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Digital Twin-Based Framework for Behavioral Modeling and Activity Recognition in Smart Homes

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Abstract—Ambient Assisted Living (AAL) systems, which combine digital healthcare technologies with Smart Home environments, play an important role in supporting independent living, especially for elderly individuals and people with physical impairments. However, the growing need to continuously monitor users, collect large and heterogeneous data streams, and anticipate abnormal or dangerous situations, has highlighted the necessity of advanced analytical frameworks capable of adapting to dynamic daily contexts.

To address this necessity, this paper proposes a framework that integrates the Digital Twin (DT) paradigm with a fully implemented simulation platform. This simulator provides the required analytical capabilities by modeling user interactions with domestic objects and environmental sensors, enabling context-aware understanding of daily activities, behavioral modeling, and the generation of alternative scenarios.

Experimental results show that the simulated activities closely reflect real-world patterns, producing distinctive temporal and contextual signatures that can be effectively recognized by classification algorithms. These findings underline the potential of combining DT concepts with simulation-based approaches to enhance situational awareness, adaptability, and user assistance in AAL environments.

Index Terms—eHealth; Digital Twin (DT); Internet of Things (IoT); Human Activity Recognition (HAR); Simulation Tool

I. INTRODUCTION

The convergence of Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) has led to the emergence of smart environments designed to improve everyday living [1]. These technologies are increasingly applied in home automation, rehabilitation, and health care, forming the foundation of modern Smart Home and eHealth systems [2].

Human Activity Recognition (HAR) is a key component of such systems, enabling the classification of daily actions from data collected by environmental and wearable sensors. Combined with IoT and intelligent analytics, HAR supports personal autonomy and improves care quality, promoting the concept of the connected patient, who actively manages health through digital and remote monitoring tools [3].

Ambient Assisted Living (AAL) extends these principles to domestic settings through sensor and wearable networks for continuous, unobtrusive monitoring. These solutions enable the detection of abnormal behaviors or deviations from routine, fostering preventive and personalized assistance that helps older adults and people with disabilities live independently and enhance their quality of life [4].

Despite significant progress, research in AAL and eHealth still faces major challenges, including high implementation costs, limited availability of realistic datasets, and privacy concerns. In addition to that, in order to obtain reliable models, datasets should rely on a large amount of heterogeneous realistic data over a sufficiently long time horizon, coming from diverse scenarios. Obtaining this through real Smart Homes requires complex infrastructures and considerable resources, making their collection expensive and difficult to scale [5].

To overcome these limitations, different research works have introduced simulators of intelligent home environments, i.e., tools capable of generating synthetic and annotated datasets for testing HAR algorithms and analyzing human behavior in AAL contexts [6], [7]. Furthermore, the concept of Digital Twin (DT) has attracted increasing attention in the built environment domain [8]. A DT creates a bidirectional correspondence between a physical system and its digital counterpart, allowing continuous synchronization, real-time monitoring, and predictive analysis. To provide the above-mentioned functionalities, DTs need to be continuously fed by Smart Home data.

Therefore, the objective of this study is to design and implement a novel DT-based Smart Home simulator capable of recognizing the activities performed by a resident within a Smart Home through the analysis of sensor behavior and interactions with smart devices in the environment. The integration between the DT framework and the simulator not only enables the replay and visualization of external logs, allowing the system to learn from real data, but also supports the synthesis of new, hypothetical scenarios for proactive evaluation and user assistance in near-future situations.

The main contributions of this work are: i) a user-centric DT architecture that jointly models user behaviors, device dynamics, and environmental context, with a focus on user behavioral modeling and activity patterns, as well as building management and energy optimization; and ii) a customizable and extensible simulation platform that allows the easy integration of new sensor and device functionalities, the modeling of additional user habits, and adaptation to evolving user needs, enabling personalized experimentation and continuous evolution of the DT ecosystem.

The paper is organized as follows. Section II reviews background and related work on AAL solutions and simulators; Section III describes the system model and DT architecture;

Section IV presents the implementation; Section V discusses validation results, and finally, Section VI concludes the paper.

