# DANOS: A Human-Centered Decentralized Simulator in SIOT

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## ABSTRACT

The added value of Social Internet of Things (SIoT) is constantly highlighted during the recent years. The idea is to exploit the social relationships among real-world smart heterogeneous objects to the benefit of their owners, through e.g., search and finding, dedicated services, tasks augmentation. In this paper we discuss a decentralized human-centered simulator, DANOS, that enhances objects' profiles and their interaction behavior with intelligence, based on specific human aspects, i.e., personality traits. Preliminary results show that when objects travel with intelligence in the virtual space, they are able to locate faster similar objects, establishing stronger and more qualitative relationships, while at the same time minimizing the network complexity and load. Such results, increase the probability of discovering faster the information based on given intents and providing best-fit recommendations with fewer costs.

## CCS CONCEPTS

**• Information systems → Personalization**; **• Networks → Network performance evaluation**; **• Human-centered computing → User models**; **• Computing methodologies → Search with partial observations**; *Intelligent agents.*

## KEYWORDS

SIoT, Human-centered Models, Personality Traits, Smart Objects

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## 1 INTRODUCTION

During the last decade, it has been extensively argued by researchers and practitioners that the potential of an Internet of Things (IoT) ecosystem could be multiplied if we enrich the communication of the connected devices with concepts and aspects from the Human-Social-Network (HSN), providing more meaningful interpretable interactions to the benefit of the unique end-user [5, 7]. In such a case, we are referring to a multidimensional communication model which establishes relationships between people-people, people-things, and things-things over a common digital reality that has two flavours; the HSN and the networks of things (or objects). This convergence brings into the surface the Social-Internet-of-Things (SIoT) that promises a more human-centered point of view and a seamless interaction of humans and smart things within a social framework [6]. The added value for people will focus on more effective navigation, service discovery, increased responsiveness, trustworthiness, etc. This could be translated as embracing a more human-centered standpoint in the definition and composition of models, methods, and paradigms that orchestrate this interplay between the involved entities. Currently, we have not come across of any SIoT research or simulators that employ, specific human characteristics or models from the area of e.g., Cognitive or Social Psychology, and which have been proved successful in the area of HSN (recognizing always the situation-specific perspectives and interpretations). Most of the works, to our knowledge, that approach the topic of a Humanized IoT (HIoT as an umbrella term that includes SIoT and Internet of People (IoP) [13, 18] are moving into more theoretical grounds trying to capture the breadth and depth of the concept or establish a framework of application rather than explicitly exploit the potential that given human factors or traits like e.g., motivation, creativity, personality, might bring into interactions and their products.

In this paper we discuss a novel human-centered simulator that resembles a decentralized network of SIOT objects, namely DANOS (Dynamic and Anthropomorphic Network of Objects Simulator). It maintains specific human factors at its core, driving the behavior and interactions of autonomous objects in the virtual space while they are attempting to discover and return the best possible result. DANOS is flexible to accommodate any human values, but for the scope of this paper (and the selected use case), we use the Five Factor Model (known also as the Big Five Inventory – BFI) [9], showing the effects and benefits. We employ an enhanced Object Profile (composed of the *User Specifics (US)*, *Interaction Specifics (IS)*, and *Object Specifics (OS)* as well as the collective intelligence of the virtual area for facilitating objects to create more stable and trustworthy relationships, while at the same time discovering faster and more accurately best-fit services recommendations for their owners based on a given intent. Preliminary evaluation of the DANOS Simulator on the search and finding SIoT process stages shows that when objects interact with intelligence, they establish more qualitative relationships (they make stronger friendships), faster and with less network resources utilization (traveling in the virtual areas).


