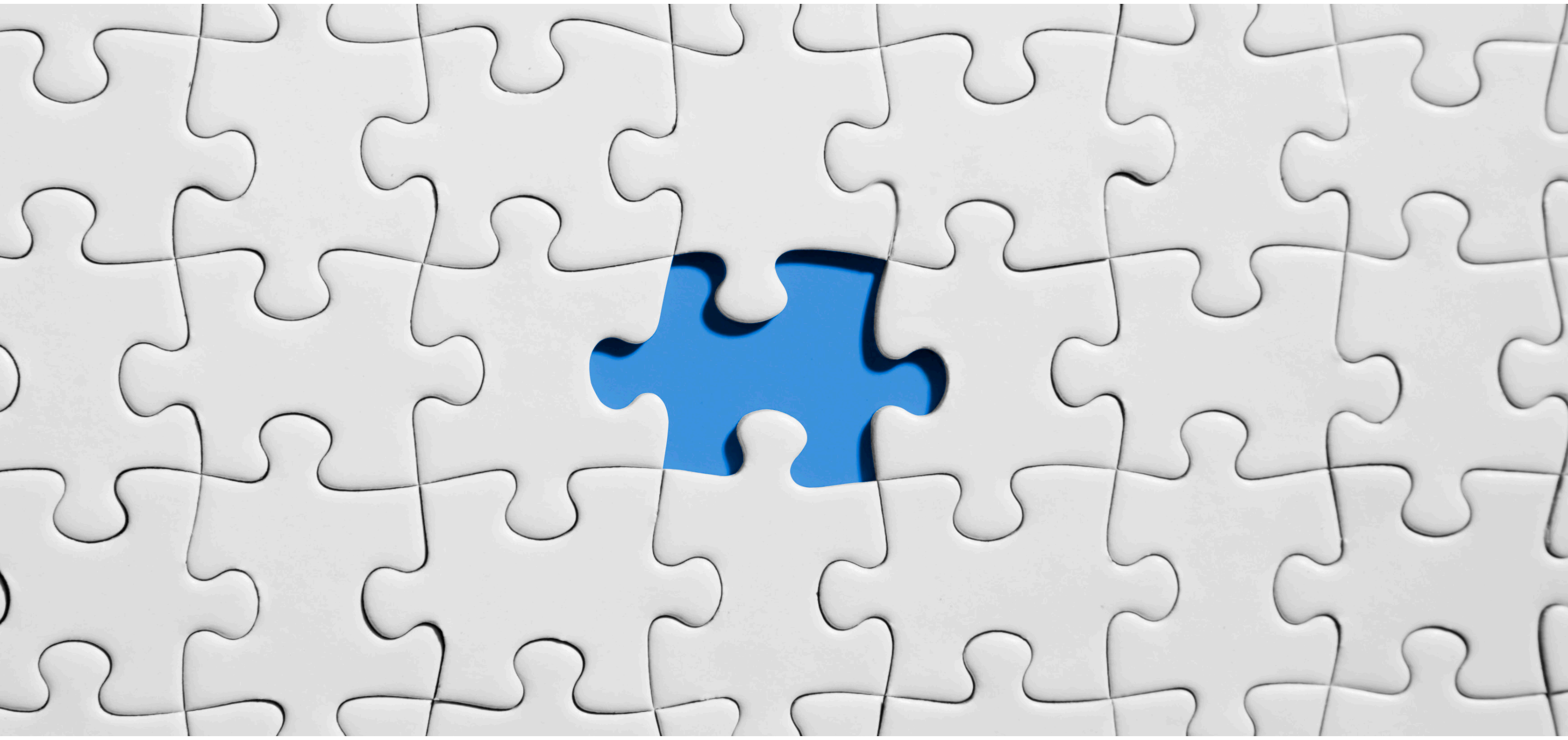
FIDELITY OF THE DIGITAL TWIN



Marina Levina

Sr. Competitive Intelligence Advisor

Dell EMC

marina.levina@emc.com

Bryan Duerk

Dell EMC

bryan.duerk@emc.com

Knowledge Sharing Article

Table of Contents

Abstract

Internet-connected devices surround us everywhere: from appliances and wearable electronics to driver-assist cars to windmill turbines. The number of sensors required to connect all these devices generate a large pool of data, fueling Internet of Things (IoT) infrastructure and software development. Today, developers create a virtual replica of the device called a Digital Twin to unlock the benefits of all the connected sensors and modules. Generated data is replicated to the Digital Twin to predict possible scenario outcomes and model the device's environment accurately. Digital Twin developers should balance the amount of data and the relevant factors needed. Real-world technical and business factors lead to the loss of fidelity while Digital Twins are created.

