Verifying Stochastic Behaviors of Decentralized Self-Adaptive Systems: A Formal Modeling and Simulation Based Approach

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Abstract—Self-adaptive software is considered as the most advanced approach and its development attracts a lot of attention. Decentralization is an effective way to design and manage the complexity of modern self-adaptive software systems. However, there are still tremendous challenges. One major challenge is to unify decentrality with traditional self-adaptive implementation framework during design and implementation activity. One is to guarantee the required global goals and performance of decentralized self-adaptive systems operating in highly dynamic and uncertain environments. Another challenge is to predict the influence of system’s internal change on its self-adaptability to the environment. To solve these problems, we combine the mechanisms of separation of concerns with modeling method using timed automata to allow the system to be analyzed and verified. Timed computation tree logic is used to specify system goals and stochastic simulations in dynamic environment are experimented to verify decentralized self-adaptive system’s adaptation properties. In this paper, we extracted a motivation example from practical applications in UAV emergency mission scenarios. The whole approach is evaluated and illustrated with this motivation example and the statistical results can be used as reference for arrangement planning of UAVs in cyber physical spaces.

Keywords—self-adaptive software; modeling; verification; timed automaton; temporal logic;

I. INTRODUCTION

Current society extensively relies on software systems to achieve specific goals. However, ensuring these required goals of software systems is a tremendous challenge since there are lots of uncertainties that the developer cannot totally understand or think about during design activity, and the changing environment and system goals lead to costly reconfiguration and time-consuming maintenance tasks [1]. Therefore, there is a high demand for managing complexity reduction and achieving desired goals within a reasonable cost and timely manner. Self-adaptive software is generally considered as one of the most promising approaches to manage the complexity and uncertainties of modern software systems since it enables a system to adapt itself autonomously to internal and environmental dynamics to achieve particular goals including performance, security, fault management, etc [2]. Self-adaptation means that a system should be self-managing, self-governing, self-maintenance and self-control, underlies to more primitive level as self-awareness (i.e., the system is aware of its own states and behaviors), and context-awareness (i.e., the system realizes its environment context) [3].

Self-adaptive systems could be either centralized or decentralized. This paper is focusing on decentralized self-adaptive systems whose behaviors and objectives have to be synthesized from the interactions of autonomous constituent subsystems [12]. There are two main characteristics of decentralized systems. On one hand, constituent subsystems are autonomous which implies that their behaviors and interactions are not coordinated by any centralized facility. On the other hand, autonomous subsystems should exhibit coherent behaviors to achieve global goals of systems and meanwhile eliminate conflicts by interacting with one another.

Decentralized self-adaptive systems are an important branch of self-adaptation and require to be studied in order to understand the most effective way to design and manage complex systems [4]. One consideration is that complex systems are usually composed of different number of subsystems, distributed in several places and connected by the Internet or the cloud. Therefore, their uncontrolled distribution easily leads to the absence of global knowledge and difficulty in sharing the global status of the system. The other thought is to ensure that systems are robust enough against failures especially single node failure.

Three fundamental challenges related to decentralized self-adaptive systems [5] have not been resolved thoroughly so far. Firstly, how to unify the features of decentralized systems with commonly used self-adaptive implementation framework (i.e., MAPE framework)? Secondly, how to ensure that decentralized self-adaptive systems satisfy their global goals and maintain a satisfactory performance under the changing environments? Thirdly, how to predict the adaptability of decentralized self-adaptive systems when there are unexpected
or uncertain changes (even irreparable damages) take place in the systems themselves? These problems can be seen in many practical applications. For example, UAVs, commonly known as drones without human pilots aboard and having a wide range of applications in many fields like environment hazards monitoring, traffic management and photogrammetry, are usually deployed in cyber physical spaces and arranged as a whole decentralized self-adaptive system to carry out search and rescue tasks which are too dirty, dangerous, or impossible for humans. Then, people may have some expectations (or goals) on the UAV-involved system, whether the system can explore the entire space and search all targets in given time under the changing environment, and whether the system is still adaptive when some UAVs crash or run out of batteries. The analogous problems can be found in amount of different decentralized self-adaptive systems.

