Model-Based Systems Design for Green IoT Systems

Kristin Majetta[a], Jan Bräunig[b], Christoph Sohrmann [c],
Roland Jancke[d] and Dirk Mayer [e]

*Fraunhofer Institute for Integrated Circuits IIS, Division Engineering of Adaptive Systems EAS,
Zeunerstrasse 38, Dresden, Germany*

{kristin.majetta, jan.braeunig, christoph.sohrmann, roland.jancke, dirk.mayer }@eas.iis.fraunhofer.de

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Abstract: The energy consumption of the Internet of Things is predicted to be about a quarter of the total world-wide energy consumption by 2030. There are already numerous approaches and operating strategies to reduce the energy consumption of wireless sensors. Nevertheless, it is essential to implement a formalized model-based development process that enables the designer of IoT nodes, platforms and systems to balance between the function and non-functional requirements with respect to energy consumption. Therefore we promote a model-based systems design methodology that employs multi-physical co-simulation in a virtual simulation environment in order to optimize the overall energy consumption.

1 INTRODUCTION

The term Internet of Things (IoT) was coined in 1999 by K. Ashton from the Massachusetts Institute of Technology. Although there is no exact definition (Prockl 2012), IoT describes linking identifiable physical objects with each other and users via an internet-like structure (Kaufmann 2020). The objects collaborate via information- and communication technologies (ICT). The term IoT is widely used nowadays and vastly popular. A study concerning IoT (Mauerer 2020) shows that companies that established IoT projects benefit from higher profitability, reduced costs and increased sales. They also record lower downtime and achive higher utilization. IoT applications can be found in nearly every application area such as productions and logistics, mobility, living and health. In the building sector multisensor systems are often used to monitor the status of technical equipment such as photovoltaic systems (Hussain 2019). Also in energy and grid management, especially in smart grids, monitoring via distributed sensors is an essential requirement (Laß 2019). In the area of smart farming IoT is used to connect hundreds of small swarm robots to sow, weed and harvest instead of using one single tractor. This allows the work to be carried out faster and more precisely. Additionally, underground wireless sensors provide information about how many nutrients have to be applied to the soil. Although (Aulbur 2019) predicts that long term "in-ground sensors will be replaced by in-vehicle sensors as the technology improves". Also in the field of productions and logistics so called smart factories are on the rise. Intelligent machines that exchange their status, filling level or maintenance cycles with each other enable production facilities to react dynamically to changes in production processes and hence become highly adaptive.

[a] https://orcid.org/0000-0003-0823-0225
[b] https://orcid.org/0000-0002-7282-723X
[c] https://orcid.org/0000-0003-1981-7216
[d] https://orcid.org/0000-0001-8857-6132
[e] https://orcid.org/0000-0002-4972-6529

(Koomey 2011) investigated the evolvement of efficiency of computation over several decades. There are strong indications that energy consumption per computational operation will decrease with the miniaturization on transistor level. According to *Koomey's law*, this will drive mobile embedded computing applications. However, Koomey also states that power consumption of memory, communication and other hardware might not necessarily follow that trend, i.e. Koomey's law might not apply to IoT applications that heavily utilize networking.

According to (Frost and Sullivan 2020), about 26 billion devices will be connected in the IoT by 2030 particularly in the fields of collaborative robots, cloud manufacturing, virtual reality, remote maintenance of machines, digital twin technology, and autonomous driving. This rapid development will be significantly accelerated by the introduction of the 5G standard for communication, that has been designed with respect to the demands of the IoT.

