A task-model based approach for detecting ADL-related anomalies

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***Abstract*—In this paper, a task model based on HAMSTERS-XL notation is proposed to represent activities of daily living (ADL). For an efficient representation of ADL, it is also a need to delimit requirements in time and location for each ADL, as well as the sensor data that define the ADL. In this sense, it is also proposed a procedure consisting of a set of step intending to delimit such time and location requirements, regarding both activities and sensors; alongside the events that need to be identified. The presented approach aims at providing an analysis tool regarding the performance of elderly/handicapped people by comparing data recovered from sensors within a smart home environment simulator to the task models. The feed oneself ADL (as well as its possible variations) is picked in order to evaluate our proposal. After proper analysis was carried out, anomalies detected during ADL performance are pointed out in order to detect possible ADL routine modification in a coherent manner through improved task models.**

***Index Terms*—Pervasive health, Ambient assisted living, Elderly behavior analysis, Model-based design, Task Modeling**

I. INTRODUCTION

In 2019, it was an estimated population of 703 million people aged 65 years or over worldwide. This number is predicted to increase to 1.5 billion in 2050 [1]. Such an increase in the population sector demands the amelioration of quality of care service alongside the reduction of medical costs. Both in Europe and the U.S.A, there is awareness concerning this topic because of the growing numbers of care dependent elderly people with age-related conditions, as well as a decrease in the primary care personnel, and cutbacks or changes in public health care finances [2, 3].

Moreover, the number of people experiencing impairment of autonomy and relying on others for achieving activities of daily living (ADL) is rising. Additionally, isolation in a care center is detrimental for the autonomy, the dignity, and the well-being of an individual [4]. To this matter, technologies aiming to monitor the health of householders asses the orchestration of assisting and surveillance solutions for people at home in a more adequate way; providing healthcare tools that may evolve into ambient and pervasive [5, 6]. Such technologies request reliable modeling and portrayal of ADL to support their automatic detection from data collected in smart home environments (SHE); where aspects such as location, physical object, and time, must be considered [7].

To this extent, ADL representation within a SHE can be assisted by task analysis considering three major elements [8]: (i) collection of data; (ii) data analysis; and (iii) modeling of the tasks. Obtaining and analysis of data can rely on IoT and Big Data techniques; besides, there exists a difference on the uniformity of task modeling and representation.

To contribute in this field, an approach for task modeling of ADL over long period of times is presented, based on HAMSTERS-XL (Human-centered Assessment and Modeling to Support Task Engineering for Resilient Systems-XL) [9], an extensible task notation and tool allowing the design, visualisation, and simulation of tasks models; as well as adapting the notation to tasks specific to a device, a context, or a domain.

In order to provide an efficient representation of ADL, the proposed approach allows delimiting requirements in time and location for each ADL, as well as the sensor data that define the ADL (e.g., every morning use the bathroom, defined by light, door, shower, washbasin sensors). This proposed approach consists of a set of step that includes: (i) creation of the initial task model for a specific ADL; where the selection of environmental sensors/data needed to detect the ADL is given; (ii) identification of the data/events provided by the sensors and map them to the tasks/data of the initial task model; (iii) collecting data from sensors (via a log file) over a period of time; (iv) analyze the log with the objective of detecting possible anomalies/problems related to the performance of the ADL; and (v) propose the display of a new task model where it will be possible to identify the differences/similarities with the initial model at the first stage.

The suitability of this approach is demonstrated in a scenario regarding the performance of elderly/handicapped people by comparing data recovered from sensors within a smart home environment simulator to the task models. The feed oneself ADL (as well as its possible variations) is picked in order to evaluate our proposal. After proper analysis was carried out, anomalies detected during ADL performance are pointed out in order to detect possible ADL routine modification in a coherent manner through improved task models.

II. RELATED WORK

Aiming to asses human activity recognition, primarily ADL within a SHE, various studies have been introduced [10, 11, 12]; pointing attention from atomic events (detected by a single sensor reading) to high-level events (detected by a combination of several sensor readings).

Sensor Network Modeling techniques are directed to the Ambient Assisted Living (AAL) field [5], in which the orchestration of an activity depends on a sequence of events identified by a sequence of sensor readings [13]. For this matter, Body Sensor Networks (BSN) as well as Personal Sensor Network (PSN) are involved aiming to define ADL within the SHE.

