On Augmenting Scenario-Based Modeling with Generative AI

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Abstract: The manual modeling of complex systems is a daunting task; and although a plethora of methods exist that mitigate this issue, the problem remains very difficult. Recent advances in generative AI have allowed the creation of general-purpose chatbots, capable of assisting software engineers in various modeling tasks. However, these chatbots are often inaccurate, and an unstructured use thereof could result in erroneous system models. In this paper, we outline a method for the safer and more structured use of chatbots as part of the modeling process. To streamline this integration, we propose leveraging scenario-based modeling techniques, which are known to facilitate the automated analysis of models. We argue that through iterative invocations of the chatbot and the manual and automatic inspection of the resulting models, a more accurate system model can eventually be obtained. We describe favorable preliminary results, which highlight the potential of this approach.

1 INTRODUCTION

Manually modeling complex systems is a daunting and error-prone endeavor. Furthermore, even after the system is modeled, ongoing tasks, such as modification and repair, continue to tax human engineers. Creating tools and methodologies for streamlining and facilitating this process has been the topic of extensive work, but many aspects of the problem remain unsolved (Pettersson and Andersson, 2016; Biolchini et al., 2005).

In recent years, the deep learning revolution has been causing dramatic changes in many areas, including computer science; and this revolution has recently taken yet another step towards general-purpose AI, with the release of ChatGPT, the learning-based chatbot (OpenAI, 2022). ChatGPT, and other, similar tools (Google, 2023; MetaAI, 2023), can be used for countless kinds of tasks — including the modeling and coding of complex systems (Surameery and Shakor, 2023). An engineer might provide ChatGPT with a natural-language description of the system at hand, and receive in return a model of the system, or even computer code that implements it; and through iterative querying of ChatGPT, the system can later be modified or enhanced. This approach has already been used in several application domains (Surameery and Shakor, 2023; Burak et al., 2023; Liu et al., 2023).

Although the ability to integrate ChatGPT[1] into the software development cycle will undoubtedly empower engineers, there are also potential pitfalls that need to be taken into account. One drawback of ChatGPT and similar tools is that the answers they provide are often inaccurate, and might overlook important aspects of the input query (Liu et al., 2023). Moreover, the input query itself might be imperfect, and the engineer might not realize this until the system is deployed. Thus, if we make the reasonable assumption that human engineers will gradually become dependent on chatbots for various tasks, the risk increases that these inaccuracies will find their way into the final models of the system at hand and the code that ensues. We are thus faced with the following challenge: how can we harness ChatGPT in a way that lifts a significant load of work off the shoulders of the engineers, but which still results in sound and accurate models?

Here, we advocate the creation of an encompassing modeling scheme that will combine ChatGPT with more traditional techniques for manual modeling of systems (Biolchini et al., 2005; Pettersson and Andersson, 2016), in a way that will achieve this goal. Our core idea is to use ChatGPT in a controlled way; i.e., to repeatedly invoke it for various tasks, but to

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[1] We will often use the term *ChatGPT* somewhat generically, to represent an arbitrary, modern chatbot.

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then thoroughly inspect and analyze its results, to ensure their soundness and accuracy. We argue that such a scheme, if designed properly, would allow software and system engineers to benefit from the capabilities of modern chatbots, but without jeopardizing the quality of the resulting products. In the long run, we regard such a scheme as a step towards the *Wise Computing* vision (Harel et al., 2018), which calls for turning the computer into a proactive member of the software development team — one which can propose courses of action, detect under-specified portions of the model, and assist in the various routine actions that naturally arise as part of the software development cycle.

In order to design such a modeling scheme, we propose to leverage the extensive work carried out in the modeling community over the years. Specifically, we propose to focus on modeling frameworks that afford two benefits that complement the capabilities of ChatGPT: (i) the models produced by the framework are naturally well-aligned with how humans perceive systems; this, we believe, will make it easier for the human engineer to inspect ChatGPT's output; and (ii) the resulting models are amenable to automated analysis tasks, such as model checking, which will support the automated detection of bugs and inconsistencies in the automatically generated models.

Several modeling approaches fit this description, and many of them can probably be used, but for the initial evaluation presented here, we focus on *scenario-based modeling* (*SBM*) — a technique that generates models comprised of simple *scenarios*, each of which describes a single aspect of the system at hand (Harel et al., 2012b; Damm and Harel, 2001). As we later discuss, this can facilitate the smooth collaboration between ChatGPT and the human engineers.

To demonstrate the potential of this combined framework, we focus on a few tasks that arise naturally as part of a system's life cycle. Specifically, we discuss the initial design of the model, its testing and the verification of its properties, its later enhancement or repair due to the discovery of inconsistencies, and also a search for under-specified portions of the model. Our results, although preliminary, are very promising, and we hope this paper will form a basis for further research in this direction.