However, the expected growth is expected to raise new challenges, especially regarding energy consumption:

While the efficiency of data transmission over the internet is expected to improve over time (Aslan 2018), there are indications that the overall energy consumption by data transmission is predicted to grow due to the steep increase in the number of networked devices enabled by the new technologies (Andrae 2015), even when accounting for the improved efficiency of 5G. (Jones 2018) estimated that the overall energy consumption of communication networks will increase due to the growing traffic, i.e. improvements in transmission efficiency would be compensated. This would be in blatant contradiction to the global goal of the international community to reduce energy consumption in order to limit the global warming to 2 K. Besides the, admittedly uncertain, energy prognoses on a global scale, energy comsumption also matters on a small scale: In case of mobile wireless IoT devices, increased energy consumption on the device level causes problems especially in mobile applications, e.g. wireless sensor networks, where data exchange is not permanent and local energy storage devices are used, that are subject to environmental conditions. The resulting demand for regular battery replacement raises challenges of maintenance of IoT devices and the question of resource efficiency of such applications in general. This aspect has been investigated by (Bonvoisin 2012) at the example of a sensor network, integrating environmental costs of production and replacement of components over the lifetime of the whole application. Besides resource awareness during the production, which is beyond the scope of this paper, the optimization of energy consumption by system design and operation will be considered here.

A number of actions to reduce the energy consumption of the IoT are already established. These include for instance (Nandyala 2016):

- Turning off inactive nodes (sleep mode)
- Sending required data only
- Using radio optimization techniques
- Using data reduction mechanisms
- Using energy-efficient routing techniques
- Using renewable green power sources such as energy harvesting

Still an open question is how to orchestrate these measures dynamically at run-time, especially in case of time-varying environments. This will require the IoT system to become an adaptive system. Considering the metamodel presented by (Sabatucci 2018), the adaptation integrates functional as well as non-functional aspects related to the energy level on the device. The result is a complex system that can adapt it's operation schedule following a multicriterial decision making process.

We therefore propose a paradigm shift towards the introduction of intelligent energy-awareness for any kind of IoT hardware nodes. While energy-analysis functionality is already featured by many nodes, there is still a great deal of unused potential for optimizing energy consumption by leveraging intelligent and adaptive operation. However, this requires new design principles such as model-based systems design. In the following, we will sketch some of the changes that are needed in the system design process to enable a more intelligent use of ressources. From this, a corresponding hardware structure including intelligent software control is derived, which is described in more detail below.

2 ENERGY AS A KEY DESIGN PARAMETER IN IOT SYSTEMS

The energy consumption of an IoT device strongly depends to the actual application scenario, i.e. the attached sensors, utilized communication technology, and many other parameters, for instance sampling rates, required on-board signal processing or quality of the radio connection. While a wireless sensor in the agricultural sector or in a smart city application might not require maintenance for years, a self-powered vibration sensor for continuous condition monitoring can still be regarded a complex task including several compromises in the design .

Therefore, there are major uncertainties regarding battery lifetime and availability, which is why many industrial applications and technologies still remain in a prototypical or even a research stage.

2.1 Main drivers of energy consumption

The common smart wireless sensor can be regarded as a local energy system, optionally powered by environmental sources (see Figure 1).

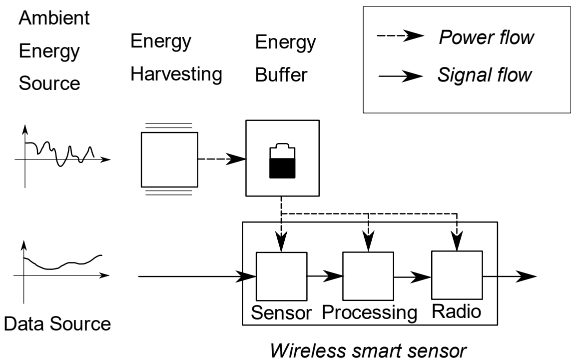

Figure 1: Energy model of a wireless sensor (according to: Martinez 2015)

Generally, the power consumption has to be balanced with the energy supply, either from an energy harvesting (EH) system or by renewing, i.e. filling up, the energy buffer e.g. by changing a battery. Thus, with respect to the energy, the general condition

$$\int_0^T P_{EH}(t)\, dt \geq \int_0^T P_{SYS}(t)\, dt \qquad (1)$$

has to be satisfied at any time T, where P_{EH} is the power on the supply side, and P_{SYS} is the power consumed by the sensor's subsystems.