This paper comes up with a novel approach to current challenges. First, we introduce a method for modeling a decentralized self-adaptive system and its environment separately. In the method, separation of concerns is applied to decompose and model each decentralized self-adaptive subsystems and its environment into several low-coupling components since there are always uncertain changes taking place in the environment and it is irrational to maintain an environment model in the system in advance. Meanwhile timed automata are adopted to model components of a decentralized system and different aspects of the environment. A timed automaton is a kind of finite automaton extended with a finite set of resettable valued clocks and it can be added with stochastic and non-linear dynamical features. Thus, the system and its adaptation behaviors can be analyzed and verified entirely. Then, we describe a method for specifying and verifying the required adaptation properties of decentralized self-adaptive systems. In the method, the primary global goals of a decentralized self-adaptive system are specified by using TCTL (timed computation tree logic), which extends computation tree logic by discrete time variables and time constraints. Meanwhile, the adaptation properties (mainly about the satisfactions of the global goals’ achievements) of a decentralized self-adaptive system in a dynamic environment are verified and validated by simulation. In this work, we adopt a statistical model checking tool to carry out the simulation by executing the formal models specified in timed automata and further verifying the adaptation properties.

To illustrate the whole approach, particularly about how the components and their behaviors of a decentralized self-adaptive system situated in an uncertain context is modeled formally and how the adaptation properties of the system is specified and verified, we describe and implement a motivation example, which is extracted from fully autonomous and decentralized UAVs emergency scenario in practical application. The statistical results of the scenario acquired from the approach can be used as reference for arrangement planning of UAVs in a real smart city.

The rest of the paper is structured as follows. Section 2 describes the motivation example extracted from UAV emergency scenarios. Section 3 introduces the overview of our approach. Section 4 presents decentralized self-adaptive architecture. Section 5 declares behaviors modeled by using timed automata. Section 6 explains property specifications by using TCTL and section 7 illustrates adaptation evaluation through simulation runs. Section 8 details some related work and the final section makes some concluding remarks on this paper and points out our future work.

II. MOTIVATION EXAMPLE

To motivate our work on decentralized self-adaptive systems we introduce an example throughout the paper. The example describes a setting including a decentralized system and its environment, illustrates two main characteristics of this system and challenges of self-adaptive behaviors in dynamic environment. This motivation example can be instantiated as a variety of searching and rescuing or surveillance scenarios where fully autonomous UAVs operate in a space-dependent environment and global properties of the system need to be formally verified.

A. Scenario Discription

In the scenario, communication infrastructure is disabled in a city due to disasters; parts of the city may be unsafe; victims might be stranded in various locations and have no idea of where the rescue center is, autonomous UAVs are dispatched to locate victims and lead them to the safe areas. Search and rescue work must be performed. Autonomous UAVs are then dispatched to locate victims, leading them to safe area. Naturally, UAVs can move in the city environment in specific ways by utilizing global knowledge of the city map and local knowledge (limited by e.g., line of sight) of positions of neighboring UAVs and victims. If a UAV is close to a victim, it can lead him to a safe zone. A safe zone is where a hospital or an ambulance locates and medical assistance can be provided for victims.

The disaster city can be divided into several different districts and each district has one rescue center. Fig.1 visualizes a possible configuration of a district. The rescue center is the safe zone mentioned above and in charge of the whole district’s safety. The district then is divided into several blocks and each block contains one building at most. The victims are spread in different blocks and have no idea of where the rescue center is since the public communication is disabled. Several drones will be arranged in each district to guide victims to the rescue center of this district. The UAVs will start from the block where the rescue center is, search for victims by local knowledge and lead them to the safe zone by global knowledge of the city map.

![Fig. 1. One configuration of a district](image-url)
B. Scenario Characteristics

Each drone in a single district can be seen as subsystems of a decentralized self-adaptive system with the following characteristics. First, due to the disable of the public communication in disaster scenarios, a centralized control center may result in unacceptable overhead and bottleneck, thus, every drone carrying private communication infrastructure is fully autonomous and decentralized without a ground control system instructing what drone needs to do. Second, even though drones search and rescue victims independently, they should cooperatively achieve the global goal of saving all the victims in their ruling district and coordinate with each other when two drones are near and possibly colliding.

The cyber physical spaces where decentralized UAVs operate are highly dynamic and uncertain. The main uncertainties of environment we consider are the movements of different victims. In a disaster scenario, since victims have no idea of where rescue centers are, their behaviors cannot be predicted easily. According to the report of psychologists from CRHNet [7], immediately following the impact of a disaster, nearly 4/5 of victims are in a state of shock and unable to cope with the situation by themselves. Thus we assume that a victim is prone to staying where he is with 80 percent probability, which means that there are still 20 percent of chance that he would choose move. Also, the directions of the victim’s movement are uncertain. Each direction, north, south, east and west can be equally treated with the same probability, each of 25 percent probability. And if the victim can reach a building where he thinks as a relative unthreatening place, it is very probable that he would just wait there for rescue. Although victims may have some knowledge of the district, this information is not considered.

