Automatic Generation of System Test Cases from Use Case Specifications: an NLP-based Approach

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Abstract—Software testing plays a crucial role to ensure the conformance of software systems with their requirements. Exhaustive testing procedures are enforced by functional safety standards which mandate that each requirement be covered by system test cases. Test engineers need to identify all the representative test execution scenarios from requirements, determine the runtime conditions that trigger these scenarios, and finally provide the test input data that satisfy these conditions. Given that requirements specifications are typically large and often provided in natural language (e.g., use case specifications), the generation of system test cases tends to be expensive and error-prone.

In this paper, we present Use Case Modelling for System Tests Generation (UMTG), an approach that supports the generation of executable system test cases from requirements specifications in natural language, with the goal of reducing the manual effort required to generate test cases and ensuring requirements’ coverage. More specifically, UMTG automates the generation of system test cases based on use case specifications and a domain model for the system under test, which are commonly produced in many development environments. Unlike existing approaches, it does not impose strong restrictions on the template of use case specifications. It relies on recent advances in natural language processing to automatically identify test scenarios and to generate formal constraints that capture conditions triggering the execution of the scenarios, thus enabling the generation of test data. In two industrial case studies, UMTG automatically and correctly translated 95% of the use case specification steps into formal constraints required for test data generation; furthermore, it generated test cases that exercise not only all the test scenarios addressed by the manually implemented test suites but also some critical scenarios not previously considered by engineers.

Index Terms—System Test Case Generation; Use Case Specifications; Natural Language Processing; Semantic Role Labeling

INTRODUCTION

The complexity of embedded software in safety critical domains, e.g., automotive and avionics, has significantly increased over the years. System test cases in these domains are often manually derived from functional requirements in natural language (NL). One important motivation is to ensure traceability between requirements and system test cases. As a result, the definition of test cases is time-consuming and challenging, especially under time constraints and when there are frequent changes to requirements. In this context, automatic test generation not only reduces the cost of testing but also helps guarantee that test cases properly cover all requirements, a very important objective in safety critical systems and for the standards they need to comply with [1], [2].

The benefits of automatic test generation are widely acknowledged today and there are many proposed approaches in the literature [3]. In many cases [4], they require that system specifications be captured as UML behavioral models such as activity diagrams [5], statecharts [6], and sequence diagrams [7]. In modern industrial systems, these behavioral models tend to be complex and expensive if they are to be precise and complete enough to support test automation, and are thus often not part of development practice. There are techniques [8] [9] [10] that generate test models from NL requirements, but the generated models need to be manually edited to enable test automation, thus creating scalability issues. In approaches generating test cases directly from NL requirements [11] [12] [13] [14], test cases are not executable and often require significant manual intervention to provide test input data (e.g., they need additional formal specifications [14]). A few approaches can generate executable test cases including test input data directly from NL requirements specifications [15] [16], but they require that requirements specifications be written according to a controlled natural language (CNL). The input specifications are translated into formal specifications which are later used to automatically generate test input data (e.g., using constraint solving). The CNL language supported by these approaches is typically very limited (e.g., it enables the use of only a few verbs in requirements specifications), thus reducing their usability.

Our goal in this paper is to enable automated generation of executable test cases from NL requirements, with no additional behavioral modelling. Our motivation is to rely, to the largest extent possible, on practices that are already in place in many companies developing embedded systems, including our industry partner, i.e., IEE S.A. (in the following “IEE”) [17], with whom we performed multiple case studies reported in this paper. In many environments like IEE, development processes are use case-driven and
this strongly influences their requirements engineering and system testing practices. Use case specifications are widely used for communicating requirements among stakeholders and, in particular, facilitating communication with customers, while a domain model clarifies the terminology and concepts shared among all stakeholders and thus avoids misunderstandings.

In this paper, we propose, apply and assess Use Case Modelling for System Tests Generation (UMTG), an approach that generates executable system test cases by exploiting behavioral information in use case specifications. UMTG requires a domain model (e.g., a class diagram) of the system, which enables the definition of constraints that are used to generate test input data. Use case specifications and domain models are common in requirements engineering practice [18], such as our industry partner’s organisation in our case studies. Consistent with the objectives stated above, we avoid behavioral modelling (e.g., activity and sequence diagrams) by applying Natural Language Processing (NLP) to a more structured and analysable form of use case specifications, i.e., Restricted Use Case Modeling (RUCM) [8]. RUCM introduces a template with keywords and restriction rules to reduce ambiguity in requirements and to enable automated analysis of use case specifications. It enables the extraction of behavioral information by reducing imprecision and incompleteness in use case specifications. RUCM has been successfully applied in many domains (e.g., [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31]). It was previously evaluated through controlled experiments and showed to be usable and beneficial with respect to making use case specifications less ambiguous and more amenable to precise analysis and design [8]. In short, UMTG attempts to strike a balance among use cases legible by all stakeholders, sufficient information for automated system test generation, and minimal modeling.

UMTG employs NLP to build Use Case Test Models (UCTMs) from RUCM specifications. A UCTM captures the control flow implicitly described in an RUCM specification and enables the model-based identification of use case scenarios (i.e., the sequences of use case steps in the model). UMTG includes three model-based, coverage strategies for the generation of use case scenarios from UCTMs: branch, def-use, and subtype coverages. A list of textual pre, post and guard conditions in each use case specification is extracted during NLP. The extracted conditions enable UMTG to determine the constraint that test inputs need to satisfy to cover a test scenario. To automatically generate test input data for testing, UMTG automatically translates each extracted condition in NL into a constraint in the Object Constraint Language (OCL) [32] that describes the condition in terms of the entities in the domain model. UMTG relies on OCL since it is the natural choice for constraints in UML class diagrams. To generate OCL constraints, it exploits the capabilities of advanced NLP techniques (e.g., Semantic Role Labeling [33]). The generated OCL constraints are then used to automatically generate test input data via constraint solving using Alloy [34]. Test oracles are generated by processing the postconditions.

Engineers are expected to manually inspect the automatically generated OCL constraints, possibly make corrections and write new constraints when needed. Note that the required manual effort is very limited since, according to our industrial case studies, UMTG can automatically and correctly generate 95% of the OCL constraints. The accuracy of the OCL constraint generation is very high, since 99% of the generated constraints are correct. Executable test cases are then generated by identifying, using a mapping table, the test driver API functions to be used to provide the generated test input data to the system under test.

This paper extends our previous conference papers concerning the automatic generation of UCTMs [35] and the automatic generation of OCL constraints from specifications in natural language [36] published at the International Symposium on Software Testing and Analysis (ISSTA’15) and at the 11th IEEE Conference on Software Testing, Validation and Verification (ICST’18). An earlier version of our tool was demonstrated [37] at the 10th Joint meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on the Foundations of Software Engineering (ESEC/FSE’15). This paper brings together, refines, and extends the ideas from the above papers. Most importantly, we extend the expressivity of the OCL constraints automatically generated, introduce an Alloy-based constraint solving algorithm that solves the path conditions in OCL, and integrate the def-use and subtype coverage strategies not presented in our previous work. Finally, the paper further provides substantial new empirical evidence to support the scalability of our approach, and demonstrates its effectiveness using two industrial case studies (i.e., automotive embedded systems sold in the US and EU markets). Our contributions include:

- UMTG, an approach for the automatic generation of executable system test cases from use case specifications and a domain model, without resorting to behavioral modelling;
- an NLP technique generating test models (UCTMs) from use case specifications expressed with RUCM;
- an NLP technique generating OCL constraints from use case specifications for test input data generation;
- an algorithm combining UCTMs and constraint solving to automatically generate test input data, based on three different coverage criteria;
- a publicly available tool integrated as a plug-in for IBM DOORS and Eclipse, which generates executable system test cases from use case specifications;
- two industrial case studies from which we provide credible empirical evidence demonstrating the applicability, scalability and benefits of our approach.

This paper is structured as follows. Section 2 provides the background on the NLP techniques on which this paper builds the proposed test case generation approach. Section 3 introduces the industrial context of our case study to illustrate the practical motivations for our approach. Section 4 discusses the related work in light of our industrial needs. In Section 5, we provide an overview of the approach. From Section 6 to Section 12, we provide the details of the core technical parts of our approach. Section 13 presents our tool support for test case generation. Section 14 reports on the results of the empirical validation conducted with two industrial case studies. We conclude the paper in Section 15.
2 BACKGROUND

In this section, we present the background regarding the Natural Language Processing (NLP) techniques which we employ in UMTG. NLP refers to a set of procedures that extract structured information from documents written in NL. They are implemented as a pipeline that executes multiple analyses, e.g., tokenization, morphology analysis, and syntax analysis [38].

UMTG relies on five different NLP analyses: tokenization, named entity recognition, part-of-speech tagging, semantic role labeling (SRL), and semantic similarity detection. Tokenization splits a sentence into tokens based on a predefined set of rules (e.g., the identification of whitespaces and punctuation). Named entity recognition identifies and classifies named entities in a text into predefined categories (e.g., the names of cities). Part-of-speech (POS) tagging assigns parts of speech to each word in a text (e.g., noun, verb, pronoun, and adjective). SRL automatically determines the roles played by the phrases in a sentence [38], e.g., the actor performing an activity. Semantic similarity detection determines the similarity between two given phrases.

Tokenization, named entity recognition, and POS tagging are well known in the software engineering community since they have been adopted by several approaches integrating NLP [39], [40], [41], [42], [43], [44]. However, none of the existing software testing approaches relies on SRL or combines SRL with semantic similarity detection.

Section 2.1 provides a brief description of SRL, while we present the basics of semantic similarity detection in Section 2.2.

2.1 Semantic Role Labeling

SRL techniques are capable of automatically determining the roles played by words in a sentence. For the sentences The system starts and The system starts the database, SRL can determine that the actors affected by the actions are the system and the database, respectively. The component that is started coincides with the subject in the first sentence and with the object in the second sentence although the verb to start is used with active voice in both. This information cannot be captured by other NLP techniques like POS tagging or dependency parsing.

There are few SRL tools [45], [46], [47]. They are different in terms of models they adopt to capture roles. Semafor [45], [48] and Shalmaneser [46] are based on the FrameNet model, while the CogComp NLP pipeline (hereafter CNP [47]) uses the PropBank [49] and NomBank models [50], [51]. To the best of our knowledge, CNP is the only tool under active development, and is thus used in UMTG.

The tools using PropBank tag the words in a sentence with keywords (e.g., A0, A1, A2, AN) to indicate their roles. A0 indicates who performs an action, while A1 indicates the actor most directly affected by the action. For instance, the term The system is tagged with A1 in the sentence The system starts, while the term the database is tagged with A1 in the sentence The system starts the database. The other roles are verb-specific despite some commonalities, e.g., A2 which is often used for the end state of an action.

PropBank includes additional roles which are not verb-specific (see Table 1). They are labeled with general keywords and match adjunct information in different sentences, e.g., AM-NEG indicating negative verbs. NomBank, instead, captures the rules of nouns, adverbs, and adjectives in noun phrases. It uses the same keywords adopted by PropBank. For instance, using ProbBank, we identify that the noun phrase the watchdog counter plays the role A1 in the sentence The system resets the watchdog counter. Using NomBank, we obtain complementary information indicating the term counter is the main noun (tagged with A0), and the term watchdog is an attributive noun (tagged with A1).

PropBank does not help identify two different sentences describing similar concepts. In the sentences The system stopped the database, The system halted the database and The system terminated the database, an SRL tool using PropBank tags ‘the database’ with A1, indicating the database is the actor affected by the action. However, A1 does not indicate that the three sentences have similar meanings (i.e., the verbs are synonyms). To identify similar sentences, UMTG employs semantic similarity detection techniques.

2.2 Semantic Similarity Detection

For semantic similarity detection, we use the VerbNet lexicon [52], which clusters verbs that have a common semantics and share a common set of semantic roles into a total of 326 verb classes [53]. Each verb class is provided with a set of role patterns. For example, ⟨A1,V⟩ and ⟨A0,V,A1⟩ are two role patterns for the VerbNet class stop-55.4, which includes, among others, the verbs to stop, to halt and to terminate. In ⟨A1,V⟩, the sentence contains only the verb (V), and the actor whose state is altered (A1). In ⟨A0,V,A1⟩, the sentence contains the actor performing the action (A0), the verb (V), and the actor affected by the action (A1). Examples of these two patterns are the database stops and the system stops the database, respectively. UMTG uses VerbNet version 3.2 [53], which includes 272 verb classes and 214 subclasses where a class may have more than one subclass.

