Learning Algorithms for Building Control Applied to the iHomeLab Lighting System

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Abstract

With the advent of BIM, IoT, Digital Twins and Machine learning, new approaches to the programming and configuration of Building Management Systems (BMS) become available. In this paper we present an approach where the BMS learns the correct behavior instead of being programmed. By continuing the learning phase into the operation phase the system can then adapt to changes in building use and optimize the user interaction or user experience. We demonstrate the approach by applying it to the control of the lighting in the iHomeLab Visitor Center. The algorithm has been tested in Simulation and will be implemented in the iHomeLab in the next months.

Keywords

Digital Twin, VR-AR, IoT, Genetic Algorithms

1. Introduction

The iHomeLab Visitor Center is a showroom dedicated to demonstrating the possibilities of Smart Building Technologies and disseminating the results of the iHomeLab Research Center in the research areas: Active Assisted Living, Smart Energy Management and Safe Building Intelligence [1]. The results of research projects are presented in the Visitor Center, which is available for custom guided tours or free public guided tours and can also be rented for an event. A key difference to other visitor centers is the use of storytelling and guided tours to make the results and possibilities accessible and understandable for the public. One of the more complex systems in the iHomeLab is the lighting system, which must react to the guide depending on the event or to react dynamically during a presentation. This currently requires a lot of manual interaction between the guide and the building, especially in special cases, for example filming videos. Over the last few years, the variety of presentations and use cases has been steadily increasing. There is a need to make the interactions simpler and increase the level of automation, while adapting to our changing needs.

Building control algorithm design is often perceived to be a relatively simple problem, as the algorithms themselves can be quite simple. Complexity arises when the number of actuators and sensors and the number of potential interactions with the occupants of the building are considered. Further complexity arises when external influences such as time or day or year, or when changing needs of the occupants are included. With the rise of BIM and Digital Twins allowing a dynamic model of the building, and the integration of a parameterization of the control system, new possibilities arise. A genetic algorithm (GA) can select potential control algorithms according to a simple fitness function. Potential occupants may then use Virtual Reality to enter and interact with the building in various situations, and thus provide additional information for the selection of the final algorithm. After the installation of the system, the system can observe the interactions of the occupants with the building in different situations, and then further optimize the algorithms to minimize the number of interactions necessary. In this way the building learns and adapts itself to the needs of the occupants.

To prove the applicability of this concept, we have applied it to the lighting system of our iHomeLab Visitor Center. In this paper we describe the technology used, and the approach taken, as well as the current state of the project and possible future work.

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2. Technology & State of The Art

2.1. Digital Twins

The first Digital Twin (DT) concept was presented by Grieves in 2002 [2] and was initially called "Conceptual Ideal for PLM (Product Lifecycle Management)". The core elements of the DT concept were present: Real Space (RS), Virtual Space (VS), the link for data flow from real space to virtual space, the link for information flow from virtual space to real space and virtual sub-spaces. The term Digital Twin was first introduced in 2010 by NASA in the publication of its technology roadmap [3]. Here a DT was described as an integrated multi-physics, multiscale simulation of a vehicle or system that uses the best available physical models, sensor up-dates, fleet history, etc., to mirror the life of its corresponding physical twin. Later in 2014, Grieves published a whitepaper [4] presenting developments of the concept after 10 years of its presentation. In this paper he states that the evolution in the field of lightweight 3d models, in that decade, made it possible to model products with the required geometry, characteristics and attributes and containing only the necessary details. Thus, enabling users to view and simulate complex models with acceptable computational cost. On the other hand, he identified the fact that the connection between the RS and the VS was still not satisfactory as the main reason why the concept of Digital Twin was not more widespread. Only after being able to establish this connection in real-time would users be able to benefit from the advantages of the DT concept. According to Grieves the DT would then be able to support three of the most powerful tools of human engineering:

- Conceptualization - DT allows a direct visualization of the information in the model. Eliminating the counterproductive mental process of decreasing the information and translating it from visual information to symbolic information and back to visually conceptual information.
- Comparison - The real-time connection enables to compare the desired result and the actual, determine a difference and decide how to eliminate or reduce it.
- Collaboration – The possibility to have this VS that reflects the RS in real-time allows to have a common visualization of the RS regardless of where it is in the world.