In the remainder of the paper, we present the key concepts of our approach, and discuss a high-level plan for the next steps. We begin by introducing the concepts of SBM and language model-based chatbots in Section 2. Next, we present the proposed integration of SBM and ChatGPT in Section 3, followed by a discussion of some of the more advanced aspects of this integration in Section 4. We discuss related work in Section 5 and conclude in Section 6.

2 BACKGROUND

2.1 Large Language Model-Based Chatbots

ChatGPT (Chat Generative Pre-trained Transformer) is a large language model (LLM) based chatbot, developed by OpenAI (OpenAI, 2022; Chang et al., 2023). The chatbot is able to conduct an iterative conversation of variable length, format, style, level of detail, and language. At each stage, the user presents a new prompt to ChatGPT, which then replies, based on all previous prompts in that conversation (the context). Following its debut in 2022, ChatGPT quickly became highly successful, and inspired multiple other companies to release their own chatbots (Google, 2023; MetaAI, 2023).

Internally, ChatGPT is implemented using a proprietary series of generative pre-trained transformer (GPT) models, which in turn are based on Google's transformer architecture (Vaswani et al., 2017). ChatGPT is fine-tuned for conversational applications, through a combination of supervised and reinforcement learning techniques, as well as manual adjustment by human engineers. ChatGPT's training, as well as its inference, are considered very costly in terms of power consumption and processing resources.

Functionality-wise, ChatGPT is highly versatile. Some of its many uses include generating student essays (AlAfnan et al., 2023), writing and debugging computer programs (Surameery and Shakor, 2023), and composing music (Lu et al., 2023). However, it will sometimes produce plausible-sounding but incorrect or nonsensical answers — a common limitation for large language models (Gregorcic and Pendrill, 2023).

2.2 Scenario-Based Modeling

Scenario-based modeling (Harel et al., 2012b) (SBM) is a modeling approach aimed at modeling complex, reactive systems. The main component in a scenario-based (SB) model is the *scenario object*, which describes a single behavior of the system at hand, whether desirable or undesirable, so that one can specify it as necessary, allowed or forbidden. Each scenario object does not directly interact with its counterparts, and can be created in isolation. Cross-scenario interaction is allowed only through a global execution mechanism, which can execute a collection of scenarios in a manner that produces cohesive, global behavior.

There exist several flavors of SBM, employing slightly different mechanisms for cross-scenario interactions. We focus here on a particular set of idioms, which has become quite popular: the *requesting*, *waiting-for* and *blocking* of discrete events (Harel et al., 2012b). During execution, each scenario object repeatedly visits designated *synchronization points*, and in each of these the global execution mechanism selects one event for triggering. A scenario object may declare events that it wishes to be triggered (*requested* events), events that it wishes to avoid (*blocked* events), and also events it does not request itself but would like to monitor (*waited-for events*). The execution mechanism collects these declarations from each of the scenario objects (or a subset thereof (Harel et al., 2013a)), selects one event that is requested and not blocked, and then informs all relevant scenario objects of this selection.

In a given synchronization point, multiple events may be requested and not blocked, and several strategies have been proposed for selecting one of them. These include an arbitrary selection, a random selection, a round-robin mechanism, and look-ahead that simulates possible progression of the execution and selects events with an attempt to achieve a desirable objective specified a-priori (e.g., the avoidance of deadlocks). Executing a scenario-based program in this manner is termed play-out (Harel and Marelly, 2003)).

Fig. 1 depicts a simple example of an SB model. The system at hand controls the water level in a water tank, which is equipped with hot and cold water taps. Each scenario object appears as a transition system, in which nodes corresponds to the predetermined synchronization points. Scenario object ADDHOTWATER repeatedly waits for WATERLOW events, and when such an event is triggered, it requests three times the event ADDHOT. Similarly, scenario object ADDCOLDWATER requests the addition of cold water. When the model includes only objects ADDHOTWATER and ADDCOLDWATER, three ADDHOT events and three ADDCOLD events may be triggered in any order during execution. If we wish to maintain a more stable water temperature within the tank, we might add the scenario object STABILITY, to enforce the interleaving of ADDHOT and ADDCOLD — through the use of event blocking. An execution trace of the model containing all three objects appears in the event log.

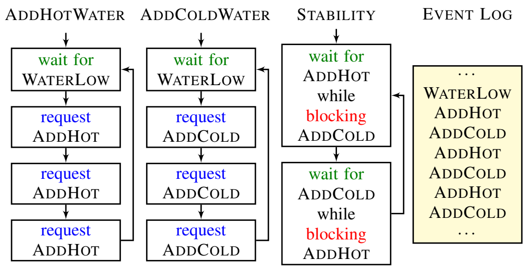

Figure 1: A scenario-based model for a system that controls the water level in a tank with hot and cold water taps (taken from (Harel et al., 2014)).

