Research-Technology Management, Volume 61, Issue 5, 2018, pp. 41-50
DOI:10.1080/08956308.2018.1495965

A Straightforward Route to Sensor Selection for IoT Systems

Paul Jones, Quentin Lonne, Pedro Talaia, Glenn Leighton, Gerardine G. Botte, Srikanth Mutnuri, and Leon Williams

Bios below

Paul Jones is a research fellow in nanostructures at Cranfield University. His areas of interest are synthesis of novel nanomaterials and systems and their integration into other products, including sensors. He has a PhD in nanomaterial synthesis and two Master's degrees, one in advanced automation and the other in nanotechnology and microsystems. p.m.jones@cranfield.ac.uk

Quentin Lonne is a research assistant at Cranfield University. He principally works on micro and nanomaterials applied to energy devices such as fuel cells, electrolysers, thermoelectric modules, solar cells, and electrochromic windows. He holds an MSc in inorganic materials and a PhD in materials science. quentin.lonne@cranfield.ac.uk

Pedro Talaia received his PhD in applied mechanics from University of West Bohemia and a Master's degree in mechanical engineering from the Universidade de Aveiro. He worked on transport, safety, biomechanics, orthopedics, aircraft, and defense. p.talaia@cranfield.ac.uk

Glenn Leighton is a lecturer in the field of functional surface engineering. His current research focuses on novel nanomaterials, nano-manufacturing, functional materials, and new piezo actuators and sensors. He has a PhD and an MSc in microelectromechanical systems and nanotechnology. g.j.t.leighton@cranfield.ac.uk

Gerardine G. Botte is a professor of chemical and biomolecular engineering and the founding director of the Center for Electrochemical Engineering Research at Ohio University. She is also the founder and Chief Technology Officer of E3 Clean Technologies Inc. She specializes in electrochemical engineering, batteries, fuel cells, and urea/urine electrolysis. botte@ohio.edu

Srikanth Mutnuri is an associate professor in applied and environmental biotechnology and the Associate Dean for International Programmes and Collaboration at the Birla Institute of Technology and Science, Pilani. His research focuses on clean water sanitation, zero hunger, affordable and clean energy, climate action, and responsible consumption and production. srikanth@goa.bits-pilani.ac.in

Leon Williams () is the head of the Centre for Competitive Creative Design at Cranfield University; his research area specialization is based on creative design innovation. His current research focuses on the development of strategic tools and frameworks to help technology leaders make more effective innovation decisions. l.williams@cranfield.ac.uk

Overview: The Internet of Things allows for remote management and monitoring of many aspects of everyday life at the individual and industrial levels. However, designing these systems within constraints of cost and operational context can be a real challenge. The sensor network must be strategically designed, which means selecting the most appropriate sensors to collect a specific measurement in a specific environment and then optimizing their deployment and utilization. To facilitate sensor selection, we propose a straightforward, color-coded, three-sieve selection tool and demonstrate the efficacy of this method through real-life exemplars. The selection tool could be applied to other kinds of technologies, as well.

Keywords: Sensor selection; Internet of Things

The concept of the Internet of Things (IoT), as it was coined by Kevin Ashton in 1999, involved connecting two key concepts from the early 1980s: the Internet and radio frequency identification (RFID) (Ashton 2009). Two years later, Gershenfeld, Krikorian, and Cohen (2004) used the term *Internet-zero* to designate an Internet protocol allowing devices to communicate with the network. Since then, IoT and the development of wireless sensor networks have rapidly expanded as the number of Internet-enabled devices available on the market has increased (Oppermann, Boano, and Römer 2014). From urban management and health care to wildlife monitoring and precision agriculture, IoT has become entwined in everyday life.

Sensors are an essential part of IoT systems, as they facilitate the measuring and monitoring of environmental and operational parameters. At its lowest level, a sensor can be reduced to a sensory element—a transduction mechanism converting an external stimulus into another form, such as the conversion of light to an electrical signal (Aktan et al. 2003; Russomanno, Kothari, and Thomas 2005). At a higher level, a sensor incorporates the sensory element, the interface required to connect it to an external system (packaging, power supply, communication port), and sometimes signal processing capabilities. A myriad of sensors are now available to measure particular conditions, such as displacement, acceleration, force, temperature, light, touch, location, gas, and biological matter, and the number is continually increasing (Shieh et al. 2001; Schmidt and van Laerhoven 2001). Given this diversity, innovators constructing IoT systems need a simple, effective process to select the optimum sensor for a particular scenario.