C. Scenario challenges

In this scenario, since this category of the system is related to human safety without slight mistake being tolerated, it must be analyzed and verified in advance and the analysis results could then be used as reference for actual deployment and dynamic adjustment.

Developing self-adaptive software deployed in each drone is not easy, but not that hard. However, ensuring the global goals, e.g., all the victims in the district can be searched and rescued in an acceptable period, brings challenges when drones are deployed in the dynamic and uncertain environment and victims’ movements are unforeseen. Also, when the internal changes of the system happen, for example, the number of drones in a district varies due to expenditure or drones’ crash in accident, predicting the self-adaptability of this decentralized self-adaptive system is another challenge worth studying. In this system, the adaptability can be measured by how fast and how well the global goals are achieved. Therefore, in the case study in this paper, we will measure the performance and efficiency of the system by simulation.

III. APPROACH OVERVIEW

Fig.2 provides an overview of our approach, which is based on modeling and simulation and divided into four phases.

Model checking provides an effective and rigorous method for verifying the self-adaptive behaviors whilst simulation implements compromised and intuitive method to foresee and validate the adaptability of self-adaptive software with less memory and time intensive.

Phase one: Analyze and design the components (or subsystems) of a decentralized self-adaptive system and the interactions among the components. While implementing a decentralized self-adaptive system, besides analyzing those application-specific components of the system, we should take into account the decentralization of subsystems and the commonly used implementation framework of adaptive systems (e.g., the MAPE framework) as well. The paper introduces the separation of concerns mechanism to architect a decentralized self-adaptive system in cyber physical spaces in order to integrate application, decentralization and adaptation features into a uniform implementation framework. Separation of concerns has become an important principle in software engineering since it simplifies development and maintenance while promoting software reusability especially for decentralized self-adaptive systems with huge complexity.

Phase two: Specify formally the behaviors and interactions (maybe stochastically) happening in cyber physical spaces. According to separation of concerns, both components of the decentralized self-adaptive system and different aspects of the environment have their own behaviors and components will communicate with other components and the environment as well. By using priced timed automata with stochastic transitions, the behaviors and interactions occurring in cyber physical spaces can be formally represented and reasoned about the time effects arising from execution of the decentralized self-adaptive system.

Phase three: Define the goals of the decentralized self-adaptive system formally. This paper adopts a subset of Timed Computation Tree Logic (TCTL) with clock variables and time constraints, as the query language, to specify the global goals of the system. The system goals are specified as TCTL.
properties, such as safety, reachability and liveness, and can be verified automatically.

**Phase four:** Simulate and evaluate the adaptability of the decentralized self-adaptive system. As mentioned before, the performance evaluation of the simulation implies the adaptability of the system. To evaluate the performance, this paper adopts statistical model-checking (SMC), which is an analysis technique used to study the performance of a system in a given stochastic environment, to perform stochastic simulation runs through timed automata designed in Phase two.

If the analysis results are not reasonable or some necessary global properties cannot be satisfied, it could trace back to the initial design of the whole system and make adjustments or modifications in responsibility partition. More details will be introduced with motivation example in the following four sections.

**IV. DECENTRALIZED SELF-ADAPTIVE SYSTEM ARCHITECTURE**

According to the principle of separation of concerns [8], our approach separates the environment from the self-adaptive system and modules of the system from special purpose concerns.

**A. Separation concerns of environment and software**

In much of the research on adaptive software, the environment is modeled in the system. However, it is unpractical to model everything about the environment in advance and maintain the environment model in a decentralized system. That will bring about problems. For instance, when the parametric changes in the environment become known or adjusted as experience gains, it still needs to modify the whole decentralized system. However, if modeling the environment and decentralized system separately, the only adjustment is very likely related to the environment while the decentralized system maintains the status quo.

In the UAV example, the objects in the environment that we need to focus on are the victims and buildings that decentralized UAV system has to make contacts with and all irrelevant things in the cyber physical space are categorized as Others, as shown in Fig.4.