Modeling and detection of complex events methods are mainly supported by languages to model events relying on a set of operators [14, 15]. For example, the Allen's temporal logical

operators [16], such as FOLLOWS (also called as SEQ or AFTER), to indicate that two events occur after each other, and OVERLAPS, to describes two events occurring simultaneously, are prevalent in every language to represent complex events.
Context-reasoning-based models correspond to ADL representation in AAL subject to reasoning and explore methods such as statistical classification (Bayesian Networks, Hidden Markov Models, Decision Trees, and Support Vector Machines) for activity detection [5, 17].

Previous works regarding **task-models-like** approaches for modeling ADL are introduced in [18, 19]. A home monitoring system is presented in [20] to track and evaluate the well-being in terms of social isolation of elderly subjects performing ADL. The analysis of the household environment was carried out through non-intrusive sensors connected to a wireless sensor network using a Raspberry Pi with Z-wave gateway. Several ADL, such as meal preparation, meal taking, activity and mobility are considered to identify social isolation of the elderly. However, the system does not provide adequate or in-depth knowledge about the elderly inhabitant daily routine, in order to detect punctual anomalies related to abnormal ADL patterns. An approach, based on intelligence compliant objects, was studied in [21]. It is able to classify the making-tea ADL, by evaluating the efficacy of a task model approach to ADL rehabilitation for stroke apraxia and action disorganisation syndrome, comparing training in making a cup of tea with a trial-and-error learning process; and to monitor progress and feedback given implementing a Markov Decision Process task model. In order to collect data, sensors were integrated into home objects used by the inhabitant for preparing tea. Nevertheless, the list of studied ADL in the living environment is only applicable to a preparing a cup of tea by the individual, not considering other ADL. In our proposal ADL, many other ADL can be described.

The above-mentioned works highlight the current interest on monitoring ADL for several applications. However, there is still absence of ADL to be modeled in terms of a succession of events, as they happen during ADL realization. Such limitations can be solved by proposing ADL task modeling.

III. Modeling of ADL based on HAMSTERS-XL

Task models consist of an abstract description of user activities structured in terms of goals, sub-goals, and actions [9]. Task models enable ensuring the effectiveness of an interactive system, i.e., to guarantee that users can perform their work and can reach their goals. Many instances of task analysis and modeling techniques exist to provide support for the design, development, and evaluation of interactive systems and of user performance while interacting with a system [9].

In the case of ADL in the context of taking care of aged people, patients' tasks strongly rely on motor, cognitive, and perceptive abilities and actions, as well as on the abilities for coordinating these actions. This type of ADL are strongly evaluated according to the patients' capacity of manipulating physical objects, as well as their capacity of processing information. Thus, a task-modeling notation that supports the description of ADL requires embedding elements to represent motor, cognitive, and perceptive actions, as well as elements to represent the temporal ordering of actions and elements to represent manipulated objects and information. The HAMSTERS-XL notation fulfills these requirements.

HAMSTERS-XL provides a tool-supported task modeling notation for representing tasks users perform when interacting with systems. HAMSTERS-XL allows representing human activities in a hierarchical temporally ordered way, with the intention of supporting modeling large sets of user tasks [22], as well as supporting consistency, coherence, and conformity between user tasks and interactive systems [23]. A task model looks like a tree diagram with nodes being either a task or a temporal ordering operator (e.g., ">>" stands for sequence, "[]" stands for choice). HAMSTERS-XL provides support to represent refined types of user tasks [24]: motor, perceptive, and cognitive (depicted in Fig. 1). Cognitive tasks can also be refined into cognitive analysis tasks or cognitive decision tasks (on the right in Fig. 1).

Fig. 1: Types of user tasks in HAMSTERS-XL notation

HAMSTERS-XL provides support to represent data such as devices, information, knowledge, and objects manipulated by users (which can be physical objects or software objects), and are depicted by using labels preceded by the abbreviation of the type of data [25]. Fig. 2 shows examples of such representation, where arcs between data and tasks represent how the data is used. In Fig. 3, from the right, the arc between the input device "in D: Kitchen presence sensor" and the input tasks "Detect entrance in kitchen" and "Detect presence in kitchen" means that the task requires the input device labelled "Kitchen presence sensor". The arc between the required duration labelled "Duration: Between 10-20 min" and the input task "Detect presence in kitchen" means that the task involves a period of time comprehending between 10 min and 20 min when performed. HAMSTERS-XL also enables to adapt the notation to tasks specific to a device, a context, or a domain [9]. Moreover, subroutines can be generated. A subroutine is a task that points out to another task model, in order to support the structuring and reuse of models [22]; as depicted on Fig. 2 (cook, take meal, open-close door).