2.2 Approaches for low-power IoT

Wireless IoT devices promise the largest benefit when they are operating fully autonomously. It is attractive to replace power supply from conventional batteries by conversion of environmental energy into electrical energy directly at the IoT device. Sources for this kind of energy harvesting are for instance solar, vibration, or thermal energy (Hadas 2010).

The main challenge in application of these renewable power sources is that the supply is often uncontrollable and even unpredictable (Kansal 2007). In turn, a system design considering uncertainties and a sufficiently sized energy buffer has to be implemented. Furthermore, adaptive energy management to schedule energy consumption according to the available energy supply is necessary as shown in (Tahiliani 2018).

A main area of research and development regarding energy reduction of wireless IoT devices is the selection of a suitable radio transmission protocol. The decision also needs to take into account the required radio transmission range. Several standards are available with different power consumptions and operating ranges: from power intensive WiFi for home networking, over Bluetooth or Bluetooth Low Energy (BLE) for nearby peripherals down to ZigBee and Z-Wave for e.g. metering and industrial applications. Other protocols like EnOcean, Long Range (LoRa), Narrow Band IoT (NB-IoT) have been added with significantly lower power budget and longer ranges for home and building automation (Krödel 2020). And even 5G with its massive Machine Type Communication (mMTC) usage scenario aims at very large numbers of connected low-power IoT devices (Lei 2020).

Another important aspect is the intelligent organization of larger networks of such nodes in order to minimize the number of active nodes for power saving purposes. This is the aim of protocols like Bluetooth Mesh, Dust Network, IQRF, and NeoCortec (Halkier 2020) as well as the model-checking approaches, as shown in (Demigha 2019).

Reducing the amount of transmitted data saves energy at the IoT device. A possible approach is the implementation of data analytics and machine learning on the smart sensor platform, which should extract the relevant information from the input data stream, e.g. acquired by sensors. An example comprises anomaly detection with an autoencoder algorithm for condition monitoring of bearings (Bose et al., 2019).

The previous example shows that there are often trade-offs that developers of such systems have to deal with: weighing computing intensive algorithms for feature extraction or data compression against power demanding data transmission. Similarly, the number of sensing events may have to be balanced against the achievable measurement accuracy. On top of that, data security and privacy requirements are demanding additional data encryption. The safer the transmission the more compute resources are required in the IoT node. In order to support the developers in taking informed decisions on such questions, model-based systems design principles and tools have to be employed.

3 MODEL-BASED SYSTEMS DESIGN AND ENGINEERING

3.1 Model-Based Systems Development

Systematic development processes of complex technical systems save time and money, while maintaining high standards of quality, reliability and safety.

Originating from the "scientific method" (Roger Bacon), methods like "Plan-Do-Study-Act" to iterative and incremental development (IID) have emerged, aiming at a continuous and iterative workflow with alternating stages of system implementation and system design (Larman 2003).

Modern systems integrate mechanical functions, actuators, sensors and information processing, which calls for development methods tailored for mechatronic systems. Validation of the system design requires complex, potentially multi-physical simulations before actually implementing the hardware. For even more complex systems that feature advanced control loops, also hybrid strategies such as hardware-in-the-loop simulation, that couple real-time simulation and hardware components, have been established (Isermann 1996). This mechatronic system design (V-model) is widely used in aerospace and automotive engineering, has also been successfully applied to autonomous systems powered by energy harvesting (Hadas 2010, Koch 2012).

Efforts have been made to transfer methods from agile software development to hardware projects. One basic idea of agile methods is the early and iterative validation and testing of product increments, including technical functions, but also acceptance by potential customers and users; in case of hardware, also a rapid implementation of prototypes is required (Schuh 2016).

The increasing complexity of cyber-physical systems, the more general case of an IoT system, raised demands for model-based design methods that allow for automation of virtual system validation. Particularly for distributed, learning (adaptive) systems-of-systems, the interactions between their subsystems sometimes cause an unpredictable system behaviour. This complicates the detection of design faults (both hardware design and software). As a potential solution, platform and contract based design methods have been proposed (Sangiovanni-Vincentelli 2012).