The SBM framework has been implemented on top of multiple high-level languages, including Java (Harel et al., 2010), C++ (Harel and Katz, 2014), Python (Yaacov, 2023), JavsScript (Bar-Sinai et al., 2018) and ScenarioTools (Greenyer et al., 2017). Furthermore, SBM has been applied in modeling various complex systems, such as web-servers (Harel and Katz, 2014), cache coherence protocols (Harel et al., 2016a) and robotic controllers (Gritzner and Greenyer, 2018). In order to simplify the presentation in the following sections, we mostly describe SB models as transitions systems.

In formally defining SBM, we follow the definitions of (Katz, 2013). A scenario object O over event set E is a tuple $O = \langle Q, \delta, q_0, R, B \rangle$, where the components are interpreted as follows:

- Q is the set of states. Each state represents a single, predetermined synchronization point;
- $q_0 \in Q$ is the initial state;
- $R : Q \to 2^E$ and $B : Q \to 2^E$ map states to the sets of events requested and blocked at these states, respectively; and
- $\delta : Q \times E \to 2^Q$ is the transition function, which indicates how the object switches states in response to the triggering of events.

Once the individual scenario objects are created, they can be composed in a pairwise fashion. Two scenario objects $O^1 = \langle Q^1, \delta^1, q_0^1, R^1, B^1 \rangle$ and $O^2 = \langle Q^2, \delta^2, q_0^2, R^2, B^2 \rangle$, specified over a common set of events E, can be composed into a single scenario object $O^1 \parallel O^2 = \langle Q^1 \times Q^2, \delta, \langle q_0^1, q_0^2 \rangle, R^1 \cup R^2, B^1 \cup B^2 \rangle$, where:

- $\langle \tilde{q}^1, \tilde{q}^2 \rangle \in \delta(\langle q^1, q^2 \rangle, e)$ if and only if $\tilde{q}^1 \in \delta^1(q^1, e)$ and $\tilde{q}^2 \in \delta^2(q^2, e)$; and
- the union of the labeling functions is defined in the natural way; i.e., $e \in (R^1 \cup R^2)(\langle q^1, q^2 \rangle)$ if and only if $e \in R^1(q^1) \cup R^2(q^2)$, and $e \in (B^1 \cup B^2)(\langle q^1, q^2 \rangle)$ if and only if $e \in B^1(q^1) \cup B^2(q^2)$.

Using the composition operator $\parallel$, we can define a *behavioral model* M as a collection of scenario objects, $M = \{O^1, O^2, \ldots, O^n\}$. The executions of M are

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defined to be the executions of the single, composite object $O = O^1 \parallel O^2 \parallel \ldots \parallel O^n$. Thus, each execution starts from the initial state of O, which is the n-tuple of the initial states of its constituent objects, and throughout the run, in each state q an enabled event $e \in R(q) - B(q)$ is chosen for triggering, if one exists. The execution then moves to a state $\tilde{q} \in \delta(q,e)$, and the process repeats.

3 INTEGRATING ChatGPT AND SBM

3.1 Basic Integration

As a first step to integrating ChatGPT and SBM, we present a simple methodology for creating scenario objects from free-text, using ChatGPT. In order to get ChatGPT to present its output as a scenario object, we propose to include in each query a *preamble* that describes the SBM semantics, as described in Section 2. This preamble instructs ChatGPT to present its output as a transition system, in which each state is labeled with requested and blocked events, and has a set of transition rules indicating its successor state, based on the event later triggered. Note that this preamble needs only be crafted once, and can then be attached to any subsequent query. If a specific implementation of SBM is used (e.g., C++, Java), the output can be crafted to match the required syntax of that implementation.

The simple preamble that we used in our initial experiments is as follows:

> I would like you to help me create a scenario-based model. A scenario-based model is comprised of a finite set of events, and scenarios. Each scenario is a sequence of states. In each state the scenario can request events, wait-for events, and block events. Afterwards, one event that is requested by at least one scenario, but is blocked by no scenario, is selected for triggering. Scenarios that requested or waited-for this scenario may then change states, and the process repeats itself. Scenarios cannot have internal loops or variables; these must be expressed using additional states.
>
> To display scenarios, please use the following format. For each state, mention the state's name, and the sets of requested and blocked events. Also, mention the transitions to other states. For example:
>
> - s1: request X, block Y. If X is triggered, go to state s2.
> - s2: request Y, block X. If Y is triggered, go to state s2.
>
> Now, here are the details of the specific scenario-based model I'd like you to create…

Given this preamble, we can use ChatGPT to produce the model we described in Section 2. To produce the AddHotWater scenario, we use the following prompt:

> Consider the event set WaterLow, AddHot, AddCold.
>
> Please suggest a scenario that waits for event WaterLow (without requesting it). When WaterLow is triggered, the scenario performs the following, 3 times in a row: request the event AddHot, and wait for it to be triggered (both in a single state). When the 3rd AddHot event occurs, the scenario transitions back to its initial state.

In response to this prompt, the chatbot replies:

> - s1: wait for WaterLow. If WaterLow is triggered, go to state s2.
> - s2: request AddHot, wait for AddHot. If AddHot is triggered, go to state s3.
> - s3: request AddHot, wait for AddHot. If AddHot is triggered, go to state s4.
> - s4: request AddHot, wait for AddHot. If AddHot is triggered, go to state s1.