Digital Twins play a key role in machine learning and developers' simulations. Operational Technologists can test and develop products safely and quickly in the simulated virtual world using virtual copies of devices. The simulation environment enables the training of machine learning algorithms to detect anomalies in the data sets produced by sensors and infrastructures of the connecting devices. Future failure can be predicted and avoided by recognizing anomalies and evaluating relationships of the different factors to the behavior of the devices. Insights gathered by evaluating virtual copies of assets produce the competitive advantage for IoT practitioners.

Engineers will benefit from the Digital Twin concept once they can solve storage, management and manipulate digital data of the product allowing for the accuracy of the virtual and digital configurations. Changes of the data management process will be necessary to achieve that goal. Manufacturers will benefit from the concept once they complete digitalization of the processes and convert their physical designs and supply information into digital models.

Digital Twins are used beyond industrial cases. Human behavior, as well as sensors and devices, produce data for use in digital copies. The human environment can be digitized and employed for modeling individual behavior. These behavioral models are important for predicting customer needs and preferences in any consumer-centric industry. Digital Twin technology can help firms understand their customers on a more personal level. Digital twin simulations provide the opportunity to gain deeper insights to customer behaviors and will power future growth by allowing for data-driven product development.

It is difficult to develop a representative Digital Twin simulation environment, particularly if the system splits processing between the Edge, Core, and Cloud. Modeling becomes even more complex once data scientists account for other factors surrounding Digital Twin leading to decrease in fidelity.

This paper describes the origins and types of Digital Twins and provides a method for analyzing the latencies within a system to accurately model a Digital Twin and help determine the best location for the associated control processing.

What is a Digital Twin?

Introduction

The concept of the Digital Twin was first introduced by NASA and Air Force researchers in 2012[1]. Researches felt that current vehicle design philosophies and the assumption of similarity between operational and testing conditions no longer adequately addressed the new requirements of extreme services conditions and other specifications. They recognized the need for a fundamental shift in design philosophy. Existing methodologies relied on legacy factors of well-researched and documented classes of unknown unknowns. However, once the similitude assumption is no longer true, this probabilistic method breaks. The similitude assumption was the main reason why the "predictive" capabilities of many programs were limited. Predictive codes produced responses that previously occurred, which means that they accounted for the events and interactions that already happened. However, new machines and materials do provide researchers with a well-understood legacy. Most of them are unprecedented and therefore, not well understood. Also, statistical approach from the past was not taking into account the overall environment, relevant to each vehicle or device.

NASA's view

Digital Twin integrates "ultra-high-fidelity simulation" with the devices' health management system on board, maintenance history, and all available data about the surrounding system to mirror the life of the original in digital form.

Digital Twins help develop and diffuse IoT by deploying predictive diagnosis and maintenance of the IoT systems. Overall digitalization needs the ability to monitor, analyze and control not just a single device but whole systems surrounding it. IoT is digital by design with the omnipresent connectivity of its elements that are formed into an ecosystem.

Digitalization and connectivity will enable systems to discover, evaluate and share intelligence across different subsystems or subunits, given that there is a system. These interconnected systems are highly integrated and will enable new functionality that improve quality of life for humanity through technological advances. Figure 1, from research firm CB Insights, reflects the most common IoT industry verticals and market players, respectively.