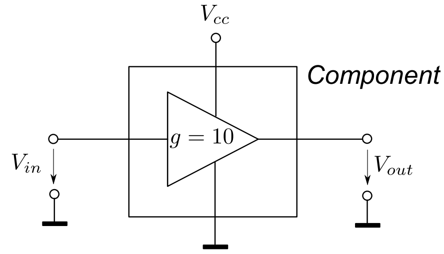

Figure 2: Example for a very simple component in a contract based design scenario

These methods are using collections of component models on different abstraction levels. The interaction of the components, defined by the system topology, is analysed by applying assume-guarantee contracts, i.e. a component is guaranteed to function properly, under the assumption that other components provide specified working conditions.

The concept shall be demonstrated by a very simple example as shown in Figure 2. An amplifying circuit will *guarantee* that it interacts with its environment variables, i.e. the input voltage V_{in} and output voltage V_{out}, according to the equation

$$V_{out} = \mathrm{g} \cdot V_{in}$$

under the *assumptions* that the conditions

$$V_{in} \leq 1\mathrm{V}$$
$$V_{cc} \geq 10V$$

are satisfied.

Contract-based design for optimization of a complex distributed control system in the IoT has been used for collaborating robots. A system simulation has been set up using ROS (Robot Operating System), a platform for the implementation and simulation of robotic systems (Spellini et al., 2019). Another application is design automation of complex building automation and energy systems (Jia 2018): Components with standardized interfaces are drawn from a library to build a complex automation system by a design automation algorithm that aims at fulfilling several functional and non-functional requirements. These approaches could be transferred to the design of networked, energy-aware smart sensors. However, this requires component models for the building blocks of a wireless sensor node that describe the function and its effect on the energy balance. Since modelling energy consumption from circuit models can be very time consuming, Martinez presented an approach to use measured power consumption data on subsystem level and estimated the energy consumption on the system level from the composition of the measured profiles (Martinez 2015).

3.2 Simulation-Based Virtual System Validation

Formalized systems development and validation requires proper metrics for the evaluation of system concepts. In the field of cellular wireless communication, several metrics as Quality of Service have been established.

For the integration of energy consumption at the device level, the metrics can be enhanced by energy related KPI (Martinez - Caro 2020):

$$\mathrm{QC} = \sum_{nodes} \sum_{states} c_{state}\, t_{state} \tag{1}$$

Where QC is the Quality Cost metric, nodes is the number of nodes, states is the number of operational states of the nodes, c_{state} is the power consumption in each state, and t_{state} the period of each state being active.

The dynamic behaviour of wireless networks can be simulated with event driven simulators such as OMNeT++. These include also the physical characteristics of the transmission paths (e.g. dense urban or rural environments etc.). An existing system simulation for a LoRa network extends the OMNeT framework by the "Quality cost" metric that considers the energy needed for the operation of the nodes (Martinez-Caro 2020). However, the behaviour of the IoT edge devices such as data acquisition and data analysis was not included in the simulation.
The interaction of adaptive (or self-learning) systems can be simulated by applying agent-based simulation frameworks. In an agent based system-of-systems, each IoT device is assumed as self-learning and autonomous, with the capability to interact with its environment including other agents. Jung et al. studied modelling networked IoT systems in a production environment (Jung 2020). The developed framework offers scalability and also the option for hybrid virtual-experimental system validation (HiL). One remaining open point is the integration of energy-awareness in modelling the agents.

Jha et al. present a simulation that extends the CloudSim framework by the energy consumption of IoT devices (Jha 2020). However, the considered IoT devices are representing rather wireless sensors without considering the option to reduce transmitted data directly on the sensor platform. In this approach, the analysis is implemented in an intermediate edge device, which can be considered to be less energy-sensitive.

Simulation of large systems can take high computation effort, slowing down the virtual testing and validation. D'Angelo et al. developed a scalable discrete event simulation framework, that distributes the simulation of the networked IoT devices in a computing cluster. Furthermore, the simulation can switch between models of different abstraction levels during runtime, so that efficient computation is combined with detailed insights whenever necessary (D'Angelo 2016).