VerbNet uses a model different than PropBank. There is a mapping between PropBank and the model in VerbNet [54]. For simplification, we use only PropBank role labels in the paper. All the verbs in a VerbNet class are guaranteed to have a common set of role patterns, but are not guaranteed

| Identifier | Definition |
|------------|------------|
| A0         | Usually indicates who performs an action. |
| A1         | Usually indicates the actor most directly affected by the action. |
| A2         | With motion verbs, indicates a final state or a location. |

| Identifier | Definition |
|------------|------------|
| AM-ADV     | Adverbial modification. |
| AM-LOC     | Indicates a location. |
| AM-MNR     | Captures the manner in which an activity is performed. |
| AM-MOD     | Indicates a modal verb. |
| AM-NEG     | Indicates a negation, e.g., ‘no’. |
| AM-TMP     | Provides temporal information. |
| AM-PRD     | Secondary predicate with additional information about A1. |

1. The term phrase indicates a word or a group of consecutive words.
to be synonyms (e.g., the verbs repeat and halt in the VerbNet class step-55.4). We employ WordNet [55], a database of lexical relations, to cluster verbs with similar meaning.

3 Motivation and Context

The context for which we developed UMTG is that of safety-critical embedded software in the automotive domain. The automotive domain is a representative example of the many domains for which compliance with requirements should be demonstrated through documented test cases. For instance, ISO-26262 [2], an automotive safety standard, states that all system requirements should be properly tested by corresponding system test cases.

In this paper, we use the system BodySense$^\text{T.M}$ as one of the case studies and also to motivate and illustrate UMTG. BodySense is a safety-critical automotive software developed by IEE [17], a leading supplier of embedded software and hardware systems in the automotive domain. BodySense provides automatic airbag deactivation for child seats. It classifies vehicle occupants for smart airbag deployment. Using a capacitive sensor in the vehicle’s passenger seat, it monitors whether the seat is occupied, as well as classifying the occupant. If the passenger seat has a child in a child seat or is unoccupied, the system disables the airbag. For seats occupied by adult passengers, it ensures the airbag is deployed in the event of an accident. BodySense also provides occupant detection for the seat belt reminder function.

Table 2 gives a simplified version of a real test case for BodySense. Lines 1, 3, 5, 7, and 9 provide high-level operation descriptions, i.e., informal descriptions of the operations to be performed on the system. These lines are followed by the name of the functions that should be executed by the test driver along with the corresponding input and expected output values. For instance, Line 4 invokes the function SetBus with a value indicating that the test driver should simulate the presence of an adult on the seat (for simplicity assume that, when an adult is seated, the capacitance sensor positioned on a seat sends a value above 600 on the bus).

| Line | Operation | Inputs/Expectations |
|------|-----------|---------------------|
| 1    | Reset power and wait |  |
| 2    | ResetPower | Time=INIT_TIME |
| 3    | Set occupant status - Adult |  |
| 4    | SetBus | Channel = RELAY Capacitance = 601 |
| 5    | Simulate a nominal temperature |  |
| 6    | SetBus | Channel=RELAY Temperature = 20 |
| 7    | Check that and Adult has been detected on the seat, i.e. SeatBeltReminder status is Occupied and AirBagControl status is Occupied. |  |
| 8    | ReadAndCheckBus | D0=OCCUPIED D1=OCCUPIED |
| 9    | Check that the AirBagControl has received new data. |  |
| 10   | CheckAirbagPin | 0x010 |

Exhaustive test cases needed to validate safety-critical, embedded software are difficult both to derive and maintain because requirements are often updated during the software lifecycle (e.g., when BodySense needs to be customized for new car models). For instance, the functional test suite for BodySense is made of 192 test cases which include a total of 4707 calls to test driver functions and around 21000 variable assignments. The effort required to specify test cases for BodySense is overwhelming. Without automated test case generation, such testing activity is not only expensive but also error prone.

Within the context of testing safety-critical, embedded software such as BodySense, we identify three challenges that need to be considered for the automatic generation of system test cases from functional requirements:

Challenge 1: Feasible Modelling. Most of the existing automatic system test generation approaches are model-based and rely upon behavioral models such as state, sequence or activity diagrams (e.g., [5], [56], [57], [58], [59]). In complex industrial systems, behavioral models that are precise enough to enable test automation are so complex that their specification cost is prohibitive and the task is often perceived as overwhelming by engineers. To evaluate the applicability of behavioral modelling on BodySense, we asked the IEE engineers to specify system sequence diagrams (SSDs) for some of the use cases of BodySense. For example, the SSD for the use case Identify initial occupancy status of a seat included 74 messages, 19 nested blocks, and 24 references to other SSDs that had to be derived. This was considered too complex for the engineers and required significant help from the authors of this paper, and many iterations and meetings. Our conclusion is that the adoption of behavioral modelling, at the level of detail required for automated testing, is not a practical option for system test automation unless detailed behavioral models are already used by engineers for other purposes, e.g., software design.

Challenge 2: Automated Generation of Test Data. Without behavioral modelling, test generation can be driven only by existing requirements specifications in NL, which complicates the identification of the test data (e.g., the input values to send to the system under test). Because of this, most of the existing approaches focus on the identification of test scenarios (i.e., the sequence of activities to perform during testing), and ask engineers to manually produce the test data. Given the complexity of the test cases to be generated (recall that the BodySense test suite includes 21000 variable assignments), it is extremely important to automatically generate test data, and not just test scenarios.

Challenge 3: Deployment and Execution of the Test Suite. Execution of test cases for a system like BodySense entails the deployment of software under test on the target environment. To speed up testing, test case execution is typically automated through test scripts invoking test driver functions. These functions simulate sensor values and read computed results from a communication bus. Any test generation approach should generate appropriate function calls and test data in a processable format for the test driver. For instance, the test drivers in BodySense need to invoke driver functions (e.g., SetBus) to simulate seat occupancy.

In the rest of this paper, we focus on how to best address these challenges in a practical manner, in the context of use case-driven development of embedded systems.
4 Related Work

In this section, we cover the related work across three categories in terms of the challenges we presented in Section 3.

Feasible Modelling. Most of the system test case generation approaches require that system requirements be given in UML behavioral models such as activity diagrams (e.g., [5], [60], [61], [62]), statecharts (e.g., [6], [56], [63], [64]), and sequence diagrams (e.g., [7], [57], [65], [66]). For instance, Nebut et al. [7] propose a use case driven test generation approach based on system sequence diagrams. Gutierrez et al. [67] introduce a systematic process based on model-driven engineering paradigm to automate the generation of system cases from functional requirements given in activity diagrams. Briand and Labiche [57] use both activity and sequence diagrams to generate system test cases. While sequential dependencies between use cases are extracted from an activity diagram, sequences in a use case are derived from a system sequence diagram. In contrast, UMTG needs only use case specifications complemented by a domain model and OCL constraints. In addition, UMTG is able to automatically generate most of the OCL constraints from use case specifications.

There are techniques generating behavioral models from NL requirements [8], [9], [10], [68], [69], [70]. Some approaches employ similar techniques in the context of test case generation. For instance, Frohlich and Link [71] generate test cases from UML statecharts that are automatically derived from use cases. De Santiago et al. [72] provide a similar approach to generate test cases from statecharts derived from NL scenario specifications. Riebisch et al. [73] describe a test case generation approach based on the semi-automated generation of state diagrams from use cases. Katara and Kervinen [74] propose an approach which generates test cases from labeled transition systems that are derived from use case specifications. Sarmiento et al. [12], [13] propose another approach to generate test scenarios from a restricted form of NL requirements. The approach automatically translates restricted NL requirements into executable Petri-Net models; the generated Petri-Nets are used as input for test scenario generation. Soeken et al. [75] employ a statistical parser [76] and a lexical database [55] to generate sequence diagrams from NL scenarios, which are later used to semi-automatically generate test cases. Hartmann et al. [77] provide a test-generation tool that creates a set of test cases from UML models that are manually annotated and semi-automatically extracted from use case specifications. All these approaches mentioned above have two major drawbacks in terms of feasible modelling: (i) generated test sequences have to be edited, corrected, and/or refined and (ii) test data have to be manually provided in the generated test models. In contrast, UMTG not only generates sequences of function calls that do not need to be modified but also generates test data for function calls.

Kesserwan et al. [78] provide a model-driven testing methodology that supports test automation based on system requirements in NL. Using the methodology, the engineer first specifies system requirements according to Cockburn use case notation [79] and then manually refines them into Use Case Map (UCM) scenario models [80]. In addition, test input data need to be manually extracted from system requirements and modelled in a data model. UMTG requires that system requirements be specified in RUCM without any further refinement. Text2Test [40], [81] extracts control flow implicitly described in use case specifications, which can be used to automatically generate system test cases. The adaptation of such an approach in the context of test case generation has not been investigated.

Automated Generation of Test Data. The ability to generate test data, and not just abstract test scenarios, is an integral part of automated test case generation [82]. However, many existing NL-based test case generation approaches require manual intervention to derive test data for executable test cases (e.g., [11], [12], [13], [78]), while some other approaches focus only on generating test data (e.g., [83], [84], [85], [86], [87], [88]). For instance, Zhang et al. [11] generate test cases from RUCM use cases. The generated test cases cannot be executed automatically because they do not include test data. Sarmiento et al. [12] generate test scenarios without test data from a restricted form of NL requirements specifications.

Similar to UMTG, Kaplan et al. [89] propose another approach, i.e., Archetest, which generates test sequences and test inputs from a domain model and use case specifications together with invariants, guardconditions and postconditions. Yue et al. [20] propose a test case generation tool (aToucan4Test), which takes RUCM use case specifications annotated with OCL constraints as input and generates automatically executable test cases. These two test generation approaches require that conditions and constraints be provided by engineers to automatically generate test data. In contrast, UMTG can automatically generate, from use case specifications, most of the OCL constraints that are needed for the automated generation of test data.

In some contexts, test data might be simple and consist of sequences of system events without any associated additional parameter value. This is the case of interaction test cases for smartphone systems, which can be automatically generated by the approach proposed by De Figueiredo et al. [15]. The approach processes use case specifications in a custom use case format to derive sequences of system operations and events. UMTG complements this approach with the generation of parameter values, which is instead needed to perform functional testing at the system level.

Carvalho et al. [90] generate executable test cases for reactive systems from requirements written according to a restricted grammar and dictionary. The proposed approach effectively generates test data but has two main limitations: (i) the underlying dictionary may change from project to project (e.g., the current version supports only seven verbs of the English language), and (ii) the restricted grammar may not be suitable to express some system requirements (e.g., the approach does not tackle the problem of processing transitive and intransitive forms of the same verb). In contrast, UMTG does not impose any restricted dictionary or grammar but simply relies on a use case format, RUCM, which can be used to express use cases for different kinds of systems. RUCM does not restrict the use of verbs or nouns in use case steps and thus does not limit the expressiveness of use case specifications. Furthermore, the RUCM keywords are used to specify input and output steps but do not constrain internal steps or condition sentences (see Section 6).
Finally, by relying on SRL and VerbNet, UMTG provides guarantees on the correct generation of OCL constraints (see Section 9), without restricting the writing of sentences (e.g., it supports the use of both transitive and intransitive forms).

Other approaches focus on the generation of class invariants and method pre/postconditions, from NL requirements, which, in principle, could be used for test data generation (e.g., [41], [42], [91]). Pandita et al. [91] focus only on API descriptions written according to a CNL. NL2OCL [41] and NL2Alloy [42], instead, process a UML class diagram and NL requirements to derive class invariants and method pre/postconditions. These two approaches rely on an ad-hoc semantic analysis algorithm that uses information in the UML class diagram (e.g., class and attribute names) to identify the roles of words in sentences. They rely on the presence of specific keywords to determine passive voices and to identify the operators to be used in the generated invariants and conditions. Their constraint generation is rule-based, but they do not provide a solution to ease the processing of a large number of verbs with a reasonable number of rules. Thanks to the use of Wordnet synsets and VerbNet classes (see Section 9), UMTG can process a large set of verbs with few rules to generate OCL constraints.

Though NL2OCL [41] and NL2Alloy [42] are no longer available for comparison, they seem more useful for deriving class invariants including simple comparison operators (i.e., the focus of the evaluation in [41]), rather than for generating pre/postconditions of the actions performed by the system (i.e., the focus of UMTG). Pre/postconditions are necessary for deriving test data in our context.