---

[1] https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20120008178.pdf

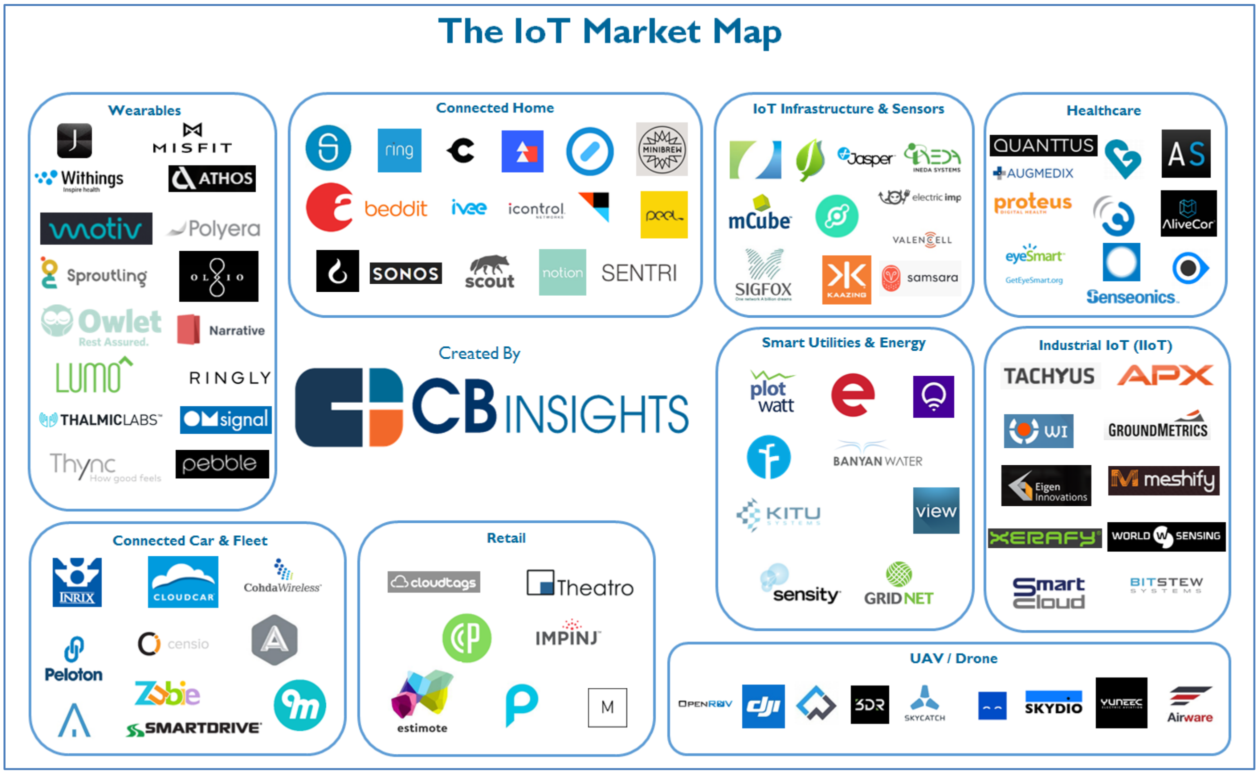


Figure 1

Source: https://www.cbinsights.com/research/industry-market-map-landscape/#IoT security

The value proposition of the IoT heavily relies on proper use of tools and technologies that will make sense of the data in the system. When connected, these devices will catalyze the development of new materials, procedures, and processes such as robotic surgery and telemedicine.

MIT View

According to Dr. S. Datta (MIT, Cambridge, MA), “The ‘twin’ is the ‘digital’ transformation which can be visualized by an analyst or manager most likely on a mobile device (phone, iSkin) in a manner that is location agnostic”[2]

There are several hurdles on the path of Digital Twin development. Some of the issues are standardization of the data requirements and processes, interoperability of the architectures, and making sense of the data with the ability to curate and analyze it at the edge (also referred to as the mist), where latency plays a crucial role. There is also an issue with the number of unknown unknowns and known unknowns that need further research and creation of the global infrastructure to keep developing and efficiently use future digitalization. Diffusion of the digital twins faces barriers due to the lack of convergence in information technology, operational

[2] Emergence of the Digital Twins. Is this the march of reasons?

technology, and telecommunications. Once the standards, interoperability and connectivity problems are addressed, integration of the time-synchronized hardware and software will warrant the Cyber-Physical System Approach for the embedded systems[3].

Behavioral Digital Twin

Digital Twins can be applied not only to the physical systems, but also can be used for consumer choice modeling. Price Waterhouse Cooper has their definition: "A digital twin is a model used to facilitate detailed analysis and monitoring of physical or psychological systems"[4].

Customer-centric industries are not producing objects, they are evolving around the quality of services (QoS) that they provide. Monetization of the outcome-based or customer service business is happening not around product delivery, but around these services. The business model is linked to the outcomes that customers expect based on their contracts. They need to measure customer satisfaction since customers will be paying for the QoS per contractual agreement. The ecosystem of the outcome-based model is very complex and will require creation of a behavioral digital twin to assess all the players and alliances.

Society of Actuaries issued a call for papers to expand understanding of behavioral economics on investment strategies of insurance policyholders and future investors. This call for papers came as a realization that the earlier modeling techniques were using assumptions of future behavior of policyholders extrapolated from their earlier behavior.

Figure 2

Source: Siemens Digital Twin

Customer-centric industries such as financial and insurance industries faced the same problem as the NASA engineers. They realized that the old way of modeling or making assumptions where the main assumption was the similitude of the present and the past behavior of human

[3] https://s3.amazonaws.com/nist-sgcps/cpspwg/files/pwgglobal/CPS_PWG_Framework_for_Cyber_Physical_Systems_Release_1_0Final.pdf
[4] http://usblogs.pwc.com/emerging-technology/top-10-ai-tech-trends-for-2018/

agents is no longer valid. Models assumed that current customers will react to the environment in the same way as they did in the past, displaying the same behavior. The current business environment demonstrated the inaccuracy of this assumption.