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## 2 RELATED WORK

The research area of SIoT has been gaining increasing popularity due to the alternative and flexible opportunities that it offers. It draws attention on the creation of innovative models, frameworks and applications that will be able to handle the huge amount of IoT objects and will deliver more effectively and efficiently services to their users, by considering the "social" interaction of heterogeneous smart devices over integrated networks, fulfilling their requirements and intents. More specifically, a comprehensive work from Atzori et al. [5] details the policies for the management of social relationships between objects and propose an architecture with functionalities liable to integrate things into a social network; Cheng et al. [6] propose a framework that facilitates the harmonious social networking among human, things and services; Ding et al. [15] describe information (via Internet), people (via HSN) and objects (via object networks) as macro elements of the human society and discuss how they can co-exist under a common framework of interaction, proposing a platform that can cluster the three together and provide the means for further observation and experimentation of the produced behaviors; Kim et al. [11] propose a system, called Socialite, that enables new IoT applications based on emerging types of social relationships and semantic models for SIoT that include device types and their capabilities, users and their relationships; while Kranz et al. [14] emphasize on the combination of social and technical networks to collaboratively provide services to both humans and systems. In addition, [1] introduces the small world concept in SIoT by integrating properties of the former with the latter paradigm. It suggests that the use of smart social agents may ensure the finding of appropriate friends and services required by the user without human intervention. Lastly, Kasnesis et al. [10] propose also an architecture and simulator (ASSIST) for supporting SIoT with the use of agents that enable device-to-device and human-to-device social communication for discovering services that satisfy the users needs.

On the other hand, the consideration of individual differences in the design and development of SIoT architectures may add significant value on the quality and performance of the generated network and its outcomes. In particular, the theory of personality traits might be respected as a well-known, steady in time, comprehensive theory that has been broadly applied through different scenarios and applications in HSN. It alludes to individual differences in preferences, behaving, thinking and feeling [17], and has been utilized by researchers to clarify behaviors and patterns of users when interacting with content and peers in HSNs, with truly empowering outcomes and demonstrated influence in particular domains. Indicatively, Hamburger and Vinitzky [2] studied the relationship of users' personality and Facebook behavior using objective measures like user information uploads; Ross et al. [20] investigated the combination of factors relating to personality and competency, trying to understand how this influences the way in which users interact with Facebook for social purposes; Selfhout et al. [16] explored the effects of personality traits on friendship selection process and the formation of social relations, and Kleanthous et al. [12] again using the Facebook platform studied how users' activities (e.g., share, like, checkin) relate to their personality, proposing in this regards a computational mechanism for implicitly extracting real-time the users' personality model in relation to their activity. In this line of research, Ferwerda and Tkalcic [8] focused on the extraction of users' personality traits from their behavior on the Instagram — they utilized user activities like uploading or the manipulation of pictures (like filters that users apply) to predict invisible personality information, Quercia et al. [19] inferred personality from users' actions on Twitter like the number of profiles a user follows, number of followers, and the number of times a user has been listed in others' reading lists, and Skowron et al. [21] used users' digital traces from a combination of social platforms, i.e., Twitter and Instagram, showing that the combination of users' simultaneous activities decreases the prediction errors when deriving the personality traits.

Henceforth, our main concern is to benefit from the successful implementation of specific human factors, like personality traits, in the modelling of related solutions in the HSN and to adopt the lessons learned and effects to the SIoT network and scenarios, making them more scalable and navigable. This could be achieved by embracing the SIoT objects a more intelligent behavior while they are interacting with each other, optimizing their tasks (e.g., search routing process), and increasing the likelihood of returning the best possible outcome on a request.

## 3 A HUMAN-CENTERED REAL-LIFE SCENARIO IN SIOT

For enhancing the understanding of DANOS simulator outlined in section 4, we discuss in this section how do we envision the human-centered daily activities, interactions, and decisions in SIoT through an end-to-end real-life scenario. Peter is a doctor in the hospital treating emergency situations. His shift ends in the evening and he is looking forward to relaxing at home with a good movie. However, he has no idea which movie to choose and also no time to invest in this secondary task, to search and find one. Hence, Peter forwards this task to his Object (a digital representation of him with his smart TV) for recommending alternative movie options to him from other objects' owners with similar characteristics. In this case, Peter's Object acknowledges some information about the smart TV (i.e., energy class, label), Peter himself (i.e., his age, personality characteristics like strong introvert, low to openness to experience and high levels in the neuroticism scale) and his preferences (i.e., action movie, science fiction) which are combined to the Object's Profile. It also considers Human-Centered behavior (HCB), which is primarily driven by the correlation of specific human factors existing in the users' profiles. In this example, HCB is adopted based on Peter's personality traits, being e.g., not that keen to approach other objects (since he is introvert) and a tendency towards a Risk Avoiding behavior (Peter wants to get recommendations only from other objects that are strictly close to him — see figure 1 for more details regarding specific personality types and expected behaviors). The object uses this profile characteristics and the HCB to build up its own social network with similar objects (also called friends, that share similar values and characteristics) to collect recommendations about movies. These recommendations from other objects-friends (names of recommended movies) will be ranked by a recommendation engine and the best possible results will be returned to Peter; who will be able to assess them by providing