2.2. Digital Twins and IoT Integration

The term "Internet of Thing" (IoT) was introduced by Ashon in 1999 [5]. Ashon had the idea to implement the Radio Frequency Identification (RFID) technology in the supply chain of P&G and connect its data with internet. This established the concept of an object ("thing") oriented architecture with services implemented based on the data made available. In the same year, Message Queuing Telemetry Transport (MQTT) was invented by Stanford-Clark and Nipper [6]. MQTT is a lightweight network protocol, that enables to publish-subscribe messages between devices that enables an IoT architecture. This was further standardized in 2009, when a group of researchers from more than 20 large industrial companies joined in Germany to create the IoT Architecture project (IoTA) [7]. The project was implemented between the years 2010 and 2013 and resulted in proposals the creation of an architectural reference model together with the definition of an initial set of key building blocks [8].

The IoT and the IoT-A provided, the first steps were taken to create the desired connection between RS and VS mentioned above. Recently with the advent of the PaaS (Platform as a service), many cloud providers such as AWS, Google IoT, Microsoft Azure and IBM have provided the infrastructure to ease linking of IoT and Digital Twins.

2.3. BIM – Digital Twins for Buildings

Building Information Model (BIM) has become a fundamental aspect in the architecture, engineering, and construction (AEC) industry. As a 3d model of a building a BIM file contains it the geometry information as every important semantic information of the building elements [9]. BIM-based framework had been developed to integrate the model during the different execution phases of a construction project [10]. During the preliminary design phase, the model is used to create Building energy performance simulations (BEPS) [11]. Taking advantage of the fact that BIM models are granted parametrically, processes based in Algorithm Aided Design (AAD) can be implemented in the detailed design phase [12]. In the construction phase the model can be incorporate with Augmented Reality (AR) and indoor positioning [13] to monitor works on site, inspect and ensure the quality of execution. The use of a well elaborated model in the subsequent phases supports the task of making commissioning fast and effective. In addition, many equipment manufacturers have developed AR applications that assist the equipment startup operations [14]. The parameters stored in the BIM models can also be used to automatically define set points and operating schedules of the different spaces, allowing a quicker and accurate configuration of the BMS (Building Management System) [15]. Finally, all system test and commissioning reports can be attached to the model. In this way, the BIM model would be able to replace the technical compilation usually delivered in the project's handover and be used later by the Facility Management Team [16]. During the operation phase, the use of BIM models and IoT (Internet of Things) enables the visualization of the building system information (temperature, humidity and pressure sensors, lighting, system errors, etc.) in real time – Digital Twin. [17]

2.4. Learning Algorithms for Building Control

In recent years, the combination of BIM and IoT-PaaS (Platform as a Service) has opened the field of applying learning algorithms for building control. In particular, the research done in [18] is worth mentioning. In this project the authors used a physical testing apparatus linked to both a digital simulation and analysis environment to develop an Intelligent Adaptive Control (IAC) framework that uses machine learning to integrate responsive passive conditioning at the envelope (adaptive facades) into the building's overall environmental control system.

Applying Machine Learning and adaptive control to building automation systems (BMS) is an approach that has already been followed in multiple research papers [19,20,21,22], and that some BMS companies already commercialize in their solutions. For example, Siemens Building Technologies [23] ensures that the Adaptive Control capability provides more efficient, robust, fast, and stable control compared to traditional PID control. Adaptive Control automatically adjusts to fluctuations in mechanical systems, loads, and seasonal changes to deliver superior performance in variable environments. Resulting in energy savings, increased component life expectancy and improved occupant comfort.

In Switzerland since 2013, a Block Research Group is developing the project HiLo [24] on the topmost platform of NEST, novel structural solutions are being studied for the building envelope of which we would like to highlight is the Adaptive Solar Façade (ASF) is a dynamic façade of thin-film photovoltaic modules with soft, pneumatic actuators for solar tracking and daylight control. The modules are controlled based on sensors as well as on input by the inhabitants. Adaptive learning algorithms facilitate the continuous improvement of the behavior and thus the adaptation of the modules to their users and the environment.

Although the technology used by BMS companies is well established, in this paper we propose a novel approach. Instead of using the error signals to adapt the control strategy, the system abstracts the relevant information from input data and redefines the design parameters. This approach is applicable to switching based systems with strong human interaction, such as the lighting systems, and not just to the control of environmental systems.