The team from PWC suggested a different approach to solving this problem. They produced a Behavioral Digital Twin – a behavioral simulation[5]. This model introduced a computer-based process that models the decision making of individuals, companies, and economies as an interaction with the environment. The key differentiation of that process was that the model could 'learn' as more data became available (effectively using Machine Learning and Artificial Intelligence principles). Model assumptions were updated and refined as the behavior was better understood and captured. This approach warrants a question about how frequently assumptions need to be updated (the time spacing issue) and where the 'sensors' or the data gathering devices should be located (physical sensor location or a 'space' issue). But first, the building blocks of the model need to be defined. In this case, it was a policyholder and the attributes that were changing the behavior of the agent-based model. The definition of the building block of the model helps understand the stratification of the data sample and metrics that will need to be monitored. Figure 3 shows the model building blocks proposed by the PWC paper.

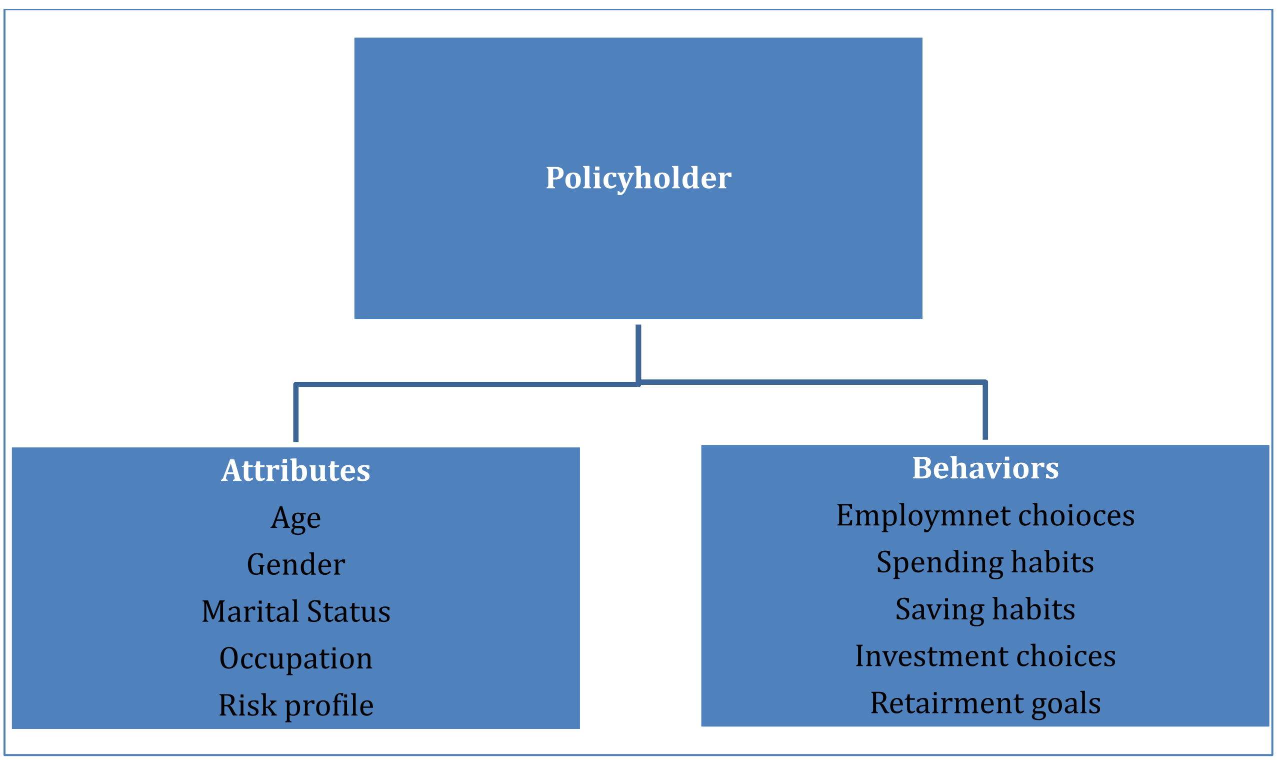


Figure 3

[5] https://www.soa.org/research-reports/2012/Behavioral-Simulations/

In addition to the building blocks, the behavioral model needs to understand or model policyholder behavior. Stochastic modeling and deterministic approach used in the past were not considering an agent's emotional, social and cognitive factors. There are also different groups of agents that have different behavioral characteristics. Therefore, the sample should be diverse enough to represent different strata. This paper illustrated that due to complexity of factors that influence policyholder behavior, modern techniques of simulation based on artificial intelligence (AI) software allows the reproduction of the complexity of the policyholder system and factors that influence the 'stage switch'. The model is only as good as the fundamental assumption that describes all possible variables, samples, outcomes and stages. Behavioral Digital Twin modeling will be a standard practice for customer-centric industries. Agent-based modeling will enable optimal product pricing and design, capital and risk management, strategic analysis and policy developments.

