Dynamic Scenario-based Selection of Data Aggregation Techniques

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Abstract—**The Internet of Things introduces a new paradigm where small scale sensor devices can be used to capture data on physical phenomena. The potential scale of data that will be captured by such devices stands to transcend the capabilities of today's client-server architectures. The necessity to reduce the data volume has been reflected in enormous research interests dedicated towards developing new data aggregation techniques for sensor networks. However, the application-specific nature of data aggregation techniques has resulted in the development of a large volume of options, thereby introducing new problems of appropriate selection. This paper introduces a unique method to deal with this problem by proposing a classification approach for data aggregation techniques in wireless sensor networks. It presents the theoretical background for the selection of a set of high-level dimensions that can be used for this purpose, while a use case is presented to support the arguments. It also discusses how the dimensions dictate data collection procedures and presents how this framework can be used to develop an adaptive model for the dynamic selection of data aggregation techniques based on the characteristics of a sensing application use case.**

Keywords–Internet of Things; Wireless Sensor Networks; Big Data; Data Aggregation; Adaptive Model.

I. INTRODUCTION

Sensor devices consist of physical devices that have sensor capabilities to capture data on selected phenomena. Examples of such phenomena include weather conditions and city pollution. They host a limited source of power, networking and memory. A combination of such devices forms a Wireless Sensor Network (WSN), which can be deployed into various environments to sense and track various forms of phenomena [1]. WSNs are especially applicable to scenarios where the environment is not conducive for human habitation, such as in earthquake, tsunami or tornado events, or in continuous monitoring situations such as city carbon monoxide pollution or for weather monitoring. Due to the characteristics of such scenarios, implying that they may never be repaired or maintained, they need to manage their processing in order to extend their internal power supplies [2], [3], [4]. In order to ensure this, the generated data needs to be accumulated and reduced in size before transmission to a base, a process referred to as data aggregation. Data aggregation becomes possible because most sensor deployments keep sensors in close proximity for communication purposes. This leads to sensors capturing similar data, which become duplicates when transmitted. Thus, the goal of a data aggregation technique is to reduce the data duplication and perform further data compression, before transmission [5], [6]. This task has also drawn much attention due to the emerging Internet of Things (IoT), where a multitude of physical objects will be equipped with sensors and networking capabilities [7], [8], [9], [10].

Data aggregation techniques need to be application-specific to manage power consumption efficiently [3], [7], [11]. This has led to the proposal of a large number of techniques for various application scenarios, thus leading to a large pool of options. Selecting the right technique for the right scenario becomes a challenge, especially for researchers [12]. This challenge becomes amplified in the IoT, where sensors would be expected to have some form of self-organization.

This paper presents a proposal for a unique classification method for data aggregation techniques used within WSNs. It identifies a set of dimensions that can be used to classify the different operational stages of a data aggregation technique. The term Dimensions in the context of this study is used to represent a high level identifiable feature of a WSN technique. It serves as an encompassing term for several low granularity characteristics. Under these dimensions, the WSN characteristics that are important for a technique, such as node homogeneity, node count and location awareness, are associated with the technique and referred to as its attributes. Several selected techniques are matched with their attributes to compile a database of associations. These data will be used to build a model to utilise the correlation to dynamically classify techniques based on application characteristics and thus, provide a recommendation in the form of one or more techniques [13], [14].

The remaining of the paper is organized as follows: Section II presents the background to our study. Section III presents a use case scenario that will serve as a reference point for our discussions. Section IV discusses our proposed method. Section V presents our evaluation plan and Section VI provides a conclusion and discusses our next steps.