An autonomous, potentially self-powered wireless sensor is a multi-physical, cyberphysical system, comprising mechanical, electromechanical, electronic components as well as software-implemented functions. For each domain, specific simulation tools are available and well established, which include *Modelica* for multi-physical systems or *SystemC* for microelectronic systems. In modern development processes, system simulations usually interface with sub-models from multiple other domains, e.g. by using the Functional Mockup Interface (FMI) standard, that has been widely adopted (Blochwitz 2011).

4 PROPOSED SYSTEMS ENGINEERING METHOD FOR GREEN IOT

The design of wirelessly connected, low-power IoT devices is a highly complex task that requires a holistic view on multiple domains and abstraction levels as well as HW/SW interaction. Functional requirements from data acquisition to data analyses have to be balanced with non-functional requirements derived from the energy consumption, storage and harvesting technologies. In the widely popular V-model development process, a requirements specification is broken down into tasks than can be implemented independently. However, especially for the analysis of energy-consumption, a more agile co-design approach is required instead. Technological details are strongly affecting the choices on architecture- as well as implementation-level. Therefore, a model-based systems engineering (MBSE) approach needs to be applied that establishes technological dependencies and constraints across the various stages of the design process. But whereas the usual model-driven development is based on static data models, we propose to go beyond that by employing of multi-domain system-simulation as the key technology for solving this multi-criterial design optimization problem. This should enable the engineers to balance the different functional and non-functional aspects (Zulkipli 2017) and help to retrieve an optimal solution in terms of energy consumption. In Figure 3 we have shown a concept for an energy-aware multi-domain simulation approach.

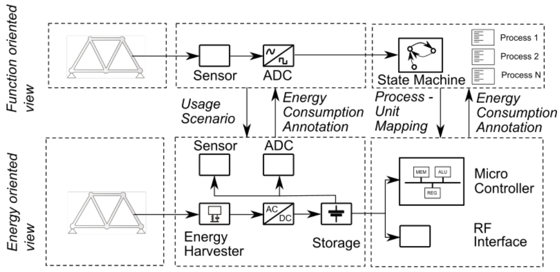

Figure 3: Energy-aware HW/SW co-simulation: physical input (left) is fed into an analog frontend model (center) which is coupled to a digital backend model (right)

The physical input is fed into a power-aware model of the analog system frontend. This frontend model includes a model of the sensor data pre-processing unit as well as the (possibly) electro-mechanical model of the energy harvester. Therefore the system is constantly aware of its internal power state. In addition, a co-simulation with a model of the digital backend (e.g. processor model) is running, which is aware of the state and duration of the currently executed processes as well as the power-consumption of the analog parts. Using this information, a power-state-machine is able to map the current state/power information into the time-dependent energy consumption. Our proposed simulation approach has to support the following set of features:

- Multi-physical simulation for realistic dynamic modelling of energy harvesting and other interactions of the IoT device with the physical world. This should be implemented using an established format standard such as FMI.
- The system simulation should be scalable, since a network might be composed from a large number of wireless IoT devices.
- The modelling environment should support parallel execution, e.g. on a high performance compute cluster.
- Each IoT device should be represented as an energy-aware agent. The device should potentially interact with its physical environment, e.g. for data acquisition at a machine or energy harvesting; also communication with other devices and the possibility to adapt to changing requirements, particularly w.r.t. energy supply, should be supported.

The sketched approach requires a robust model coupling interface in the analog and digital domains. For the physical models, we suggest to use the Functional Mock-up Interface (FMI) technology. As of today, FMI is supported by more than 100 modelling tools, such as Matlab and many of the Modelica simulators. On the digital side, we suggest to use SystemC TLM technology, which has the required flexibility and performance to model entire processors including the software.

From the above system-simulation approach, a continuous and seamless energy-aware design flow can be created. The feasibility of the IoT application considering the given functional and energy-related requirements is assessed from the early beginning to the final implementation. Model based validation should start with coarse estimations of feasibility and should be refined during the design process. This includes a step-wise integration of hard- and software in terms of co-design and in-the-loop (XiL) methods, as shown in Figure 4.

