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A multi-level simulation framework for IoT-based elderly care systems

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Abstract

An IoT-based multi-level simulation framework is designed with the purpose of accounting for strategic (resource allocation) and tactical-operational planning (activity scheduling and medical service) in home assistance of elderly people. The idea behind the intended two-level conceptual framework is centered on the use of simulation i) at the higher end (level 0) to mimic system organization, rules and behavior of a realistic district-operated home assistance network for the elder and ii) at the lower end (level 1) to mirror the stream of real-time incoming data from IoT devices that register the health conditions of patients and, thus, trigger real-time "service requests". The key findings of this combination of operations research and IoT-based solutions allow to properly address performance issues (e.g. average waiting times, queue lengths, resource utilization) pertaining to the current practices in the elderly care system considered, as well as tailor resource redistribution and activity scheduling with respect to dynamic and non-deterministic patient "calls". Ad hoc scenarios can be simulated to verify the value of strategic, tactical and operational decisions of healthy living for the elder.

Keywords: Multi-level simulation; Internet of Things; Elderly care

1. Introduction

The main reason for simulation's increasing popularity is its ability to deal with very complicated models of correspondingly complicated systems across many fields, industries, and applications. This makes it a versatile and powerful tool that has also experienced an obvious improvement in performance/price ratios of computer hardware, making it even more cost effective to do what was prohibitively expensive computing just a few years ago (Kelton et al., 2002).

These days, simulation faces new and bigger challenges with the advent of the Internet of Things (IoT). The huge-scale of the IoT and the heterogeneity among the devices are exactly the two features that call for the usefulness of simulation in the attempt to understand quantitative and qualitative aspects of such a large system.

We address this challenge in the very important and dynamic field of healthcare. To do so, an IoT-based multi-level simulation framework is designed with the purpose of accounting for strategic (resource allocation) and tactical-operational planning (activity scheduling and medical service) in home assistance of elderly people. The idea behind the proposed two-level conceptual framework is centered on the use of simulation i) at the higher end (level 0) to mimic system organization, rules and behavior of a realistic district-operated home assistance network for the elder and ii) at the lower end (level 1) to mirror the stream of real-time incoming data from IoT devices that register the health conditions of patients and, thus, trigger real-time "service requests".

The paper is structured as follows. Some previous studies are discussed in Section 2. Section 3 describes the multi-level simulation framework. Section 4 presents the two-level simulation model in Arena, while Section 5 provides conclusions and ideas for future work.

2. State of the art

IoT-based healthcare is the natural response, on one side, to the growing elderly population and the related quest to successfully treat chronic diseases, and, on the other, computers getting smaller, faster and more connected. In the literature, many studies tackle the methodological problems inherent in interoperability or the technical issues associated with the use of specific devices, while others consider a wide range of potential IoT applications in healthcare services. In the following, we focus on the latter, but this section is not intended to be a literature review. Rather, it provides a close up on a few significant and very recent studies that describe different aspects of IoT-based healthcare. In particular, they are centered on i) patient monitoring with existing technological systems (Pinto et al., 2017; Hua et al., 2018) and ii) patient care simulation with the objective of forecasting the performance of project-developed technological systems (Perez et al., 2018).

Our work proposes a simulation-based approach to be carried out within a multi-level framework that accounts for both activity scheduling and medical service. This approach is similar to the one used by (Ferretti et al., 2017) in their seek for scalability and accuracy when simulating IoT environments. The authors apply it to study the development of smart services to be deployed over decentralized territories that are not provided with a full wireless cellular network coverage. The novelty of our multi-level simulation framework is represented by the "tuning" phase. Tuning points are triggered by disruption events occurring along the communication network in the proposed IoT-based healthcare solution for elderly home assistance.

3. A Multi-level Simulation Framework

The basic idea behind a multi-level modeling approach is to work at different levels of system specification with the aim of composing larger and larger systems from the previously constructed level-components. The ability to compose these systems leads to a hierarchical construction which bears a well-designed structure and behavior and has recognized input and output ports through which all interaction with the environment occurs (Ziegler et al., 2000). When simulation is used as the solution approach at each level, the corresponding models each represent a different level of detail. To begin with, a "high-level" simulator starts the simulation and works at a coarse-grained level of detail. When and where a more detailed model is needed, the high-level simulator activates and coordinates the execution of one or more lower level simulators. Such coordination capabilities might be performed by the higher level simulator or also by some external coordinator module (Ferretti et al., 2017).

In general, the above solution approach is applicable in a much broader sense (D'Angelo et al., 2017b; Ferretti et al., 2017; Gaud et al., 2008; Kormányos and Pataki, 2013; Zobrist and Leonard, 1997). Here, it has been used to design our IoT-based multi-level simulation framework for integrated decision making in assistance of elderly people. Integration of strategic, tactical and operational decisions within the overall framework is provided by a feed-forward scheme.

