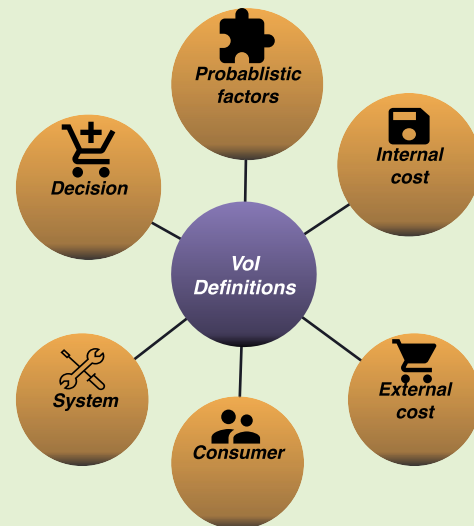


Value of Information in Wireless Sensor Network Applications and the IoT: A Review

Faiga Alawad¹, Graduate Student Member, IEEE, and Frank Alexander Kraemer², Member, IEEE

Abstract—Value of Information (VoI) is a concept to assess the usefulness of information for a specific goal, and has in the last decade experienced a growing interest also for Wireless Sensor Network (WSN) applications and the Internet of Things (IoT). By making the value of information explicit in the form of VoI, WSN and IoT applications should be able to better assess which information to spend their constrained resources on. However, the definition of VoI is highly application-dependent, which has led to a fragmented understanding of VoI, and there is a lack of a comprehensive overview. In this structured review, we first categorize application use cases and examine what VoI is used for, and explore the different approaches to defining VoI. We then provide a well-structured and comprehensive discussion of the specific approaches used in the literature to determine VoI, together with examples of use cases. We categorize the different approaches to calculating VoI, describe their properties systematically and distinguish between observed VoI and expected VoI. We also discuss adaptive VoI approaches and point towards future directions within the field.

Index Terms—Data collection, data reduction, Internet of Things, machine learning, scheduling algorithms, sensor data, sensor networks, wireless sensor networks, value of information.



I. INTRODUCTION

WIRELESS sensor networks (WSNs) are at the core of the Internet of Things (IoT), and the basis for many sensing applications. In these systems, information is measured and collected by sensor nodes, further processed, and forwarded to an information sink. Here information is used to monitor and document a phenomenon, and is often taken as a basis to make informed decisions and take action. In most cases, the WSN components are severely resource-constrained, in terms of available energy, communication opportunities or computational power [1].

There are various ways to address these constraints, for instance by more energy-efficient computing platforms, more suitable communication protocols, better energy supplies, energy buffers or energy harvesting techniques [2]. In addition

to such measures, proper resource management can improve the efficiency further, by controlling *how* the system fulfills its purpose. In most applications, just more information does not imply a better utility of the system to the user. If the purpose of the system is to monitor a slowly changing value, such as an outdoor temperature, sampling with a high frequency does not necessarily improve the value to the end user [3]. If a system involves mobile nodes, it may be more valuable to visit places with unknown values than those already visited, which means that a system should be able to prioritize among different sensing options [4].

Intuitively, constrained systems should only spend their resources on data items of high value, as opposed to those that are redundant or of little utility. This is where Value of Information (VoI) comes in. The concept was first described by Howard [5] in 1966 as an information metric for data prioritization. The theory highlights the importance of probabilistic and economic factors in the evaluation of information. In this definition, VoI is the change in the expected utility obtained by observing the information. The concept of VoI has since been applied to various domains, among them WSNs and IoT, and we observe a growing body of literature that applies VoI.

However, despite the simplicity of the principle, there exist many different definitions of VoI in the domain of WSNs and

Manuscript received December 21, 2021; revised March 31, 2022; accepted March 31, 2022. Date of publication April 8, 2022; date of current version May 13, 2022. The associate editor coordinating the review of this article and approving it for publication was Dr. Wei Dongyan. (Corresponding author: Faiga Alawad.)

The authors are with the Department of Information Security and Communication Technology, Norwegian University of Science and Technology, 7491 Trondheim, Norway (e-mail: faiga.alawad@ntnu.no; kraemer@ntnu.no).

Digital Object Identifier 10.1109/JSEN.2022.3165946

many approaches to calculating or estimating it. One reason is that assessing the value of an information item may be highly dependent on the application, the subjective experience of an end user, or a complex decision process. Another reason is that VoI can be multi-objective in nature. For that reason, many approaches only approximate the VoI using other information metrics like Quality of Information (QoI) [6], or the timeliness with which information items are delivered, also called Age of Information (AoI) [7].

As a result, the literature on VoI in WSNs and IoT appears fragmented and lacks a structure or foundation that goes beyond the intuitive concept of VoI. This is unfortunate since we expect that the concept of VoI has the potential to address the ubiquitous problem of resource constraints in many applications if it would be applied more systematically.

In this structured literature review, which is the first of its kind, we hence provide a systematic overview of the growing body of literature on VoI in WSNs and the IoT. The foundation is a structured overview of use cases that apply the VoI concept, with a focus on which role VoI plays. We then provide an in-depth overview of the different classes of approaches to define and implement VoI in WSNs, and categorize their properties. This overview allows us to structure our exposition of VoI definitions and approaches categorically. This structure can be used as a taxonomy for the field, as it covers analytical, statistical, information-theoretic methods and also information value theory. We elaborate on the important but often overlooked difference between *observed* VoI and *expected* VoI. We identified two patterns for adaptive VoI solutions, namely *Human-in-the-Loop* and *Model-in-the-Loop*, and elaborated on the potential of machine learning for the prediction and approximation of VoI. In our discussion, we mention under-developed research areas and point out research opportunities for the field.

The rest of this paper is organized as follows. After an overview of the methodology used for this review in Section II, Section III presents a discussion of use cases that apply VoI in the domain of WSNs, and Section IV presents definitions for VoI we found in the literature. Section V categorizes the use cases, the decisions that informed by VoI, and presents a categorization of the specific VoI assessment techniques. Section VI discusses and explains the analytical assessment methods for observed VoI, followed by Section VII which explains how to assess the expected value of information. Section VIII discusses how VoI assessment can be made adaptive. Section IX is the discussion, Section X highlights the lessons learned, and we finally conclude in Section XI. Fig. 1 shows the complete layout of this article.

II. METHODOLOGY

We have used a systematic literature review method in this review paper. This method was adapted from chapter 4 of the book by Wohlin *et al.* [8], which provides general guidelines for systematic review papers in software engineering. Below is a comprehensive description of our methodology:

- We used the search keywords *Value of information* and *Wireless sensor networks*.

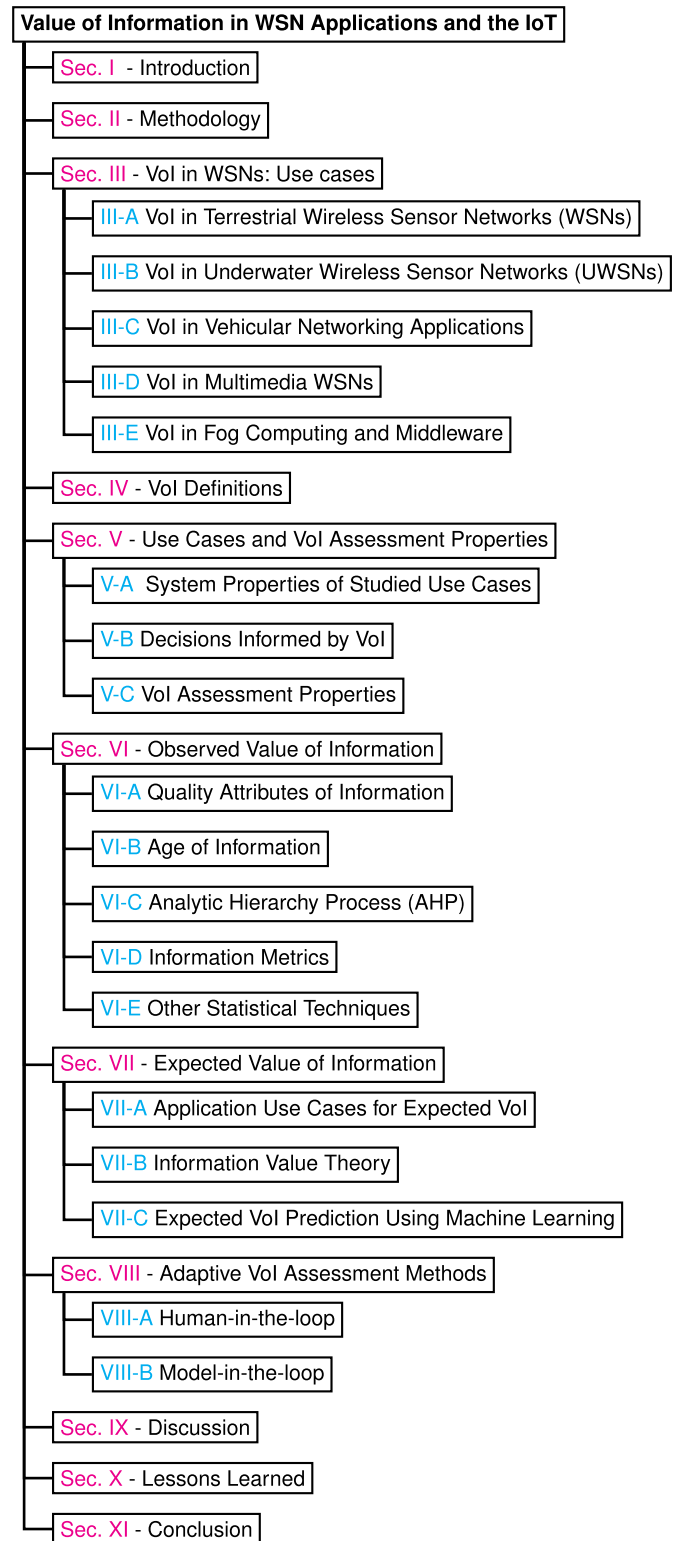


Fig. 1. The layout of the article.

- We selected five databases; IEEE Xplore, ACM Digital Library, Springer Link, Science Direct, and Scopus.
- We searched for articles published between 1996 and 2020.

We obtained 704 results for the keywords in the selected databases and then applied the time limitation.



Fig. 2. Publications on VoI in WSNs per year.

- Subsequently, inclusion and exclusion criteria were applied by reading titles and keywords.
- Duplicate publications have been eliminated.

The main inclusion criterion is that articles must be in the domain of WSNs; therefore, articles that apply VoI in other domains were rejected. We ended up with 616 publications after this step. Fig. 2 illustrates the yearly breakdown of these publications. From Fig. 2, we can see that VoI has been around for decades in WSNs, but with growing attention in the last decade.

- We then applied the inclusion and exclusion criteria by reading the abstracts.
- We added an additional exclusion criterion, to only include publications that apply VoI within a defined application context or introduce a new VoI definition.
- We applied the snowballing method using the references in and the citations of the selected publications to find other relevant publications.
- We then read the full papers.

We ended up with 50 core papers, some of which are summarized in Tables I and II. We excluded papers that lack any practical implementation.

III. VOI IN WSNs: USE CASES

VoI was first introduced to WSNs in 1996 by Cook *et al.* [38] for use in tactical networks. They introduced a sensing approach aiming to maximize the expected VoI of the collected information without exposing the information source to enemies. Collecting information requires the information source to be moved to positions of interest, but hiding from the enemies by maintaining stealth is a conflicting requirement. VoI is used in this context to optimize the tradeoff between collecting information and exposure to the enemy.