Project Goals

The choice of location for IoT processing is strongly affected by the latency of the sensors transmitting useful signals to the control system. The required set of inputs needed to make a decision about how frequently to place sensors and how frequently to read them, is described in this paper as the fidelity of the digital twin representation. Most systems use arbitrary requirements or naively base the overall control placement on the latency of individual sensors. This paper describes a method to determine the frequency or and the number of readings that are a true representation of the aggregated state, and thus estimate of the latency of the aggregated ensemble between state changes. Once the latency of the assembled digital twin is determined, it can be compared to the latency of the network connection to suggest if processing can be handled remotely or should be local, assuming sufficiently reliable networks to both locations. Conversely, if the response requirement is insufficient for the control system, this method will uncover sources of delay in the sensor configuration, which can be compared with the control location to suggest the best place to optimize.

Physical Switch Example

As an example, suppose a physical switch takes a full second for an individual to move from *on* to *off* or back. If the system electronically reads the state of the switch every 10ms, readings will exist that are halfway between *on* and *off* and therefore indeterminate. Since the switch readings would need to be aggregated across 100 samples to determine the true current state, the latency is not that of the sensor, but of the system including 100 samples.

Similarly, if the system holds two switches that may be manipulated separately, the time to read the state of the system is affected by the combined time to get a stable signal for each sensor, roughly 1 second; the overlap of potential starting points – i.e. on switch was hit 250ms. after the first, and the signal propagation time between the sensors.

If in this example the time for both switches to reach a stable state is 1.5 seconds, and a reliable cloud connection is 300ms round trip, it may make sense to place the control in the cloud as the signal stabilization time far exceeds the latency to the control system.

Assume instead the switch is electronic and the switching time is 10ms, the same as the signal read latency. In this case, there is still a possibility of reading the switch in an indeterminate state. Several readings would increase the time to get a true state read to ~30ms, and reading our two switches may be 50ms.

In this case, the digital twin representation time of 50ms is significantly less than the cloud connection time of 300ms. If the requirement is for faster response, moving the control system closer to the switches at the edge would optimize response time better than improving the individual switch response time.

Some Criteria for model actualizations

Fidelity of the digital twin can be assessed by looking at the frequency of the model updates. Let’s imagine that our client is a maintenance company that runs multiple apartment buildings in different geographical areas. Cost of heating and cooling is included in the rental agreements of the tenants and our client's company is given a budget for the utilities. If they can remain under given budget and tenants are happy, the budget surplus is distributed as a bonus at the end of each quarter. We suggested creating Digital Twin copies for apartments to troubleshoot any issues with heating and cooling that will make our tenants unhappy, increase the utility costs and use any surplus from the budget that the maintenance company was given.