Several selection methods have been proposed through the years, but their implementation often requires a high level of expertise. The task of sensor selection is complicated by the lack of a universal vocabulary to precisely characterize existing sensors and their specifications.[1] For example, criteria can also be referred to as requirements, constraints, or parameters (Shieh et al. 2001; Sowers 2012). Moreover, the selection process can itself be complex, requiring the balancing of an array of different requirements and constraints, and systems created to manage it often require the utilization of advanced software and specialized approaches (Aktan et al. 2003; Sowers

2012). The aim of this work is to develop a straightforward, more generalized sensor selection methodology that can be used by novices as well as experts.

Background

A number of sensor selection methods have been described in the literature and applied in practice; most of these rely on a graphical, semantic, or modeling process (Table 1). A general approach to the selection process was suggested by Paul Regtien (2005). His process starts with an exhaustive list of the operating, environmental, physical, and cost specifications for the system. Then, practitioners build an in-depth understanding of the physics and other circumstances defining the system's use context in order to identify required objects of measurement. The third step is to assess the merits and shortcomings of various sensing methods in the environmental conditions of the use context. Finally, the practitioner selects the sensor that best fits the constraints of the scenario. Although Regtien did not offer a particular selection tool, the basic concepts he describes can be found in most of the selection methods that follow.

---Table 1 near here---

Shieh et al. (2001) offer a graphical toolset based on performance charts. In this process, the most significant characteristics for each sensor type are defined based on manufacturers' data sheets. This information is then plotted on two-dimensional charts, with relevant sensor performance indices as the axes; the result is a graph that illustrates various trade-offs, for instance resolution vs. range or frequency vs. range. The criteria used for a particular type of sensor correspond to the specifications commonly described by the manufacturers technical specifications. However, there is no systematic method to guide practitioners in the pairing of attributes within the 2D performance chart, resulting in an unstructured and variable outcomes. These charts are then used to identify the strongest sensor candidates; the final selection is made from this subset with consideration of cost, practicality, and reliability. The value of this charting method, according to the authors, lies in its ability to give an overview of sensor performance, thus graphically illustrating the sensor type best suited to a given requirement. However, although the charts can constitute a straightforward, visual selection tool, they may become difficult to interpret when there are many sensors to compare.

More recently, solution selection matrices, such as the one included in the Lean Six Sigma toolset, could offer a less specialized, but still useful approach (Antony, Vinodh, and Gijo 2017; Swan 2018). The first step in adapting such a tool to sensor selection is to list all the relevant selection criteria and assign a weight to each, from 1 to 9, depending on its relative importance; those criteria become the columns in the solution matrix, with the candidates making up the rows. The candidates are then scored for each criterion, from 0 (poor) to 5 (very good). The final assessment of a candidate is created by multiplying its score for each criterion by the criterion weight and summing those products. The process seems straightforward, but it has not been applied to sensor selection. Moreover, this method is intended as a discussion tool for managers, not as a selection tool, and is not intended to provide a definitive decision. Anthony, Vinodh, and

Gijo (2017) suggest that the candidate with the highest score may not necessarily be the right choice in every circumstance.

Semantic, taxonomic, and ontological approaches offer another powerful sensor selection approach. Schmidt and van Laerhoven (2001) propose a semantic approach, whose application they illustrate using the case of a mobile phone. The approach begins with an analysis of the situation in which the sensors will be used and what information they should collect; this defines the requirements for and constraints on sensor performance. Those requirements and constraints are then converted, via a computer-assisted process, into semantic cue and context algorithms. For example, for the selection of an accelerometer, a constraint on the frequency at which the sensor can operatencould be converted into the cue “base frequency of 10 Hz” and the corresponding context could be “moving.” Final selection is made by applying a cost function to the results of the algorithm process. Babu, George, and Samuel (2016) propose another semantic-based method in which sensors are selected based on contextual requirements established from the user point of view, such as the object of measurement (what to sense?) and the technology (how to sense?). In this process, a system analysis first defines what needs to be sensed, how, and in what context. These definitions map the constraints; relative values are then assigned to each constraint according to user preference. These attributes are then used to compare each sensor’s characteristics to user needs and preferences, the ultimate purpose being to assign a unique identification to each sensor. Final selection is made using a semantic querying algorithm. The complexity of this approach makes it difficult to use outside of an academic environment, and the professional software involved is likely to be time-consuming and expensive.