II. BACKGROUND

A. Wireless Sensor Networks and Data Aggregation

Distributed data aggregation involves the decentralized computation of significant properties within a network that can be utilized by applications . Examples include the average workload distribution across the network or the number of nodes active on the network. Such a task is especially applicable within a WSN, where the aggregation or compression of data is based on the several network-based parameters such as node location, distribution and resource distribution

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TABLE I. LIST OF VARIOUS CLASSIFICATION APPROACHES

Article & Author	Dimensions used for classification
A Survey of Distributed Data Aggregation Algorithms [6]	Data aggregation function types (e.g. duplicate sensitive and duplicate insensitive); Communication requirements; Routing protocol; Network Type (e.g. structured-hierarchical, unstructured-flooding/broadcast, etc.)
Data Aggregation in Wireless Sensor Networks: Previous Research, Current Status and Future Directions [12]	Topology type; Objective
Practical data compression in wireless sensor networks: A survey [16]	Energy efficiency
A Taxonomy of Wireless Micro-Sensor Network Models [17]	Communication function; Data delivery model; Network dynamics with respect to power demand
Issues of Data Aggregation Methods in Wireless Sensor Network: A Survey [18]	Strategy; Delay; Redundancy; Accuracy; Energy consumption; Traffic load
Data-aggregation techniques in sensor networks: A survey [19]	Network lifetime; Latency; Data accuracy; Security
A survey on sensor networks [20]	Protocol layer

[6], [15]. Researchers have in the last decade, proposed numerous techniques for data aggregation dedicated to unique WSN scenarios. The volume of options has grown to such unmanageable proportions and presented a new challenge of selecting right technique for the right application. This has motivated other researchers to propose classification methods for the various options.

B. Classification Approaches

While most technique classification approaches are based on surveys, they have selected a set of WSN characteristics to guide their classification method. Some approaches identified in literature are listed in Table I.

Table I presents the classification approaches taken by several researchers. The right column shows the various WSN characteristics used as yardsticks in the classification process, which provide a reliable means of evaluating the techniques. The following observations can be made: a group of WSN techniques, which have optimised certain characteristics to achieve efficient data aggregation, have been compared by the authors based on those characteristics; based on the approach taken by the authors, minimal effort has been applied to establishment of correlations between two or more techniques. In contrast to these, this paper proposes a uniquely different approach. We identify dimensions to enable us classify WSN characteristics within the scope of data aggregation. The dimensions will allow us to develop correlations between techniques and their attributes. For example, the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol [21] utilises an algorithm, random cluster head rotation, in order to evenly distribute energy consumption accross all nodes. This algorithm would be categorized under a dimension, referred to as *Algorithms*, and associated with the LEACH technique as an attribute. The association of attributes to techniques will help us to compare and contrast them with similar techniques, as well as to relevant application scenarios. This strategy also enables us to explore opportunities for new approaches to data aggregation [22]. The next section discusses the theoretical background of the identified dimensions.

C. Dimensions

The top goals of a data aggregation technique as used in a WSN include the minimization of energy consumption, latency, bandwidth, and the extension of network lifetime. In order to achieve these goals, a data aggregation technique needs to closely match the target application scenario. To develop a model that will enable this functionality, there is need to develop a classification method to identify appropriate techniques based on the use case. This approach involves the definition of a set of dimensions into which WSN characteristics can be classified. Afterwards, the characteristics can be associated with techniques. In summary, we identified seven dimensions namely: *Assumptions*, *Objectives*, *Specifications*, *Algorithms*, *Applications*, *Performance Metrics*, and *Evaluation*. While the dimensions are expected to follow an order as presented, a subject that is expatiated further in a later section, the theoretical background for their identification is presented in the following paragraphs.

Most WSN applications have inherent constraints that are determined by their topology, network structure and acceptable communication channels. For example, a wildfire event demands that sensors are deployed after the event has started, and that sensors are well protected and have similar characteristics in order to obtain reliable data. Within literature, such constraints are stated as assumptions. For instance, in [23] assumptions are made about sensor nodes having a single sensor, while the network consists of a single cluster. In [24], the authors highlight the need for nodes to have prior knowledge of the network-wide data correlation structure. In [2], the authors specify that all nodes use a fixed compression factor. We selected the term *Assumptions* as one of our dimensions based on further literature review. Within our context, we therefore define *Assumptions* as the set of pre-conditions under which a technique must operate. Thus, the variables representing assumptions are considered immutable during the operation of the technique.