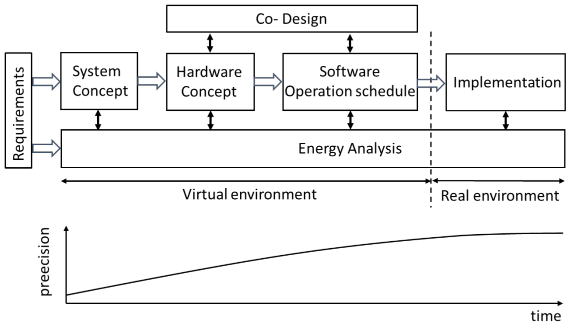

Figure 4: Integration of energy awareness into MBSE

5 CONCLUSIONS

Innovations in microelectronics and communication technology enable a rapidly growing number of applications for wireless and smart IoT devices. However, considering energy consumption in the design process is essential to ensure an autonomous long-term operation of wireless sensor platforms as well as to reduce the overall power consumption of large IoT networks.

As discussed in this paper, the system design process of IoT applications is a complex task that has to consider functional aspects in parallel to the energy sensitivity on device and system level and adaptive, time-varying characteristics of the IoT devices.

The most promising way to cope with this challenge seems the adoption of design methods and tools for mechatronic systems and integrate them with tools from the design of communication systems and agent based systems-of-systems. Only with such a model-based systems design approach, the full potential for lower-power design of green IoT systems can be leveraged.

REFERENCES

Prockl G., Pflaum A., 2012. Mehr Transparenz in der Versorgungskette durch das „Internet der Dinge". In *Business Innovation in der Logistik*. Business Innovation Universität St. Gallen (Profilbereich Business Innovation). Springer Gabler, Wiesbaden. https://doi.org/10.1007/978-3-658-00644-0_5

Kaufmann, T., Servatius, H.-G., 2020. *Das Internet der Dinge und Künstliche Intelligenz als Game Changer*. Springer Vieweg, Wiesbaden. https://doi.org/10.1007/978-3-658-28400-8

Mauerer, J., 2020. Studie Internet of Things 2019/2020. IDG Business Media GmbH (Ed.). https://www.tuvsud.com/de-de/-/media/de/cyber-security/pdf/allgemein/marketing/studie_internet-ofthings_2019_2020.pdf?la=de-de&hash=A7B2170BE5F8474914E1458F94D9EF76

Hussain, S. S., Khurram, S. K., Khan, A., et al., 2019. Cyber Physical System for Solar Energy Monitoring. In *2019 International Conference on Frontiers of Information Technology (FIT)*, 185–1855, 2019. https://doi.org/10.1109/FIT47737.2019.00043.

Laß, D., Brockmann, C. Stube, B., et al., 2019. Autarke Mikrosysteme – Anwendungen in der Energiewirtschaft, Wireless Sensor Networks (WSN) – Applications for Utilities. https://www.forschungsfabrik-mikroelektronik.de/content/dam/ipms/forschungsfabrik-mikroelektronik/de/Unser-Angebot/Anwendungsangebot/Energy/Dokumente/Paper%20Autarke%20Mikrosysteme%20in%20der%20Energiewirtschaft.pdf

Aulbur, W., Henske, R., Uffelmann, W., et. al. 2019. Farming 4.0: How precision agriculture might save the world. Berger, R. (Ed.) https://www.rolandberger.com/de/Publications/Landwirtschaft-4.0-Digitalisierung-als-Chance.html

Koomey, J., Berard, S., Sanchez, M., & Wong, H. 2011. Implications of Historical Trends in the Electrical Efficiency of Computing. *IEEE Annals of the History of Computing*, 33(3), 46–54. https://doi.org/10.1109/MAHC.2010.28

Frost and Sullivan, 2020. Role of 5G Communication Revolutionizing Industrial Internet of Things. Landscape and Opportunities Assessment In Industrial Operations.