For highly complex systems with a large number of interacting parameters, modeling tools and software may be needed to guide sensor selection. The Drexel Intelligent Infrastructure and Transportation Safety Institute detailed a methodology to be applied to sensor selection for bridge health monitoring (Aktan et al. 2003). The initial step in this process consisted of analyzing the bridge and surroundings to characterize the relevant measurements to be collected, as well as the environmental conditions in which the sensors would need to work. Following this analysis, candidate sensors are assessed against three criteria: performance characteristics, environmental constraints, and economic considerations. Sowers (2012) presents a systematic sensor selection strategy (S4) for aerospace vehicle design that supports the selection of a suite of sensors adapted to a system in a particular situation. The whole-system analysis and selection process relies on a process of iterative optimization. It requires successive computer-assisted analyses to establish constraints (performance, cost, design), elaborate required algorithms, and develop software modules. Both Aktan and colleagues’ (2003) and Sowers’s (2012) methods address very complex situations requiring large numbers of interacting sensors. Consequently, the selection processes suggested require advanced modeling software and algorithms; they can be both time-consuming and expensive to implement. Hence these selection methods, although powerful, are only viable for complex systems and not particularly useful as a general tool.

Some general conclusions can be drawn from this review. First, whether it is based on charts, complex computer modeling, or semantic methods, the sensor selection process always begins with an analysis of the system. Second, in all cases, the properties of candidate sensors must be compared to specific system and environmental requirements defined by the analysis and by initial design constrains. And finally, economic considerations are typically taken into account only at the end of the process, after technical requirements have been defined and considered.

Moreover, it seems that there is a real need for a general, approach that can be used by all practitioners, regardless of their expertise with regard to semantic processes or complex selection algorithms. Such a selection method should include an easy-to-read graphical tool, use a simple vocabulary based on sensor manufacturers' terms, and provide an easy-to-implement selection tool.

A Simple Sensor Selection Method

To address these needs, we propose a flexible, straightforward methodology, incorporating a system analysis that feeds into a selection tool, that can be adapted to nearly any IoT system or situation (Figure 1). Briefly, the results of a five-step analysis based on performance data from sensor manufacturers are used to populate a three-sieve selection tool, represented as a succession of color-coded matrices. The tool is easily implemented with a spreadsheet; each matrix facilitates a simple go/no go decision for each sensor, based on key criteria, so that the number of candidates is reduced progressively. Finally, after the final matrix analysis, the sensor with the highest aggregate score is chosen.

---Figure 1 near here---

Five-Step System Analysis

Meaningful sensor selection can proceed only in the context of a full understanding of the system as a whole. To create that understanding, we engage in a five-step system analysis:

1. *Develop an understanding of the complete system and its fundamental processes.* The complexity of this analysis can vary, depending on the complexity of the system. For example, health monitoring systems, such as for a bridge or a jet engine, require quantitative approaches such as finite element analysis, computer modeling, and simulation to understand their dynamic operation (Aktan et al. 2003; Sowers 2012). Techniques such as fault tree analysis can be used to understand possible failure mechanisms. At a lower level of complexity, for systems performing simpler tasks such as wildlife habitat or personal assistance monitoring, a simpler qualitative analysis may be sufficient (Mainwaring et al. 2002; Mubashir, Shao, and Seed 2013).

2. *Define the parameters to be measured.* For example, the amount of a fluid inside a tank could be found by measuring either the mass (scale or pressure sensor) or the volume (gauging rule, level detector) of the fluid (Regtien 2005). In general, several parameters need to be measured during a process, sometimes simultaneously.

3. *Define the performance requirements for the sensors needed for each measurement parameter.* These requirements could be related to the measurement range, accuracy, resolution, sensitivity, discrimination, linearity, hysteresis, repeatability, stability, or response time, among other attributes (Cheng, Azarian, and Pecht 2010).

4. *Consider the environment in which the system will operate.* This will determine the physical constraints and environmental factors affecting the sensors. Environmental factors include but are not limited to temperature, humidity, pressure, shock, strain, stress, acoustic level, vibrations, electrical noise, and the presence of possible contaminants. Physical constraints inherent to the system could relate to the size, weight, shape, packaging, and mounting of the sensor, among other factors.