**B. Separation concerns of functional behaviors in system**

Crosscutting concerns need more than single program location modifications when the system’s requirement changes or new functions are added to the system. Therefore, separating crosscutting concerns from functional behaviors could reduce the cost of modification.

In a self-adaptive system, adaptive behaviors are achieved by implementing the activities of the MAPE (Monitoring, Analysis, Planning, Execution). The monitoring part collects, aggregate, and filter information from managed environment. Analysis part analyzes the information and identifies the configurations that can achieve the system’s goals. The Planning module encloses the strategy constructing the actions needed to better achieve the goals. During the execution, the adaptation strategy is enacted on the system.

However, to achieve the global goals, the autonomous subsystems in the decentralized system take actions independently and they should interact with others to exhibit coherent behaviors. Therefore, in a decentralized self-adaptive system, every subsystem must combine the features MAPE loop for adaptation with a communication mechanism for coordination among decentralized subsystems. As shown in Fig.3. Monitoring part should be responsible for interacting with the whole context, which means not only the changing environment but other subsystems in the decentralized system. Analysis part should also analyze whether subsystems have potential conflicts in achieving the global goals through communication and coordination. Planning and Execution parts are the same as in the MAPE loop. Each module can be subdivided into different components according to more refined functional behaviors specific to the application.

![Fig. 3. Interactions between modules in decentralized system and environment](image1)

![Fig. 4. Architecture of the decentralized self-adaptive drone system and environment](image2)
Victim Organizer and Drone Communicators, to analyze the victim information and neighboring drones in avoidance of potential collision. Routine Generator is the kernel part of the local drone system, responsible for planning the movement strategy. Since the execution part is to enact the strategies made by the planning part and the only action specified by the strategies in motivation example is movement, the planning and execution are integrated as one module.

V. BEHAVIORS MODELLED BY USING TIMED AUTOMATA

A modeling formalism for a decentralized self-adaptive system should allow the representation of uncertain behaviors of the system and communications among its subsystems. It should also enable to reason about the time effects arising from concurrent executions of subsystems involved in the decentralized system. However, formalisms such as Process Calculi and Markov Decision Process are not supportive enough of mechanisms to reason about both stochastic behaviors and real-time effects.

The model of timed automata is one of the prominent classical formalisms for describing behaviors of real-time systems. A timed automaton (TA) with inputs and outputs is defined as a seven tuple as shown below: \( Q \) is a finite set of locations (or states as in a finite state automaton), \( q_0 \) belongs to \( Q \) and it is the initial location. \( X \) is the finite set of clocks. \( I \) and \( O \) represent input events and output events, respectively. \( \text{Inv} \) are functions that define invariants correspondingly to states. \( T \) is the set of transitions and \( T \subseteq Q \times I \cup O \times B(X) \times 2^X \times Q \), where \( B(X) \) is the set of Boolean constraints involving clocks of the form \( x \land A \) (\( x \in X, A \in \{ \leq, =, \geq, >, \} \) and \( A \) is an integer constant).

\[ TA = (Q, q_0, X, I, O, T, \text{Inv}) \]

A transition can be specified as a tuple as well, e.g., \( t = (q, q', a, g, r) \), which specifies a transition from state \( q \) to \( q' \) with (either input, output, or internal) \( t \) event \( a \), guard \( g \) and clock \( r \), where \( q, q' \in Q, a \in I \cup O \cup \tau, g \in B(X), r \subseteq X \) and it is the set of clocks to be reset.

However, with the complexity of cyber-physical spaces, timed automaton is not expressive enough since model checking problems need to be decidable while the realistic problems are not. A solution of the above mentioned problem is to introduce both stochastic and non-linear dynamical features to timed automata. Concretely, a state might have multiple targeted states with the same guard and event, with certain proportion of probability weight. Also, the variable clocks in an automaton can evolve with various rates and such rates can be specified.