Clearly, decision making based on sensor data has become increasingly common, with sensors playing a primary role in supply chain automation (Wang and Liu, 2005), environment monitoring (IRIS), smart cities (Cicirelli et al., 2017; D'Angelo et al., 2017a), smart homes/buildings (Fortino et al., 2013) and, of course, elder-care (Hua et al., 2018). The Artificial Intelligence community is quite busy developing large bodies of probabilistic modeling/inference techniques that focus on the reduction of errors and gaps in sensor data stream (Russel and Norvig, 2003), whereas the community of the Simulation-based approaches is busy deciding how to incorporate the IoT-based feast of data into the model. To this respect, we use a two-step procedure by first using the sensor-fed data directly to fit a distribution probability and then considering tuning-updating actions.

Bearing this in mind, a description for both levels is provided in the following.

Level 0 – For a given resource/budget availability and assignment, a discrete-event simulation module is used to test alternative rules and/or practices in activity scheduling within a realistic district-operated home assistance network for the elder. These may include the evaluation of priority rules with respect to average waiting times, queue lengths and/or resource utilization, while accounting for number and type of resources (personnel and/or equipment) to be deployed, service duration, service location and coverage, under a given profile and number of patient "calls" per time unit. Although most off-the-shelf commercial simulation packages provide default (point or interval) estimates for the above performance indices, resorting to general-purpose programming languages is always an alternate and valid option, especially when focusing on highly-customized (event-driven) context-specific models.

Level 1 – This low-level simulation module represents the actual occurrence of process disturbances and disruptions related to, for instance, delays along the communications network or sensor inaccuracy due to frequent failure or limited capacity to collect data on an entire region of interest. Depending on the level of specification required, to simulate this huge amount of IoT data, possible choices range from low-level detailed network simulators, such as OMNeT++, ns-2 or ns-3, or commercial simulation packages that feature "resource failure" options (e.g. count-based or time-based failure criterion). At this point, it is easy to comprehend the importance and opportunity of bearing a "tuning" point within the framework. The actual occurrence of process disturbances and disruptions at the operational level (e.g. delays along the communications network or sensor failure) could affect the upper level and, thus, call for activity tuning herein. As a result, this will activate a feedback cycle in the framework to transfer upwards the finer-grained data returned from level 1.

This combination of operations research, simulation and IoT-based approaches allows us to address performance issues (e.g. average waiting times, queue lengths, resource utilization and throughput) pertaining to the current practices in the elderly care system considered, as well as tailor resource assignment and (re)distribution and activity scheduling with respect to dynamic and non-deterministic patient "calls".

4. The Simulation Model

The model developed herein, under Arena version 15.00.00004 (Copyright© 2016 Rockwell Automation Technologies, Inc.) is an illustrative model. It can mirror care and support services provided by both public and private-run organizations that deliver, for example, palliative care in different places including homes, hospitals, care homes, nursing homes and hospices located in a specific area of interest.

As a starting point, we consider a district as our principal geographical reference. A district is divided into minor areas that, in turn, due to distance, population and/or density are considered elementary units generating IoT-based requests for home assistance services. Satisfying a request from one of these areas first requires the acquisition of a certain number and type of resources, including the communications network. All requests share the same resources and, whatever be the area of origin of the request, it is the type of request that determines the order in which patients obtain resource assignment. Thus, how patient requests are queued depends on the priority expressed by the type of request: the lower the priority number, the higher the urgency. A request is serviced by delivering a three-stage process involving both medical personnel and equipment: transportation to the target home, operation of the service on the premises and transportation back from the target home, after which all resources are released. A similar flow is based on the assumption that the underlying communications network is 100% available. Should there be a disruption of the network, then no IoT-based request can be delivered. So, technically speaking, a disruption causes a 100% preemption or failure of the network. The consequences are twofold. On one side, without network availability, patient requests grow in number and experience greater waiting times, also causing a trashing phenomenon of the system throughput; on the other, input models are no longer representative of the current time span. This misalignment calls for a tuning on the input data from the low-level simulation model (level 1) upwards towards the higher one of the multi-level framework (level 0).

Besides comprehending the above logic that runs the system, in order to complete the implementation of the multi-level framework in Arena, we need to define the various parts of the simulation model.

Entities - Service requests for home assistance are the dynamic entities moving throughout the system. In an IoT-based system, they are basically generated by smart objects among which, but not limited to, smart phones, smart household appliances, care alarms, wearables such as wristbands and so on.

Attributes - A service request for home assistance is individualized by its attributes. The common characteristics for all entities are listed in Tables 1 and 2. They refer to both the area from which the request comes (i.e. area ID, one-way transport time necessary to reach the area and the percentage frequency), resource availability during shifts for team work (Legato and Mazza, 2016) and the specific request of service (i.e. service type meaning its priority, the frequency of each different type of service request, the duration of the service request and, finally, the number and type of resources that are simultaneously required to successfully respond to a request).

Variables - The global variables (i.e. pieces of system information that can be accessed by any entity, even if they are in no manner tied to specific entities) of our interest are quite standard, for example, the number of service requests in queue, number of busy resources and simulation time, all of which happen to fall into the category of Arena built-in variables.