2.5. Learning Algorithms for Building Control

The Genetic Algorithm is an adaptive heuristic approach to Machine Learning. It belongs to the class of Evolutionary Algorithms. Based on a parameterization of the solution space, candidates are evaluated based on a fitness function, and then the best are recombined in the following generation. The population size is preserved throughout each generation. The new generation is created by recombination of the parameterized potential solutions, in some cases this is modified with random changes. After a set number of generations, the best solution according to the fitness function is chosen as the solution. See for example [25] for an accessible introduction. The concept of applying genetic algorithms for design optimization has been explored in the past, see for example [26], and has been applied to lighting control [27]. However, these applications were aimed at optimizing power consumption, and were not aimed at optimizing the user experience, as developed in this paper.

3. Lighting Control of the iHomeLab

3.1. Digital Twin of iHomeLab

The iHomeLab Digital Twin project aims to explore new infrastructure technologies using the iHomeLab as a use case. For this propose, in the beginning of the project a BIM model was developed to serve as a basis for the remaining fields of application (Figure 1).

Figure 1: Digital Twin of iHomeLab

Using this model, two other use-cases were explored. The investigation of a Virtual or Augmented Reality experience of the iHomeLab (Figure 2)

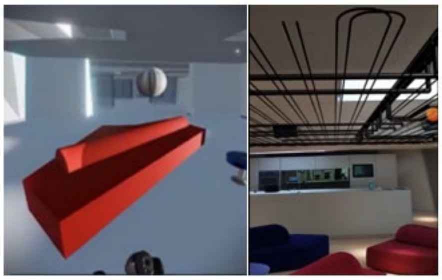

Figure 2: Virtual (left) and Augmented Reality (right) in the iHomeLab Digital Twin

The toolchain architecture established in the project is shown in Figure 3. The iHomeLab sensors are connected to a KNX network using a Raspberry-Pi as an IoT Gateway. We chose AWS IoT as a IoT cloud service that receives the MQTT messages and enables representation in the BIM model, which is imported to Amazon Sumerian. Amazon Sumerian is a service from AWS that allows the creation and execution of 3D, Augmented Reality (AR) and Virtual Reality (VR) applications.

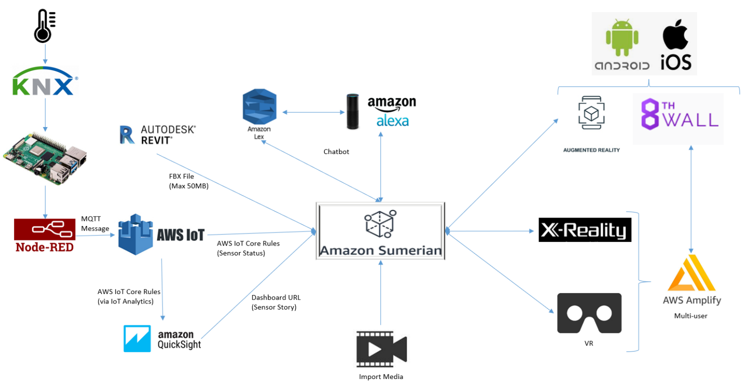

Figure 3: Toolchain Architecture

3.2. Lighting Control Concept

As presented in Sections 1 and 3 the iHomeLab Visitor Center is used for different types of events. All the events are scheduled in the iHomeLab Calendar, each event contains the following information (Main Variables):

- Type of event, which determines the sub-events
- Name of the guide
- Number of people participating in the event
- Date & Time of the day and duration of the event.

In an iHomeLab event the guide triggers the start of a sub-event, the switching control then consists of a series of Lighting Status Signals (LSS). Each LSS consists of a timestamp, a light designation, and the new status – on/off, color and intensity. The main variables influence the specific sequencing and choice of LSSs. These control rules were defined based on the experience and intuition of the guides.

