) or by automated graph approximation (referred to as “lifting”), or by graph query engines with [27]. As a key difference, our approach carries out model refinement while simultaneously evaluating graph query evaluation in an automated process.

Rule-based Instance Generators. A different class of model generators relies on rule-based synthesis driven by randomized, statistical or metamodel coverage information for testing purposes [65–67]. Some approaches support the calculation of effective metamodels [68], but partial snapshots are excluded from input specifications. Moreover, WF constraints are restricted to local constraints evaluated on individual objects while global constraints of a DSL are not supported. On the positive side, these approaches guarantee the diversity of models and scale well in practice [67, 69].

Iterative Approaches. Iterative approaches generate models by multiple solver calls. In [24] models are generated in by calling Alloy in multiple steps, where each step extends the instance model by a few elements. This approach scaled up to 50 object in 45s for generating valid Yakindu Statecharts. An iterative approach is proposed specifically for allocation problems in [70] based on Formula. Models are generated in two steps to increase diversity of results by first creating non-isomorphic submodels from an effective metamodel fragment followed by a problem-specific symmetry-breaking predicate [71] to ensure that no isomorphic models are generated twice while constraint checks are postponed to the very final stage. An iterative, counter-example guided synthesis is proposed for higher-order logic formulae in [22], but the size of derived models is fixed and smaller than 50 objects.

Symbolic Model Generation Technique Certain techniques use abstract (or symbolic) graphs for analysis purposes. A tableau-based reasoning method is proposed for graph properties [72–74], which automatically refine solutions based on well-formedness constraints, and handle state space in the form of a resolution tree. As a key difference, our approach refines possible solutions in the form of partial models, while [72, 73] resolves the graph constraints to a concrete solution. Therefore our approach is able to exploit efficient graph query engines to evaluate partial solutions, while those approaches are demonstrated on small (<10 objects) graphs or with no scalability evaluation at all.

Additionally, different approaches use abstract interpretation [29, 30], or predicate abstraction [31] for partial modeling. In those approaches, concretization is used to materialize (typically small) counter-examples for designated safety properties in a graph transformation system. However, their focus is to support model checking of abstract graph transformation systems, which can evaluate complex trajectories, but do not scale in the size of the models.

6 CONCLUSION AND FUTURE WORK

We presented a novel graph solver to generate consistent models of a designated size from a specification defined by a metamodel and a set of WF constraints. Unlike existing approaches which map the model generation problem to logic solvers (dominantly SAT or SMT-solvers), we address the model generation problem of consistent instances directly over graphs by combining advanced graph-based techniques with core SAT-solving rules. Our approach is fully automated and available as an open source tool [52].

Our experimental evaluation carried out over three industrial domains confirmed that our solver is able to synthesize consistent graph models with over 500-6000 objects with similar quality guarantees as provided by the popular relational model finder Alloy. The scalability of our solver is 1-2 orders of magnitude better than existing mapping based approaches using Alloy with a SAT-solver in the background. Such a difference in scalability likely indicates not only the benefits of our approach but also the inherent problems of mapping based model generation approaches deriving and solving a SAT problem. Thus our solver can serve as the output of mappings that previously used Alloy for model generation purposes. Altogether, our technique has the potential to be used in many testing scenarios including validation of large industrial DSLs, but its scalability is not yet sufficient for benchmarking purposes.

We have no precise claims on the diversity and realistic nature of our model generator. In the future, we aim to extend the framework to synthesize a set of graph models which are consistent, diverse and realistic at the same time. Numerous studies [24, 25, 51] have demonstrated that neither traditional SAT-solvers nor SMT-solvers provide sufficient diversity for their outcome when called repeatedly.