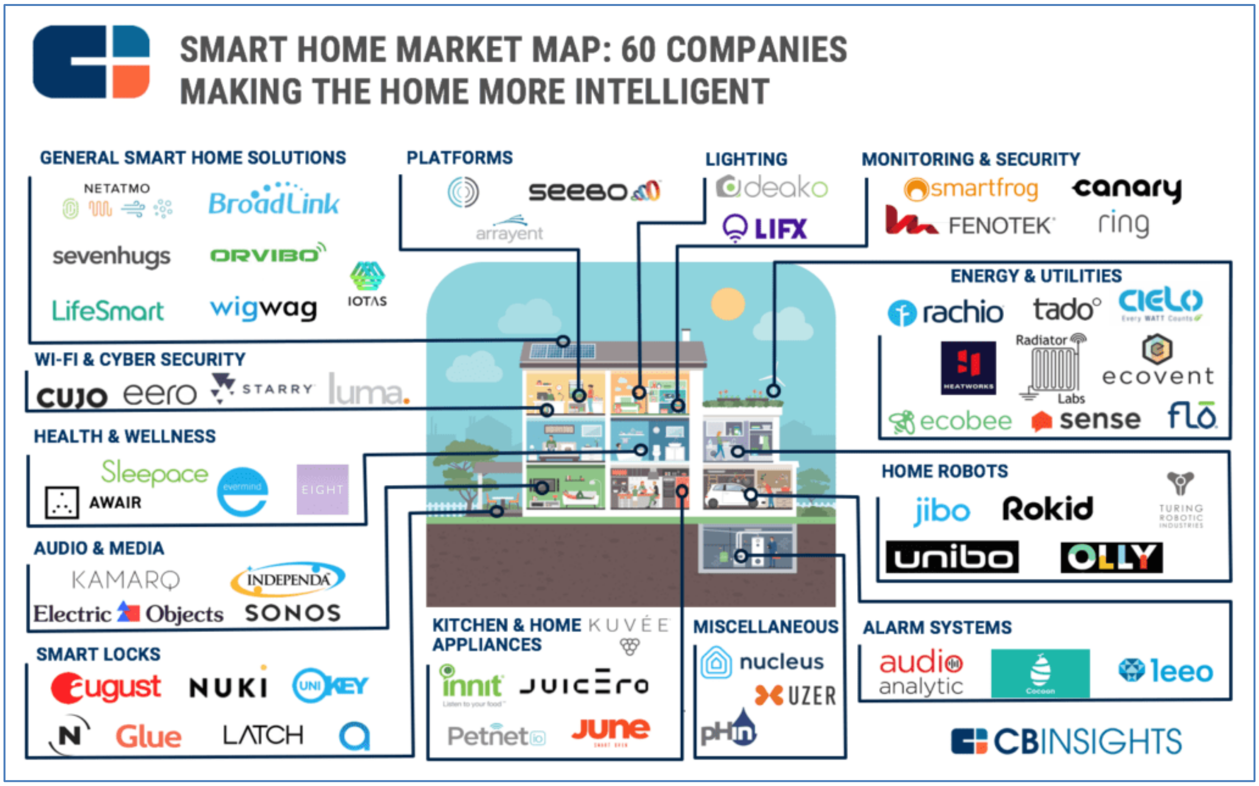


Figure 4

Source; June 2017 https://www.cbinsights.com/research/smart-home-market-map-company-list/

We need to evaluate requirements for the model of the systems to deploy a trustworthy digital twin. The goal is to be able to remotely control temperatures inside the apartments and proactively identify any issues with heating and cooling systems of the apartments. The temperature inside apartments and buildings would be a *continuous input function*. Ability to construct a 'true' digital twin system will depend on multiple factors. We will evaluate methods of determination of how many data points are needed to keep the fidelity of the digital twin.

There will be three classes of the input functions for the digital twin model:

- Time
- Space
- Mixed- space and time

Time input function

Time input will be the criteria of how frequently (in hours, minutes, seconds, etc.) sensors will need to be read to keep accurate information about the system. That frequency will depend on the requirements for the precision of the system requirements as well as on factors that influence changes in the system.

For example, in the San Francisco Bay area air temperatures are fluctuating less during the calendar year compared to temperature fluctuations in New England. The air temperature will influence the temperature inside the building and therefore inside the apartments. The more precise the requirements for the temperature are, the more frequent sensors will need to be read. Since we are talking about temperatures inside apartments and not for manufacturing, we can be less precise in the measurements (i.e. no need to evaluate to $10^{-3}C^{0}$).

To derive a number of measurements needed for accurate representation of the system we suggest following the approach below (assuming continuous function for time, the discrete function will warrant a slightly different approach):

1. Take as many temperature measurements as possible during the day.
2. Compile measurements into realizations and look at the ensemble of measurements.
3. Take an average of the ensemble at each point (average function of the ensemble of realizations) [6]

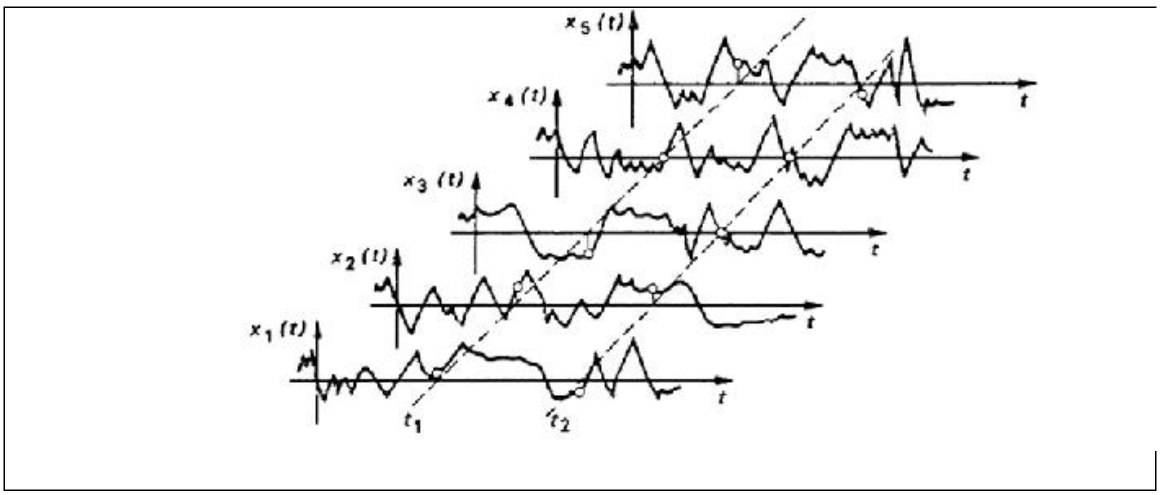


Figure 5

4. After collecting ensembles, take the average of them, which will provide a more accurate representation of the realizations at each point of measurement. Measurements should be taken as often as possible and then, based on their fluctuations, 'noise measurements' will be separated from the 'real' measurements by 3σ Rule[7]. Note that sigma could be derived from the measurements or can be supplied by the gadget manufacturer. Measurements outside 3σ will be considered 'noise'.