Most WSN and IoT applications deal with constrained resources, for example restricted communication, availability of storage, computational resources or energy in general. All use cases we found use VoI to make the most of these limited resources by filtering or prioritizing information items

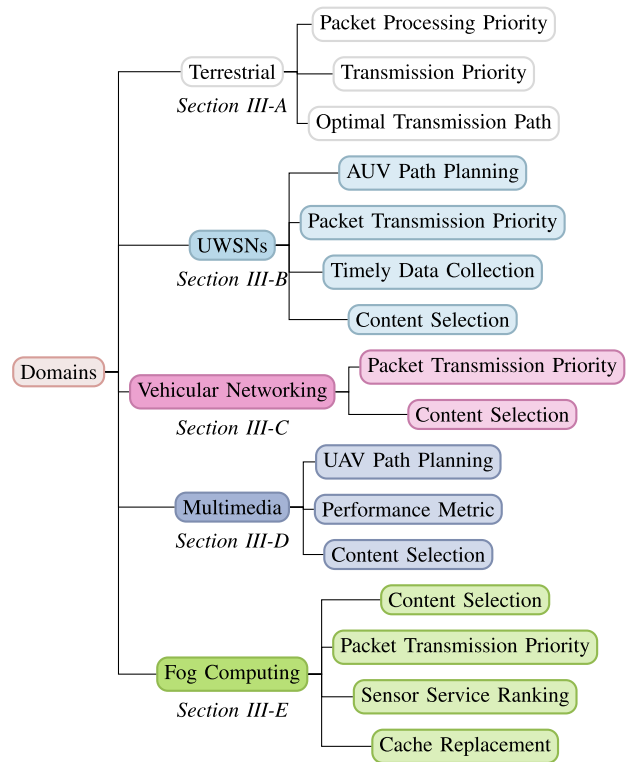


Fig. 3. VoI domains and application use cases.

or computational tasks. As a result, system resources are not wasted in transmitting or processing low-value information.

Tables I and II summarize the reviewed cases [4], [9]–[37]. Fig. 3 shows the domains of the use cases along with the more detailed application areas that we identified in the reviewed literature. We distinguish between terrestrial WSNs, underwater WSNs (UWSNs), vehicular networking, and multimedia WSNs. In addition comes fog computing as an architectural paradigm in IoT.

A. VoI in Terrestrial Wireless Sensor Networks (WSNs)

In the domain of terrestrial WSNs, sensor devices are used for applications like structural health monitoring, environmental monitoring and general cyber-physical systems. Therefore VoI has been implemented in this domain to aid the optimal allocation of energy to the most important information (i.e., the information with the highest VoI). For instance, Patil and Fiems [14] study a WSN that has static sensors which observe the environment and a mobile sink which moves to collect the sensed observations from the static sensor nodes. Sensors can transmit their observations to the sink node when they are within the transmission range and if they have enough energy. The VoI is used to decide whether to transmit when both requirements are satisfied. In [15] they point out how VoI plays a more important role when the sensor is running out of energy, in which case the sensors are more careful about what to transmit. Similarly, Zhang *et al.* [12] use VoI to prioritize processing data packets with high value.

Singh and Al-Turjman [11] incorporated VoI in the context of cognitive, information-centric sensor networks. They present a multi-hop scenario in which VoI is used to choose the optimal delivery path to the sink, taking into account

TABLE I
USE CASES IN REVIEWED PAPERS RELATED TO TERRESTRIAL AND UNDERWATER WSNs

Reference	Year	Application	Mobility	Topology ¹	Communication	Decision	Decision Type ²	Sense ³	Transmit ³	Expected VoI ⁴	Stochasticity ⁵	User Influence ⁶	Method ⁷
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Terrestrial Wireless Sensor Networks													
[9]	2020	Structural health monitoring	–	–	–	Optimal number of sensors	I	●	○	●	P	O	ΔUtility
[10]	2018	Structural health monitoring	–	Cent.	Periodic	Delay construction work	E	○	○	●	P	O	ΔUtility
[11]	2017	Environmental monitoring	Nodes and sink mobility	Dec.	–	Select the next node to visit	I	○	●	○	D	O	$f(QoI)$ AoI
[12]	2016	Environmental monitoring	–	–	–	Processing sensing data	I	○	○	●	P	O	KL
[13]	2016	Cyber-physical systems	Sensors attached to a robot	Dec.	On-demand	Content selection	I	●	○	●	P	O	ΔUtility
[4]	2012	Environmental monitoring	Mobile sensors	–	–	Sample location	E	○	○	●	P	O	ΔUtility
[14]	2018	Environmental monitoring	Mobile sink	Dis.	On-demand	Content selection	I	○	●	○	D	O	$f(QoI)$
[15]	2018	Environmental monitoring	Mobile sink	Dis.	Event	Content selection	I	○	●	○	D	O	$f(QoI)$
Underwater Wireless Sensor Networks													
[16]	2020	–	Mobile sink	Dec.	On-demand	Select the next node to visit	I	○	●	○	D	O	$f(QoI)$
[17]	2020	–	Mobile sink	Dec.	On-demand	Select the next node to visit	I	○	●	○	D	O	$f(QoI)$
[18]	2020	Marine	–	Dis.	Periodic	Transmission priority	I	○	●	○	D	O	$f(QoI)$
[19]	2019	–	Passive nodes mobility	Dis.	Periodic	Transmission priority	I	○	●	○	D	O	AoI
[20]	2019	–	Mobile sink	Dis.	Periodic, On-demand	Transmission priority	I	○	●	○	D	O	$f(QoI)$
[21]	2014	–	Mobile sink	Dis.	On-demand	Select the next node to visit	I	○	●	○	D	O	AoI
[22]	2015	Oil spill monitoring	Mobile sink	Dis.	On-demand	Select the next node to visit	I	○	●	○	D	O	AoI
[23]	2016	–	Mobile sink	Dis.	On-demand	Select the next node to visit	I	○	●	○	D	O	AoI
[24]	2018	Oil spill monitoring	Mobile sink	Dis.	Event	Select the next node to visit	I	○	●	○	D	O	AoI
[25]	2018	Underwater cyber-physical systems	Passive nodes mobility	Dis.	Periodic	Content selection	I	○	●	○	D	O	$f(QoI)$
[26]	2018	–	Mobile sink	Dec.	On-demand	Select the next node to visit	I	○	●	●	D	O	AoI

¹ Topology: **D**istributed, **C**entralized, or **D**ecentralized, see Section V-A

² Decision Type: **E**xternal or **I**nternal, see Section V-B

³ ● If the decision prevents sensing or transmission

⁴ ● Expected VoI or ○ Observed VoI, see Section V-C

⁵ Stochasticity: **D**eterministic or **P**robabilistic, see Section V-C

⁶ User Influence: **S**ubjective or **O**bjective, see Section V-C

⁷ VoI Assessment Method: see Section V-C, VI and VII

Quality of Service (QoS) parameters like reliability, latency, and throughput. Simulations showed that VoI assisted handling of heterogeneous network flow, by optimally choosing the number of transmitting nodes in a manner that improved the monitored QoS parameters.

B. VoI in Underwater Wireless Sensor Networks (UWSNs)

Underwater WSNs help to monitor and control operations in offshore and underwater environments. Harsh conditions and

remote locations result in intermittent connectivity, generally restricted communication and energy constraints. We observe that VoI has been studied and applied quite extensively in this domain. One of the methods to improve communication is topology control, in which communication nodes are moved to new locations [39]. Here, Autonomous Underwater Vehicles (AUVs) move alongside predefined trajectories. VoI is used to find the best trajectory of an AUV in UWSNs. Observations at each node are assigned a VoI to reflect the importance of the observations for a targeted application, and

TABLE II
USE CASES IN REVIEWED PAPERS RELATED TO VEHICULAR NETWORKS, MULTIMEDIA WSNs AND FOG COMPUTING

Reference	Year	Application	Mobility	Topology	Communication	Decision	Decision Type			Expected VoI	Stochasticity	User Influence	Method
1	2	3	4	5	6	7	8	9	10	11	12	13	14
Vehicular Networks													
[27]	2019	Traffic monitoring, Driver assistance	Sensors attached to vehicles	Dis.	Periodic	Broadcasting info	I	○	●	●	D	O	$f(QoI)$
[28]	2019	Coordinated driving	Sensors attached to vehicles	Dis.	Periodic	Content selection	I	○	●	●	P	O	KL
Multimedia Wireless Sensor Networks													
[29]	2020	Habitat monitoring	Mobile sink	Dec.	On-demand	Select the next node to visit	I	○	●	○	D	O	$f(QoI)$
[30]	2015	Habitat monitoring	Mobile sink	Dec.	Event	Select the next node to visit	I	○	●	○	D	O	$f(QoI)$
[31]	2017	Habitat monitoring	Mobile sink	Dis.	On-demand	Content selection	I	○	●	○	D	O	$f(QoI)$
[32]	2018	Habitat monitoring	Mobile sink	Dis.	Event	Quality of the AUV path	-	-	-	○	D	O	AoI
Fog Computing													
[33]	2020	Smart cities	-	-	-	Sensor selection	I	●	○	○	D	S	$f^*(QoI)$
[34]	2019	Sensing as a service	-	Cen.	Periodic, On-demand	Sensor selection	I	●	○	○	D	O	$f(QoI)$
[35]	2018	Cache replacement	-	-	-	Content selection	I	○	●	○	D	S	$f^*(QoI)$, AoI
[36] [37]	2016 2019	Smart cities	-	-	-	Transmission priority	I	○	●	○	D	O	$f(QoI)$

accordingly the importance of the nodes that made those observations. Then, the AUV will plan its trajectory in a way that maximizes the overall VoI delivered to the application.

AUVs are also used in applications that require timely data collection, like the monitoring of oil spills. The task of the AUV is to collect observation data from the sensor nodes and offload it to a base station above sea level. Khan *et al.* [21] propose a greedy path planning method for AUVs, based on a time-sensitive VoI definition, in which the AUV visits nodes that hold observations with high VoI first. This approach is further extended to handle multiple vehicles [22]. The aim is to maximize the overall VoI, and their algorithms plan which nodes to visit next based on the priority, where the priority is assigned according to the VoI. In [23], they propose a genetic algorithm to find the optimal resurfacing time for the AUV that maximizes the collected VoI. The results in [24] indicate an improvement of the information quality collected by the AUV when incorporating VoI in path planning algorithms.

Gjanci *et al.* [26] introduce an adaptive heuristic path finding method for the AUV. Sensor nodes send summaries of observed events that characterize the event type and importance to an AUV using a short communication link. The AUV estimates the expected value of information and updates its route accordingly, so it can collect data with high expected VoI first. Also related to AUV path planning, Duan *et al.* [16] propose a VoI definition that considers the timeliness and the

importance of an information item. A similar definition has been introduced by Xia *et al.* [17] for information collection based on VoI. The communication between the base station and the AUV is modeled as a contract, where the AUV acts as the seller and the base station as the buyer of the information. The exchange unit between seller and buyer is energy, and the AUV will get charged with energy equivalent to the VoI contained in the information it offloads to the base station.

In marine applications, Zhao *et al.* [18] use VoI to determine the priority of data transmissions. They introduce VoI levels that correspond to different thresholds, and data packets are stored in different queues that correspond to their VoI levels. Queues with the highest VoI are assigned the fastest link, so that the most valuable data items can be transmitted first.

Nodes in UWSNs can also move passively due to underwater currents, leading to a dynamic topology. Chang *et al.* [19] consider VoI-based data forwarding in UWSNs with such passive mobility. In this study, sensors will transmit packets with high VoI (defined by timeliness) when the sink is within the transmission range. Yan *et al.* [25] also consider passive mobility, and propose a path planning algorithm for the AUV, in which they optimize the total VoI, the AUV travel distance and the traveling time. Han *et al.* [20] use VoI to decide the transmission priority of a packet to the cluster head, in a network composed of multiple clusters.

C. VoI in Vehicular Networking Applications

Vehicular networks allow ad-hoc, vehicle-to-vehicle communication. Since connections are transient, VoI can be useful to prioritize transmissions. Giordani *et al.* [27] distinguish between safety and traffic management applications. Safety applications have the goal to avoid collisions and require low-latency communication. In such a scenario, the VoI is high if vehicles are physically close [27]. The application of traffic management involves the creation of local, dynamic maps by incorporating sensor data collected from vehicles. Compared to safety applications, traffic management is more tolerant of delays. VoI thus depends less on the distance between vehicles [27], because sharing the information between vehicles can be important for constructing local maps despite their distance. These two cases show that even within the same domain, VoI can be application-dependent. Higuchi *et al.* [28] apply VoI to cooperative perception applications, in which neighboring vehicles share sensor data to increase their overall knowledge. Each sender node estimates the expected VoI for the receiving node and only sends packets with VoI higher than a certain threshold, which improves overall performance.

Tactical networks represent a particular type of vehicle networks where VoI was implemented. Suri *et al.* [40] implemented a middleware solution for tactical networks that uses VoI to prioritize the transmission of high priority information, and drop information objects with VoI below a certain threshold.