Although the LSS are predefined to perform automatically during the event and its sub-events, manual interactions can be introduced by the person who conducts the event. These changes are performed using a mobile app to communicate with the BMS System. Manual interventions are stored as additional LSSs for that event. The system filters the pre-programmed LSSs to ensure they do not contradict the manual interactions. LSSs that are not executed are effectively replaced by the manual LSS in the event record. All the data of an event is stored in an IoT cloud Database via MQTT messages. The objective of the learning algorithm is to analyze the data and explicitly redefine the control parameters to minimize the number of manual changes during an event. This is done by calculating the difference between the pre-programmed lighting sequence and the actual lighting sequence as the objective for the fitness function in the genetic algorithm. The algorithm can used in 3 phases of the operation of the lighting system of the iHomeLab:

1. Design Phase: When creating a new event type, the user interacts with the algorithm in virtual reality to evaluate and possibly modify the interaction.
2. Pre-Event Check: The Guide has the option of checking the lighting interactions and modifying the settings before an event.
3. Post-Event Learning: The system automatically reviews the interactions and determines whether the settings need to be adjusted (learning step).

In the Design Phase and the operation of the iHomeLab, a database of LSS-Sequence-Pairs is created. Each pair consists of the planned and actual LSS sequences. The elements of the genetic algorithm are then:

- <u>Fitness</u>: The difference between the actual and planned LSS sequences
- <u>Population</u>: The set of individuals
- <u>Individual</u>: The set of LSSi-vectors, one for each type of subevent (i)
- <u>History</u> - Storage of the new population DATA for each Generation (n):
    - New LSSi,n from sub-event preprogrammed sequences
    - New LSSi,nVR from sub-event VR scene inputs
    - New LSSi,nDT from sub-event DT scene inputs
    - New LSSi,nRE from sub-event Real Event manual inputs
- <u>Evaluation</u>: In each generation the algorithm calculates the difference Δ between the preprogrammed values LSSi and the other input vectors LSSi,nVR, LSSi,nDT and LSSi,nRE. The inputs from the different categories of events are weighted to assign a greater degree of importance to the data collected in the following order VR, DT, RE. The fitness functions are composed by the sum of all the three weighted Δs.
- <u>Evolution (between generations):</u> The optimization algorithm minimizes the fitness function by evolving each LSSi,n. The algorithm will use all the previous generation data to improve the event lighting settings. The result of the evolve phase is a new definition for each set of LSSi,n+1 that will be considered as the new preprogrammed sequences to use in the next generation. Figure 4 presents the overall concept diagram.

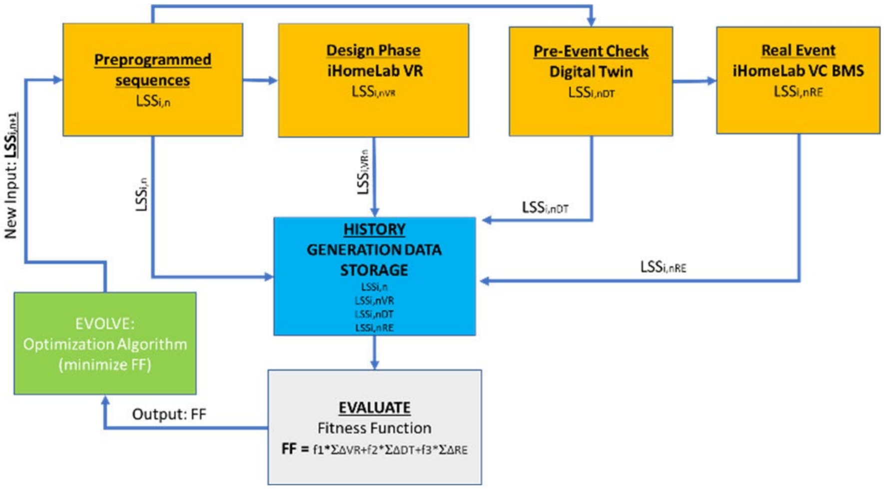

Figure 4: Concept Diagram

In this research project, we apply the algorithm in two use cases for the Visitor Center. Firstly, for the presentation of research projects to the public by a guide. And secondly, for events where the VC is rented and used according to the organizer's needs. Both cases are described in detail in the following sections.

3.3. Genetic Algorithm Use Case 1 - Guided Tours

During the guided visits to the IHL VC, several research projects are presented through iterative demonstrations. Each demonstration was designed to convey the project's key results and is accompanied by a different LSS sequence. The LSSs are predefined in the BMS, however the actuation time of each set can be manually controlled by the guide. Before a guided tour, the LSSs are selected based on the number of people attending the demonstration. The GA can then use the difference between the planned LSSs and the actual LSSs to adapt the LSSs for the tour. This is done in the learning phase using VR, and then in the operation phase using DT and the reality. Therefore, the GA enables learning during operation of the Visitor Center. Figure 6 shows the pseudo code for the GA implementation for this use case.