[6] http://www.astro.cornell.edu/~cordes/A6523/StochasticProcesses2015.pdf

[7] https://www.spcforexcel.com/knowledge/control-chart-basics/three-sigma-limits-control-charts

5. The average ensemble function then needs to be transformed for the estimation of power spectral density using Fourier transformation[8], from where the amplitude of the spectrum will be derived through Parsevals' theorem[9] (note, that A^2 is a function of temperature fluctuations in time)

where $S_n = A_n^2 * \sin(\omega t)$

$\omega = 2\pi f$ (where f is a frequency of measurements)

6. Now we can compare the power spectral density of the average of our ensembles (A_n^2 - a maximum temperature fluctuation in our case) with the power spectral density for the sensors' measurement uncertainty (which is supplied by the manufacturers or established via measurements).
7. The functional form for the measurement uncertainty of the sensor is following Gaussian function, which after the Fourier transformation will be a constant (also referred to as white noise)[10]

$G(\omega) = e^{(-\omega^2\sigma^2)/2}$ is a constant

$\sigma \quad standart\ deviation\ for\ the\ sensor$

Intercept of the S_n and $G(\omega)$ will be fs , which is a frequency of measurements that need to happen

$f = fs$ will be the derived frequency of measurements

8. By Nyquist's theorem (Nyquist criterion[11]) will be derived as a frequency at which the measurements should be taken (in time).

$$\Delta t \gg 1/2 * fs$$

Example: if f_s = 100Hz, measurements will need to be made every 0.005 sec. Which means that there will be 720,000 data points for the temperature.

Space Input Function and Combination

Space input function will be derived using similar logic. However, the measurements will be recorded based on their coordinates or special orientation in the buildings. This measure will consider positions of the sensors relative to the source of heat and cold in the example with the

---

[8] https://pdfs.semanticscholar.org/e633/45b4243e2376720a4e66373fdffe7a7d6be0.pdf
Welch, P. (1967). *The Use of Fast Fourier Transformation for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms.* https://pdfs.semanticscholar.org/e633/45b4243e2376720a4e66373fdffe7a7d6be0.pdf

[9] https://en.wikipedia.org/wiki/Parseval%27s_theorem
[10] http://www.cse.yorku.ca/~kosta/CompVis_Notes/fourier_transform_Gaussian.pdf
[11] https://en.wikipedia.org/wiki/Nyquist%E2%80%93Shannon_sampling_theorem

temperature control in the buildings. Therefore, the λ will be measured as a distance, i.e. as a frequency of sensors

$$\lambda = (m^{-1}).$$

The combination of the two functions will result in an optimal position of the sensors that would allow for the optimal update of the model with the optimized number of sensors. The optimal position will be derived as a product f_s and λ. The product will be a number of data points needed for the fidelity of the 2D model. Note if there are more dimensions (i.e. height or depth) it will add another component to the product.

$$n = \lambda * f\text{s}$$

Where $n \text{ is the number of signals or data points}$

Development of the software product that will allow determining fidelity of the digital twin from the temporal-special perspective will differentiate vendors in the market and allow for highly accurate and efficient digital twin models.

Signal transmission optimization will insure fidelity of the digital twin of the whole system.

Discrete-time function creates several issues. Some of them are[12]:

- Need for the time stamp to process events correctly
- Clock synchronization across distributed platforms
- Definitions of when it is safe to process events (i.e. if the port has received all future events and events at different ports cannot affect each other)

For the current model assessment continuity of the time function was assumed.

Memory and Bandwidth Concerns

The process described above is targeted at latency, but it also approximates the memory and bandwidth requirements of the sensor set. Since the algorithm described above provides for the minimum number of samples required to create a full digital twin, the sum of the sample sizes is the required amount of memory or bandwidth not including system overhead. The system can split the processing to reduce bandwidth requirements and divide the memory requirements between the edge and the core or cloud stages. The most basic technique to accomplish this is to complete the temporal ensemble at the edge, then sending only the stabilized reading onto the next stage. More advanced techniques could complete both a temporal and a space ensemble before forwarding the result to the next stage. This needs to be balanced with the local processing and memory capacity of the edge device handling the aggregation.

[12] https://www2.eecs.berkeley.edu/Pubs/TechRpts/2008/EECS-2008-72.pdf

Complex Sensors

From the standpoint of this algorithm, some subsystems may be represented as single sensors. For example, if using a camera to place bounding boxes around a targeted object, the actual sensor reading for use in the algorithm is the boundary box, not the camera frame. This means the time to complete one reading, as well as the error rate, is determined by the result of the visual pipeline, which may be less than the frame rate of the camera. As this is a computed signal, the error rate must be determined experimentally.