Subsequently, the representation of ADL by means of task modeling is introduced.

IV. Use case description

The difficulty in determining the values of ADL relys on the fact that some can be measured directly, such as opening or closing a door, whereas some others, such as "cook" or "take meal", have a complex context to be determined based on the values of a number of sensors within a time range.

In order to evaluate the proposed approach, we show its applicability to evaluate the capacity of an inhabitant to take their own meal (serving and eating), which is a complex ADL [26]. Fig. 2 shows the task model for feed one self.

The proposed approach states for each subroutine in Fig. 2, a set of steps, as follows:
Step 1. Identify the criteria over the time and location of the ADL, as well as the detection of the events needed to be

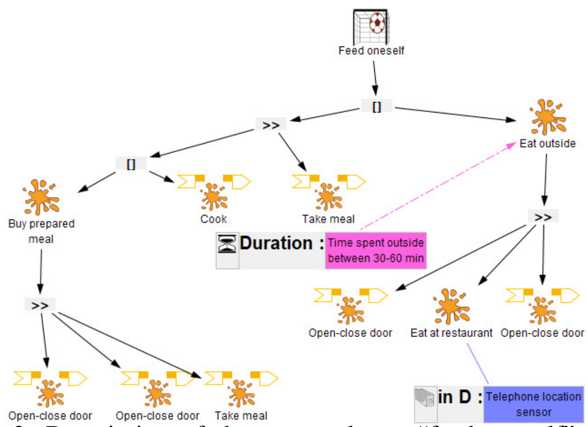

Fig. 2: Description of the user tasks to “feed oneself” with HAMSTERS-XL notation.

identified. In this case, all activities related to feeding oneself, are conformed by: (i) open-close entrance door; (ii) cook; (iii) take meal; (iv) eat outside. The timeline depends on the choices of the resident.

Step 2. Different types and location of sensors are considered to detect the events identified in the previous step. The orchestration of the identified events and the sensors needed according to the task model is determined, as shown on Table I.

TABLE I: Orchestration of the feed-oneself ADL

Open/close entrance door	**Cook**	**Take meal**	**Eat outside**
	Detected activities		
Open entrance door	Presence in kitchen	Presence in dining room	Eat at restaurant
	Open fridge door	Sit down	
	Open cabinet door	Place meal on table	
	Use of stove	Spend time eating	
	Spend time cooking		
	Employed sensors		
Entrance door sensor	Kitchen presence sensor	Dining room presence sensor	Telephone-based location sensor
	Fridge door sensor	Chair pressure sensor	
	Cabinet door sensor	Table pressure sensor	
	Stove electrical switch		

Step 3. This step consists on arranging the scenario for an elderly indoor daily routine regarding the accomplishment of feeding oneself by following any of the sub-goals of the proposed task model in Fig. 2.

Step 4. Modeling the subroutines The feed oneself ADL might present several options for its accomplishment while carried out. To this extent, task models for its representation are introduced hereafter.

Step 4.1. Modeling the subroutine ”open-close door”, depicted in Fig. 4. The user has to perform the following sequence of ”interactive input tasks”, conformed by sequence of a ”user motor task” and an ”input task” (tasks described under the sequence “>>” operator):

- Open entrance door: open entrance door (”user motor task”) and detect open entrance door (”input task” relying on a door sensor).
- Close entrance door: close entrance door (”user motor task”) and detect closed entrance door detection (”input task” relying on a door sensor).