**Deployment and Execution of the Test Suite.** The generation of executable test cases impacts on the usability of test generation techniques. In code-based approaches (e.g., [92], [93]), the generation of executable test cases is facilitated by the fact that it is based on processing the interfaces used during the test execution (e.g., test driver API).

In model-based testing, the artefacts used to drive test generation are software abstractions (e.g., UML models). In this context, the generation of executable test cases is usually based on adaptation and transformation approaches [94]. The adaptation approaches require the implementation of a software layer that, at runtime, matches high-level operations to software interfaces. They support the execution of complex system interactions (e.g., they enable feedback-driven, model-based test input generation [95]). The transformation approaches, instead, translate an abstract test case into an executable test case by using a mapping table containing regular expressions for the translation process. They require only abstract test cases and a mapping table, while the adaptation approaches need communication channels between the software under test and the adaptation layer, which might not be possible for many embedded systems. Therefore, UMTG uses a mapping table that matches abstract test inputs to test driver function calls.

Model Transformation by Example (MTBE) approaches aim to learn transformation programs from source and target model pairs supplied as examples (e.g., [96], [97], [98]). These approaches search for a model transformation in a space whose boundaries are defined by a model transformation language and the source and target metamodels [99]. Given the metamodels of abstract and executable test cases,
Once the domain model is complete, most of the OCL constraints are automatically generated from the extracted conditions (Step 5). The engineer manually writes the few OCL constraints that cannot be automatically generated (Step 6). UMTG further processes the use cases with the OCL constraints to generate a use case test model for each use case specification (Step 7). A use case test model is a directed graph that explicitly captures the implicit behavioral information in a use case specification.

UMTG employs constraint solving for OCL constraints to generate test inputs associated with use case scenarios (Step 8). We use the term use case scenario for a sequence of use case steps that starts with a use case precondition and ends with a postcondition of either a basic or alternative flow. Test inputs cover all the paths in the testing model, and therefore all possible use case scenarios.

The engineer provides a mapping table that maps high-level operation descriptions and test inputs to the concrete driver functions and inputs that should be executed by the test cases (Step 9). Executable test cases are automatically generated through the mapping table (Step 10). If the test infrastructure and hardware drivers change in the course of the system lifespan, then only this table needs to change.

The rest of the paper explains the details of each step in Fig. 1, with a focus on how we achieved our automation objectives.

## 6 Elicitation of Requirements

Our approach starts with the elicitation of requirements in RUCM (Step 1 in Fig. 1). RUCM has a template with keywords and restriction rules to reduce ambiguity in use case specifications [8]. Since it was not originally designed for test generation, we introduce some extensions to RUCM.

Table 3 provides a simplified version of three *BodySense* use case specifications in RUCM (i.e., Identify Occupancy Status, Self Diagnosis, and Classify Occupancy Status). We omit some basic information such as actors and dependencies.

The use cases contain basic and alternative flows. A basic flow describes a main successful scenario that satisfies stakeholder interests. It contains a sequence of steps and a postcondition (Lines 5-11). A step can describe one of the following activities: an actor sends data to the system (Lines 5 and 39); the system validates some data (Line 7); the system replies to an actor with a result (Line 9); the system sets the occupant class (Line 15). The inclusion of another use case is specified as a step using the keyword **INCLUDE USE CASE** (Line 6). All keywords are written in capital letters for readability.

The keyword **VALIDATES THAT** indicates a condition (Line 7) that must be true to take the next step (Line 8), otherwise an alternative flow is taken (Line 20).

Alternative flows describe other scenarios than the main one, both success and failure. An alternative flow always depends on a condition. In RUCM, there are three types of alternative flows: **specific**, **bounded** and **global**. For specific and bounded alternative flows, the keyword **RFS** is used to refer to one or more reference flow steps (Lines 21 and 13). A specific alternative flow refers to a step in its reference flow (Line 21). A bounded alternative flow refers to more than one step in the reference flow (Line 13) while a global alternative flow refers to any step in the reference flow.

### 6.1 Use Case Specifications

| Step | Description |
|------|-------------|
| 1.   | **Use Case** Identify Occupancy Status |
| 1.1  | **Precondition** |
| 1.1.1| The system has been initialized. |
| 1.2  | **Basic Flow** |
| 1.2.1| The system sends the occupant class to AirbagControlUnit. |
| 1.2.2| The system sends the occupant class for seat belt reminder to SeatBeltControlUnit. |
| 1.3  | **Specific Alternative Flow** |
| 1.3.1| The system sends the occupant class to AirbagControlUnit. |
| 1.3.2| The system validates the capacitance is above 600. |
| 1.3.3| The previous occupant class for seat belt reminder has been set to SeatBeltControlUnit. |
| 1.4  | **Specific Alternative Flow** |
| 1.4.1| The system sends the previous occupant class for seat belt reminder to SeatBeltControlUnit. |
| 1.5  | **Basic Flow** |
| 1.5.1| The system sets the occupant class for airbag control to Init. |
| 1.5.2| The system sets the occupant class for seat belt reminder to Init. |
| 1.5.3| The system sets the occupant class for airbag control to Empty. |
| 1.5.4| The system sets the occupant class for seat belt reminder to Empty. |
| 1.5.5| The system sets self diagnosis as completed. |
| 1.5.6| The system sets the occupant class for seat belt reminder to Occupied. |
| 1.5.7| The system sets the occupant class for airbag control to Occupied. |
| 1.5.8| Postcondition: An adult has been detected on the seat. |
| 1.6  | **Specific Alternative Flow** |
| 1.6.1| The system sets the occupant class for airbag control to Empty. |
| 1.6.2| The system sets the occupant class for seat belt reminder to Empty. |
| 1.6.3| Postcondition: An adult has been detected on the seat. |
| 1.6.4| **Exit** |
| 1.7  | **Precondition** |
| 1.7.1| The system has been initialized. |
| 1.7.2| The system sets the occupant class for airbag control to Empty. |
| 1.7.3| The system sets the occupant class for seat belt reminder to Empty. |
| 1.7.4| Postcondition: A child has been detected on the seat. |
| 1.7.5| **Exit** |
| 1.7.6| **Postcondition**: The seat has been recognized as being empty. |

Specific alternative flows begin with the keyword **IF .. THEN** for the condition under which the alternative flow is taken (Line 14). Specific alternative flows do not necessarily begin with **IF .. THEN** since a condition...
may already be indicated in its reference flow step (Line 7). The alternative flows are evaluated in the order they appear in the specification.

We introduce extensions into RUCM regarding the IF conditions, the keyword EXIT, and the way input/output messages are expressed. UMTG prevents the use of multiple branches within the same use case path [18], thus enforcing the adoption of IF conditions only as a means to specify guard conditions for alternative flows. UMTG introduces the new keywords SENDS ... TO and REQUESTS ... FROM for the system-actor interactions. Depending on the subject of the sentence, the former indicates either that an actor provides an input to the system (Line 5) or that the system provides an output to an actor (Line 9). The latter is used only for inputs, and indicates that the input provided by the actor has been requested by the system (Line 39). UMTG introduces the keyword EXIT to indicate use case termination under alternative valid execution conditions (Line 69 describing the case of a child being detected on a seat). The keyword EXIT complements the keyword ABORT, which is used to indicate the abnormal use case termination (Line 17).

7 NLP PIPELINE FOR UMTG

We implemented an NLP application to extract the information required for three UMTG steps in Fig. 1: evaluate the model completeness, generate OCL constraints, and generate the use case test model.

The NLP application is based on the GATE workbench [100], an open source NLP framework, and implements the NLP pipeline in Fig. 2. The pipeline includes both default NLP components (grey) and components built to process use case specifications in RUCM (white). The Tokenizer splits the use cases into tokens. The Gazetteer identifies the RUCM keywords. The POS Tagger tags the tokens according to their nature: verb, noun, and pronoun. The pipeline is terminated by a set of transducers that tag blocks of words with additional information required by the three UMTG steps. The transducers integrated in UMTG (1) identify the kinds of RUCM steps (i.e., output, input, include, condition and internal steps), (2) distinguish alternative flows, and (3) detect RUCM references (i.e., the RFS keyword), conditions, and domain entities in the use case steps.

Fig. 3 gives an example transducer for condition steps. The arrow labels in higher case represent the transducer’s input, i.e., tags previously identified by the POS tagger, the gazetteer or other transducers. The italic labels show the tags assigned by the transducer to the words representing the transducer’s input. Fig. 4 gives the tags associated with the use case step in Line 60 of Table 3 after the execution of the transducer in Fig. 3. In Fig. 4, multiple tags are assigned to the same blocks of words. For example, the noun phrase ‘the capacitance’ is tagged both as a domain entity and as part of a condition.

8 EVALUATION OF THE DOMAIN MODEL COMPLETENESS

The completeness of the domain model is important to generate correct and complete test inputs. UMTG automatically identifies missing domain entities to evaluate the model completeness (Step 3 in Fig. 1). This is done by checking correspondences between the domain model elements and the domain entities identified by the NLP application.

Fig. 5. Part of the domain model for BodySense.

Domain entities in a use case may not be modelled as classes but as attributes. Fig. 5 shows a simplified excerpt of the domain model for BodySense where the domain entities ‘occupant class for airbag control’ and ‘occupant class for seat belt reminder’ are modelled as attributes of the class OccupancyStatus. UMTG follows a simple yet effective solution to check entity and attribute names. For each domain entity identified through NLP, UMTG generates an entity name
by removing all white spaces and by putting all first letters following white spaces in capital. For instance, the domain entity 'occupant class for airbag control' becomes 'OccupantClassForAirbagControl'. UMTG checks the string similarity between the generated entity names and the domain model elements. Engineers are asked to correct their domain model and use case specifications in the presence of confirmed mismatches.

9 Generation of OCL Constraints

To identify test inputs via constraint solving, UMTG needs to derive OCL constraints that capture (1) the effect that the internal steps have on the system state (i.e., the postconditions of the internal steps), (2) the use case preconditions, and (3) the conditions in the condition steps. For instance, for the basic flow of the use case Classify Occupancy Status (Lines 57 to 63 in Table 3), we need a test input that satisfies the condition ‘the capacitance is above 600’ (Line 60).

As part of UMTG, we automate the generation of OCL constraints (Step 5 in Fig. 1). Using some predefined constraint generation rules (hereafter transformation rules), UMTG automatically generates an OCL constraint for each precondition, internal step and condition step identified by the transducers in Fig. 2. The generated constraint captures the meaning of the NL sentence in terms of the concepts in the domain model. Table 4 shows some of the OCL constraints generated from the use case specifications in our case studies in Section 14.

Section 9.1 summarizes our assumptions for the generation of OCL constraints. Section 9.2 describes the constraint generation algorithm. In Section 9.3, we discuss the correctness and generalizability of the constraint generation.

9.1 Working Assumptions

The constraint generation is enabled by three assumptions.

Assumption 1 (Domain Modelling). There are domain modelling practices common for embedded systems:

A1.1 Most of the entities in the use case specifications are given as classes in the domain model.

A1.2 The names of the attributes and associations in the domain model are usually similar with the phrases in the use case specifications.

A1.3 The attributes of domain entities (e.g., Watchdog.counter in Fig. 5) are often specified by possessive phrases (i.e., genitives and of-phrases such as of the watchdog in S12 in Table 4) and attributive phrases (e.g., watchdog in S13) in the use case specifications.

A1.4 The domain model often includes a system class with attributes that capture the system state (e.g., BodySense in Fig. 5).

A1.5 Additional domain model classes are introduced to group concepts that are modelled using attributes.

A1.6 Discrete states of domain entities are often captured using either boolean attributes (e.g., isAccessible in Fig. 5), or attributes of enumeration types (e.g., BuildCheckStatus::Passed in Fig. 5).

To ensure that Assumption 1 holds, UMTG iteratively asks engineers to correct their models (see Section 8). With Assumption 1, we can rely on string similarity to select the terms in the OCL constraints (i.e., classes and attributes in the domain model) based on the phrases appearing in the use case steps. String similarity also allows for some degree of flexibility in naming conventions.

Assumption 2 (OCL constraint pattern). The conditions in the use case specifications of embedded systems are typically simple and capture information about the state of one or more domain entities (i.e., classes in the domain model). For instance, in BodySense, the preconditions and condition steps describe safety checks ensuring that the environment has been properly set up (e.g., S3 in Table 4), or that the system input has been properly obtained (e.g., S5), while the internal steps describe updates on the system state (e.g., S2). They can be expressed in OCL using the pattern in Fig. 6, which captures assignments, equalities, and inequalities.