5. *Estimate the total cost of implementation for the sensor.* This economic analysis should consider the availability, unit cost, delivery time, installation time and costs, maintenance requirements, reliability (mean time between failures, or MTBF), and total life of the sensors.

The five-step system analysis provides an in-depth understanding of the processes occurring within the system and facilitates the identification of meaningful parameters for measurement. The performance requirements, along with the physical, environmental, and cost constraints, defined in the analysis are used in the three-sieve tool to identify the most appropriate sensor from the pool of candidates.

Three-Sieve Selection Tool

In the selection phase, the information gathered in the five-step system analysis is fed into a three-sieve selection tool that provides a process for selecting sensors that can collect the measurements identified in Step 2 and meet the requirements defined in Steps 3–5. Because we assume that each sensor collects only one measurement parameter—that is, a single device is not measuring multiple physical inputs—the selection tool must be run independently for each measurement parameter. The template for this tool is based on Collins and Williams's (2014) three-stage filter for technology selection. In this study, technologies were assessed and compared using three prioritized filters: key functional attributes, primary attributes, and contextual attributes. This system assigned a score to each technology under consideration; the scores were linked to a color code, which allowed quick, visual comparison of the various technologies under consideration.

The three-sieve sensor selection tool presented here uses a standard spreadsheet program to facilitate analysis.[2] That analysis proceeds by filtering candidate sensors first by their ability to meet performance requirements (Sieve 1), then by their conformance to physical constraints and ability to withstand environmental factors (Sieve 2), and finally by cost of implementation (Sieve 3). Each sieve is represented as a table in which each column corresponds to a specific requirement or constraint and each row corresponds to a candidate sensor (Figure 2). The tables are populated with data obtained in the system analysis. Each sensor is rated by its ability to meet each requirement or constraint; the ratings are color coded—red if a requirement is not met (NOT OK), yellow if it is met (OK), and green if the sensor exceeds the requirement (OK+). For example, where the data being collected is temperature and the performance requirement is to measure the range of 20–60°C, a sensor with a range of 30–50°C would be rated red, a sensor with a range of 20–60 °C would be rated yellow, and one with a range of 10–70°C would be rated green.

---Figure 2 near here---

Only candidate sensors that meet the requirements of one sieve—that is, that are rated yellow or green—pass to the next one. There is no use in assessing physical, environmental, or cost constraints if the sensor does not meet the performance requirements of the system. Similarly, it is pointless to assess the implementation costs of a sensor that cannot meet system constraints or function under the environmental conditions in which the system will operate. Thus, Sieve 1 focuses on sensor performance, based on the requirements defined in step 3 of the system analysis; Sieve 2 focuses on the physical and environmental requirements mapped in step 4 of the analysis; and Sieve 3 analyzes the total cost of implementation for those sensors that passed through the first two steps. Sieve 3 always includes two standard criteria—availability and unit cost—but other criteria, such as installation or maintenance cost—may also be considered. The availability parameter is crucial in this step—a sensor that is not available within the time frame of the project, no matter how superbly it performs, simply cannot be a candidate. The unit cost is the cost per sensor, which may vary depending on the number of pieces ordered; the unit cost often decreases when a larger number of pieces is ordered. The unit cost is normalized to a scale of 1–10 to simplify comparison in when there is a large pool of candidates.

The totals in the last column of each sieve are aggregate scores designed to represent the compatibility of any given sensor to a particular system. Typically, the total score would be a simple product of the sensor's scores on each criterion. If a more fine-grained analysis is needed, a weighting formula can be used to capture the relative importance of each criterion, similar to the process used in the Lean Six Sigma solution selection matrix (Antony, Vinodh, and Gijo 2017). In any case, the candidate with the highest score in Sieve 3 should be chosen as the most adapted to the system.

The Three-Sieve Selection Method in Practice

To test the viability of the three-sieve selection tool, we performed analyses of several scenarios based on real-life cases. Here, we show how the tool can be used to select an accelerometer for a laboratory-scale demonstrator used as a testbed for IoT and augmented reality research.[3]

We began with the system analysis:

1. *Understand the complete system:* The system, which was developed at Cranfield University (UK), consists of a series of gears that drive a frictional brake mechanism mounted on a linear actuator (Figure 3). The speed of the drive shaft, the position of the gears, and the vibrations generated are passed via a wireless link to a tablet PC for information overlay and retrieval.