II. RELATED WORK

The continuous advancement of IoT, sensors, and actuators in the field of home automation has driven the development of intelligent environments designed to support essential functions in activities of daily living (ADL) [9], driven by an aging population, rising healthcare costs, and the demand for independent living solutions. Several studies have explored the integration of IoT-based AAL systems aimed at monitoring and assisting users in their daily routines. For example, [10] presents a comprehensive review of intelligent systems for home-based assistance, discussing how sensor networks and intelligent algorithms can improve safety and support independent living. Authors in [11] proposed a conversational system that combines environmental sensing and dialogue-based interaction to discover behavioral patterns and detect early deviations in daily routines, supporting proactive health monitoring at home. Similarly, in [12], an IoT-based health monitoring system is developed and implemented, which makes use of anomaly detection algorithms in order to identify irregular physiological or behavioral conditions, enabling timely interventions for elderly users.

Since AAL systems handle personal data, they must ensure ethical and secure management while following user-centered design principles that promote usability, accessibility, and long-term adoption [13], [14].

To address some of these issues, the literature has proposed several Smart Home simulators capable of generating synthetic datasets. The use of such tools has proven to have a significant impact on improving the quality and reproducibility of research [15]. For example, Open-SBS (Smart Building Simulator) [7] enables the reproduction of virtual buildings through an extensible device library and ontology-based modeling, supporting simulations under different environmental and energy conditions. Another notable example is Home Sensor Simulator [16], which supports multi-inhabitant activity simulation and complex behavioral modeling, allowing more realistic interactions within domestic scenarios.

On the other hand, these tools limit the possibility for users to modify, extend, or customize the simulator's behavior, thus restricting their adaptability to new scenarios or research requirements.

Moreover, in recent works, the DT paradigm has emerged as a promising evolution of these simulation frameworks for Smart Home management and next-generation AAL systems, enabling real-time synchronization between the physical and digital domains. DTs enable design, testing, and optimization solutions before they are implemented in the real world, reducing costs and improving comfort and experiences for the users [17]. In particular, in [18], a Digital Twin framework for personalized building management in AAL contexts is presented, integrating user behavior and environmental data to enable context-aware control and energy efficiency inside buildings.

In light of these observations, a new integrated approach is needed. The proposed simulator is therefore conceived as a flexible and extensible tool, developed to reproduce user activities and device interactions in a Smart Home environment, while enabling advanced experimentation and integration with DT models for predictive and assistive analysis.

III. SYSTEM MODELING

Considering the DT paradigm as discussed in [18], in this study, the concept is adapted to focus on the user's daily activities and appliance usage patterns, which are modeled as integral elements of the home's digital representation.

The aim is to create a virtual ecosystem that mirrors the real dynamics of a home, where user interactions with sensors and devices generate behavioral traces that can be monitored, interpreted, and analyzed for assisted living. In this context, the simulator acts as the main part of the DT ecosystem, providing visualization, real-time synchronization, and analytical tools for the study of user activities, energy-related behaviors, and comfort management.

A. Reference Scenario

The reference scenario considered in this work is that of a Smart Home environment equipped with a heterogeneous set of sensors and IoT devices. These might include motion sensors (PIR), magnetic switches, temperature sensors, smart meters, and weight sensors. The environment is designed to monitor the occupants' behavior and recognize daily activities to support them in informed decision-making processes.

Each component of the environment is associated with a corresponding digital entity within the simulator. Similarly, the user is represented by a virtual agent whose interactions with the environment generate events and activity patterns. This solution provides a controllable and safe framework for testing HAR algorithms, studying sensor deployment strategies, and visualizing energy data.

Indeed, the dual representation allows real-time synchronization between the physical and digital layers: when an action occurs in the real world, like a user turning on an appliance, the corresponding state in the virtual model is updated, enabling the observation of aggregated metrics such as energy consumption or contextual variables like room temperature and presence. By continuously observing user routines, the system can learn daily routines and assist in everyday tasks, for example, turning on the water heater at the appropriate time to match the user's usual shower schedule. This solution not only enhances comfort and energy efficiency but can also help with the detection of anomalies or deviations from habitual activities, potentially triggering alerts or interventions.