After a realization of the constraints of the application context, identified as assumptions of the technique, the objectives of the technique can be stated. In [24], the authors define the application context in which their objective of “solving the Slepian Wolf coding problem” can be realized. In [25], the authors state their objective as “Efficient Cluster Head Selection Scheme”, while also defining the context in which the objective will be realised. In [26], the authors state their objective, based of group communications in multiple target scenarios, thereby implying the constraints. This essentially motivated us to select *Objective* as a high-level dimension to use in our classification process.

On identifying the constraints and objectives of the technique, a set of parameters are selected. Such variables are considered mutable and used to optimize the technique. In this paper we refer to such variables as *Specifications*. Such variables have been used extensively in literature on data aggregation. For instance, [23] emphasise the need to specify appropriate number of nodes in their technique to apply the K-means algorithm. [26] proposed an algorithm, the Two-Tier Aggregation for Multi-target Apps (TTAMA), which is expected to be aware of the communication settings of nodes in order to effectively perform aggregation. [27] use node count in the network to adjust the response of their technique based on the objective to develop a low-cost topology construction al-

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gorithm. In conclusion, we define a technique's *Specifications* as the parameters that can be modified during the operation of the technique, and thus, are applicable for optimization.

With the combination of the assumptions, objectives and specifications, the technique requires a set of algorithms to perform its functions. Essentially, a data aggregation technique achieves its objective based on selected algorithms. For instance, the Shortest Path Tree [28], Minimum Spanning Path [29], and use of Euclidean Distance [30]. In [28], the authors combined the sleep and awake algorithm, with a threshold-based control system to apply adaptability to their technique. [31] proposed a structure-free protocol to aggregate redundant data in intermediate nodes to dynamically compute the data transmission delay for nodes based on their position. In [32], a framework to enable decentralized data aggregation was developed by using a routing algorithm based on a gossip protocol. In [33], the authors developed a gossip-based decentralised algorithm for data aggregation that relies on crowd-sourced data and computational resources. In this paper, we have thus, selected *Algorithms* as a dimension.

After the last four dimensions, a simulation is essential to generate data that can be used to validate that the technique has met its objectives. This strategy is demonstrated by many proposals from literature [26], [28], [34]. We identify this step as a dimension called *Application*, since it represents the running of the technique in a given use case.

After the simulation, the technique can be evaluated based on generated data. In our classification approach, we have identified two more dimensions to cater for this: *Performance Metrics*, and *Evaluation*. We define the *Performance Metrics* as the selected attributes of a technique that can be used to evaluate its performance. These are expected to relate directly to the set of objectives and specifications as discussed earlier [12]. For instance, authors in [35] selected metrics such as energy dissipation over time, data received over time, and node lifetime over time, in order to compare the LEACH and LEACH-C techniques. In [28], in order to evaluate the Adaptive Energy Aware Data Aggregation Tree (AEDT) technique, which targets extending network lifetime, the authors selected metrics such as average end-to-end delay, average packet delivery ratio, energy consumption and network lifetime. Similarly, in evaluating the TTAMA technique [26], the authors selected number of communication rounds and node energy level after each round.

The dimension termed *Evaluation* has been chosen to represent the values that can be used to compare techniques based on their performance. Thus, *Evaluation* holds the results of *Simulations* and *Measurements* with respect to the *Performance Metrics*. It is hoped that a generalized reference point can be developed to be utilized in the comparison of techniques using the values under this dimension.

III. Contribution

Our contribution in this paper includes the proposal of a unique classification approach for data aggregation techniques as used in WSNs. These dimensions will enable the classification of techniques based on selected WSN characteristics. The dimensions will be used to develop an adaptive model that will enable the dynamic selection of techniques based on the context. From an academic perspective, such a model would enable researchers to identify relevant and related characteristics of different techniques and their applicable scenarios. It also enables a researcher to strategically select a technique based on a set of characteristics representing a target application scenario.