Step 4.2. Modeling the subroutine ”cook”. With the purpose to exemplify events taking place during the cooking ADL, Fig. 3 shows the actions sequence that must be performed:

- Enter kitchen area (”interactive input task” refined by sequence of a ”user motor task” and a ”input task”): enter kitchen area (”user motor task”) and detect presence in kitchen (”input task” by means of a presence sensor).
- The user has to perform the following tasks (tasks described under the order-independent operator “|=|”):
  - Open-close fridge door (”interactive input task”: sequence of a ”user motor task” and an ”input task”): open-close fridge door (”motor task”) and detect open-closed fridge door (”input task” by means of a door sensor).
  - Open-close cabinet door (”interactive input task”: refined by a ”user motor task” and an ”input task”): open-close cabinet door (”motor task”) and detect open-closed cabinet door (”input task” by means of a door sensor).
  - Turn on/off stove (”interactive input task”: conformed by a ”user motor task” and an ”input task”): turn on/off stove (”motor task”) and detect stove is on/off (”input task” by means of an electrical switch sensor).
  - Detect presence in kitchen (”input task” by a presence sensor, with a duration between 18-20 min).

Step 4.3. Modeling the subroutine ”take meal”. Aiming to present a task model where the performance steps for the taking meal are described, Fig. 5 depicts its requirements. The task sequence is as follows:

- Access dining room area (”interactive input task” refined by sequence of a ”user motor task”, and an ”input task”)
  - Access dining room area (”user motor task”).
  - Detect entrance in dining room (”input task”, by means of a presence sensor).
- The next tasks occur under the ”concurrent” operator:
  - The order-independent operator “|=|” indicates the performance of following tasks:
    - Place meal on table (”interactive input task”, described by a sequence): place meal on table (”user motor task”) and detect pressure on table (”input task”, relying on a pressure sensor).
    - Sit on chair (”interactive input task”, described by a sequence): sit on chair (”user motor task”) and detect pressure on chair (”input task”, relying on a pressure sensor).
  - Detect presence in dining room (”input task”, by means of a presence sensor, between 18-20 min).
  - Detect table pressure sensor is on (”input task”, by a pressure sensor, between 18-20 min).
  - Detect chair pressure sensor is on (”input task”, relying on a pressure sensor, between 18-20 min).

Next, the introduced task models are simulated with the aim to analyze the proposed approach.

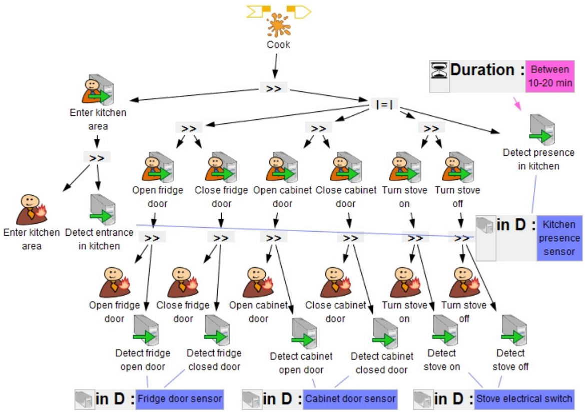

Fig. 3: Tasks to subroutine "cook"

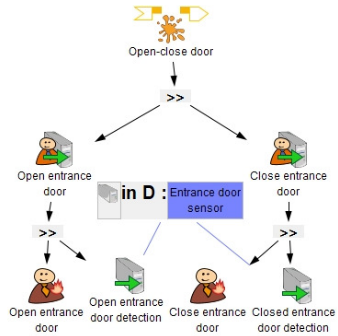

Fig. 4: Tasks to subroutine "open-close door"

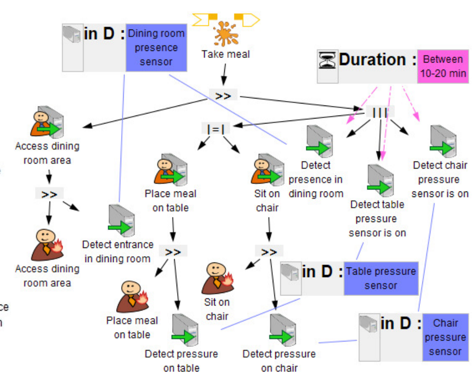

Fig. 5: Tasks to subroutine "take meal"

V. Models analysis and discussion

Due to the fact that most of the surveilling approaches are real-time monitoring approaches, we also propose a supporting tool, shown in Fig. 6, able to: (i) identify the data/events provided by the sensors and map them to the tasks/data of the initial task model; (ii) collect data from sensors (via a log file) over a period of time; (iii) analyze the log with the objective of detecting possible anomalies/problems related to the performance of the ADL; and (iv) propose the display of a new task model where it will be possible to identify the differences/similarities with the initial task model.