---Figure 3 near here---

2. *Define the parameters to be measured:* The rotational speed of the gears and the frictional force of the brake create vibrations within the system. An accelerometer is needed to measure the vibrations generated during operation.

3. *Define sensor performance requirements:* The system analysis shows that the vibrations are not expected to exceed 1g and an accelerometer sensitivity of at least 1200 mV/g will be required to interface with the monitoring electronics.

4. *Consider the operational environment:* The system operates in a range of temperatures, so the sensor must perform across that full range, 15–30°C. Size constraints within the system mean that the sensor must have a volume of no more than $\leq 400\ mm^3$.

5. *Estimate the cost of implementation:* The project demands that costs be kept as low as possible; further, the supplier must have at least 50 units in stock to meet likely project needs.

This information is then converted into constraints and entered into the three tables of the three-sieve tool (Figure 4). To simplify this example, only single-axis analog devices will be considered; multi-axis and digital output sensors are automatically discarded; further, constraints are limited to two per sieve. In this example, in Sieves 1 and 2, color codes are keyed to scores: red = 0, yellow = 1, and green = 2. The total score for each candidate is calculated by multiplying together the scores for each constraint. In our example, the total scores for Sieves 1 and 2 are calculated as follows:

---Figure 4 ----

$$\text{Total Score Sieve 1} = \text{Peak Acceleration Score} \times \text{Sensitivity Score} \quad (1)$$

$$\text{Total Score Sieve 2} = \text{Operating Temperature Score} \times \text{Volume Score} \quad (2)$$

Thus, the highest total score achievable in the first two sieves is 2n, with n being the number of constraints—in our sample, the maximum possible score is 4; three of the sensors evaluated achieve this score in sieve 1. Further, a candidate that fails to meet any one constraint will have a total score of 0, as with S4 in Sieve 1, and will be discarded. All candidates with a score greater than 0 will be passed on to the next Sieve. It should be noted that, as long as the sensor meets basic criteria, a higher total score in one sieve does not necessarily mean the sensor is superior for the given application. The final decision will be based on the outcome of sieve 3, which will balance performance and cost to determine whether exceeding specification is desirable in the context of other constraints.

In Sieve 3, the availability of the part is a simple go/no go criteria—if the sensor is not available, it cannot be used. Thus, scores in that column are limited to 1 (green) if the required number of sensors is available in stock or 0 (red) if the stock is less than required. Unit cost is the best price the supplier can offer—£16.53/piece for more than 10 pieces in the case of S1 and £32.90/piece for 50 pieces in the case of S5. The unit cost constraint is not color coded; its score is normalized on a scale of 1–10, which simplifies comparison in the case of a large data set. The formula used to normalize the cost is:

$$\text{Normalized cost} = a + (c - A) \times (b - a) / (B - A) \quad (3)$$

where a is the minimum value in the scale (1 in this case), b is the maximum value in the scale (10 in this case), A is the minimum cost value in the data set (£5.26), B is the maximum cost value in the data set (£32.90), and c is the cost value to be normalized. The total score in Sieve 3 is calculated to include consideration of the candidate's performance at Sieves 1 and 2:

$$\text{Total Score Sieve 3} = \text{Total Score Sieve 1} \times \text{Total Score Sieve 2} \times \text{Availability Score/Normalized Cost Score} \quad (4)$$

This formula yields a ratio between the relevant properties (captured in sieve 1 and sieve 2 scores) and the price (captured as normalized cost), while discarding unavailable candidates. In this example, S3 and S5 emerge as two viable candidates; S3 has a higher final score and thus is the final choice.

Discussion

The three-sieve methodology integrates the three main features present in most sensor selection processes, as described in Regtien (2005)—it starts with a system analysis, assesses candidate sensors against specific requirements identified by that system analysis, and facilitates a final decision based on economic considerations. Nonetheless, a few key differences set the three-sieve method apart from other methods and tools.

First, the sieve method simplifies analysis by progressively focusing attention on the sensors most likely to perform as needed. The six constraints considered in our very simple example would, in the graphical method proposed by Shieh et al. (2001), generate three 2D graphs. No candidates are discarded between graphs in this method; thus, analysis requires the simultaneous comparison of multiple graphs. In the case of a large pool of candidates or constraints, this task could quickly become unmanageably complex. The use of a matrix tool like the Lean Six Sigma solution matrix may seem easier, but it may also suffer under the weight of multiple comparisons and constraints. Gathering all the criteria (performance, environmental, environmental, cost) with their different weights and all the sensor candidates in one table can flatten differences and, again, call for complex simultaneous comparisons. On the other hand, in the three-sieve tool, progressive and systematic discarding of sensors that do not meet defined criteria, paired with a color code and simple numerical scoring system, streamlines the selection process.