Which is equivalent to the transition system we presented in Fig. 1. The AddColdWater scenario can be generated symmetrically. Now, if we wish to incrementally modify the system by introducing the Stability scenario, we can issue the following prompt:

> Please suggests a scenario that ensures that uses blocking to ensure that no two consecutive AddHot events can be triggered, and that no two consecutive AddCold events can be triggered; that is, once AddHot is triggered, AddCold must be triggered before AddHot can be triggered again, and vice versa. This scenario should not request any events, and should work regardless of any WaterLow events.

And in response, the chatbot produces the Stability scenario, as described in Fig. 1.

We note a subtle difference between the way we prompted ChatGPT for the first two scenarios,

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ADDHOTWATER and ADDCOLDWATER, and our prompting for STABILITY. In the former two cases, our prompt contained information that roughly described the transition system itself, whereas in the third case our description was more high-level, and did not mention the word "state". Still, in both cases, ChatGPT produced the desired result. This demonstrates the wide range of specifications with which the chatbot can successfully deal, and suggests that it can be used even when the engineers are themselves not entirely certain of the structure of the scenario they require. While it stands to reason that more accurate descriptions would lead to more accurate results, it appears that even high-level descriptions can be very useful, especially when combined with the automated analysis techniques that we discuss next.

3.2 The Proposed Methodology

Building upon this basic integration of ChatGPT and SBM, we now outline a structured LLM-agnostic and language-agnostic methodology for creating complex *reactive models*, i.e., models of systems that interact with their environment repeatedly over time, and receive external inputs (Harel and Pnueli, 1985). Numerous modern, critical systems can be regarded as reactive (Aceto et al., 2007), and consequently there has been extensive research on developing tools and methods for modeling these systems. Despite this tremendous effort, there still remain significant gaps, which could result in models that are inaccurate or that are difficult to maintain. The present work, which can be seen as an element of the Wise Computing vision (Harel et al., 2018), seeks to mitigate these gaps, through the creation of advanced, intelligent tools that will begin to undertake the software and system development tasks that are normally assigned to humans. The core of the approach is to have system components be generated, iteratively and incrementally, with the help of an LLM; and to have the LLM's outputs checked systematically, and perhaps automatically, using various tools and methods.

1. Describe the problem and the environment textually, in natural language.
2. Choose a compositional, scenario-based modeling language, which has well-defined execution semantics and is suitable for the incremental development of the system.
3. Obtain an LLM that is familiar with the application domain in general, or can readily gain extensive knowledge about that domain, and which can (or can be taught to) generate code in the chosen scenario-based language.
4. Describe, perhaps iteratively, the semantics of the scenario-based language to the LLM as a preamble. Confirm that the LLM indeed internalizes the details of the language semantics by teaching it to execute (i.e., play out (Harel and Marelly, 2003)) systems described as scenarios or rules in the chosen language, where the LLM outputs logs of triggered events, scenario states, composite system states, values of environment variables and changes thereto, etc.
5. Iteratively add scenarios and refine existing ones, as follows:
   (a) Describe in a prompt one or more scenarios for certain not-yet-specified requirements or aspects of the system.
   (b) Have the LLM generate actual scenarios for the prompt, in the chosen language.
   (c) Have the LLM generate natural language description of properties to be verified, executable test cases, and assertions for formal verification tools, per the original requirements. This constitutes stating the requirement at hand from different perspectives.
   (d) Carry out initial testing and validation within the LLM, challenging the LLM to find gaps and incorrect execution paths on its own. Correct the natural language specification and prompts as needed.
   (e) Systematically check the LLM output outside of the LLM, using any or all of the following: code reviews by human engineers, unit testing of individual scenarios, subsystem testing with some or all of the already-developed scenarios, model checking of the new scenarios, as well as those of the composite system, etc. The testing is to be carried out in the execution environment of the language, and model checking is to be carried out using a suitable formal verification tool. Both should be independent of the LLM environment. Possibly automate the subjecting of generated scenarios to testing and model checking.
   (f) When errors are found, do not modify the generated code. Instead, revise the LLM prompts until correct system scenarios and verification and testing properties are generated. This step is critical for aligning the stakeholder (i.e., customer) view of the requirements, the developer's understanding, and the actual code.
   (g) Once the set of generated scenarios seems ready, repeat the likes of step (d), asking the LLM to find gaps or potential failures in this set of scenarios; specifically look for LLM

suggestions of new environment considerations that prevent the system from working correctly. This step simulates the common system engineering task of having external experts or potential customers review advanced prototypes of systems. Repeat earlier steps as needed.

Next, we elaborate on some of these steps, and provide simple, illustrative examples.