B. System Architecture

The system architecture represented in Fig. 1 extends the multi-layer DT structure introduced in [18], adapting it to activity-based monitoring. It is organized into three layers:

- Physical Layer: represents the real environment, including the sensors, appliances, and the occupants. It produces

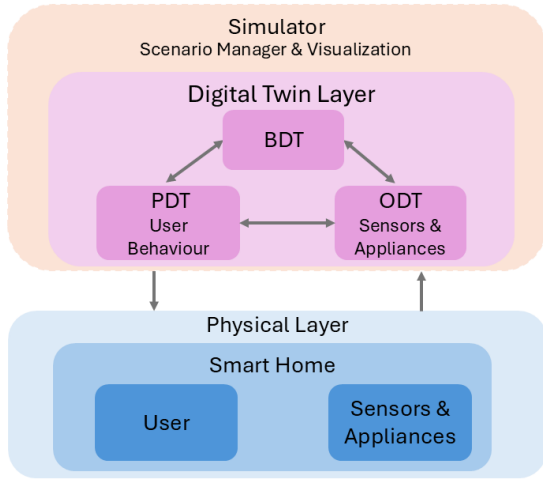


Fig. 1: System architecture of the proposed simulator integrating Digital Twin entities

real data that reflects the observable phenomena in the home.

- **Digital Twin Layer:** contains the virtual representations of all physical entities. Each real object has a corresponding digital instance whose state mirrors the real one. This layer models the relationships between Personal DT (PDT), Object DT (ODT), and the Building DT (BDT) entities, e.g., how user actions affect energy consumption, and enables context-awareness and behavioral inference. The PDT represents the users and models their behavior patterns; the ODT includes all sensors, actuators, interfaces, and controllers; the BDT models the building dynamics and characteristics. More details about the ontology under these entities and the relationships that govern them can be found in [18].
- **Simulator Implementation:** this layer concretely implements the DT through the simulation software that has been developed. It provides the graphical interface for configuring the home layout, controlling simulations, visualizing sensor data, and recognizing activities. It also includes the data-processing and reasoning logic responsible for activity recognition, logging, and the generation of synthetic or what-if scenarios.

This modular design allows the simulator to operate both as a replica of real sensor networks and as a synthetic data generator, enabling a flexible testbed for the development of HAR and decision-support algorithms.

C. Activity Modeling and Twin Synchronization

Each activity in the home combines sensor activations and device states over time. The DT layer continuously monitors these signals and updates the linked instances accordingly. Activities such as *Cooking*, *Sleeping*, or *Leaving Home* are recognized through temporal correlations among specific sensors (e.g., PIR + smart meter + switch).

This continuous synchronization process enables the DT to replicate the real environment's evolution over time. In addition, by modifying specific digital entities, for example, by changing an appliance cycle or user schedule, the simulator can reproduce alternative behavioral patterns, supporting the generation of synthetic data and what-if experiments for predictive analysis in AAL domains.

IV. SIMULATION-BASED DATA GENERATION

The simulator was designed with the objective of developing a system capable of recognizing the activities carried out by an inhabitant inside their home, through the analysis of the behavior of the sensors and devices that make up the environment. To achieve this goal, the development process began with identifying key functionalities and best practices to guide the system architecture. An additional key requirement concerned the implementation of an intuitive and easy-to-use graphical user interface, accessible to all categories of users.

The simulator was developed using the Python programming language, which was chosen not only for its widespread use, but also for its clear and readable syntax that facilitates both implementation and maintenance of the code. In addition, Python makes available a large set of libraries and functions that proved to be particularly well suited to the project objectives. When the program is started, a graphical user interface is generated that presents two main menus: one dedicated to scenario creation and one reserved exclusively for simulation.

The source code is available at [SmartHome-HAR-Simulator \(GitHub\)](#).