Fig.5 is an example of timed automaton with non-linear dynamical features and it specifies a timer for a decentralized self-adaptive drone system, which allows the drones to detect the environment, be coordinated with other drones, plan for movement strategies and take movement actions in a constraint time. This automaton has 7 states, Initial, T1, T2, ..., T6, where Initial is the initial state of this automaton, and has only one clock, i.e., \( c \), in this automaton, input events (whose identifiers are followed by \( ? \)) are receiving signals whilst output events (whose identifiers are followed by \( ! \)) are emitting signals by channels. There are only output events, i.e., env_detect, drone_communicate, and generate_routine, in this automaton. Each state is associated with an invariant, for instance, invariant \( "c==0" \) means that the changing rate of clock \( c \) should be equal to 0 in \( T1 \), in other words, clock of \( c \) in this state should not change (the changing rate of clock \( c \) can be set by different values as non-linear dynamic features); invariant \( "c\leq 10\times roundT+4" \), where \( roundT \) is a local variable representing the number of blocks a drone has already searched, specifies that the clock should be always less than the value on the right side in state \( T2 \). A guard is a conjunction of constraints, for instance, guard \( \text{"all\_victim\_safe()==false"} \) controls the transition from \( T1 \) to \( T2 \) and the transition can happen only when the guard expression is valid. From Initial to \( T1 \), the assignment expressions \( "c==0" \) and \( "roundT==0" \) are internal events. The interested reader can refer to the work [9] for complete description on timed automata.

It should be explained that this automaton itself does not show up in Fig.4 because its function has nothing to do with the goals of saving victims but record the needed time which can be used to statistical analysis in later section.

To describe stochastic behaviors in timed automata, a probability transition function \( \rho: I \cup O \times T \rightarrow [0, 1] \) is introduced to extend timed automata. Suppose \( T_\rho \) is the non-empty set of transitions starting from \( q \), then for all \( q \in Q, \sum_{t \in T_\rho} \rho(a, t) = 1 \). Given the state \( q \) and event \( a \), probabilities of different transitions can be present by probability weight according to their proportion.

Let’s take victim in the environment as an example. The automaton is shown in Fig.6. At the initial position, the victim judges whether he is near the rescue center by himself with a probability (in this motivation scenario, the probability may be very low in the disaster situation). If he judges that he is not near the center, there is 20 percent chance that he will move (i.e., the state transits from Judging to Move by 20% probability) whilst 80 percent chance of standing still (i.e., the state transits from Judging to Standstill by 80% probability). In the automaton, these two transitions are weighted 1 and 4, respectively, with two different target states but same guard. At state Move, the victim has equal chances randomly choosing a direction to a contiguous block, in other words that each direction shares the same probability weight 1. This is a way of introducing probabilistic transitions to model stochastic behaviors. Another way is using random() function and
bounding the returning double value to generate different probability proportion. After updating the position information, signal vic_bd_chan is emitted if there is building surround. If the victim is in state StayOutside, and he knows that he is detected by a drone through the broadcasting channel drone_vic_chan, he will follow the drone tightly until receiving the signal victim_safe of reaching the rescue center and then he will finish his behaviors (i.e., the automaton reaches the terminal state—Safety).

To analyze and verify the decentralized self-adaptive drone system in motivation example of UAV Emergency Response Scenario, each component of the system is modeled as automata with stochastic transitions. Given the space limitation, these components will only be introduced briefly without concrete models.

**Monitoring Subsystem**: Monitoring Subsystem detects the environment and other drones in the system from the perspective of a drone and is modeled as three extended automata: Building Detector, Victim Detector and Drone Detector, whose concerns are to detect the building, victim information and check if there are multiple drones in the same block. This subsystem can be modeled as more automata with higher granularity to detect different information in environment separately when the situation is much more complicated in a concretized scenario.

**Analysis Subsystem**: Analysis Subsystem is modeled as two automata: Victim Organizer, maintaining a rescued queue information for the drone collected from monitoring environment, and Drone Communicator, analyzing saved victims’ information in two neighboring drones. This subsystem provides basis for making plans in planning phase.

**Planning & Execution Subsystem**: Routine Generator is responsible of generating the rational position for next step according to saved victims information in rescued queue provided by Victim Organizer, and taking actions.

According to the timed automata with stochastic behaviors and non-linear dynamical features described above, Fig.7 shows the interactions between all components of a drone system and the disaster environment. In the figure, signal messages sent/received between the components are labeled on arrowed lines. All the components can be synchronized through binary channels between two automata or broadcasting channels among corresponding multi automata.

**VI. ADAPTATION GOALS SPECIFIED BY TCTL**

To ensure a decentralized self-adaptive system satisfies its primary global goals under the changing environment, we use a subset of Timed Computation Tree Logic (TCTL) to specify the adaptation goals formally so that the goals can be verified based on timed automata.