IV. Use Case Description

We present a use case in this section to serve as an illustration for further discussions. Wildfires are a frequent occurrence in summer weather, where high temperature levels remain persistent in the midst of low humidity [36]. They present a situation where several uncontrolled events lead to tremendous damage if left unabated. In order to monitor the wildfire event, the value of a few context-based parameters need to be known. For example, in order to detect the movement or direction of the fire, it is necessary to observe the temperature distribution in the region in real-time. This will require frequent sensing of temperature levels as the fire moves across the region. In order to ensure that the nodes can continue to provide this data, they could be made homogenous, implying that they have similar computing, sensing or power capabilities. This reduces the inherent complexity of calculating approximate temperatures since only an average need be obtained across all nodes on a frequent basis. This demonstrates the necessity for the right data aggregation technique to be chosen for a given scenario. The selected technique must be able to obtain accurate values for the network-wide resource distribution and application context parameters such as the need for real-time frequent sensing.

The above scenario represents one out of numerous use case scenarios. While a huge number of techniques have been proposed in the past, there remains the possibility that one or more use cases have not been catered for. The IoT in conjunction with new 5G services is especially expected to provide new use cases that have not been considered yet. This underscores our proposal for the need to develop an adaptive and dynamic model for data aggregation techniques. Such a model can be used to assess current and new application contexts, to select the right data aggregation techniques and procedures, as well as establish new approaches for new scenarios.

V. Proposed Method

A. Framework Development

Based on the foregoing discussions, Figure 1 presents the workflow across the mentioned dimensions. We discuss the diagram with respect to the numbering of the paths. A data aggregation technique is developed for a particular set of *Objectives*. However, before these objectives can be realised, the application context constraints must be identified. This relationship is identified by line 1. Once the objectives are stated, they should be validated when the technique is applied to a use case. This is possible by selecting appropriate parameters that can be used to represent the objective. For instance, a technique targeting energy reduction needs to select energy consumed, etc., as an evaluation metric. In order to effectively use this parameter for evaluation, its value needs to be adjustable in order to compare different states of the technique's operation. The set of parameters that will enable this adjustment fall into the *Specifications* dimension of the technique. These relationships are represented on paths 2 and 7. On selecting the specification parameters and stated

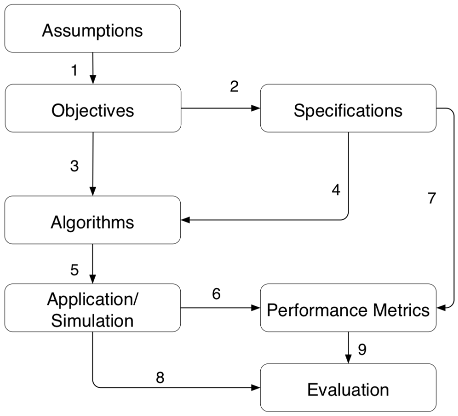

Figure 1. Links/workflow between the various high-level dimensions

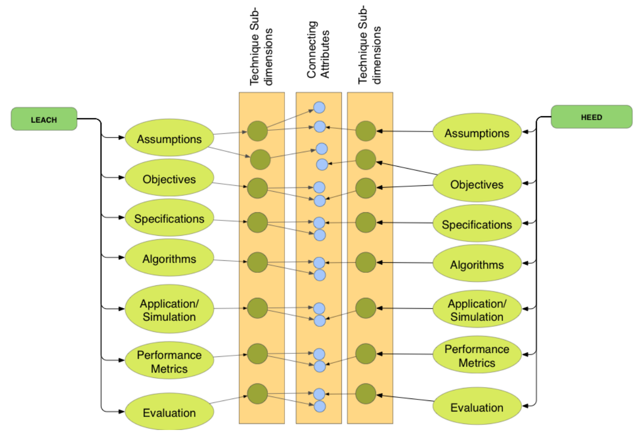

Figure 3. Illustrating how high-level dimensions enable identification of correlations between two data aggregation techniques

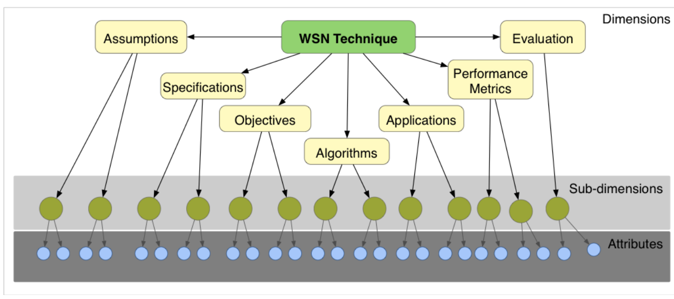

Figure 2. Representation of hierarchical dimensions that enable the categorization of technique characteristics