D. VoI in Multimedia WSNs

A demanding type of networks are multimedia WSNs in which multimedia is the main type of data that is sensed and transmitted by the sensors. This requires a high-capacity channel for communication to transfer high data volumes with a low delay.

Multimedia WSNs are used in applications like habitat monitoring, in which detecting the presence of an animal and classifying its type are the main application goals. Cameras are mounted to the sensor nodes, and data can be collected using a mobile sink such as an unmanned aerial vehicle (UAV), that fly from one sensor node to the next, following a predetermined or adaptive trajectory. Xu *et al.* [30], [32] use VoI in the path planning algorithm for the UAV to maximize the overall collected VoI. In [30], VoI has been incorporated in the reward function of the Markovian decision-based path planning algorithm. In [32], VoI is used as a performance metric for the path planning algorithm. The algorithm incorporates a prediction model for the animal distribution from historical data, and solves the path planning problem as a simplified traveling salesman problem. Han *et al.* [29] incorporate VoI of the collected data and the remaining UAV power in the reward function of a deep reinforcement learning model that aims to find the optimal path for the UAV and its recharging schedule.

Xu *et al.* [31] illustrate the use of mobile phones as data collectors in the application of habitat monitoring. In this scenario, mobile users only have a short time within the transmission range of sensor nodes, and it is hence beneficial to prioritize the collection of data with high value.

Szymanski *et al.* [41] presented a scenario in a parking garage, where a sensor network is deployed with both microphones and cameras. Compared to the microphones, the cameras provide more accurate information about the events, but with a high energy cost and the need for more maintenance. VoI is used to determine the optimal time to switch between the use of the microphone and the camera as information sources.

E. VoI in Fog Computing and Middleware

Fog computing is an architectural paradigm in which computation happens closer to endpoints, for instance directly in the sensing nodes, in access points, base stations or gateways. At this level, VoI is used to optimize the usage of system resources at a network level and by ranking services provided by the network.

Tortonesi *et al.* [42] demonstrate the use of VoI within fog services for prioritization of information for processing and dissemination tasks. They present a processing model (called SPF for *Sieve, Process, and Forward*) that disseminates information based on its VoI [36]. In [37] they apply SPF in a smart city context, to overcome the problem of the demanding processing tasks for massive data, with scarce processing, computation and communication resources. SPF optimizes these tasks by filtering data with low VoI. The model is implemented using Software Defined Networking (SDN) so it can be deployed into the network infrastructure.

Bharti *et al.* [34] propose a VoI-based sensor ranking mechanism running on gateways. When a user requests a sensor service, the ranking mechanism chooses the service with the highest VoI. The authors demonstrate how this VoI-based ranking can outperform other methods as it takes the residual energy as well as the QoS required by the users into account. Similarly, Mocnej *et al.* [43] demonstrate the use of VoI in the gateway service layer for selecting data, in which the VoI corresponds to the significance level of the data to a specific application.

Al-Turjman [35] proposes a VoI-based cache replacement strategy for fog computing applications. With this strategy, data with high VoI will stay longer in the cache than data with lower VoI. The advantage of this caching method is that the replacement of data in the cache will follow the user requirements. For instance, in a city traffic application, a user requirement may be to obtain only data about the traffic within the last hour. Data outside this time frame is discarded.

Poltronieri *et al.* [33] proposed a user-specific VoI model by adding a user-specific utility component, which takes each individual user receiving messages into account. This work uses a simulation-based approach [44] for calculating the VoI in fog services. When created, an initial VoI attribute is assigned to the raw data, which is sampled from a random VoI distribution model associated with its source. The simulator allows each message to have a temporal decay and spatial decay, which follow a linear, exponential or no-decay profile. In Section VI-B we discuss the temporal decay with more details.

Another middleware solution that takes subjective users into account is FireDex [45]. It is a cross-layer middleware

that estimates end-to-end response time for emergency events, specifically for fire detection in smart buildings. FireDex defines a utility function to capture VoI for each user depending on their use case. The VoI is then used to prioritize network resources, and only information with high VoI is allowed to use high bandwidth.

IV. VOI DEFINITIONS

There exists a wide range of definitions and terminology for VoI within the area of WSNs. They range from a simple metric that is attached to an information object, such as in Fernandez-Bes *et al.* [46] who simply refer to VoI as the *importance of a message*, to more elaborate definitions that take the subsequent decision processes into account. Before we look at how VoI can be calculated in Sections VI, VII, and VIII, we present below an overview of VoI definitions organized by their focus.

a) Focus on internal system costs: VoI can be defined based solely on internal system costs, such as energy consumption for measurement, processing or transmission, or networking resources used. Mahajan [47] defines VoI for a data point as the communication cost at which the sensor is indifferent between transmitting or not transmitting the information. Soleymani *et al.* [48] define VoI as *the maximum value an observer would be willing to pay for the transmission of a measurement*.

b) Focus on probabilistic factors: Howard [5] introduced the value of information theory, which considers the probabilistic and economic factors that affect decision-making. This goes beyond information theory, which only focuses on the probabilistic factors regarding obtaining information. Instead, the information value theory also takes the importance or relevance of the information to the user into account. Given a clairvoyant that can tell us the information before we actually spend effort on its collection, the VoI will be equivalent to the difference between the expected profit we gain from information collection and the expected profit from not collecting the information in the first place. In this sense, VoI can also be understood as the difference between the maximum prior and posterior expected benefits [9]. The probabilistic nature of this definition stems from the use of expectations, and its economic side from the use of cost-benefit methods to quantify the profit of information acquisition.

c) Focus on decision-making: VoI can be defined based on the decision the IoT system is trying to support. In this context, VoI aims at reducing uncertainty in the decision situation by gaining *valuable* observations before making the decision. VoI can hence be defined as the increase in the expected value stemming from making the optimal decision when having the information versus making the decision without the information [49]. Tortonesi *et al.* [42] define VoI as the quantified degree of benefit an information object provides to the decision maker. Similarly, Eidsvik *et al.* [50] define VoI as the price at which the decision maker is indifferent between having the information or not. VoI is a way of representing the expected utility of collecting additional observations rather than making a decision without information, while taking into account the cost of collecting the information [51]. The decision maker must choose an alternative from a given set,

with each option having a utility that captures the resulting gain for each alternative. If this gain is higher than the cost of observing the information, the decision maker may continue to collect it [52]. The collection of new information is dependent upon the anticipated cost and usefulness of the additional information.

d) Focus on system utility: Utility is a measure of how beneficial something is within a specific context and a defined domain. The utility of a system evaluates its usefulness to the end user, including the actions and decisions taken by the system. Many applications in WSNs capture application requirements via utility functions [53], which compute the value or efficacy of an action taken by an agent in a specific context [54]. The information utility measures how useful sensed information is and how scarce the sensing resources are for the information gathering task [55]. VoI assesses the utility of information in a certain context [34], [56], [57]. Hence, VoI is a subjective measure of the information utility for the consumer in a decision-making situation [40]. Therefore, one can understand VoI also as a system utility assessment [34]. In that sense, VoI can be defined as the estimated utility of information provided for the information consumers based on their context [36]. Cook *et al.* [38] define VoI as the difference between the expected value of an action taken based on the information, and the action taken without it.

e) Focus on information consumers: A more pragmatic definition of VoI is based on the application goals and the utility that information will bring to the information customers. Bölöni *et al.* [58] define VoI as the sum of values resulting from all the customer's actions within a strategy that is based on the information extracted from the data. Further, they introduce a conditional VoI definition as the value of receiving a data chunk given all the data received before, so the assessment of the conditional value does not only depend on the current data but the transmission history as well. Turgut and Bölöni [59] assume that the value of any information goes to zero if the customer cannot take any action in response. They argue that value judgments are much easier when considering the application domain model compared to models that are independent of applications.

f) Focus on external system costs: Information economics are concerned with pricing information and consider it an intangible good that can be sold in markets [60]. In this context, VoI might refer to the monetary value from using the information, based on an economic comparison of the decision results with information and without it [61]. Similarly, in a business context, VoI can be defined as the avoided loss from taking a decision, for example *to not invest* in accordance with the information [62]. Turgut and Bölöni [63] discuss the value of information in the context of privacy of customers. From a customer's viewpoint, the perceived value of a service must cover the cost of privacy as well as other service payments. The information the service provider receives is important for its ability to provide the service. Risk of Information (RoI) represents the risk that information providers are exposed to when sharing their information. VoI represents the gain the service provider gets from obtaining the information. Thus, RoI and VoI may be compromised to strike a balance between

the utility acquired by the consumer and the risk experienced by the provider [64]. Similarly, Mayle *et al.* [65] propose a model where VoI is expressed in terms of cost of privacy. This cost corresponds to the amount of money the service customer gets from the service provider when sharing information.

V. USE CASES AND VOI ASSESSMENT PROPERTIES

In this section, we present a categorization of system properties for the use cases we studied in Tables I and II, followed by a description of the decisions ultimately influenced by the VoI assessment in the use cases. We then examine the properties which characterize the VoI assessment.

A. System Properties of Studied Use Cases

We categorize the use cases by their mobility, topology and communication patterns.

1) *Mobility*: WSNs can have various forms of mobility, as shown in column 4 in Tables I and II. Sensors can move to take measurements at different places, move with the water (i.e., passively) as in UWSNs, or be attached to vehicles. There are also cases where both the sensor nodes and the sink nodes are mobile. We observed that all methods of analytical evaluation (column 11, Table I and Table II) were used regardless of the mobility style. However, what differs is the reason *why* to consider VoI: When the sensors are mobile, the question of *where* to make measurements need to be answered before the sensing task. Ballari *et al.* [4], for example, decide on the appropriate locations to sample the data and the mobile sensor to move to take the measurements. When the sink is mobile, the main task is to plan the sink path by selecting the next node to visit. In multimedia WSNs, the UAVs fly to collect sensing data from the sensor nodes. AUVs also travel underwater to collect sensing data in UWSNs. This type of mobility is structured mobility, as a consequence of path planning algorithms, and VoI is used in this context to optimize path planning. Conversely, mobile device users move in a free pattern and collect sensing data from sensors in their vicinity. They exhibit unstructured mobility like in [31], VoI in this case used for content selection. Mobile sensor decisions differ from those associated with static sensor networks; for instance, VoI helps determine the next node to visit in [11], [16], [17], [21], [26], [29], [30].

2) *Topology*: Column 5 indicates the system topology and VoI evaluation placement. The VoI can be calculated in different system tiers. In the cases studied, three VoI evaluation locations for VoI can be identified:

- *Distributed*: VoI can be computed in a distributed way, within each sensor node individually.
- *Centralized*: VoI can be centrally calculated in a sink node or fusion center, which receives data from all sensor nodes of the network.
- *Decentralized*: In a variation of the central topology, VoI can also be computed in a decentralized way. This corresponds to a system with multiple clusters and sink nodes that aggregate data from the sensor nodes.

3) *Communication Pattern*: Column 6 lists the methods of communication used between the sensors and the sink nodes. Three variations were identified:

- *Periodic*: Sensor nodes send information to the sink nodes at periodic intervals.
- *Event-driven*: The sensors take the initiative to send information based on the detection of an event.
- *On-demand*: The sink node initiates the requests for information from the sensor node.

B. Decisions Informed by VoI

In this part of the table, we categorize what the VoI assessment is used for, that means, *why* the VoI is calculated. We were able to identify the specific decisions that were based on the VoI assessment, shown in column 7 in Tables I and II. The decision can be external or internal to the WSNs system, as indicated by column 8. *External* decisions directly relate to an external user of the system, or an intermediary information user, like an application service. In structural health monitoring, where buildings and other infrastructure are monitored by networks of sensors, such a decision may be whether the construction work should be postponed [10]. *Internal* decisions, on the other hand, relate to operational issues within the system. These decisions often relate to the constrained resources of systems and consider the value or utility of information in relation to their cost. Our study of use cases reveals that most VoI applications in WSNs are linked to such internal decisions. Some approaches optimize the operation of their network by deciding whether to transmit information or not, or more generally, which subset of measurements to transmit. This leads to VoI-based content selection [13]–[15], [25], [28], [35], VoI-based transmission priorities [18]–[20], [36], [37] and the decision of which data to process [12].