3.4. Genetic Algorithm Use Case 2 – Events

The second use-case developed is applicable in situations where the IHL VC is rented for events. In these cases, there are no exhibition demonstrations in which the lighting environment was previously designed to convey the intended message. In this way, the event organizer has the possibility to choose the lights he wants to turn on as well as their color and intensity during the different activities of the event. Generally, these types of events include as main activities a welcome session, an introductory lecture, a presentation or a video and a question-and-answer session. In many cases, they are followed by a break and an Apéro. Each activity needs adjustments in the lighting conditions of the space. Since the time that each activity lasts depends largely on the organizer that is using the space, unlike the previous study case, in this case we do not intend to control the timing of the transition between LSS, but rather to predefine in a generative way the lighting settings for each type of event. To this end, a LSS for each lighting equipment will be predefined according to the type of activity. During the event, information on manual changes (in VR, DT, and reality) implemented for the different activities by the event organizer will be collected, as well as general feedback from participants through an IoT feedback button, with these inputs a satisfaction value of the lighting definitions for each activity will be calculated. This is then used for the GA in learning the better settings. Figure 6 describes the pseudo code used in the GA implementation for this use case.

```
FOR Number of Generations
   FOR each Virtual Event VR
       FOR each Predefined Event PD
          IF VR.NumberPeople=PD.NumberPeople, THEN
              FOR each VR.ActionTime
                 Δ.VR.PD= ABS (PD.Action.Time – VR.Action.Time)
                 ADD Δ.VR.PD to Δs.VR.PD
              END FOR
           END IF
       END FOR
   END FOR

   FOR each Real Event RE
       FOR each Predefined Event PD
          IF RE.NumberPeople=PD.NumberPeople, THEN
              FOR each E.ActionTime
                 Δ.E.PD= ABS (PD.Action.Time – RE.Action.Time)
                 ADD Δ.RE.PD to Δs.RE.PD
              END FOR
          END IF
       END FOR
   END FOR

   FOR each PD
       FitnessFunction = Δs.RE.PD+ Δs.VR.PD
       ADD PD and FitnessFunction to RankedPD
   END FOR

   SORT RankedPD Low to High

   IF RankedPD[0].FitnessFunction = 0
       Break
   ELIF RankedPD[0] = RankedPD_LastGeneration
       Break
   ENDIF
   RankedPD_LastGeneration = RankedPD[0]
   BestRankedPD = RankedPD [0,10]

   FOR Generative Study Number of Population
       NewPD = Function (MUTATE BestRankedPD.Action.Time,
       CROSSOVER BestRankedPD.Action.Time)
       ADD NewPD to PD
   END FOR
END FOR
```

```
FOR each event E
  E.SatisfactionValue=0
  FOR each Virtual Event VR
    FOR each LSS in Real event RE
      IF VR.LSS=!PD.LSS, THEN
        E.SatisfactionValue = E.SatisfactionValue – 0.5
      ELIF RE.LSS=!PD.LSS, THEN
        E.SatisfactionValue = E.SatisfactionValue – 1
      END IF
      E.LSS.UserFeedback = GET IoT Users Feedback for each LSS (0 to 5)
      E.SatisfactionValue = E.SatisfactionValue + E.LSS.UserFeedback
     ADD (PD.LSS, E.SatisfactionValue) to RankedPD
    END FOR
  END FOR
END FOR

SORT RankedPD by E.SatisfactionValue
IF RankedPD[0]. E.SatisfactionValue  = 5
  PD= RankedPD[0]
ELIF
  FOR Each RankedPD[0].LSS
    rand = a random number between 1 and 1.1
    RankedPD[0].LSS= RankedPD[0].LSS+ RankedPD[0].LSS*Rand
    PD = RankedPD[0]
```

Figure 6: Pseudo Code Use Case 1 (left) and Use Case 2 (right)

4. Implementation and Results

To verify the applicability of the algorithm presented above, the pseudo-code was implemented in Python. It was necessary to generate scenarios for hypothetical events, with simulated sets having been defined with different performance times for the different actions and number of people present at the event. The algorithm proved to be able to evaluate all the predefined (PD) solutions for each simulated event (Real and VR) and ranked each PD Set. The ranking was done in accordance with the fitness function value (FFV), that presents the sum of the difference of the actuation times of each PD Set and all the simulated events. A set with a lower FFV get a higher Rank. Then the PD 10 highest ranked sets are selected and used to create the next generation. To create the new generation the previews sets were changed using a mutation and crossover function. The number of new PD Sets are defined in accordance with the generative study population. To test the algorithm, different population sizes for the generative study were used (10, 50, 100, 250, 500 and 1000 individuals). The results are presented in table 1.