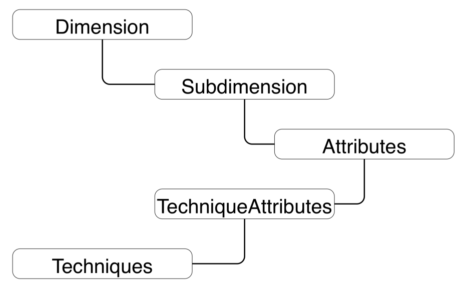

Figure 4. Database structure for storage of technique attributes

objectives, a group of *Algorithms* (paths 3 and 4) are applied to implement the technique. Parameters under the foregoing dimensions can then be used to develop a simulation of the technique for a specific application, represented as path 5. The application (simulation) will generate data that can be used to validate the objectives by applying the *Performance Metrics* (path 6). The results obtained from applying the metrics to the application would provide the *Evaluation* results (path 8 and 9).

Figure 2 represents the full illustration of a WSN technique based on our proposed framework. It shows a hierarchy with three levels, specifying levels on which a technique can be defined. The top level is referred to as *Dimensions*. The second level, named *Subdimensions* provides a categorization function for the set of characteristics. The third level, called *Attributes*, represents the WSN characteristics.

A further illustration of how this framework can be used to identify the relationship between two techniques is shown in Figure 3. In this case, the techniques LEACH [21] and HEED (Hybrid Energy-Efficient Distributed) [3] are chosen as sample techniques. Their associated attributes are used to build an association between the two enable a process of matching the techniques. In Figure 3, the middle column with blue circles represents the commonly shared attributes between the two techniques. For instance, both techniques, i.e. LEACH and HEED, share the attribute *homogeneous network*, a characteristic that falls under the *Assumptions* dimension. This creates an association between the two techniques.

B. *Data Collection*

Based on the defined framework, data needed to be gathered from sources that could provide primary descriptions for new data aggregation techniques. Based on this, the primary source of data were academic articles on data aggregation techniques, supported by books that discussed data aggregation in WSNs. The framework was used as a guide to select values for the attributes, and to build the subdimensions. Figure 4 shows the database structure that was used to store the data. The boxes represent the tables in the database, while the lines between them indicate that they share foreign key relationships.

Presently, the number of techniques stored is 125, while 7 dimensions, 132 subdimensions, and 385 attributes have been identified. An example of a technique "signature" based on the content of the database is shown in Table II represented in JSON format.

VI. Model Design and Evaluation

Some analysis of the data already stored within the database is shown in Figure 5. It represents the currently identified correlations between techniques and their attributes. The x axis holds a number for each attribute, while the y axis shows the total number of techniques that have the same attribute. Figure 5 presents a high level visualisation of the correlation between techniques and attributes.

Figures 6 and 7 depict the preliminary plan for the architecture of the model, indicating the expected input and

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TABLE II. JAVASCRIPT OBJECT NOTATION (JSON) REPRESENTATION OF A TECHNIQUE BASED ON THE DEFINED FRAMEWORK

LEACH {
assumptions: [“homogenous initial energy”],
objectives: [“Extend Network Lifetime”],
specifications: [“2-Stage Operation”, “Centralised Control”, “Periodic Sensing”],
algorithms: [“stochastic election”, “TDMA Timing”, “Code Division Multiple Access”, “Uniform Initial Energy”, “Cluster Formation by Associates”],
performance_metrics: [“network lifetime”],
application: [“base in proximity”, “packet size”, “network size”, “node count”, “radio propagation power”],
evaluation: [] }