With regard to internal decisions, sensor nodes generally perform one of three operations: sensing, processing, or transmission. Column 9, *Sense* indicates if the decision is whether a sensor node should take a measurement or not. Column 10, *Transmit* indicates if the decision is whether data should be transmitted or not. Interestingly, the processing of data was not a major concern in the use cases, which is why it is not a separate column.

C. VoI Assessment Properties

We identified the following properties that characterize VoI assessment in our review.

1) *Unit of Vol*: All use cases model VoI as a positive amount because new observations will only enhance knowledge. The unit can be linked to the one for the utility function. It may be a concrete unit like energy [12], communication channel fees [47], or money [10]. When VoI is valued in monetary terms, it is commonly known as the *economic VoI* as described in section IV. In most use cases we studied, VoI is not given an explicit unit.

2) *Stochasticity*: The stochasticity (column 12 in Tables I and II) describes whether the VoI is calculated using probabilistic or deterministic methods. Zöllner *et al.* [66] discuss how the two types of models differ. The deterministic model can be valued and monetized. In contrast, the probabilistic model cannot be directly determined because it

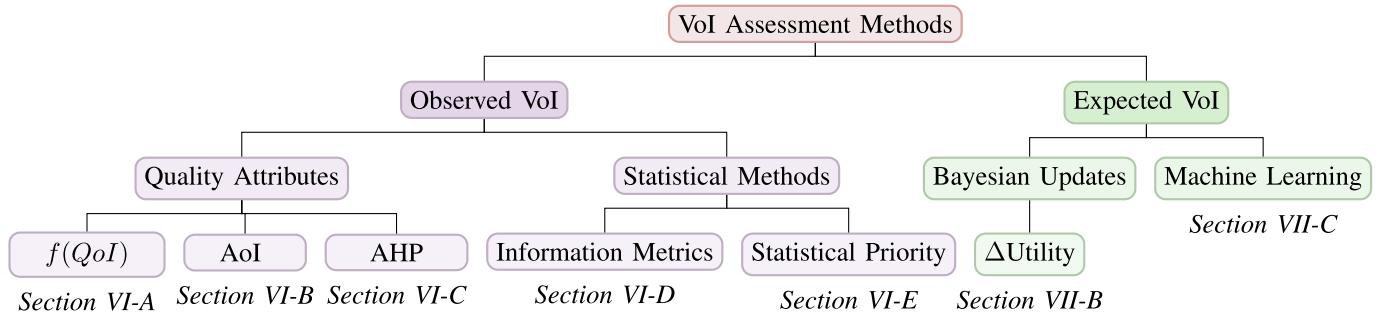


Fig. 4. Overview of value of information assessment methods in WSNs.

depends on many factors or is merely subject to uncertainties. Probabilistic methods seek to model uncertainties around the system and information. In addition, assessing the estimated information that was not previously collected will result in greater uncertainty than the information that has already been collected.

3) *Observed Vs. Expected VoI*: A major distinction in assessment methods regards *when* the VoI is calculated. The *observed* VoI applies to an information item that is already measured, where the information item itself can be input to the VoI assessment process. On the other hand, the *expected* VoI estimates the VoI of an information item that we have yet to obtain. Fig. 4 shows an overview of the different VoI types and assessment methods, where the first distinction is based on this criterion. In the following, we will refer to the latter always as *expected* VoI, whereas observed VoI is referred to as simply *VoI*. We will further elaborate on expected VoI in Section VII.

4) *User Influence*: VoI assessment methods can be *objective* or *subjective*, as indicated in column 13. *Objective* approaches concentrate on the intrinsic attributes of the information object and can usually be calculated without additional context or user-specific information. In contrast, *subjective* approaches take the utility for individual users into consideration. In most cases we investigated, VoI was evaluated on attributes that concern the internal organization of systems, and are hence objective. We identified only two use cases that take explicit account of the user's perspective.

5) *Assessment Time Horizon*: With regard to the time horizon for the VoI assessment, we can distinguish two types of approaches for VoI: *Myopic* methods assess the information sequence one step at a time [67], whereas *non-myopic* methods evaluate information sequentially [68] or make sequential decisions [69]. We did not identify any non-myopic approaches in the studied use cases. Frazier *et al.* [70] discuss the non-myopic VoI that can be used in sequential information gathering to perform adaptive sampling. However, they argue that non-myopic methods often lead to non-feasible solutions and can be hard to evaluate.

6) *VoI Assessment Method*: Finally, column 11 in Tables I and II describes the specific methods used to calculate VoI. Giordani *et al.* [71] categorize VoI valuation methods into four categories: *Heuristic* approaches [72] that apply greedy methods and exhaustive searches; *Adaptive* approaches [59] which exploit feedback from users to refine the VoI

assessment; The use of *machine learning* [13] to predict the VoI; and *Analytical* approaches which apply well-defined mathematical models to assign the VoI. Our study shows that most of the approaches used in WSNs fall under the analytical category. Approaches marked with $f(QoI)$ derive the VoI from quality attributes of the data, discussed in Section VI-A. Approaches marked with *AoI* base the VoI on the timeliness of the data, discussed in Section VI-B. Approaches marked with *AHP* use the Analytical Hierarchy Process to systematically combine VoI from QoI properties, discussed in Section VI-C. Approaches marked with *KL* use information metrics such as the KL-divergence for VoI calculation, discussed in Section VI-D. Approaches marked with $\Delta Utility$ use information value theory, discussed in Section VII-B.

VI. OBSERVED VALUE OF INFORMATION

The analytical methods described in the following have in common that they assess an existing information item, i.e., they assess the *observed* VoI.

A. Quality Attributes of Information

Some recent studies in the literature, such as [73], do not differentiate between VoI and Quality of Information (QoI), which is defined by Sachidananda *et al.* [6] as “*the user's perceived quality towards the information.*” However, Geyik *et al.* [74] distinguish between VoI and QoI, and Bisdikian *et al.* [56] introduce a taxonomy for both QoI and VoI attributes. Both consider QoI as an objective measure of the information utility which can be determined from the information object only. In contrast, they consider VoI as a more subjective measure that conducts an assessment of the information utility in relation to an end user. Accordingly, we find a number of approaches that base their VoI assessment on QoI attributes.

QoI attributes belong primarily to the objective category, since they can often be calculated from the attributes of the information object alone. We observe that many approaches base their VoI assessment mainly on QoI parameters regardless of individual users. However, the value of an information object to a user is indirectly taken into account by selecting the relevant quality attributes and combining them together. This means that despite the objectivity of the metrics employed, their selection may be subjective or based on empirical considerations.

Many attributes of information quality have been studied in the literature, for example, in Rogova and Bosse [75] with an emphasis on attributes of information quality from the perspective of the information sink. Tortonesi *et al.* [42] assess the information objects for each user request according to four attributes: application priority, number of requests, timeliness and proximity.

Below we provide examples of use cases where QoI attributes were used to estimate the value of the information object. The following attributes describe the information based on its content:

- **Relevance** judges the information based on the context provided in the initial request for information. For example, Han *et al.* [20] define *relevance* as the correlation between the signal requested by the application and the signal measured by the sensor. Relevance includes spatiotemporal correlation as well as the completeness of the information.
- **Proximity** has been used in many applications [27], [33], [34], [37]. In fog computing applications, the proximity of the request is one attribute for information valuing. Also in habitat monitoring applications, the proximity of the event source to the sensor is an important factor in assessing the information.
- **Timeliness** describes the freshness of information. Sinha and Roy [76] view it as an attempt to reduce staleness. This aspect of information is of such significance that it is also referred to as *Age of Information* (AoI), and treated separately in Section VI-B. AoI indicates the extent to which data are available in a timely manner [77]. Timeliness is often used combined with other information attributes. Duan *et al.* [16], for instance, evaluate information based on timeliness and energy load balancing. Xia *et al.* [17] assess information by timeliness and importance.

The following are attributes that describe the information with regard to the application in which the information will be used.

- **Importance** describes the importance of the information for the purposes of the application [17], [18], [20], [25], [29], [31]. In many use cases in the literature, importance has been used in combination with timeliness attributes. Cheng and Li [78] define the importance level of the data as the difference from the mean. They assumed a normal distribution, and then the data position in the normal distribution defines its significance. This definition assumes that the uniqueness of the data correlates with its importance.
- **Concentration** describes the amount of information duplication received by the same sink node or cluster head [20]. In some cases, receiving the same information from multiple sources may indicate its significance, but it may also decrease its value due to duplication, depending on the application.
- **Popularity** measures the number of received requests for the information from different users [35]. The more popular the information object, the more valuable it is.

In an application context with n information quality attributes IQ , the VoI can then be calculated as a linear combination of the individual attributes:

$$VoI_{\{QoI\}} = \alpha_1 IQ_1 + \alpha_2 IQ_2 + \dots + \alpha_n IQ_n. \quad (1)$$

Al-Turjman [35], for instance, determines VoI by combining the total delay (IQ_1), time-to-live (IQ_2) and the popularity of the information packet (IQ_3).

Yan *et al.* [25] combine AoI with the importance of an information object. They explore the tradeoff between the importance (IQ_1) and timeliness of information (IQ_2) by introducing a tradeoff factor β for an event k ,

$$VoI_{\{QoI^*\}}^k = \beta_k IQ_1^k + (1 - \beta_k) IQ_2^k, \quad (2)$$

where β_k is the trade-off factor associated with the event's importance I_k . This allows measurements about an important event k to keep a high value even if they are collected by the sink at a late time. A formula similar to (2) is used in [16], [18], [25]. A modified formula is used in [20], where IQ_2 represents the information concentration along with the timeliness.

B. Age of Information

Age of information (AoI) refers to a category of techniques that emphasize time as a factor for the value of an information item [16], [19], [27], [29], [33], [79]–[81], implying that the value of an information item decreases with time. Most approaches in this category combine a base value V_{max} with a decay function $f(t, t_0)$, where an information object generated at time t_0 has value V_{max} which then decays over time. Most commonly used are exponential decay functions [19], [24], [32]. At time t , the VoI can for instance be expressed as

$$VoI_{\{AoI_{exp}\}} = V_{max} e^{-\gamma(t-t_0)} \quad t > t_0. \quad (3)$$

The factor γ affects how fast the value decays. Some approaches like Chang *et al.* [19] or Zou *et al.* [80] additionally set the value to zero after some deadline or maximum time-to-live t_{max} . However, in complex systems with complex dynamics, it is difficult to set a deadline for information decay [27]. There are also approaches that define no decay (corresponding to $\gamma = 0$). Instead the value stays constant for some time, but drops to zero after a deadline [82]:

$$VoI_{\{AoI_{nD}\}} = \begin{cases} V_{max}, & t < t_{max}, \\ 0, & t \geq t_{max}. \end{cases} \quad (4)$$

Further, Gjanci *et al.* [26] explore two types of decay to plan paths for underwater vehicles: exponential decay and no-decay. When the event is first observed, the sensor node adds information about the decay type and the urgency of the event to the data packet of the event. Additionally, they used two types of models: *uniform* and *heterogeneous*. In the uniform model, all information items decay with the same decay pattern, either exponentially or with no decay. In the heterogeneous model, half of the information items decay with exponential decay and the other half have no decay. To ensure a high total delivered VoI to the base station at the surface, the AUV visits first nodes with exponential decay, then nodes with

no-decay. Zou *et al.* [80] define a linear AoI decay function for packets in a status update system with various initial values for V_{max} ,

$$VoI_{\{AoI_L\}} = V_{max} - \frac{V_{max}}{t_{max}} t. \quad (5)$$

Some authors like Chang *et al.* [19] select a constant base value V_{max} . This implies that the value of each information object is initially the same and then depends on the age of the information object. Such methods assess acquisition time only, and are hence limited to one dimension of the information classes while they fail to assess the others.

In contrast to this objective form of AoI, other approaches choose values for V_{max} depending on the information object and the application. In these approaches, AoI is combined with other techniques to determine or assign an information value. Depending on how V_{max} is determined, AoI can hence also take subjective characteristics into consideration. Xu *et al.* [30] compute V_{max} for event detection in an animal monitoring network based on domain-specific attributes like animal type (IQ_1), detection credibility (IQ_2), duration of the detected event (IQ_3), and the distance to the animal (IQ_4),

$$V_{max} = IQ_1 \times IQ_2 \times IQ_3 \times IQ_4. \quad (6)$$

A similar formula for VoI is used in [37] in the context of fog computing. In addition to AoI, the information attributes used are a service-dependent parameter (IQ_1), the priority of the fog service (IQ_2), number of requests for the fog service (IQ_3), and the proximity relevance (IQ_4).