TCTL is an extension of Computation Tree Logic (CTL) [10], a branching-time logic with tree-like structure in which the future is nondeterministic and any branch might be an actual path that will be realized. Compared to CTL, TCTL adds clock variables and clock constraints. TCTL is composed of state formulae and path formulae. A state formula \( \varphi \) involves a single state and it is to test whether \( \varphi \) holds or not in that state, whilst a path formula \( \varphi \) is to assert whether \( \varphi \) holds over a path. Clock variables and clock constraints can be defined as atomic TCTL state formulae to reason about clock values.
TCTL path formulae can be used to specify some specific properties of a system, such as safety, reachability and liveness. A safety property is used to verify that “something bad will never happen”. A reachability property is used to check whether a given state formula can be satisfied by any reachable state. A liveness property is used to verify that “something good will eventually happen”. Table I illustrates different types of properties.

**Safety Property**: This type of property is to check that something dissatisfying the goals will never happen or the system should hold some formula related to goals in every state. There are two ways for checking safety properties, and

\[ A □ φ \]

and

\[ E □ φ \]

where \( □ \) represents that all states should satisfy the state formula \( φ \) in a certain path. The property \( A □ φ \) (referred as *Invariantly*) evaluates to true if and only if all reachable states from all paths satisfy \( φ \) while the property \( E □ φ \) (referred as *potentially always*) means that an existing path either infinite, or self-absorbed in the maximal path always satisfies \( φ \).

**Reachability Property**: This type of property is to check whether the system can reach some states satisfying the goals. \( A ◇ φ \) and \( E ◇ φ \) are the two ways for checking reachability properties, where \( ◇ \) represents that a state in future can satisfy state formulae \( φ \) from current state. The property \( A ◇ φ \) (referred as *eventually*) evaluates to true if and only if all possible transition sequences eventually reaches a state satisfying \( φ \) while \( E ◇ φ \) (referred as *possibly*) only needs one transition sequence reaches that state.

**Liveness Property**: This type of property is to check something satisfying the goals will eventually happen as long as executing self-adaptive behaviors. This property (referred as *Leads to*) is expressed as “\( φ \) implies \( ψ \)” and the semantic of this property is whenever \( φ \) holds, eventually \( ψ \) will happen as well.

| Property   | Name            | Expression     |
|------------|-----------------|----------------|
| Safety     | Invariantly     | \( A □ φ \)    |
|            | Potentially     | \( E □ φ \)    |
| Rechability| Eventually      | \( A ◇ φ \)    |
|            | Possibly        | \( E ◇ φ \)    |
| Liveness   | Leads to        | \( φ \) implies \( ψ \) |

For a decentralized self-adaptive system, its adaptation goals can be specified and checked as the combinations of safety, reachability and liveness properties. In the motivation example of the decentralized self-adaptive system, it has a list of adaptation goals as follows.

First, all drones should function properly. Concretely,

1) a drone and its components should continue functioning. Corresponding to the formal model for a drone, all timed automata should not be trapped into deadlocks. This can be specified as a safety property of TCTL.

\[ A □ not deadlock \]

2) A drone should generate routines to lead victims to the rescue center after it detects victims. This can be specified as a liveness property.

\[ A ◇ VictimOrganizer0. VictimReceiving implies RoutineGenerator0. NaviMode. \]

3) All drones should not malfunction in turn. On one hand, a drone cannot search and rescue more victims than that actually appearing in the district and this can also be specified as a safety property.

\[ A □ not VictimOrganizer0. len(VictimNum). \]

4) A drone cannot miscount the number of victims that it has searched and rescued. Specifically, if it has unfortunately not searched any victims yet, the length of its maintained victim queue should always be zero. This can be defined as a safety property as well.

\[ E □ VictimOrganizer0. len(VictimNum) = 0 \]

Second, the system should search and lead all victims to rescue centers, which is the primary adaptation goal, and this can be specified as a reachability property. According to the time automata, all victims should reach the state “Safety” in all possible transition sequences.

\[ A ◇ forall (i: id_t) victim(i).Safety \]

To reach the “Safety” state, a victim may luckily reach the rescue center by himself before detected by drones since he may loaf randomly in his districts. In other words, a victim has chance to save himself without needing drones’ search and rescue. This can also be specified as a reachability property.

\[ E ◇ not victim(0). WaitingForHelp \]

Meanwhile, a victim can also be saved after being detected by a drone. Correspondingly to the automaton of Victim, the victim should be able to reach state WaitingForHelp eventually and then definitely be guided to rescue center (i.e., reaching state Safety). This property can be specified as a liveness property.

\[ A ◇ victim(0). WaitingForHelp implies victim(0). Safety \]