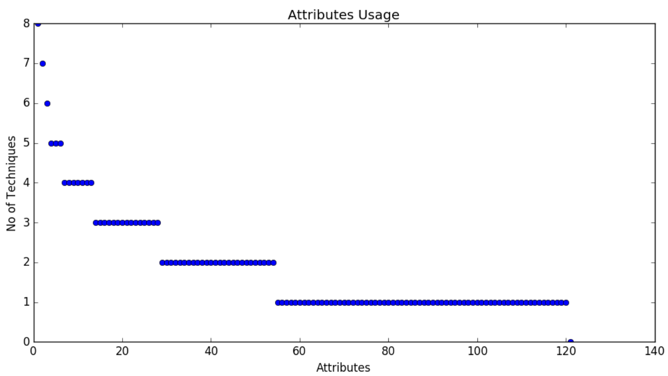

Figure 5. Technique-Attributes correlations graph based on the data stored within the database

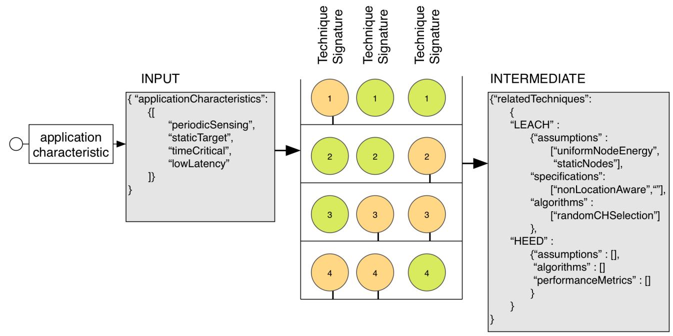

Figure 6. Preliminary plan for an advanced stage of the model — first part

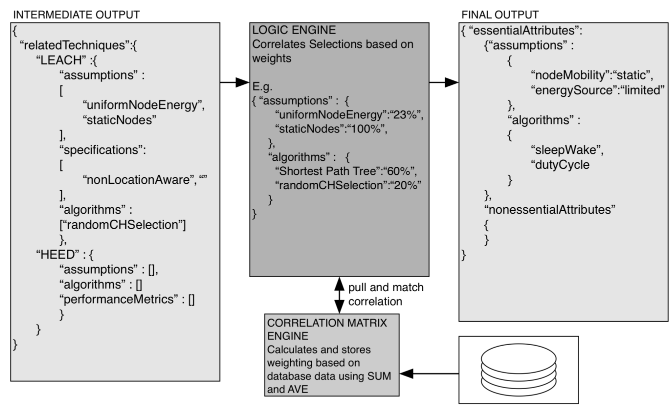

Figure 7. Preliminary plan for an advanced stage of the model — second part

output formats. The figures present a single use case scenario where application characteristics serve as the input data. The term “technique signature” is used in Figure 6 to indicate that a set of attributes can be used to uniquely distinguish a technique from another, otherwise referred to as its signature. Figure 6 indicates that the input is expected to be in JSON and should describe the request based on a format that will need to be determined. Each circle represents a single attribute, such as location awareness. Thus, a combination of circles arranged vertically represent a single technique’s set of attributes and is referred to as a “Technique Signature”. A technique signature is expected to uniquely distinguish a technique. The group of 3 shown in Figure 6 represents a larger collection of techniques that are used at this stage to compare and match input requirements with stored or learned correlations between techniques and attributes. Thus, this stage could be implemented as an Artificial Neural Network. The input will consist of a specification describing the application scenario and set of requirements. The output will consist of a recommendation of a technique or a combination of techniques applicable to the given scenario. Figure 7 represents the stage that receives the output from Figure 6, where the output is validated based on prior learning. The output from this next stage provides the expected output from the model. The design will be improved upon as we progress.

VII. CONCLUSION

In this paper, we have presented a design of our proposal for an adaptive model that is able to dynamically select data aggregation techniques based on application context metadata. This capability finds utilization in the emerging Internet of Things where the number of active sensors, and subsequently the generated data, is expected to grow exponentially. We intend to improve on the output shown in Figure 5 by obtaining more data, while ensuring that the data is consistently cleansed to make it suitable for its purpose. We will then apply machine learning to the final data in order to develop the adaptive model. A set of use cases will be developed to test the model to ensure its effectiveness.

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