Khan *et al.* [21] optimize the routes of underwater vehicles to collect data from sensor nodes. The V_{max} considered in their work is of a categorical nature. Moreover, a different V_{max} is assigned depending on whether a sensor is located within a hotspot or not.

$$V_{max} = \begin{cases} A_1, & \text{for normal,} \\ A_2, & \text{for hotspot,} \end{cases} \quad \text{where } A_1 < A_2. \quad (7)$$

Giordani *et al.* [27] use AoI in vehicular networks in combination with other elements like proximity and expected camera image quality. They combine these elements using AHP (described in Section VI-C).

In update systems, VoI consists of two factors, according to Hribar *et al.* [83]. The first is the age of information update (AoIU), which is the time from the last received information update for the same status. The second factor is the correlation between the information sources.

The value of an information item at the moment it is acquired is always higher than the value after being transmitted as a data digest due to two factors: urgency and summarizability. Urgency is another way to refer to AoI whereas summarizability indicates how replacing the initial data by a digest affects its value and mainly depends on the data structure [58].

Singh *et al.* [84] concluded their work by stating that minimizing the AoI does not necessarily maximize the performance. Indeed, methods that use AoI as a representation of the VoI have a valid point. However, it is an incomplete point of view, because it does not take into account the various quality

attributes of the information. In time-insensitive information systems, AoI is an impractical measure of the value of the information.

C. Analytic Hierarchy Process (AHP)

We have seen above that various criteria can be used to assess the value of an information object. To make this process more systematic, Bisdikian *et al.* [56] propose the use of the Analytic Hierarchy Process (AHP) within WSNs to derive VoI from QoI attributes. AHP was introduced by Saaty [85] as a general framework for decision-making in the presence of multiple criteria. Using this technique, a user first rates the importance of criteria in pairs. These pairwise comparisons are then arranged in a matrix, from which a total weighting of the criteria can be calculated. The approach also assigns a consistency score to the matrix that shows if pairwise importances are consistent or if they contradict each other. Using a sensitivity analysis, the impact of the weights on the decision can be studied.

Within WSNs, AHP is used, for instance, by Giordani *et al.* [27] in the context of vehicular networks to combine different QoI attributes for an overall VoI,

$$VoI_{\{AHP\}} = \sum_{\forall a} (w_a \times v_a), \quad (8)$$

where w_a is the attribute weight for each conditional VoI v_a corresponding to the attribute a . Similarly, AHP is used to structure the decisions related to the routing of information objects along a path in the context of fog computing [35] and environmental monitoring [11]. Here, AHP is used to find what the authors call an *effective QoI* based on latency, reliability and throughput. It is evaluated at each network node to determine the next hop.

AHP can take any attribute as input, and can therefore account for both subjective and objective criteria [56]. However, AHP still requires subjective judgments from experts and engineers to set the relative weights. So, albeit the method adds transparency and consistency to the process, it still implies a certain degree of arbitrariness, as Giordani *et al.* [27] point out.

D. Information Metrics

Information metrics evaluate the VoI by measuring the amount of information contained in the observations. Information metrics provide the probabilistic representation of VoI to quantify the reduction of uncertainty in the actions taken and for modeling the environment. Following a Bayesian approach, new observations update the prior belief about the probability distribution of the environmental model. Therefore, the difference between the prior and posterior probabilities can be used to represent the information gain [55]. We found three information metrics that quantify the amount of information based on this intuitive principle.

1) *Kullback-Leibler Divergence*: This metric, also known as *relative entropy* or just *KL-divergence*, was first introduced by Kullback and Leibler [86]. KL-divergence is a measure of how one density function is different from another. For a

random variable x , if an information object x_i changes our prior knowledge $f_{prior}(x)$ to the posterior knowledge $f_{post}(x)$, the KL divergence-based VoI from x_i can be written as

$$VoI_{KL}(f_{post}(x)||f_{prior}(x)) = \int_{-\infty}^{\infty} f_{post}(x) \log \frac{f_{post}(x)}{f_{prior}(x)} dx. \quad (9)$$

In the domain of vehicular networking, Higuchi *et al.* [28] use the information relative entropy as a way to value the information. The sending vehicle uses the KL-divergence to anticipate the difference in the knowledge of the receiving vehicle after receiving the information. In this use case, $f_{prior}(x)$ is the knowledge of the receiving vehicle, and the $f_{post}(x)$ is the estimated posterior knowledge of the receiving vehicle, from the sending vehicle's vantage point.

Padhy *et al.* [55] used the KL-divergence to assess the value of an observation compared to the prediction of the next observation in a linear Bayesian regression model. In this use case, $f_{prior}(x)$ is the prior distribution for estimating the next observation, and the $f_{post}(x)$ represents the posterior distribution for the next observation. Only data observations with a KL-divergence above a certain threshold are collected to improve the prediction model. Although Zhang *et al.* [12] did not elaborate on their prior and posterior functions, they used the KL divergence-based VoI for content selection.

2) *Fisher Information*: Fisher [87] uses the variance of the score as an information measure. In statistics, the *score* (also known as the *informant*) is the gradient of the logarithmic likelihood function [88]. Fisher information is the curvature of the KL divergence [89]. Therefore, measuring one of the two information metrics will be sufficient to obtain the other.

Assuming that the random variable x is carrying information about an unknown parameter θ , and that $f_{post}(x)$ is parameterized over θ_1 and $f_{prior}(x)$ over θ_2 , we can write the Fisher information-based VoI as the following:

$$VoI_{FI} = \frac{\partial^2}{\partial \theta_1 \partial \theta_2} VoI_{KL}. \quad (10)$$

Kho *et al.* [54] quantify the uncertainty in the distribution of an environmental variable using the mean Fisher information on the posterior predictive distribution of that variable. They follow what we call a *model-in-the-loop* approach, further explained in Section VII-C.

3) *Mutual Information*: Mutual information measures the amount of shared information between two variables. For two random variables x and y , their mutual information is the KL-divergence between their joint distribution $P(x, y)$ and the product of their marginal distributions $P(x)$ and $P(y)$ [90]:

$$VoI_{MI} = VoI_{KL}(P(x, y)||P(x)P(y)). \quad (11)$$

It measures the uncertainty reduction in one of the variables if the other is known. Kadambe and Daniell [91] used mutual information as a metric for the fusion of sensor data by comparing the mutual information from two sensors, and conditioning on the prior knowledge of the sink. Then sensors with observations with high VoI_{MI} are chosen.

E. Other Statistical Techniques

Mostafa and Gadallah [92] introduced statistical priority (SP) methods in the scenarios of machine-to-machine communications. SP is a quantification of VoI used to prioritize important information characterized by high VoI, and similar to other VoI methods, it is application-dependent. They presented SP-based VoI in three use cases: environmental monitoring, video data, and alarm data. In environmental monitoring, where sensors monitor, for instance temperature, humidity, or luminosity, the methods used are *threshold*, *data similarity*, and *trend similarity*.

a) *Threshold*: Environmental data can be of higher value if it exceeds a threshold compared to data inside the threshold boundaries. Therefore, SP-based VoI is an offset from a case-specific threshold.

b) *Data similarity and trend similarity*: Statistically different data from previously measured data are considered to have great value. Data similarity methods examine the temporal relationship of observations, then reward the uniqueness of value and punish duplications. Here SP-based VoI for a data point is its difference from the previous data point. Further, a constant trend with an increase or a decrease can be more valuable than oscillating values with small changes around an average value. In trend similarity, SP-based VoI is the degree of the trend matching.

c) *2-D frame correlation*: Video sensing data can be collected from multimedia WSNs. Camera nodes are used in numerous applications, such as animal surveillance. Such data require high data rates and low delays. 2-D frame correlation is used as an SP-based VoI method for video data.

Video sensing data are assessed frame by frame. A frame can be of high value if it is significantly different from the ones before it. A surveillance camera deployed for animal monitoring will carry useful information when the frames are different, which might indicate the detection of a moving animal. Statistical similarity measures such as correlation can be used. A 2-D time autocorrelation can be used between the video frame at the current time, and the video frame from the previous sensing cycle.

d) *Alarm data*: Alarm data are used to push information about the event occurrence or an abnormal condition detection. An example is a fire detection application. Alarm data are time-sensitive by nature, hence they should be prioritized over other types of data during a resource allocation task. In the SP model by Mostafa and Gadallah [92] all alarm data are assigned the highest priority in the system. A simple alarm system can be seen as a two-event detection system: activate alarm or deactivate alarm. Assuming the simple case, they assigned the highest VoI to the active alarm and lowest otherwise. Bhuiyan *et al.* [3] presented *e-sampling*, an autonomous adaptive sampling algorithm based on event detection. Each sensor node switches between high and low sampling intervals, the default is low sampling intervals. When an event is detected, the sensor nodes temporarily switch to a high sensing rate. The sending interval will be marked as important and its data are described as *interesting data*.

VII. EXPECTED VALUE OF INFORMATION

Most of the techniques above have in common that they perform VoI assessment on *observed* information. Since considerable resources may be involved in obtaining the information items, it would be beneficial to assess their value *before* spending the energy to obtain them in the first place. This family of approaches is called *Expected Value of Information* (EVoI) [38]. EVoI is similar to the prediction-model-based data reduction methods [93], but with the difference that it does not try to predict the measurement value, just how *valuable* knowing this value is.

Tables I and II mark use cases that utilize EVoI in column 11. Given that the analytical methods from above require data at hand, it is natural that most use cases employing EVoI utilize probabilistic methods (col. 12), especially the information value theory. Before we explore these methods, we will first provide an overview of EVoI use cases.

A. Application Use Cases for Expected VoI

In structural health monitoring, EVoI is used as an optimality criterion. Particularly, VoI is used to deal with a tradeoff between the amount of data collected for the monitoring task and the cost of deployments for the monitoring sensors. Cantero-Chinchilla *et al.* [9] used this optimality criterion to determine the number of ultrasonic sensors to deploy for detecting the places with the highest risk of damage in a construction place. This decision happens at design time when there are not yet any experimental data available. Consequently, VoI expectations are used and different sources of uncertainty are considered.

In the domain of vehicular networks, Higuchi *et al.* [28] propose a value anticipation networking model, in which each vehicle anticipates VoI for the data packet from the perspective of the receiving vehicle. They used $VoI_{\{KL\}}$ as in (9). Despite the fact that the actual VoI will only be known by the receiving vehicle, the estimate of the sending vehicle is quite accurate. The value anticipation is based on a value model specific to the application, the vehicles' prior knowledge of the road, the network and connected vehicles. Data packets with high EVoI will be prioritized over those with low EVoI when there is network congestion. This model leads to a better packet reception ratio because it reduces the insignificant data load of the network. Similarly, Giordani *et al.* [27] used $VoI_{\{AHP\}}$ as in (8) in a vehicle-to-vehicle transmission scheduler to select data with high EVoI.

We discussed path planning for mobile sinks in Section III. Most of these use cases work with EVoI. Mobile sensor networks require two important decisions regarding sensor mobility: a) *where to sample*, that means, finding the best location to sample; b) *which sensor to move* to collect the measurements. Ballari *et al.* [4] addressed these two decisions using EVoI and mobility constraints. EVoI was used to inform the first decision, *where to sample*, in a way that maximizes the utility of the system. The EVoI is used to assess the relevance of the observations for improving the phenomenon model before obtaining the observations. The EVoI in this use case is given as the expected reduction in the cost of making wrong

predictions about the phenomena. Mobility constraints helped in informing the second decision, that means which sensor to move. Similarly, in Gjanci *et al.* [26], a UAV receives a signal from a sensor when an event happens, upon which it will estimate its EVoI. Based on this expected value, it can then update its priorities of nodes to visit and accordingly update its path.

In a coal production application, Yüksel *et al.* [94] use VoI to understand the utility gain from adding online sensor readings to a model that predicts the ash percentage. VoI is defined in terms of the costs of deviating from the application targeted quality, and calculated as the ash percentage. For an intruder tracking system, Turgut and Bölöni [95] proposed the Information Value-Energy tradeoff (IVE) protocol. Sensor nodes assess their sensed information based on the expected contribution to enhancing the model of the environment. The protocol restricts the transmission by sensor nodes to observations with a higher EVoI than a defined threshold.