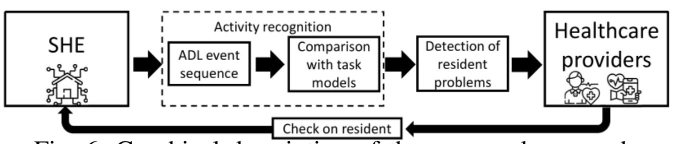

Fig. 6: Graphical description of the proposed approach.

For the evaluation as well the comparison of different tasks models, the HAMSTERS-XL environment provides the ability to instantiate task models. The purpose of such instantiations is the representation of the performance of each user action on a specific task model as depicted on Fig. 7. Subsequently, the possible scenarios for the study are generated.

A comparison between the original task model introduced in Section III and the events occurred within a SHE following the task model requirements is necessary in order to assess the above-mentioned approach. To this end, a SHE simulation over a one-week period is evaluated by means of the framework introduced in [14, 15]; consisting on three modules:

The **Descriptor module** provides a Graphic User Interface (GUI) where all the criteria over the time dimension, location, and events are described as well as the required scenarios for the simulation. Also, sensors to identify the ADLs have to be specified through the GUI.

The **Simulator module**, where the activities performed by the subject are carried out and information is recovered from sensors located within the SHE. As the Simulator module, iCASA [27] is integrated; which is a smart home simulator which allows to have control over: time, environment, inhabitants, devices, a graphical user interface, scripting facilities (for the environment), and notification facilities.

The **Analyzer module** analyzes all the collected data in order to classify them and evaluate if the ADL of the case study have been carried out to completion. The Analyzer consists of: (i) a Record filter, which organizes the resulting data into a set of records; (ii) an Event detector, for the detection of the performed activities; (iii) a Variable calculator, for determining whether the ADL have been performed successfully or not.

The **simulation procedure** is described in the following:

(i) The first step is to specify the criteria over the time and location of activities, type and location of sensors, and events that have to be detected (in this case, ADL related to cooking and feeding one-self), and prepare the scenario for an elderly indoor daily routine over the course of one week[1] All this is done in the GUI of the Descriptor module. The primary source of information used to generate the scenario is the schedule proposed by [28], but many modifications take place in order to make the scenario more suitable for the simulation.

(ii) Then, the Simulator module, i.e., the iCASA framework, executes the simulation according the information provided by the Descriptor module.

(iii) After the simulation is performed, the record filter component of the Analyzer module organizes the resulting data into a set of records, each of which represents an action captured by a sensor within the SHE. Each record consists of data fields, such as the time it occurred (according to the simulator clock), the sensor ID and the sensed value. These are raw data and need to be examined by the Analyzer module in order to generate the detection of events and then calculate the ADL. Next, it is the detection of events. An event is a composite act that is observed using more than one sensor, meaning that an event has more than one record in raw data.

Once the simulation has been performed, a comparison between the detected events and the proposed task model must be carried out. For this matter, raw data obtained after the SHE simulation is utilised. Fig. 8 shows the expected number of events (in blue); as well as the collected events after simulation (in red). These events are related only to the task model subroutine "take meal". It is shown that despite the number of records in the simulated scenario related to "take meal" did not change considerably (i.e., Mon, Wed, Thu) compared to the expected scenario. However a difference with "take meal"

[1]https://www.careworkshealthservices.com/daily- routine-for-seniors/

Fig. 7: "Cook" instantiated scenario.

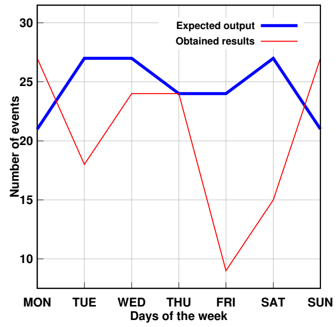

Fig. 8: "Take meal" events.

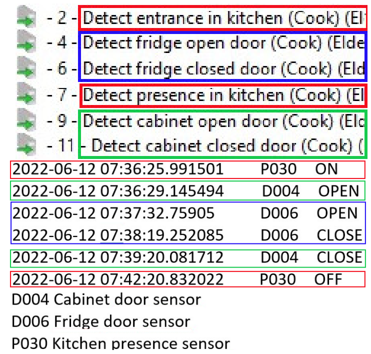

Fig. 9: Tasks to subroutine "take meal"

ADL was detected. During three days (Tue, Fri, and Sun) the expected number of events decreased. From this image, it can be inferred that the inhabitant did not carry out ADL as indicated, by either performing (or not) a different ADL, or eating outside.