Resources - The resources for which IoT-based patients requests compete with each other for service consist in both personnel (doctors, paramedics and drivers) and equipment (ambulances, medical cars and telecommunications network), as shown in Table 3. Moreover, according to the type of home service requested, in this use case, an entity needs simultaneous service from multiple resources, as specified by the last column in Table 2.

Table 1. Area features.

Area	Transport Time	Description	Frequency
1	Normal(5;0,5)	urban/local	35%
2	Normal(10;0,4)	city outskirts	30%
3	Normal(20;0,3)	Suburbs	25%
4	Normal(40;0,1)	border areas	10%

Table 2. Resource schedule for mobile units.

Resource	Day Shift	Night Shift
Doctors (DR)	6	2
Paramedics (P)	9	3
Drivers (D)	9	3
Ambulances (A)	6	3
Medical Cars (MC)	8	4
Network (N)	∞	∞

Table 3. Home service features.

Priority	Frequency	Duration	Resources
1	10%	60	(N,DR,P,D,A)
2	15%	48	(N,DR,P,D,A)
3	20%	35	(N,DR,P,D,A)
4	25%	20	(N,P,D,MC)
5	30%	15	(N,D,MC)

Queues - A service request in need to seize a unit of resource that is already tied up with another request waits in a queue that is of unlimited capacity, but managed according to a priority rule defined on the service type and, for the same kind of service types, according to a first-come-first-served queue admission policy.

Statistical accumulators - As the simulation progresses over time, these variables are used to collect (intermediate and per run) results in order to obtain the output performance measures of interest. In our use case, we wish to obtain measures of average waiting times, queue lengths, resource utilization and system throughput. Luckily, like many commercial software packages, Arena automatically takes care of most statistical accumulation.

Events - The events that drive our (discrete-event) simulation model (e.g. arrival of a sensor-based patient call, completion of a service request, etc.) and the calendar in which these events are stored and sorted are currently managed by Arena. As a matter of fact, given the general knowledge of the application domain, we do not need to adopt a different event logic to represent something very peculiar to the model that Arena isn't set up to do directly.

The model depicted in Figure 1 is a quasi-final representation of the Arena network used to implement the patients IoT-based requests per time unit (level 1) and the working schedule (level 0), as well as "manual tuning" between these sub-models, once the equipment and medical personnel is allocated to the district sub-areas. The model is obtained by connecting **Create**, **Assign**, **Process**, **Decide**, **Record** and **Dispose** modules, which are all flowchart modules properly connected to establish the sequence that all entities follow as they progress through the network from one module to another. To provide the overall model with a greater readability, only a limited number of record modules that generate point and/or interval estimates are displayed.

For the time being, with exception to model verification, here we have intentionally overlooked some of the core activities that require a great deal of attention and time in a simulation study: input and output analysis, model validation and calibration. These steps obviously depend on the availability of real/realistic data as well as a clear reference to an existing or soon-to-be real model. Both of these directions are currently under development as the starting point for a potential joint investigation with a local healthcare district in Cosenza on the use of a multi-level simulation model to compare standard forms of home assistance versus IoT-based elderly care systems.

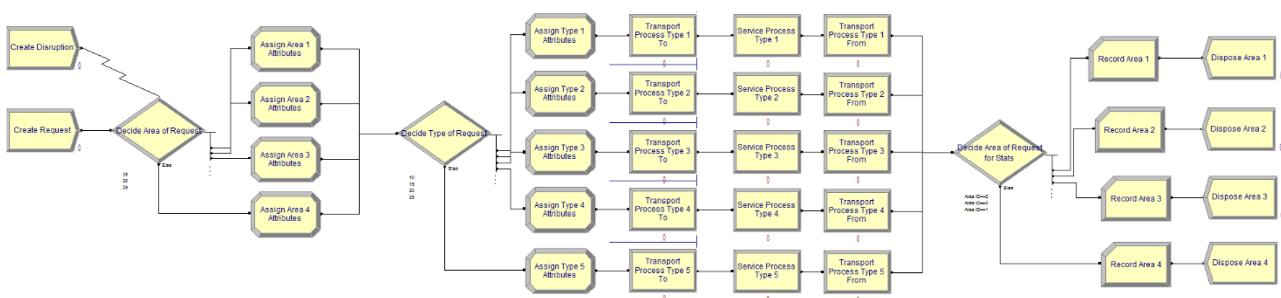

Figure 1. The simulation of levels 0 and 1 in Arena

5. Conclusions and Future Work

In its current form, the proposed multi-level framework uses discrete-event simulation modules to test, on one level, alternative rules and/or practices in activity scheduling and, on the other, process disturbances and disruptions occurring along the telecommunications infrastructure within a realistic district-operated home assistance network for the elder. In order to automate tuning between the two levels, an optimization module will be embedded. This third level will allow to search intelligently and efficiently among the tricking number of possible input-parameter combinations for a model configuration that appears to be optimal with respect to resource and/or budget availability.

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