Semantic-oriented selection methods, which allow computers to handle the comparisons, can be quite complex. Users must master a very specific technical and programming vocabulary to be able to translate technical knowledge into semantic cues and queries and run complex algorithms using specific software tools (Babu, George, and Samuel 2016). For instance, in Schmidt and van Laerhoven's (2001) algorithm, *moving* means *nonzero* *acceleration* for an accelerometer, but it could mean *skin temperature* in the case of a passive infrared detector. Advanced modeling selection methods are very powerful, capable of addressing highly complex situations such as bridge health monitoring or aerospace vehicle design (Aktan et al. 2003; Sowers 2012); they are also, as a consequence, unnecessarily time-consuming for simpler needs. The three-sieve tool simplifies the semantic approach by employing the vocabulary commonly used by suppliers and by avoiding the need for heavy-duty software. Only basic equations and a spreadsheet are necessary to implement the three-sieve method.

In contrast to these complex, and sometimes specialized approaches, the three-sieve tool offers a more general approach, easily adaptable to any situation.

Conclusion

The three-sieve selection tool we have developed is a straightforward method for sensor selection that balances performance requirements, environmental constraints, and other factors with economic considerations. The tool is flexible enough to be used by practitioners at any level of expertise; the template makes the decision-making process clear across teams and collaborators. Indeed, it provides a clear account of what sensors have been considered and which have been rejected, and for what reason, that can streamline decision making within the team by providing a logical rationale. Furthermore, as the tool is adaptive, practitioners can update it with new sensors as they emerge on the market to assess how they compare to the sensors currently being used.

This publication is based on research funded by the Bill & Melinda Gates Foundation. The findings and conclusions contained within are those of the authors and do not necessarily reflect positions or policies of the funders.

References

Aktan, A. E., Catbas, F. N., Grimmelsman, K. A., and Pervizpour, M. 2003. Development of a model health monitoring guide for major bridges. Contract/order No. DTFH61-01-P-00347. June. Drexel Intelligent Infrastructure and Transportation Safety Institute. https://fr.scribd.com/document/343127708/Development-of-a-Model-Health-Monitoring-Guide-for-Major-Bridges

Antony, J., Vinodh, S., and Gijo, E. V. 2017. Basic and advanced tools of Lean and Six Sigma for SMEs. In *Lean Six Sigma for Small and Medium Sized Enterprises: A Practical Guide*, 83–142. CRC Press.

Ashton, K. 2009. That "Internet of Things" thing. *RFiD Journal*, June 22. http://www.rfidjournal.com/articles/view?4986

Babu, K. R. R., George, S. J., and Samuel, P. 2016. Optimal sensor selection from sensor pool in IoT environment. In *2016 2nd International Conference on Applied and Theoretical Computing and Communication Technology (ICATccT)*, ed. S. K.

Niranjan, 697–702. New York: Institute of Electrical and Electronics Engineers. doi: 10.1109/ICATCCT.2016.7912089.

Cheng, S., Azarian, M. H., and Pecht, M. G. 2010. Sensor systems for prognostics and health management. *Sensors* 10(6): 5774–5797. doi: 10.3390/s100605774.

Collins, M., and Williams, L. 2014. A three-stage filter for effective technology selection. *Research-Technology Management* 57(3): 36–42. doi: 10.5437/08956308X5702155.

Gershenfeld, N., Krikorian, R., and Cohen, D. 2004. The Internet of Things. *Scientific American* 291(4): 76–81.

Mainwaring, A., Culler, D., Polastre, J., Szewczyk, R., and Anderson, J. 2002. Wireless sensor networks for habitat monitoring. In *Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications*, 88–97. WSNA ’02. New York: ACM. doi: 10.1145/570738.570751.

Mubashir, M., Shao, L., and Seed, L. 2013. A survey on fall detection: Principles and approaches. *Neurocomputing* 100(Supplement C): 144–152. doi: 10.1016/j.neucom.2011.09.037.