### VII. Adaptation Evaluation by Using Simulations

Statistical model-checking (SMC) [11] is a recent approach introduced as an analysis technique to study performance of the system in a given stochastic environment. Due to the features of large memory requirement, many realistic models are untreatable in model checking. SMC, bypassing decidability issues and no need to store the state space, is a
SMC can deal with two main problems. One is threshold problem whether the probability measure of query meets the bound. The other is estimation problem that what is the probability measure of a certain query. SMC generates finite trajectories through discrete-event stochastic simulation from given model within a bound for the desired level of approximation. Through these simulation runs, the approximate answer whether property can be reason about from given model will be given with a bounded error probability to the threshold problem and an approximate estimate of probability to the estimation problem.

UPPAAL-SMC, a stochastic and statistical model checking extension of UPPAAL, relies on a series of extensions of the SMC approach to handle real-time systems and estimate nondeterministic problems. UPPAAL-SMC has advantage of specifying complex problems in an efficient manner as well as getting feedback in the form of probability distributions, which can be used to analyze performance aspects of systems [12].

In UPPAAL-SMC, the approximate answer to threshold problem can be estimated by following query format: $Pr[\text{bound}] > p$ and the probability confidence interval can be estimated to estimation problem by: $Pr[\text{bound}] > p$, where bound is a constraint expression, $\phi$ is the state formulae and $p$ is a positive floating number not exceeding one. There are three ways to bound the runs. One is implicitly by time by specifying $c \leq A$, which constrains the implicit global time within a positive integer A. One is explicitly by cost with $c \leq A$ where $c$ is a specific defined clock less than A. Another one is by number of discrete steps with $# \leq A$ where # is the total number of transitions between states.

In the motivation example, the global time and the number of discrete steps are uncertain due to stochastic transitions. However, what can be estimated is constraint timer for drones introduced in modeling. Under the presumption that all the drones arranged in the district are of the same type, the time used in each block for a drone is an approximate estimated value. Therefore, the value of clock variable in timer can be mapped to the time in reality. The probability query is $Pr[c \leq 10000]$. The threshold set as 10000 which is far more than in demand is trying to sweep up all the possible values of clock $c$. The probability distribution and cumulative probability diagrams are shown in Fig.8, according to different number of drones from 2 to 6, respectively, arranged in the district. Positions of all the objects concerned in the environment, including rescue center, buildings and victims, are initialized with locations as shown in the Fig.1.

The scenario challenge guaranteeing primary global goals under changing environment could be settled by verifying reachability properties (e.g., all victims should reach the state “Safety”) through verification tools. The other challenge predicting the self-adaptability under changing internal structures (i.e., the number of drones arranged in the district varies in the motivation example) of system itself would be solved by comparing and analyzing statistical results through SMC. To measure the performance and efficiency, three concretized questions are present to rephrase this challenge.

Q1: Given the number of drones, what is the average time the system needs to save all the victims in a district? The average values of $c$ (i.e., clock variable in timer referring to Fig.5) are shown in Table II integrated from probability distribution diagrams.

Q2: Given the time constraints and probability threshold, how many drones should be arranged in the district to make the probability exceeds this threshold? The data in Table III are the average clock values in need to make the probability exceed some threshold given the number of drones, integrated from cumulative probability confidence intervals diagrams. The answer to this question could be found as the minimum number of drones meeting the condition.

![Fig. 8. Experiment with different number of drones](image-url)
Q3: Given the number of drones and time constraints, what is the probability that all victims in a district can be saved? The answer could be found immediately from the probability confidence intervals diagrams.

\[
\begin{array}{|c|c|c|c|c|c|}
\hline
\text{# drones} & 2 & 3 & 4 & 5 & 6 \\
\hline
\text{Average clock} & 288.2 & 221.2 & 182.9 & 159.2 \\
\hline
\end{array}
\]

TABLE III. AVERAGE CLOCK VALUE BASED ON PROBABILITY THRESHOLD

The decentralized self-adaptive drone system has different satisfactions of the global goals’ achievements with corresponding numbers of subsystems. The experimental results to these detailed questions using SMC could be used as reference for arrangement planning of UAVs before actual deployment and dynamical adjustment in real time to reduce expenditures while maintaining high performance and efficiency.

VIII. RELATED WORK

Our work makes a novel contribution in general process to verify stochastic behaviors of decentralized self-adaptive systems qualitatively and quantitatively, and touches a number of related areas.