A. Scenario Manager

The “Scenario” menu includes several options that allow the user to create a virtual Smart Home from scratch, delimiting rooms with walls and doors, and inserting objects, sensors, and devices of various kinds. In particular, five types of sensors have been implemented:

- PIR, which detects the presence of a person;
- Temperature, which records thermal changes in a room;
- Switch, placed at doors, detects openings and closings;
- Smart Meter, associated with a device, monitors energy consumption;
- Weight, which detects a load exerted on it (e.g., if placed on a chair, it detects the presence of a seated person).

Similarly, several devices can be selected, including refrigerator, oven, washing machine, dishwasher, computer, and coffee machine. Each appliance is associated with a predefined power consumption profile, derived from Smart Meter datasets collected for that specific device.

The “Scenario” menu also allows the created configuration to be saved in a CSV file, which stores the coordinates and characteristics of the various household components in a structured format. Alternatively, the scenario can be loaded directly from a file: in fact, the simulator can read documents in CSV and TXT formats, automatically reproducing the layout of the elements contained within them.

B. Simulation Engine

The “Simulation” menu offers two distinct modes: manual and automatic.

In manual mode, the user must first set up a scenario. Then, by selecting the corresponding option, a timer equipped with *Start* and *Stop* buttons is activated, with the possibility of specifying the start time of the simulation (in the format HH:MM, with default value 00:00). The timer speeds up the passage of time: simulation minutes correspond to real seconds, while simulation hours correspond to real minutes. This choice was made for the sake of convenience to reduce testing time. Once the timer is started, the user can control a virtual avatar, moving it around the environment, and having it interact with doors, devices, and sensors through simple mouse clicks.

At the end of the simulation, the system allows the user to view graphs that relate the status of each sensor to the timestamp (date and time). In addition to the graphs, sensor logs are available, showing information such as location coordinates, name, type, status value, and timestamp. In the case of Smart Meters, there is also data on the energy consumption of the associated device. An activity log is also generated, listing all actions recognized by the simulator with start and end times. Finally, the user can export to a CSV file the entire path followed by the avatar, including movements and interactions with devices and sensors.

Activity recognition is handled during the execution of a simulation by analyzing the state of sensors and devices in relation to the passage of time. Activities currently recognized include:

- Cooking: oven on monitored through a Smart Meter and PIR sensor active in the Kitchen area;
 - Laundry: washing machine on, detected via the Smart Meter;
 - Dishwasher: similar to laundry, detected by Smart Meter;
 - Office: energy consumption detected by the Smart Meter associated with the computer;
 - Leaving home: opening and closing the front door (switch named “Door Switch”), followed by the absence of motion on all PIR sensors within five simulated minutes;
 - Returning home: coincides with the end of the Leaving Home activity; requires opening and closing the front door (detected via the switch), followed by the activation of at least one PIR sensor inside the home;
 - Sleeping: continuous presence detected for more than ten minutes simulated by a weight sensor placed next to an object named “Bed”;
 - Eating (breakfast, lunch, dinner): activation of a PIR sensor in the kitchen (user near the oven), associated with presence for at least ten simulated minutes detected by a weight sensor placed near an object named “Table.”
- The distinction between meals is based on the time slot: breakfast from 7:00 a.m. to 9:00 a.m., lunch from 12:00 to 2:00 p.m., and dinner from 8:00 p.m. to 10:00 p.m.

As an example of how the simulator identifies activities

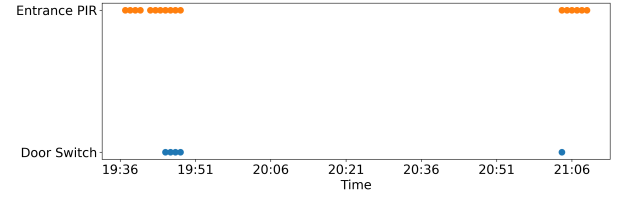


Fig. 2: Timeline of events for “Leaving Home” and “Entering Home” Activities

through sensor state transitions, Fig. 2 shows the temporal logic used to detect Leaving Home and Returning Home events.