Aslan, J., Mayers, K., Koomey, J. G., & France, C. 2018. Electricity Intensity of Internet Data Transmission: Untangling the Estimates. *Journal of Industrial Ecology*, 22(4), 785–798. https://doi.org/10.1111/jiec.12630

Andrae, A., Edler, T., 2015. On Global Electricity Usage of Communication Technology: Trends to 2030. *Challenges*, 6, 117--157. https://doi.org/10.3390/challe6010117

Jones, N., 2018. How to Stop Data Centres from Gobbling up the World's Electricity. In *Nature 561, Nr. 7722 (12. September 2018)*: pp. 163–66. https://doi.org/10.1038/d41586-018-06610-y.

Bonvoisin, J., Lelah, A., Mathieux, F., & Brissaud, D. 2012. An environmental assessment method for wireless sensor networks. Journal of Cleaner Production, 33, 145–154. https://doi.org/10.1016/j.jclepro.2012.04.016

Nandyala, C. S., Haeng-Kon K., 2016. Green IoT Agriculture and Healthcare Application (GAHA). In *International Journal of Smart Home* 10, Nr. 4 (30. April 2016): pp. 289–300. https://doi.org/10.14257/ijsh.2016.10.4.26.

Sabatucci, L., Seidita, V., Cossentino, M., 2018. The Four Types of Self-adaptive Systems: A Metamodel. In *Intelligent Interactive Multimedia Systems and Services 2017* (S. 440–450). Springer International Publishing. https://doi.org/10.1007/978-3-319-59480-4_44

Tang, X., Wang, X., Cattley, R., Gu, F., & Ball, A. D., 2018. Energy Harvesting Technologies for Achieving Self-Powered Wireless Sensor Networks in Machine Condition Monitoring: A Review. *Sensors*, 18(12), 4113. https://doi.org/10.3390/s18124113

Martinez, B., Montón, M., Vilajosana, I., & Prades, J. D., 2015. The Power of Models: Modeling Power Consumption for IoT Devices. *IEEE Sensors Journal*, 15(10), 5777–5789. https://doi.org/10.1109/JSEN.2015.2445094

Hadas, Z., Singule, V., Vechet, S., Ondrusek, C., 2010. Development of energy harvesting sources for remote applications as mechatronic systems. In *Proceedings of 14th International Power Electronics and Motion Control Conference EPE-PEMC*, https://doi.org/10.1109/EPEPEMC.2010.5606867

Koch, M., Kurch, M., Mayer, D., 2012. On a Methodical Design Approach for Train Self-Powered Hot Box Detectors. Proceedings of the First International Conference on Railway Technology: Research, Development and Maintenance. In: *Proc. First International Conference on Railway Technology: Research, Development and Maintenance*. https://doi.org/10.4203/ccp.98.90

Kansal, A., Hsu, J., Zahedi, S., & Srivastava, M. B., 2007. Power management in energy harvesting sensor networks. *ACM Trans. on Embedded Computing Sys.*, 6, pp. 32

Krödel, M., 2020. Trends im Umfeld von ‚Smart Buildings' sowie Eignungsvergleich funkbasierter Übertragungs-protokolle. White Paper. https://www.enocean-alliance.org/wp-ontent/uploads/2020/06/Funkbasierte-SB-U%CC%88bertragungsprotokolle.v2.pdf

Lei, W., Soong, A.C.K., Jianghua, L. et al., 2020. *5G System Design. An End to End Perspective*. Springer, Cham, 1st edition. ISBN 978-3-030-22238-3

Halkier, T.S., 2020. Funksensornetzwerke – Protokoll für sich dynamisch verändernde Netzwerke. Elektronik Business & Märkte 2020, H. 5-6, S. 8-13

Bose, S. K., Kar, B., Roy, M., Gopalakrishnan, P. K., & Basu, A., 2019. ADEPOS: anomaly detection based power saving for predictive maintenance using edge computing. In *Proceedings of the 24th Asia and South Pacific Design Automation Conference* (pp. 597--602). ACM. https://doi.org/10.1145/3287624.3287716

Larman, C., Basili, V. R., 2003. Iterative and incremental developments. a brief history. *Computer*, 36, 47--56. https://doi.org/10.1109/MC.2003.1204375