4 USING THE METHOD IN THE DEVELOPMENT CYCLE

4.1 Code Generation

Code generation is probably the most straightforward chatbot capability that we propose be integrated into the development cycle. In Section 3 we showed that ChatGPT can generate an (executable) SB model — a capability that has also been demonstrated with other languages (Surameery and Shakor, 2023; Burak et al., 2023; Liu et al., 2023). A unique advantage in the context of SB systems is the ability to generate standalone scenarios, which can be reviewed and tested separately, and then be incrementally added to the system under development. In our preliminary testing for this paper, we experimented with code generation for requirements in the realms of autonomous vehicles, algorithms on data structures, simulating natural phenomena, and control systems. In all of these, the ChatGPT/SBM integration proved useful.

4.2 Modeling

Once ChatGPT understood the principles underlying scenario-based models, it was able to combine its knowledge of the problem domain, the world at large, and logic, in order to develop or enhance a model. It was able to introduce new environment events, describe the sensor scenarios that are required for triggering these events, and then add the necessary application scenarios that react to these events. For example, when we asked ChatGPT to generate scenario-based code for a bubble-sort algorithm to be used by a robot moving numbered tiles on a sequence of cells, it was able to introduce the events of detecting the arrival of a tile at the tail-end of the array, as well as scenarios for reacting to such events.

4.3 Play Out & Simulation

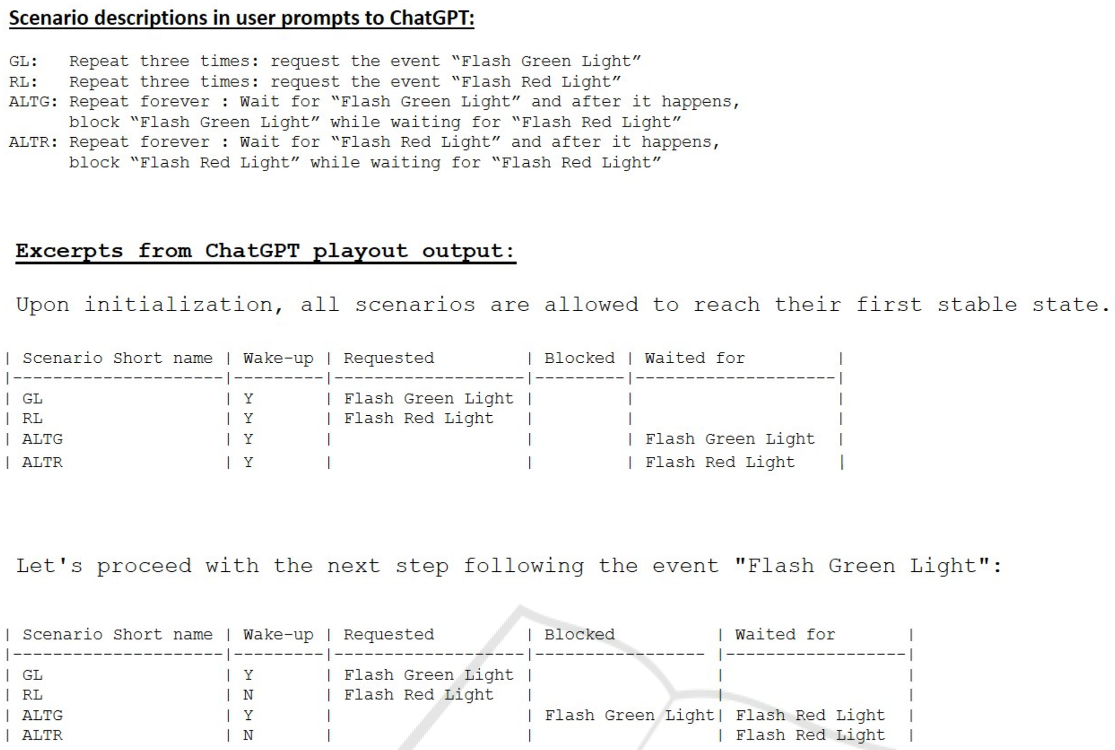
After a few iterations, we were able to teach ChatGPT to produce an execution log of an arbitrary scenario-based specification. At first we observed “wishful thinking”, where ChatGPT described the run as it should be per the problem description. However, as illustrated in Fig. 2, ChatGPT was then able to follow the execution steps correctly, displaying at each synchronization point the event that triggered the state transition that led to this synchronization point, and a table of all scenarios, indicating for each one whether or not it was put into action by the triggered event, and providing its declaration of requested, blocked and waited-for events.

4.4 SMT-Like Model Analysis

One of the advantages of scenario-based modeling is its amenability to formal verification with appropriate tools, both by exhaustive model checking traversing all paths, and by using domain knowledge for Satisfiability Modulo Theory (SMT) verification (Harel et al., 2011; Harel et al., 2013b). This is accomplished by virtue of the abstraction and encapsulation of domain-specific processes, actions and conditions as events and states. System complexity thus emerges from the composition of relatively small intuitive scenarios reflecting individual requirements, and not from the intricate conditional flow of delicate and sensitive processes with numerous steps.