During the simulation, the identified activities are displayed in real time within the interface via a dedicated label, which shows the name of the recognized activity. The system is also capable of handling simultaneous activities, displaying multiple labels of the activities simultaneously when they coexist. Fig. 3 shows an example of a manual simulation of a user performing the activities of having lunch while the dishwasher is switched on. Objects are represented in blue, while sensors and smart meters appear in green when active and in red when inactive.

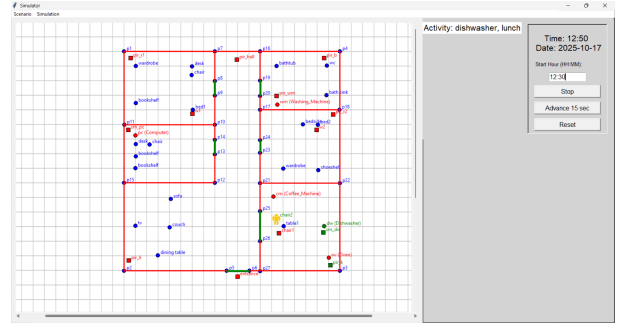


Fig. 3: Manual simulation with recognition of “dishwasher” and “lunch” activities

The automatic mode, when selected, opens a dedicated interface separate from the main one. It provides two variants: folder and user path. In the “folder” variant, the user can load a directory containing sensor-related log files and select those of interest, so that corresponding graphs are automatically generated. In the “user path” variant, the program reads a CSV file related to an entire path executed by the user during a simulation. Again, it is possible to view graphs of the sensors involved or to access the complete logs, which report sensor values with the corresponding timestamp.

The simulator enables the user to save graphs and logs, as well as specify the name and storage path.

V. VALIDATION AND RESULTS

A. Simulated Activities Validation

To assess and validate how well the simulator characterizes and recognizes everyday activities in a Smart Home, the ten activity classes described in Section IV have been analyzed

in terms of their duration and their linkage to environmental sensors that interact with the occupant during each activity. For each activity, 20 simulated runs were manually executed. Fig. 4 reports boxplots of the activity duration over the 20 simulations per class. The distributions indicate time spans that are in line with plausible real-world durations for the same activities. As shown in Fig. 5, the durations were obtained from the Aruba real-world dataset from the CASAS smart environment project of Washington State University [19], considering only those activities that correspond to the ones simulated, which are reported here for comparison.

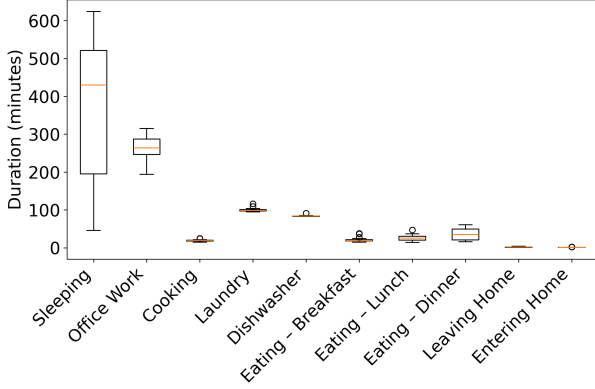


Fig. 4: Duration of Simulated Smart Home Activities

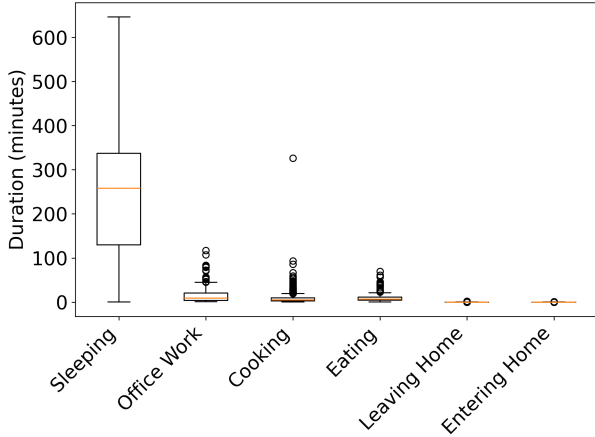


Fig. 5: Duration of Real-World Smart Home Activities from Aruba dataset [19]