The constraint patterns include an entity name (ENTITY in Fig. 6), an optional selection part (_SELECTION), and a query element (QUERY). The query element can be specified according to three distinct sub-patterns: FORALL, EXISTS and COUNT. FORALL specifies that a certain expression (i.e., EXPRESSION) should hold for all the instances i of the given entity; EXISTS indicates that the expression should hold for at least one of the instances. COUNT is used when the expression should hold for a certain number of instances. Examples of these three query elements are given in the OCL constraints generated for the sentences S4, S10, and S11 in Table 4, respectively. In the pattern, EXPRESSION contains a left-hand side variable (hereafter lhs-variable), an OCL operator, and a right-hand side term (hereafter rhs-term), which is either another variable or a literal. The lhs-variable indicates an attribute of the entity whose state is captured by the constraint, while the rhs-term captures the state information (e.g., the value expected to be assigned to an attribute). The optional selection part selects a subset of all the available instances of the given entity type based on their subtype; an example is given in the OCL constraint for S6 in Table 4.

Assumption 3 (SRL). The SRL toolset (the CNP tool in our implementation) identifies all the semantic roles in a sentence that are needed to correctly generate an OCL constraint. Our transformation rules use the roles to correctly select the domain model elements to be used in the OCL constraint (see Section 9.2).
### 9.2 The OCL Generation Algorithm

We devised an algorithm that generates an OCL constraint from a given sentence in NL (see Fig. 7). We first execute the SRL toolset (the CNP tool) to annotate the sentence with the SRL roles (Line 2 in Fig. 7). We select and apply the transformation rules based on the verb in the sentence (Lines 3 to 7). The same rule is applied for all the verbs that are synonyms and that belong to the same VerbNet class. In addition, we have a special rule, hereafter we call *any-verb transformation rule*, that is shared by many verb classes. Each rule returns a candidate OCL constraint with a score assessing how plausible is the constraint (Section 9.2.5). We select the constraint with the highest score (Line 10).

For each verb, we classify the SRL roles into: (i) *entity role* indicating the entity whose state needs to be captured by the constraint, and (ii) *support roles* indicating additional information such as literals in the rhs-terms (see Fig. 6).

We implemented our transformation rules according to the pairs *(entity role, {support roles})* we extracted from the VerbNet role patterns. The role patterns provide all valid role combinations appearing with a verb.

Table 5 shows the role pairs for some of our transformation rules. For example, the verb ‘to erase’ has two VerbNet role patterns *(A0, V, A1) and *(A0, V, A1, A2)* where V is the verb, and A1 and A2 are the SRL roles. The first pattern represents the case in which an object is erased (e.g., the measured voltage in S7 in Table 4), while, in the second one, an object is removed from a source (e.g., the occupant class being removed from the airbag control unit in S8). The transformation rule for the verb ‘to erase’ has thus two role pairs: *(A1, null)* and *(A2, {A1})* (see Rule 4 in Table 5). Each transformation rule might be associated with multiple support roles; this is the case of the verb ‘to set’ whose role pair *(A1, {A2, AM-LOC})* appears in Rule 3 in Table 5.

Each transformation rule performs the same sequence of activities for each pair *(entity role, {support role})* (see Fig. 8). A rule first identifies the candidate lhs-variables (Line 3 in Fig. 8), and then builds a distinct OCL constraint for each lhs-variable identified (Lines 5 to 15). Finally, it returns the OCL constraint with the highest score (Line 18).

In Sections 9.2.1 to 9.2.5, we give the details of the algorithm in Fig. 8, i.e., identifying the lhs-variables (Line 3), selecting the rhs-terms (Line 6) and the OCL operators (Line 7), and scoring the constraints (Line 12).

#### 9.2.1 Identification of the Left-hand Side Variables

To identify the lhs-variables, the transformation rules follow an algorithm using the string similarity between the names of the domain model elements (i.e., the classes, attributes and associations) and the phrases in the use case step tagged with the entity and support roles (see Fig. 9). Based on Assumption 3, we expect that the phrase tagged with the entity role provides part of the information to identify the lhs-variable (e.g., *itsNVM* in S3 in Table 4), while the
Based on A1.1, a domain model class best matches the phrase tagged with the entity role (Line 6). Based on A1.5, we recursively traverse the associations starting from this class to identify the related attributes that best match the phrases tagged with the support roles (Lines 8-11). The matching attribute might be indirectly related to the starting class. We give a higher priority to the directly related attributes. Therefore, the score of the matching attribute is divided by the number of traversed associations (Line 9). We add the best matching attributes to the list of the lhs-variables (Line 10). For example, for S2 in Table 4, the lhs-variable BodySense.itsNVM is in the list of the lhs-variables because it terminates with NVM tagged with A1 (i.e., the entity role).

Based on A1.1 and A1.2, we look for the domain model class that best matches the phrase tagged with the entity role (Line 6). Based on A1.5, we recursively traverse the associations starting from this class to identify the related attributes that best match the phrases tagged with the support roles (Lines 8-11). The matching attribute might be indirectly related to the starting class. We give a higher priority to the directly related attributes. Therefore, the score of the matching attribute is divided by the number of traversed associations (Line 9). We add the best matching attributes to the list of the lhs-variables (Line 10). For example, for S2 in Table 4, the lhs-variable BodySense.itsOccupancyStatus.occupantClassForAirbagControl is identified by traversing the association itsOccupancyStatus from the system class BodySense. Its similarity score is 0.5 because one association has been traversed (itsOccupancyStatus) and there is an exact match between the attribute name and the noun phrase tagged with A1.

We further refine the lhs-variables with a complex type (i.e., a class or a data type). For each attribute and association in the list of the lhs-variables, we traverse the related associations to identify the attributes and associations that best match the phrases tagged with the support roles (Lines 14 to 17). In S3, BodySense.itsNVM is refined to BodySense.itsNVM.itsAccessible since the class NVM has a boolean attribute (itsAccessible) with a name similar to the phrase tagged with AM-PRD (accessible).

Based on A1.3, when the phrase tagged with the entity role includes a possessive or attributive phrase, we look for attributes/associations in the domain model that reflect the relation between the possessive/attributive phrase and the main phrase in the entity role phrase (e.g., the watchdog and counter in sentence S12 in Table 4). We rely on the NomBank tags generated by CNP to identify the main phrase and the possessive/attributive phrases. In the domain model, the main phrase usually best matches an attribute/association that belongs to an owning entity. The owning entity is either (1) a class that best matches the possessive/attributive phrase or (2) a class referred by an

| Rule ID | Verb | Entity roles | Support roles |
|---------|------|--------------|---------------|
| 1       | to be| A1           | AM-PRD, AM-MNR, AM-LOC |
| 2       | to enable | A1     | AM-MNR |
| 3       | to set | A1     | A2, AM-LOC |
| 4       | to erase | A1     | A1 |
| 5       | any verb | A1     | AM-PRD, Verb |

Fig. 8. The algorithm followed by each transformation rule.

Fig. 9. The algorithm to identify lhs-variables.

The algorithm is influenced by domain modelling practices (Assumption 1). Assumptions A1.1 and A1.2 influence the criteria to select terms for the OCL constraint based on phrases in the use case step. Assumptions A1.1 - A1.5 influence the order in which noun phrases are processed.

Based on A1.1, a domain model class best matches a phrase when its name shows the highest similarity with the phrase. To identify the matching classes and phrases, we employ the Needleman-Wunsch string alignment algorithm [102], which maximizes the matching between characters with some degree of discrepancy. In the context of embedded software development, attributes and associations often correspond to acronyms (e.g., RAM, ROM, and NVM) which are short with a small alignment distance, but have different meanings. Therefore, we do not use the string alignment algorithm for attributes and associations. Based on A1.2, an attribute or association in the domain model best matches a given phrase (i) if it is a prefix or a postfix of the phrase, (ii) if it starts or ends with the phrase, or (iii) if it is a synonym or an antonym of the phrase. We ignore spaces and articles in the phrases. For each matching element, we compute a similarity score as the portion of matching characters.

The algorithm iterates over each phrase tagged with an entity role (Lines 2-3 in Fig. 9). Based on A1.2 and A1.4, we have to the list of the lhs-variables the system class attributes and associations that best match the phrase (Lines 4-5). In S3 in Table 4, BodySense.itsNVM is in the list of the lhs-variables because it terminates with NVM tagged with A1 (i.e., the entity role).

Based on A1.1 and A1.2, we look for the domain model class that best matches the phrase tagged with the entity role (Line 6). Based on A1.5, we recursively traverse the associations starting from this class to identify the related attributes that best match the phrases tagged with the support roles (Lines 8-11). The matching attribute might be indirectly related to the starting class. We give a higher priority to the directly related attributes. Therefore, the score of the matching attribute is divided by the number of traversed associations (Line 9). We add the best matching attributes to the list of the lhs-variables (Line 10). For example, for S2 in Table 4, the lhs-variable BodySense.itsOccupancyStatus is identified by traversing the association itsOccupancyStatus from the system class BodySense. Its similarity score is 0.5 because one association has been traversed (itsOccupancyStatus) and there is an exact match between the attribute name and the noun phrase tagged with A1.

We further refine the lhs-variables with a complex type (i.e., a class or a data type). For each attribute and association in the list of the lhs-variables, we traverse the related associations to identify the attributes and associations that best match the phrases tagged with the support roles (Lines 14 to 17). In S3, BodySense.itsNVM is refined to BodySense.itsNVM.itsAccessible since the class NVM has a boolean attribute (itsAccessible) with a name similar to the phrase tagged with AM-PRD (accessible).
attribute of the main system class that best matches the possessive/attributive phrase. For example, in the case of S13, the attribute counter (i.e., the main phrase in S13) belongs to the entity class referenced by the attribute watchdog (i.e., the possessive/attributive phrase) of the main system class. Based on this observation, to identify the model elements that reflect the relation captured by a possessive/attributive phrase, we perform an execution of the function findVariables where we treat possessive/attributive phrases as the entity role and the main phrase as a support role. The possessive/attributive phrase is thus used to identify the owning entity while the main phrase is used to identify the owned attribute/association. In the case of S13, UMTG looks for an attribute of the system class that best matches watchdog and then further refines the search by looking for a contained attribute that best matches counter.

9.2.2 Identification of the Right-hand Side Terms

The rhs-term can be a literal or a variable. It is identified based on the lhs-variable and on the support roles that have not been used to select the lhs-variables. If the lhs-variable is of a boolean or numeric type, the rhs-term is a boolean or numerical value derived from a phrase tagged with one of the support roles. Therefore, we look for a phrase that matches the terms ‘true’ and ‘false’ or that is a number.

When the lhs-variable is boolean and the verb is negative, we negate the rhs-term. When the lhs-variable is boolean and there is no support role to identify the rhs-term, we use the default value true for the rhs-term. For example, in S4 in Table 4, all the support roles have already been used to identify the lhs-variable and there is no support role left for the rhs-term. Therefore, we use true for the rhs-term.

When the lhs-variable is of an enumeration type, we identify the enumeration literal in the domain model that best matches the phrases tagged with the support roles. For instance, in S5 in Table 4, BodySense.buildCheckStatus is the lhs-variable which is of an enumeration type, i.e., BuildCheckStatus. Since this enumeration contains a term that matches the root of the verb in S5 (pass), the literal BuildCheckStatus::Passed is selected as the rhs-term.

9.2.3 Identification of the OCL operators

The OCL comparison operators are identified based on the verb in the use case step. The operator ‘=’ is used for most verbs. For the verb ‘to be’, we rely on Roy et al. [103] which, for example, identify the operator ‘=’ for “capacitance is above 600”. More precisely, we apply Roy’s approach on the phrase tagged with the support-role used to identify the rhs-term. If antonyms have been used to identify the lhs-variable and the rhs-term, we negate the selected operator, for instance, by replacing ‘=’ with ‘! =’ in S9 in Table 4.

Regarding the selection operator, we are limited to the pattern in Fig. 6, i.e., the exclusion of some class instances in a set. The selection operator is introduced when the phrase tagged with A1 contains the keyword except (e.g., S6 in Table 4). To identify the types of the instances to be excluded, we rely on the tags generated based on SRL NomBank. We look for the phrases tagged with A2 to identify the adverbial clause. We identify all the distinct noun phrases within the clause (e.g., voltage errors and memory errors in S6).

9.2.4 Identification of the Type of OCL Query Element

The query elements in our OCL pattern are used to check if an expression holds for a set of instances (see Fig. 6). The key difference among them is the number of instances for which the expression should hold. Since the number of subjects referred to in a sentence in English is specified by the determiners and quantifiers, we identify the type of the query element based on the determiners and quantifiers in the phrase tagged with an entity role. We consider entity roles because a domain entity is selected based on its similarity with the phrase tagged with an entity role.