Our experiments have shown that ChatGPT is able to leverage this kind of abstraction and encapsulation to identify cases that a specification either omitted or handles incorrectly. For example, we presented ChatGPT with the following three requirements for an autonomous vehicle: (i) always stop at a red light; (ii) always obey a police person’s instructions; (iii) never injure a person. ChatGPT readily recognized that these requirements may be in conflict with each other. Given the safety property of not entering an intersection when the traffic light is red, it pointed out that the AV may be unable to stop if the road is icy, that it may enter the intersection involuntarily if after stopping it is hit from behind by a car that did not stop, and, furthermore, that it may injure a person without moving, if a person walks behind the AV, and another vehicle hits the person who is then thrust against the AV.

In a mathematical, SMT-like analysis, ChatGPT was able to identify a particularly interesting execution path. We presented it with a system consisting of the following four scenarios: the first requests flashing a red light briefly in response to an external time tick event, and then waits for any event; the second does the same with a green light; the third scenario blocks the event of flashing the red light every third tick, and another blocks flashing the green light every



Scenario descriptions in user prompts to ChatGPT:

```
GL:   Repeat three times: request the event “Flash Green Light”
RL:   Repeat three times: request the event “Flash Red Light”
ALTG: Repeat forever : Wait for “Flash Green Light” and after it happens,
      block “Flash Green Light” while waiting for “Flash Red Light”
ALTR: Repeat forever : Wait for “Flash Red Light” and after it happens,
      block “Flash Red Light” while waiting for “Flash Red Light”
```

Excerpts from ChatGPT playout output:

```
Upon initialization, all scenarios are allowed to reach their first stable state.

| Scenario Short name | Wake-up | Requested          | Blocked | Waited for         |
|---------------------|---------|--------------------|---------|--------------------|
| GL                  | Y       | Flash Green Light  |         |                    |
| RL                  | Y       | Flash Red Light    |         |                    |
| ALTG                | Y       |                    |         | Flash Green Light  |
| ALTR                | Y       |                    |         | Flash Red Light    |


Let's proceed with the next step following the event "Flash Green Light":

| Scenario Short name | Wake-up | Requested          | Blocked          | Waited for       |
|---------------------|---------|--------------------|----------------- |------------------|
| GL                  | Y       | Flash Green Light  |                  |                  |
| RL                  | N       | Flash Red Light    |                  |                  |
| ALTG                | Y       |                    | Flash Green Light| Flash Red Light  |
| ALTR                | N       |                    |                  | Flash Red Light  |
```

Figure 2: *A simulation of scenario execution with ChatGPT.* Top: textual description of scenarios in user prompts. Middle and bottom: The first two entries in ChatGPT's output when requested to play out the execution, showing triggered events, the scenarios that reacted to the triggered events, and the declarations of each scenario at the next synchronization point.

five ticks. We then added the requirement that at least one light must be flashed between any two consecutive time ticks. ChatGPT was able to respond that the requirement is not satisfied, and that every 15 time ticks ($3 \cdot 5$) both events will be blocked. ChatGPT apparently recognized this by arithmetic calculation and not by step-by-step simulation, as it was able to quickly reach the same conclusion for arbitrarily large numbers.

Here is an excerpt from this conversation, after describing the scenarios. When prompted with

> now a new requirement came in: always, after every tick, *at least one light* must be flashed. Does the combined system of red flashing and green flashing with the 3 and 5 restrictions satisfy the requirement?

ChatGPT replies:

> To analyze whether the combined system satisfies the new requirement that at least one light must flash after every tick, we must consider the synchronization points of both the red and green systems with their respective restrictions:
>
> The red system flashes on every tick, except every third one. The green system flashes on every tick, except every fifth one. If we consider the sequence of ticks and apply both restrictions, the combined system would not flash a light on a tick that is both a multiple of three and five — specifically, on ticks that are multiples of fifteen, since 15 is the least common multiple of 3 and 5. At such ticks, both systems would be blocking their respective lights from flashing due to their individual restrictions.
>
> Therefore, on ticks that are multiples of fifteen (like the 15th, 30th, 45th tick, and so on), neither light would flash, violating the new requirement that at least one light must flash after every tick.
>
> In conclusion, the combined system of red flashing and green flashing with the restrictions of not flashing on ticks divisible by three and five, respectively, does not satisfy the requirement that at least one light must be flashed after every tick.

ChatGPT also successfully discussed generalizations of this computation, including calculating the

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number of composite system states that would have to be traversed in exhaustive model checking.

It is interesting to note though, that while the LLM was able to apply its logic to find system execution paths with special properties, it did not do well when asked to list *all* the execution paths possessing a certain property. For example, we presented it with a 4-by-4 grid of cells, and asked for the steps that a robot may take from (0,0) at the bottom left to (3,3) at the top right, using the events for right, left, up, and down motions. We also required that the path remains within the grid. ChatGPT was able to list paths like *right,right,right,up,up,up* and *right,up,right,up,right,up*, but when asked to list all the paths that go through (1,3) it failed, listing several paths that do not reach the desired target, including *up,up,up,right,down,down,right,up,right*. ChatGPT is thus not yet ready to carry out exhaustive model checking on scenario-based systems. This is not really an issue, however, since with the proposed methodology verification of the LLM's outputs will be carried out independently of the LLM environment.