Isermann, R., 1996. Modeling and design methodology for mechatronic systems. *IEEE/ASME Transactions on Mechatronics,* 1, 16--28. https://doi.org/10.1109/3516.491406

Schuh, G., Schröder, S., Lau, F., Wetterney, T., 2016. Next generation hardware development: Requirements and configuration options for the organization of procurement activities in the context of Agile new Product Development. In *2016 Portland International Conference on Management of Engineering and Technology (PICMET)* (pp. 2583--2591). https://doi.org/10.1109/PICMET.2016.7806809

Jia, R., Jin, B., Jin, M., Zhou, Y., Konstantakopoulos, I. C., Zou, H., Kim, J., Li, D., Gu, W., Arghandeh, R., Nuzzo, P., Schiavon, S., Sangiovanni-Vincentelli, A. L., & Spanos, C. J., 2018. Design Automation for Smart Building Systems. *Proceedings of the IEEE*, 106(9), 1680–1699. https://doi.org/10.1109/JPROC.2018.2856932

Martinez-Caro, J.-M., & Cano, M.-D., 2020. A novel holistic approach for performance evaluation in Internet of Things. *International Journal of Communication Systems*, 2020, e4454. https://doi.org/10.1002/dac.4454

Jung, T., Jazdi, N., Krauß, S., Köllner, C., & Weyrich, M., 2020. Hardware-in-the-Loop Simulation for a Dynamic Co-Simulation of Internet-of-Things-Components. *Procedia CIRP*, 93, 1334--1339. https://doi.org/10.1016/j.procir.2020.03.073

Sangiovanni-Vincentelli, A., Damm, W., & Passerone, R., 2012. Taming Dr. Frankenstein: Contract-Based Design for Cyber-Physical Systems, *European Journal of Control*, 18(3), 217–238. https://doi.org/10.3166/ejc.18.217-238

Spellini, S., Lora, M., Fummi, F., & Chattopadhyay, S., 2019. Compositional Design of Multi-Robot Systems Control Software on ROS. *ACM Transactions on Embedded Computing Systems,* 18(5s), 1–24. https://doi.org/10.1145/3358197

Jha, D. N., Alwasel, K., Alshoshan, A., Huang, X., Naha, R. K., Battula, S. K., Garg, S., Puthal, D., James, P., Zomaya, A., Dustdar, S., & Ranjan, R., 2020. IoTSim-Edge: A simulation framework for modeling the behavior of Internet of Things and edge computing environments. *Software: Practice and Experience*, 50, 844--867. https://doi.org/10.1002/spe.2787

D'Angelo, G., Ferretti, S., & Ghini, V., 2016. Simulation of the Internet of Things. In *2016 International Conference on High Performance Computing Simulation (HPCS)* (pp. 1--8). https://doi.org/10.1109/HPCSim.2016.7568309

Blochwitz, T., Otter, M., et al., 2011. The Functional Mockup Interface for Tool independent Exchange of Simulation Models. In: *Proceedings of the 8th International Modelica Conference*, Seiten 105-114. Linköping University Press. 8th International Modelica Conference, 20.-22 März 2011, Dresden. ISBN 978-91-7393-096-3 ISSN 1650-3740

Zulkipli, N., Alenezi, A. and Wills, G., 2017, IoT Forensic: Bridging the Challenges in Digital Forensic and the Internet of Things. DOI: 10.5220/0006308703150324 In *Proceedings of the 2nd International Conference on Internet of Things, Big Data and Security* (IoTBDS 2017), pages 315-324, ISBN: 978-989-758-245-5

Tahiliani, V., Digalwar, M., 2018, Green IoT Systems: An Energy Efficient Perspective. In *Proceedings of 2018 Eleventh International Conference on Contemporary Computing (IC3)*, 2-4 August, 2018, Noida, India.

Demigha, O., Khalfi, C., 2019, Formal Analysis of Energy Consumption in IoT'S. In *Proceedings of the 4th International Conference on Internet of Things, Big Data and Security (IoTBDS 2019)*, pages 103-114, ISBN: 978-989-758-369-8