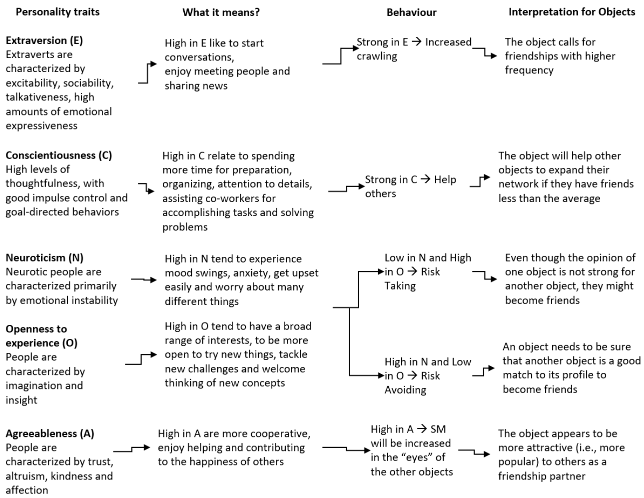



**Figure 1: Objects behavior based on their Personality**

his feedback. However, given the vast amount of diverse objects in the network, how can the object find quickly those that have a good match for this request, i.e., to find a movie for Peter? More specifically, where should Peter's virtual object travel in the Cyber World to find the best possible similar objects so to establish beneficial relationships? Subsequently, it needs to first locate the area in the Cyber World where movies recommendations are traded, and then to find the cells where there is an increased probability of finding the most similar objects, by generating a traveling route. A high-level description of those process is described below.

**Phase A: Object Request Traveling Route.** To calculate the traveling route, the object initially receives the intent (e.g., find movies) from its owner and queries the *Intent Manager* to get the area address that handles the movies. The Intent Manager calculates the *Intent Similarity* with each area and returns the address of the required area (that monitors the given intent). Through this address, Peter's object contacts the area's *Schedule Manager*, which generates the traveling route. This consists of a list of cells with high probability to find similar objects. To find the best traveling route, the Schedule Manager has to calculate the similarity between the *Object Profile* of Peter's object with each *Cell Proxy* (an aggregation of Object Profiles from previous successfully proposed objects' recommendations) through the *Cell Similarity Component* and to return the cell addresses where Peter's object has the highest similarity towards the Cell Proxy. The Schedule Manager suggests that Peter's object needs to travel to cells A and B.

**Phase B: Traveling and Establishing Friendships.** After Peter's object receives the *traveling route* (a list of cell addresses), it starts to travel to cell A, where the chances to find similar objects are the highest. The process of traveling and friendship acquisition is shown in figure 2. Peter's object travels to A by sending the targeted cell position A to the Travel Engine of the area (1). The Travel Engine, unregisters Peter's object from the old position (1.1) (initialized with a waiting position) and registers it at cell A through the *Registration Engine* (1.2). This process is called traveling. After Peter's object has traveled to cell A, it starts to call for friendships by requesting the *Friendship Acquisition Management Engine* of the cell (2). Cell A requests all objects for their Object Profiles (2.1). The