4.5 Identifying Under-Specification

Even when the created model addresses the stated requirements perfectly, as may be possible with synthetic or reduced problem descriptions, there may be additional areas of the broader problem domain that can or must be handled. In response to appropriate prompts ChatGPT was able to significantly enrich a developed model, or helped restate the explicit boundaries and expected scope of the intended system.

For example, in (Harel et al., 2023) we presented ChatGPT with a scenario-based model that was developed for science teaching purposes. The model describes how bees depend on the ambient temperature for switching between hibernation and being active, flower plants depend on hours of daylight in order to start blooming, and active bees depend on blooming flowers for survival. In the original model, average temperatures and number of daylight hours were parameters that students could adjust to see how certain combinations of settings might be sustaining while others can cause the bees to die out due to hunger.

When we asked ChatGPT to offer enhancements to the education model, it suggested to consider weather-related variations that modify the prespecified fixed average temperature and the number of daylight hours for a given time of year.

4.6 Explainability

Given a certain observed or expected behavior of the system, ChatGPT is able to produce a natural language description of the cause of that behavior, finding a reasonable balance between the arcane details of the complete execution trace, and the overall requirement that ”this is what the system was supposed to do”.

For example, following a paragraph on the semantics of SB modeling we presented the following prompt:

> In a system with two scenarios, one waits for time tick events and after each time tick requests a short beep (100 msec). The other scenario waits for time ticks, and after each such event requests a long beep (500 msec). Each of these scenarios waits for both the short and long beep events, so that after each time tick, exactly one beep occurs. Actuator scenarios actually cause the respective beeping action. Time tick events are injected by the environment every one second. A user reported that it watched the system for 20 seconds, and never heard a long beep. Can you explain why this may have happened?

ChatGPT response was:

> The user's report of not hearing a long beep in a system with two scenarios—one requesting a short beep after each time tick, and the other requesting a long beep after each time tick—can be explained through the principles of Scenario-based Modeling (SBM).
>
> In SBM, when multiple scenarios request different events after a shared trigger event, the execution environment selects one of these requested events to occur. The selection can be arbitrary or follow a specific strategy, such as alphabetic or lexical order, priority, random, round-robin, etc. In this case, if the event selection strategy prioritizes the short beep over the long beep (for example, due to alphabetic order, where “short beep” comes before “long beep”), then the short beep will always be selected to occur after each time tick, and the long beep will never be executed. Since time tick events are injected by the environment every second, and both scenarios are waiting for this event, each time tick leads to both scenarios being activated. However, if the system consistently selects the short beep event over the long beep event after each time tick, the scenario requesting the long

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> beep will never progress to the state where it actually triggers the long beep. As a result, only short beeps will be heard.
>
> In summary, the user's observation of not hearing any long beeps can be attributed to the event selection mechanism within the SBM framework, which in this case consistently favors the short beep event over the long beep event. This could be due to the selection strategy used by the system (like alphabetic order) or other operational logic specifics.

We then challenged ChatGPT again:

> Thank you. Assume that the developers changed the selection algorithm and they now select events randomly. The user tested the system many times, for hours, and never heard a long beep. Can you try to explain?

To this, ChatGPT produced a very comprehensive answer, covering possible issues with application scenarios, the execution infrastructure, and human-machine interaction. Here are some excerpts:

> If the event selection algorithm was changed to randomly select between the short beep and long beep events, but the user still never hears a long beep, there are several potential explanations:
>
> Implementation Error in Random Selection: The most straightforward explanation could be a bug or implementation error in the random selection algorithm. It might not be truly random, or it could be incorrectly favoring the short beep event due to a coding mistake.
>
> Issue with the Long Beep Scenario: There might be a problem with the scenario that requests the long beep. This could be a coding error or a logical flaw in the scenario itself, preventing it from properly requesting the long beep event.
>
> User Perception or Reporting Error: Finally, there could be an issue with how the user is perceiving or reporting the beeps. They might be missing the long beep due to distraction, ambient noise, or misunderstanding what constitutes a long beep in the context of this system.
>
> To diagnose the issue accurately, developers would need to conduct thorough testing and debugging, looking into each of these potential areas to find where the problem lies.

While such explanations are impressive, they were not perfect. We had cases where we presented ChatGPT with well specified scenarios and a description of an observed execution log, i.e., an event sequence, but ChatGPT was not able to retrospectively produce a step by step play-out sequence that would generate this execution log. Instead, it provided incorrect explanations for that event sequence. While frequently providing ChatGPT with better reminders and interactive practice of its knowledge of semantics and play-out may remedy such issues, this caveat is a reminder that all outputs produced by the LLM must be formally checked.