In English, the indefinite articles a and an and the determiner some refer to particular members of a group. Therefore, if a phrase tagged with an entity role includes an indefinite article or the determiner some, we generate an OCL query following the EXISTS sub-pattern (see Fig. 6). For phrases with a quantifier referring to a certain number of members of a group (e.g., at least five), we generate expressions following the COUNT sub-pattern. We also rely on Roy’s approach [103] to generate a quantifier formula with an operator and a numeric literal.

For all other cases, we generate expressions that follow the FORALL sub-pattern. These cases include phrases with universal determiners referring to all the members of a group (e.g., any, each, and every) and phrases with the definite article the. The definite article is used to refer to a specific entity (e.g., the measured voltage in S7 in Table 4) and typically leads to the definition of an attribute or association in the domain model (e.g., the measured voltage matches an attribute of the system class BodySense). Since there might be multiple class instances with the corresponding attribute (or association), we rely on the FORALL sub-pattern to match all of them. A detailed description of how the universal determiners and the definite article influence the scoring of the generated constraints is provided in Section 9.2.5.

9.2.5 Scoring of the OCL Constraints

The score of an OCL constraint accounts for both the completeness and correctness of the constraint. Completeness relates to the extent to which all the concepts in the use case step are accounted for. Correctness relates to how similar the variable names in the constraint are to the concepts in the use case step.

We measure the completeness of a constraint in terms of the percentage of the roles in the use case step that are used to identify the terms in the constraint.

To compute the correctness of a constraint, we use correctness = (lhsScore + rhsScore + matchUniversalDeterminer) / (numConstraints) where lhsScore and rhsScore are the similarity scores for the lhs-variable and the rhs-term, respectively. lhsScore is the average of the scores of all the attributes/associations in the variable. When the rhs-term is a boolean, numeric or enumeration literal generated from a phrase in the use case step, rhsScore is set to one; otherwise, rhsScore is computed like lhsScore. matchUniversalDeterminer is 1 when universal determiners (e.g., any, every, or no) are properly reflected in the constraint. We consider a universal determiner to be properly reflected in the constraint (1) when it is not in the noun phrase tagged with an entity role and the constraint refers to a specific instance associated with the
system class (e.g., S3), and (2) when it is in the noun phrase tagged with an entity role and the constraint refers to all the instances of the class matching the phrase (e.g., S6). Universal determiners are important to derive the correct constraints. For example, for S3, we build two constraints C2 and C3 in Table 6. We select C3 because the use case step does not explicitly indicate that all the NVM components should be considered.

The final score is computed as the average of the completeness and correctness scores (see Table 6).

### 9.3 Correctness and Generalizability

The adoption of verb-specific transformation rules may limit the correctness and generalizability of constraint generation due to the considerable number of English verbs. For example, the Unified Verb Index [104], a popular lexicon based on VerbNet and other lexicons, includes 8,537 English verbs.

To ensure the correctness of constraint generation, we use our transformation rules on the VerbNet role patterns. These role patterns capture all valid role combinations appearing with a verb. The rules are applied according to the entity and support role pairs \{entity role, \{support roles\}\} we extracted from the role patterns (see Table 5). For example, the transformation rule of the verb ‘to erase’ has two role pairs \{A1, null\} and \{A2, \{A1\}\} extracted from the VerbNet role patterns (see Rule 4 in Table 5). If the sentence contains A1 without A2, then A1 is used to identify the entity to be erased, i.e., the attribute in the lhs-variable (see S7 in Table 4). If the sentence contains both A1 and A2, then A2 is used to identify the entity and A1 provides some additional information (i.e., the attribute of the entity to be erased). As an example of the latter case, in S8 in Table 4, we identify the entity name (AirbagControlUnit) and the attribute in the lhs-variable (occupantClass).

To ensure the generalizability of the constraint generation, we employ three key solutions which prevent the implementation of hundreds of rules. First, we rely on the VerbNet classes to use a single rule targeting different verbs. Since all the verbs in a VerbNet class share the same role patterns, we reuse the same rule for all the verbs in the VerbNet class that are synonyms according to WordNet.

Second, we excluded some VerbNet classes of verbs, i.e., 225 classes and 175 subclasses, that are unlikely to appear in specifications (see Table 7). We manually inspected all the VerbNet classes to identify them (e.g., verbs describing human feelings). Our analysis results are available online [105].

Third, we further analyzed the remaining classes to determine the verbs that are processed by our any-verb transformation rule. This analysis shows only 33 verb-specific rules are required to process 87 classes of verbs.

### 10 Generation of Use Case Test Models

UMTG generates a Use Case Test Model from an RUCM use case specification along with the generated OCL constraints (Step 7 in Fig. 1). The model makes the implicit control flow in the use case specification explicit and maps the use case steps onto the test case steps. Fig. 10 gives the metamodel for use case test models.

![Fig. 10. Metamodel for use case test models.](image-url)
Output steps are not represented in use case test models because UMTG does not rely on them to drive test generation. Although output steps might be used to select outputs to be verified by automated oracles during testing, UMTG relies on postconditions to generate test oracles because they provide more information (e.g., the system state and the value of an output, which are not indicated in output steps).

For each textual element tagged with `Input`, `processes the use case steps annotated by the NLP pipeline` and `Identify Occupancy Status` from the use case `Include`. `Fig. 11. Part of the use case test model for Identify Occupancy Status."

Fig. 11 shows part of the use case test model generated from the use case `Identify Occupancy Status` in Table 3. UMTG processes the use case steps annotated by the NLP pipeline in Section 7. For each textual element tagged with `Input`, `Include`, `Internal`, or `Condition`, a Step instance is generated and linked to the previous `Step` instance. For each domain entity in the use case specification, a `DomainEntity` instance is created and linked to the corresponding `Step` instance.

For each specific alternative flow, a `Condition` instance is generated and linked to the `Step` instance that represents the first step of the alternative flow (e.g., the `Condition` instance for Line 7 in Fig. 11).

Global and bounded alternative flows begin with a guard condition and are used to indicate that the condition might become true at run time and trigger the execution of the alternative flow (e.g., as an effect of an interrupt being triggered). For each step referenced by a global or bounded alternative flow, an `InterruptingCondition` instance is created and linked to the `Step` instance that represents the reference flow step (e.g., the three `InterruptingCondition` instances for Line 14 linked to the `Step` instances for Lines 6, 7, and 8 in Fig. 11).

For multiple alternative flows depending on the same condition, `Condition` instances are linked to each other in the order the alternative flows appear in the specification. For an alternative flow in which the execution is resumed back to the basic flow, an `Exit` instance is linked to the `Step` instance that represents the reference flow step.

### 11 Generation of Use Case Scenarios and Test Inputs

UMTG generates, from a use case test model along with OCL constraints, a set of use case scenarios and test inputs (Step 8 in Fig. 1). A scenario is a path in the use case test model that begins with a `UseCaseStart` node and ends with an `Abort` node or an `Exit` node with the attribute `next` set to null (i.e., an Exit node terminating the use case under test). A scenario captures the sequence of interactions that should be exercised during testing.

UMTG needs to identify test inputs in which the conditions in the scenario hold. For example, to test the scenario for the basic flow of the use case `Classify Occupancy Status` in Table 3, we need test inputs in which the capacitance value is above 600 (see Line 60 in Table 3). We use the term `path condition` to indicate a formula that conjoins all the conditions (OCL constraints) in a given scenario. If the path condition is satisfiable, we derive an object diagram (i.e., an instance of the domain model in which the path condition holds). For a given scenario, test input values are extracted from the object diagram that satisfies the path condition.

```
function GenerateScenariosAndInputs(tm) returns ScenariosInputs, ScenariosSet
  ScenariosSet ← newList() // list of pairs (Scenario, pc)
  ScenariosInputs ← newList() // list of feasible scenarios
  repeat
    ScenariosInputs ← GenerateScenariosAndInputs(tm, ScenariosInputs, ScenariosSet)
    for each pair (Scenario, pc) in ScenariosSet do
      objectDiagram ← Solve(Scenario, pc)
      if objectDiagram = null then // the scenario is infeasible
        remove (Scenario, pc) from ScenariosSet
      else // the scenario is feasible
        ScenariosSet ← ScenariosSet \ {{Scenario, pc}}
      end if
    end for
    until coverageSatisfied(tm, ScenariosSet) or max number of iterations reached
  end repeat

function GenerateScenariosAndInputs(tm, ScenariosInputs, ScenariosSet)
  ScenariosInputs ← newList() // list of ScenariosInputs
  for each Scenario in ScenariosInputs do
    objectDiagram ← Solve(Scenario, pc)
    if objectDiagram = null then // the scenario is infeasible
      remove (Scenario, pc) from ScenariosSet
    else // the scenario is feasible
      ScenariosSet ← ScenariosSet \ {{Scenario, pc}}
    end if
  end for

function Solve(Scenario, pc)
  pc ← pc.next
  pc ← pc.next
  //add the scenario to the results to be returned
  //the scenario is infeasible
  //list with feasible scenarios
  //max number of iterations reached
```

Fig. 12. Algorithm for generating use case scenarios and test inputs.

We devise an algorithm, `GenerateScenariosAndInputs` in Fig. 12, which generates a set of pairs of use case scenarios and object diagrams from the input use case test model `tm`. Before calling `GenerateScenariosAndInputs`, the use case test model `tm` is merged with the use case test models of the included use cases in a way similar to the generation of interprocedural control flow graphs [106]. The `Include` instances in `tm` are replaced with the `UseCaseStart` instances of the included use cases; the `Exit` instances of the basic flows of the included use cases are linked to the `Node` instances following the `Include` instances in `tm`.

To generate use case scenarios, we call the function `GenerateScenarios` with `tm` being a use case test model, `Scenario` being an empty list, `tm.start` being the `UseCaseStart` instance in `tm`, `pc` being a `null` path condition, `ScenariosInputs` being an empty list, and `ScenariosSet` being an empty list (Line 7 in Fig. 12). UMTG employs the Alloy analyzer [34] to generate
an object diagram in which the path condition in OCL holds for a given scenario (Line 9). It makes use of existing model transformation technology from OCL constraints to Alloy specifications [107].

Some of the generated scenarios may be infeasible. These are the scenarios that cannot be exercised with any set of possible values (e.g., because they cover alternative flows for auxiliary cases). We exclude such infeasible scenarios (Lines 10 and 11).

We execute GenerateScenarios multiple times until a selected coverage criterion is satisfied or the number of iterations reaches a predefined threshold (Line 17). We set the threshold to ten in our experiments. UMTG supports three distinct coverage criteria, i.e., branch coverage, a lightweight form of def-use coverage, and a form of clause coverage that ensures each condition to be covered with different entity types. All these three coverage strategies are described in the following sections.

Section 11.1 describes the scenario generation algorithm (Line 7), while Section 11.2 provides details about the generation of object diagrams that satisfy path conditions (Line 9).

### 11.1 Generation of Use Case Scenarios

The function GenerateScenarios performs a recursive, depth-first traversal of a use case test model to generate use case scenarios (see Fig. 13). It takes as input a use case test model \( tm \), a node in \( tm \) to be traversed \( node \), and four input lists (i.e., \( Scenario, pc, Prev, and Curr \)) which are initially empty and are populated during recursive calls to GenerateScenarios. Scenario is a list of traversed nodes in \( tm \), \( pc \) is the path condition of the traversed nodes, \( Prev \) is a list of feasible scenarios traversed in previous iterations, while \( Curr \) is a list of pairs \( ⟨Scenario, pc⟩ \), containing the scenarios identified during the current iteration and their path conditions.

Fig. 14 shows three scenarios generated from the use case test model in Fig. 11. Scenario A covers, without taking any alternative flow, the basic flow of the use case Identify Occupancy Status and the basic flows of the included use cases Self Diagnosis and Classify Occupancy Status in Table 3. Scenario B takes two specific alternative flows of the use cases Self Diagnosis and Identify Occupancy Status, respectively. It covers the case in which a TemperatureError has been detected (Lines 44 to 48 in Table 3) and some error has been qualified (Lines 20 to 27). Scenario C covers the case in which some error has been detected but no error has been qualified (Lines 28 to 33).