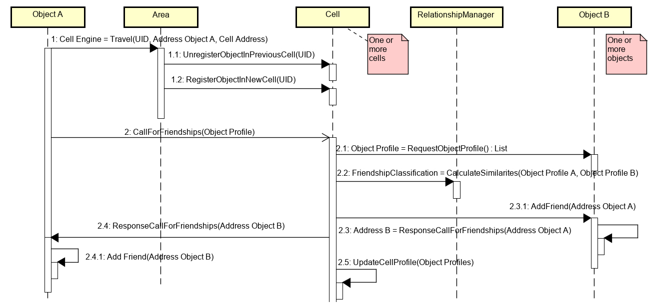



**Figure 2: Objects Traveling and Establishing Friendships**

cell forwards Peter's and the collected Object Profiles to the Relationship Manager (2.2) which calculates the similarity between each pair to decide if two objects will become friends. The calculation of the similarity is divided into the similarity of the Preferences, IS, US, and OS [what are these?]. For each specific type the Relationship Manager: (a) calculates the similarity — which is in the range between 0 and 1, where 1 means completely similar, (b) combines these into a single similarity metric and (c) adapts the preference similarity to it generating the *similarity metric (SM)* [3] [unhide paper info]. The outcome is a list of possible friendships. For each one of them, the cell forwards the address of Peter's object to the other objects (2.3), which in turn they add it to their friend's list (2.3.1) — the address of an object is a unique address like a URL that other objects can send messages to without entering the Cyber World. This process establishes a decentralized SIoT network of recommendations. The cell also forwards the addresses of the other objects to Peter's object (2.4), which also adds these objects to its friend list (2.4.1). If at a later stage a recommendation is successfully shared, the cell recalculates the Cell Proxy considering Peter's Object Profile and the Object Profile from the object-friend which gave the successful recommendations (2.5). In our example, the other object successfully recommends Peter the movie Star Wars, and so the Cell Proxy increases the probability to find science fiction movies and users with similar personality characteristics.

**Phase C: Generating Recommendations.** Andrea is the owner of another object, which is already in a friendship with Peter's object. While Peter waits for a movie recommendation, Andrea is watching the Star Wars movie which she likes very much. Andrea's object recognizes this behavior and recommends the movie to Peter's object. Peter reacts to the recommendation of his object also positively, by giving the feedback to his object that this is what he was looking for, so Peter's object will consider recommendations from Andrea's object more often in the future, as it is a friend that it can trust. Both Object Profiles and the recommendation will be fused as feedback to the cell where they had established their friendship so that the Cell Proxy can learn and the recommendation can be used in future requests.

## 4 THE DANOS SIMULATOR

The DANOS simulator shows how the system enables SIoT objects to create autonomous context-aware relationships with other objects to share best-fit recommendations among them and with their owners. It has been developed using the programming languages Google Go 1.12 with the library gonum v1 for statistical evaluation. For the front-end we use Angular, visualizing the objects' movement and information cards that facilitate the observation of the objects traveling and friendship establishment in space over time (see figure 3). Following our example scenario in the previous section 3, the user with his device (i.e., smart TV) and experience, in DANOS, will be represented by an ***object*** (a bubble in figure 3). An object contains the Object Profile which will be used in the similarity calculation with other objects inside the Cyber World to find the best similar pairs to ask them for their recommendations. The object can execute its travelling route based on an intent in the Cyber World to find other similar objects. An intent could be regarded as a request that might be linked to a specific goal during the execution of a user's activities, e.g., as a user I need a specific recommendation for a product (i.e., a movie) or a service (e.g., premium package for series). The object can be deployed on the user's devices, e.g., on a Smartphone, Laptop or Raspberry Pi. The ***Cyber World*** is divided into independent areas where each one of them is associated with an intent (the map in figure 3 represents the area for the intent 'find a movie'). Each area is subdivided into 1 to n *cell spaces* (see the grid in figure 3), where each cell defines the scope for requesting friendships and learns its context (includes the users' preferences and the Object Profiles from previous successful interactions between object pairs with the same intent). Through its hierarchical design, the Cyber World scales and thus can handle the huge amount of possible objects, while the cells are detached from each other (no communication between them). To establish a friendship, both objects need to be at a specific time in the same cell. If too many objects are in a cell, a cell can be cloned during runtime, with the new cell to be registered to the area. Accordingly, if there is the need for a new intent, a new area is being created. Cells and areas can be deployed distributed on any device that belong to class 1 object as described in [4]. As mentioned, main job of the object is to collect recommendations based on the profile similarity. The ***User Adaptation*** component (currently under development) builds the bridge between the interaction with the User and the object and adapts all data based on mapping rules (between the content and the user profile) and learning that is being generated in time. The User Adaptation ranks the recommendations (in the current scenario names of movies) through the Recommendation Engine that uses a reputation matrix (each friend has a reputation value) and presents them to the user by utilizing various adaptive conditions through the UI Adaption Engine (e.g., in more textual or diagrammatic). The reputation matrix enables the object to have always the best possible quality of friends' network (based on a given data-set), as follows: If the user selects one recommendation and indicates that he likes it through the User Interface (e.g. deployed on the Smartphone), the User Adaptation increases the reputation of the friend as well as stores this information to the respective cell where the relationship has been initially established (enabling the creation of end-to-end semantic graphs). If a friend only gives bad recommendations (the user dislikes what he receives), the friendship will be revoked in time (since its reputation will drop and the recommendations will not be considered). In perspective, DANOS Simulator enables objects to: Find the cell where other similar objects are mostly expected (section 3 Phase A); establish friendships given the strength of their similarity (section 3 Phase B); ask them for their best recommendations; rank them and provide the most relevant ones adapted to the object's user (section 3 Phase C). The