Oppermann, F. J., Boano, C. A., and Römer, K. 2014. A decade of wireless sensing applications: Survey and taxonomy. In *The Art of Wireless Sensor Networks*, ed. H. M. Ammari 11–50. Springer, Berlin, Heidelberg. doi: 10.1007/978-3-642-40009-4_2.

Regtien, P. L. 2005. Selection of sensors. In *Handbook of Measuring System Design*, ed. P. H. Sydenham and R. Thorn, Part 7.2:116. New York: Wiley & Sons. doi: 10.1002/0471497398.mm069.

Rowaihy, H., Eswaran, S., Johnson, M., Verma, D., Bar-Noy, A., Brown, T., and La Porta, T. 2007. A survey of sensor selection schemes in wireless sensor networks. In *Proceedings of the Society of Photo-Optical Instrumentation Engineers 6562A*, Unattended Ground, Sea, and Air Sensor Technologies and Applications IX, ed. Edward M. Carapezza, 1–11. Bellingham, Washington, USA. doi: 10.1117/12.723514.

Russomanno, D. J., Kothari, C., and Thomas, O. 2005. Sensor ontologies: From shallow to deep models. In *Proceedings of the Thirty-Seventh Southeastern Symposium on System Theory, 2005. SSST ’05*, 107–112. New York: Institute of Electrical and Electronics Engineers. doi: 10.1109/SSST.2005.1460887.

Schmidt, A., and van Laerhoven, K. 2001. How to build smart appliances? *IEEE Personal Communications* 8(4): 66–71. doi: 10.1109/98.944006.

Shieh, J, Huber, J. E., Fleck, N. A., and Ashby, M. F. 2001. The selection of sensors. *Progress in Materials Science* 46(3): 461–504. doi: 10.1016/S0079-6425(00)00011-6.

Sowers, T. S. 2012. Systematic sensor selection strategy (S4) user guide. Technical report, February. NASA/CR—2012-215242. https://ntrs.nasa.gov/search.jsp?R=20120003357

Swan, E. 2018. Solution selection matrix. *GoLeanSixSigma*. https://goleansixsigma.com/solution-selection-matrix/

Notes

1. In order to avoid confusion, it should be noted that *sensor selection* has two meanings in the field. One refers to the selection of sensors from the set already deployed into a network; the selection process is used to optimize the network by choosing which sensors will be active at a given time (Rowaihy et al. 2007). The meaning intended in this work refers to the selection of sensors to be integrated into a system during the design and build process; in this case, the selection process is focused on incorporating the most appropriate sensors for the task at hand (Regtien 2005).

2. A spreadsheet template for the three-sieve selection tool is available at https://doi.org/10.17862/cranfield.rd.5809329.

3. More complex test cases, including selection of a strain gauge for a synthetic femur subjected to anatomical loads and pH and temperature requirements and selection of a methane sensor for a remote system monitoring operational conditions in a toilet, are reported at https://doi.org/10.17862/cranfield.rd.5809329.

Table 1.—Comparative table: The three-sieve method vs. common sensor selection methods

Name	**Required Level of Expertise**	***Selection Process*** **Method**	**Tool**	**Source**
General insight	Basic	Empirical	None	Regtien 2005
Performance chart	Moderate	Graphical	2D charts	Schieh et al. 2001
Solution selection matrix	Moderate	Graphical	Spreadsheet	Antony, Vinodh, and Gijo 2017
Cue- and context-oriented method	Advanced	Semantic	Layered architecture application based on clustering algorithms	Schmidt and van Laerhoven 2001
Query- and context-oriented method	Advanced	Semantic	Specialized databases and clustering algorithms	Babu, George and Samuel 2016
Model health-monitoring guide	Advanced	Modeling	Finite element analysis and CAD	Aktan et al. 2003
Systematic sensor selection strategy (S4)	Advanced	Modeling	Iterative model based on statistical evaluation algorithms	Sowers 2012

Figure captions

Figure 1.—Simple sensor selection process

Figure 2.—Three-sieve selection tool template

Figure 3.—Laboratory-scale demonstrator used as a testbed for IoT and augmented reality research

Figure 4.—Selection of an accelerometer using the three-sieve tool

A straightforward route to sensor selection for IoT systems

Jones, Paul M.

2018-09-12

Jones PM, Lonne Q, Talaia P, et al., A straightforward route to sensor selection for IoT systems. Research-Technology Management, Volume 61, Issue 5, 2018, pp. 41-50

https://doi.org/10.1080/08956308.2018.1495965