B. Information Value Theory

Howard [5] defines VoI as the profit obtained by hiring a clairvoyant that can give perfect information c_x about a variable of interest x . Hence the VoI for a perfect information c_x from a clairvoyant is the difference between the expected profit v obtained with and without the clairvoyance c_x ,

$$VoI_{\{\Delta Profit\}} = \mathbb{E}(v|c_x \zeta) - \mathbb{E}(v|\zeta), \quad (12)$$

where ζ signifies the knowledge the system already has. Moskowitz *et al.* [96] conclude that information about two variables gives higher VoI compared to the sum of the VoI given information about each of the variables separately.

Applying Howard's VoI definition to WSNs translates to the difference in the system utility achieved through observing additional information. This means the difference between the expectation of the posterior utility function $\mathbb{E}(f_{\text{post}})$ and prior utility function $\mathbb{E}(f_{\text{prior}})$

$$VoI_{\{\Delta Utility\}} = \mathbb{E}(f_{\text{post}}) - \mathbb{E}(f_{\text{prior}}). \quad (13)$$

In the following paragraphs, we give examples of such utility-based VoI calculations $VoI_{\{\Delta Utility\}}$.

Ballari *et al.* [4] propose the implementation of EVoI as the difference in the cost of wrong predictions between the prior and posterior predictions. A smaller number of wrong predictions for unobserved locations indicate a reduced cost of wrong predictions due to observing more information at that location.

Malings and Pozzi [10], [97] define VoI in the task of sensor placement as the difference between the prior and posterior expected losses under different information gathering schemes. Hence, VoI helps choosing the optimal set of measurement locations and schedule that provide the lowest expected loss. The loss function in this use case is a general loss function which includes among many other aspects operational cost and reduction of performance. Cantero-Chinchilla *et al.* [9] define VoI in terms of the maximum benefit gain from adopting a sensor placement configuration, as such f_{post} is the maximum benefit gained with the information and f_{prior} is the maximum benefit gained without the information.

In the economics of the Internet of Things Niyato *et al.* [60] define VoI as the difference between the payoff of the decision before (f_{prior}) and after (f_{post}) having the information.

Since the calculations of utility-based VoI can be computationally demanding, approximation techniques may be needed. For instance, Eidsvik *et al.* [98] explore simulation-regression approximation in the context of geophysical data.

C. Expected VoI Prediction Using Machine Learning

Since the expected value is an estimation that can be based on experience with historically observed values, the assessment of expected VoI can be data-driven, and there exist a few approaches that utilize machine learning techniques for its prediction.

Lore *et al.* [13] developed a deep learning model that estimates VoI in the context of indoor mobile agents. The model uses measurement from sensors and observations from humans who provide information in response to queries. They trained a neural network model that predicts the VoI given the state and action map of the moving agent. They defined VoI based on the utility of receiving observations as a result of querying sensor nodes, to be the difference between the expected utility before (f_{prior}) and after (f_{post}) obtaining the observations.

To prevent scheduling problems, Lore *et al.* [7] highlight the possibility of using machine learning models to predict AoI, so that data with lower age can be prioritized.

In addition, Giordani *et al.* [99] suggest the use of generative deep neural networks to learn value scores based on a mutual information metric, but they do not provide implementation details.

VIII. ADAPTIVE VOI ASSESSMENT METHODS

Many of the studied use cases involve some form of adaptation, so that either VoI calculation or its interpretation also depend on another, dynamic context and not only the information item itself. In the following we discuss different techniques, we found to realize *adaptive* VoI assessment.

The analytical assessment methods in Section VI can be combined with a variable VoI threshold to provide some form of adaptation. Here decisions made in the system depend on VoI threshold levels. For instance, Zhang *et al.* [12] continuously update the VoI threshold that controls the remaining energy budget for a sensor node.

Whereas such approaches only adapt the necessary VoI threshold to perform an action, hence how the VoI is *interpreted*, other methods also adapt how the VoI is *calculated*, that means, have a direct effect on the VoI value. AHP models (Section VI-C), can also be used in an adaptive form. For instance, the work of [100] adapts the weights used in the AHP calculation, so that it calculates a single QoI metric from dynamic weights.

In adaptive systems, there is often a feedback loop which updates system parameters at runtime. In this respect, we identified two kinds of loops for adaptive VoI assessment, namely *human-in-the-loop* and *model-in-the-loop*, explained in the following.

A. Human-in-the-Loop

Users can be directly part of the VoI assessment process and hence adapt its calculation. In [59] user decisions update the VoI assessment results in the domain of intruder tracking. In this system, the user or a decision agent can look at the type of the detected intruder. As a result, the user can increase the threat level of the intruder leading to an increase in the value of the information received about it.

Although outside the realm of WSNs, Kamar and Horvitz [51] present another example where users are directly involved in the VoI assessment. They propose a method that is used for learning the name of a galaxy from a set of images. The data is manually labeled by a group of voters, where the majority vote decides the right answer. Then the prediction model is tested against the voters. However, instead of using all the voters' data, VoI helps to select the best set of images.

Poltronieri *et al.* [33] proposed a user-specific VoI model. They added a utility component that assesses the utility for the exchanged sensing message for each user. This custom definition of user-by-user utility has made their evaluation more subjective. Similarly, Al-Turjman [35] proposed a VoI assessment model in software-defined networks, which can be customized based on user request and traffic type. It should be noted that the distinction between objective and subjective can be subtle; we can argue that some of the objective approaches involve subjective considerations when determining the weights of parameters for their specific assessment methods.

B. Model-in-the-Loop

In many WSN and IoT applications, sensor data is used to create machine-learning models that represent certain environmental phenomena, often with the intention to predict future values or interpolate for missing measurements. Models are built based on training data that originates from the sensors, and hence there is a tradeoff between the amount of training data versus the operational cost of the system to obtain it.

Since the environmental phenomena are typically stochastic in nature, not all training samples are equally relevant for the quality of the model. This motivates approaches that base their policies of when to collect training data on the uncertainty of the model. The VoI of an information item can hence be defined based on how useful it is for the quality of a specific machine learning model. As these models learn over time, the value of information items adapt based on the knowledge of the machine learning model under construction. We call this pattern *model-in-the-loop*.

Kho *et al.* [54] use Fisher information (see Section VI-D.2) as a way to determine when a sensor should take measurements. The goal of the application is to provide training data for a Gaussian process for locally fine-grained tidal height prediction in coastal areas. The Gaussian process provides a probabilistic prediction of the phenomenon. The sensors place their measurements so that the Fisher information over the prediction of the Gaussian process model is maximized. Therefore, the system estimates at which sampling points the training data potentially has the highest value, i.e., the system

indirectly estimates the expected VoI. The system hence places measurements where the prediction model for the phenomenon is most uncertain.

Whereas Kho *et al.* [54] use a heuristic to determine the optimal sampling points, Murad *et al.* [101] use reinforcement learning (RL) to determine the best times when a sensor should sample. As usual in RL, a reward function is used to train an agent. Here, Fisher information is used to reward the agent to sample at points when an environmental model (again a Gaussian process) exposes high uncertainty. Indirectly this means that agents learn when the expected VoI is high and place the limited number of possible measurements into these intervals.

Reinforcement learning is also used in other approaches, such as [19], [20], [29], which use VoI as part of their reward function, alongside other components such as AUV power or residual energy in the sensor node. In [29] the task is to plan the optimal path of the AUV, which makes it possible to collect data with a high VoI using a low energy consumption.

IX. DISCUSSION

From the papers surveyed, we observe that most approaches apply VoI to optimize the *internal* operation of systems. This focus is expected, since limited resources are a major design constraint in WSNs and IoT. VoI is hence used to filter redundant data that would not contribute to the utility of the system. In the case of the expected VoI, the systems are even more frugal and try to avoid spending the effort to acquire data through measurements or retrieval in the first place.

Apart from filtering or prioritization, VoI is used in WSNs as a metric used in tradeoffs to plan the allocation of system resources. Examples of such tradeoffs are cost versus timeliness [81], processing speed versus accuracy [37], cost versus amount of information [9], or QoS requirements versus energy consumption [34], all of which are effectively tradeoffs between system utility and internal or external system costs.

Quantifying the effect of VoI on a general level is difficult as cases vary and comparison baselines are not obvious. However, we believe that taking VoI into account is a significant step towards better resource utilization, especially compared to solutions that just sense without any awareness of the utility of the collected data. For instance, Zhang *et al.* [12] experimented with reducing the sampling rate for an environmental variable, luminous intensity in their case. Their results show that using only 8% of the total energy was sufficient to obtain 95% of the original VoI.

As shown in Section III, VoI has been applied in many domains. We observe that it depends largely on the specific use case and application to determine what signifies *valuable* observations that are worth measuring, processing and forwarding. This is challenging for the design of such applications, as a specific solution must be developed for each use case. Here, VoI can serve, similarly to the concept of QoS, as a more generic concept applied across several domains. However, a single definition for VoI that fits all use cases is not available. There are significantly different approaches towards VoI (observed vs. expected, deterministic vs. probabilistic, adaptive vs. static), and the utility of an application is difficult

to capture formally in the first place. Instead, many approaches define VoI based on proxy metrics, such as QoI parameters or statistical measures, as explained in Section VI. Once this step is taken, there is a wide range of generic assessment methods that we described and that can be parameterized or adapted to a wider range of use cases.

One of the challenges in existing and future IoT systems is their heterogeneity, that means, the diversity of devices, operation environments and usage requirements that are different to each device instance. Optimizing operations require handling this heterogeneity. Due to their scale, this implies autonomous adaptation, as a manual adaptation of IoT devices would be unfeasible. To avoid over-provisioning and inefficient operation on the one side, but also failure due to insufficient resources on the other side, autonomy of these systems implies that they are aware of their resources and their provided utility. Being able to make tradeoffs can avoid or mitigate failure situations and optimize operation, which ultimately affects the cost and sustainability of these systems.

In the future, we expect an increasing significance and more opportunities for the application of VoI. There is a rapid development of energy-efficient machine learning also for constrained devices, which also become computationally more and more powerful. This may increase the number of use cases in which it is economical to spend more computational effort to decide if a certain measurement should be taken in the first place. This is why we see the application of expected VoI in resource-constrained networks as especially intriguing. Here we expect that machine-learning-based approaches to estimate VoI as outlined in Section VII-C are an interesting area for further development.

X. LESSONS LEARNED: VOI IN WSN APPLICATIONS

In this section, we present a summary of the lessons learned from the review of VoI in IoT applications with respect to the design and implementation of autonomous adaptive sensing systems. The first step in implementing VoI-based sensing systems is to clearly define the system's utility and its available resources. Systems where resources are limited often require a trade-off between goals and resources.

In addition, one must choose between the observed or the expected value of information. The observed VoI may contribute to a reduction in transmission costs, whereas EVoI makes it possible to reduce both the sensing and the transmission costs. Moreover, using the observed VoI, machine learning models can be trained to predict the expected VoI for measurements which are not yet observed.

Secondly, a choice of VoI approach for prioritizing information in the sensing system must be chosen. Each of the analytical methods reviewed in Section VI presents its own advantages and disadvantages, depending on the context of the application. For example, AoI can focus on the timeliness of information, but fails in non-real-time scenarios. AHP is suited for multi-objective sensing systems. In addition, information metrics are purely objective methods without any user requirements being highlighted. However, the information value theory offers a more subjective alternative to implementing VoI. A high-level implementation choice is to integrate users into

the design loop by implementing a VoI-based sensing metric to measure the quality of the sensing system.

XI. CONCLUSION

In this literature review, we studied the application of the concept of the Value of Information (VoI) within WSN and IoT applications. We presented the various applications, definitions and techniques employed in a wide range of domains. We observed that the approach towards VoI and its utilization varies with each use case and the concept is applied in an application-specific manner. Yet we managed to identify different VoI methods and describe common approaches used for its calculation, which is useful as a guideline for how to integrate VoI into new applications.

There are various approaches to make WSN and IoT systems more efficient in their operation, and by that cheaper and more sustainable, or feasible at all. Whereas all of these approaches can and should be followed, limited resources will remain one of the main design constraints in these systems. In this context, VoI is the concept that generalizes the idea of not spending effort on collecting, processing and forwarding data of little value, and hence is at the center of the overall optimization problem inherent to IoT and WSN.