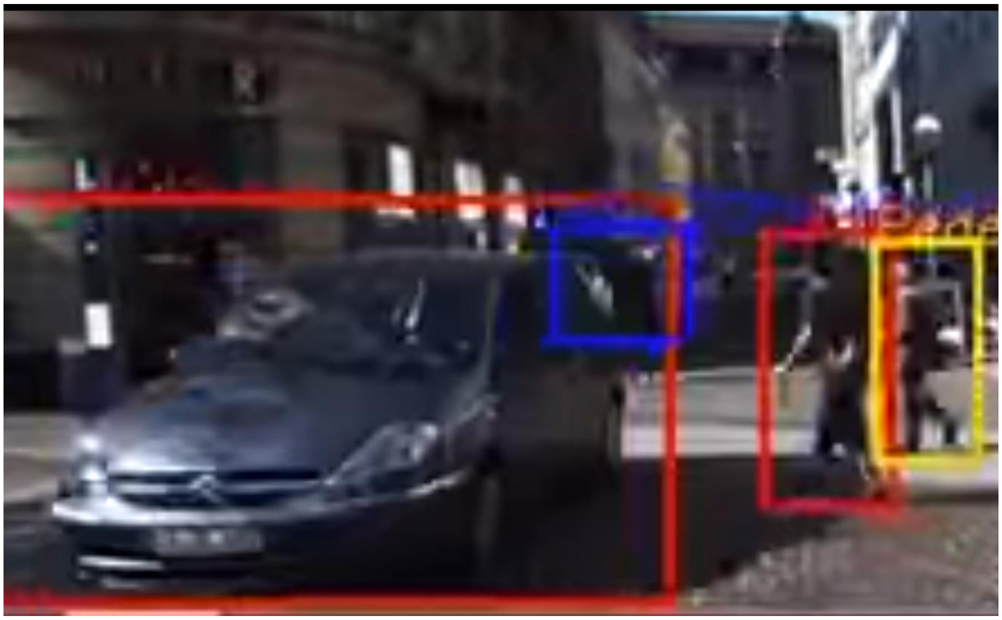


Figure 6

Dangerous object detection with CNN: https://www.youtube.com/watch?v=G5tf4O16Jf4

Conclusion

High-fidelity Digital Twins are a critical component of the Internet of Things revolution. Using this methodology, IoT developers can apply rigor into their control and data architecture, and therefore make informed decisions around processing placement, be it at the edge using embedded processing units, in-between using core processing on embedded PCs, appliances or in local data centers, or further away in remote data centers or the cloud. This technique helps balance the latency with the accuracy of the Digital Twin model, laying bare the trade-offs inherent in the system.

The methodology described can be used to develop software that proposes a blueprint for the sensors or signal systems with the optimal fidelity of the digital twin. The above-mentioned software could be a differentiator when proposing IoT solutions. The solution will start from the lay out of the sensors to the platform and infrastructure of the system, including data processing and analytics.

References

[1] https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20120008178.pdf
[2] Emergence of the Digital Twins. Is this the march of reasons?
[3] https://s3.amazonaws.com/nist-sgcps/cpspwg/files/pwgglobal/CPS_PWG_Framework_for_Cyber_Physical_Systems_Release_1_0Final.pdf
[4] http://usblogs.pwc.com/emerging-technology/top-10-ai-tech-trends-for-2018/
[5] https://www.soa.org/research-reports/2012/Behavioral-Simulations/
[6] http://www.astro.cornell.edu/~cordes/A6523/StochasticProcesses2015.pdf

[7] https://www.spcforexcel.com/knowledge/control-chart-basics/three-sigma-limits-control-charts
[8] https://pdfs.semanticscholar.org/e633/45b4243e2376720a4e66373fdffe7a7d6be0.pdf

[9] https://en.wikipedia.org/wiki/Parseval%27s_theorem
[10] http://www.cse.yorku.ca/~kosta/CompVis_Notes/fourier_transform_Gaussian.pdf
[11] https://en.wikipedia.org/wiki/Nyquist%E2%80%93Shannon_sampling_theorem
[12] https://www2.eecs.berkeley.edu/Pubs/TechRpts/2008/EECS-2008-72.pdf

P-5 Figure 1: https://www.cbinsights.com/research/industry-market-map-landscape/#IoT security

P-6 Figure 2: Siemens Digital Twin

P- 7 Figure 3: 2012, Behavioral Simulations Using agent- based modeling to understand policy-holder behaviors, Lombardi, Paich, Rao.

P-10 Figure 4 June 2017 https://www.cbinsights.com/research/smart-home-market-map-company-list/

P-11 Figure 5

P-14 Figure 6 Dangerous object detection with CNN:
https://www.youtube.com/watch?v=G5tf4O16Jf4