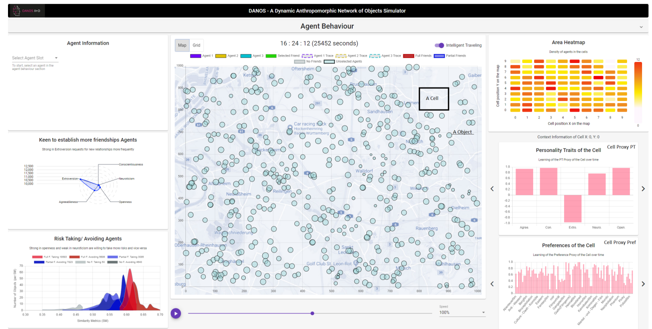



**Figure 3: The DANOS Simulator**

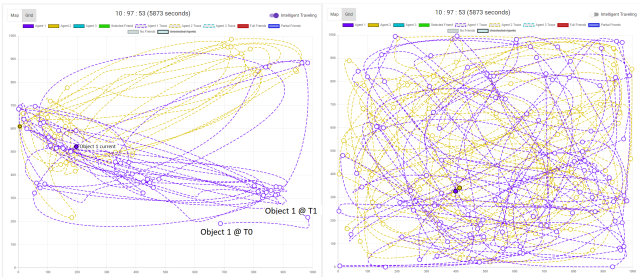
Object Profile, Similarity Calculation, HCB adaption, and the Relationship classification of the Relationship Manager have been primarily discussed in [3]; while the User Adaptation, containing the Recommendation Engine, is part of current/ future work.

## 5 EVALUATION

We evaluate the DANOS simulator by focusing on the search and find SIoT process stages (the evaluation of the recommendation engine is part of future work). Consequently, we formulated three research questions: ***RQ1:*** How is the generated Cells' (clusters of information) context learning optimized over time? ***RQ2:*** How does the intelligent (human-centered) traveling influence the quality of established friendships between objects over time and the number of friends generated? ***RQ3:*** How does the intelligent traveling influence the performance of similar object pairs (object's clone) so to find each other faster? For addressing the research questions we evaluate DANOS by comparing two different configurations: a) the simulation including the search and finding through the intelligent traveling which will be processed by the *Schedule Manager* and *Cell context learning*, and b) the simulation where search and finding take place randomly for object pairs bonding.

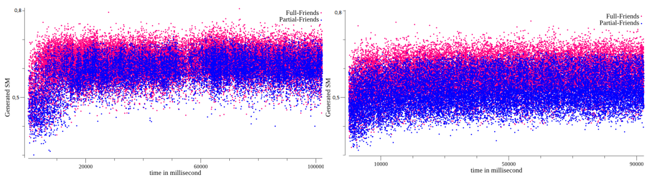
### 5.1 Simulation Setup and Execution

We have created 2000 objects to answer RQ1, RQ2 and RQ3 (for RQ3 we created 1000 objects and for each one of those a clone) and assigned to them with randomly distributed values for their OS and US in their OP. The values for the IS are created dynamically as objects travel in space. We use the intent movie for which only one area is needed. The following parameters for configuring the simulation are defined: (1) *Cell:* A cell defines the scope for friendship calls. We are using 400 cells; (2) *Cell Memory:* The cell has a memory size of 30. The memory will be initialized with randomly generated values; (3) *Time as object activities:* In order for the simulations to be comparable, the simulation time must be standardized. To avoid the association with any computational limitations, we do not use a time measure. Instead, we use the number of processed object activities, in our case, the simulation for RQ1 has 240000 object activation until it stops (For RQ3 the simulation stops if every object has found its clone); (4) *Object Activities:* An object will be periodically active. When an object turns active it will travel and has the probability to call for friendships (between 0.5 and 1); and (5) *Optimization:* Object pairs come only once together during the lifetime of the simulation.