REFERENCES

- [1] M. Kocakulak and I. Butun, "An overview of wireless sensor networks towards Internet of Things," in *Proc. IEEE 7th Annu. Comput. Commun. Workshop Conf. (CCWC)*, Jan. 2017, pp. 1–6.
- [2] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," *Comput. Netw.*, vol. 38, no. 4, pp. 393–422, 2002.
- [3] M. Z. A. Bhuiyan, J. Wu, G. Wang, T. Wang, and M. M. Hassan, "e-sampling: Event-sensitive autonomous adaptive sensing and low-cost monitoring in networked sensing systems," *ACM Trans. Auton. Adapt. Syst.*, vol. 12, no. 1, pp. 1–29, 2017.
- [4] D. Ballari, S. de Bruin, and A. K. Bregt, "Value of information and mobility constraints for sampling with mobile sensors," *Comput. Geosci.*, vol. 49, pp. 102–111, Dec. 2012.
- [5] R. A. Howard, "Information value theory," *IEEE Trans. Syst. Sci. Cybern.*, vol. 2, no. 1, pp. 22–26, Feb. 1966.
- [6] V. Sachidananda, A. Khelil, and N. Suri, "Quality of information in wireless sensor networks: A survey," in *Proc. 15th Int. Conf. Inf. Qual. (ICIQ)*, 2010, pp. 1–15.
- [7] R. D. Yates, Y. Sun, D. R. Brown, S. K. Kaul, E. Modiano, and S. Ulukus, "Age of information: An introduction and survey," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1183–1210, May 2021.
- [8] C. Wohlin, P. Runeson, M. Höst, M. C. Ohlsson, B. Regnell, and A. Wesslén, *Experimentation in Software Engineering*. Berlin, Germany: Springer, 2012, doi: [10.1007/978-3-642-29044-2](https://doi.org/10.1007/978-3-642-29044-2).
- [9] S. Cantero-Chinchilla, J. Chiachío, M. Chiachío, D. Chronopoulos, and A. Jones, "Optimal sensor configuration for ultrasonic guided-wave inspection based on value of information," *Mech. Syst. Signal Process.*, vol. 135, Jan. 2020, Art. no. 106377.
- [10] C. Malings and M. Pozzi, "Value-of-information in spatio-temporal systems: Sensor placement and scheduling," *Rel. Eng. Syst. Saf.*, vol. 172, pp. 45–57, Apr. 2018.
- [11] G. Singh and F. Al-Turjman, "A data delivery framework for cognitive information-centric sensor networks in smart outdoor monitoring," in *Cognitive Sensors and IoT*. Boca Raton, FL, USA: CRC Press, 2017, pp. 107–148.
- [12] J. Zhang, Z. Li, and S. Tang, "Value of information aware opportunistic duty cycling in solar harvesting sensor networks," *IEEE Trans. Ind. Informat.*, vol. 12, no. 1, pp. 348–360, Feb. 2016.
- [13] K. G. Lore, N. Sweet, K. Kumar, N. Ahmed, and S. Sarkar, "Deep value of information estimators for collaborative human-machine information gathering," in *Proc. ACM/IEEE 7th Int. Conf. Cyber-Phys. Syst. (ICCPSS)*, Apr. 2016, pp. 1–10.
- [14] K. Patil and D. Fiems, "The value of information in energy harvesting sensor networks," *Oper. Res. Lett.*, vol. 46, no. 3, pp. 362–366, May 2018.
- [15] K. Patil, K. De Turck, and D. Fiems, "A two-queue model for optimising the value of information in energy-harvesting sensor networks," *Perform. Eval.*, vol. 119, pp. 27–42, Mar. 2018.
- [16] R. Duan, J. Du, C. Jiang, and Y. Ren, "Value-based hierarchical information collection for AUV-enabled internet of underwater things," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 9870–9883, Oct. 2020.
- [17] Z. Xia, J. Du, J. Wang, Y. Ren, G. Li, and B. Zhang, "Contract based information collection in underwater acoustic sensor networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2020, pp. 1–6.
- [18] Z. Zhao, C. Liu, W. Qu, and T. Yu, "An energy efficiency multi-level transmission strategy based on underwater multimodal communication in UWSNs," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Jul. 2020, pp. 1579–1587.
- [19] H. Chang, J. Feng, and C. Duan, "Reinforcement learning-based data forwarding in underwater wireless sensor networks with passive mobility," *Sensors*, vol. 19, no. 2, p. 256, 2019.
- [20] G. Han, Z. Tang, Y. He, J. Jiang, and J. A. Ansere, "District partition-based data collection algorithm with event dynamic competition in underwater acoustic sensor networks," *IEEE Trans. Ind. Informat.*, vol. 15, no. 10, pp. 5755–5764, Oct. 2019.
- [21] F. A. Khan, S. A. Khan, D. Turgut, and L. Boloni, "Greedy path planning for maximizing value of information in underwater sensor networks," in *Proc. 39th Annu. IEEE Conf. Local Comput. Netw. Workshops*, Sep. 2014, pp. 610–615.
- [22] F. A. Khan, S. A. Khan, D. Turgut, and L. Boloni, "Scheduling multiple mobile sinks in underwater sensor networks," in *Proc. IEEE 40th Conf. Local Comput. Netw. (LCN)*, Oct. 2015, pp. 149–156.
- [23] F. A. Khan, S. A. Khan, D. Turgut, and L. Boloni, "Optimizing resurfacing schedules to maximize value of information in UWSNs," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2016, pp. 1–5.
- [24] F. Khan, S. Butt, S. Khan, L. Bölöni, and D. Turgut, "Value of information based data retrieval in UWSNs," *Sensors*, vol. 18, no. 10, p. 3414, Oct. 2018.
- [25] Y. Jing, Y. Xian, X. Luo, and C. Chen, "Energy-efficient data collection over AUV-assisted underwater acoustic sensor network," *IEEE Syst. J.*, vol. 12, no. 4, pp. 3519–3530, Jan. 2018.
- [26] P. Gjanci, C. Petrioli, S. Basagni, C. A. Phillips, L. Bölöni, and D. Turgut, "Path finding for maximum value of information in multimodal underwater wireless sensor networks," *IEEE Trans. Mobile Comput.*, vol. 17, no. 2, pp. 404–418, Feb. 2018.
- [27] M. Giordani, T. Higuchi, A. Zanella, O. Altintas, and M. Zorzi, "A framework to assess value of information in future vehicular networks," in *Proc. 1st ACM MobiHoc Workshop Technol., Models, Protocols Cooperat. Connected Cars (TOP-Cars)*, 2019, pp. 31–36.
- [28] T. Higuchi, M. Giordani, A. Zanella, M. Zorzi, and O. Altintas, "Value-anticipating V2V communications for cooperative perception," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2019, pp. 1947–1952.
- [29] X. Han, W. Yang, M. Li, L. Zhang, F. Yan, and X. Ma, "A trajectory planning algorithm for data collection in UAV-aided wireless sensor networks," in *Proc. IEEE 6th Int. Conf. Comput. Commun. (ICCC)*, Dec. 2020, pp. 846–851.
- [30] J. Xu, G. Solmaz, R. Rahmatizadeh, D. Turgut, and L. Boloni, "Animal monitoring with unmanned aerial vehicle-aided wireless sensor networks," in *Proc. IEEE 40th Conf. Local Comput. Netw. (LCN)*, Oct. 2015, pp. 125–132.
- [31] G. Xu, C.-H. E. C.-H. Ngai, and J. Liu, "Ubiquitous transmission of multimedia sensor data in Internet of Things," *IEEE Internet Things J.*, vol. 5, no. 1, pp. 403–414, Feb. 2018.
- [32] J. Xu, G. Solmaz, R. Rahmatizadeh, L. Boloni, and D. Turgut, "Providing distribution estimation for animal tracking with unmanned aerial vehicles," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2018, pp. 1–6.
- [33] F. Poltronieri, M. Tortonesi, A. Morelli, C. Stefanelli, and N. Suri, "Value of information based optimal service fabric management for fog computing," in *Proc. IEEE/IFIP Netw. Operations Manage. Symp. (NOMS)*, Apr. 2020, pp. 1–9.
- [34] S. Bharti, K. K. Pattanaik, and P. Bellavista, "Value of information based sensor ranking for efficient sensor service allocation in service oriented wireless sensor networks," *IEEE Trans. Emerg. Topics Comput.*, vol. 9, no. 2, pp. 823–838, Apr. 2021.
- [35] F. Al-Turjman, "Fog-based caching in software-defined information-centric networks," *Comput. Electr. Eng.*, vol. 69, pp. 54–67, Jul. 2018.