4.7 Accommodating Semantic Flexibility

Most software development studios are tied to specific languages and their associated semantics. In our experiments, ChatGPT was able to accommodate, and discuss, alternative semantics.

For example, in the water tap example in Section 2, when the scenario AddHotWater is in any of the states where it requests AddHot, it cannot react to WaterLow, since it is not waiting for that event. By contrast, in the semantics of the LSC scenario-based language, the infrastructure constantly listens for all events that are waited for in the first state of all scenarios. When such an event occurs, the infrastructure instantiates another copy of the scenario. In fact, from our first textual descriptions of SBP, ChatGPT understood this semantics to be the default.

In another example, we asked ChatGPT to generate scenarios for Quicksort. Before starting, it commented that it will be hard, as classical solutions are recursive. We then pointed out to ChatGPT that there is a published implementation that is iterative, not recursive (Harel et al., 2021), that is structured as instructions to human workers arranging cars in an automobile dealership parking lot according to, say, window-sticker price, where each employee had one narrow role. ChatGPT readily accommodated the new mindset and produced the desired scenario-based specification.

4.8 Interactive Mutual Learning

In our experiments, we noticed that ChatGPT learns from multiple prompts, discussions and exploration better than from concise or detailed descriptions. We believe that the same may hold for software and system developers. Interactive, agile development processes may not be just trial and error, or spiral convergence to and discovery of a predefined but poorly specified goal. Rather, they are often constructive processes, where stakeholders and developers build

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their wishes and plans, as they refine their own understanding of the environment, the systems, their needs, and their future interactions with the system.

An important part of this refinement is producing more explicit definitions of elements that are outside the scope of the system. In contrast, such definitions are often totally absent from classical system specifications.

5 RELATED WORK

Recent advances in LLM-based chatbots have made a considerable impact on numerous domains. Researchers and engineers are now examining the potential applications of this technology in education (AlAfnan et al., 2023), music (Lu et al., 2023), academia and libraries (Lund and Wang, 2023), healthcare (Li et al., 2023), and many other areas.

Within the field of software engineering, which is our subject matter here, attempts have been made to apply chatbots to evaluate the quality of code (Burak et al., 2023), to correct bugs (Surameery and Shakor, 2023), and to generate code automatically or semi-automatically (Feng et al., 2023; Dong et al., 2023). The general consensus appears to be that chatbots will play a key role in code generation in years to come. Our work here outlines a possible path towards allowing this integration in a safe and controlled manner.

Our proposed methodology for integrating ChatGPT into the software engineering process leverages the large body of existing work on scenario-based modeling (Harel et al., 2012b; Damm and Harel, 2001). Specifically, we propose to make use of the amenability of SBM to formal analysis techniques (Harel et al., 2015a; Harel et al., 2015b), such as verification (Harel et al., 2011; Harel et al., 2013b), automatic repair (Harel et al., 2012a), and synthesis (Greenyer et al., 2016). Despite our focus on SBM, other modeling approaches, with similar traits, could be used in a similar manner.

Finally, our work here can be regarded as another step towards the *Wise Computing* vision (Harel et al., 2016a; Harel et al., 2016b; Harel et al., 2018), which seeks to transform the computer into an active member of the software engineering team — raising questions, making suggestions and observations, and carrying out verification-like processes, even without explicitly being asked to do so.

6 CONCLUSION

The appearance of large language models, and the subsequent release of advanced chatbots, is a major development, and it is likely to revolutionize the domain of software engineering in coming years. However, because of inaccuracies and errors that are inherent to the outputs of these chatbots, such an integration must be performed with care. We outline here a possible method for such an integration, which makes use of the advanced features of chatbots, but which also puts an emphasis on inspecting and analyzing the results of the integration. We are hopeful that our work will trigger additional research in this important direction.

Moving forward, we plan to continue this work along several axes. First and foremost, we intend to implement the necessary tools and environments needed to fully integrate ChatGPT with SBM, and then use these tools and environments in large, real-world case studies that will demonstrate the usefulness of the approach as a whole.

In addition, we expect that this line of work will require us to enhance and modify existing tools, both on the SBM said and on the chatbot one. For instance, with the current version of ChatGPT, every conversation starts from a blank slate, whereas for the ongoing development of a system, as part of the Wise Computing vision, it would be more useful to have the chatbot remember and use previous conversations. This could be achieved, for instance, by summarizing each conversation as it ends, and then feeding these summaries back to the chatbot when a new conversation starts. In fact, with the newly announced GPTs feature introduced in ChatGPT one can build a chatbot that is customized specifically for developing SB models and programs.

Ideally, LLMs will be able learn immediately from ongoing conversations, yet they will do so selectively, learning over time, to select what should be retained in each conversation and for how long.

These developments can also be beneficial in a broader perspective: prompt engineering methods and practices that would be developed along the way for such interactive, incremental development may prove useful not only in teaching computers, but in enhancing the training and everyday communications of human engineers.

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