Regarding appliance-driven activities, i.e., Dishwasher and Laundry, which use the washing machine, the energy consumption profiles used in the simulator are taken from real smart-meter readings [20]. At present, the simulation includes one usage pattern per appliance; future versions will incorporate additional real consumption traces to better capture the diversity of real usage. Even with a single pattern, these traces already provide a reasonable indication of in-home energy demand during these activities. Fig. 6 presents heatmaps relating activities to sensor activations within the corresponding

activity windows. These maps show that each activity tends to engage a specific subset of sensors (e.g., kitchen PIRs and power meters during cooking), making the activities spatially and functionally circumscribed in terms of sensing.

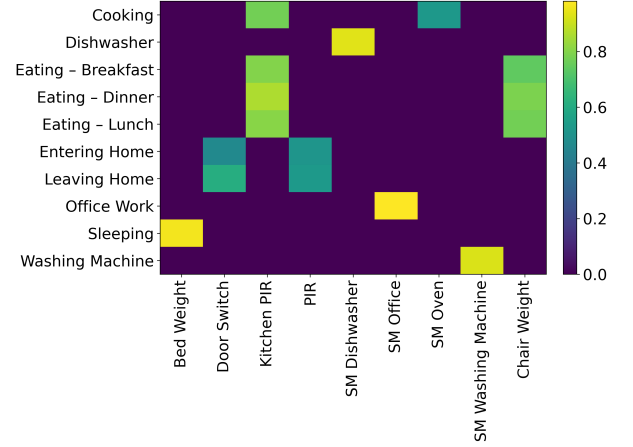


Fig. 6: Sensors Activation Ratio per Activity (SM stands for Smart Meter)

B. Classification Performance

Finally, to prove separability between activities, a Random Forest classifier has been trained. For the training phase, 14 simulations per activity class were used, while 6 per class were taken for testing. The feature set included: (i) duration; (ii) number of events; (iii) per-sensor activation ratios computed within the activity window; and (iv) time-of-day encoded via a cosine transform.

Initially, the classifier performance was evaluated using only features (i)–(iii). As expected, this configuration led to confusion among breakfast vs. lunch vs. dinner when relying only on sensor activations, since the same sensors are used across the three activities. However, adding time-of-day as a feature enables perfect disambiguation of these eating sub-activities, as shown by the confusion matrix in Fig. 7.

These results are preliminary but consistent with real events and support the validity of the simulator. A practical advantage of our setup is that the simulator can ingest real text logs of sensor activations and human–environment interactions, enabling the realization of adaptive and predictive AAL applications. Furthermore, the simulator is designed to generate structured temporal and contextual features that can be directly used as input for supervised or unsupervised learning models, enabling data-driven activity discovery and adaptation beyond predefined rules in future extensions.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, a new Smart Home simulator has been proposed and implemented, integrating the concept of DTs for HAR and Smart Home management. The proposed framework allows for the generation of synthetic sensor data that replicates residents' daily activities. It achieves this by modeling



Fig. 7: Confusion Matrix for Activity Classification using Random Forest

the user's interactions with environmental sensors and smart devices, capturing realistic timing and behavioral patterns. The simulator also offers a controllable and cost-effective platform for developing and testing HAR algorithms.

Preliminary results show that the simulator can generate consistent and separable activity patterns validated in terms of HAR classification performance using a Random Forest algorithm. Moreover, by replaying and processing external logs, the use of the simulator allows the system to synchronize with real-world data, learn from actual behaviors, and adapt to different physical environments, thereby enabling robust assistive and predictive analysis in AAL contexts.

However, the current implementation assumes a single inhabitant and ideal sensor behavior, without explicitly modeling multi-user interference, noisy activations, or missing sensor events. Future works will mainly focus on the integration in living environments for real-time feedback and validation, and on expanding the overall model in order to consider a larger number of sensors and devices, more inhabitants, and include more activities to reproduce and recognize.

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