The preconditions of the UseCaseStart instance is added to the path condition for the initialisation of the test case (Lines 8 to 12 in Fig. 13). Input instances do not have associated constraints to be added to the path condition (Lines 13 to 16). We recursively call GenerateScenarios for the nodes following the UseCaseStart and Input instances (Lines 11 and 15). For instance, Scenario A in Fig. 14 starts with the UseCaseStart instance of the use case Identify Occupancy Status followed by an Input instance, and proceeds with the UseCaseStart instance of the included use case Self Diagnosis.

For each Condition instance which is not of the type InterruptingCondition, we first visit the true branch and then the false branch to give priority to nominal scenarios (Lines 17 to 29). In the presence of a coverage-based stopping criterion, prioritizing nominal scenarios is useful to generate relatively short use case scenarios covering few alternative flows (i.e., what happens in realistic executions) instead of long use case scenarios covering multiple alternative flows. Bounded and global alternative flows are taken in the true branch of their InterruptingCondition instances. Therefore, to give priority to nominal scenarios, we first
visit the false branch for the InterruptingCondition instances (Lines 30 to 39). For each condition branch taken, we add to the path condition the OCL constraint of the branch (Lines 21, 27 and 37) except for the false branch of the InterruptingCondition instances; indeed, the condition of a bounded or global alternative flow is taken into account only for the scenarios in which the alternative flow is taken. For example, Scenarios A and B do not cover the condition of the bounded alternative flow of the use case Identify Occupancy Status. We call GenerateScenarios for each branch (Lines 22, 28, 33 and 38).

The Internal instances represent the use case steps in which the system alters its state. Since state changes may affect the truth value of the following Condition instances, the postconditions of the visited Internal instances are added to the path condition (Line 42). We call GenerateScenarios for the nodes following the Internal instances (Line 43).

To avoid infinite cycles in GenerateScenarios, we proceed with the node following an Exit instance only if the node has not been visited in the current scenario more than a number of times $T$ specified by the software engineer (Lines 46 and 47). The default value for $T$ is one, which enables UMTG to traverse loops once. An Exit instance followed by a node represents either a resume step or a final step of an included use case. An Exit or Abort instance which is not followed by any node indicates the termination of a use case. For instance, Scenario A terminates with the Exit instance of the basic flow of the use case Identify Occupancy Status, while Scenario B terminates with the Abort instance of the first specific alternative flow of the same use case. When the current scenario ends, we add the scenario and its path condition to the set of pairs of scenarios and path conditions to be returned (Line 57), if it improves the coverage of the model based on the selected coverage criterion (Line 56).

The algorithm is guided towards the generation of scenarios with a satisfiable path condition (Lines 5 to 7). To limit the number of invocations of the constraint solver and, consequently, to speed up test generation, the function unsatisfiable (Line 5) does not execute the constraint solver to determine satisfiability but relies on previously cached results. It returns false if the path condition has been determined to be unsatisfiable by the solver during the generation of test inputs (Line 9 in Fig. 12); otherwise it assumes that the path condition is satisfiable and returns true. This is why GenerateScenarios is invoked multiple times by GenerateScenariosAndInputs and constraint solving is executed after all the path conditions have been collected (Line 9 in Fig. 12).

Scenario generation terminates when the selected coverage criterion is satisfied (Lines 2 to 4) or the entire graph is traversed. The depth-first traversal ensures that all edges are visited at least once. UMTG supports three coverage criteria: branch coverage, a lightweight form of def-use coverage, and a form of clause coverage that we call subtype coverage.

The branch coverage criterion aims to maximize the number of branches (i.e., edges departing from condition steps) that have been covered. Coverage improves (Line 56 in Fig. 13) any time a scenario covers a branch that was not covered yet.

Our def-use coverage criterion aims to maximize the coverage of entities referred (i.e., used) in condition steps that present attributes defined in internal steps. We identify definitions from the postconditions associated to internal steps. More precisely, each postcondition generally defines one entity, i.e., one that owns the lhs-variable appearing in the postcondition; postconditions that join multiple OCL constraints using the operators and/or can define multiple entities. Sentence S4 in Table 4 defines one entity, TemperatureLowError. We identify uses from condition steps’ constraints; used entities are the ones that own the terms appearing in condition steps’ constraints. More formally, our coverage criterion matches the standard definition of all p-uses [108] except that we treat positive and negative evaluation of predicats as different def-use pairs. This is done to enforce the pairing of each definition with both the true and false evaluation of the constraints in which it is used. The def-use pairs covered by each scenario are computed by traversing the scenario and by identifying all the pairs of use case steps $\langle s_d, s_u \rangle$, where $s_d$ defines an entity and $s_u$ uses the same entity or one of its supertypes. Def-use coverage improves any time a new def-use pair is observed in a scenario.

Def-use coverage leads to scenarios not identified with branch coverage. In our running example, by maximizing the branch coverage criterion we ensure that both Scenario B and Scenario C in Fig.14 are covered. Indeed, the entity TemperatureLowError is defined in Line 46 and used by the constraint C13, which is referenced in the condition step in Line 22; this leads to two def-use pairs, one covered by Scenario B (C13 evaluates to true) and one by Scenario C (C13 evaluates to false). In addition to these two scenarios, the def-use coverage criterion also ensures that a TemperatureHighError is covered in two additional scenarios (not shown in Fig.14) that pair the definition of TemperatureHighError in Line 52 with its uses in Line 22.

The subtype coverage criterion aims to maximize the number of entity (sub) types with an instance referenced in a satisfied condition. For each scenario, it leads to a number of object diagrams such that each condition is satisfied with all the possible entity (sub) types referenced by the condition. For example, in the presence of a condition step referring to the generic entity type Error, it generates a number of object diagrams such that, for each subtype of Error, there is at least one instance satisfying the condition.

To apply the subtype coverage criterion, the algorithm GenerateScenariosAndInputs further processes the generated scenarios with function maximizeSubTypeCoverage (Line 19 in Fig. 12). Function maximizeSubTypeCoverage appears in Fig. 15. It identifies all the constraints appearing in condition steps that are evaluated to true (Line 5 in Fig. 15). For each of these constraints, it re-executes constraint solving multiple times, once for each type $sT$ that is a subtype of the entity used by the constraint (Line 6). Constraint solving is forced to generate a solution that contains at least one instance of the subtype $sT$ that satisfies the constraint (Line 8). For each scenario, we keep only the object diagrams that contain assignments not observed before (implemented by function coverageImproved, see Lines 9-11).

In our example, to maximize subtype coverage, we need to cover C13 in Scenario B in Fig. 14 with three instances of subtypes of the Error entity: TemperatureLowError (i.e., an instance of TemperatureLowError should have the attribute qualified set to true), TemperatureHigh-
Error, and VoltageError. In Scenario B, to ensure that C13 is covered with an instance of TemperatureLowError, the function solveWithSubType (Line 8 in Fig. 15) extends the path condition of the scenario with the additional condition TemperatureLowError.allInstances() \(\rightarrow\) exists(i|i.qualified = true), which is automatically derived from constraint C13 by replacing the entity type used in the constraint. The same is repeated also for TemperatureHighError and VoltageError. In our implementation, the subtype coverage criterion is combined with the def-use coverage criterion to ensure that constraints using input types are exercised with all the possible input subtypes. In our running example, the subtype coverage metric ensures that Scenario B is covered with a TemperatureLowError being both detected and qualified.

11.2 Generation of Object Diagrams

UMTG employs the Alloy analyzer to generate an object diagram which satisfies the path condition of a given scenario (Line 9 in Fig. 12). Test input values are later extracted from the generated object diagram (see Section 12).

The Alloy analyzer does not return a solution for unsatisfiable path conditions. These path conditions are usually associated with infeasible scenarios (i.e., scenarios which cannot be tested and verified by any set of possible input values). However, we may also observe unsatisfiable path conditions with feasible scenarios. These scenarios include an internal step that overrides the effects of the previous internal step (e.g., redefines the value of a variable). For instance, in Scenario B in Fig. 14, the constraints C12 (i.e., TemperatureLowError.allInstances() \(\rightarrow\) forAll(i|i.detected = true)) and C2 (i.e., TemperatureError.allInstances() \(\rightarrow\) forAll(i|i.detected = false) ) cannot be satisfied in the same path condition since TemperatureLowError is a subclass of TemperatureError. The
internal step with C12 (Line 46 in Table 3) sets a temperature error to detected after the internal step with C2 (Line 38 in Table 3) sets all the temperature errors to undetected. We identify such feasible scenarios having unsatisfiable path conditions by incrementally re-executing the Alloy analyzer.

When the Alloy analyzer does not solve a path condition, we automatically rerun it incrementally, by following the order of the steps in the scenario, until it identifies an unsatisfiable prefix of the path condition and returns the unsat core. For instance, for Scenario B, UMTG runs the Alloy analyzer on (C1), (C1 ∨ C2), (C1 ∨ C2 ∨ C3), and (C1 ∨ C2 ∨ C3 ∨ C12), respectively. For (C1 ∨ C2 ∨ C3 ∨ C12), the Alloy analyzer returns (C2 ∨ C12) as the unsat core.

If the last OCL constraint added to the path condition (e.g., C12 in our example) belongs to an internal step $s_i$, we conclude that $s_i$ overrides the effects of previous internal steps. The other constraints in the unsat core can thus be safely removed from the path condition if they refer to the same attributes referred by this last OCL constraint. UMTG proceeds to incrementally solve the remaining constraints in the scenario. Otherwise, if the last added OCL constraint does not belong to an internal step or if the other constraints in the unsat core refer to different variables, the scenario is considered infeasible. For instance, both C2 and C12 belong to internal steps in Scenario B; C12 is the last constraint added to the path condition before the unsat core is returned. Therefore, C2 is removed from (C1 ∨ C2 ∨ C3 ∨ C12). We incrementally rerun the Alloy analyzer by adding the remaining constraints in Scenario B to (C1 ∨ C3 ∨ C12). Constraint solving proceeds until the scenario is deemed infeasible or the entire path condition excluding the removed OCL constraint(s) is solved. In this case, the Alloy analyzer returns an object diagram that satisfies the entire path condition for Scenario B shown in Fig. 14 excluding C2. The OCL constraints removed from the path condition during incremental constraint solving belong to internal steps that perform initial setups and thus do not have any effect on the identification of test inputs.

2. The unsat core is the minimal subset of OCL constraints that cannot be solved together [109]

12 Generation of Test Cases

UMTG uses the set of pairs $(\text{scenario}, \text{objectDiagram})$ to generate test cases (Step 10 in Fig. 1). It performs three activities: identify input values, generate high-level operation descriptions, and generate test driver function calls (see Fig. 16). Test driver function calls are tailored to the test case format in Table 2 but can be adapted, while following similar principles, to different test case formats for different test infrastructures and hardware.

### Table 8

| Line | Operation | Inputs/Expectations |
|------|-----------|---------------------|
| 1    | Input     | System.initialized = true |
| 2    | ResetPower| Time=INIT_TIME      |
| 3    | Input     | System.seatSensor.capacitance = 601 |
| 4    | SetBus    | Channel=RELAY Capacitance=601 |
| 5    | Input     | System.temperature = 20 |
| 6    | SetBus    | Channel=RELAY Temperature = 20 |
| 7    | Check     | An adult has been detected on the seat. |
| 8    | ReadAndCheckBus | D0=OCUPIED |
| 9    | Check     | The occupant class for airbag control has been sent to AirbagControlUnit. The occupant class for seat belt reminder has been sent to SeatBeltControlUnit. |
| 10   | CheckAirbagPin | 0x010 |

Table 8 shows the test case automatically generated from Scenario A in Fig. 14. The test cases generated by UMTG follow the structure presented in Section 3. The odd lines contain high-level operation descriptions followed (even line numbers) by the name of the functions that should be executed by the test driver along with the corresponding input and expected output values. Lines 1, 3, 5, 7 and 9 are high-level operation descriptions; Lines 2, 4, 6, 8 and 10 are test driver function calls. The test case corresponds to the manually written test case in Table 2.

The input values are extracted from the object diagram generated from the path condition of the given scenario (Activity 1 in Fig. 16). To this end, UMTG looks for the attributes that appear both in the diagram and the path condition.