Additionally, due to the fact that time represents one of the main parameters of the analysis, information such as start/finish time can be recovered from the obtained data records, helping to establish a comparison between the proposed task model and the simulation results, as presented in Fig. 9. This enables the identification of anomalies regarding the activity duration; as well as determining was carried out as scheduled.

Moreover, during a one-week period, it can be remarked that some of the events regarding the feed oneself ADL were not performed according to the proposed task models. In this regard, some modifications need to take place – i.e., in most of the days the inhabitant spend between 15 and 20 minutes while taking meal, instead of 10-20 min initially introduced. Also, due to the fact that events concerning placing meal on table and sitting occur in a sequenced manner, a revision would be necessary respecting the order-independent operator. Fig. 10 illustrates the above-mentioned adjustments.

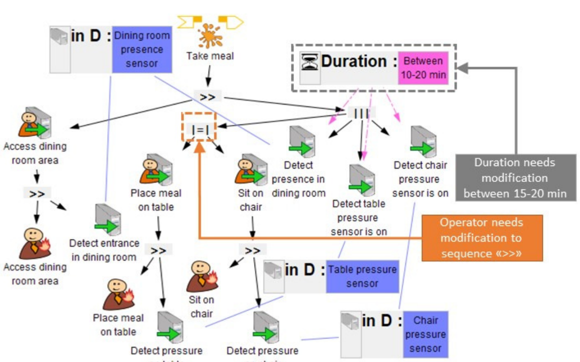

Fig. 10: Task model modified for taking meal events.

Furthermore, for the cooking ADL, events with respect to the turn-stove-on/off sequence can be placed in accordance with the simulation results, which demonstrate that it this action always happens after the use of both the fridge and the cabinet. For this matter, the order-independent operator must remain only for the tasks open/close fridge/cabinet door, whereas the stove-on/off sequence should be located subsequently (see Fig. 11).

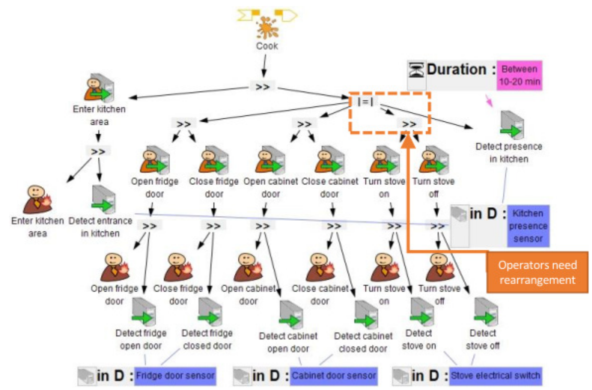

Fig. 11: Task model modified for cooking events.

With the purpose to create a tool to disambiguate events occurred during ADL performance, as well as their possible modifications, the aforementioned results aims to provide support to healthcare/assistance providers in a more explicit manner, allowing the use of task modelling as a graphical manner to interpret ADL events as performance steps; e.g., it can be possible to denote the use or not of certain sensors, to propose warnings in relation to the improper progress of the activity. This task model can be used by the practitioner to explain to the patient what is wrong with their ADL performance and needs to be changed in the routine. Furthermore, emphasis should be placed on detecting degradation over long periods of time without this degradation having been subsequently compensated.

VI. Conclusions

In this paper, activities of daily living (ADL) representation based on task models is introduced. To this extent, task modelling of ADL by means of HAMSTERS-XL is presented. The proposed approach aims to illustrate ADL carried out by the inhabitant within a smart home environment (SHE). A series of steps with the purpose of setting up parameters (time, location, type of sensors, and the events that need to be detected), is established; in order to generate scenarios for subsequent simulations. The results of simulated scenarios are analyzed and data obtained by means of the previous methodology are compared to the prior task models in order to examine the developed criteria and generate the necessary modifications.

Future work may include the extension of the approach to study other ADLs, as well as ADL simulations over longer periods of time, in order to validate it further.

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