Self-adaptation is a hot topic with increasing complexity of current systems. A MAPE loop is a primary framework of achieving self-adaptive behaviors. Paolo et al. exploits the concept of multi-agent Abstract State Machines to specify distributed and decentralized adaptation control in terms of MAPE-K control loops [13]. Danny et al. introduces multiple MAPE loops to solve heterogeneous systems and make decisions to decentralize each of the MAPE functions [14]. Luciano et al. outlines an architecture for the design of component-based of distributed self-adaptive systems and reason on properties through data collection, correlation, aggregation and analysis [15]. However, these literatures do not take interactions between elements in decentralized system into account or implicitly embedded these into MAPE loops. In our design framework, we explicitly consider features of self-adaptation control loop and decentralization of systems together and combine them into a new MAPE loop.

systems analysis at early stage and modeling with timed automata has been put great effort. Kahina et al. formalize home care plans as timed automata generated from user-oriented abstractions [16]. Guillermo et al. discusses how to model the different types of relationships among computer clocks of a distributed system, namely, ideal clocks, drifting clocks, and synchronized clocks with timed automata [17]. Nicolas et al. develop an approach towards modeling socio-technical systems in general and socio-technical attacks using timed automata and illustrate its application by a complex case study [18]. However, the model checking problems in those literatures are deterministic whereas the realistic problems are not. We introduce both stochastic and non-linear dynamical features to timed automata to model uncertainties in both environments and system behaviors.

In terms of evaluation, SMC is a powerful and flexible approach for formal verification of computational models. David et al. use SMC to estimate the probability with which the property holds on the system and develop a distributed SMC tool [19]. Zohra et al. model the MAC level protocol in WSNs and use SMC to make qualitative and quantitative verification of this protocol [20]. Dehui et al. propose a quantitative analysis approach based on statistical model checking technique for project schedules to reduce the human results [21]. In our work, we use SMC as well, as a compromise way to mainly solve estimation problems relating to the performance of decentralized self-adaptive systems.

In our motivation example, we introduce UAV emergency mission scenarios which are common in practical. UAV related research in fact has been considered extensively in literature. For example, Farhan et al. discusses the applications of UAVs in the city of Dubai as an example, their opportunities and challenges [22]. Hamid et al. describe the possible Intelligent Transportation Systems applications that can use UAVs, and highlights the potential and challenges [23]. Mario et al. proposes an implementation of an emergency-management service by cloud robotics in a smart city scenario with the goal of providing aerial support to citizens, however, its UAVs system is centralized [24]. As far as we are aware, existing research have not involved into decentralized UAV Emergency missions.

IX. CONCLUSION AND FUTURE WORK

There is a growing importance in self adaptation recently. Though numerous excellent research efforts have been put into this area, Self-adaptation field is still in its newly born stage, and existing knowledge and approaches are not adequate enough to address today’s dynamic and ever-changing environments. Therefore, self-adaptation poses not only opportunities, but also many challenges, such as guaranteeing the required global goals and performance of systems operating in highly dynamic and uncertain environments. In this paper, we mainly focus on the decentralized aspects on self-adaptive system and provide a whole process to verify and evaluate the adaptability of decentralized self-adaptive systems with stochastic behaviors. Firstly, we introduce a method for modeling a decentralized self-adaptive system and its environment separately, and adopt timed automata to model different components of the system and different aspects of the environment. Secondly, we describe a method for specifying and verifying the required adaptation properties of decentralized self-adaptive systems and adopt a statistical model checking tool to verify and validate the properties by simulation runs. We also contribute a novel example extracted from practical applications in UAV usage scenarios to illustrate the feasibility of the whole approach.
In our future research, we plan to further elaborate on the work presented in this paper by applying the method to practical scenarios. The motivation example is kind of simplified to represent reality of the world. We have considered the uncertainties of victim behavior, however, there are still many remaining issues. For example, buildings could be collapsed; drones might be crashed by falling objects; victims may be injured and cannot move. All of these situations has very high probability taking place and complicate the modeling. The first idea to deal with it is to add more features and insert more specific components to system design, which is fuzzy but realizable in short term. Another idea is to try to find a method of filling the gap between modeling of system in cyber physical spaces and use case, and try to synchronize the modifications. This will make the approach more applicable to a wider set of physical environments. We are also considering using different formal model method to see whether it can better describe adaptive behaviors during plan making in one step or look-ahead horizon.

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