UMTG then generates the high-level operation descriptions, i.e., the Input, Setup, and Check operations (Activity 2 in Fig. 16). The Input and Setup operations are associated with the input values (Activities 2.1 - 2.3). For each Input and Interrupt step in the scenario, we generate a test line including an Input operation. The Input operation is associated with a set of input values which belong to an attribute or an entity referenced in the use case step. For instance, in Activity 2.2, ‘BodySense.seatSensor.capacitance = 601’ is selected because of the Capacitance entity. We generate a test line including the Setup operation for each attribute that appears in an OCL constraint belonging to UseCaseStart or Condition steps but not to Input and Interrupt steps. For instance, in Activity 2.1, ‘BodySense.initialized = true’ is selected because the attribute initialized is referenced in the use case precondition The system has been initialized. Finally, for the postcondition of each Exit step, we create a test line including the Check operation and the postcondition in NL (Activities 2.4 - 2.6).
Test Case Generation:
1. Identify input values
   - BodySense.initialized = true
   - BodySense.temperature = 20
   - SeatSensor.capacitance = 601

2. Generate high-level operation descriptions
   2.1 Process the precondition step of line 3: add the following line to the test case
      ```
      Setup BodySense.initialized = true
      ```
   2.2 Process the Input step of line 5: add the following line to the test case
      ```
      Input BodySense.temperature = 20
      ```
   2.3 Process the Input step of line 39: add the following line to the test case
      ```
      Input BodySense.temperature = 20
      ```
   2.4 Process the Exit step of line 43: add the following line to the test case
      ```
      Check Error conditions have been examined.
      ```
   2.5 Process the Exit step of line 63: add the following line to the test case
      ```
      Check An adult has been detected on the seat.
      ```
   2.6 Process the Exit step of line 11: add the following line to the test case
      ```
      Check The occupant class for airbag control and the occupant class for seat...
      ```

3. Generate the final test case appearing in Table 9 by adding calls to driver functions according to the Mapping Table.

Finally, to generate the test driver function calls, UMTG processes the high-level operation descriptions by using the mapping table provided by the engineers (Activity 3 in Fig. 16). Table 9 shows part of the mapping table for BodySense. The first two columns provide the operation names and the regular expressions that match the high-level operation descriptions in the test case. The last two columns provide the test driver function calls to be added to the test case when the first two columns match the high-level operation descriptions. For instance, the `Input` operation and the expression `BodySense.seatSensor.capacitance = (.*)` in the first row of Table 9 matches the high-level operation description in Line 3 in Table 8, which leads to the generation of Line 4. We follow the Java regular expressions’ syntax [110], which provides the grouping feature to extract char sequences from matching strings. For example, we use the grouping pattern ‘(.*)’ to copy the values of the high-level operation descriptions, which are extracted from the object diagram, into the test driver function calls (e.g., value 601 in Activity 2.2).

Test oracles are the test driver function calls which are generated from the high-level operation descriptions with the `Check` operation (e.g., Lines 8 and 10 in Table 8).

To simplify the writing of mapping tables, engineers can create them iteratively and incrementally. They define mappings for the first test case and then introduce (and refine) regular expressions for the following test cases. Moreover, when the grouping feature of regular expressions is used to copy input values generated by the OCL solver into executable test cases, the same mapping table can be reused for test cases generated with different coverage criteria. Indeed, test cases derived with different coverage criteria differ only with respect to the values assigned to inputs and the order of operations. Finally, mapping tables can be shared across all the systems tested on a given test infrastructure.

13 TOOL SUPPORT

To ease its industrial adoption, we implemented UMTG as a toolset that extends IBM Doors [111] and Eclipse IDE [112]. Additional information about the UMTG toolset, including executable files, download instructions and a screencast covering motivations, are available on the tool’s website at https://sntsvv.github.io/UMTG/.

Fig. 17 shows the tool architecture. The main components are two plug-ins that extend IBM Doors and Eclipse IDE. They orchestrate the other components in Fig. 17.

The IBM Doors plug-in activates the UMTG steps for use case elicitation while the steps for test case generation are activated by the Eclipse plug-in. The toolset can also process use case specifications in plain text files to avoid any dependence on IBM Doors for requirements elicitation.

The Eclipse plug-in architecture enables us to rely on third party plug-ins. We rely on the Eclipse Web Browser to visualize the missing entities in the domain model, the Eclipse OCL editor [113] to edit the OCL constraints, the Eclipse Text Editor to present the abstract test cases, the default Eclipse Table Editor (e.g., Microsoft Excel) to edit the mapping table, and the Eclipse Project Explorer to list the UMTG artefacts. To create the domain model, the user can use the IBM Rhapsody plug-in [114] or the Eclipse Papyrus plug-in [115]. UMTG requires that the domain model be saved in the XMI format.
The components in Fig. 17 automate Steps 3, 5, 7, 8, and 10 in Fig. 1. The NLP Processor contains the NL pipeline in Section 7 to implement parts of Steps 3, 5 and 7. It is based on the GATE workbench [100], an open source NLP framework. To load use case specifications from IBM Doors, we use Doors Document Exporter, an IBM Doors API that exports the Doors content as text files.

The Consistency Checker and the Abstract Tests Generator implement Steps 3 and 8, respectively. Step 5 is implemented by the OCL Generator. The OCL Solver employs the Alloy analyzer [34] to implement part of Step 8.

The Executable Test Generator takes the mapping table and abstract test cases as input, and generates the executable test cases as output (Step 10). It exploits the Door eXtension Language (DXL) to load the generated test cases into IBM Doors. The DXL is also used to automatically generate trace links between use cases and generated test cases, an important feature to support testing of safety critical systems.

14 Empirical Evaluation

In this section, we investigate, through two industrial case studies in the automotive domain, the following Research Questions (RQs):

- **RQ1. Does the approach automatically generate the correct OCL constraints?** The generation of OCL constraints is a major building block of our approach. With this research question, we aim to measure the precision (i.e., the fraction of the generated OCL constraints that are correct) and recall (i.e., the fraction of the required OCL constraints that are correctly generated) of the OCL generation algorithm in Section 9.

- **RQ2. How does the approach compare to manual test case generation based on expertise?** In the second research question, we evaluate (i) if the approach generates test cases that exercise the same use case scenarios exercised by test cases manually written by engineers and (ii) if it discovers additional scenarios not exercised by the manually written test cases.

- **RQ3. How does the approach compare to manual test case generation in terms of resources?** This research question aims to compare our approach with manual test case generation in terms of engineers’ effort and time required to generate test cases.

14.1 Subjects of the Evaluation

The subjects of our evaluation are BodySense and Hands Off Detection (HOD), two embedded systems developed by our industry partner, IEE [17].

BodySense is a car seat occupant classification system that enables smart airbag deployment; it has been introduced in Section 3. HOD is an embedded system that checks if the driver has both hands on the steering wheel. It is used to enable and disable automatic braking with driver-assist features for safety. For instance, a car should not automatically brake if the driver does not have both his hands on the steering wheel. HOD measures the capacitance between a conductive layer in the steering wheel and the electrical ground in the car body or in the seat frame. It notifies the autonomous driving assistance system when the driver does not have both his hands on the steering wheel. The complexity of these two systems lies mostly in how they deal with errors, e.g., sensor break-downs. Therefore, their test suites mostly concern the verification of system behaviour in the presence of errors. The two case studies are representative of automotive embedded systems and share their typical characteristics, such as handling multiple types of errors and communicating results to other components based on error status and sensor data.

| TABLE 10 | Overview of the BodySense and HOD use case specifications. |
|----------|------------------------------------------------------------|
|          | All | Use cases Included | Entry | Use case flows | Steps |
| BodySense| 7   | 5             | 11    | 59             | 266   |
| HOD      | 17  | 6             | 11    | 27             | 76    |

In IEEs business context, like in many others, use cases are central development artifacts which are used for communicating requirements among stakeholders, such as customers. Use case specifications provide a systematic description of system-actor interactions. UMTG requires use case specifications in the RUCM template. For BodySense, the specifications had been initially elicited by IEE engineers following the Cockburn template [116]. They were later rewritten according to the RUCM template. The HOD specifications, instead, were already written by IEE engineers using RUCM with the UMTG and RUCM tools [37].

Table 10 reports on the size of the use case specifications of the case studies. The BodySense and HOD specifications include 7 and 17 use cases, respectively. The number of use case flows is 59 for BodySense and 27 for HOD, which indicates that the systems must deal with multiple alternative executions (e.g., alternative flows in the case of errors). The difference in the number of use case flows is largely explained by HOD specifications being less complete than BodySense specifications. In BodySense, all error conditions are modeled by means of condition steps that explicitly indicate error types for anomalous sensor data (e.g., sensor data not in a given range as in Line 40 of Table 3). The HOD specifications, instead, do not include this type of condition steps but only describe how the system should behave in the presence of a specific error (e.g., Line 7 of Table 3). For HOD, the descriptions of error conditions are given in other documents. In general, we consider use case specifications to be complete when their condition steps fully characterize equivalence classes for system inputs. Use case specifications are incomplete when such equivalence classes are partially modeled. The impact of the completeness of use case specifications on test generation is discussed in the following sections.

In Table 10, we report the number of use cases that are included by other use cases and the number of use cases that are entry points for testing (i.e., the main use cases for deriving system test cases).

14.2 Results

This section discusses the results of our case studies, addressing in turn each of the research questions.
14.2.1 RQ1: Does the approach automatically generate the correct OCL constraints?

To respond to RQ1, we used UMTG to automatically generate the OCL constraints required to drive test generation for BodySense and HOD. We compared the automatically generated OCL constraints with the OCL constraints manually generated by the first author of the paper. The latter were written together with IEE engineers in dedicated workshops. The comparison was fully automated by means of string matching.

We computed precision (i.e., the fraction of automatically generated constraints that are correct) and recall (i.e., the fraction of the required constraints for test case generation that are correctly generated by UMTG). A sentence may appear in multiple use case steps. To fairly compute precision and recall, we considered these sentences only once.

Table 11 presents the results for RQ1. UMTG generated 71 and 35 constraints from 87 and 37 sentences for BodySense and HOD, respectively. The number of the processed sentences is lower than the number of the use case steps because UMTG does not need to generate constraints from input, output, and exit steps. Out of 71 and 35 constraints, 69 and 35 are correct, respectively. Precision is 0.97 for BodySense and 1.00 for HOD. These results are highly promising since almost each generated constraint is correct.

| Processed sentences | Generated constraints | Not Generated | Precision | Recall |
|---------------------|-----------------------|---------------|-----------|--------|
| BodySense           | 87                    | 71            | 2         | 69     | 0.97  | 0.77 |
| HOD                 | 37                    | 35            | 0         | 35     | 1.00  | 0.95 |

Table 12 presents the results obtained with the improved specifications and models, which in practice can be easily obtained by carefully comparing the specifications and domain models, a task our tool now supports. Unsurprisingly, UMTG achieves a particularly high recall, above 0.9 in both case studies. Overall, it achieves a precision of 0.99 and a recall of 0.95, another promising results indicating the potential usefulness of our constraint generation in practical settings. Among the sentences that are not correctly translated into OCL constraints, we identify (a) three sentences capturing internal behavior not useful for test input generation (e.g., 'The system loads the default calibration data'), (b) one sentence referring to concepts having names that are similar to other concepts in the domain model, which, in turn, leads to the identification of the wrong entity for the constraint, and (c) one sentence not correctly parsed because it contains two subjects, a situation currently not supported by our tool.

14.2.2 RQ2: How does the approach compare to manual test case generation based on expertise?

To respond to RQ2, we compared the test cases automatically generated by UMTG (hereafter UMTG test cases) with the test cases manually written, based on extensive expertise, by IEE engineers (hereafter manual test cases) for BodySense and HOD. We focused on use case scenarios and test inputs used to exercise the scenarios.

To compare the test cases based on use case scenarios, we inspected all the manual test cases and mapped them to the scenarios in the use case test models. To compare the test cases based on test inputs, we identified equivalence classes for each input domain and all the input partitions (i.e., the combination of equivalence classes) that might be considered for each scenario. We kept track of the input partitions covered by UMTG and manual test cases. We use the term input scenario, different than use case scenario, to refer to use case scenario being exercised with a specific input partition.

Table 13 presents the number of test cases belonging to the test suites considered in our evaluation (i.e., the manual test suite developed by IEE and the test suites generated with three UMTG coverage strategies). An in-depth discussion concerning the size and the complementarity of the generated test suites is reported at the end of this section.

Table 14 presents the number of use case scenarios exercised by manual test cases and the percentage of these scenarios exercised by UMTG test cases. Except for branch coverage in BodySense, the UMTG test cases exercise all the scenarios exercised by the manual test cases. The UMTG test cases for branch coverage do not exercise all the scenarios.
covering the detection of each type of error in the presence of qualified errors given that branch coverage is satisfied when at least one test case covers the branch for error qualification. Note that the UMTG test cases cover all the branches covered by the manual test cases.