**(a) Intelligent Traveling** **(b) Random Traveling**

**Figure 4: The trajectory of two helpful Objects**




**(a) Intelligent Traveling** **(b) Random Traveling**

**Figure 5: Similarity Metric over time**

## 5.2 Analysis and Discussion of the Results

*5.2.1 RQ1: How the generated cells' (clusters of information) context learning is optimized over time.* Initially, with the help of DANOS simulator, we wanted to observe how objects are traveling with and without intelligent behavior, in order to understand how this will affect their learning. Thus, we visualize in Figure 4 how two different objects, which adopt the helpfulness behavior, travel in the network over time to find possible friends. The two dotted lines, purple and yellow, present the traveling route, or trajectory, of the two objects. Figures 4a and 4b correspond to intelligent and to random traveling, respectively. We see that although both objects are sharing some common values, they have the following personality characteristics — Intermediate in Agreeableness, strong in Conscientiousness, intermediate in Extroversion, weak in Neuroticism, and strong in Openness to Experience; they differ in the IS, OS, and Preference characteristics, resulting in exercising different behaviors while moving in an area for finding their friends (looking at figure 4a, the white dots indicate where the objects stop during their traveling to establish friendships – object 1 is in cell X:1,Y:5 and object 2 in cell X:0,Y:6 at time 5873). Moreover, figure 4a shows that both objects visit the same cells periodically (e.g. cell X:1,Y:5; X:0,Y:6), but also visit different cells (e.g. object 1 is the only object that visits the cell X:8,Y:3); while figure 4b depicts that both objects visit the cells randomly and reveals that they may not meet each other at the same time. Traveling objects with intelligent behavior optimizes the learning process over time producing distinctive clusters of information (i.e., collective intelligence — data that relate to the Object Profile specifics, intents and feedback), and minimize the time that objects need to find the expected cells to travel.

*5.2.2 RQ2: Number and quality of established friendships.* Figure 5 shows the similarity metric that is calculated through the *Relationship Manager* if two objects come together, assuming intelligent and random traveling. Observing the plots, which depict the aggregation of all objects (for visualization clarity we plot only the first

**Table 1: Evaluation for Full-Friendships (FF)**

| | (a) Intelligent | (b) Random | Difference (D) |
|---|---|---|---|
| Relationships | 132146 | 306861 | 56,9% |
| Mean similarity | 0.6278 | 0.5934 | 5,8% |
| Variance | 0.0019 | 0.0029 | 34,5% |
| Std-Dev | 0.0443 | 0.0539 | 17,8% |

**Table 2: Evaluation for Partial-Friendships (PF)**

| | (a) Intelligent | (b) Random | Difference (D) |
|---|---|---|---|
| Relationships | 56859 | 236086 | 75,9% |
| Mean similarity | 0.5945 | 0.5379 | 10,5% |
| Variance | 0.0024 | 0.0029 | 17,2% |
| Std-Dev | 0.0499 | 0.0539 | 7,4% |

4000 points), we can derive that although similarity is lower at the beginning of the simulation, its increases steadily over time and then stabilizes between 0.5 and 0.7. A simple explanation for this behavior is that the relative difference of the experience generated by the IS at the beginning of the simulation (e.g., the number of friends), has more impact on the SM that determines the relationship between two objects at this point in time compared to the later stages of the simulation (e.g., some objects at the beginning might have 10 friends whereby others 50; after some time a more balanced situation might be created, with objects to have e.g., 80 and 90 friends respectively, closing the gap of the experience between them). Figure 5a also shows that the learning of the cells increases more rapidly with intelligent traveling at the early stages of the simulation in comparison to the random configuration (see figure 5b). Also, the similarity metric in the first configuration reaches a higher value compared to the second one, which indicates that objects are more similar. To evaluate how strong is the increase of the SM in figure 5a we calculate the learning of the threshold in a specific cell [not clear]. The results reveal that more objects establish a full-friendship at the beginning of the simulation because the threshold has not been adjusted yet to the growing, influenced by the intelligent traveling, similarity (stabilizing over time around 0.6).