Table 1
Use Case 1 Results

	10 Individuals			50 Individuals			100 Individuals			250 Individuals			500 Individuals			1000 Individuals		
Test n.	**Number of Generations**	**Computation Time [s]**	**Fitness Value**	**Number of Generations**	**Computation Time [s]**	**Fitness Value**	**Number of Generations**	**Computation Time [s]**	**Fitness Value**	**Number of Generations**	**Computation Time [s]**	**Fitness Value**	**Number of Generations**	**Computation Time [s]**	**Fitness Value**	**Number of Generations**	**Computation Time [s]**	**Fitness Value**
1	2	1.2	713.0	6	3.6	669.2	8	6.0	668.0	7	7.7	668.0	6	9.6	668.0	5	11.9	668.0
2	8	4.1	682.6	6	3.7	670.0	9	7.0	668.0	7	7.6	668.0	7	12.1	668.0	5	11.7	668.0
3	9	4.6	705.0	9	5.6	668.0	5	3.5	668.5	7	7.6	668.0	5	7.1	668.0	4	8.6	668.0
4	2	1.3	711.2	8	4.9	668.0	13	11.4	668.8	5	4.8	668.0	5	7.2	668.0	5	11.8	668.0
5	7	3.9	678.9	5	3.0	669.8	5	3.5	668.0	6	6.3	668.0	5	7.2	668.0	4	8.8	668.0
Min	**2**	**1.2**	**678.9**	**5**	**3.0**	**668.0**	**5**	**3.5**	**668.0**	**5**	**4.8**	**668.0**	**5**	**7.1**	**668.0**	**4**	**8.6**	**668.0**
Max	**9**	**4.6**	**713.0**	**9**	**5.6**	**670.0**	**13**	**11.4**	**668.8**	**7**	**7.7**	**668.0**	**7**	**12.1**	**668.0**	**5**	**11.9**	**668.0**
Avg	**5.6**	**3.0**	**698.1**	**6.8**	**4.2**	**669.0**	**8.0**	**6.3**	**668.3**	**6.4**	**6.8**	**668.0**	**5.6**	**8.6**	**668.0**	**4.6**	**10.6**	**668.0**

Based on these results, it is possible to verify that the algorithm finds better solutions when using a population of individuals equal to or greater than 250. We also observe a decrease in the number of generations necessary for the algorithm to converge to the solution as the population of individuals growth. As expected, there is also an increase in computation time with the increase in the number of individuals.

The GA for the second use case has not yet been verified. Due to the lack of previous data that can be used to correctly model the human behavior of visitors, it is more complex to simulate realistic values for feedback from iHomeLab VC visitors, which is required by algorithm to rank the LSS Sets. Therefore, we will verify this algorithm after implementation in the Visitor Center.

5. Conclusions & Further Work

These preliminary results show that it is possible to establish a connection between various technologies (BIM, IoT, Machine Learning) to obtain a final solution (Digital Twin) that allows simulation, adaption, and improvement of the response of a BMS system to the needs of its user. It was also possible to verify the applicability of a genetic algorithm that evaluates predefined sets and optimizes in accordance with the user's expectations. The GA concepts presented in this paper are novel in that they allow the BMS to learn sequences of actions based on VR and Reality, and the adaption is based on user feedback – both direct feedback in Use Case 1, and indirect feedback as in Use Case 2. Further work is necessary to further verify and refine the GA using human interaction on real events. Currently, the project is in the final phase of the IoT connection with the lighting system of the iHomeLab VC. Simultaneously the generative algorithm will be implemented and integrated with the IoT database using a cloud machine learning service. After the complete implementation of the concept, it will be necessary to perform tests through real events of the iHomeLab. The results of the continuous improvement will be analyzed and if it is found to be useful, the same concept can be expanded to elements of the building (e.g. walls, doors, curtains, façade) that have mechanical actuators that allows their movement during the events.

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