- [36] M. Govoni, J. Michaelis, A. Morelli, N. Suri, and M. Tortonesi, "Enabling social- and location-aware IoT applications in smart cities," in *Proc. Conf. GOODTECHS, Smart Objects Technol. Smart Good*, Venice, Italy. Cham, Switzerland: Springer, 2016, pp. 305–314, doi: 10.1007/978-3-319-61949-1_32.
- [37] M. Tortonesi, M. Govoni, A. Morelli, G. Riberto, C. Stefanelli, and N. Suri, "Taming the IoT data deluge: An innovative information-centric service model for fog computing applications," *Future Gener. Comput. Syst.*, vol. 93, pp. 888–902, Apr. 2019.
- [38] D. J. Cook, P. Gmytrasiewicz, and L. B. Holder, "Decision-theoretic cooperative sensor planning," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 18, no. 10, pp. 1013–1023, Oct. 1996.
- [39] R. W. Coutinho, A. Boukerche, L. F. Vieira, and A. A. Loureiro, "Underwater wireless sensor networks: A new challenge for topology control-based systems," *ACM Comput. Surv.*, vol. 51, no. 1, pp. 1–36, 2018.
- [40] N. Suri, G. Benincasa, R. Lenzi, M. Tortonesi, C. Stefanelli, and L. Sadler, "Exploring value-of-information-based approaches to support effective communications in tactical networks," *IEEE Commun. Mag.*, vol. 53, no. 10, pp. 39–45, Oct. 2015.
- [41] B. Szymanski, S. Yousaf Shah, S. C. Geyik, S. Das, M. Chhabra, and P. Zerfos, "Market mechanisms for value of information driven resource allocation in sensor networks," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PERCOM Workshops)*, Mar. 2011, pp. 20–25.
- [42] M. Tortonesi, J. Michaelis, A. Morelli, N. Suri, and M. A. Baker, "SPF: An SDN-based middleware solution to mitigate the IoT information explosion," in *Proc. IEEE Symp. Comput. Commun. (ISCC)*, Jun. 2016, pp. 435–442.
- [43] J. Mocnej, W. K. G. Seah, A. Pekar, and I. Zolotova, "Decentralised IoT architecture for efficient resources utilisation," *IFAC-PapersOnLine*, vol. 51, no. 6, pp. 168–173, 2018.
- [44] F. Poltronieri, C. Stefanelli, N. Suri, and M. Tortonesi, "Phileas: A simulation-based approach for the evaluation of value-based fog services," in *Proc. IEEE 23rd Int. Workshop Comput. Aided Modeling Design Commun. Links Netw. (CAMAD)*, Sep. 2018, pp. 1–6.
- [45] K. E. Benson *et al.*, "FireDeX: A prioritized IoT data exchange middleware for emergency response," in *Proc. 19th Int. Middleware Conf.*, 2018, pp. 279–292.
- [46] J. Fernandez-Bes, J. Cid-Sueiro, and A. G. Marques, "An MDP model for censoring in harvesting sensors: Optimal and approximated solutions," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 8, pp. 1717–1729, Aug. 2015.
- [47] A. Mahajan, "Remote estimation over control area networks," in *Proc. IEEE 86th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2017, pp. 1–5.
- [48] T. Soleymani, S. Hirche, and J. S. Baras, "Optimal self-driven sampling for estimation based on value of information," in *Proc. 13th Int. Workshop Discrete Event Syst. (WODES)*, May 2016, pp. 183–188.
- [49] J. M. Keisler, Z. A. Collier, E. Chu, N. Sinatra, and I. Linkov, "Value of information analysis: The state of application," *Environ. Syst. Decisions*, vol. 34, no. 1, pp. 3–23, Mar. 2014.
- [50] J. Eidsvik, T. Mukerji, and D. Bhattacharjya, *Value of Information in the Earth Sciences: Integrating Spatial Modeling and Decision Analysis*. Cambridge, U.K.: Cambridge Univ. Press, 2015.
- [51] E. Kamar and E. Horvitz, "Light at the end of the tunnel: A Monte Carlo approach to computing value of information," in *Proc. Int. Conf. Auto. Agents Multi-Agent Syst.*, 2013, pp. 571–578.
- [52] R. Laxminarayan and M. K. Macauley, *The Value of Information: Methodological Frontiers and New Applications in Environment and Health*. Springer, 2012.
- [53] F. Bian, D. Kempe, and R. Govindan, "Utility based sensor selection," in *Proc. 5th Int. Conf. Inf. Process. Sensor Netw. (IPSN)*, 2006, pp. 11–18.
- [54] J. Kho, A. Rogers, and N. R. Jennings, "Decentralized control of adaptive sampling in wireless sensor networks," *ACM Trans. Sensor Netw.*, vol. 5, no. 3, pp. 1–35, May 2009.
- [55] P. Padhy, R. K. Dash, K. Martinez, and N. R. Jennings, "A utility-based adaptive sensing and multihop communication protocol for wireless sensor networks," *ACM Trans. Sensor Netw.*, vol. 6, no. 3, pp. 1–39, Jun. 2010.
- [56] C. Bisdikian, L. M. Kaplan, and M. B. Srivastava, "On the quality and value of information in sensor networks," *ACM Trans. Sensor Netw.*, vol. 9, no. 4, pp. 1–26, Jul. 2013.
- [57] D. Cansever, "Value of information," in *Proc. IEEE Mil. Commun. Conf. (MILCOM)*, Apr. 2013, pp. 1105–1108.
- [58] L. Boloni, D. Turgut, S. Basagni, and C. Petrioli, "Scheduling data transmissions of underwater sensor nodes for maximizing value of information," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2013, pp. 438–443.
- [59] D. Turgut and L. Boloni, "A pragmatic value-of-information approach for intruder tracking sensor networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, vol. 1, Jun. 2012, pp. 4931–4936.
- [60] D. Niyato, X. Lu, P. Wang, D. I. Kim, and Z. Han, "Economics of Internet of Things: An information market approach," *IEEE Wireless Commun.*, vol. 23, no. 4, pp. 136–145, Aug. 2016.
- [61] S. Tan, C. Jiang, and Y. He, "A research on information value in energy internet based on risk theory," in *Proc. IEEE Conf. Energy Internet Energy Syst. Integr. (EI2)*, Nov. 2017, pp. 1–6.
- [62] L. Bölöni and D. Turgut, "Value of information based scheduling of cloud computing resources," *Future Gener. Comput. Syst.*, vol. 71, pp. 212–220, Jun. 2017.
- [63] D. Turgut and L. Boloni, "Value of information and cost of privacy in the Internet of Things," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 62–66, Sep. 2017.
- [64] S. Chakraborty, K. R. Raghavan, M. B. Srivastava, C. Bisdikian, and L. M. Kaplan, "An obfuscation framework for controlling value of information during sharing," in *Proc. IEEE Stat. Signal Process. Workshop (SSP)*, Aug. 2012, pp. 157–160.
- [65] A. Mayle, N. H. Bidoki, S. Masnadi, L. Boeloeni, and D. Turgut, "Investigating the value of privacy within the Internet of Things," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2017, pp. 1–6.
- [66] S. Zoller, C. Vollmer, M. Wachtel, R. Steinmetz, and A. Reinhardt, "Data filtering for wireless sensor networks using forecasting and value of information," in *Proc. 38th Annu. IEEE Conf. Local Comput. Netw.*, Oct. 2013, pp. 441–449.
- [67] R. Pradhan, S. Bykau, and S. Prabhakar, "Staging user feedback toward rapid conflict resolution in data fusion," in *Proc. ACM Int. Conf. Manage. Data*, May 2017, pp. 603–618.
- [68] A. Krause and C. E. Guestrin, "Near-optimal nonmyopic value of information in graphical models," 2012, *arXiv:1207.1394*.
- [69] L. Burks *et al.*, "Collaborative human-autonomy semantic sensing through structured POMDP planning," *Robot. Auto. Syst.*, vol. 140, Jun. 2021, Art. no. 103753.
- [70] P. I. Frazier, J. Xie, and S. E. Chick, "Value of information methods for pairwise sampling with correlations," in *Proc. Winter Simulation Conf. (WSC)*, Dec. 2011, pp. 3974–3986.
- [71] M. Giordani, A. Zanella, T. Higuchi, O. Altintas, and M. Zorzi, "Investigating value of information in future vehicular communications," in *Proc. IEEE 2nd Connected Automated Vehicles Symp. (CAVS)*, Sep. 2019, pp. 1–5.
- [72] A. Raghavan and J. S. Baras, "Detection of Markov chain models from observed data using binary hypothesis testing and consensus," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 3893–3898, 2017.
- [73] A. S. Arsalaan, H. Nguyen, A. Coyle, and M. Fida, "Quality of information with minimum requirements for emergency communications," *Ad Hoc Netw.*, vol. 111, Feb. 2021, Art. no. 102331.
- [74] S. C. Geyik, S. Y. Shah, B. K. Szymanski, S. Das, and P. Zerfos, "Market mechanisms for resource allocation in pervasive sensor applications," *Pervasive Mobile Comput.*, vol. 8, no. 3, pp. 346–357, Jun. 2012.
- [75] G. L. Rogova and E. Bosse, "Information quality in information fusion," in *Proc. 13th Int. Conf. Inf. Fusion*, Jul. 2010, pp. 1–8.
- [76] D. Sinha and R. Roy, "Optimal scheduling for maximizing information freshness and system performance in industrial cyber-physical systems," *Comput. Commun.*, vol. 169, pp. 33–47, Mar. 2021.
- [77] M. Stawowy, W. Olchowik, A. Rosiński, and T. Dąbrowski, "The analysis and modelling of the quality of information acquired from weather station sensors," *Remote Sens.*, vol. 13, no. 4, p. 693, Feb. 2021.
- [78] C.-F. Cheng and L.-H. Li, "Data gathering problem with the data importance consideration in underwater wireless sensor networks," *J. Netw. Comput. Appl.*, vol. 78, pp. 300–312, Jan. 2017.
- [79] Z. Chen, N. Pappas, E. Bjornson, and E. G. Larsson, "Optimizing information freshness in a multiple access channel with heterogeneous devices," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 456–470, 2021.
- [80] P. Zou, O. Ozel, and S. Subramaniam, "On age and value of information in status update systems," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, May 2020, pp. 1–6.
- [81] K. Patil, K. De Turck, and D. Fiems, "Optimal data collection in wireless sensor networks with correlated energy harvesting," *Ann. Telecommun.*, vol. 74, nos. 5–6, pp. 299–310, Jun. 2019.
- [82] H. M. Gursu and W. Kellerer, "Gains of deadline based discarding (DBD) over lossy wireless sensor networks," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Mar. 2017, pp. 1–6.

- [83] J. Hribar, M. Costa, N. Kaminski, and L. A. DaSilva, "Updating strategies in the Internet of Things by taking advantage of correlated sources," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2017, pp. 1–6.
- [84] R. Singh, G. K. Kamath, and P. R. Kumar, "Optimal information updating based on value of information," in *Proc. 57th Annu. Allerton Conf. Commun., Control, Comput. (Allerton)*, Sep. 2019, pp. 847–854.
- [85] T. L. Saaty, "What is the analytic hierarchy process?" in *Mathematical Models for Decision Support* (NATO ASI Series), vol. 48. Berlin, Germany: Springer, 1988, pp. 109–121, doi: 10.1007/978-3-642-83555-1_5.
- [86] S. Kullback and R. A. Leibler, "On information and sufficiency," *Ann. Math. Statist.*, vol. 22, no. 1, pp. 79–86, 1951.
- [87] R. A. Fisher, "On the mathematical foundations of theoretical statistics," *Philos. Trans. Roy. Soc. London A, Math. Phys. Sci.*, vol. 222, nos. 594–604, pp. 309–368, 1922.
- [88] N. Chentsov. (2011). *Informant. Encyclopedia of Mathematics*. Accessed: Sep. 15, 2021. [Online]. Available: <http://encyclopediamath.org/index.php?title=Informant&oldid=52232>
- [89] C. Gourieroux and A. Monfort, *Statistics and Econometric Models*, vol. 1. Cambridge, U.K.: Cambridge Univ. Press, 1995.
- [90] R. Ince, S. Panzeri, and S. Schultz, "Summary of information theoretic quantities," in *Encyclopedia of Computational Neuroscience*. New York, NY, USA: Springer, 2015, pp. 2924–2928, doi: 10.1007/978-1-4614-7320-6_306-1.
- [91] S. Kadambe and C. Daniell, "Sensor/data fusion based on value of information," in *Proc. 6th Int. Conf. Inf. Fusion*, 2003, pp. 25–32.
- [92] A. E. Mostafa and Y. Gadallah, "A statistical priority-based scheduling metric for M2M communications in LTE networks," *IEEE Access*, vol. 5, pp. 8106–8117, 2017.
- [93] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, "Energy conservation in wireless sensor networks: A survey," *Ad Hoc Netw.*, vol. 7, no. 3, pp. 537–568, May 2009.
- [94] C. Yüksel, C. Minnecker, M. S. Shishvan, J. Benndorf, and M. Buxton, "Value of information introduced by a resource model updating framework," *Math. Geosci.*, vol. 51, no. 7, pp. 925–943, Oct. 2019.
- [95] D. Turgut and L. Boloni, "IVE: Improving the value of information in energy-constrained intruder tracking sensor networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2013, pp. 6360–6364.
- [96] I. S. Moskowitz, S. Russell, and N. Suri, "The value of information and the Internet of Things," in *Artificial Intelligence for the Internet of Everything*. Amsterdam, The Netherlands: Elsevier, 2019, pp. 145–169.
- [97] C. Malings and M. Pozzi, "Conditional entropy and value of information metrics for optimal sensing in infrastructure systems," *Structural Saf.*, vol. 60, pp. 77–90, May 2016.
- [98] J. Eidsvik, G. Dutta, T. Mukerji, and D. Bhattacharjya, "Simulation–regression approximations for value of information analysis of geophysical data," *Math. Geosci.*, vol. 49, no. 4, pp. 467–491, 2017.
- [99] M. Giordani, A. Zanella, T. Higuchi, O. Altintas, and M. Zorzi, "Investigating value of information in future vehicular communications," in *Proc. IEEE 2nd Connected Automated Vehicles Symp. (CAVS)*, Sep. 2019, pp. 1–5.
- [100] K. Chan, K. Marcus, L. Scott, and R. Hardy, "Quality of information approach to improving source selection in tactical networks," in *Proc. 18th Int. Conf. Inf. Fusion (Fusion)*, Jul. 2015, pp. 566–573.
- [101] A. Murad, F. A. Kraemer, K. Bach, and G. Taylor, "Information-driven adaptive sensing based on deep reinforcement learning," in *Proc. 10th Int. Conf. Internet Things*, Oct. 2020, pp. 1–8.



Faiga Alawad (Graduate Student Member, IEEE) received the B.Sc. degree in electrical and electronics engineering from the University of Khartoum, Khartoum, Sudan, in 2013, and the M.Sc. degree in computer science from the University of Milan, Italy, in 2018. She is currently pursuing the Ph.D. degree in information security and communications technology with the Norwegian University of Science and Technology, Trondheim, Norway. Her current research interests include machine learning and dynamic data collection.



Frank Alexander Kraemer (Member, IEEE) received the Dipl.-Ing. degree in electrical engineering from the University of Stuttgart, Stuttgart, Germany, in 2003, the M.Sc. degree in information technology from the University of Stuttgart, and the Ph.D. degree in model-driven systems development from the Department of Telematics, Norwegian University of Science and Technology (NTNU), Trondheim, Norway, in 2008. He is an Associate Professor with the Department of Information Security and Communication Technology, NTNU, and worked previously as a Technology Manager at a startup for IoT software that he co-founded. His current research interests include the Internet-of-Things architectures and application development, embedded and autonomous sensor systems, and the application of statistical methods and machine learning in constrained settings.