Next, we wanted to detect the difference of the SM and the spread of values in the network for the two configurations. Hence, we calculated the mean and standard deviation of the two simulations, with intelligent (Simulation A) and random (Simulation B) traveling respectively, as shown in tables 1 and 2. For this analysis we split the data-set in the middle and use only the second part, to ensure that the threshold and the cell learning will be stabilized over time. The improvement is calculated as a percentage value of the difference $D$ between Simulation A and B. The results show, that the mean of the similarity metric increases for Simulation A compared to B with regard to the two types of relationships ($D_M = 5,8\%$ for FF, and $D_M = 10,5\%$ for PF), while the variation and standard deviation decreases ($D_{\sigma^2} = 34,5\%$, $D_{SD} = 17,8\%$ for FF, and $D_{\sigma^2} = 17,2\%$, $D_{SD} = 7,4\%$ for PF). This outcome could be interpreted that on one hand the objects come together and establish friendships with a higher similarity, and on the other hand that the cluster density is stronger (since there is a decrease in the variation and standard deviation) so that only the more similar objects coupled in a cell. Finally, the count of established relationships $R$ in each friendship cluster decreases ($D_R = 56,9\%$ for FF, and $D_R = 75,9\%$ for PF) indicating that the objects need fewer connection resources. In summary, we observe that by employing the intelligent traveling

**Table 3: Evaluation of Objects' Clones Discovery**

| | (a) Intelligent | (b) Random | (b)/(a) |
|---|---|---|---|
| Time needed | 50367 | 5571681 | 110,6 |
| All friendships | 89410 | 1831195 | 20,5 |

we ensure that only friends with higher similarity will be coupled, establishing more qualitative and stronger relationships, and by using less network resources.

*5.2.3 RQ3: Performance benchmark to find similar objects.* To evaluate the performance, we have created 1000 objects and for each object one clone resulting in an overall of 2000 objects. Every clone creates its own experience (IS) in the network. To benchmark the performance, we measure the time that it takes until every object finds its clone in the area. Each object with its clone generates different SM referring to different IS which is generated by their different experience in the network. At the beginning of the simulation, most of the objects found their clone, which suggests that the learning ability of the intelligent traveling has already been established at around 2000 milliseconds. After 200.000 milliseconds each object has found its clone (in comparison to the random traveling where each object has found its clone at around 14.000.000 milliseconds).

To get a clearer comparison for the performance benchmark between intelligent traveling and random traveling, we observe the count of object activities (which is independent of the performance of the machine) needed till every object finds its clone. We also calculate the time and count of relationships generated over time (see table 3), underlying that all objects with intelligent traveling have found their pair at time 50.367 (count object activities) while with random traveling at 5.571.681. Such a difference uncovers a significant increase in the performance of the configuration with the intelligent traveling, reaching even at 110,6 times faster than the one with the random traveling when objects seeking for their clones. We also observe that the generated count of total friendships over time is clearly higher (20,5 times) in the latter case (1.831.195) as opposed to the former (89.410), which means that objects with random traveling have traveled considerably longer compared to those with intelligent traveling to find their clones, producing more load for the network.

## 6 CONCLUSION

In this work, we explore the potential of utilizing human factors, the research outcomes and lessons learned from the field of HSN for proposing a human-centered decentralized SIoT simulator, that enables the intelligent traveling, interaction and establishment of friendships between autonomous smart objects. Accordingly, best-fit recommendations are expected to be provided on given users' requests and intents, minimizing at the same time the network complexity and load. We put the simulator into use through a real-life scenario, detailing the workflow process of an object discovering and recommending best-fit movies alternatives to its owner after it has interacted and exchanged information with its friends in the network of objects. In this paper, the evaluation of the simulator focused on the search and find SIoT process stages with really encouraging results for the future of this work. When objects travel with intelligence (HCB) in the virtual space, they find other similar objects faster, establish more qualitative long-term relationships between them, and at the same time generate less network load.

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