Table 15 shows the number of input scenarios exercised by manual test cases and the percentage of these input scenarios exercised by UMTG test cases. UMTG fares worse with with branch coverage because the test cases do not exercise scenarios with all input partitions. With def-use coverage, UMTG achieves a much better result for BodySense, i.e., 97.76% of the manual scenarios being exercised. This happens because the use case specifications of BodySense are complete and capture all conditions that lead to error detection. Therefore, the use case scenarios that can be covered only by one single input partition make def-use coverage sufficient to cover all the input scenarios. A different result is achieved for HOD with def-use coverage. The HOD specifications are incomplete, which leads to multiple input partitions per use case scenario. Therefore, in HOD, subtype coverage is necessary to exercise the input scenarios covered by the manual test cases.

Table 16 presents the number of use case scenarios exercised by UMTG test cases and the percentage of these scenarios exercised by manual test cases. UMTG test cases exercise more use case scenarios than manual test cases. For example, in BodySense, only 68% of the scenarios for branch coverage are exercised by manual test cases. With branch coverage, UMTG systematically covers all the scenarios derived from bounded and global alternative flows. It is difficult to manually identify these scenarios because engineers need to create a scenario for each reference flow step which a bounded (or global) flow refers to. Therefore, engineers tend not to test all the scenarios that can be derived from bounded and global alternative flows. With def-use coverage, UMTG systematically covers all def-use pairs.

In our case studies, the def-use pairs consist of internal steps reporting the presence of specific errors and condition steps verifying the presence of these errors. In turn, UMTG ensures that the systems are tested for each error in all possible combinations of condition steps verifying the presence of the error (e.g., Scenarios B and C in Fig. 14). Such systematic combination coverage is hard to achieve for engineers. By definition, with the subtype and def-use coverage criteria, UMTG generates the same use case scenarios.

Table 17 shows the number of input scenarios exercised by UMTG test cases and the percentage of these input scenarios exercised by manual test cases. UMTG test cases exercise more input scenarios than manual test cases. For the branch and def-use coverage criteria, the numbers of input and use case scenarios exercised by UMTG test cases are the same (see Tables 16 and 17). With subtype coverage, UMTG systematically covers each condition step for all possible subtypes (e.g., for all error types in our case studies). In our case studies, to speed up manual test case generation, engineers do not consider all error types in condition steps.

To summarize our findings, Fig. 18 presents four bar charts comparing all the use case and input scenarios exercised by the manual and UMTG test suites. In the charts, each data point on the vertical axis represents a use case or input scenario exercised by one or more test suites. When a scenario is exercised by a test suite, a blue horizontal line is drawn in the vertical axis. A blue bar indicates a group of test cases in a test suite. For example, the BodySense use case scenario matching data point 50 is exercised by four test suites, while the use case scenario for data point 10 is not exercised by the branch coverage test suite. We sort the data points to simplify the visual comparison of their coverage.
Branch coverage is the least effective one because it leads to test suites that do not exercise all the scenarios exercised by the manual test suite. For example, in BodySense, the branch coverage test suite exercises 20 use case scenarios that are not exercised by the manual test suite (the data points between 65 and 84 are covered only by the branch coverage test suite) but it does not exercise 48 use case scenarios in the manual test suite (the data points below 49 are not covered by the branch coverage test suite). Unsurprisingly, def-use coverage subsumes branch coverage. Finally, the chart shows that subtype coverage is the only criterion that exercises all the use case and input scenarios in the manual test suite in addition to input scenarios not exercised by the manual test suite. Unfortunately, the associated high number of test cases increases the cost of testing. On the other hand, subtype coverage is necessary only when specifications are incomplete, i.e., the HOD case where def-use coverage misses a lot of input scenarios. Indeed, in BodySense, the def-use coverage test suite exercises all the input scenarios covered by the manual test suite except three input scenarios. These three input scenarios exercise a use case scenario that concerns a change in the occupancy status of the seat in the presence of specific errors being both detected and qualified. However, UMTG covers the same use case scenario with other types of errors not considered in the manual test suite. There is no specific reason for testing the above-mentioned use case scenario with a specific subset of errors rather than another. Therefore, we conclude that def-use coverage is sufficient to generate a test suite for BodySense that is as exhaustive as the manual one.

14.2.3 RQ3: How does the approach compare to manual test case generation in terms of resources?

RQ3 is concerned with the effort and time required to generate test cases. IEE engineers, for each manual test case, write a scenario including executable instructions and provide a descriptive comment in each executable instruction. In UMTG, engineers review automatically generated OCL constraints, write missing constraints, and define a mapping table for a given test infrastructure, reusable across systems. We do not consider the effort required to derive use case specifications and domain models since they are typically produced during requirements analysis for other purposes [18].

Table 18 presents the data characterizing the manual activities in our case studies. In manual test case generation, IEE engineers had to write a large number of sentences to document the test cases, i.e., 2476 and 419 for BodySense and HOD, respectively. The test cases of the two systems include a total of 8886 and 1229 executable instructions and code comments. Thus, manual test case generation is expensive and generally takes several days (at least five working days for each case study).

In UMTG, engineers reviewed 71 and 35 OCL constraints for BodySense and HOD, respectively. The review was fast (on average less than two minutes per constraint) since the constraints are short and follow a well-defined pattern. The number of constraints written by engineers is low, i.e., 20 for BodySense and 2 for HOD. The mapping tables for BodySense and HOD include 67 and 51 lines, respectively. The time taken to write the mapping tables is limited, i.e., 135 minutes for BodySense and 100 minutes for HOD. Mapping table generation is much faster than manual test case generation which may last days. In the case studies, the mapping tables for the three code coverage strategies are the same. When use case specifications are complete, the specific values that trigger error conditions (e.g., BodySense.temperature = 100) are generated by the constraint solver and processed in the mapping table by means of the grouping feature of regular expressions (e.g., Line 6 of Table 8). When use case specifications are incomplete, test case generation identifies the error condition that should hold in a scenario (e.g., TemperatureHighError.isDetected = true) and the mapping table is used to translate such conditions into concrete values (i.e., TemperatureHighError.isDetected = true is mapped to SetBus: Channel=RELAY Temperature = 20). When specifications are incomplete, mapping tables become more complex. Incomplete use case specifications force engineers to encode system-specific, functional parameters in mapping tables, a practice that may limit the reuse of mapping tables across systems. Therefore, we recommend that engineers produce complete use case specifications.

Table 19 presents the time, in minutes, that UMTG took to automatically generate test cases for BodySense and HOD. Since test cases for different scenarios can be generated in parallel, we report the time of the longest test case generation. We omit the time taken to generate OCL constraints because it took less than ten minutes to automatically generate all the OCL constraints for BodySense and HOD. To generate test cases, UMTG needed more time for BodySense.

![Table 17: Input scenarios in the UMTG test cases that are also exercised by the manual test cases.](image1)

| Case study | Input scenarios covered by the generated test cases | Branch | Def-use | Subtype |
|------------|--------------------------------------------------|--------|---------|---------|
|            | All Exercised by manual | Exercised by manual | Exercised by manual |
| BodySense  | 63 (68.25%) | 97 (65.98%) | 867 (8.54%) |
| HOD        | 22 (81.82%) | 22 (81.82%) | 71 (78.87%) |

![Table 18: Information to be manually provided when relying on UMTG and manual test case generation.](image2)

| Case study | Manual testing | UMTG | Lines in mapping table |
|------------|----------------|------|------------------------|
|            | Sentences (words) in scenarios descriptions | Executable instructions | Reviewed constraints | Manually written OCLs |
| BodySense  | 2476 (38716) | 8886 | 71 | 20 | 67 |
| HOD        | 408 (3890) | 1229 | 35 | 2 | 51 |

![Table 19: UMTG test generation time and number of calls to constraint solver.](image3)

| Case study | Max test generation time for all the scenarios (minutes) | Calls to constraint solver (total for all the scenarios) |
|------------|----------------------------------------------------------|--------------------------------------------------------|
|            | Branch | Def-use | Subtype | Branch | Def-use | Subtype |
| BodySense  | 330    | 720     | 7200    | 908    | 2762    | 23913   |
| HOD        | 2      | 2       | 4       | 43      | 46      | 154     |
because its use case specifications have more alternative flows which, in turn, lead to larger use case test models to be traversed and more path conditions to be solved. With branch and def-use coverages, it took from 1 minute to 12 hours, which is acceptable since it is fully automated and still faster than manual test case generation. Manual test case generation took between two and five working days for the case studies. With subtype coverage, UMTG needed time up to 120 hours (5 days). Technological improvements such as parallel execution of constraint solving (we have 23913 invocations to the constraint solver) may drastically reduce test case generation time. Subtype coverage is built on top of def-use coverage. Engineers can execute test cases generated based on def-use coverage and start repairing some of the faults to be detected by subtype coverage. This can significantly speed up system testing.

Based on our observations above, we are confident that, in practice, UMTG requires less effort and time than manual test case generation. It can be easily integrated into the development process and provides better guarantees for achieving use case and input scenario coverage.

14.3 Discussion
The modelling effort required for testing a software system with UMTG is minimized thanks to the automated generation of OCL constraints. Our results show that UMTG automatically and correctly generated 95% of the constraints required for testing the two systems in our evaluation.

Among all the coverage strategies in UMTG, def-use coverage performs the best. Indeed, it enables the generation of test cases that exercise all the use case scenarios covered by the manual test suites; in the presence of complete specifications, it enables engineers to automatically cover all the input scenarios considered in the manual test suites. To cover an adequate set of input partitions (at least the ones covered by manual test case generation), engineers should select the coverage criterion based on the completeness of specifications. Def-use coverage is sufficient when specifications are complete (i.e., when they capture all input partitions by means of condition steps) while subtype coverage is needed when specifications are incomplete (i.e., when they do not explicitly capture input partitions by means of condition steps). Based on our experience, test case generation for these two cases can be performed overnight, which makes UMTG appealing in industrial contexts.

UMTG leads to significantly less test generation time than manual test case generation. The latter also consumes substantial human effort (days) whereas the former mostly requires computation time along with hours of human effort, including writing constraints and mapping tables. This is in practice an important distinction as computation time is much more readily available than human skills. Also, in the presence of specifications that are often updated (e.g., to reconfigure the system because it is part of a product line), automated test case generation relieves engineers from the burden of the manual identification of use case scenarios that need to be tested with newly implemented test cases.

14.4 Threats to Validity
The main threat to validity in our study relates to generalizability, a common issue with industrial case studies. To deal with this threat, we consider two representative automotive embedded systems implementing very different functionalities, sold to different customers, with specifications written by different sets of people following different requirements analysis practices (BodySense specifications are complete, while HOD specifications are incomplete).

In addition, in Section 9, we show that the OCL pattern handled by UMTG is expressive enough for embedded systems, while the requirements specification format processed by UMTG (use case specifications) is common in industrial settings that require precise requirements elicitation shared by multiple stakeholders.

15 Conclusion
In this paper, we introduced UMTG, an automated approach for system test case generation including test data and executable test cases. It is driven by use case specifications augmented with a domain model. Our motivation is to achieve automated test case generation by largely relying on what is common practice to document requirements for communication purposes among stakeholders in embedded system domains.

To enable the automatic identification of use case scenarios and test inputs, we combine NLP and constraint solving. To extract behavioral information from use case specifications by means of NLP, we rely upon a restricted use case modelling method called RUCM. We use an NLP solution (i.e., semantic role labeling) to automatically generate OCL constraints that capture the pre and postconditions of use case steps. We designed an algorithm that identifies use case scenarios based on the branch, def-use, and subtype coverage criteria. It builds feasible path conditions that capture OCL constraints under which the alternative flows in each scenario are executed. Test inputs are determined by solving the path conditions with the Alloy analyzer.

Two industrial case studies show that UMTG effectively generates system test cases for automotive sensor systems. UMTG can automatically and correctly generate 95% of the OCL constraints for test case generation. The precision of the OCL generation process is very high; 99% of the generated constraints are correct. The coverage criteria implemented in UMTG enable the identification of use case scenarios missed by engineers, thus highlighting its usefulness in safety domains. Also, with the def-use and subtype coverage criteria, UMTG generates test cases that cover all the scenarios exercised by the test cases manually written by engineers, with test inputs belonging to the same input partitions. This is achieved by automatically generated test suites that have the same size as the manually implemented ones, thus not affecting testing cost. Our experience indicates that the requirements modelling required by UMTG is feasible in an industrial context. Furthermore, manual test case generation requires significantly more effort than UMTG.

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